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Influence of daylight on real estate housing prices. A multiple regression model application in Turin

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ABSTRACT

Daylight is crucial in architecture, influencing human health, well-being, energy efficiency, and the post-COVID-19 perception of residential spaces. People often consider daylight among the most important features when buying a home, which potentially affects real estate asset pricing. Within this framework, this study explored the impact of daylight on real estate asset pricing, particularly focusing on its role in the Italian market. The research employed two approaches: (i) simulations of 100 units to determine a large set of daylight metrics and (ii) a statistical approach, applying Hedonic Analysis principles to investigate how house attributes influence pricing. A data sample of 100 housing units was selected in Turin (Italy), including variables such as location, floor area, construction year, façade type, and daylight metrics. By using Multiple Regression Analysis, after Exploratory Analysis and outlier management, we identified significant variables influencing housing listing prices, such as energy class, conservation status, elevator presence, terraces/balconies, and frame type. Notably, two daylight metrics (annual sunlight exposure and useful daylight illuminance) were found to be significant, while others, like average daylight factor and spatial daylight autonomy, were not. The final model was validated by means of a control sample, demonstrating the relevance of daylight in real estate pricing. This research contributes to the literature, providing an in-depth exploration of the impact of daylight on hedonic analysis in a relatively underexplored research space. Precisely, the work contributes to bridging the literature gap about the detection of the influence of daylight on real estate market pricing processes by means of regression analysis.

1. Introduction

It is widely acknowledged that daylighting in residential buildings holds a pivotal role in shaping not only the physical environment but also the well-being of occupants. Beyond mere lighting, the strategic integration of natural light contributes to several benefits, ranging from physiological health to energy efficiency. This particularly fosters sustainable and human-centric living spaces regarding several aspects [1–10]: first of all, exposure to daylight has profound effects on human health, particularly in residential settings where people spend a significant portion of their time; daylight helps regulate circadian rhythms, thus influencing sleep patterns and overall physiological well-being in terms of improved mood, increased productivity, and reduced stress levels. Besides, adequate daylighting

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enhances visual comfort by providing a balanced and dynamic light environment, reducing eye strain, supporting visual performance, and enhancing the perception of space; in dwellings where users engage in a variety of activities, from work to leisure, optimizing visual comfort through daylighting positively impacts the overall quality of life. Another aspect concerns energy efficiency: daylighting is a sustainable design strategy that reduces the reliance on electric lighting during daylight hours, with reduced utility bills. Moreover, integrating daylight into residential spaces establishes a tangible connection to the outdoors; access to daylight allows occupants to experience the changing patterns of daylight, weather conditions, and time going by, with an increased satisfaction and a sense of well-being for residents. Finally, daylighting enhances the aesthetics of residential interiors, creating visually appealing spaces that evolve throughout the day; well-lit spaces tend to appear more spacious, welcoming, and aesthetically pleasing, which are features that are especially important in residential settings in terms of contribution to a positive living experience.

Daylighting is also known as a driving force for the value and marketability of real estate properties: dwellings with well-designed daylighting are often more attractive to prospective buyers. The emphasis on daylight is a sought-after quality in the real estate market, and daylighting can enhance the resale value and marketability of residential properties [11]. The presence of daylight plays a role not only in terms of architectural and aesthetic quality, which is highly appreciated by consumers and capable of influencing their willingness to pay, but also in terms of the potential to generate consumption savings. This is in accordance with a growing consumer awareness regarding economic-environmental issues in response to the environmental policies.

Last but not least, it is worth emphasizing that in recent years, particularly after the COVID-19 pandemic, there has been a shift in perspective towards dwellings. The prolonged lockdown periods have altered people's mobility patterns by decreasing outdoor social interaction and increasing the time spent at home for work and personal life. Consequently, an increased value has been attributed to ambient quality aspects such as indoor daylighting, balconies, and terraces, providing residents with spaces to spend time outside the indoor residential space [12,13].

Therefore, daylight emerges as a highly valued feature for individuals, at both a conscious and a sub-conscious level; for this reason, it is frequently highlighted as one of the pivotal factors influencing decisions related to purchasing or leasing an apartment. Notably, terms associated with daylighting, such as 'bright', 'panoramic', 'excellent view', are commonly featured in the text of advertisements as especially attractive attributes. It seems that daylight can play a crucial role in determining prices in the real estate market: in a previous study by the authors, the participants in a survey mentioned daylighting as the first aspect they consider when deciding to buy a new house [14].

1.1. Problem statement

While the significance of daylighting in both the residential and non-residential indoors is widely acknowledged, establishing a direct link between the amount of natural light and the pricing of an apartment proves to be challenging: there seems to be a research gap in translating the social benefits of daylight into economic value as a marginal contribution to the listing price and what dwellers are willing to pay. To the authors' knowledge, this topic has been rarely addressed in the literature, especially for residential buildings. A limited literature can be traced also in relation to other segments of the building sector. Among the few examples, an interesting experiment is contained in two studies by Turan et al. [15,16] on office spaces in Manhattan, New York. A database of 5154 offices was analyzed to investigate the impact of daylight on office rent by determining the marginal value of daylight [16], as well as the correlated impact of the view to the outside [15]. As for daylighting, the findings showed that "*occupied spaces with access to high amounts of daylight (as measured by over 55 % spatial daylight autonomy) have a 5–6% value premium over occupied spaces with low amounts of daylight (as measured by less than 55 % spatial daylight autonomy)*". As for the view, the analysis showed that "*spaces with high access to views have a 6 % net effective rent premium over spaces with low access to views. This financial impact is independent of other value drivers like daylight*". Another study was carried out by Zhong et al. [17]: they empirically studied the non-marketed value of sunlight with respect to the view orientation of an apartment in the context of the housing market by analyzing over 40,000 transactions in Shanghai, China. They observed that homeowners, on average, are willing to pay an extra 7.2 % for apartments with high direct solar exposure (located on top floors or facing South versus facing North).

1.2. Research goal

Within this framework, the study aimed to highlight the importance of daylighting for a higher quality of life and investigate its monetary value in the real estate market, in terms of marginal price. The research employs data sampling, utilizing both qualitative and quantitative data, and employs Multiple Regression Analysis to quantify the monetary value of the marginal contribution of daylight. Note that listing prices are used in the study, as in Italy – as will be stressed in the Discussion section of the paper – it is difficult to obtain selling prices, the latter being non-public information. Thus, as consolidated in the literature, listing prices are analyzed as a proxy of selling prices [18–21].

Overall, the paper seeks to bridge the gap in understanding daylight and its significance, especially within the real estate sector. In more general terms, the work aims to contribute to orienting sustainable architectural design, from the earliest stages onward, assuming an economic-environmental-social sustainability concept. It also aims to support decision-making processes involving private developers in their investment choices or public subjects in the definition of governance policies and regulations.

Based on these premises, the main research questions were set as follows: "*Can the impact of daylight be properly monetized in terms of marginal contribution in the real estate dwelling pricing process?*" "*Which are the most significant metrics in modeling daylight contribution to real estate property pricing*?"

With this aim, the Authors present an application of the Hedonic Analysis, through the Multiple Regression Model, focusing on the daylighting attribute measurement by means of specific simulations. The process is applied to a case study, examining a sample of the real estate market in Turin, Northern Italy (latitude: 45°N). The relationship between daylighting and the price of the apartments is analyzed, particularly by aiming to identify which daylight metrics can be significant in an estimation model that can be built through regression techniques [22].

2. Daylighting metrics in legislation and regulations: the situation in the Italian context

At an international level, daylighting research has evolved in the direction of the so-called climate-based daylighting modeling (CBDM). Several metrics were introduced and have become the reference for daylighting analyses and are the reference for some projects also in Italy. A first reference in this regard is the LEED protocol v4.1, 2023 [23], which contains a daylighting credit that relies on spatial daylight autonomy $sDA_{300.50\,\%}$ and annual sunlight exposure $ASE_{1000.250h}$ [24]: 1 point is attributed to spaces with $sDA_{300.50\,\%}>40$ %, 2 points to spaces with $sDA_{300.50\,\%}>55$ %, and 3 points to spaces with $sDA_{300.50\,\%}>75$ %; in every case, the points are attributed in combination with $ASE_{1000.250h}<10$ % through the use of movable shades.

Another reference is the EN 17037:2018 'Daylighting in buildings' [25], which includes different daylighting analyses, such as: (i) a 'climate-based' daylight factor, whose target values are set as a function of the median diffuse horizontal illuminance measured year-round at the specific location considered; (ii) a space fraction with a target illuminance level: 50 % of each regularly occupied space must receive at least 300 lx, 500 lx, or 750 lx for a performance that is labeled as 'minimum', 'medium', and 'high', respectively; and (iii) view top the outside, categorized into three layers: sky, landscape, and ground, each contributing different types of information. The quality of the view depends on factors such as the size of the opening, angle of vision, number of layers, and distance from the external view. The classification of view-out quality is based on the visibility of different layers, with a preference for a wide and distant view. According to the standard, 75 % of a regularly occupied space must have a horizontal view angle through the openings higher than 14° and one layer, higher than 28° and two layers, and higher than 54° and all three layers for a 'minimum', 'medium', or 'high' performance, respectively.

Finally, the metric 'useful daylight illuminance' UDI, introduced by Nabil and Mardaljevic [26], belongs to the set of CBDM metrics.

With particular attention to the Italian context, daylighting is primarily ruled by the two Legislative Decrees: the first one is the Legislative Decree issued by the Ministry of Health on July 5, 1975, on residential buildings [27]: it set that adequate daylight is mandatorily required for all rooms except for toilets, corridors, staircases, and storage rooms; according to Article 5, the window area must be proportionate to ensure an average daylight factor (DF_m) over 2 %, while the openable window surface must exceed 1/8 of the floor surface (window-to-floor ratio $WFR = S_{window,\ openable}/S_{floor} \geq {}^{1}/_{8}$) for each living space; such '1/8 rule' is an empirical criterion used in several other countries (with modifications into a '1/10 rule'), whose scientific evidence is unclear [28], but which has become quite popular among professionals [29]. More recently, another Legislative Decree was issued by the Ministry of Environment [30] on minimum environmental criteria (CAM) on October 11, 2017: this sets minimum environmental criteria for new constructions, restoration, and maintenance of public buildings. It confirms the previous requirement for daylighting and ventilation in terms of $DF_m > 2$ % in all regularly occupied spaces and $WFR > {}^{1}/_{8}$. In June 2022, a new version of the CAM was issued by the Ministry of Ecological Low-carbon Transition [31]: this also included dwellings and adopts the approach set in EN 17037, by imposing that at least 50 % of the regularly occupied space in a room exceeds 300 lx for at least half of the daytime hours.

In the context of Turin, the Municipality issued a local regulation, where daylighting is addressed among the factors that contribute to increasing the energy-environmental quality of a building [32]. It includes mandatory and voluntary requirements and promotes the application of its recommendations through a tax reduction system. Daylight is included in the voluntary requirements only, along with summer shading and winter radiation of the glazed surfaces. The metric used is the average daylight factor, but with increased minimum target values, claiming for a performance of $DF_m > 3$ % to get a 3-point credit or $DF_m > 4$ % to get a 5-point credit.

3. Method

The workflow of the research relies on different steps, as illustrated in Fig. 1.

In detail.

STEP 1: Literature review. Research on the state of the art was carried out to acquire the basic theoretical aspects in both fields, on the one hand on the importance of daylighting for the well-being of humans and the understanding of related indicators and legislations, on the other hand on the use of simple and Multiple Regression techniques for the construction of an estimation model

STEP 2: Case study identification. The 'Pozzo Strada' district in Turin was chosen as a suitable area for analysis. This urban zone aligns with a specific real estate submarket identified as the 'D7 - Pozzo Strada' zone in OMI geo-databases. It is further sub-divided into three historical sub-micro-zones named Rivoli, Monte Cucco-Bardonecchia, and Ruffini. Comprehensive listings were accessed for each of these sub-areas during the period October–December 2022

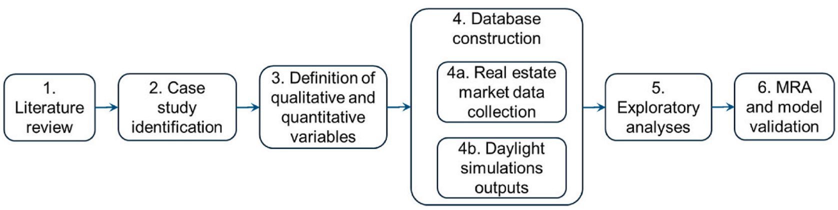

Fig. 1. Methodological workflow.

STEP 3. Definition of qualitative and quantitative variables related to four macro-aspects: (i) extrinsic variables, related to the context; (ii) intrinsic variables; (iii) energy efficiency-related variables; and (iv) daylight-related variables. For each variable, a relevant set of categories was established to characterize the data sample apartment units

STEP 4: Database Construction. The final database was assembled, integrating data from the sample of 100 units and the results of daylighting simulations:

STEP 4a: Real estate market data collection. A sample of 100 condominium apartments was collected within the specified timeframe, following predefined criteria. These criteria excluded apartments on the ground floor, attics, lofts, and other special building categories, with listing prices not including shared or private garages. Certain variables, such as price, surface areas, address, floor, and photos, were mandatory, while others were optional

STEP 4b: Daylight simulations outputs. To calculate the daylight-related variables, 3D models of the 100 selected units were created using floor plan images from the advertisements and a GIS city map provided by the Municipality of Turin. These 100 3D models were used to run daylighting simulations through the validated software ClimateStudio. All simulation results were categorized in quantitative terms.

STEP 5: Exploratory analyses. Iinitial investigations involved descriptive statistical measures and graphical representations to identify patterns, trends, outliers, and potential correlations within the dataset. Such analyses were the basis for a more in-depth examination of the relationships between various factors and real estate pricing in the subsequent stages of the study

STEP 6: Multiple Regression Analysis (MRA) and model validation. A Multiple Regression Analysis (MRA) was conducted by randomly selecting 90 units from the database. The process relied on selecting one dependent variable and iteratively adjusting explicative variables until the final model was not established. Rigorous refinement ensued, ensuring that all variables in each model were both significant and uncorrelated. The final model revealed the price per square meter as the resultant independent variable, driven by the identified significant variables. As a last step, the model efficacy was assessed using data from the 10 units not utilized in its construction. This validation step aimed to scrutinize the model's ability to accurately predict prices by comparing predicted values against the actual prices of these 10 units.

3.1. Daylighting simulation

The first phase of the data sampling process involved the spatial modeling of the Pozzo Strada area. This was achieved by partitioning the zone into three distinct files, corresponding to the sub-micro-zones of Rivoli, Monte Cucco-Bardonecchia, and Ruffini. The Geo-portal of Turin was used, which offers city mapping in SHP (shapefile) format, providing essential information such as the construction year of buildings, the number of floors, and the total height. Revit was employed to import the file, utilizing building outlines for accurate location and size determinations, subsequently cross-verified via Google Maps. To factor in potential obstructions, trees were later incorporated based on observations from Google Maps views. This comprehensive approach ensured a thorough and precise dataset for the study.

The following step consisted in individually modeling each apartment selected for the database. Real estate photos and interior images from online advertisements served as the basis for modeling each unit in Revit. Given the absence of measurements in many floor plans, scaling was achieved by referencing the city outline provided by the Geo-portal. This approach allowed the creation of 3D models that accurately represented windows, wall thickness, height, internal doors, openings, and balconies or terraces. This meticulous process ensured that the models were a reliable representation of the physical characteristics of the buildings.

All 3D models were then imported into Rhino 7 to assign materials and run simulations using the plug-in ClimateStudio-for-Rhino.

Table 1
Opaque materials and visible reflectance R_v. Transparent materials (glazing) and thermal transmittance U-value, visible transmittance T_v, and global solar transmittance g-value.

Element	Radiance material from ClimateStudio library	Value
OPAQUE MATERIALS		
sidewalk	(concrete)	R_v = 15.3 %
street	(asphalt)	R_v = 12.3 %
surrounding buildings	floor: 30 % reflectance	R_v = 30 %
grass	grass: 7.4 % reflectance	R_v = 7.4 %
apartment ceiling	ceiling: 70 % reflectance	R_v = 70 %
apartment wall	wall: 50 % reflectance	R_v = 50 %
apartment floor	floor: 30 % reflectance	R_v = 30 %
apartment window and door frames	wall: 50 % reflectance	R_v = 50 %
apartment railing	(balconies/terraces)	R_v = 39.8 %
apartment roof	floor: 30 % reflectance	R_v = 30 %
TRANSPARENT MATERIALS		
single pane glazing	clear: 87.7 % transmittance	T_v = 87.7 % g-value = 81.8 % U-value = 5.82 W/m^{2}K
double pane glazing	clear Solarban (Argon): 87.7 % transmittance	T_v = 70 % g-value = 46 % U-value = 1.34 W/m^{2}K
woven blinds with a 6.6 % clearance	sheer weave 2390 + V22 charcoal grey	T_v = 7.2 %.

Caption: R_v: light reflectance [%]; T_v: light transmittance [%]; g-value: global solar transmittance; U-value: thermal transmittance [W/m^{2}K].

ClimateStudio is a validated professional tool for daylighting and energy analyses developed by Solemma, founded by Christoph Reinhart [33].

The material properties that were assumed are listed in Table 1.

It is worth pointing out that all the materials and colors were standardized for all the units, and the furniture was not modeled. Similarly, all glazing and blinds were assumed to have the same light transmittance value, simply distinguishing single-pane glazing from double-pane glazing. This was done to remove the material variability among the 100 units selected and to focus on the other variables that can have an impact on the formation of the price in the real estate market. As for the control logic to operate blinds, the one defined in the IES-LM-83-12 [24] was assumed: for each hour of the year, if more than 2 % of the occupied area received direct sunlight (defined as more than 1000 lux directly from the solar disc, including the glazing visible transmittance but excluding all reflections outside and inside the building), the blinds were operated (closed) until less than 2 % of the room area was sunlit.

As a final step, the Radiance simulation parameters were set (particularly assuming ambient bounce ab = 6 and ambient sampling ab = 64), and an occupancy profile was chosen: units were assumed to be occupied every day, from h8 until h18, resulting in 3650 h/year, according to the occupancy profile set in the IES-LM-83-12 document [24] and in the LEED verification process for the calculation of sDA and ASE metrics [34]. Daylighting simulations were eventually run for each unit, focusing on the regularly used spaces (kitchen, living rooms, bedrooms), while bathrooms, halls, corridors, and distribution spaces were excluded. A grid of calculation sensor points was created in each selected room: this covered the whole room area and was set 80 cm above the finished floor, with a spacing of 25 cm. The following daylight metrics were simulated at each sensor point: DF_m, $sDA_{300,50\ \%}$, $ASE_{1000,250h}$, $UDI_{fell\text{-}short}$, $UDI_{achieved}$, $UDI_{exceeded}$, E_m, frequency of use of blinds in the closed position, view, plus vertical sky component (VSC) on façade centers [35]. As for the view, the software calculated the horizontal angles under which windows were seen at each sensor point of the grid to then check if these angles were compliant with the specification set in EN 17037:2018.

The definition and the meaning of each daylight metric is reported in Table 2. It is worth mentioning that daylight has three main components: direct (from the sun, commonly referred to as 'direct sunlight'), diffused (by the sky dome, commonly referred to as 'diffuse skylight') and reflected (both off exterior surfaces such as building façades or the natural landscape, and inside the room considered): a metric can address a specific component rather than overall daylight.

3.2. Ordinary least regression

Spatial regression models serve as powerful tools for both descriptive insights and predictive analyses to comprehensively assess the influence of various building and housing characteristics on property prices. Exploratory Data Analyses (EDAs) were initially employed to uncover potential spatial autocorrelation and linear correlation among the variables that were examined [36,37]. Additionally, the analysis scrutinized outliers and assessed the distribution curve of the sample. Special emphasis was given to investigating some sustainability features in housing, particularly focusing on information related to energy efficiency and daylight variables. After this, a conventional Ordinary Least Squares (OLS) model was implemented [38–40]. Spatial autocorrelation was not considered, given the scope limitation of the data sample within a confined urban area that falls under the same sub-sector of the real estate market (OMI zones).

The OLS model is formally expressed as follows (Eq. (1)):

$$Y = \alpha_k + \sum_{i=1}^{n} \alpha_i \, X_{ik} + \ldots + \sum_{i=1}^{n} \beta_i \, Z_{im} + \varepsilon \tag{1}$$

where.

Y dependent variable,
α_k model intercept,
X_{ik} variables introduced for each of the n observable characteristics,
α_i, β_i hedonic weights assigned to each variable, reflecting their contribution to the price value,
ε error term.

The regression expresses the ability and influence that each level of each considered variable can have on the formation of the market price of a real estate unit. Only the significant variables are to be considered for the composition of the final model. For this purpose, in the last part of the implementation, a control sample was constructed, randomly extracted from the total data sample, to validate the model by applying the estimated marginal prices to real cases.

4. Case study and data sampling

The Pozzo Strada borough includes diverse building typologies and has good infrastructure and two large green areas. It serves as an ideal example of a semi-peripheral residential area, ensuring ample and accessible data for the study. The historical development of Pozzo Strada borough was considered crucial for approaching data sampling in the study and understanding the formation of the prices in real estate. The district is strategically located between Porta Susa train station and Rivoli: it was once an area with villas and agricultural units, featuring intensive cultivation near the Dora Riparia River, but it transitioned from industrial to residential area over time.

The Italian Real Estate Market Observatory (OMI) regularly records technical and economic information on housing values. Residential unit quotation in Pozzo Strada ranged between 1500 and 3200 €/m^2 in 2022 whereas economic units fell in the 1300–1900

Table 2
Daylight metrics calculated through simulations: symbols, definition, and meaning.

Symbol and unit	Name and definition	Meaning
DF_m [%]	average daylight factor: ratio of the average illuminance in a room over the work plane (calculated as average value of individual daylight factor values determined over a grid of sensors) and the external unobstructed diffuse illuminance	Measure of the diffuse skylight amount in a room with an overcast sky
$sDA_{300,50\ \%}$ [%]	spatial daylight autonomy: fraction of space where Daylight Autonomy DA >50 %; DA is calculated as the frequency of time during the occupancy pattern on an annual basis when illuminance due to daylight alone is over 300 lx	Measure of daylight (sunlight + skylight) illuminance sufficiency for a given area, reporting a percentage of floor area that exceeds a 300 lx for a specified number of annual hours (50 % of the hours from 8AM to 6PM)
$ASE_{1000,250h}$ [%]	annual sunlight exposure: fraction of space where the illuminance due to direct sunlight only exceeds 1000 lx for over 250 h during the occupancy pattern on an annual basis	Measure of the potential discomfort due to penetration of sunlight into a space (all reflections being ignored)
H_{-short} [%]	useful daylight illuminance fell-short: frequency of time during the occupancy pattern on an annual basis when illuminance due to daylight alone is less than 100 lx	measure of daylight (sunlight + skylight) illuminance that is too scarce, thus resulting in a high probability that supplementary electric lighting is needed
$UDI_{achieved}$ [%]	useful daylight illuminance achieved: frequency of time during the occupancy pattern on an annual basis when illuminance due to daylight alone is in the 100–3000 lx range	measure of daylight (sunlight + skylight) illuminance that is in a comfort range for the occupants
$UDI_{exceeded}$ [%]	useful daylight illuminance exceeded: frequency of time during the occupancy pattern on an annual basis when illuminance due to daylight alone exceeds 3000 lx	measure of daylight (sunlight + skylight) illuminance that reveals a potential visual and thermal discomfort for the occupants
E_m [%]	average illuminance: average value of the illuminance values across a space; each illuminance is in turn the average of illuminances that are determined during a year	measure of the daylight (sunlight + skylight) illuminance that is present in a space in absolute terms (without any threshold)
BCL [%]	time when blinds are closed: percent of time during the occupancy pattern on an annual basis when blinds are operated to control sunlight	measure of the frequency of use of blinds to control direct sunlight to prevent from overheating and thus visual and thermal discomfort
VSC [%]	vertical sky component: ratio of the illuminance at a given point of a vertical plane due to the light received directly from an overcast sky to the illuminance on an unobstructed outside plane under the same sky (CIE standard overcast sky)	measure of the diffuse skylight amount on a façade or on glazing under an overcast sky; conceptually speaking, it corresponds to the daylight factor concept, but applied to a façade

€/m^2 range. Since these prices are not available at the small scale of the research project, point data (point of interest – POIs) were then collected from the Immobiliare.it[1] online platform.

The sample used for the present research is then composed of 100 POIs in a unique sub-segment of the city of Turin. This sub-segment can be considered an independent sub-market, respecting a fundamental condition for testing the model proposed. Thus, the location was not considered among the set of variables selected for detecting the influence on the price of the properties.

Before applying the model, the normality of the dependent variable (listing price) was tested, and the calculation of confidence intervals (whenever necessary and possible per average data sample) as well as boxplots for the detection of outliers was performed.

The 100-unit database is distributed across micro-areas as follows: 46 units in Rivoli, 34 in Monte Cucco-Bardonecchia, and 20 in Ruffini. This variance is explained by variations in the sizes of the micro-zones and their distinct purposes. For instance, in the case of the Ruffini sub-micro-zone, which is the smallest portion of Pozzo Strada (27 % of the total surface), the reduced extension and the presence of a large park explains the lower number of housing units. Differently, Rivoli stands out due to its larger size (39 % of the total surface) and has the highest number of apartments, while Monte Cucco-Bardonecchia accounts for the remaining 34 % of the total area (Fig. 2).

Considering that market values are dynamic and susceptible to inflation over time, only advertisements published in the last quarter of 2022 were considered in the study. This ensured that the dataset reflected the most recent market conditions and values, enhancing the accuracy and relevance of the analysis to the current real estate landscape.

4.1. Definition of the variables assumed in the study

Upon identifying the case study, the data sampling process began with the systematic organization of all variables to be included in the study. These variables represented features of the housing units under consideration, encompassing both quantitative and qualitative (dummy) aspects. However, all variables had to be transformed into quantitative measures for the regression analysis.

The variables and their respective values as assumed for the study are outlined in Table 3. These assumptions were informed by pertinent literature, such as [41–44]. The selected values align with the scope of the paper, contributing to a comprehensive and purposeful dataset for subsequent analyses. Table 3 displays all the 37 variables present in the full database, categorized into four sets. The variables related to “Context and Building Features” and “Residential Unit Features” were typically found in real estate listings and were partially deducible from the Geographical Information System (GIS) of the City of Turin. On the other hand, the variables pertaining to “Energy Efficiency” were only partially available in listings but it was possible to deduce them through direct observation

[1] Immobiliare.it (accessed on DATA) is one of the biggest web platforms of housing market listings in Italy. See more at https://www.immobiliare.it/.

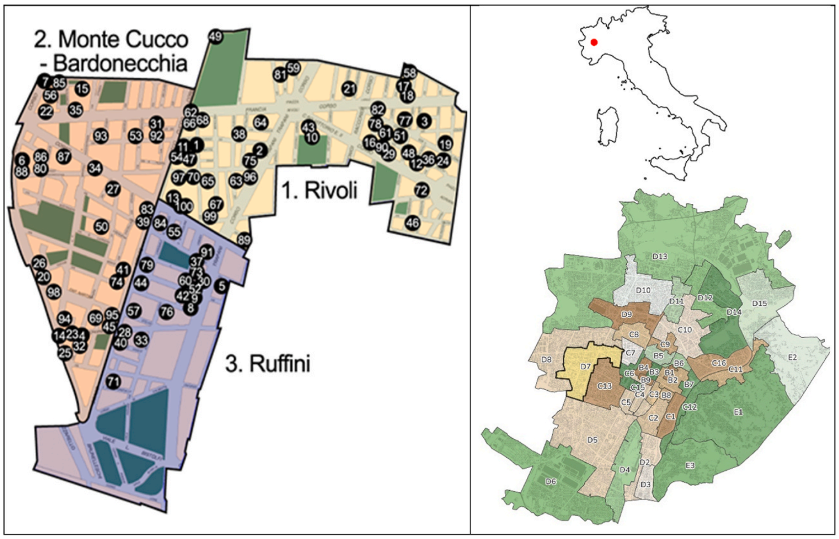

Fig. 2. Pozzo Strada borough and its three sub-zones, with the position of the 100 units selected.

of photographs. Within the dataset, the variables defined by “Daylight Simulation Output” were dummy variables derived from classifying the results of daylight simulations, which is the primary focus of this paper.

5. Results

5.1. Daylighting simulations

Fig. 3a,b,c show the results obtained from ClimateStudio simulations.

Based on the insights presented in Fig. 3a,b,c and in Table 4 provides a more detailed understanding of the simulated daylight characteristics for the sampled residential units by showing how each variable was categorized.

As mentioned before, the different daylight metrics reported in Table 4 are based on different rationales: some are static, such as DF_m, since they are constant over time as referred to an overcast sky condition, and some are dynamic (CBDM metrics), since they consider the statistical alternation of real sky conditions (clear, intermediate, cloudy, overcast); some are a direct measurement of the daylight amount in a space (DF_m, E_m), while some are defined through specific performance thresholds, as the frequency of illuminance values lying in a certain range (UDI) or as a fraction of space where a daylight metric exceeds a given value (sDA, ASE). However, the information on the daylighting amount calculated in the 100 units through different metrics seems to be consistent, as a given unit showed a comparable performance regardless of the metric used. For instance, the highest daylighting amount was attributed to the same unit (unit 49) in terms of DF_m, sDA, UDI.A, E_m. In more detail, the following considerations can be drawn.Fig. 3c

- most of the apartments showed a low-average daylighting amount: considering the 2 % threshold for DF_m [27], for instance, 90 units showed $DF_m < 2$ % (63 + 27 = 90 cases, sum of categories 1 and 2), with 27 units showing $DF_m < 1$ % (‘scarce’ daylighting category); oppositely, 10 units only showed $DF_m > 2$ % (9 + 1 = 10 cases, sum of cat. 3 and 4). It could be argued that DF_m is a penalizing metric, as it refers to overcast skies, not particularly representative of sky conditions in Turin: on the other hand, it is worth stressing that Bournas [45] carried out a study on daylight compliance in almost 11,000 residential spaces in Sweden and found out that also in a context where overcast skies are predominant the daylight-factor-based criterion of EN17037 yielded very low compliance, unlike UDI, which was associated with compliance in most cases
- considering a climate-based daylight metric, such as sDA, the results were of the same magnitude: most units (72) would not qualify for any point according to the LEED protocol (sDA <40 %, cat. 1), while 19 would qualify for the 1-point criterion (cat. 2), only 2 for the 2-point criterion (cat. 3), and only 1 for the 3-point criterion (cat. 4); interestingly, also in the studies by Turan et al. [15,16], it was found that most office spaces throughout Manhattan (74 %) had low daylight, based on sDA values lower than 55 %
- this is probably because dwellings in Italy are typically designed to meet the WFR criterion (openable window area $>^1/_8$ of the floor area), which is a ventilation rather than a lighting rule; only a minor share of units that comply with the WFR requirement can also comply with the DF_m criterion of 2 % minimum value. This is consistent with the findings from a previous study by one of the authors [29] on daylighting in buildings in Turin, where the Municipality of Turin complained that most of the projects submitted were consistent with the WFR requirement but without any daylighting verification in terms of DF_m.

5.2. Exploratory analyses and multiple regression model

The method progressed with the Multiple Regression implementation. Then, the exploratory analyses encompassed summary statistics, data distribution, outlier management, and correlation analysis of variables. Outliers, defined as data deviating from most observations, were investigated using boxplots, initially focusing on price and subsequently on price/m^2: the few anomalies that were

Table 3
Dependent and explanatory variables summary statistics.

DS (90 Data)					
Variable	Description	Type	Levels	Mean	St. Dev.
CONTEXT AND BUILDING FEATURES					
SZ	Sub-micro-zones Pozzo Strada	dummy	(1) Rivoli, (2) Montecucco-Bardonecchia, (3) Ruffini	1.74	0.77
TLP	Total listing price (Euro)	numeric	–	187340	92675.84
ULP	Unitary listing price (Euro/m^2)	numeric	–	1983.62	502.10
FA	Floor area (m^2)	numeric	–	92.84	35.25
BT	Property type	dummy	0) NA, (1) balcony (2) multi-family house (3) condominium/multi-story	2.87	0.44
FT	Façade typology	dummy	1) simple façade, 2) articulated façade, 3) horizontal façade, 4) balcony facade	2.35	1.12
YOC	Year of construction	dummy	(1)1919–1945 (2)1946–1969 (3)1961–1990 (4)1991–2000 (5) after 2000.	2.61	0.79
BC	Building category	dummy	(0 = NA, (1) popular-economic, (2) medium, (3) classy-noble	2.22	0.82
US	Unit status	dummy	(0) NA, (1) to be renovated, (2) good condition, (3) excellent condition, (4) new	2.33	0.62
EL	Presence of the elevator	dummy	(0 = no, 1 = yes)	0.82	0.38
GA	Presence of a green area	dummy	(0 = no, 1 = yes)	0.34	0.47
VOQ	View quality	numeric	(1) landscape layer, (2) landscape layer + either sky or ground, (3) all layers (landscape + sky + ground)	2.16	0.81
NP	Noise Pollution	dummy	(1) very light, (2) medium, (3) very high	1.36	0.57
RESIDENTIAL UNIT FEATURE					
NR	Number of rooms	numeric	–	3.25	1.08
NB	Number of Bathrooms	numeric	–	1.28	0.47
KT	Kitchen type	dummy	(1) kitchen corner, (2) kitchenette, (3) semi-habitable, (4) habitable	2.46	1.05
OR	Orientation	dummy	(1) East-West, (2) North-South, (3) Northeast-Southwest, (3) Northwest-Southeast	2.68	1.10
NV	Number of views	numeric	–	2.10	0.52
NBA	Number of Balconies	numeric	–	1.51	1.02
NT	Number of Terraces	numeric	–	0.42	0.73
WFR	Window-Floor Ratio (openable window area/floor area)	dummy	(0) < 0.1 does not comply, (1) 0.1–0.15 comply to regulations, (2) >0.15 high performance	1.61	0.63
ENERGY EFFICIENCY					
WGT	Window Glazing Typology	dummy	(1) single glazing, (2) double glazing	1.57	0.50
WFT	Window Frame Typology	dummy	(1) wood, (2) aluminum, (3) PVC	1.69	0.92
EPC	Energy performance certificate	dummy	(1) E-F-G-, (2) C-D, (3) A-B	1.39	0.62
HT	Heating Typology	dummy	(1) centralized, (2) autonomous	1.16	0.37
HST	Heating system typology	dummy	(1) radiators, (2) floor radiant panels, (3) air	1.09	0.47
HS	Heating source	dummy	(1) methane, (2) district heating, (3) gas	1.19	0.72
CO	Presence of cooling system	dummy	(0) absent, (1) present/predisposition	0.34	0.47
DAYLIGHT SIMULATION OUTPUT					
DF_m	Average Daylight Factor [%]	dummy	(1) 0–1% scarce, (2) 1–2% medium, (3) 2–3%good, (4) high	1.37	0.52
sDA	Spatial Daylight Autonomy ($sDA_{300/50\%}$) [%]	dummy	(1) <40 % scarce, (2) 40–55 % medium, (3) 55–75 % good, (4) >75 % high	33.44	18.31
ASE	Annual Sunlight Exposure ($ASE_{1000,250h}$) [%]	dummy	(0)<10 %, (1) >10 %	6.2	5.43
UDI.F	Useful Daylight Illuminance – fell-short [%]	dummy	(1) 60–100 % critical, (2) 30–60 % medium, (3) 0–30 % optimal	35.44	14.34
UDI.A	Useful Daylight Illuminance – Achieved [%]	dummy	(1)0–15 critical, (2) 15–30 medium, (3) 30–50 good, (4) >50 optimal	33.43	12.60
UDI.E	Useful Daylight Illuminance – excessive [%]	dummy	(0)>0.75 critical, (1) < 0.75 acceptable	0.38	0.37
E_m	Average Illuminance [lx]	dummy	(1) <200 critical, (2) 200–400 acceptable, (3) 400–500 high, (4) >500 very high	277	93
BCL	Blinds closed [%]	dummy	(1) >20 % excessive use, (2) 10–20 % normal use, (3) <10 % minimal use	10.53	5.85
VSC	Vertical Sky Component [%]	dummy	(0) 0–15 % critical, (2) 15–27 % medium, (3) >27 % optimal 2 cases	26.96	10.66

identified were replaced. In the final sample, only three units over 160 m^2 were deemed integral to the same price and market segment, requiring no further removal or substitution.

The Spearman model was preferred to determine the correlation between variables, especially with dummy variables [46,47]: a value closer to 1 indicates a stronger correlation. In this study, 4 out of the initial 34 variables were found to be correlated and subsequently excluded from the Multiple Regression Model. The Ordinary Least Squares Model (OLS) was employed using the Gretl software [48,49], creating models with a dependent variable (price/m^2) and multiple independent variables. The chosen independent variables were non-correlated and included daylighting variables.

Various models were defined and analyzed, considering linear and logarithmic scales of the dependent variable, as well as using the price in € or the price/m^2 as the dependent variable. Following multiple refinements, the best model was identified and is presented in

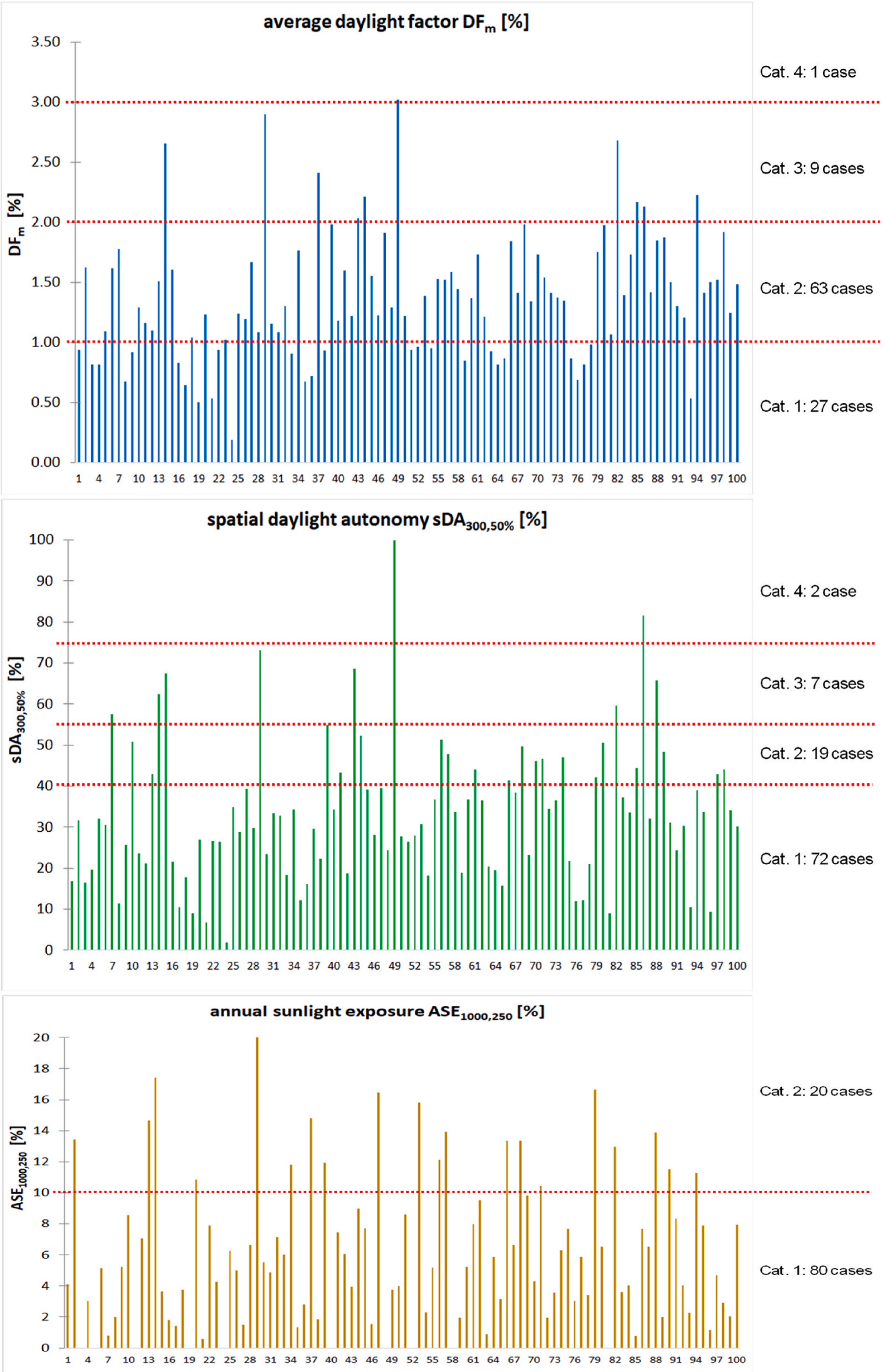

Fig. 3.a. Results from ClimateStudio daylighting simulations: (a) DF_m, sDA, and ASE.

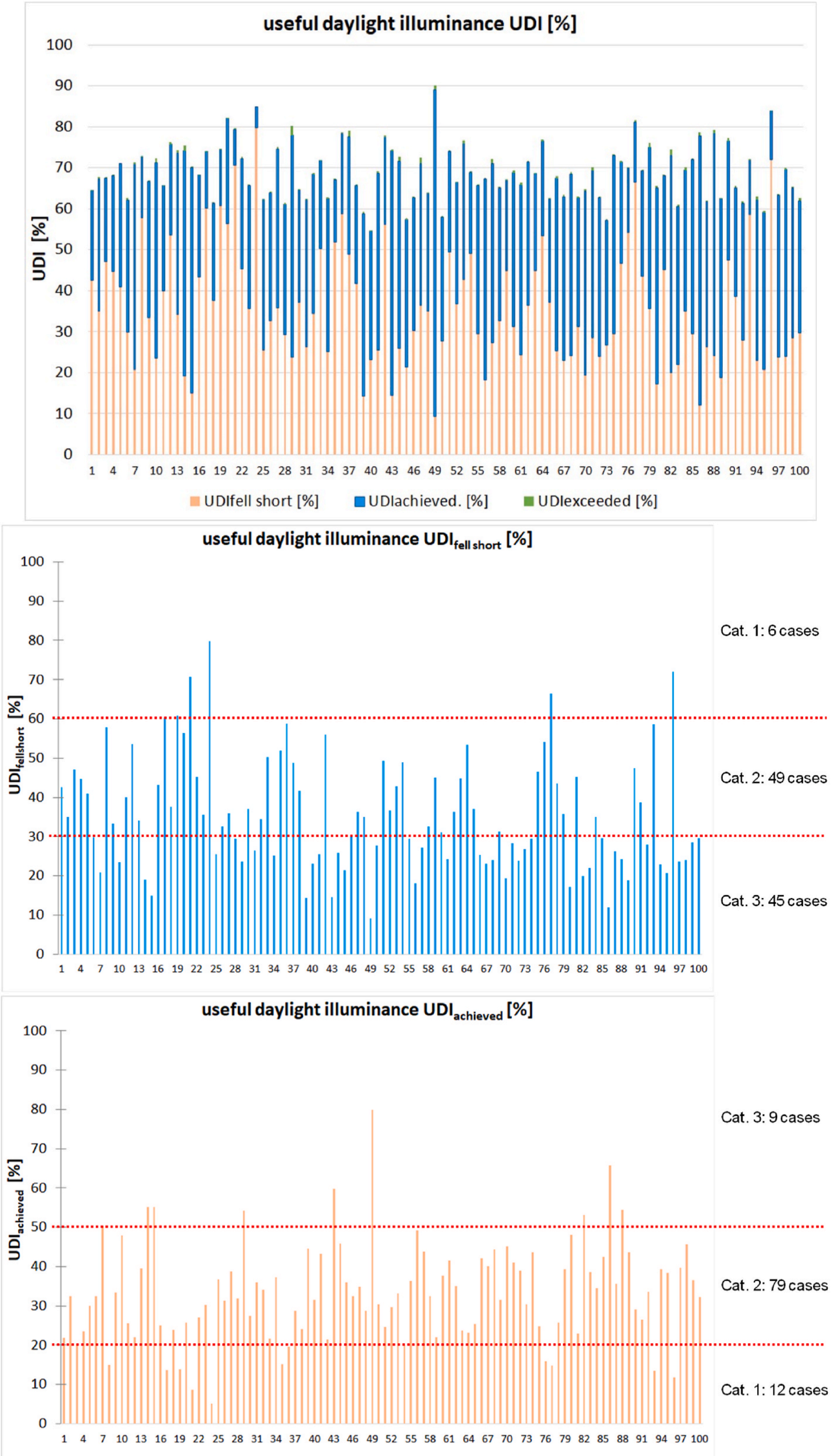

Fig. 3.b. Results from ClimateStudio daylighting simulations: (b) UDI (Source: Authors' elaboration).

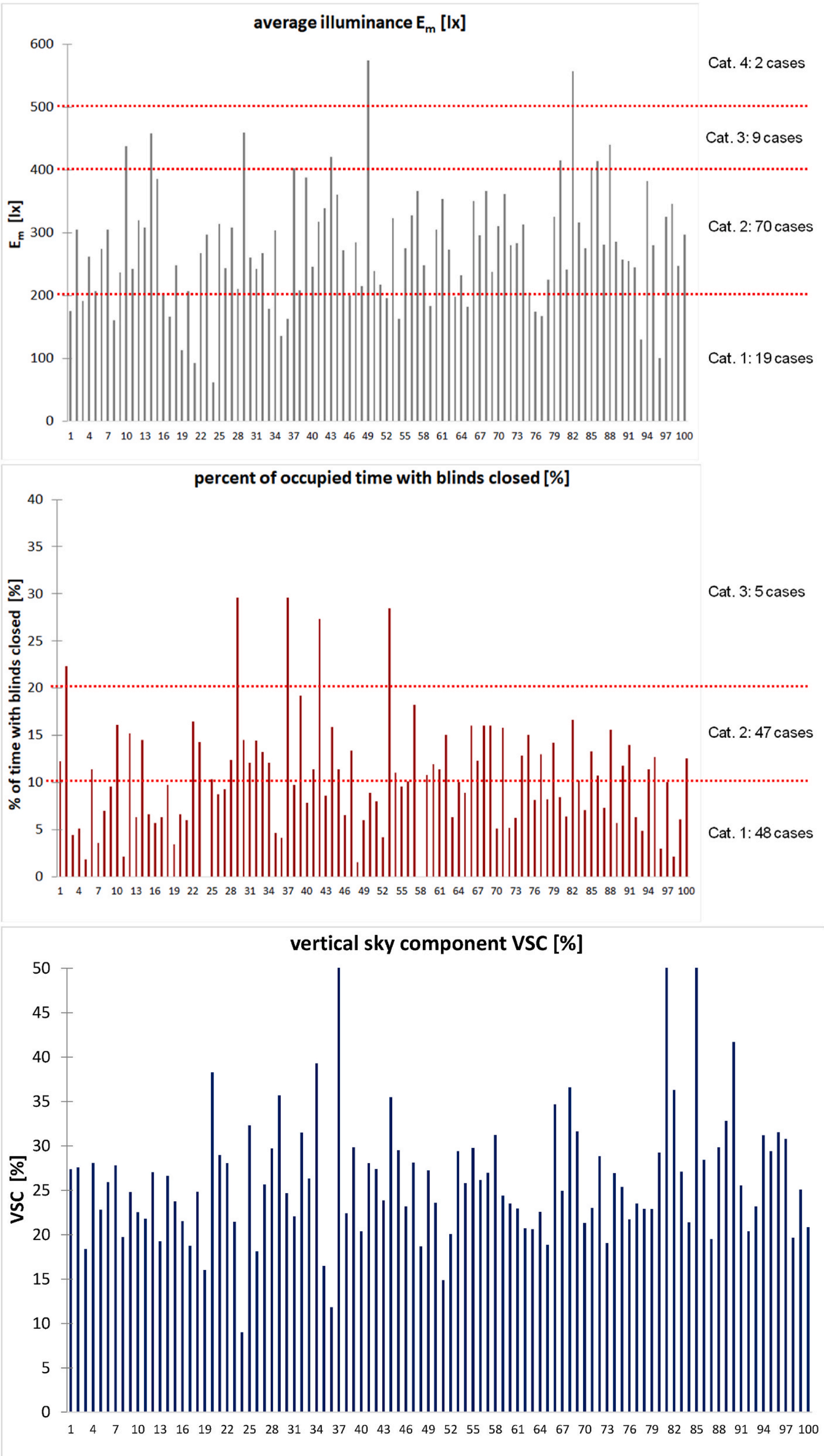

Fig. 3.c. Results from ClimateStudio daylighting simulations: (c) E_m, blinds closed, and VSC.

Table 4
Categorizations of ClimateStudio simulation results for the calculation of several daylight metrics.

			0	1	2	3	4
DF_m	Average Daylight Factor	(1) 0-1% scarce, (2) 1-2% medium, (3) 2-3%good, (4) high	NA	27	63	9	1
sDA	Spatial Daylight Autonomy (% of space)	(1) <40% scarce, (2) 40-55% medium, (3) 55-75% good, (4) >75% high	NA	72	19	7	2
ASE	Annual Sunlight Exposure (% of space)	(0) <10%, (1) >10%	80	20	NA	NA	NA
UDI fell-short (UDI.F)	Useful Daylight Illuminance – fell-short (% of occupied time)	(1) 60-100% critical, (2) 30-60% medium, (3) 0-30% optimal	NA	6	45	49	NA
UDI achieved (UDI.A)	Useful Daylight Illuminance – Achieved (% of occupied time)	(1) 0-15 critical, (2) 15-30 medium, (3) 30-50 good, (4) >50 optimal	NA	12	79	9	NA
UDI exceeded (UDI.E)	Useful Daylight Illuminance – excessive (% of occupied time)	(0) >0.75 critical, (1) < 0.75 acceptable	13	87	NA	NA	NA
E_m	Average Illuminance (lx)	(1) <200 critical, (2) 200-400 acceptable, (3) 400-500 high, (4) >500 very high	NA	19	70	9	2
BCL	Blinds closed (% of occupied time)	(1) >20% excessive use, (2) 10-20% normal use, (3) <10% minimal use	NA	5	47	48	NA
VSC	Vertical Sky Component	(0) 0-15% critical, (2) 15-27% medium, (3) >27% optimal	NA	3	56	41	NA

Table 5
OLS model results.

Regression Model: Ordinary Least Squares					
Dependent Variable: Unitary price (UP Euro/sqm)					
Independent Variables	Coefficient	Std.Error	z-Value	Probability	
constant	6.74994	0.111803	60.37	<0.0001	***
EPC_EFG	−0.0953317	0.0437072	−2.181	0.0321	**
US	0.195370	0.0335338	5.826	<0.0001	***
EL	0.442907	0.0514271	8.612	<0.0001	***
NT	0.0754482	0.0328095	2.300	0.0240	**
NBA	0.0627784	0.0222355	2.823	0.0060	***
WFT	−0.0703697	0.0218395	−3.222	0.0018	***
ASE	0.138613	0.0508181	2.728	0.0078	***
UDI.A_015	0.200886	0.0734538	2.735	0.0077	***
Number of observations	90	SQM dependent variable		0,282916	
Average dependent variable	7.547641	regression standard error		0.180604	
R^2	0.629	R^2-corrected		0.593	
Log likelihood ratio test	31.06719	P-value(F)		1.19e-14	
Schwarz criterion	−21.63609	Hannan-Quinn		−35.06174	
Akaike criterion	−44.13437	F(8, 81)		17.17490	
Sum of residual squares	2.642038				

Notes: Significant Codes: 0'***' 0.001'**' 0.01'*' 0.05 '.' 0.1 "1.

Table 5.

The corrected correlation index (R^2-corrected) 0.59 indicates that the model can account for 59 % of the price formation process, leaving 41 % unexplained. Both the Akaike criterion and the Schwarz Criterion produced the lowest results compared to all other models examined, suggesting the superior performance of the current model.

Most marginal coefficients are positive: this means that the higher the category, the higher the economic value. For example, the conservation condition of the units (Unit Status-US) has a positive coefficient of +0.195, which means that the higher the category, the better the conservation condition. The presence of an elevator (Elevator – EL) is a commonly significant variable in the literature as well: a positive coefficient correlated with the presence of the elevator in the building, which clearly is a feature highly appreciated by potential buyers, especially for units located at highest floors. The same applies to the variables "BALCONIES-NBA" and "TERRACES-NT", whose presence is sought by potential buyers. This behavior has probably increased over the last years after the pandemic lockdown, a period when people started valuing more and more the possibility of having some external spaces outside their apartments.

Among daylight metrics, two metrics were found to have a significant impact on the price: (i) the Annual Sunlight Exposure $ASE_{1000,250h}$ of the regularly occupied spaces of a unit: this is a dichotomous variable where 1 is obtained when the ASE >10 %, and the implicit marginal coefficient related to this variable is 0.139; and (ii) the useful daylight illuminance achieved UDI.A: this represents the percentage of occupied time when illuminance is in the comfort range 100–3000 lx; ideally, UDI.A should be as high as possible, thus reducing the values of UDI.F (insufficient daylight) and of UDI.E (excessive daylight).

The marginal coefficients for two other variables, namely the energy class and the window frame typology, exhibit negative values. The energy class, as expressed through the Energy Performance Certificate (EPC_EFG) in classes E, F, or G, indicates lower energy efficiency, leading to a negative influence on the price formation process. The negative coefficient signifies that houses with lower energy efficiency tend to have a depreciating effect on their price according to the model. As for the window frame typology (WFT), the negative coefficient arises from the categorization method, with (1) assigned to wooden window frames, (2) to aluminum frames, and (3) to PVC frames. The findings suggest that, when buying a new house, buyers show a preference for wooden window frames over PVC or aluminum. This preference, expressed by the market, may be attributed to factors such as visual aesthetics, material durability, as well as the perceived higher thermal comfort associated with wooden frames.

5.3. *OLS model validation with a control sample*

To validate the model obtained through regression, a random sample of 10 % of the entire dataset, consisting of 10 data points, was extracted, and used as a control sample. Although aware of the limitations of this methodology with such small numbers, the random extraction of the control sample was chosen to statistically represent the entire dataset well. The effectiveness of the model was tested by calculating the marginal prices of individual variables based on their corresponding attributes and the final price. This was done using the formula expressed as follows.

$$\text{PRICE/m}^2 = 6.750\ (\text{constant}) - 0.095{*}\text{EPC\_EFG} + 0.195{*}\text{STATUS} + + 0.443{*}\text{ELEVATOR} + +0.075{*}\text{TERRACES} + 0.063{*}\text{BALCONIES} - 0.070{*}\text{WIDOWS FRAME} + 0.139{*}\text{ASE} + 0.201{*}\text{UDI.A} \tag{2}$$

In the model, where price/m^2 is the predicted value of the Total Listing Price expressed in logarithm form, the constant represents the baseline. The variables introduced for each analyzed characteristic include Energy Performance Certificate (EPC), Unit Status (US), Presence of an Elevator (EL), Presence of Terraces and Balconies (NT, NBA), Window Frame Typology (WFT), Annual Sunlight Exposure ($ASE_{1000,250h}$), and Useful Daylight Illuminance – Achieved (ADI.A).

Subsequently, each estimated price was compared to the actual listing price collected during the data sampling phase; the results are presented in Table 6.

Considering that the developed regression model can only explain 59 % of the formation of the listing price in the collected dataset, there is both positive and negative variation in the estimated prices compared to the actual ones, both deemed acceptable. Analyzing the differences in absolute value (DELTA%_ABS), the average value was less than 12 %. In the case of apartments with lower listing prices, higher positive deltas were noticeable (ID31 and ID45), while there was no consistent pattern for negative deltas. The model, in fact, underestimates both high and low prices (ID55, ID7, and ID6). Considering that the two variables with the highest marginal coefficients in this part of the city were the presence of an elevator (0.443) and UDI.A (0.201), refining the model will likely require a more in-depth analysis of issues related to accessibility and daylighting in the apartments.

6. Discussion

The study aimed to investigate the role of daylight in dwelling pricing and addressed two main questions: how to quantify daylight and whether this holds value in the real estate market. Various daylight metrics, both static and climate-based, were explored alongside factors like construction year, conservation condition, presence of terraces/balconies, and more. Using a data sample of 100 units in Turin, the study found that certain daylight metrics, such as ASE and UDI.A, were more significant in determining property value than metrics currently used in standards, such as DF_m. The results explained 59 % of the market listing price, suggesting that further exploration is needed for the remaining 41 %.

6.1. *Significant variables in the model*

The following variables concerning the context and architectural features of apartments and buildings were found to be significant in the model that was developed.

- *conservation condition of the apartment*: this variable refers to apartments to be renovated (category 1) rather than in good condition or habitable (category 2), or in excellent condition after renovation or refurbishment (category 3). Clearly, the condition of the

Table 6
Estimation of listing prices in the control sample.

Regression Model: Ordinary Least Squares				
Observations ID	price/m^2 estimated	price/m^2 listing	delta%	delta%_abs
6	1390.34	1600.00	−13.10	13.10
7	1674.65	1987.50	−15.74	15.74
31	2181.40	1877.78	16.17	16.17
43	1951.63	2037.04	−4.19	4.19
45	1933.11	1650.00	17.16	17.16
50	2542.82	2838.10	−10.40	10.40
55	2246.93	2821.43	−20.36	20.36
73	2181.40	2090.40	4.35	4.35
87	1782.93	1944.44	−8.31	8.31

apartment is of utmost importance to potential buyers as it has a strong economic impact on the price: currently, buyers have to face an extra economic effort for an apartment to be refurbished, which impacts the final price they need to pay. This result is in line with other studies conducted on Turin submarkets, in which building/apartment conservation status and location emerge as the most impacting attributes on prices [50].

- *presence of an elevator*: this was quite an expected result, as there is evidence in the literature (see for example [51]) that people list an elevator among the most appreciated features, especially for apartments on top floors, which can be associated with better panoramic views and daylighting
- *presence of balconies and/or terraces*: having at least one balcony or one terrace has a significant impact on the price of an apartment. This seems to be particularly important to potential buyers, especially after the pandemic lockdown, a period when people started valuing more and more the possibility of having an external space outside the apartment [52].
- *frame type*: the negative coefficient expresses the fact that the general feeling of buyers when buying a new house is that they prefer wooden window frames over PVC or aluminum ones. This seems to be due to both the visual aesthetics and the material durability, as well as the thermal comfort idea that is typically associated with wooden frames
- *energy class (APE)*: the energy performance of the unit, in terms of energy efficiency and energy consumption for heating, cooling, domestic hot water, and lighting plays a monetary role in the price, which was identified in the model. This shows that buyers value an apartment with a high energy class and thus an increased energy efficiency, which allows reduced utility bills. This aspect is deeply explored in the recent literature, and the results are in line with the evidence that emerged in other studies (see, for example: [53–58])

The following variables concerning daylight were found to be significant in the model.

- *ASE*: this metric is meant to account for the incidence of sunlight in a space, which can cause glare or thermal discomfort (due to space overheating); actually, if the value exceeds 10 %, the LEED protocol requires that a strategy be defined in terms of moveable blinds. ASE is recognized in the economic model of estimation as associated with an idea of thermal discomfort in the summer period: an aspect to which potential buyers pay attention; on the other hand, people seem to appreciate the presence of sunlight inside a space, if it does not cause thermal discomfort, which means that sunlight can be perceived as beneficial beyond the summer months; therefore, ASE seems to be the right metric as it accounts for direct sunlight [59,60].
- *UDI*achieved *(UDI.A)*: it refers to the 'positive' daylight amount present in a space (in the comfort range 100–3000 lx), without being too high nor too scarce. In this regard, the higher the $\mathrm{UDI}_{\mathrm{achieved}}$ value, the better, and this is identified in the literature [14, 61–63].

6.2. Non-significant variables in the model

Among daylight metrics, some that are widely used in the literature were not found to be significant.

- DF_{m} is the reference metric in Italian building legislation and regulations. Being referred to overcast skies only, it is unsuitable to account for actual sunlight and daylighting conditions that dynamically change during a year and this is probably why it was not found significant for the determination of the price
- VSC: by definition, VSC corresponds to the daylight factor calculated on the façade of the apartment; consequently, the same consideration made for DF_{m} applies to this metric as well
- sDA: this is the most important metric that the LEED protocol relies on, along with ASE: unlike ASE and UDI, sDA was not significant, probably due to its inherent definition. It seems to be more oriented to energy savings (electric lighting can be switched off when $E > 300$ lx for at least 50 %) rather than to comfort, like UDI. This particular property makes the difference resulting in UDI being identified in the model, while sDA is not
- E_{m}: this is in direct ratio with the daylighting amount in a space, without using thresholds like sDA, ASE, or UDI; for this reason, one could expect this metric to be significant and it was a surprise to find out it was not. Apparently, there is no reason to explain such a behavior.

It is worth mentioning that there is a large number of other variables considered in the study that were not found to be significant in the determination of the price of a dwelling: for instance, the difference between single-pane and double-pane glazing, which can represent a plus for an apartment in terms of potential energy saving in winter months, was found to be non-significant. However, it is also true that energy efficiency is globally accounted for through the energy class APE_EFG, which was significant. Other variables that did not prove to be significant were the construction year and the building type.

Among the variables related to the architectural features of the residential units, the following were also found to be non-significant.

- Room orientation: the dataset of 100 units was quite balanced in terms of orientation, with 20 % of rooms facing East and West, 21 % of rooms facing North and South, 30 % of rooms facing North-East and South-West, and the remaining 29 % of rooms facing North-West and South-East. In the literature, the orientation and the consequent solar exposure was proven to impact on the preferences expressed by occupants: for instance, Jovanovic et al. (2014) [64] analyzed students' preferences in existing multi-story student houses in Serbia: students showed preferences for southern orientations regardless of the fact that they are more frequently overexposed to direct sun, in contrast with local regulations that require or recommend an even daylight distribution and avoidance of direct sunlight for achieving good environments. However, the orientation was not found to be a significant variable in the model for the formation of the price; on the other hand, the ASE metric, which specifically quantifies the penetration of direct sun, was significant, as discussed earlier.

- Window-to-floor ratio (WFR): this geometric variable was found to be non-significant, which can be explained by the fact that it is concerned with ventilation rather than with daylighting. It frequently happens that rooms compliant with WFR requirements (WFR $\geq$1/8 in Italy, for instance) do not comply with the DF_m regulations ($DF_m \geq 2$ %, for instance) due to the different obstructing settings or visible glazing transmittance [29]. Sepulveda et al. (2023) [65] analyzed the properties of office building façades through a corrected factor WFR*T_v, in terms of compliance with the rules set in EN 17037:2018. Other studies in the literature analyzed the link between WFR and DF_m to modify the simple WFR rule and to adapt it to the peculiar climate conditions of a specific context: for instance, Vaisi and Kharvari (2019) [66] used DF_m to assess the validity of current standard WFR suggested by Iran's National Building Daylight Regulation and found that the current WFR was not accurate and had to be increased to an optimal 15–24 % range to optimize daylighting while controlling glare and overheating at the same time. Similarly, Phuong et al. (2019) [67] found that for tropical climate in Vietnam, WFR values need to be in the 15.2%–18.5 % range to comply with the recommended target Daylight Factor of 1.35 %. Differently, Fadzil et al. (2013) [68] found that the WFR requirement of 35 % and 17 % for rooms in the Malaysian context have daylight levels exceeding daylighting standards and therefore proposed to change the by law rule for openings for daylight from "WFR $\geq$10 %" to "WFR <10 %" because of the nature of the bright Malaysian skies.

6.3. Occupancy profile assumed for simulations

Another aspect that is worth discussing is the occupancy profile assumed for the simulations, which was from h8 until h18 every day throughout a year. In this regard, it should be noted that sDA and ASE were defined in the IES-LM-83-12 document [24], which states in the introduction that "*IES LM-83-12 was created to develop a new suite of metrics capable of describing multiple important dimensions of daylighting performance in an existing building and a new design. The intent of these new climate-based metrics is to improve on the predictive performance of historical metrics, such as Daylight Factor, and define a consistent calculation methodology that would allow for multiple design alternatives of proposed designs, day-lit buildings, and/or climatic locations to be compared, in a consistent manner*". Accordingly, the document defines a daily occupancy profile (h8-h18), resulting in 3650 h/year, including weekends. This shows that the intent is to provide an assessment of the daylight supply in a space on an annual basis, regardless of its function and to allow different building usages to be compared from a daylighting viewpoint. Other important factors were taken into account for the selection of the h8-h18 occupancy profile: (i) the inconsistent and non-univocal definition of occupancy patterns in dwellings; for instance, ASHRAE offers several occupancy profiles for dwellings to account for different types of occupants; (ii) the purpose of the study was to assess daylighting through daylighting metrics and its impact on the formation of price in the real estate market; for this reason, it wouldn't make any sense to use any occupancy profile that includes early mornings and late afternoons (typical patterns of people who are not at home, being at work in weekdays) as the daylighting quantity in the spaces would be very low if not absent; and (iii) especially after the COVID pandemic lockdown, it has become quite typical to turn some dwelling spaces into work spaces. This latter is a consequence of the work-from-home mode (WFH) people have experienced during the lockdown. A body of research highlights that a significant portion of workers has opted for or desired WFH post-pandemic. Griszbacher (2023) [69] found that even after the pandemic, employees strongly desired to retain the benefits of remote work, presenting challenges for managers reintegrating them into traditional office settings. While the optimal balance between remote and office work remains unclear, the future likely involves a hybrid approach. Appel-Meulenbroek et al. (2022) [70] suggested that future work will blend office-oriented tasks (communicative work) with home-based tasks (concentration work). Smite et al. (2022) [71] studied remote work trends through 22 internal employee preference surveys and 26 post-pandemic policies by 17 companies across 12 countries. Their findings indicated a shift in the psychological contract between employees and managers, with WFH transitioning from an exclusive perk to a core entitlement. In Italy, Tagliaro and Migliore (2022) [72] examined how COVID-19 altered work habits in a Milan-based company through a survey of 90 employees. They identified a new work mode, "COVID-working," and observed a significant shift from traditional office work to pure WFH. However, they noted that research on COVID-working is still emerging and primarily found in grey literature due to its novelty. This is also confirmed by McPhail et al. (2024) [73], who conducted an exploratory scoping review of both academic and grey literature on the pandemic's impacts on people, productivity, and the environment, focusing on remote work and the post-pandemic workplace. They noted that most post-pandemic studies are data-driven, with some anecdotal elements, rather than theory-based. Nevertheless, certain trends have been observed globally.

Based on all the above reasons, it was eventually decided to assume the IES-LM-83-12 h8-h18 occupancy profile. This was also consistent with similar assumptions in other studies in the literature: for instance, Wang et al. [74] carried out a study to assess the acceptable daylight quantity in typical dwellings in Hong Kong through subjective analyses and CBDM simulations: they also assumed the IES-LM-83-12 h8-h18 occupancy pattern for their simulations. Differently, Bournas [7] stated in his study on daylight quality of dwellings in the Swedish context that "due to inconsistent occupancy patterns in dwellings, the time basis was not set to a fixed occupancy schedule (e.g. from 9:00 to 17:00) but to 70 % of the daylight hours of the year (3066 h). The criterion was that a room should achieve a UDI100-3000 >70 % across half of the room area". Using the same approach, Turin has an amount of 4472 h of daylight per year: compared to this data, the 3650 h per day assumed in the IES-LM-83-12 represent 81.6 % of daytime, slightly above 80 %. A criterion to investigate the UDI100-3000 >80 % was therefore assumed in the present study, consistently with Bournas' approach, with the difference that the reference threshold was increased from 70 % to 80 %. This seems reasonable considering the difference between the two contexts (Sweden vs. Northern Italy).

6.4Merits and limits

In the authors' opinion, the study has the pioneering merit of expanding the analysis of the monetary significance of daylight metrics in the residential building segment in the real estate market. The research contributes to the literature, providing an in-depth exploration of the impact of daylight on hedonic analysis in a relatively underexplored research space. Precisely, the work contributes to bridging the literature gap about the detection of the influence of daylight on real estate market pricing processes by means of regression analysis.

A single study was found to be consistent with the topic and the method presented in the study [17], dealing with dwellings in Shanghai, while a few other similar studies were carried out on the rent price in office buildings. The authors of [17] focused on sunlight exposure relying on the information found in the transactions, without analyzing in detail the daylighting performance of the huge sample that they considered. Differently, the present study carried out simulations to determine the value of several daylight metrics to understand which ones could be significant in a model for the price/m^2. To the authors' knowledge, applying this type of study to dwellings is a new approach and bridges a methodological gap and findings for this market segment.

As a general premise, it is worth mentioning that in Italy selling prices of real estate assets are not public information, and it is therefore difficult to monitor housing prices and their intrinsic/extrinsic features, considering the different territorial segments of the city (submarkets). For this reason, listing prices are frequently adopted in studies and market analyses. Analyzing the literature shows that listing prices are fundamental for explaining the asset pricing process, being capable of influencing the selling processes and price estimation [21,75]. Research discusses the difference between the listing price and selling price and various authors explored the use of listing prices as a proxy for selling prices (see f.i. [18–21]). Thus, listing prices were adopted as information available to analyze house pricing processes in many studies in Italy, paying attention to the fact that listing prices are a function of dwelling/building attributes, able to impact the bargaining processes [76].

Besides the merits, the study acknowledges certain limitations.

A first limit concerns the size of the data sample: the price prediction model was built on a data sample of 100 cases, which may not fully represent the entire population. The choice of 100 cases was a trade-off between data resolution and simulation time. While more data would have been ideal, the size was comparable to a similar study [77], justifying its significance.

Another limit concerns the homogeneity of the context: the analysis focused on a relatively homogeneous context, suggesting a need for extension or replication in diverse building locations within Turin or even in its suburbs and countryside. This would provide a broader range of building types and daylight access variability. Similarly, it is recommended to replicate the research in different geographical locations, considering varied climate zones in Italy or even different countries. This approach would explore the impact of daylight perception and its value in diverse settings.

Another aspect is concerned with the geometrical models that were created for the simulations: in some cases, the 3D models of the units were approximated due to poor-quality information from advertisements, such as inaccurate floor plans or window sizes: this may have had some impact on the simulation results.

7. Conclusions and future insights

The paper focuses on highlighting the significance of daylight in the real estate market, extending the knowledge established in previous studies about its importance in work environments to residential units. The main objectives include demonstrating the quantifiable impact of daylight on real estate pricing, determining its value beyond being a descriptive feature, and identifying the most significant daylight metrics in modeling property pricing. The Ordinary Least Squares (OLS) model that was developed successfully explained 59 % of the price formation process. The model was validated with the control sample, which suggests its suitability for predictive applications. During the development of this study, all the main daylight metrics, from the Daylight Factor to more complex climate-based metrics, were categorized and included in the data sample through ClimateStudio simulations. Their inclusion in Multiple Regression analysis demonstrated their potential monetary role, confirming their value as previously done in working environments. In fact, in recent years, it has become more and more frequent for many workers to use their homes as workplaces, diminishing the differences between offices and houses and creating multi-purpose spaces.

Using Multiple Regression analysis, the significance of a huge set of variables was detected. These were of four types: extrinsic, related to context and building features; intrinsic, related to the apartment features; related to energy efficiency; and related to daylight, calculated through simulations. Many of them, unfortunately, were not significant in the final model, such as the average illuminance, while others showed a very positive correlation, such as the frame typology (FRAME), the Annual Sunlight Exposure (ASE), and the achieved useful daylight illuminance (UDI.A). The average Daylight Factor (DF_m), instead, along with the window-to-floor ratio (WFR), which are the reference metrics in Italian building legislation and regulations, were not significant, which shows their inability to represent daylight in real estate. It is also worth stressing that not all the climate-based metrics turn out to be significant: for instance, the popular sDA, adopted as the main metric in the LEED protocol, was not found to be significant in the model developed in the study, unlike ASE and UDI.

Future developments of this study can include expanding the data sample to other areas of Turin, as well as other cities, also including locations within the significant variables and obtaining a higher statistical significance and assigning to such variables a larger share of the real estate property prices.

CRediT authorship contribution statement

Serena Loro: Writing – review & editing, Validation, Software, Data curation. **Valerio R.M. Lo Verso:** Writing – original draft, Resources, Methodology, Conceptualization. **Elena Fregonara:** Writing – review & editing, Methodology, Conceptualization. **Alice Barreca:** Writing – review & editing, Writing – original draft, Resources, Methodology, Data curation.

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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