THE IMPACT OF LATE DESIGN CHOICES ON DAYLIGHT AND ENERGY USE IN BUILDINGS

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Master thesis in Energy-efficient and Environmental Buildings
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Lund University

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The degree project is the final part of the master's programme leading to a Master of Science (120 credits) in Energy-efficient and Environmental Building Design.

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Abstract

Daylight analysis is often carried out when definitive decisions about space characteristics such as materials, colours, window characteristics and furnishing have not yet been made. Such late design choices, which are first introduced or can still be changed late in the design process or even after its conclusion, impact the daylight levels of interior spaces. This study explored the impact of late design choices on interior daylight and energy use of generic office spaces located in the southern Nordics. Nine late design choices, defined as factors introduced by industry professionals after initial decisions about building volume, orientation, window-to-wall ratio and relation to environmental context etc. have been made, or factors decided by interior designers or building occupants after the building has been constructed (floor, ceiling and wall reflectance, visual transmittance of windows, windowsill and head height, the amount and reflectance of furniture as well as height of workspace partitions), and seven daylight metrics ($DF_{Average}$, DF_{Median}, DF_{Point}, DA, sDA, LD and UDI) were studied for a set of building models of varying orientation, size and WWR with different underlying daylight conditions (nine for static daylight simulations and twelve for dynamic). Daylight simulations were performed according to the 4CM using Honeybee by Ladybug Tools for Grasshopper in Rhinoceros 3D. The energy use of electric lighting with fluorescent and LED lamps was calculated based on simulated LD values. The influence of individual late design choices on each daylight metric was investigated by global sensitivity analysis according to the method of Morris (Elementary Effects Method) using the SALib package for Python. The visual transmittance of windows and amount of furniture were identified as the most impactful factors. Windowsill and head heights, furniture reflectance and partition height had an inconclusive impact, but could be considered medium on average. Floor, ceiling, and wall reflectance displayed the least effect on interior daylight. In certain situations, the variability from late design choices was larger than the difference between target levels in environmental certification schemes. It was concluded that late design choices could have a significant impact on interior daylight. If professionals are aware of this variability, they can take proactive measures to ensure the resilience of interior spaces.

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Abbreviations

General

AFS	Arbetsplatsens utformning
BBR	Boverkets Byggregler
BREEAM	BRE (Building Research Establishment) Environmental Assessment Method
CIE	Commission Internationale de l′ Éclairage
CBDM	Climate-Based Daylight Modelling
FAST	Fourier Amplitude Sensitivity Testing method
LEED	Leadership in Energy and Environmental Design
PSBP	Priority School Building Program

Nomenclature

DA/%	Daylight autonomy
$DF_{Average}$/%	Average daylight factor
DF_{Median}/%	Mean daylight factor
DF_{Point}/%	Daylight factors point
$E_{Average}$/lux	Average daylight illuminance
E_{Min}/lux	Minimum daylight illuminance
LD/%	Lighting dependency
sDA/%	Spatial daylight autonomy
UDI/%	Useful daylight illuminance
$R_{Surface}$/-	Reflectance of a surface
τ_{Visual}/-	Visual transmittance of glazing
WWR/-	Window-to-Wall Ratio
ab/-	Ambient bounces
ad/-	Ambient divisions
as/-	Ambient samples
ar/-	Ambient resolution
aa/-	Ambient accuracy
lw/-	Limit weight
lr/-	Limit reflection

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1 Introduction

Daylight has been the primary source of illumination throughout most of human history. Since ancient times, the urge to fill our buildings and structures with daylight has been propelling innovation in architecture and engineering. The Romans developed arches, barrel vaults and domes to eliminate thick, load bearing walls and allow daylight to penetrate deep into their structures (Nyole, 2013). European builders in medieval times perfected the pointed arches and flying buttresses in their gothic cathedrals to be able to make structures dominated by windows and hide structural and load-bearing elements away from the interior space (Phillips, 1997). It is only since the invention of electric light that we have fully decoupled from the cycle of day and night and electrically lit the spaces we have created. Daylight is, in a sense, now being rediscovered as its significance for the human experience and the built environment become increasingly apparent.

It has been said that "*using lighting in the right way in buildings means principally starting by studying the possibility of daylight use*" (van Bommel, 2009). A space designed to achieve good daylight conditions could be defined as "a *space that is primarily lit with natural light, and that combines high occupant satisfaction with the visual and thermal environment with low overall energy use for lighting, heating and cooling*" (Reinhart and Wienold, 2011).

1.1 Background

Our built environment and its development are significant contributors to the global energy demand and the subsequent climate emergency inducing greenhouse gas emissions. Globally, existing buildings and construction of new ones were responsible for more than a third (35%) of the total energy use and two fifths (38%) of the CO_2-equivalent emissions. They also lay behind over half (55%) of the total electricity demand during 2020 (United Nations Environment Programme, 2020), of which electrical illumination of interior spaces was 17% (EIA, 2020). The need for electric lighting is due to insufficient use of daylight to provide baseline illumination and its large electricity demand partly due to the use of inefficient light sources and luminaires. Investing in energy-efficient lighting is one of the most cost-effective approaches to eliminating CO2 emissions (Enkvist et al., 2007). Using efficient daylight and existing technology can cut down 50% of electricity use for lighting (Borup et al., 2005; Bülow-Hübe, 2008).

Besides having the potential for energy saving, daylight is an essential factor of human life and experience regarding both physical and psychological aspects. It profoundly impacts the human mental state, mood, and emotions. It promotes better visual performance, a feeling of security and connection, reduced stress levels, increased productivity, and higher occupant satisfaction. The dynamic nature of daylight stimulates the perceptive organs, enhancing activation, alertness, and concentration (Dubois et al., 2019). People prefer daylight over electric illumination in work environments and reportedly feel elevated psychological comfort in naturally lit spaces (Heerwagen and Heerwagen, 1986).

Past years have seen increasing requirements on daylighting design, and analysis of the daylight conditions within interior spaces is increasingly being conducted early in the design process. At early stages, and even later in the design process, several factors such as surface colours, window characteristics and furnishing may not yet have been decided. In such instances daylight specialists often turn to environmental certification schemes, building standards and regulations for reference values (Interviews, 2021). Some of these parameters are also prone to change late in the design process, or even later when the building has been constructed. These late design choices are defined as design decisions which the architect, engineer or daylight specialist can make late in the design process, or choices that are more often made by the interior designer or the space's occupants. They have an impact on the daylight levels within an interior space, but more research is needed about their importance and the implication of the variability of interior daylight they contribute to.

1.2 Objectives

The study aimed to investigate the variability of selected daylight performance metrics and energy use for electric lighting based on late design choices. To this end, the variability of seven daylight metrics appearing in environmental certification schemes for buildings, building standards and regulations, as well as architectural and daylight handbooks was investigated. Nine late design choices, defined as factors introduced by industry professionals after initial decisions about building volume, orientation, window-to-wall ratio and relation to environmental context etc. have been made, or factors decided by interior designers or building occupants after construction, based on literature and input from professionals in the daylight industry were ranked according to their degree of influence on the selected daylight metrics. The energy use of electric lighting was estimated based on the Lighting Dependency (LD/%) comparing two common light sources.

1.3 Research questions

- What is the variability of selected interior daylight performance metrics due to the studied late design choices?
- What is the implication of the variability of selected daylight metrics due to the studied late design choices regarding target daylight levels in environmental certification schemes, building standards and regulations?
- What is the variability of electricity use due the studied late design choices?
- How do the studied late design choices rank according to their degree of influence on selected interior daylight performance metrics?

1.4 Hypothesis

The hypothesis is that late design choices such as the reflectance of interior surfaces, the amount, size, and colour of furniture, as well as window parameters such as visual transmittance, windowsill and head height do have a significant impact on the daylight levels in interior spaces.

1.5 Scope and limitations

The study was limited to a selection of grid-based daylight metrics appearing in environmental certification schemes, building standards and regulations, as well as handbooks. It was further limited to a selection of late design choices based on studied literature and interviews with professionals in the daylight industry. Image-based daylight metrics were disregarded, and the number of late design choices included was deliberately kept low to limit the computational load. It was further limited to a generic, single-story, ground level, side-lit space with an open plan, located in the southern Nordics. Detailed geometry such as shading devices, window frames and furniture details, and context geometry such as surrounding buildings and vegetation, were omitted. Because of these limitations, the results of the study should not be generalised.

2 Literature review

2.1 Types of reviewed resources

Environmental sustainability certification schemes for buildings play a crucial role in promoting sustainable architectural design. They offer a quantitative and comparative measure of the degree to which new or existing development adheres to a set of standardised criteria to limit the environmental impact. In many cases, certification schemes also make up for the lack of specific building legislation needed to meet countries and regions' commitments to various environmental goals and emissions targets (United Nations Environment Programme, 2020). The use of environmental certification schemes is widespread across all continents (with the possible exception of Africa[1]), and to some degree, mandatory in large swathes of Europe and the USA, China, Australia, among other countries (United Nations Environment Programme, 2020). Two prominent international environmental certification schemes are BREEAM (British Research Establishment's Environmental Assessment Method) from the UK and LEED (Leadership in Energy and Environmental Design) from the USA. In Sweden, Miljöbyggnad is the leading environmental certification scheme, but rather ambitious alternatives such as NollCO_2 and Living Building Challenge from the USA were introduced during 2020 (Solenco, 2020; Sweden Green Building Council, 2020a).

Building standards and regulations form a basic framework and establish boundaries for a design. Building regulations are binding documents architects, engineers and designers are required to follow, while standards are in and of themselves non-binding guidelines, although are often referred to in regulations. They sometimes regulate design details, but more often, the overall quality of a space and how it is experienced by its users. Building design in Sweden is primarily regulated by Boverkets byggregler (BBR), of which the current version at the time of writing was BBR29 (Boverket, 2020). Specifically, workplaces are regulated by Arbetsplatsens utforming (AFS), of which the current version was AFS 2020:1 (Arbetsmiljöverket, 2020). In the UK, rather ambitious specialised regulation has been introduced to the design of schools in the form of the Priority School Building Program (PSBP) launched in 2014. It puts detailed requirements on building design and focuses on schools in urgent need of renovation (Education Funding Agency and Cundall, 2014). Several European standards also aim to regulate the design of buildings. Daylight in buildings is regulated by the aptly named Daylight in Buildings, SS-EN 17037:2018 (Swedish Standards Institute, 2018, p. 17). Energy use by electric lighting in buildings is regulated by Energy Performance of Buildings - Energy requirements for lighting - Part 1: Specifications, Module

[1] Data over the use of environmental certification schemes for buildings was unavailable in the 2020 Global Status Report for Buildings and Construction (United Nations Environment Programme, 2020) for most countries on the African continent.

M9, SS-EN 15193-1:2017 (Swedish Standards Institute, 2017, p. 15). The lighting of workplaces, in particular, is regulated by Light and Lighting - Lighting of work places - Part 1: Indoor work places, SS-EN 12464-1:2011 (Swedish Standards Institute, 2011).

Handbooks are an integral part of any design practice. Whether they are based on research, standards and regulations or collected experience by professionals, they are bound to impact the spaces the architects, engineers, and lighting professionals using them are shaping. In Sweden, Arkitektens handbok (Bodin et al., 2019) is arguably one of the most prominent resources available to building designers. It is a comprehensive collection of a wide range of design guidelines. Internationally, Neufert Architects' Data (Neufert and Neufert, 2012) is a well-regarded resource. It is a well-rounded resource containing a wealth of design guidelines. There are also specialised handbooks dedicated to lighting design, such as the SLL Lighting Handbook (The Society of Light and Lighting, 2018) which was also consulted in this study.

Sometimes, written sources such as environmental certification schemes, building standards and regulations, and handbooks and research papers may be insufficient. One goal of the study was to consider how professionals within the daylight field work in practice with the design to influence interior daylight levels and how they tackle late design choices. This target is arguably best achieved by learning directly from the professionals. Thus, this study included interviews with four daylight professionals with several years of experience currently active within the industry about their day-to-day work. They were from four different companies: two major contractors, one major architectural firm and one specialised consultancy, all active in Sweden. Their insights in part influenced what other resources were consulted and informed the choice of which late design choices (input variables) to investigate.

Two relevant literary resources consulted in the study were Daylighting and Lighting Under a Nordic Sky (Dubois et al., 2019) for theory of daylight and light in general, and about daylight simulation in particular, as well as Global Sensitivity Analysis: The Primer (Saltelli et al., 2008) for the theory of sensitivity analysis and sampling methods.

2.2 Late design choices

Late design choices are defined as design decisions which the architects, engineers or daylight specialists can make late in the design process, or choices that are more often made by the interior designer or the space's occupants when it has already been constructed. These choices are not limited to factors first introduced late in the design process but also include those that are still able to be changed in these stages, although they may have first been introduced earlier. The building volume, its orientation and relation to surrounding context, the floor plan and façade openings are decided early in the design process and have a major impact on the final interior daylight. These decisions are often hard to revert at later stages. Several factors remain however after these initial decisions which also affect the interior daylight. Some of these factors, such as window transmittance and surface reflectance, may have been introduced early in the design process as measures to comply with building standards and regulations, but are at times still able to be changed later. Others are however not introduced until late in the design process, such as static or movable permanent shading (outside the scope of this study), as deliberate measures to control daylight. Still other factors are decided after construction by interior designers or the occupants themselves who may have little to no knowledge about daylight. Some may be deliberate decisions to control the interior daylight, such as shading in the shape of roller blinds and curtains (outside the scope of this study). Others are informed more by desired functions or user preferences, such as the flooring material, colour of walls and ceilings, as well as the amount, size, and colour of furniture, but inadvertently affect the interior daylight without the knowledge of the decision-makers.

For the space boundary surfaces, reflectance (which is determined by colour) is the primary design choice made in the late design phase. Daylight professionals often refer to environmental certification schemes or building standards and regulations for reference reflectance values for the interior surfaces to apply in daylight simulations (Interviews, 2021).

Table 1 Compilation of recommended reflectance values.

Element	**Standard**	**Reflectance/-**
Wall	BREEAM	-
	LEED	0.5
	Miljöbyggnad	0.8
	SS-EN 17037	0.5–0.8
	SS-EN 12464	0.5–0.8
	PSBP	0.5
	Neufert	0.5
	CIBSE	0.5–0.8
Ceiling	BREEAM	-
	LEED	0.8
	Miljöbyggnad	0.9
	SS-EN 17037	0.7–0.9
	SS-EN 12464	0.7–0.9
	PSBP	0.7
	Neufert	0.7
	CIBSE	0.7–0.9
Floor	BREEAM	-
	LEED	0.2
	Miljöbyggnad	0.3
	SS-EN 17037	0.2–0.4
	SS-EN 12464	0.2–0.4
	PSBP	0.2
	Neufert	-
	CIBSE	0.2–0.4
Furniture	BREEAM	-
	LEED	-
	Miljöbyggnad	-
	SS-EN 17037	-
	SS-EN 12464	0.2–0.7
	PSBP	-
	Neufert	0.2–0.5
	CIBSE	0.2–0.5
(Partitions)	CIBSE	0.5–0.8

Table 1 presents a compilation of reflectance values suggested by the reviewed resources. Most give similar recommendations for the elements relevant to the study. The maximum interval for every element, between the lowest recommended value and the highest one independent of source, was applied in the study. A 2015 study conducted a sensitivity analysis regarding the impact of interior surface reflectance on interior daylight and concluded that ceiling reflectance had the most impact, followed by walls and exterior ground reflectance whereas floor reflectance contributed least to the variability of daylight (Brembilla et al., 2015). The study applied a reflectance interval of 0.01–0.99 for all variables. This assumption does not reflect real life values generally found in buildings but was used to rank the importance of input variables without any initial bias. The simulation results when applying combinations of very high reflectance values are however not physically accurate as Radiance (the simulation engine used in the study) is designed to work with building models having an average reflectance around 0.5 (Ward, 2005). A 2018 follow-up study by the same authors instead applied realistic reflectance ranges and this study concluded that the exterior ground reflectance had the most impact, followed by wall and ceiling reflectance. The floor reflectance exhibited the smallest influence on all studied metrics (Brembilla et al., 2018). The study also showed slight changes in input variable influence rankings because of geometric variations between the studied spaces, meaning that underlying daylight conditions because of geometrical and spatial context influenced how much the reflectance of different surfaces could impact the final interior daylight.

Furniture involves late design choices taken by interior designers after the building has been constructed but could also be left to the users of a space rather than a professional. Furniture is very variable in the shape, size, and colour of individual pieces and compositions within an interior space. Moreover, furnishing of a space could change considerably during the building lifetime, depending on its usage and the preferences of its tenants. Furthermore, furniture increases the complexity of the digital models daylight specialists use during analysis, which adversely affects computational load. Furniture is thus generally left out of interior daylight analyses. All of the daylight professionals interviewed for this study stated that they do not include furniture in their daylight simulations (Interviews, 2021). A 2001 study showed that furnished rooms consistently measured lower illuminance levels on the work plane, ceilings and lateral walls compared to empty ones. The relative difference increased with the distance from windows (Dubois, 2001). Additionally, it demonstrated that the impact of furniture on interior daylight depended highly on furniture position and the sun angle as this influenced weather it reflected the direct sunlight further into the room or shaded the workplane. Similarly, a 2018 study found that furniture could reduce $DF_{Average}$ levels by 11% on average, and that it always had an adverse effect on interior daylight in general. The influence was higher when furniture was arranged to prevent daylight from penetrating deep into the space (Mousavi et al., 2018). Furniture extending above the simulation plane such as partitions between workspaces often seen in open office layouts have an especially high impact on the interior daylight. A 2010 study found that decreasing partition heights in an office from 1.50 m to 1.15 m above floor level could lead to a 20% increase of daylight availability (Saxena and Heschong Mahone Group, 2010). A 2015 study presented slight differences in simulated sDA results between unfurnished and furnished spaces, and that decreasing partition heights from 2.13 m to 1.1 m lead to a 12% increase of sDA (Mohsenin and Hu, 2015). A 2016 study contrastingly showed that furniture below the work plane had a small influence on interior daylight levels (Brembilla et al., 2016). The IES standard LM-83-12 suggests that interior obstructions extending 0.9 m above floor level should be modelled with and accuracy of 15 cm (Illuminating Engineering Society, 2012).

Finally, the light source itself has a profound impact on the level and character of light in a space, be it natural daylight or electric. The visual transmittance of windows is one of the main properties regulating how much visible daylight enters a space through the windows. It is often a goal of daylight simulation to establish what window transmittance is needed to meet daylight target levels. It can however be considered a late design choice in cases where daylight analysis is not done until late in the design process, and as transmittance is relatively easy to change by prescribing a specific choice of windows. The transmittance is also variable as it depends on the frequency with which the windows are cleaned and could change if the property owner wishes to replace windows during the building's lifetime. Several of the interviewed daylight professionals explained that in some instances they could also alter the shape or position of the windows, even late in the design process (Interviews, 2021). It is thus possible to consider windowsill height and window head height, in addition to visual transmittance as late design choices.

Several studies have demonstrated the importance of window configurations in determining the daylight in interior spaces. Its intensity and distribution could be improved significantly with greater window height and larger window-to-wall ratio (WWR) which extends the daylit zone in the space (Baker and Steemers, 2013). A 2000 study conducted a survey of over 1800 Danish office workers and found a strong preference for workspaces near windows, despite the risk for glare (Christoffersen et al., 2000). The study determined that a WWR of 25% to 30% is ideal to maximize the number of satisfied occupants. A 2013 study examining the interior daylight based on visual transmittance values and glazing colour observed that these variables have a profound impact (Husin and Harith, 2012). A 2001 study made an inventory of typical glazing types used commercially in Sweden and compared their transmittance characteristics (Bülow-Hübe, 2001) (see Table 2).

Table 2 (Bülow-Hübe, 2001) visual transmittance of glazing types.

Glazing type	**τ_{Visual}/-**
Double, clear	0.80
Triple, clear	0.72
Triple, e10%	0.69
Triple, e10%+Ar	0.69
Triple, 2e10%+2Kr	0.66

T_{Visual} is the visual transmittance, indicating the capacity of a window to let the light passes through its panes, including the effect of internal reflection in between glass surfaces. It is a unit commonly appearing in commercial markets. Interviews with daylight professionals suggested that window transmittance values as low as 0.5 may be used in daylight simulations (Interviews, 2021).

The requirement for electric light is tied to the daylight levels within a space, as well as occupation hours and user preferences. For energy, and an indoor climate standpoint is desirable to achieve some level of baseline illuminance with natural daylight and only use electric light for specific areas and tasks when needed. One choice the lighting designer has to make is one of luminaires and lamps. Electric lighting is further discussed in section 2.6 (p.15).

2.3 Scenarios

Factors such as building volumes and their orientation, space sizes, and WWR, as well as environmental context such as topography, surrounding buildings and vegetation have a dominant impact on the underlying interior daylight conditions. Interior daylight is only secondarily affected by late design choices, and the potential of these factors to impact daylight levels is dependent on the underlying daylight conditions of a space (Brembilla et al., 2018). Environmental certification schemes, building standards and regulations, and handbooks give suggestions about or put requirements on the design of interior spaces to regulate these underlying interior daylight conditions.

BREEAM gives recommendations on the WWR depending on the distance between the furthermost workspace and windows (see Table 3).

Table 3 BREEAM suggestion regarding room depth depending on the window to wall ratio.

Distance from window to the furthermost workspace / m	**WWR / %**
<7	20
8 to 11	25
11 to 14	30
>14	35

It also makes suggestions about maximum room depth, specifically for side-lit spaces, depending on window head height, average room surface reflectance and the room width (see Table 4).

Table 4 BREEAM recommendation regarding room depth based on window head height, room width and average surface reflectance.

Average reflectance / %	40		50		60	
Room width / m	3	10	3	10	3	10
Window head height / m	**Maximum room depth / m**					
2.5	4.5	6.7	5.4	8.0	6.8	10.0
3.0	5.0	7.7	6.0	9.2	7.5	11.5
3.5	5.4	8.6	6.5	10.4	8.1	13.0

BREEAM contains a definition of “small spaces” as those less than 40 m^2 (Sweden Green Building Council and BRE Global, 2018).

LEED specifically states not to include furniture in the daylight simulations. However, it does not make any recommendations about window transmittance or building geometry (U.S. Green Building Council, 2019).

BBR 29 puts requirements on window area and room height. It requires a glazing area of no less than 10% of the floor area and a floor-to-ceiling height of at least 2.4 m (Boverket, 2020).

AFS 2020 requires a ceiling height of 2.7 m for office spaces but makes an exception for workspaces with a small number of workers where a ceiling height of 2.4 m is deemed sufficient. It gives no suggestions about other building geometry and instead refers to SS-EN 17037 for verification of daylight requirement compliance.

PSBP suggests a floor-to-ceiling height of 3 m and also a maximum room depth of 7.2 m. Furthermore, it recommends a WWR of at least 30% (Education Funding Agency and Cundall, 2014).

CIBSE LSS Lighting Handbook makes suggestions about a floor-to-ceiling height between 2.5 m and 3.5 m.

Neufert’s Architect’s Data recommends room depths of 15 m and 9 m for “large” and “small” offices, respectively. Furthermore, it suggests a minimum desk area for a single workstation of 160 cm × 80 cm in the handbook (Neufert and Neufert, 2012).

Recommendations about building geometry are relatively scarce and not very detailed in the consulted material. PSBP gave the most detailed suggestions about design, but overall, the following conclusions could be made: Floor-to-ceiling height should be between 2.7 m and 3 m. Space should be at most about 15 m deep. The WWR should be around 30%. A WWR at or over the threshold could constitute a well-lit or space, and under the threshold, a dimly lit one.

2.4 Daylight metrics

Daylight metrics represent ways of measuring daylight levels in an interior or exterior space or on a surface. They could be divided into image-based metrics and grid-based ones. Image-based metrics measure the level or character of daylight in a specific view relying on luminance, for example the glare levels at a particular workstation. Grid-based metrics employ an analysis grid in which daylight levels are measured based on illuminance. In this study, only grid-based daylight metrics applicable to interior spaces were considered. These can further be divided into two types: static daylight metrics and dynamic daylight metrics. Static daylight metrics are measures of daylight which do not take local climate, weather variations or building orientation into account (Reinhart et al., 2006). When simulated, they are done so using standardised sky models such as the CIE (Commission Internationale de l’Eclairage) Standard Overcast Sky. They are frequently employed in environmental certification schemes, standards, and regulations. Dynamic daylight metrics are diverse and increasingly represented in literature. They are simulated with climate-based daylight modelling, using standardised weather files such as Energy Plus Weather (EPW) files.

Dynamic daylight simulations are advantageous compared to static metrics because they represent more accurately the quantity, quality, and character of daily and seasonally variable daylight (Reinhart et al., 2006). Metrics found in environmental certification schemes, building standards and regulations were of particular interest as these are often the ones used by daylight professionals (Interviews, 2021).

BREEAM is proposing two grid-based strategies to assess interior daylight in addition to image-based methods (which are not covered here). One is intended for places with temperate or subarctic climate where overcast and cloudy skies are dominant (such as Sweden), and the other for places with a hot and sunny climate. The strategy proposed for Sweden utilises two daylight metrics simultaneously to assess the daylight characteristics. The first is Average Daylight Factor ($DF_{Average}$/%) over an area fraction. For office spaces in southern Sweden (latitude 55°–60°), it is ≥2.1% over 80% of the analysis area. The second is the Daylight Uniformity Ratio (U_o/-). It is the ratio between the DF in the worst-performing point of the analysis grid and the $DF_{Average}$. It should be no less than 0.3. The strategy proposed for places with hot and sunny climates uses Average Daylight Illuminance ($E_{Average}$/lux) over an area fraction, as well as a minimum illuminance threshold in the worst point, both for a specified duration of time. It requires an average of at least 300 lux over 80% of the area for 2000 h/year, and no less than 90 lux in the worst-performing point for 2000 hours per year. Although this strategy is intended to be used in hot and sunny climates, it is permitted for use to prove compliance in Sweden too (Sweden Green Building Council and BRE Global, 2018).

LEED gives two options for simulation and one for measurement. The first option for simulation uses Spatial Daylight Autonomy (sDA/%) with a threshold of 300 lux for 50% of annual sunlit hours over a fraction of the regularly occupied area based on credit target, as well as Annual Sunlight Exposure with a threshold of 1000 lux for 250 hours over maximum 10% of the regularly occupied area. The second option for simulation uses Illuminance (E/lux) with a target between 300 lux and 3000 lux over a fraction of the regularly occupied area at 09:00 and 15:00 on the days of equinox. The option for measurement similarly uses Illuminance (U.S. Green Building Council, 2019).

Miljöbyggnad uses two metrics alternatively, point and median Daylight Factors (DF_{Point}/%, DF_{Median}/%) with thresholds between 0.8% and 1.3% based on credit target (Sweden Green Building Council, 2020b).

Swedish building regulations BBR 29 refer to SS-EN 17037 but uses Average Daylight Factor ($DF_{Average}$/%) in a rule of thumb, stating that the window-to-floor-area ratio should be no less than 10% in order to achieve a $DF_{Average}$ of 1% (Boverket, 2020).

SS-EN 17037 uses targets for Average Illuminance ($E_{Average}$/lux) over 50% of the analysis area and Minimum Illuminance (E_{Min}/lux) over 95% of the area; both for half of the day lit hours per year. Minimum target levels are 300 lux and 100 lux respectively), medium targets are 500 lux and 300 lux, and finally high are 750 lux and 500 lux respectively. These illuminance targets regard vertical side lighting (Swedish Standards Institute, 2018).

SS-EN 12464 uses two illuminance-based metrics simultaneously, Maintained Illuminance ($\bar{E}_m$/lux), which essentially is a measure of minimum average illuminance, and Illuminance Uniformity (U_0/%) which is the ratio between minimum and average illuminance and is also given as a minimum threshold. It puts the following requirements for office spaces: $\bar{E}_m$>75 lux with $U_0 \geq 10\%$ on walls and $\bar{E}_m$>50 lux with $U_0 \geq 10\%$ on the ceiling (Swedish Standards Institute, 2011, p. 12).

PSBP uses Useful Daylight Illuminance (UDI/%), a measure of the fraction of time over the analysis period when illuminance is within a specific range. The target is between 100 and 3000 lux for a minimum of 80% of the annual sunlit hours. It also employs sDA similarly to LEED, but with a target of 50% (Education Funding Agency and Cundall, 2014).

Neufert Architects' Data gives guidelines on illuminance level, namely that it should be between 300 lux and 500 lux (Neufert and Neufert, 2012).

Table 5 Compilation of daylight performance metrics.

Standard	Daylight metric	Description	
BREEAM	$DF_{Average}$/%	Average Daylight Factor	$DF_{Average} \geq 2.1$ over 80% of the analysis area.
	U_0/%	Daylight Uniformity	$U_0 \geq 0.3$
LEED	sDA/%	Spatial Daylight Autonomy	$sDA_{300/50\%} \geq 55\%$
	ASE/%	Annual Sunlight Exposure	$ASE_{1000/250} \leq 10\%$
Miljöbyggnad	DF_{Median}/%	Median Daylight Factor	DF_{Median} or $DF_{Point} \geq 0.8\%$ for Bronze, 1% for Silver and 1.3% for Gold rating.
	DF_{Point}/%	Point Daylight Factor	
BBR 29	$DF_{Average}$/%	Average Daylight Factor	$DF_{Average} \geq 1\%$
SS-EN 17037	$E_{Average}$/lux	Average Daylight Illuminance	$E_{Average} \geq 300$ lux over 50% of the analysis area for half of day lit hours.
	$E_{Minimum}$/lux	Minimum Daylight Illuminance	$E_{Minimum} \geq 100$ lux over 95% of the analysis area for half of day lit hours.
SS-EN 12464	$\bar{E}_m$/lux	Maintained Illuminance	$\bar{E}_m \geq 75$ lux on walls and 50 lux on ceiling
	U_0/%	Illuminance Uniformity	$U_0 \geq 10\%$
PSBP	UDI/%	Useful Daylight Illuminance	100 lux ≤ UDI ≤ 3000 lux for at least 80% of annual sunlit hours.
	sDA/%	Spatial Daylight Autonomy	sDA ≥ 50%
Neufert Architects' Data	$\bar{E}_m$/lux	Maintained Illuminance	300 lux ≤ $\bar{E}_m$ ≤ 500 lux

Table 5 presents a compilation of daylight metrics recommendation of different environmental certification schemes, building standards and regulations, and handbook.

A variation of DF and some illuminance metric is prevalent among the reviewed resources. However, due to limitations in the Honeybee version (1.1) used for daylight simulations, it was not possible to simulate any illuminance metrics aside from UDI. sDA is also used in some resources. One metric not employed by any of the reviewed resources is Daylight Autonomy (DA/%), defined as the percentage of occupied time in the analysis period when the minimum illuminance requirement is met by daylight alone (Reinhart and Walkenhorst, 2001). It could be used to calculate Lighting Dependency (LD/%), which is the percentage of occupied time in the analysis period when the minimum illuminance requirement cannot be met by daylight alone, and electrical light is needed to elevate the illuminance levels. LD can subsequently be used to calculate energy use for the said electrical lighting requirement. LD can be calculated according to Equation 3.

$$LD = 100 - DA \text{ [\%]} \tag{3}$$

2.5 Daylight simulation

Daylight simulations are used to artificially measure the metrics described in section 2.4 (p.10). As with daylight metrics themselves, daylight simulations can likewise be divided into image-based simulations and grid-based ones. As only grid-based metrics were considered in this study, only grid-based simulations too were considered. The analysis grid is an array of virtual sensors at a specific distance from each other and the surrounding walls, as well as at a specified height above the floor plane. The resolution of the analysis grid affects the accuracy of the simulated values, where a denser grid produces more accurate results, but it also increases the computational load. Grid-based simulations can further be divided into static daylight simulations and dynamic daylight simulations. Static daylight simulations are independent of location, climate, weather, or time. They are simulated using standardised sky models such as the CIE Standard Overcast Sky, a model of a completely overcast sky three times brighter at the zenith than the horizon (Piderit et al., 2014). Dynamic daylight simulations, or climate-based daylight modelling, uses standardised weather files such as Energy Plus Weather (EPW) files. These files contain, among other things, hourly direct and diffuse irradiation and other weather data measured at a specific location. A weather file for Copenhagen, Denmark was used in this study (ASHRAE, 2001).

Climate Based Daylight Modelling (CBDM) can be performed according to several different methods. These methods include the 2-phase (or 1-phase, or DC) method, 3-phase method, 5-phase method, the DAYSIM method, and the Four Component Method (4CM). The 4CM is the most rigorously validated simulation method and was employed in this study. It gets its name from the four components from which light calculated by the method: 1. direct sunlight, 2. indirect sunlight, 3. direct skylight and 4. indirect skylight. The direct light components are derived by deterministic raytracing, while the indirect light components are computed stochastically (Mardaljevic, 2000). When running daylight simulations according to the 4CM in Honeybee (Ladybug Tools, 2020) (which was employed in this study), the backward raytracing engine Radiance (Ward, 2020) is utilised. Backward ray tracing implies that the virtual light rays are traced from the virtual analysis sensor to the light source instead of the other way around, as is the case in nature. This method is more computationally efficient as only the “interesting” light rays, i.e. those that actually would reach the virtual sensor, are computed. Radiance calculates the direct component (the light ray travelling directly from the light source to the sensor) as well as the specular and diffuse indirect components (the light rays that are being reflected off surrounding surfaces). Raytracing with Radiance is dependent on a range of parameters affecting the direct and indirect components of the traced light. The parameters affecting the indirect components generally have a larger effect on the simulation results and their accuracy when assessing interior daylight, as most of the light in the space is interacting with the surfaces within it (Dubois, 2001). With daylight simulations, these parameter settings are usually a trade-off between simulation accuracy and computational load. The primary Radiance simulation parameters are (Jacobs, 2012; Larson et al., 1998):

- Ambient accuracy (aa/-) defines the magnitude of error allowed in the interpolation of calculations. A lower ambient accuracy value gives more accurate simulation results. Halving the value likely quadruples the computational load.
- Ambient bounces (ab/-) is the number of diffuse reflections computed. A higher value for ambient bounces results in more reflections. Doubling could double the computational load.
- Ambient divisions (ad/-) sets the number of rays reflecting off a surface in a diffuse reflection of an incoming light ray. A higher value for ambient divisions results in the incoming ray being split into more reflected rays. Doubling could double computational load.
- Ambient resolution (ar/-) is used to prevent the simulation from overloading, which could be caused by small geometry in the model. Doubling could quadruple computational load.
- Ambient super-samples (as/-) controls the number of extra rays being sampled to increase accuracy in areas of high contrast. A higher value for ambient super-samples results in more rays being sampled.
- Limit weight (lw/-) is the minimum contribution a light ray could make before being terminated. A higher limit weight results in rays being terminated when their contribution is higher. Decreasing the limit weight could slightly increase the computational load.

Table 6. (Jacobs, 2012; Larson et al., 1998) Radiance parameter settings.

Parameter	Description	Min	Fast	Accurate	Very accurate	Max
aa/-	Ambient accuracy	0.5	0.2	0.15	0.05	0
ab/-	Ambient bounces	0	0	2	5	8
ad/-	Ambient divisions	0	32	512	2048	4096
ar/-	Ambien resolution	8	32	128	512	0
as/-	Ambient super-samples	0	32	256	512	1024
lw/-	Limit weight	0.05	0.01	0.002	0.0004	0

Table 6 shows Radiance parameter settings suggested in literature (Jacobs, 2012; Larson et al., 1998).

LEED requires the analysis grid to be 0.76 m above the floor plane and to have a maximum distance between virtual sensors of 0.6 m (U.S. Green Building Council, 2019).

Miljöbyggnad requires the analysis grid for DF_{Median} simulations to be 0.8 m above the floor plane, between 0.1 and 0.5 m from walls, and with a maximum distance of 0.5 m between virtual sensors. DF_{Point} is simulated in a point 0.8 m over the floor plane, 1 m from the darkest side wall, at half the room depth (Sweden Green Building Council, 2020b).

SS-EN 17037 requires the analysis grid to be 0.85 m above the floor plane (Swedish Standards Institute, 2018).

Daylight simulations are computationally heavy operations, while sensitivity analysis often requires a large amount of data to deliver stable and accurate results. Consequently, the need of finding a balance between accuracy and simulation time for any study to be feasible arises. In such cases, the safest option may be to follow precedent set by previous studies on the subject. The 4DM is preferable as it is the most validated and most accurate CBDM methods, as well as the method the authors are most familiar with.

2.6 Electric lighting

Electric lighting is a major factor of energy use in buildings, constituting over 15% of the overall electricity demand and up to 25% during peak hours (Kralikova et al., 2015). In Sweden, electric lighting makes up 20% to 45% of the total electricity demand of non-residential buildings (Borup et al., 2005; Swedish Energy Agency, 2007). Older, existing office spaces usually have an electricity use for electric lighting around 24 kWh/m^2 per year, while newly constructed ones use only about 11 kWh/m^2 per year (Borg, 2009) as old, inefficient light sources are abandoned in favour of modern, energy-efficient ones. The development of new materials, technology, microelectronics, and computer technology allows for innovations in lighting technology, reducing the electricity demand of electric lighting while improving interior light quality (Habel and Žák, 2011). A 2011 study revealed that replacing old T12 fluorescent lamps with modern, energy-efficient T5 lamps with high-frequency ballast could reduce the electricity demand by up to 40%. Additionally, using task lights, occupancy controlled switch-on or off, and dimming when daylight provides satisfactory illumination could yield an additional 40% reduction of the electricity demand (Dubois and Blomsterberg, 2011). Two studies have shown that electricity demand due to electric lighting could be reduced by 50% using existing technology and lighting control strategies (Borup et al., 2005; Bülow-Hübe, 2008).

Installation of electric lighting represents only 15% of the overall environmental impact of electric lighting. The greatest environmental impact is from the operation, constituting 70% of the total (Månsson et al., 2010). A 2007 study indicated that using energy-efficient lighting is one of the most profitable approaches to mitigate CO_2 emissions and the environmental impact of the electric lighting system (Enkvist et al., 2007). Besides the direct energy savings, reducing the electric lighting demand or improving its energy efficiency also contributes to the lower heat gains, resulting in indirect energy savings from the reduced cooling demand (Athienitis and Tzempelikos, 2002; Hanselaer et al., 2007).

A study in 2000 did a survey with 1800 Danish office workers and found that many switched on general lighting even though daylight levels were deemed sufficient (Christoffersen et al., 2000). It also concluded that the use of electric lighting depended on workspace positioning, and that effective zoning and lighting control showed great potential for reducing energy demand.

For general office lighting, the typical Lighting Power Density (LPD) using a T5 fluorescent lighting system and efficient LED lamps is estimated at 8 W/m^2–12 W/m^2 and 4 W/m^2, respectively (Dubois et al., 2015; Dubois and Blomsterberg, 2011; Gentile and Dubois, 2017). In this study, a LPD of 10 W/m^2 for T5 fluorescent lamps and 4 W/m^2 for LED lamps was applied in electric lighting calculations according to section 3.5.

2.7 Sensitivity analysis

Sensitivity analysis is "the study of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input" (Saltelli et al., 2004). In the context of this study: how much an input variable (late design choice) is affecting the result of a daylight simulation (interior daylight). Sensitivity analysis can be used to assess the robustness of a model or decrease uncertainties within it, to simplify the model, or as is the goal of this study, to map the relationship between the input variables and the output of a model. Sensitivity analysis can be divided into local and global types. Local sensitivity analysis is conducted by varying the value of one input variable at a time in increments of a predefined range. It is a brute-force approach, and the accuracy benefits from having increments vanishing towards zero. This could make local sensitivity analysis computationally demanding for complex models. Global sensitivity analysis on the other hand generally considers the entire sample space for all input variables simultaneously and can sometimes also give more detailed results. Its methods could be divided into three types: screening methods, regression methods and variance-based methods. Screening methods give an overview of the effect and importance of the input variables. They employ a global one-at-a-time (OAT) approach similar to local sensitivity analysis, but where the increments do not have to vanish towards zero to retain accuracy. This decreases computational load. Regression methods are used for a wide range of purposes within statistical modelling, and there are methods more or less suitable for any given purpose. They use several sensitivity metrics known as "standardised regression coefficients" and can employ different sampling strategies. The most common is the linear regression method using least-square computation, which is based on the squared difference between the output produced by the regression model, and the actual studied model. The immediate drawback of the linear regression method is its limited applicability to models with non-linear input variable to output relations (Saltelli et al., 2008). Variance-based methods decompose the variance of the model output into the parts attributable to each input variable. They can differentiate between the direct influence of individual input variables, interaction effects and the total effects. The Fourier Amplitude Sensitivity Test (FAST) method and the Sobol method are both variance-based methods. They use the sensitivity metrics: first-order index (direct influence of an input variable), second-order index (interaction effect between input variables) (only Sobol) and the total order index.

The immediate drawback of the variance-based sensitivity analysis methods is their high computational cost (Saltelli et al., 2008).

A 2010 study compared several methods within of the aforementioned types, using the Sobol method as a baseline. It found a screening method (the method of Morris) to be the least computationally costly while still delivering stable results. Regression methods and variance-based methods were significantly costlier (Confalonieri et al., 2010). A 2020 paper made a comprehensive inventory of building performance simulation studies that have performed sensitivity analyses (Pang et al., 2019). Several such studies have employed the method of Morris (Heiselberg et al., 2009; Hopfe and Hensen, 2011; McLeod et al., 2013). It was used in a 2018 paper about the impact of surface reflectance on daylight in several real-world spaces. That study used eight levels and eight trajectories for five input variables using the local optimisation strategy, resulting in a total of 48 samples (Brembilla et al., 2018).

The method of Morris, otherwise known as the Elementary Effects method, is a screening method using a global OAT approach. The value of one input variable is changed at a time in increments determined at the sampling stage (see section 2.8, p.18) within predefined ranges (see section 2.2, p.5) and the resulting change of the model output is measured. Changes in the model output can thus be attributed to the change in only one particular input variable. It is a simple yet effective way of determining which groups of input variables have more/less impact on the output, and if they are linear/non-linear. Non-linearity may imply that input variables interact with each other. It uses two sensitivity measures: the mean value of the distribution of elementary effects (μ) or the mean absolute value of the distribution (μ^*), which can be understood as the influence of the input variable on the output, and the standard deviation of the elementary effects (σ), which indicates if the relationship between an input variable and the model output is linear/non-linear (Campolongo et al., 2007; Morris, 1991; Saltelli et al., 2008). When plotting the standard deviation against the mean a studied input variable can be considered to have a linear relation to the output if $\sigma/\mu^* \leq 0.1$, monotonic relation if $\sigma/\mu^* \leq 0.5$, almost monotonic relation if $\sigma/\mu^* \leq 1$ and a non-linear relation if $\sigma/\mu^* \geq 1$, indicating that it may be interacting with other input variables (Brembilla et al., 2018). The computational cost of screening methods like the method of Morris is low, but the result is also less detailed. It can, for example, not distinguish between non-linearity and interaction, and thus neither give any further information about the degree of interaction, which variables are interacting, and their individual impact on the result due to this interaction (Rackauckas, 2020).

Sensitivity analysis can be performed with different tools. One is the Python package SALib (Herman et al., 2020) which is a comprehensive toolset for sensitivity analysis according to several of the methods mentioned above available for the Python programming language. Another is SobolGSA (Kucherenko and Zaccheus, 2020), a standalone software also able to perform sensitivity analysis according to several of the discussed methods.

As daylight simulation is a computationally demanding operation the feasibility of any sensitivity analysis depends on the sample size, and thus the number of simulations required by a sensitivity analysis method to produce stable and accurate results. A method such as the method of Morris which is resource-effective and has been shown to produce input variable influence rankings of acceptable accuracy is preferable to the other alternatives. Its history of application not only in building performance simulation studies, but specifically in daylight simulation studies, demonstrates its robustness for such purposes.

2.8 Sampling

A crucial step in sensitivity analysis is to sample values from the input variable value ranges. The goal is to create a subset of the values input variables can take in a fashion that gives the most accurate representation of the entire sample space while reducing the computational load of the analysis. This can be done through many different methods, but the sampling method is often defined by the sensitivity analysis method itself. The most obvious method is true random sampling, where values in a range for every input variable are equally likely to be sampled. The immediate draw-back of this method is lacking control over sample distribution. Randomly sampled values run the risk of clustering around a specific point in the sample space, which would result in misrepresentative simulation results. This risk can be reduced by employing a pseudo- or quasi-random sampling method, or a factorial sampling method. The pseudo- and quasi-random sampling methods create low-discrepancy sequences by introducing a random sampling algorithm with bias towards already selected values in the sample space. These algorithms are random in the sense that individual values are randomly chosen, but while keeping the density of values distributed across the entire sample space constant. They could however require a relatively large number of samples to give accurate representations of the sample space and are thus computationally costly. Factorial sampling methods divide the sample space into levels based on the probability distribution function of the input variables and the resolution necessary to produce accurate representations of the sample space. A value is then sampled from each level according to different strategies such as the median value of each level or a random value from within the range of a level etc. Several variations of factorial sampling aim to lower the amount of samples needed to give stable and accurate results (Saltelli et al., 2008).

The method of Morris employs a global OAT sampling method combined with the Latin hypercube factorial sampling method. The sample space is divided into non-overlapping regions (levels) from which a value for each input variable is sampled at random. A direction in which to change the value is then chosen, and the value is changed in the chosen direction for the next sample. Thus, the value of only one input variable is changed in between consecutive samples. This process is repeated for a number of trajectories, which essentially is the number of times a value is sampled from every level and moved in a random direction. Local optimization can be deployed as a strategy to optimise the distribution of the chosen values across the sample space, which ensures a true representation of the value ranges of the input variables, while keeping the sample size as low as possible. A large number of trajectories are then used in the sampling of which a smaller subset that creates the most diverse walk across the sample space is chosen (Ruano et al., 2012). The advantage of the OAT sampling method combined with Latin Hypercube sampling which is used in the method of Morris is that its mean converges faster towards a true mean than that of simple random sampling for example, and that it consequently is likely to give a better representation of the full sample space while significantly reducing the number of simulations needed to produce stable and accurate results. The number of samples N obtained from r trajectories and k input variables can be calculated as N=r(k+1) (Saltelli et al., 2008).

3 Methodology

Figure 1 illustrates the workflow of this study, which consisted of three main topics and their subtopics.

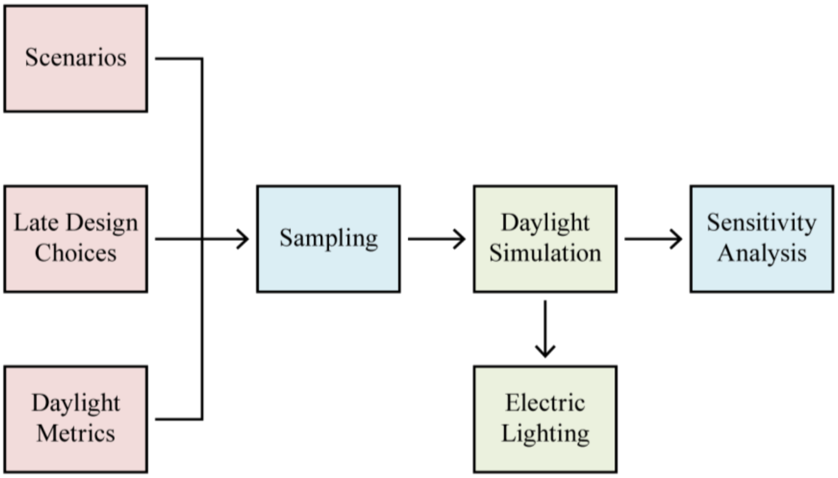

Figure 1 Workflow.

The first topic (red) concerned the determination of inputs and outputs. A set of scenarios was designed to assess changing underlying conditions such as space size, baseline irradiation, and light orientation. Late design choices were chosen from reviewed literature and interviews with lighting professionals. Daylight metrics to include were also chosen from literature.

The second topic (green) regarded daylight simulation using Honeybee 1.1 (Ladybug Tools, 2020) and calculating electricity use for electric illumination.

The third topic (blue) concerned the sensitivity analysis. Samples were created for the late design choices using the modified OAT sampling method employed by the method of Morris. The impact of said late design choices was assessed by sensitivity analysis according to the method of Morris using the SALib Python package (Herman et al., 2020).

3.1 Late design choices

Late design choices to include as input variables in the study were based on literature and interviews with professionals in the daylight industry as discussed in section 2.2 (p.55).

Table 7 Input variables.

Input variable	Range
Floor reflectance/-	0.20–0.40
Ceiling reflectance/-	0.70–0.90
Wall reflectance/-	0.50–0.80
Furniture reflectance/-	0.20–0.70
Visual transmittance/-	0.50–0.80
Window head height/m	2.00–2.70
Window sill height/m	0.00–0.70
Furniture density/-	0.05–0.40
Partition height/m	0.70–2.00

Table 7 shows the investigated input variables with corresponding value ranges. The value range for each variable was based on the consulted material. The probability distributions of these ranges were considered uniform as designers were assumed to be equally likely to choose any of the values suggested by environmental certification schemes, building standards and regulations, and handbooks.

Furniture was modelled as desks with 1.6 m wide and 0.8 m deep, 0.7 m above the floor plane following recommendations in architectural design handbooks (Bodin et al., 2019; Neufert and Neufert, 2012). Desks were separated with partitions on either end, as often seen in open offices. This partition could be variable in height between the desk height (0.7 m) and 2 m above the floor plane (see Figure 2).

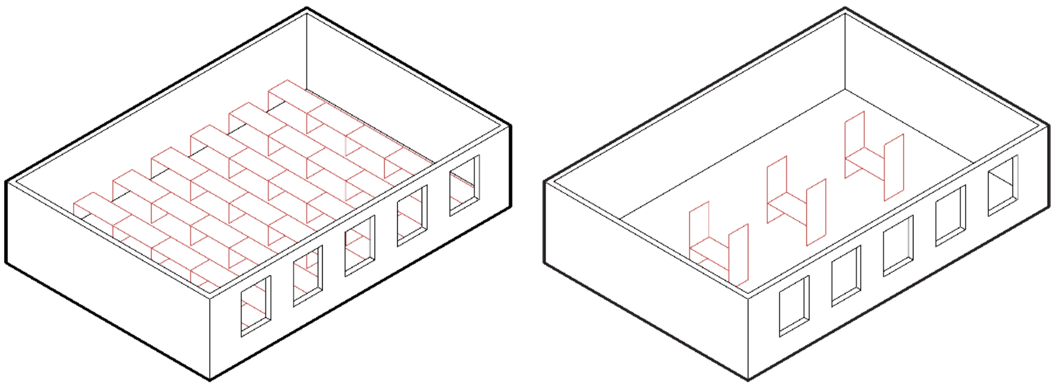

Figure 2 Furniture layout.

Desks were distributed in rows, with a distance of at least 1.6 m following architectural design handbooks (Bodin et al., 2019; Neufert and Neufert, 2012), and at most 3.2 m (see Figure 2). Furniture density is the ratio between furniture surface area and floor area and was used as a proxy for the amount of furniture in the space.

3.2 Scenarios

To avoid misrepresentation of the analysis results due to underlying daylight conditions, which may influence the degree to which a particular late design choice can impact the interior daylight levels, a set of scenarios were modelled to create various lighting conditions.

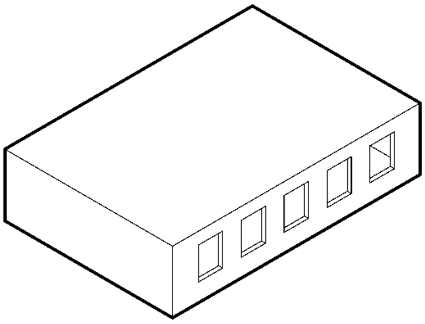

Figure 3 Base case.

The changes in each scenario were applied to a base case (denoted 'M' for medium size and WWR) modelled according to recommendations in literature. The space was 12 m wide and 8 m deep. The floor-to-ceiling height was 2.7 m in accordance with AFS09 and CIBSE which remained unchanged in all scenarios. It had a WWR of 30% according to BREEAM and PSBP recommendations, with windows only on one side, facing south (see Figure 3).

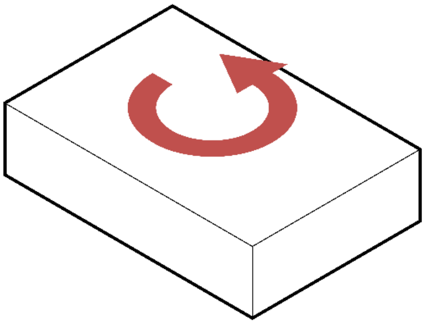

Figure 4 Orientation.

In order to assess the influence of the incoming light directionality, the model was rotated around the Z-axis in increments of 90° so that the windows were facing each cardinal direction (donated 'S' for the South, 'E' for the East, 'N' for North and 'W' for West). As the CIE Standard Overcast Sky is not influenced by orientation, rotation was not included in static simulations. The effect of orientation could thus be compared against the effect of increasing space size and WWR independently (see Figure 4).

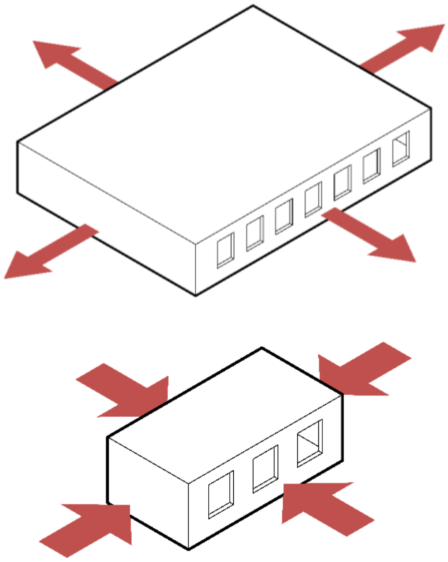

Figure 5 Size.

The space dimensions were changed from the base case into two configurations; one larger (denoted 'L') with a width of 16 m and depth of 12 m and one smaller (denoted 'S') with a width of 8 m and depth of 4 m, in order to assess the influence of changing interior surface area ratio which received direct illumination (see Figure 5).

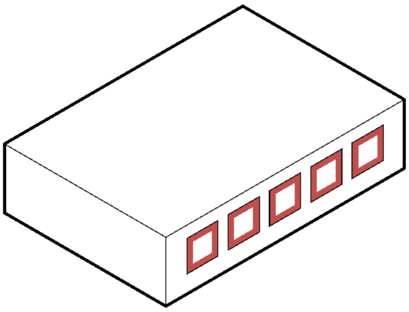

Figure 6 Window-to-wall ratio.

The WWR was changed from the base case into two configurations; one larger WWR (denoted 'L') of 40% and one smaller (denoted 'S') WWR of 20%, in order to assess the influence of changing baseline irradiation levels (see Figure 6).

Combinations of space dimensions and WWR configurations were also tested, all with openings oriented towards south to assess the combined effect of changing space volume and baseline irradiation. These were one with a larger space and larger WWR, a bigger space with smaller WWR, a smaller space but with larger WWR, and a smaller space with smaller WWR.

Table 8 Scenarios.

Scenario	Description	Width/m	Depth/m	WWR/-	Orientation
MMS	Medium volume, medium openings, south orientation.	12	8	0.3	South
MME	Medium volume, medium openings, east orientation.	12	8	0.3	East
MMN	Medium volume, medium openings, north orientation.	12	8	0.3	North
MMW	Medium volume, medium openings, west orientation.	12	8	0.3	West
LMS	Large volume, medium openings, south orientation.	16	12	0.3	South
SMS	Small volume, medium openings, south orientation.	8	4	0.3	South
MLS	Medium volume, large openings, south orientation.	12	8	0.4	South
MSS	Medium volume, small openings, south orientation.	12	8	0.2	South
LLS	Large volume, large openings, south orientation.	16	12	0.4	South
LSS	Large volume, small openings, south orientation.	16	12	0.2	South
SLS	Small volume, large openings, south orientation.	8	4	0.4	South
SSS	Small volume, large openings, south orientation.	8	4	0.2	South

Table 8 shows the dimensions, WWR and window orientation for each of the 12 scenarios.

Table 9 Scenario implementation.

Scenario	Static simulation	Dynamic simulation
MMS	✓	✓
MME		✓
MMN		✓
MMW		✓
LMS	✓	✓
SMS	✓	✓
MLS	✓	✓
MSS	✓	✓
LLS	✓	✓
LSS	✓	✓
SLS	✓	✓
SSS	✓	✓

Table 8 shows the dimensions, WWR and window orientation for each of the 12 scenarios.

Table 9 shows which scenarios were implemented in either static or dynamic daylight simulations. As previously stated, the CIE Standard Overcast Sky used in static daylight simulations is insensitive to orientation, which is why the rotation scenarios were not included in static simulations.

3.3 Daylight metrics

Daylight metrics to include as output variables were chosen from consulted standards and environmental certification schemes as described in section 2.4 (p.10).

Table 10 Daylight metrics.

Output variable	Description
$DF_{Average}$/%	Average Daylight Factor
DF_{Median}/%	Median Daylight Factor
DF_{Point}/%	Point Daylight Factor
DA/%	Daylight Autonomy
sDA/%	Spatial Daylight Autonomy
LD/%	Lighting Dependency
UDI/%	Useful Daylight Illuminance

Table 10 shows the daylight metrics used as model output variables. DA and LD were recorded with an illuminance threshold of 300 lux. An illuminance threshold of 300 lux and time threshold of 50% of the occupied hours was used for sDA in accordance with LEED. A lower threshold of 100 lux and an upper threshold of 3000 lux was used for UDI according to PSBP. An occupation schedule with occupied hours between 09:00 and 17:00 on weekdays (Monday through Friday) was used for the dynamic metrics.

3.4 Daylight simulation

The daylight simulations were run in Grasshopper for Rhinoceros, using Honeybee 1.1 (Ladybug Tools, 2020) a Radiance-based ray-tracing engine that allows for climate-based simulation (Ward, 2020).

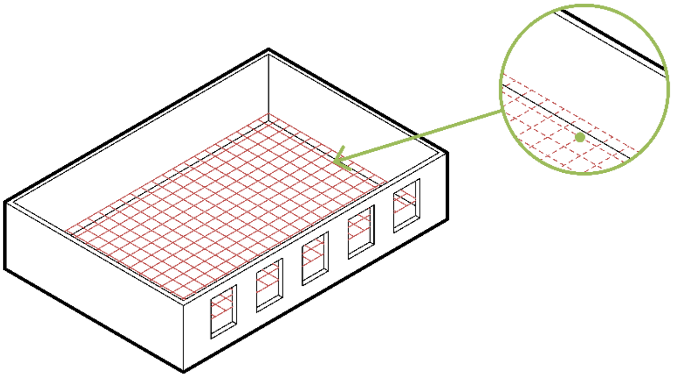

Figure 7 Analysis grid.

Analysis points were distributed in a grid with 0.5 m between points, starting half a meter from surrounding walls, at 0.8 m above the floor plane according to Miljöbyggnad 3.1 (Sweden Green Building Council, 2020b). DF_{Point} was measured in an analysis point 1 m from the darkest side wall, at half the room depth and 0.8 m over the floor plane also in accordance with Miljöbyggnad 3.1 (Sweden Green Building Council, 2020b). $DF_{Average}$, DF_{Median} and DF_{Point} were assessed by static simulation using a CIE Standard Overcast Sky as the light source. DA, sDA, UDI and LD were assessed by dynamic simulation using the Energy Plus Weather (EPW) file for Copenhagen (ASHRAE, 2001) (see Figure 7).

Table 11 Radiance simulation settings.

Radiance parameter	Description	Value
aa/-	Ambient accuracy	0.2
ab/-	Ambient bounces	5
ad/-	Ambient divisions	2048
ar/-	Ambient resolution	128
as/-	Ambient super samples	256
lw/-	Limit weight	0.005

Table 11 shows the used Radiance simulation settings.

Sensitivity analysis samples were fed from the sensitivity analysis Python script to Grasshopper, cycled through using the Anemone plugin for Grasshopper developed by Mateusz Zwierzycki and passed to the simulation engine. Simulation results were then calculated and fed back to the sensitivity analysis script. One daylight simulation was performed per sensitivity analysis sample, in every scenario, for both static and dynamic simulations, resulting in a total of 720 static daylight simulations and 960 dynamic daylight simulations.

3.5 Electric lighting

The electricity use of electric lighting was calculated based on LD, which is the percentage of occupied time when satisfactory illumination cannot be achieved by daylight alone. The energy use was calculated for all 80 samples of the 12 scenarios for which LD was simulated, using two different light sources: fluorescent and LED. It was normalized over the area of the space. An occupied time of 2500 hours was used in calculations according to SS-EN 15193-1:2017 (Swedish Standards Institute, 2017, p. 15).

Table 12 Power density of lamps.

Lamp	LPD/ W/m^2
Fluorescent	10
LED	4

Table 12 shows the lighting power density of the two types of electric lamps used in energy calculations according to literature as discussed in section 2.6 (p.15).

3.6 Sensitivity analysis

Sensitivity analysis was conducted according to the method of Morris (Elementary Effects Method) (Campolongo et al., 2007; Morris, 1991) using the Python package SALib (Herman et al., 2020). Results from daylight simulations corresponding to the sensitivity analysis samples were fed from Grasshopper to the Python script. Analysis was done to a confidence interval of 95%.

```
Y=simulation_results

sensitivity_analysis=SALib.analyze.morris.analyze(problem, X, Y,
num_resamples=1000, num_levels=8)
```

See Appendix A for full code reference. The sensitivity analysis according to the method of Morris gave three sensitivity measures, the mean elementary effect distribution (μ), the absolute mean elementary effect distribution (μ*) and the standard deviation of the elementary effect distribution (σ). If μ* was high for a certain input variable, its effect on the simulation output was large. If σ of an input variable was high, it had a non-linear relation to the output, and may have been interacting with other input variables. μ* was normalized against the maximum value in each scenario in order to produce input variable influence rankings for every daylight metric. σ of every input variable was plotted against its μ* in every scenario and for every daylight metric to determine its relation to the output and whether it may be interacting with other input variables or not.

3.7 Sampling

Sensitivity analysis samples required by the method of Morris (Elementary Effects Method) for the input variables were generated using the Python package SALib (Herman et al., 2020). It uses a combination of the OAT sampling method and the Latin hypercube sampling method as described in section 2.8 (p. 18).

```
problem={'num_vars':9,
         'names':['RFloor', 'RCeiling', 'RWall', 'RFurniture',
         'TVisual', 'Window_Head_Height', 'Window_Sill_Height',
         'Furniture_Density', 'Partition_Height'],
         'bounds':[[0.2, 0.4], [0.7, 0.9], [0.5, 0.8],[0.2, 0.7] , [0.5,
         0.8], [2.0, 2.7], [0.0, 0.7], [1.6, 3.2], [0.7, 2.0]]}

X=SALib.sample.morris.sample(problem, N=128, optimal_trajectories=8,
local_optimization=True, num_levels=8)
```

See Appendix A for the full code reference. Sampling was done to eight levels and eight trajectories with local optimisation, resulting in a total of 80 samples. The sample space was divided into eight levels, from which a value was sampled at random for every input variable according to the Latin hypercube sampling method. The value for only one input variable was changed in between consecutive simulations according to the OAT sampling method. The cycle was repeated for 128 trajectories, of which the eight forming the most accurate representation of the entire sample space were kept according to the local optimisation strategy. These samples were fed to Grasshopper, cycled through using the Anemone plugin for Grasshopper, and passed to the simulation engine to be used in daylight simulations. One sample represented the geometrical and material characteristics settings of one daylight simulation. See Appendix B for complete sample reference.

4 Results

4.1 Daylight simulation

Daylight simulations were performed according to the 4CM as described in section 3.4 (p.25).

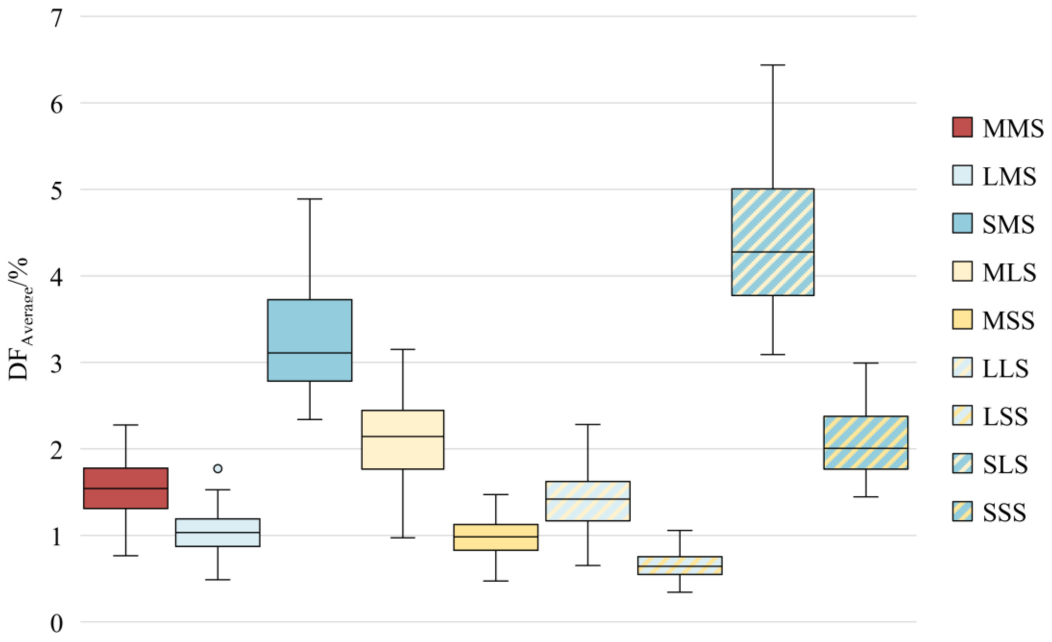

Figure 8 Distribution of $DF_{Average}$ per scenario.

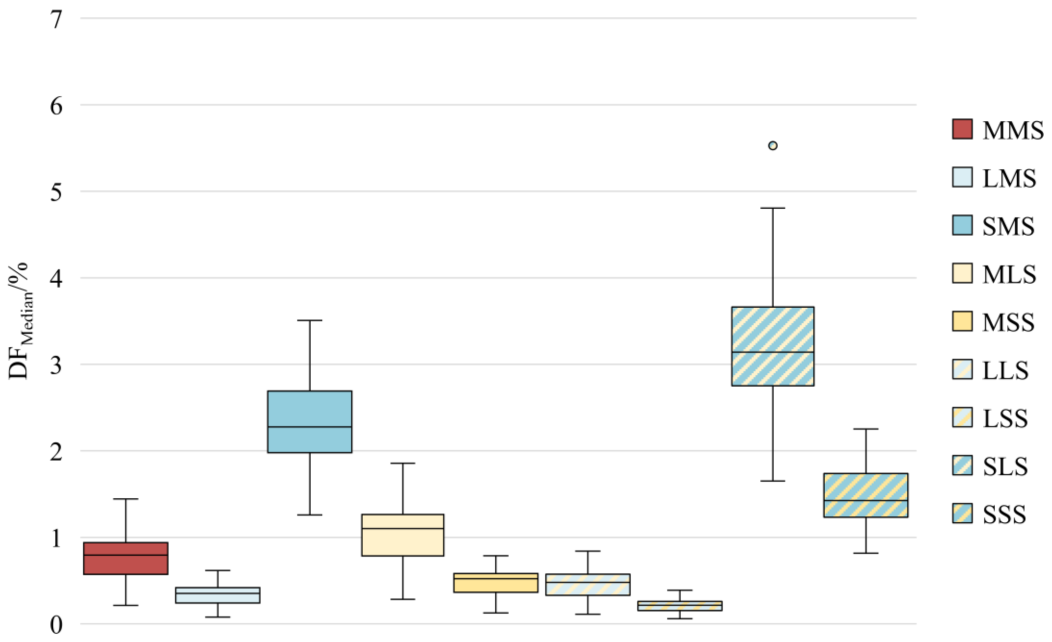

Figure 9 Distribution of DF_{Median} per scenario.

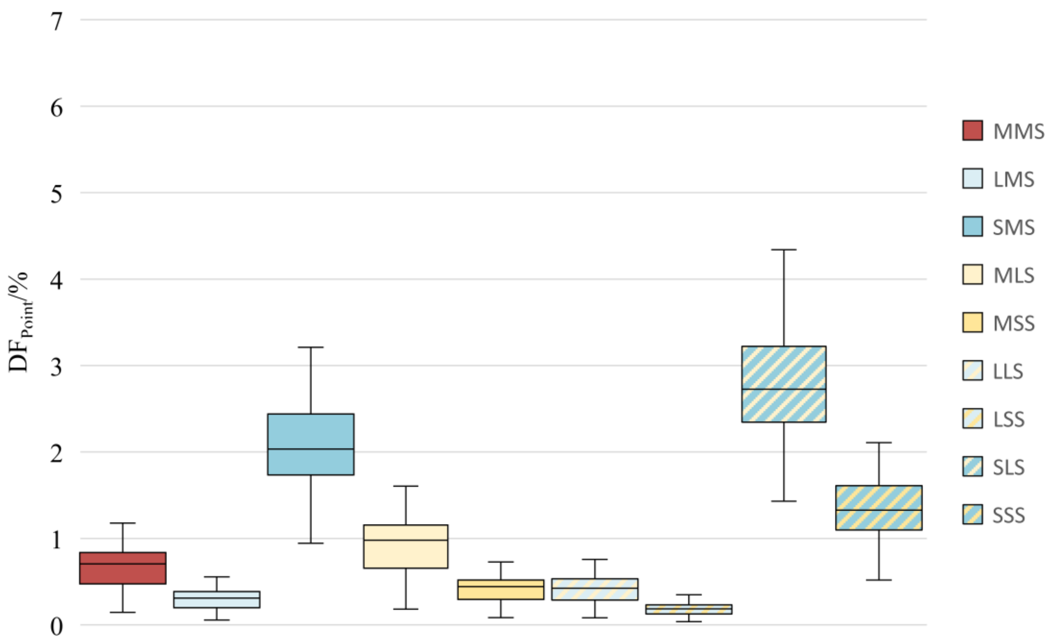

Figure 10 Distribution of DF_{Point} per scenario.

Figure 8 to Figure 10 show the static daylight metrics ($DF_{Average}$, DF_{Median} and DF_{Point}) for every sample in each scenario. 50% of the 80 simulated values in a scenario are within the box. The line in the box is the median value of the series. The whiskers show the minimum and maximum values, unless there were outlies which are displayed as points. The static daylight metrics were mostly affected by the size of the space, as evident by the fact that all scenarios with a smaller space than the base case (SMS, SLS and SSS) had higher median DF value, and all scenarios of larger space (LMS, LLS and LSS) had lower median than those measured in the base case. The daylight levels seemed to increase logarithmically with space size, but future studies with a broader range of space sizes are needed to confirm this. The interior surface area that receives skylight depends on the character of the façade openings and external obstacles and is independent of the size of the interior space. Thus, DF in the small spaces was higher because a larger proportion of the interior surface area received skylight directly compared to the large spaces in which the surfaces mostly received daylight reflected off the surfaces. They were also influenced to a lesser degree by WWR, as scenario MLS (same size as the base case but with the larger WWR) had higher median value than MMS, while scenario LLS (larger space and larger WWR than base case) had a lower median, indicating that the increase in DF from the higher WWR did not match the decrease because of the larger space. The average deviation from the median of each scenario shows the degree to which the metric was influenced by changes to the input variables.

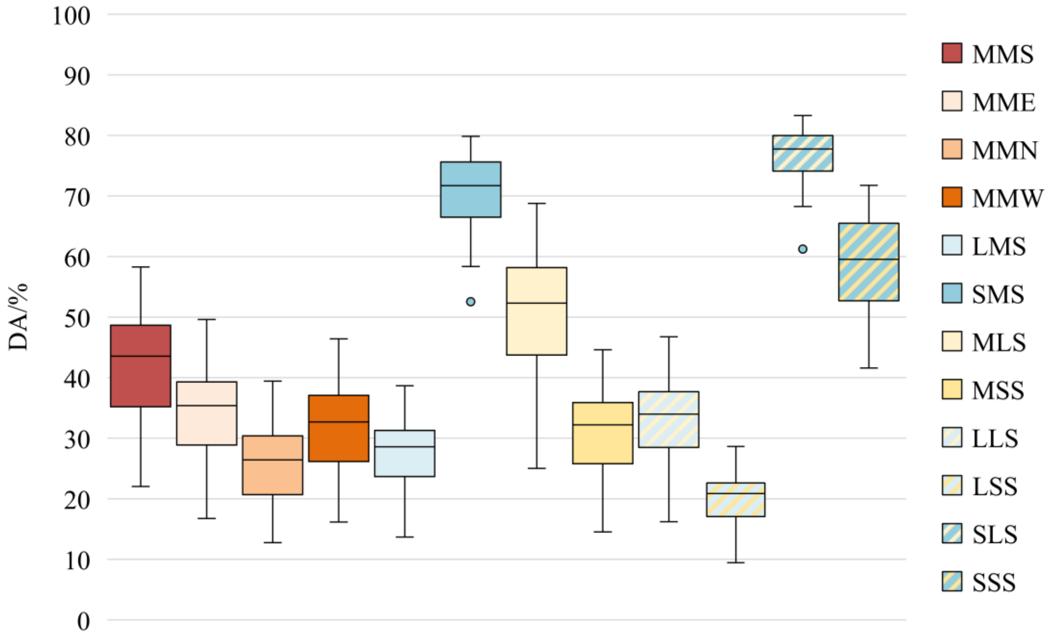

Figure 11 Distribution of DA per scenario.

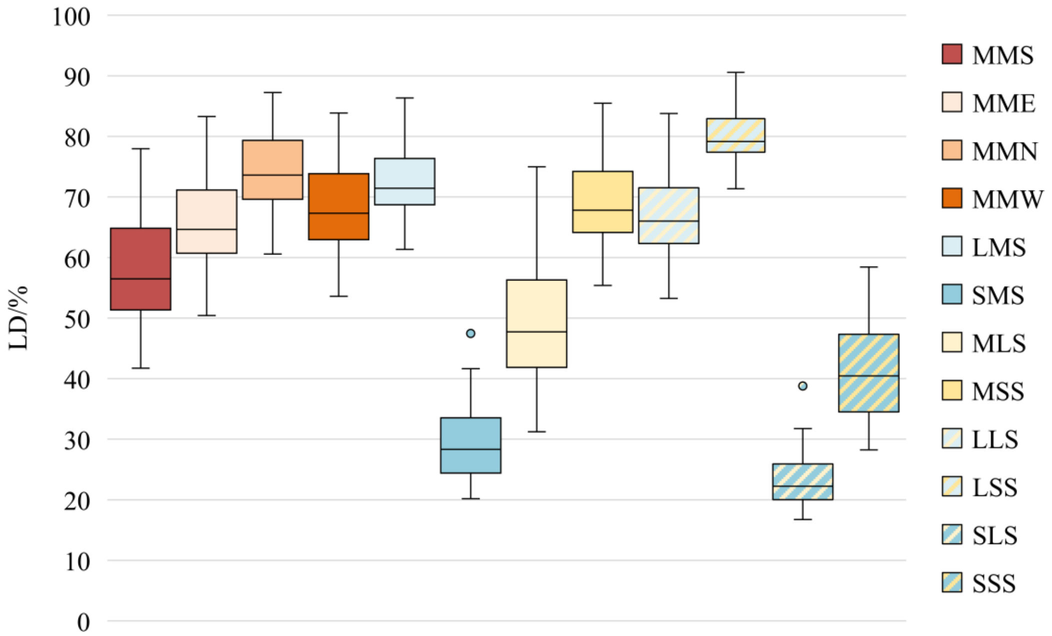

Figure 12 Distribution of LD per scenario.

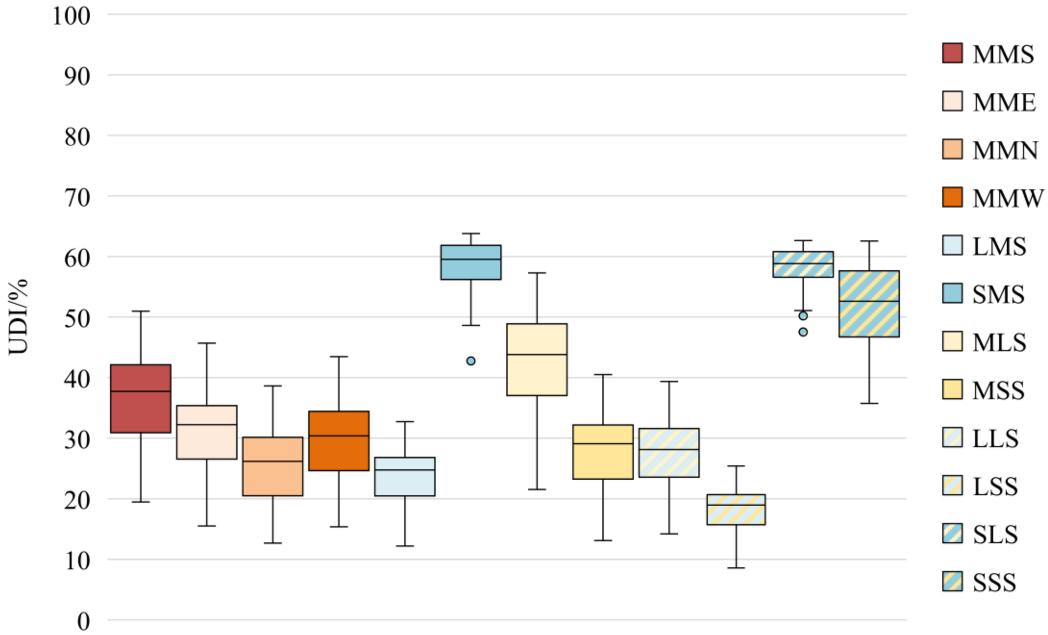

Figure 13 Distribution of UDI per scenario.

Figure 11 to Figure 13 show three of the dynamic daylight metrics (DA, LD and UDI) in every sample for each scenario. They too were influenced most by the size of the space, just like the static daylight metrics. All scenarios of smaller size (SMS, SLS and SSS) had a median DA and UDI higher than those of the base case, and scenarios of a larger size (LMS, LLS AMD LSS) recorded lower median DA and UDI. As LD is the inverse of DA, the effect on it by changing the size of the space was also inversed. They were to a lesser extent also affected by WWR, but not to the degree that it rivalled the effect of size, as evident by the fact that scenario MLS (size as base case but larger WWR) had higher median DA and UDI, and lower median LD than MMS, but scenario LLS had lower median DA and UDI, and higher median LD. Rotation by 90° from south had an effect comparable to that of decreasing the WWR by 10% points. sDA was constant at 100% for all samples in every scenario. This is because the daylight in every simulation was above the illuminance threshold (300 lux) for more than the time threshold (50% of the occupied hours). It was thus unaffected by changes to the input variables in this study. This is typical of a metric with a saturation threshold that can be met in practical cases, above which all information about the effect of changing conditions is lost. For this reason, sDA results were not presented with a figure in this section and are not included in any further analysis.

4.2 Electric lighting

The energy consumption for electric lighting was calculated according to section 3.5 (p.27). It was derived from LD presented in Figure 12 (p. 32).

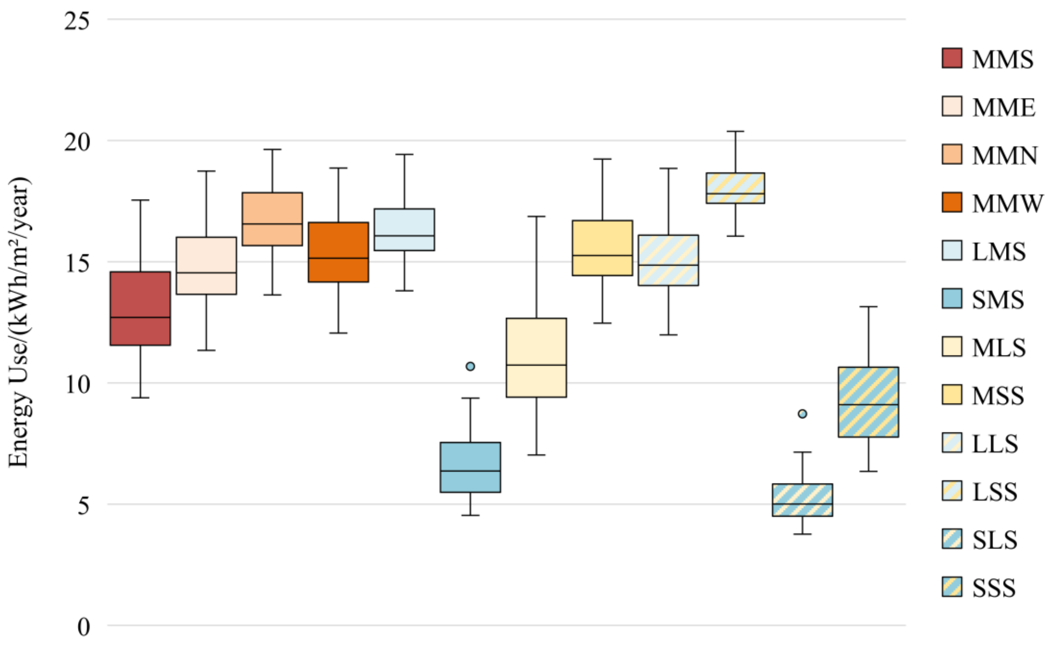

Figure 14 Distribution of electric lighting energy consumption of fluorescent lamps per scenario.

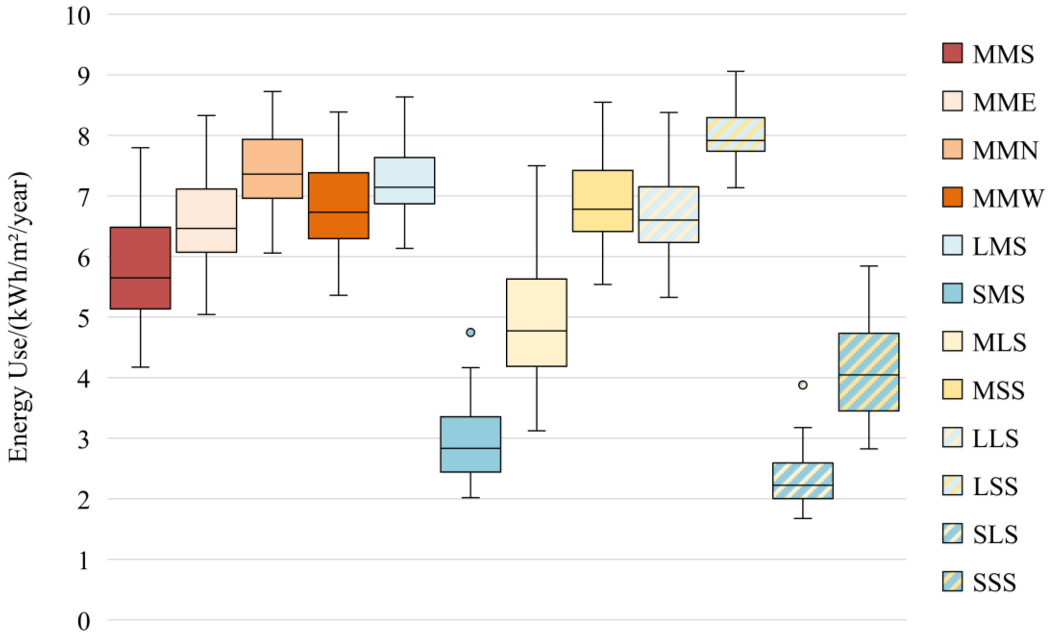

Figure 15 Distribution of electric lighting energy consumption of LED lamps per scenario.

Figure 14 and Figure 15 show the distribution of electricity consumption for electric lighting across all samples for every scenario using fluorescent and LED lamps. The energy use followed the same pattern as LD shown in Figure 12 (p. 32). The three scenarios with a larger space (LMS, LLS and LSS) displayed the highest energy demand for electric lighting, whereas the scenarios with a smaller space had the lowest. In terms of orientation, the space with windows oriented towards the north (MMN) exhibited a higher energy demand than the east (MME), west (MMW) or south (MMS) oriented scenarios, of which south orientation performed best. This is because rotation away from the south reduced the amount of direct light penetration into the space, which increased the need for electric illumination. The effect of rotating 90° away from the south was comparable to that of decreasing the WWR by 10%-points.

4.3 Sensitivity analysis

Sensitivity analysis was performed according to the method of Morris as described in section 3.6 (p.27). The two sensitivity metrics μ*/% (the absolute mean elementary effect distribution (Campolongo et al., 2007)) and σ/% (the standard deviation (Morris, 1991)) were further analysed in order to rank the input variables according to their degree of influence on each daylight metric and to establish the nature of the relationship between input variables and the output.

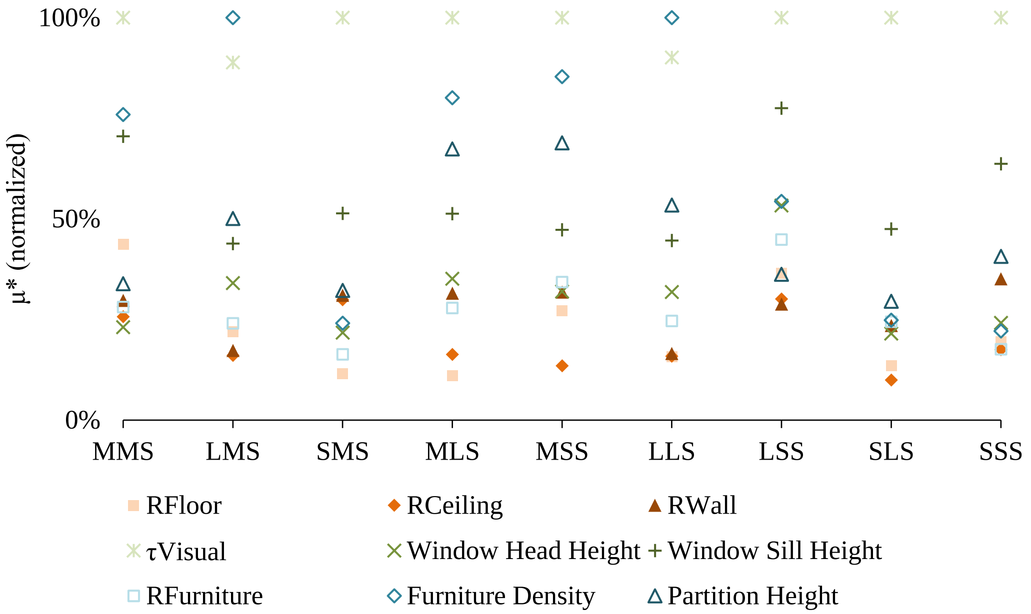

Figure 16 $DF_{Average}$ μ^* (normalized) per scenario and input variable.

Table 13 $DF_{Average}$ μ^* per scenario and input variable. Maximum values highlighted.

	MMS	**LMS**	**SMS**	**MLS**	**MSS**	**LLS**	**LSS**	**SLS**	**SSS**
R_{Floor}	0.36	0.14	0.19	0.12	0.13	0.13	0.12	0.34	0.20
$R_{Ceiling}$	0.21	0.10	0.50	0.18	0.07	0.13	0.10	0.25	0.18
R_{Wall}	0.25	0.11	0.52	0.35	0.16	0.13	0.09	0.59	0.35
τ_{Visual}	0.83	0.55	1.68	1.11	0.49	0.73	0.33	2.52	1.01
Window Head Height	0.19	0.21	0.37	0.39	0.16	0.26	0.17	0.54	0.24
Window Sill Height	0.58	0.27	0.86	0.57	0.23	0.36	0.25	1.20	0.64
$R_{Furniture}$	0.23	0.15	0.27	0.31	0.17	0.20	0.15	0.62	0.18
Furniture Density	0.63	0.62	0.40	0.89	0.42	0.81	0.18	0.63	0.22
Partition Height	0.28	0.31	0.54	0.75	0.34	0.43	0.12	0.74	0.41

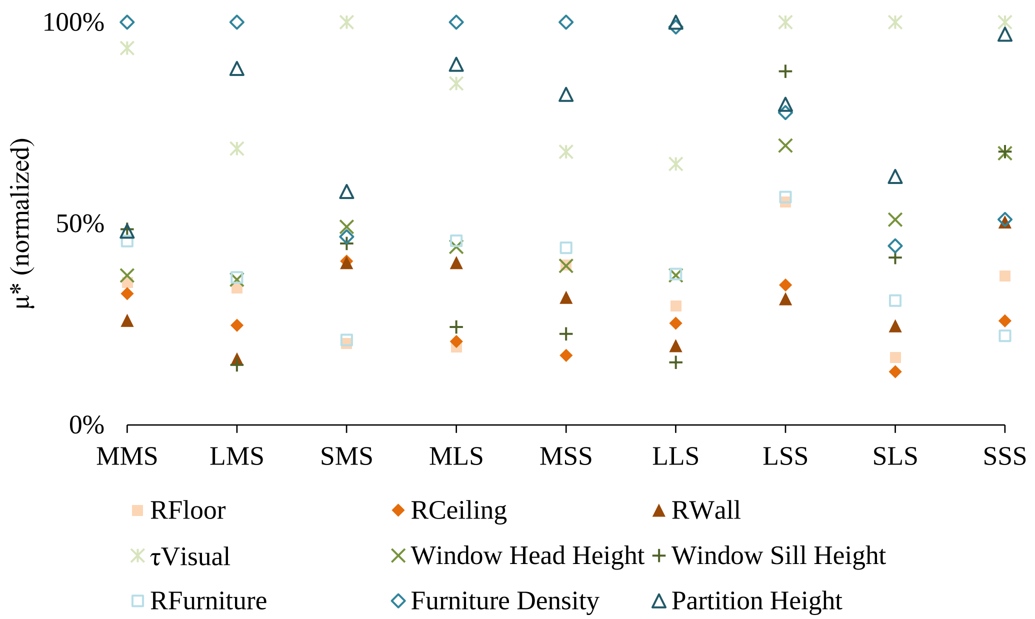

Figure 17 DF_{Median} μ (normalized) per scenario and input variable.*

Table 14 DF_{Median} μ per scenario and input variable. Maximum values highlighted.*

	MMS	LMS	SMS	MLS	MSS	LLS	LSS	SLS	SSS
R_{Floor}	0,19	0,10	0,26	0,13	0,14	0,11	0,06	0,33	0,25
$R_{Ceiling}$	0,17	0,07	0,52	0,14	0,06	0,09	0,04	0,26	0,18
R_{Wall}	0,14	0,05	0,51	0,27	0,11	0,07	0,04	0,48	0,34
τ_{Visual}	0,50	0,20	1,28	0,57	0,24	0,23	0,12	1,94	0,68
Window Head Height	0,20	0,10	0,63	0,30	0,14	0,13	0,08	0,99	0,46
Window Sill Height	0,26	0,04	0,58	0,16	0,08	0,06	0,10	0,81	0,46
$R_{Furniture}$	0,24	0,11	0,27	0,31	0,16	0,14	0,07	0,60	0,15
Furniture Density	0,53	0,29	0,60	0,68	0,35	0,36	0,09	0,86	0,35
Partition Height	0,26	0,26	0,74	0,61	0,29	0,36	0,09	1,20	0,66

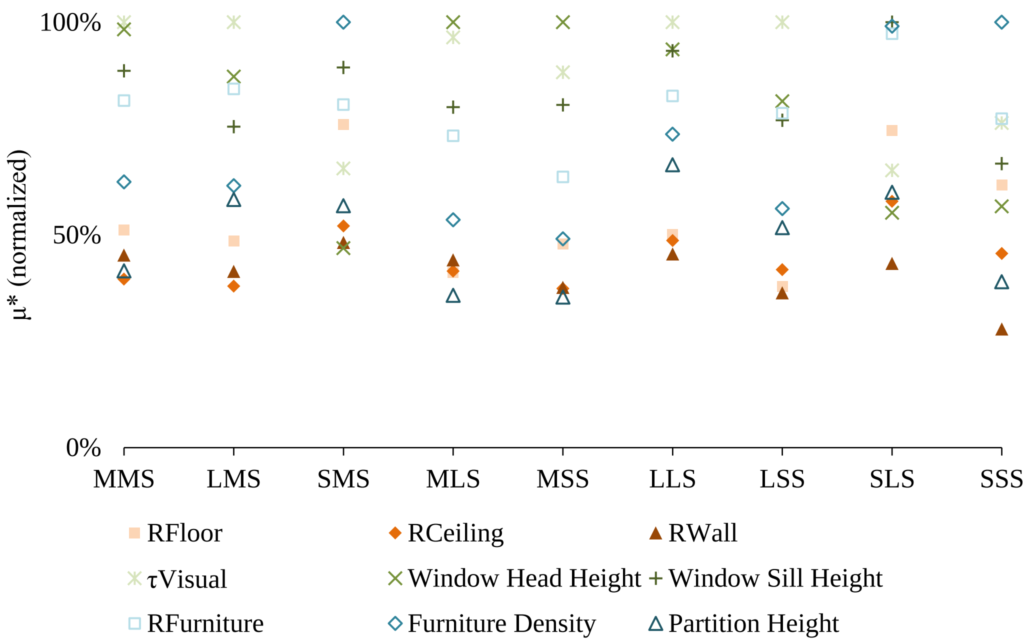

Figure 18 DF_{Point} μ (normalized) per scenario and input variable.*

Table 15 DF_{Point} μ per scenario and input variable. Maximum values highlighted.*

	MMS	LMS	SMS	MLS	MSS	LLS	LSS	SLS	SSS
R_{Floor}	0.18	0.09	0.58	0.23	0.12	0.12	0.05	0.72	0.35
$R_{Ceiling}$	0.14	0.07	0.40	0.23	0.09	0.12	0.05	0.56	0.26
R_{Wall}	0.16	0.08	0.37	0.24	0.09	0.11	0.04	0.42	0.16
τ_{Visual}	0.36	0.18	0.50	0.53	0.22	0.24	0.12	0.63	0.44
Window Head Height	0.35	0.16	0.36	0.55	0.25	0.22	0.10	0.53	0.32
Window Sill Height	0.32	0.14	0.68	0.44	0.20	0.22	0.09	0.96	0.38
$R_{Furniture}$	0.29	0.15	0.62	0.40	0.16	0.20	0.09	0.93	0.44
Furniture Density	0.23	0.11	0.76	0.29	0.12	0.17	0.07	0.95	0.57
Partition Height	0.15	0.11	0.44	0.20	0.09	0.16	0.06	0.58	0.22

Figure 16 to Figure 18 show μ*/% of the static daylight metrics ($DF_{Average}$, DF_{Median} and DF_{Point}) normalized against the maximum value in each scenario, per scenario and input variable. 100% on the scale represents the maximum value recorded in a specific scenario, and the values of every input variable were compared to this maximum. The percentage value of an input variable indicates its importance in relation to the most impactful one in the scenario. For example, an input variable with a normalized μ* of 50% had half the impact on the daylight metric compared to the most influential input variable in the scenario. The order of appearance on the y-axis from 100% to 0% is the importance ranking of the variable. For example, the input variable at the top of the y-axis (always with a normalized μ* value of 100%) was the one with highest impact on the daylight metric in the scenario, and the bottom most input variable on the y-axis was the least influential one. A large gap between consecutive points means that there was a large difference between the impact of input variables above and below the gap.

Table 13 to Table 15 show μ*/%-points for each input variable in every scenario, with the maximum value in each scenario highlighted to indicate the most impactful input variable. The values indicate the total impact each input variable could have on the output in the metric's unit, or in other words: the potential variability of each daylight metric induced by late design choices in DF percentage points. The visual transmittance of the windows and the amount of furniture were on average the two most influential input variables, followed by the height pf workspace partitions and windowsill height for $DF_{Average}$, and partition height and window head height for DF_{Median} and DF_{Point}. The reflectance of the floor, ceiling and walls were consistently the least impactful input variables on all three daylight metrics regardless of scenario.

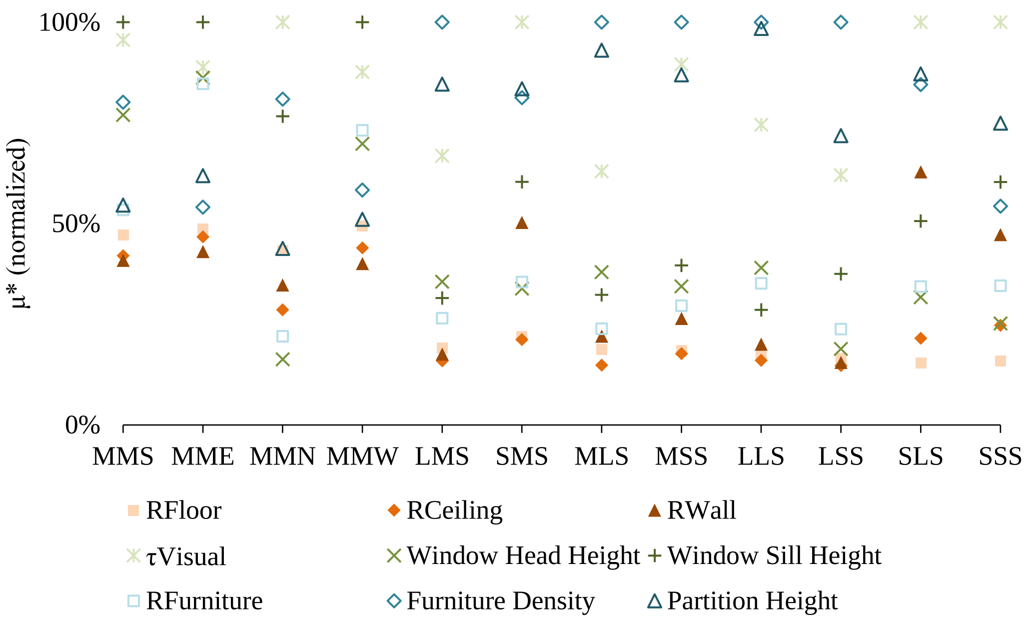

Figure 19 DA μ (normalized) per scenario and input variable.*

Table 16 DA μ per scenario and input variable. Maximum values highlighted.*

	MMS	MME	MMN	MMW	LMS	SMS	MLS	MSS	LLS	LSS	SLS	SSS
R_{Floor}	6,43	5,97	5,60	6,32	2,50	2,34	4,00	2,67	2,51	1,88	1,25	2,67
$R_{Ceiling}$	5,72	5,73	3,70	5,63	2,08	2,24	3,18	2,55	2,32	1,67	1,74	4,17
R_{Wall}	5,57	5,28	4,49	5,13	2,30	5,32	4,72	3,82	2,90	1,77	5,07	7,96
τ_{Visual}	13,02	10,90	12,92	11,22	8,74	10,59	13,48	12,92	10,79	7,05	8,08	16,84
Window Head Height	10,48	10,57	2,11	8,93	4,65	3,58	8,12	4,97	5,65	2,15	2,56	4,25
Window Sill Height	13,62	12,26	9,90	12,80	4,12	6,39	6,91	5,72	4,13	4,26	4,09	10,16
$R_{Furniture}$	7,28	10,39	2,84	9,36	3,46	3,76	5,11	4,27	5,09	2,70	2,78	5,83
Furniture Density	10,92	6,63	10,45	7,46	13,07	8,60	21,40	14,43	14,47	11,36	6,82	9,15
Partition Height	7,44	7,59	5,66	6,53	11,06	8,84	19,91	12,54	14,25	8,16	7,04	12,62

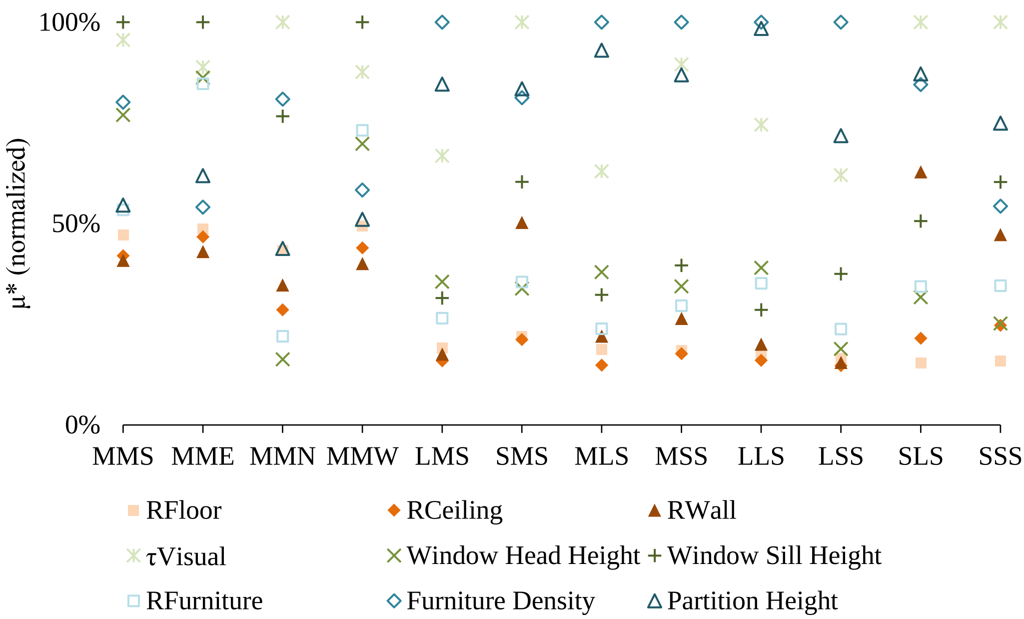

Figure 20 LD μ (normalized) per scenario and input variable.*

Table 17 LD μ per scenario and input variable. Maximum values highlighted.*

	MMS	MME	MMN	MMW	LMS	SMS	MLS	MSS	LLS	LSS	SLS	SSS
R_{Floor}	6,43	5,97	5,60	6,32	2,50	2,34	4,00	2,67	2,51	1,88	1,25	2,67
$R_{Ceiling}$	5,72	5,73	3,70	5,63	2,08	2,24	3,18	2,55	2,32	1,67	1,74	4,17
R_{Wall}	5,57	5,28	4,49	5,13	2,30	5,32	4,72	3,82	2,90	1,77	5,07	7,96
τ_{Visual}	13,02	10,90	12,92	11,22	8,74	10,59	13,48	12,92	10,79	7,05	8,08	16,84
Window Head Height	10,48	10,57	2,11	8,93	4,65	3,58	8,12	4,97	5,65	2,15	2,56	4,25
Window Sill Height	13,62	12,26	9,90	12,80	4,12	6,39	6,91	5,72	4,13	4,26	4,09	10,16
$R_{Furniture}$	7,28	10,39	2,84	9,36	3,46	3,76	5,11	4,27	5,09	2,70	2,78	5,83
Furniture Density	10,92	6,63	10,45	7,46	13,07	8,60	21,40	14,43	14,47	11,36	6,82	9,15
Partition Height	7,44	7,59	5,66	6,53	11,06	8,84	19,91	12,54	14,25	8,16	7,04	12,62

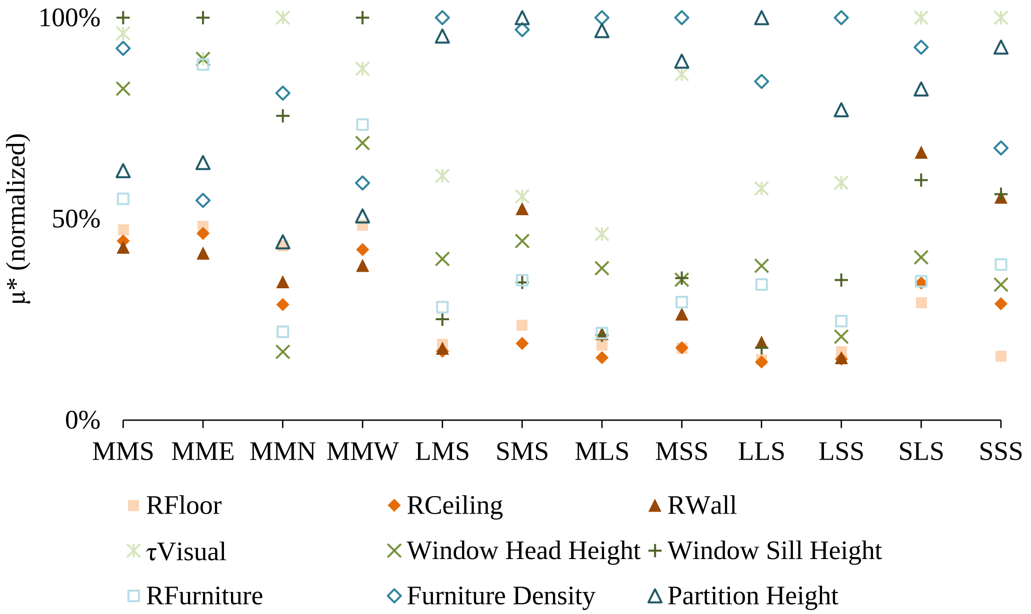

Figure 21 UDI μ (normalized) per scenario and input variable.*

Table 18 UDI μ per scenario and input variable. Maximum values highlighted.*

	MMS	MME	MMN	MMW	LMS	SMS	MLS	MSS	LLS	LSS	SLS	SSS
R_{Floor}	5,07	5,20	5,47	5,71	1,98	1,59	3,27	2,31	1,90	1,69	1,31	1,99
$R_{Ceiling}$	4,77	5,01	3,63	5,00	1,79	1,28	2,72	2,33	1,83	1,51	1,53	3,60
R_{Wall}	4,61	4,48	4,35	4,54	1,87	3,54	3,77	3,42	2,45	1,54	2,99	6,91
τ_{Visual}	10,31	9,70	12,64	10,30	6,36	3,75	8,10	11,16	7,30	5,86	4,49	12,46
Window Head Height	8,83	9,69	2,14	8,12	4,19	3,00	6,61	4,53	4,86	2,06	1,82	4,19
Window Sill Height	10,72	10,80	9,56	11,79	2,63	2,30	3,70	4,58	2,28	3,46	2,68	7,00
$R_{Furniture}$	5,90	9,54	2,77	8,66	2,94	2,34	3,78	3,80	4,27	2,44	1,55	4,82
Furniture Density	9,91	5,89	10,27	6,95	10,47	6,54	17,52	12,98	10,66	9,93	4,17	8,43
Partition Height	6,65	6,91	5,60	5,99	9,99	6,74	16,96	11,58	12,67	7,66	3,70	11,55

Figure 19 to Figure 21 show μ*/%-points of the dynamic daylight metrics (DA, LD and UDI) normalized against the maximum value in each scenario, per scenario and input variable.

Table 16 to Table 18 show μ* for each input variable in every scenario, with the maximum value in each scenario highlighted to indicate the most impactful input variable. sDA was omitted as it did not display any variability during daylight simulations due to saturation and thus could not be a subject of sensitivity analysis. Visual transmittance, the amount of furniture and the height of workspace partitions were on average the most impactful input variables. In scenarios MMS, MME and MMW windowsill height was also among the more influential input variables. This is because the sill height affects the direct light influx, which is particularly important at high latitudes as the incidence angle is low throughout most of the year. Towards the east and west, the effect is further amplified as the low-incidence direct light of the rising or setting sun can penetrate deep into the space in the absence of shading. The reflectance of the floor, ceiling and walls had the least impact on the dynamic daylight metric.

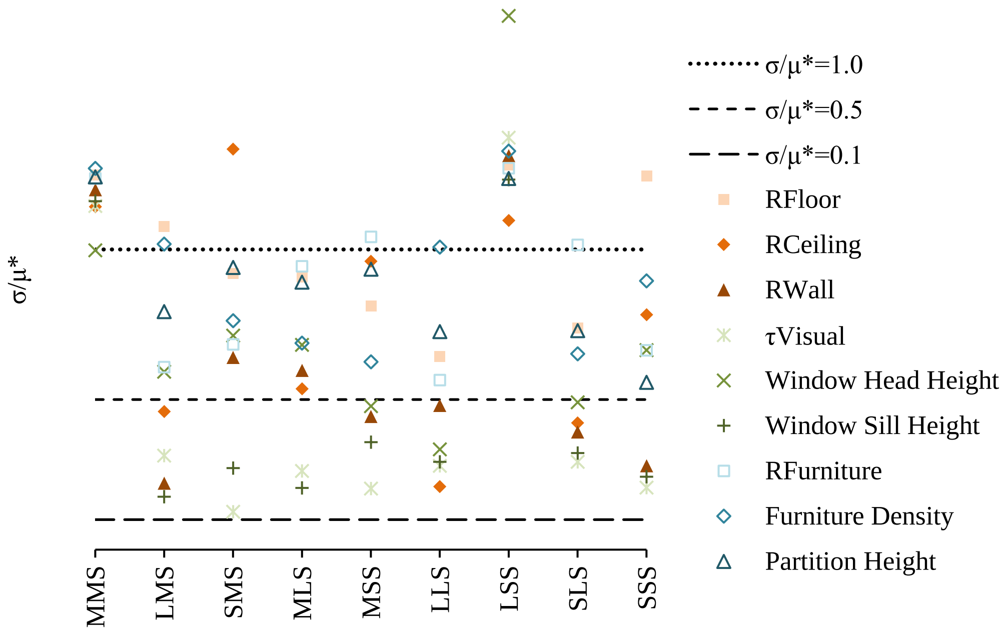

Figure 22 $DF_{Average}$ σ over μ, per scenario and input variable.*

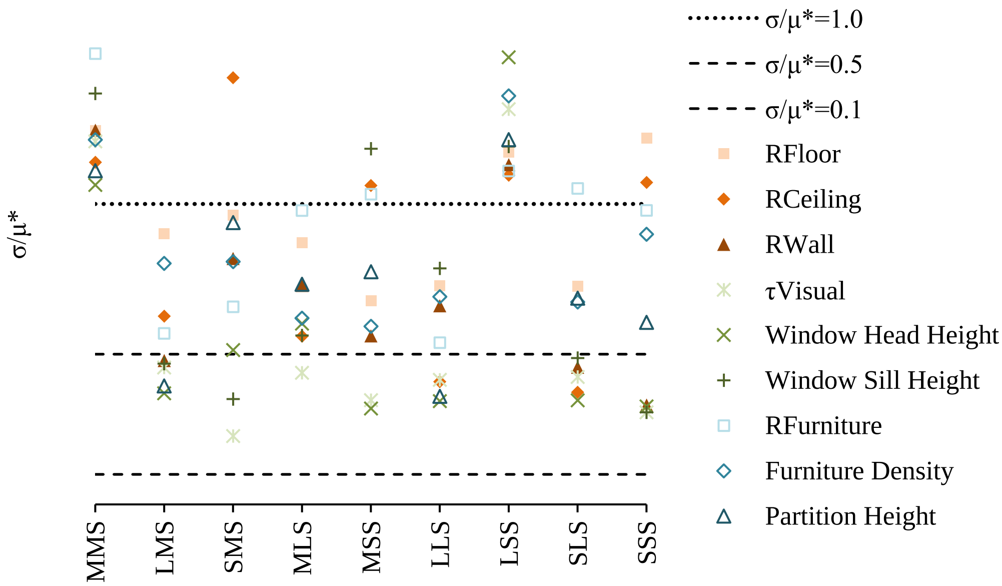

Figure 23 DF_{Median} σ over μ, per scenario and input variable.*

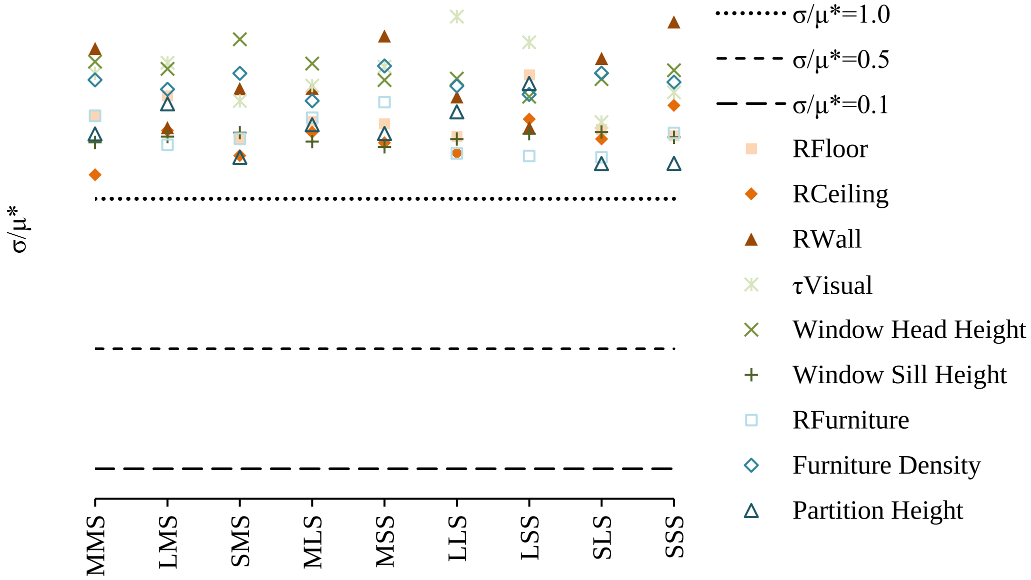

Figure 24 DF_{Point} σ over μ^*, per scenario and input variable.

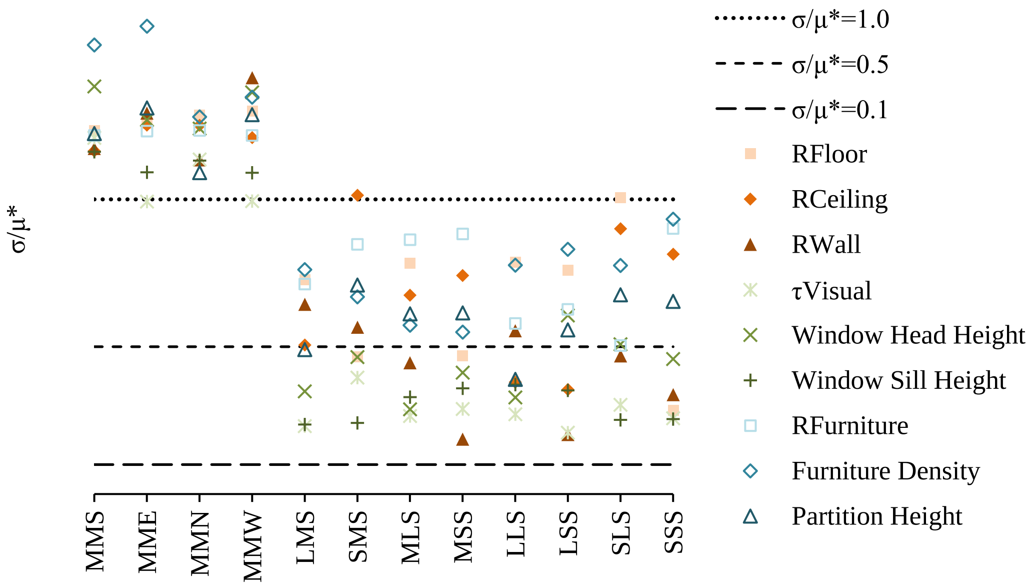

Figure 25 DA σ over μ^*, per scenario and input variable.

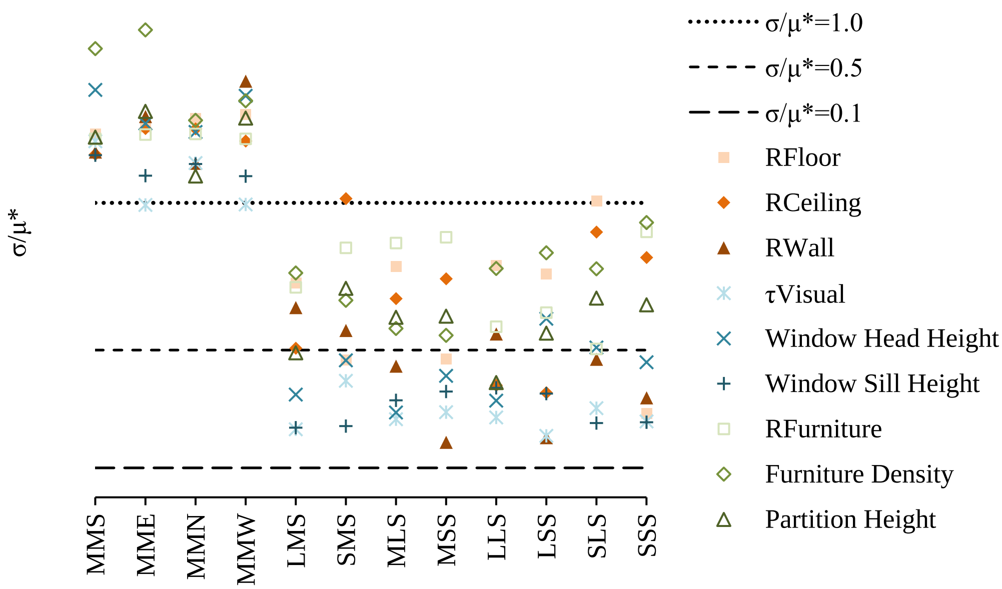

Figure 26 LD σ over μ, per scenario and input variable.*

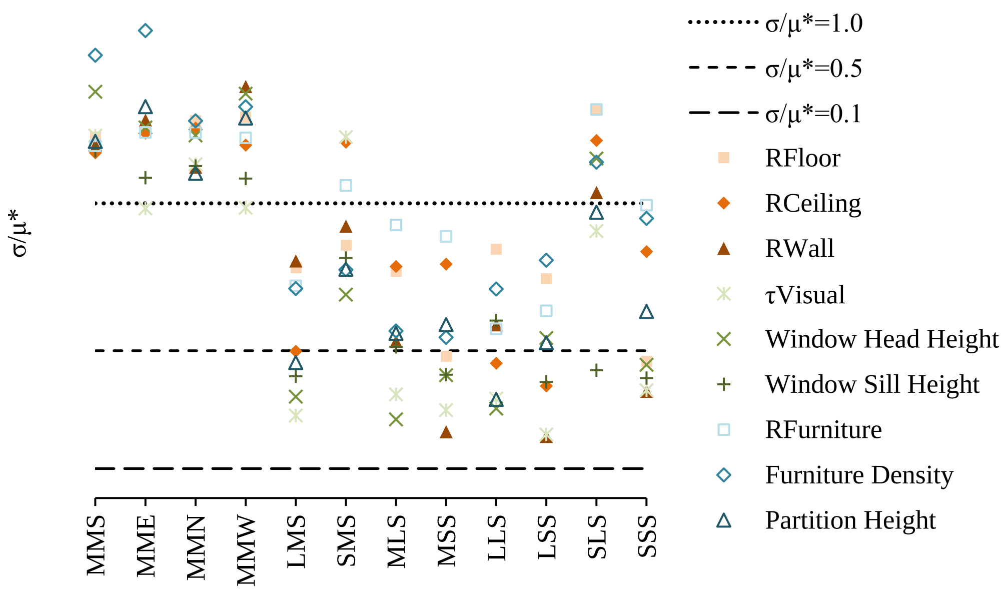

Figure 27 UDI σ over μ, per scenario and input variable.*

Figure 22 to Figure 27 show σ over μ^* of the daylight variables in every scenario for each input variable. It indicates whether the relationship between the input variable and the output was linear or non-linear, which could mean it interacted with other variables. If $\sigma/\mu^* \leq 0.1$, the relationship can be considered linear, if $\sigma/\mu^* \leq 0.5$ it was monotonic, almost monotonic if $\sigma/\mu^* \leq 1$ and non-linear if $\sigma/\mu^* \geq 1$ or implying that it may have been interacting with other input variables. All input variables displayed a highly non-linear relation to the output in at least a few scenarios for each daylight metric. However, the method of Morris cannot distinguish between non-linearity and interaction, neither can it give further insights about the degree of any potential interaction. Further analysis about the behaviour of the input variables using the methods employed in this study was thus not possible.

5 Discussion

Figure 8 (p. 29) to Figure 13 (p. 33) show the value of each daylight metric per sample in every scenario. By analyzing the average deviation from the mean in every scenario for each daylight metric, the degree to which changes to the input variables influenced the metric could be investigated. Or, in other words, the metric's sensitivity to late design choices. DF_{Point} and DF_{Median} were the daylight metrics most responsive to changes to the input variables. This is likely due to their analysis points being located deeper in the space: at half the room depth from the windows. Thus, predominantly indirect light (which was being scattered in the space through specular or diffuse reflection, and therefore depended highly on the geometrical and material characteristics of the space) reached the points and was measured. On the whole, the three static daylight metrics ($DF_{Average}$, DF_{Median} and DF_{Point}) were consistently more responsive to changes of the input variables than the dynamic metrics (DA, sDA, LD and UDI). The mean deviation from the median value for each metric across all scenarios was on average 17% for $DF_{Average}$, 24% for DF_{Medain} and 27% for DF_{Point}, while the mean deviation from the median for the dynamic daylight metrics never exceeded 18%. However, this is not to say the dynamic metrics cannot accurately represent the character of daylight in a space, but instead that they are likely more affected by spatial and geometrical context rather than late design choices. This is noteworthy because it highlights the need of considering several daylight metrics during the design process, as each metric can give different insights into the impact design decisions have on the daylight in interior spaces.

The high variability of the daylight metrics due to late design choices suggests that the analyzed input variables have a profound impact on the daylight in interior spaces. It is interesting to investigate how this impact measures up against the requirements made in environmental certification schemes.

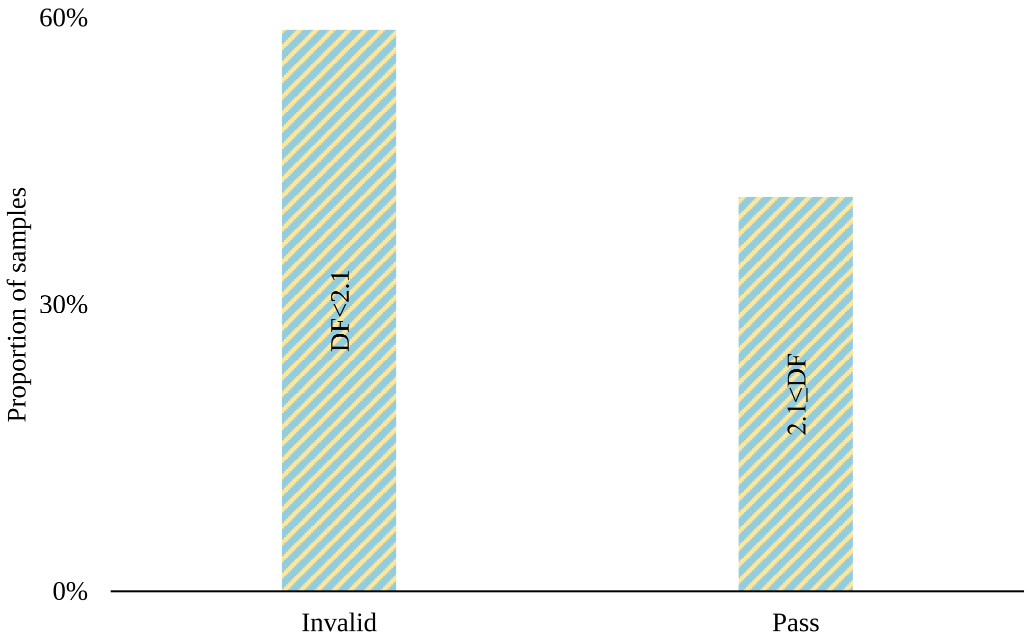

Figure 28 Distribution of BREEAM grading based on $DF_{Average}$ for samples in scenario MLS.

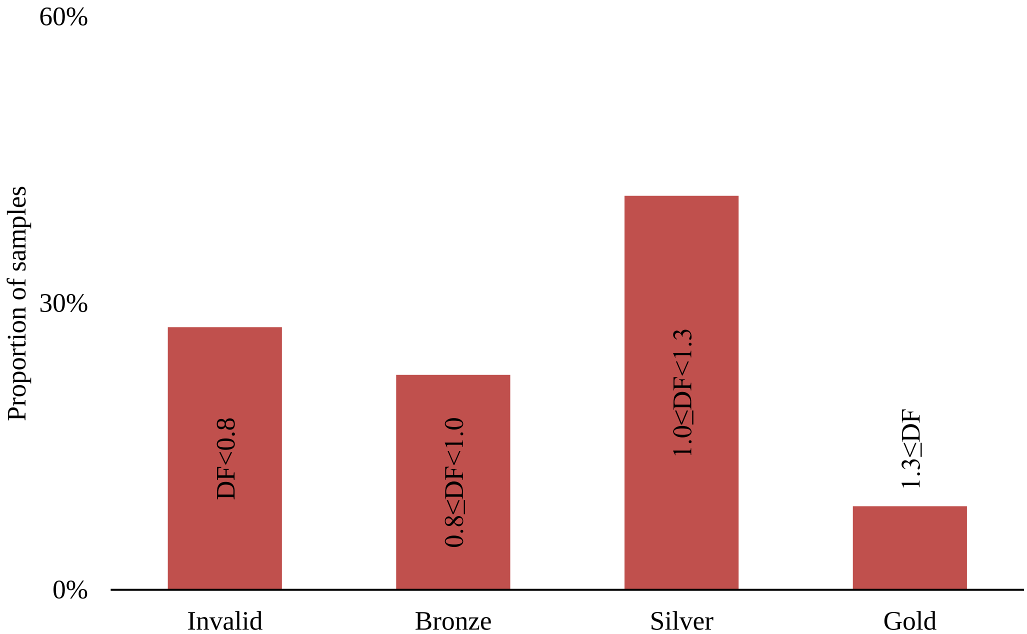

Figure 29 Distribution of Miljöbyggnad grading based on DF_{Median} for samples in scenario MMS.

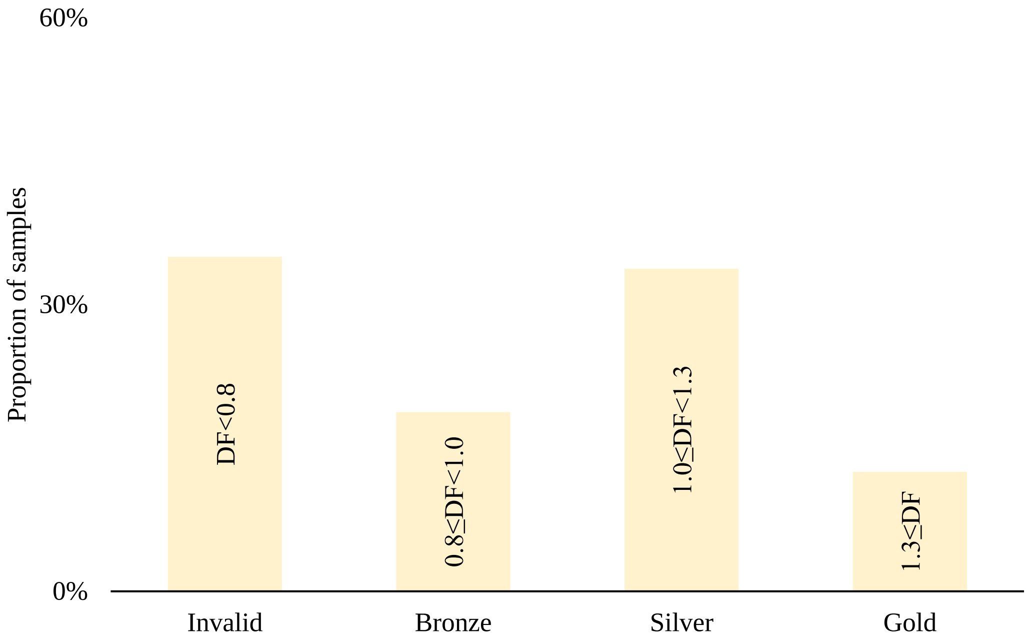

Figure 30 Distribution of Miljöbyggnad grades based on DF_{Point} for samples in scenario MLS.

Figure 28 shows the proportion of samples in scenario SSS fulfilling or failing the requirements for certification in BREEAM based on $DF_{Average}$. Figure 29 and Figure 30 show the proportion of samples in scenario MMS and MLS fulfilling the requirements of each grade (Bronze, Silver and Gold) in Miljöbyggnad, or failing certification, based on DF_{Median} and $DF_{Point,}$ respectively. These scenarios were chosen for illustrative purposes, but the findings hold true in a majority of the scenarios for at least one of the metrics. It is evident that all possible outcomes from certification using any of the three metrics in either BREEAM or Miljöbyggnad were present within each displayed scenario. As major design factors affecting the underlying daylight conditions (such as WWR and space size) were unchanged within each scenario, the fluctuation of the daylight metrics is attributable solely to late design choices. As sDA did not display any variability, further analysis of its distribution over LEED and PSBP thresholds could not be conducted. Since no threshold for DA and LD were used, such an analysis was not relevant for these metrics. UDI did not exhibit the same behaviour as the static metrics due to it never fulfilling the requirements according to PSBP. It is evident that the variability of daylight due to late design choices in certain situations could be larger than the difference between thresholds for bronze and gold ratings in Miljöbyggnad. This highlights It is thus interesting to determine which of the analysed input variables had the most/least impact on the interior daylight levels.

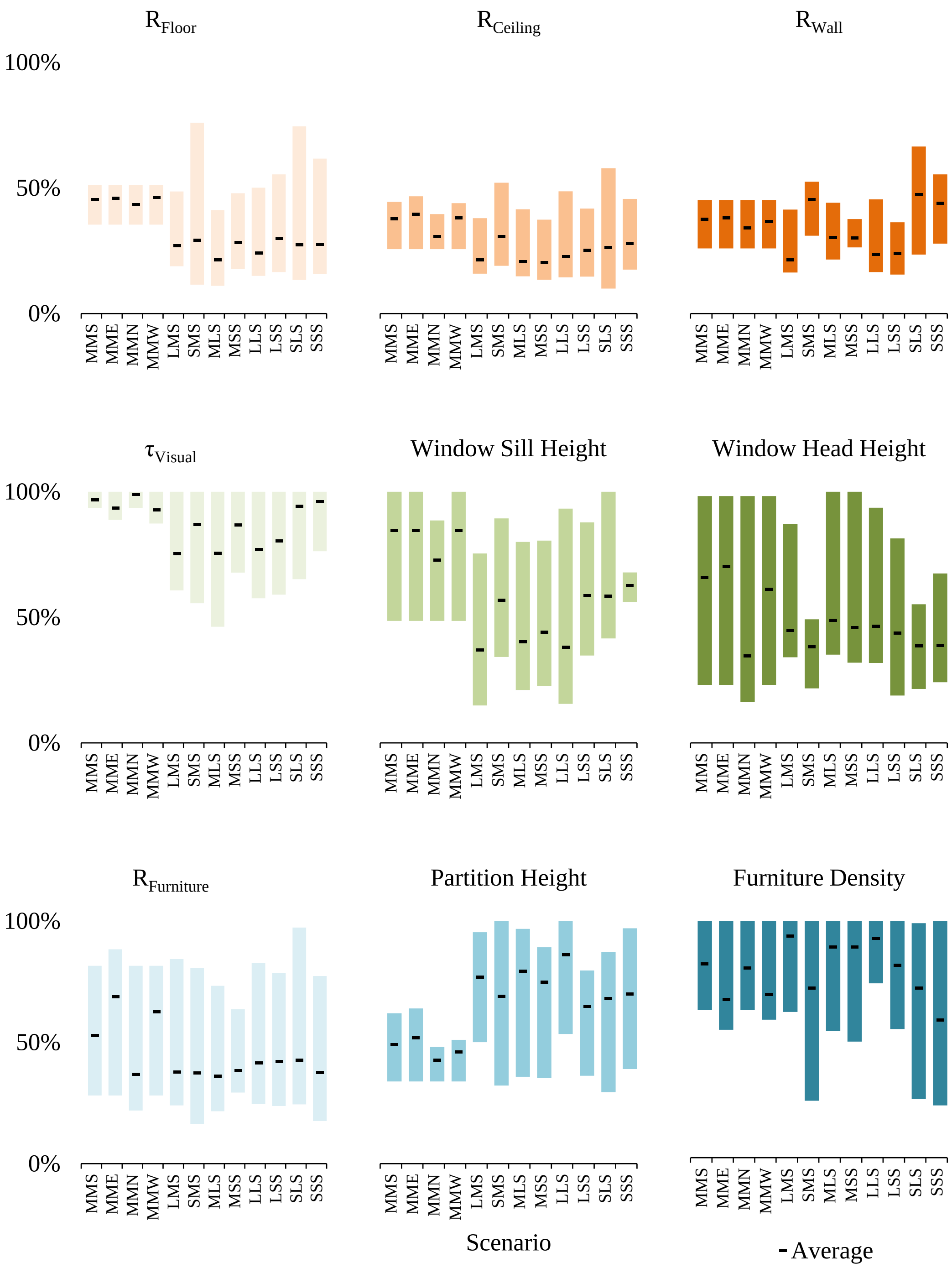

Figure 31 Spread of μ (normalized).*

Figure 31 shows the μ* normalized against the maximum in the scenario for each daylight metric per input variable, and the average μ* between all daylight metrics. For reasons of coherent visualization, the values for the static daylight metrics ($DF_{Average}$, DF_{Median} and DF_{Point}) in scenario MME, MMN and MMW (indicating orientation) were extrapolated from MMS as these metrics are independent of rotation, and their values would be identical in these four scenarios. The figure is essentially a compilation of the results presented in Figure 16 (p. 36) to Figure 21 (p. 42) and it shows which late design choices on average could be considered to have more or less of an impact on interior daylight. If the spread is low, there was little difference between the influence ranking of the input variable between different daylight metrics. If the spread is large however the opposite is true: the difference in ranking using different daylight metrics was large, and the result is inconclusive. The influence of these late design choices is very different for the variety of metrics used in the assessment but could be considered medium on average. If the average value is high, the input variable in question generally had a large impact on the interior daylight, and if the value is low the impact was small. It is evident that the visual transmittance of windows and the furniture density were overwhelmingly the most influential input variables on average. These were followed in ranking by windowsill and head heights, furniture reflectance and partition height. These late design choices all had large spreads, meaning their influence on daylight is inconclusive and depends on the metric used for assessment, but could be considered medium on average. The least influential late design choices on average were floor, ceiling and wall reflectance.

The high impact of visual transmittance as well as windowsill and head height was expected as these variables influence the influx of direct light into the space, which in turn has a much stronger effect on the overall daylight levels than diffuse light. However, it is interesting that the input variables regarding furniture at times had a significant impact on the daylight metrics, and especially that they commonly exceeded the importance of floor, ceiling, and wall reflectance. This and the findings presented in Figure 28 to Figure 30 are noteworthy since environmental certification schemes, building standards and regulations commonly used in the industry do not require furniture to be included in the daylight analysis, and in certain cases (such as LEED) specifically state that furniture should not be included. Indeed, all interviewed daylight professionals asserted that they do not include furniture in their daylight analyses. The implication is that under certain conditions the variability of interior daylight due to late design choices (and especially furniture, which designers have no control over and do not analyse) could be larger than the difference between the target daylight levels from different grades in environmental certification schemes. The solution is however likely not to include furniture in daylight simulations. Furniture is very variable and is likely to change many times during the usage of a space according to the needs and preferences of the tenants. Thus, any furniture model is inherently an inaccurate representation of the different interior configurations of a space during its lifetime. The increased model complexity, and resulting computational load posed by furniture is a further argument against the inclusion of it in daylight simulations. Instead, if architects, engineers, designers as well as daylight specialists are aware of this fundamental variability, they can take proactive measures to ensure the resilience of spaces.

Additional research is needed about the impact of late design choices across a wider range of spaces, and more daylight performance metrics to draw precise conclusions about the importance of late design choices. Future studies should consider more input variables such as window frame size and reflectance, as well as shading types and their characteristics. The argument for further study is also emphasized by the fact that the input variables sometimes displayed a highly non-linear relation to the simulation results. Figure 22 (p. 44) to Figure 27 (p. 46) show σ over μ* of the input variables in every scenario for each daylight metric, which indicates whether the relationship between an input variable and the output was linear or non-linear. Non-linearity could mean it interacted with other variables. If the input variables were indeed interacting with each other, it could suggest that a small change to one variable's value might have a large effect on the model output. The method of Morris can however not distinguish between non-linearity and interaction. The implication from this is that the variables displayed behaviour that could not be further investigated using the methods employed in this study. Whether or not input variables were interacting, the degree of this interaction, and the individual effect from the input variables due to interaction could be investigated using the Sobol sensitivity analysis method. This should be the focus of future research. However, the overall conclusion from this study is expected to hold true regardless of whether interaction took place or not.

6 Conclusion

The study showed that late design choices such as the colour of surfaces, the characteristics of windows and the type and distribution of furniture indeed have a significant impact on the daylight levels in interior spaces and the energy use of electric lighting. They could be ranked as having the most, medium/inconclusive, and least impact on the daylight levels as follows:

- Most impact: visual transmittance and furniture density.
- Medium/inconclusive impact: windowsill and head height, furniture reflectance and partition height.
- Least impact: floor, ceiling, and wall reflectance.

Furthermore, it was shown that the variability of interior daylight due to late design choices was larger than the difference between target daylight levels for different gradings in Miljöbyggnad. In certain situations, late design choices (some of which architects, engineers, designers, or daylight specialists have no control over and do not include in their daylight analyses) could thus have major implications regarding the interior daylight. If professionals are aware of this variability, they can take proactive measures to ensure the daylight resilience of interior spaces.

Future research should expand the scope to encompass more late design choices such as the size and reflectance of window frames as well as different shading types and their characteristics. Additional studies could also increase the diversity of studied spaces and include a wider range of daylight performance metrics. The non-linear relation between several of the late design choices and the daylight levels, which could be evidence of interaction between input variables, also merits further investigation.

7 Summary

The built environment and its development are significant contributors to the global energy demand and the subsequent climate emergency inducing greenhouse gas emissions. Buildings lay behind over half the total electricity demand during 2020, of which electric lighting of interior spaces was almost a fifth. The use of daylighting to achieve baseline illumination in combination with energy efficient electric lighting systems has been shown to provide up to a 50% reduction of electricity demand in buildings. Besides having the potential for energy saving, daylight is an essential factor of human life and experience regarding both physical and psychological aspects. It profoundly impacts the human mental state, mood, and emotions. It promotes better visual performance, a feeling of security and connection, reduced stress levels, increased productivity, and higher occupant satisfaction. Daylight analysis of interior spaces is increasingly being conducted early in the design process when several design factors have not yet been fully decided. These factors are first introduced or could be changed either by professionals later in the design process or by the building occupants after it has been constructed. This study aimed to investigate the variability of interior daylight and energy use in buildings due to such late design choices.

Late design choices are defined as factors which are introduced after the distribution of building volumes, their orientations, and window-to-wall ratios as well as relation to surrounding environmental context such as topography, buildings and vegetation has been decided. The study included nine such design choices that professionals could make or change in the later stages of a project. Sometimes, these factors might have been introduced at an earlier stage but are still able to be changed later. Other times it is not architects, engineers, or daylight professionals with knowledge of daylight who take decisions about these factors, but instead interior designers or the occupants of a building themselves after it has been constructed. The visual transmittance of windows, namely how much light can pass through the windows, and the amount of furniture in the space were identified as the most impactful factors. Windowsill and head heights, the colour/material (reflectance) of furniture and the height of workspace partitions had a medium influence. Finally, colour (reflectance) of the floor, ceiling, and walls proved to be the least impactful late design choices. In certain situations, these late design choices could have a significant impact on the interior daylight. The average variability could be as large as 27%, depending on what daylight metric was used in the assessment. Compared to target daylight levels in environmental certification schemes this variability is significant. It was shown that, in certain situations, the variability of interior daylight due to late design choices could be larger than the difference between thresholds for bronze and gold ratings in Miljöbyggnad.

In current practice, daylight analysis is often carried out when definitive decisions about space characteristics such as materials, colours, window characteristics and furnishing have not yet been made. Industry professionals were interviewed and environmental certification schemes, building standards and regulations were consulted to determine which factors could be changed late in the design process and what values these factors usually take in practical settings. Seven daylight metrics from literature often used by industry professionals to assess daylight were included in the study to produce a broad overview of the impact of the studied factors. These daylight metrics were $DF_{Average}$/% according to BREEAM, DF_{Median}/% and DF_{Point}/% according to Miljöbyggnad, DA/%, sDA /% according to LEED, LD/% to calculate the need for electric lighting, and finally UDI/% according to PSBP and LEED. It could thus be established which late design choices were more or less influential on average. Design decisions often taken early on, such as distribution of building volumes, orientation, and window-to-wall ratio, as well as environmental context such as surrounding topography, buildings and vegetation have a dominant impact on interior daylight. It has been shown by previous studies that these underlying daylight conditions influence how much the daylight is finally impacted by late design choices. To avoid misrepresentation of the analysis results a set of building models were designed to create various lighting conditions. These building models (twelve in total) were of varying orientation, size, and window-to-wall ratio. The building models were used for daylight simulations in Honeybee by Ladybug Tools, a plugin for Grasshopper in Rhino 3D. The static daylight metrics $DF_{Average}$, DF_{Median} and DF_{Point} were simulated using a CIE Standard Overcast Sky. As static metrics are intendent of rotation building models of varying orientations were omitted from these simulations. The dynamic daylight metrics DA, sDA, LD and UDI were simulated using an EPW file for Copenhagen, Denmark. The simulation results were fed to a global sensitivity analysis script written with the SALib package for Python. With sensitivity analysis according to the method of Morris the impact each late design choice had on the final daylight levels in each building model could be determined. A total of 80 samples were produced from 8 levels, 8 trajectories with local optimization according to the OAT and Latin Hypercube sampling method utilized by the method of Morris. The value of only one factor was varied in between consecutive simulations, meaning one sample equalled one daylight simulation.

The results of the study were not as straight forward as one late design choice being the most influential across the board. Instead, by studying several daylight metrics across a verity of different spaces, it could be determined which late design choices had a stronger or weaker influence on the interior daylight levels on average. It also highlighted that every building is unique, and that interior daylight is not equally affected by late design choices in all cases. The conclusion was that in certain situations late design choices could have a quite large impact on the daylight in interior spaces. If architects, engineers, interior designers, and daylight specialists are aware of variability due to late design choices, they can take proactive measures to ensure the resilience of interior spaces.

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Appendix A

```
#Import the required packages
import SALib
import numpy as np
import pandas as pd

#Define the problem
problem={'num_vars':9,
         'names':['RFloor', 'RCeiling', 'RWall','RFurniture' , 'TVisual',
         'Window_Head_Height', 'Window_Sill_Height', 'Furniture_Density',
         'Partition_Height'],
         'bounds':[[0.2, 0.4], [0.7, 0.9], [0.5, 0.8],[0.2, 0.7] , [0.5,
         0.8], [2.0, 2.7], [0.0, 0.7], [1.6, 3.2], [0.7, 2.0]]}

#Make samples
param_val=SALib.sample.morris.sample(problem, N=128,
optimal_trajectories=8, local_optimization=True, num_levels=8)
print(param_val)

#Export samples to CSV
pd.DataFrame(param_val).to_csv('samples.csv')

#Continue in Grasshopper

#1: Analyze static simulation results
#Import results from CSV
static_results_0=np.genfromtxt('static_results.csv', delimiter=',')
static_results=np.delete(static_results_0, 0, 0)

#Split results
dfavg_results=np.delete(static_results, [1, 2], 1)
print(dfavg_results)
dfmed_results=np.delete(static_results, [0, 2], 1)
print(dfmed_results)
dfpt_results=np.delete(static_results, [0, 1], 1)
print(dfpt_results)

#Run sensitivity analysis
dfavg_sa=SALib.analyze.morris.analyze(problem, X=param_val,
Y=dfavg_results, num_resamples=1000, num_levels=8)
print(dfavg_sa)
dfmed_sa=SALib.analyze.morris.analyze(problem, X=param_val,
Y=dfmed_results, num_resamples=1000, num_levels=8)
print(dfmed_sa)
dfpt_sa=SALib.analyze.morris.analyze(problem, X=param_val, Y=dfpt_results,
num_resamples=1000, num_levels=8)
print(dfpt_sa)

#Export SA results to CSV
pd.DataFrame(dfavg_sa).to_csv('DFavg.csv')
pd.DataFrame(dfmed_sa).to_csv('DFmed.csv')
```

```
pd.DataFrame(dfpt_sa).to_csv('DFpt.csv')

#Copy the files and start over.

#2: Analyze dynamic simulation results
#Import results from CSV
dynamic_results_0=np.genfromtxt('dynamic_results.csv', delimiter=',')
dynamic_results=np.delete(dynamic_results_0, 0, 0)
print(dynamic_results)

#Split results
da_results=np.delete(dynamic_results, [0, 2, 3], 1)
print(da_results)
sda_results=np.delete(dynamic_results, [0, 1, 3], 1)
print(sda_results)
ld_results=np.delete(dynamic_results, [1, 2, 3], 1)
print(ld_results)
udi_results=np.delete(dynamic_results, [0, 1, 2], 1)
print(udi_results)

#Run sensitivity analysis
da_sa=SALib.analyze.morris.analyze(problem, X=param_val, Y=da_results,
num_resamples=1000, num_levels=8)
print(da_sa)
sda_sa=SALib.analyze.morris.analyze(problem, X=param_val, Y=sda_results,
num_resamples=1000, num_levels=8)
print(sda_sa)
ld_sa=SALib.analyze.morris.analyze(problem, X=param_val, Y=ld_results,
num_resamples=1000, num_levels=8)
print(ld_sa)
udi_sa=SALib.analyze.morris.analyze(problem, X=param_val, Y=udi_results,
num_resamples=1000, num_levels=8)
print(udi_sa)

#Export SA results to CSV
pd.DataFrame(da_sa).to_csv('DA.csv')
pd.DataFrame(sda_sa).to_csv('sDA.csv')
pd.DataFrame(ld_sa).to_csv('LD.csv')
pd.DataFrame(udi_sa).to_csv('UDI.csv')

#Copy the files and start over.

#Congrats, you're done!
```

Appendix B

Table 19 Samples.

Sample	R_{Floor} [-]	$R_{Ceiling}$ [-]	R_{Wall} [-]	R_{Fur} [-]	τ_{Vis} [-]	Head height [m]	Sill height [m]	Furniture density [m]	Partition Height [m]
1	0.2	0.73	0.67	0.7	0.54	2.1	0.5	2.51	2
2	0.2	0.73	0.67	0.7	0.54	2.1	0.5	1.6	2
3	0.2	0.73	0.67	0.7	0.71	2.1	0.5	1.6	2
4	0.2	0.84	0.67	0.7	0.71	2.1	0.5	1.6	2
5	0.2	0.84	0.67	0.7	0.71	2.5	0.5	1.6	2
6	0.3	0.84	0.67	0.7	0.71	2.5	0.5	1.6	2
7	0.3	0.84	0.5	0.7	0.71	2.5	0.5	1.6	2
8	0.3	0.84	0.5	0.7	0.71	2.5	0.5	1.6	1.26
9	0.3	0.84	0.5	0.7	0.71	2.5	0.1	1.6	1.26
10	0.3	0.84	0.5	0.41	0.71	2.5	0.1	1.6	1.26
11	0.2	0.79	0.67	0.34	0.5	2	0.7	3.2	1.81
12	0.2	0.79	0.5	0.34	0.5	2	0.7	3.2	1.81
13	0.2	0.79	0.5	0.34	0.5	2	0.7	3.2	1.07
14	0.2	0.79	0.5	0.63	0.5	2	0.7	3.2	1.07
15	0.2	0.9	0.5	0.63	0.5	2	0.7	3.2	1.07
16	0.2	0.9	0.5	0.63	0.5	2.4	0.7	3.2	1.07
17	0.3	0.9	0.5	0.63	0.5	2.4	0.7	3.2	1.07
18	0.3	0.9	0.5	0.63	0.5	2.4	0.7	2.29	1.07
19	0.3	0.9	0.5	0.63	0.5	2.4	0.3	2.29	1.07
20	0.3	0.9	0.5	0.63	0.67	2.4	0.3	2.29	1.07
21	0.3	0.87	0.76	0.56	0.76	2.2	0.7	1.6	1.26
22	0.4	0.87	0.76	0.56	0.76	2.2	0.7	1.6	1.26
23	0.4	0.87	0.76	0.56	0.76	2.6	0.7	1.6	1.26
24	0.4	0.87	0.76	0.27	0.76	2.6	0.7	1.6	1.26
25	0.4	0.87	0.76	0.27	0.76	2.6	0.7	1.6	2
26	0.4	0.87	0.76	0.27	0.76	2.6	0.7	2.51	2
27	0.4	0.87	0.76	0.27	0.59	2.6	0.7	2.51	2
28	0.4	0.87	0.76	0.27	0.59	2.6	0.3	2.51	2
29	0.4	0.87	0.59	0.27	0.59	2.6	0.3	2.51	2
30	0.4	0.76	0.59	0.27	0.59	2.6	0.3	2.51	2
31	0.3	0.9	0.59	0.41	0.8	2	0.4	2.51	1.63
32	0.3	0.9	0.59	0.41	0.8	2	0	2.51	1.63
33	0.3	0.9	0.76	0.41	0.8	2	0	2.51	1.63
34	0.3	0.9	0.76	0.7	0.8	2	0	2.51	1.63

35	0.3	0.9	0.76	0.7	0.8	2	0	2.51	0.89
36	0.3	0.9	0.76	0.7	0.63	2	0	2.51	0.89
37	0.4	0.9	0.76	0.7	0.63	2	0	2.51	0.89
38	0.4	0.9	0.76	0.7	0.63	2	0	1.6	0.89
39	0.4	0.9	0.76	0.7	0.63	2.4	0	1.6	0.89
40	0.4	0.79	0.76	0.7	0.63	2.4	0	1.6	0.89
41	0.3	0.81	0.63	0.56	0.5	2.7	0.7	3.2	1.81
42	0.3	0.81	0.63	0.56	0.5	2.7	0.7	3.2	1.07
43	0.3	0.81	0.8	0.56	0.5	2.7	0.7	3.2	1.07
44	0.3	0.7	0.8	0.56	0.5	2.7	0.7	3.2	1.07
45	0.4	0.7	0.8	0.56	0.5	2.7	0.7	3.2	1.07
46	0.4	0.7	0.8	0.56	0.5	2.7	0.3	3.2	1.07
47	0.4	0.7	0.8	0.56	0.67	2.7	0.3	3.2	1.07
48	0.4	0.7	0.8	0.27	0.67	2.7	0.3	3.2	1.07
49	0.4	0.7	0.8	0.27	0.67	2.7	0.3	2.29	1.07
50	0.4	0.7	0.8	0.27	0.67	2.3	0.3	2.29	1.07
51	0.3	0.87	0.63	0.63	0.63	2.7	0.1	1.6	1.26
52	0.3	0.87	0.63	0.34	0.63	2.7	0.1	1.6	1.26
53	0.3	0.76	0.63	0.34	0.63	2.7	0.1	1.6	1.26
54	0.2	0.76	0.63	0.34	0.63	2.7	0.1	1.6	1.26
55	0.2	0.76	0.8	0.34	0.63	2.7	0.1	1.6	1.26
56	0.2	0.76	0.8	0.34	0.8	2.7	0.1	1.6	1.26
57	0.2	0.76	0.8	0.34	0.8	2.7	0.1	1.6	2
58	0.2	0.76	0.8	0.34	0.8	2.7	0.5	1.6	2
59	0.2	0.76	0.8	0.34	0.8	2.7	0.5	2.51	2
60	0.2	0.76	0.8	0.34	0.8	2.3	0.5	2.51	2
61	0.2	0.9	0.67	0.2	0.63	2.4	0.2	2.06	0.7
62	0.2	0.9	0.67	0.2	0.63	2.4	0.2	2.97	0.7
63	0.2	0.9	0.5	0.2	0.63	2.4	0.2	2.97	0.7
64	0.2	0.9	0.5	0.49	0.63	2.4	0.2	2.97	0.7
65	0.2	0.79	0.5	0.49	0.63	2.4	0.2	2.97	0.7
66	0.2	0.79	0.5	0.49	0.63	2.4	0.6	2.97	0.7
67	0.2	0.79	0.5	0.49	0.8	2.4	0.6	2.97	0.7
68	0.2	0.79	0.5	0.49	0.8	2	0.6	2.97	0.7
69	0.3	0.79	0.5	0.49	0.8	2	0.6	2.97	0.7
70	0.3	0.79	0.5	0.49	0.8	2	0.6	2.97	1.44
71	0.4	0.81	0.63	0.2	0.59	2.4	0.4	2.97	1.81
72	0.4	0.7	0.63	0.2	0.59	2.4	0.4	2.97	1.81
73	0.4	0.7	0.63	0.2	0.76	2.4	0.4	2.97	1.81
74	0.4	0.7	0.8	0.2	0.76	2.4	0.4	2.97	1.81

75	0.4	0.7	0.8	0.2	0.76	2	0.4	2.97	1.81
76	0.3	0.7	0.8	0.2	0.76	2	0.4	2.97	1.81
77	0.3	0.7	0.8	0.2	0.76	2	0	2.97	1.81
78	0.3	0.7	0.8	0.2	0.76	2	0	2.06	1.81
79	0.3	0.7	0.8	0.49	0.76	2	0	2.06	1.81
80	0.3	0.7	0.8	0.49	0.76	2	0	2.06	1.07

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