Supporting the EU Mission "100 Climate-Neutral Cities by 2030": A Review of Tools to Support Decision-Making for the Built Environment at District or City Scale

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Abstract. Human activities are responsible for vast environmental impacts, including carbon emissions contributing to climate change. The urban environment is a main source of many of these impacts, and accordingly, the European Union has launched the "100 climate-neutral cites" mission to operationalize a carbon-free urban future. This paper investigates the various evaluation tools supporting the Decision-Makers (DMs) and stakeholders in their effort to achieve the carbon-neutral transition. Using the scientific database Scopus, we conducted a literature review focused on different keywords comprising widely used evaluation methods. The focus of the research is on different aspects and scales of the urban systems, considering the multi-dimensional nature of the decision problems at such scale. Specifically, the study presented here analyzes the way in which these methods deal with large scales, either with a bottom-up or a top-down approach, and how different categories of Key Performance Indicators (KPIs) and changes in the DMs system of values can influence their preferences. We find that Lifecycle Assessment (LCA) is the most used support tool at the district or city level, and most indicators focus on energy consumption and carbon emissions. A smaller share of studies reviewed are based on multi-domain evaluation methods.

Keywords: Climate-neutral cities · Low carbon · Energy transition · Urban regeneration · Decision-making tools · District · Neighborhood · Urban scale

1 Introduction

To advance the European Green Deal's climate neutrality pledge, the European Union (EU) recently launched the mission "100 climate-neutral cities by 2030 – by and for the citizens". The project envisages 100 cities (or districts thereof) with minimum population 50,000 as innovation hubs leading other cities ahead of the 2050 deadline. To participate, cities mitigate and offset all greenhouse gases (GHG) considered Scope 1 (direct emissions from buildings, industry, transport, waste treatment, agriculture, forestry, and other

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activities within the city boundaries) and Scope 2 (GHG from grid-supplied energy). Also recommended is mitigation of Scope 3 emissions (out-of-boundary GHG arising from consumption within boundaries) [1].

For the mission to be successful, a key focus must be the building sector, which accounts for 40% of energy consumption and 36% of energy-related GHGs in the EU [2]. Supporting the transition in the building sector, the European Green Deal and Sustainable Europe Investment Plan will spend €1 trillion on climate action in the coming years [3], and the EU's Renovation Wave will foster deep renovation, double the annual energy renovation rate, and complete 35 million building renovations by 2030 [2].

There is no prescriptive path for a city to achieve climate neutrality, nor completed precedents of such cities. However, one can draw experience from substantial energy reduction in district or neighborhood examples. Among these are positive energy districts (PEDs), of which there are at least 60 projects in Europe in planning, implementation, or operational stages [4]. PEDs are districts or neighborhoods which produce more energy than they consume over the average course of the year, typically through locally produced renewable energy, thus reducing GHG from fossil fuel use [5].

As cities pursue climate neutrality through a series of district-level projects, they require support to develop and evaluate action plans [6]. The aim of this paper is thus to provide support for Decision Makers (DMs) in planning and policy implementation who seek strategies for zero-carbon buildings and neighborhoods, by reviewing literature on decision-making tools for the built environment at the district or city scale. Our approach includes a focus on decision-making inputs and Key Performance Indicators (KPIs) to provide DMs context required to use the decision-making tools and metrics to evaluate decisions. We focus on the building sector as it is the top energy consumer and emissions producer in the EU [2], and we consider other urban sectors such as transport and waste management as they arise within the built environment research.

With an estimated cost of €96 billion for the 100 cities participating in the new mission alone [1], it is essential to use decision-making tools to optimize climate-focused urban interventions. Research indicates that it is difficult for DMs to select among numerous retrofit and renewable energy system intervention scenarios, pointing to Multi-Criteria Analysis (MCA) as a basket of tools to make better decisions [7]. In addition to MCA, other decision-support tools such as Life Cycle Assessment (LCA), Life Cycle Costing (LCC), Cost-Benefit Analysis (CBA) and other methods can be used to assess intervention scenarios and justify decisions [8, 67, 70, 72].

This work investigates the following research questions, each of which referring to the built environment at the district or city scale:

- Q1. On district- or city-level projects, how do studies deal with larger scale?
- Q2. What are the decision-making support and evaluation tools used at district or city scale?
- Q3. What are the KPIs and other inputs used with the decision-making tools?

This paper is structured as follows: Sect. 2 presents the research methodology; Sect. 3 discusses results to the research questions; and Sect. 4 provides conclusions.

2 Research Methodology

The literature review was conducted by using the database SCOPUS on March 16, 2022. We used different keywords to focus our review on decision-making tools for the building sector at the district or city scale. Specifically, the keywords used can be classified into four macro-groups: 1) "Decision-Making Tools", 2) "Building Sector", 3) "Climate Neutrality", and 4) "Scale of Intervention". In addition, we limited the research for the first three macro-groups to keywords, and for the last group regarding scale, we limited to article title. The keywords used for the different groups are:

1 Macro-group "Decision-Making Tools": ("Outranking" OR "Hedonic" OR "Stakeholder analysis" OR "SWOT" OR "Cost Benefit Analysis" OR "CBA" OR "Discounted Cash Flow Analysis" OR "DCA" OR "DCFA" OR "Contingent Valuation Method" OR "Discrete Choice Models" OR "Cost Effectiveness Analysis" OR "Risk Benefit Analysis" OR "Planning Balance Sheet" OR "Community Impact Evaluation" OR "Environmental Impact Assessment" OR "Strategic Environmental Assessment" OR "DPSIR" OR "NAIADE" OR "Evamix" OR "Lexicographic" OR "Cluster" OR "Analytic" OR "Input Output" OR "Concordance/discordance analysis" OR "Multiattribute Value Theory" OR "Multi-attribute Value Theory" OR "MAVT" OR "Multiattribute Utility Theory" OR "Multi-attribute Utility Theory" OR "MAUT" OR "Analytic Hierarchy Process" OR "AHP" OR "Analytic Network Process" OR "ANP" OR "Spatial Multicriteria Analysis" OR "SMCA" OR "SS-MCDA" OR "Dominance-based Rough Sets" OR "Non Additive Robust Ordinal Regression" OR "Choquet Integral" OR "ELECTRE" OR "PROMETHEE" OR "LCA" OR "LCC" OR "Life cycle" OR "Lifecycle" OR "ROI" OR "Return on investment" OR "SROI" OR "Social return on investment").
2 Macro-group "Building Sector": ("Built environment" OR "building" OR "dwelling").
3 Macro-group "Climate Neutrality": ("Energy" OR "efficiency" OR "efficient" OR "climate neutral" OR "carbon neutral" OR "zero carbon" OR "low carbon").
4 Macro-group "Scale of Intervention": ("District" OR "City" OR "Urban" OR "Neighborhood" OR "Neighbourhood" OR "Block" OR "precinct").

We used one comprehensive search string, using the "AND" operator to link macro-groups. We limited the search to peer-reviewed journals, yielding 249 results. Subsequently, we eliminated articles not relevant to the study in three steps. First, we removed articles deemed irrelevant based on title, resulting in 83 articles being excluded. Second, we read all abstracts and eliminated articles out of scope, excluding an additional 86 documents and resulting in 80 articles. Last, we read full articles, removing 24 further irrelevant papers, for a total of 56 articles reviewed in this work.

3 Results and Discussion

Of the 56 articles reviewed, the majority included Life Cycle Assessment (LCA), with 28 studies using LCA as the sole decision-making tool, and an additional seven studies using

LCA in combination with another tool. Energy Simulation (ES) was the second-largest category, with a total of seven studies using the tool. Figure 1 shows the percentage of studies reviewed by decision-making tool.

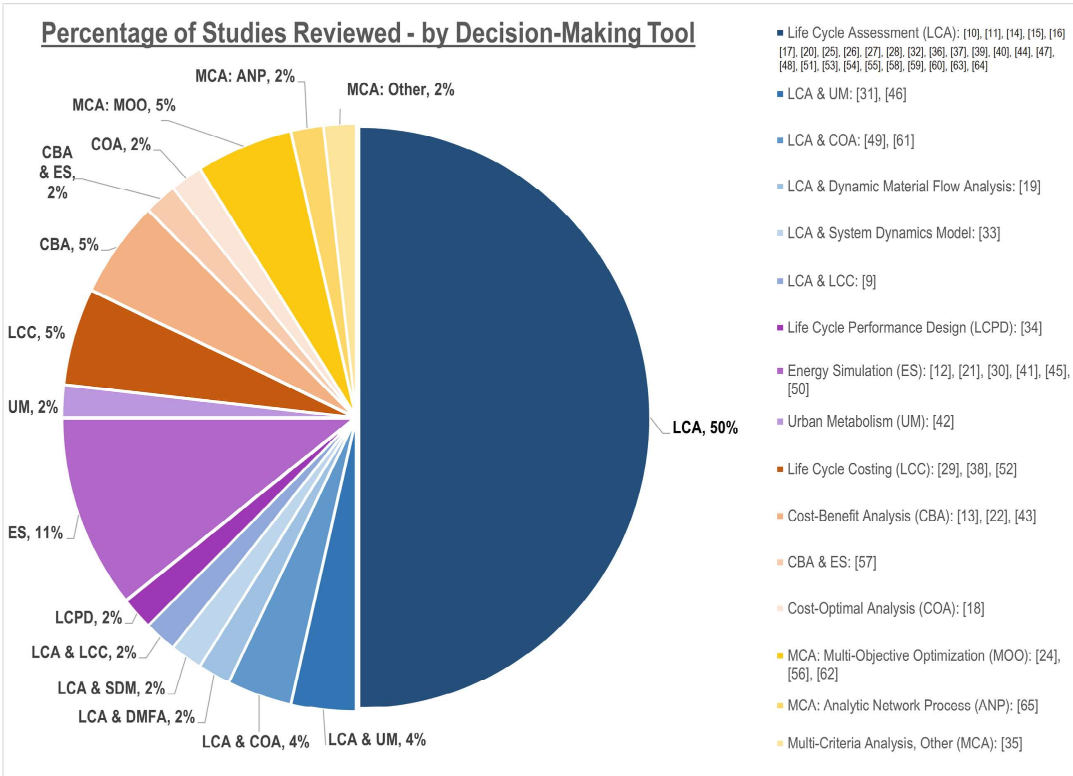

Fig. 1. Studies reviewed by decision-making tool

3.1 How Studies Deal with Greater Scale

Moving from models based on the building scale to larger scales, including district or city scale, requires strategies to deal with vastly greater building geometries and other parameters among hundreds or thousands of structures. In the studies reviewed, the strategies can be classified as geospatial and non-geospatial methods. As shown in Fig. 2, these methods can be further divided into approaches including archetype, sampling, individual building, scaling top-down data, and hybrid and other approaches. Most of the approaches can be considered "bottom-up" approaches, which analyze individual buildings and then extrapolate results to a greater scale, whereas the approach of scaling top-down data begin with macro-economic, national-level, or other aggregated data and apply downscaling ratios to arrive at the building level [67].

3.1.1 Geospatial Methods

Over 40% of reviewed studies used geospatial methods. Such methods usually rely on geographic information systems (GIS), enabling semi-automatic extraction of building geometry and other data, such as floor area, number of stories, building elevation, etc.

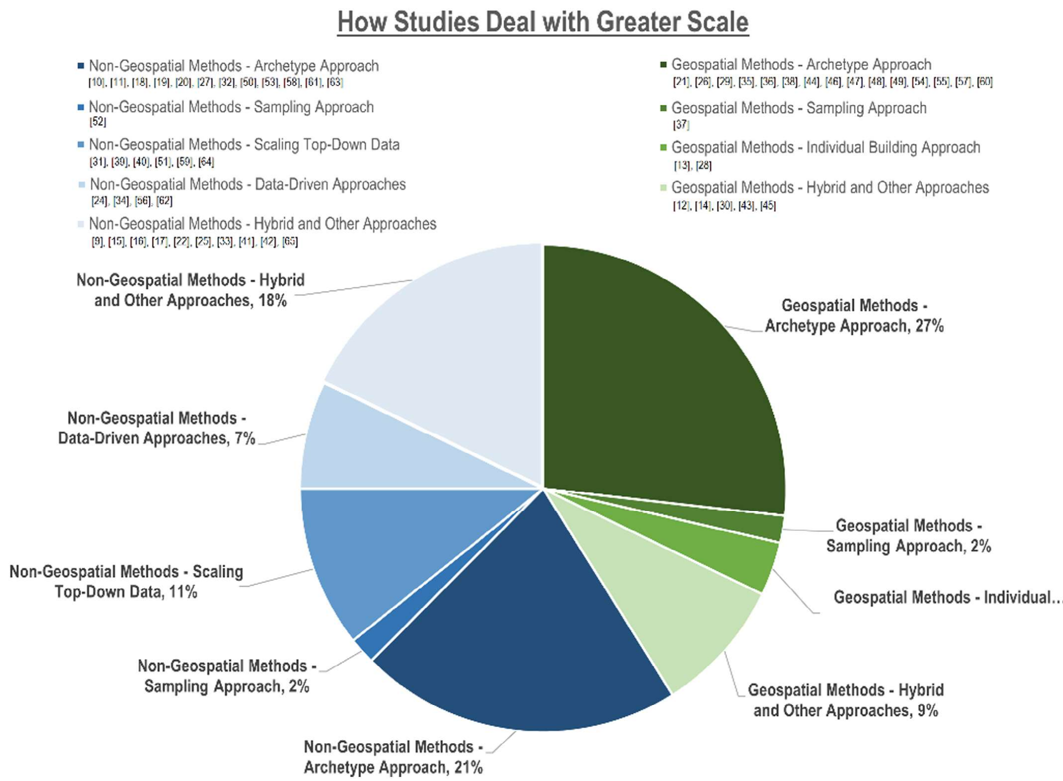

Fig. 2. How the studies reviewed deal with district or city scale.

Use of *building archetypes* was the most common single approach within the reviewed articles. The archetypes provide building characteristics to be used in the modelling such as construction materials, insulation values (U-values), glazing ratios, infiltration levels, and mechanical system efficiencies [47, 56]. Once the buildings in the GIS model are classified according to each archetype, the investigated characteristics are scaled to the real buildings. Archetypes in the reviewed studies are largely based on period of construction and building typology [35, 45, 47, 54, 59]. Different sources are used to define the archetypes such as the EU TABULA project [21, 48], national building libraries [53], and expert opinions and/or past studies [43, 45, 47, 54, 59].

The archetype approach is useful on very large scales, such as in [15] where 656,531 buildings were modelled across Barcelona. In another evaluation tool known as urban building energy modeling (UBEM), not reviewed in this work, research notes that upscaling building archetypes can average out inaccuracies of individual building models, with error ranges of 7–21% for heating loads and 1–19% for energy use intensity, deemed to be acceptable to guide decisions affecting multiple buildings [66].

The *individual building approach,* where each building is separately modelled using actual characteristics, was completed in two of the reviewed studies, and both on small district projects (8 and 4 buildings) [13, 27].

Next, a *sampling approach* was used as a single approach in one study [36] involving 1,092 in-person questionnaires with building residents in Xiamen, China, to retrieve building information, obtain energy bills, and ascertain occupant energy-saving awareness. The sample data were then normalized and scaled up across the city using GIS.

Finally, some studies adopted *hybrid and other approaches*. [44] used sampling in a hybrid approach to validate energy outcomes of geospatial archetype analysis. [12] used sampling energy bills in conjunction with data-driven analysis to create building clusters (similar to archetypes). In a study of urban heat island (UHI) effect and building energy demand, the researchers collected local climate zone data with GIS and subsequently used machine learning to compute optimal cool pavement solutions [14]. In a study on optimal selection of green roof areas across Seoul, South Korea [42], geospatial data was first used to help determine expected costs and benefits of green roofs on each building, before selecting optimal locations of green roofs in the city.

3.1.2 Non-geospatial Methods

About 57% of the studies reviewed used non-geospatial methods. In contrast to geospatial, non-geospatial methods often rely on statistical data instead of individual land parcel and building data [67]. These methods include archetype, sampling, scaling top-down data, and hybrid approaches.

Like its geospatial counterpart, the non-geospatial *archetype approach* uses building typologies for analysis, with sources such as expert opinion, statistics on the building stock, or reference buildings [67]. This is the most common approach of the non-geospatial methods, representing 12 of the reviewed studies. One study in Abu Dhabi, United Arab Emirates, [50] used an engineering consultant's report on the national building stock to create one average building archetype, then multiplied by 5,500 buildings to reach the total national amount of annual electricity consumption. In recent case studies from Norway [11, 19, 20], archetypes based on Norwegian Passive House standards were created and then multiplied by the 1,000 buildings in the Ydalir positive energy district. Reyna & Chester [52] used 16 reference buildings over three time periods, for a total of 42 building archetypes. They subsequently ran 42 LCAs and normalized them on a per-unit-area basis, multiplying these values by the area of each building archetype according to Los Angeles County Assessor statistics.

Another among non-geospatial methods is the *sampling approach*, used in one study as a single method [51] as well as in hybrid approaches. In Gonen, Turkey, researchers sampled 56 out of 300 buildings connected to an existing district heating system [51]. The sampled buildings were measured, surveyed, and/or the architectural drawings were studied to create an average set of building statistics to be modelled.

Four of the reviewed studies [23, 33, 55, 61] employed a *data-driven approach* to overcome the need for physical building models. Whereas classical modeling requires numerous building parameters as inputs into modelling software [33] (e.g. EnergyPlus or TRNSYS, as used in several of the bottom-up approaches mentioned above), if adequate consumption data are available for use in computational analysis, these can be used to create reliable estimation models for energy consumption [68]. In a study in the Netherlands [33], energy consumption data for 19 buildings, both from building energy management systems and statistical sources, were used to computationally create a life cycle performance design (LCPD) model. In Seoul, South Korea, researchers used clustering and evolutionary algorithm methods to analyze over 10^5 buildings with about 10^3 optimized future scenarios [23]. In a district project in Norway [55], researchers used computation with an evolutionary algorithm to solve the optimization of energy system selection with 1.66 x 10^{65} possibilities. In a district study in San Francisco [61], researchers used an evolutionary algorithm to determine thousands of optimal solutions.

Another non-geospatial approach was *scaling top-down data*, as seen in six of the reviewed studies. In a LCA study in Wuhan, China [58], the authors used data from national and provincial statistical yearbooks as inputs, scaling them to the city level to determine energy consumption at building material production, construction and demolition, and building operations. In a LCA and Urban Metabolism (UM) study comparing two Spanish cities [30], the authors used national and regional data and applied ratio-based downscaling based on the population and gross domestic product (GDP) in each city. In two district LCA projects in Australia [39, 50], the authors scaled statistical data to the local scale. Embodied energy of buildings was calculated based on energy intensities and floor areas, and operational energy was calculated from normalized per unit energy consumption and average per capita daily consumption. A study of cities in 84 countries around the world [38] scaled data related to heating and cooling degree days as well as population and income per capita to create city-level LCAs.

Finally, many of the non-geospatial methods adopted *hybrid or other approaches*, representing 10 of the studies reviewed. One study in Barcelona [40] combined resident interviews and energy bill data surveys to collect data, then applied data-driven analysis using clustering methods, generative topographic mapping and k-means, to obtain reference dwellings to represent different energy patterns and energy systems of the neighborhood. Both sample and scaled top-down data were used in a city-wide LCA study in Shenzhen, China [8]. A city-level study in Beijing creating a Life Cycle Dynamic model (LCDM) also used a combination of questionnaire surveys and field investigations plus top-down statistical data; econometric theory and system dynamics theory are used to process the data [32].

3.2 LCA and Related Decision-Making Tools

As noted, the majority of the analyzed papers use LCA, which aims at quantifying the environmental impacts of a system throughout different stages from beginning of life (BoL) to End of Life (EoL), avoiding the shift of impacts among different stages [65]. The LCA methodology is well defined, derived from Industrial Ecology [65], dating back to the 1970s [31], and used lately as a basis to evaluate the different dimensions of sustainability. These dimensions include social, economic, and environmental, and lead to the definition of the equation: LCSA = LCA + LCC + SLCA, where Life Cycle Costing (LCC) deals with the economic aspect assessment, Social Life Cycle Assessment (SLCA) deals with social aspects, and combined with LCA's analysis of environmental impacts, yield the total Life Cycle Sustainability Assessment (LCSA).

The LCA studies reviewed focus on three main aspects of the urban environment: energy intensity [15]; environmental impact, in terms of Global Warming Potential (GWP) and/or embodied carbon [27, 35, 36, 43, 52, 58, 59, 62], or as a wider spectrum of impacts, such as acidification of soil and water, eutrophication, photochemical ozone creation potential [17, 31, 54]) and the input-output of materials [19, 41].

The application of LCA at a scale greater than the building level dates back to 1996 [31], and has been applied to several studies both in evaluation of new construction of urban areas [46] and urban renovation analysis [10, 11, 25, 47, 53].

[46] use a LCA approach to compare six different scenarios for the planning of a new district of 100,000 m^2 in Granada, Spain, including 225 to 480 residential units. They consider the impact of the new dwellings by means of archetypes, as well as the impacts of road network and different land uses (leisure space, sport installation, school, commercial and social uses), identifying the best alternative in terms of carbon dioxide (CO_2) emissions and Embodied Energy (EE).

[53] focus on a city quarter of 1,148 buildings in Stuttgart, Germany, completing a LCA for all the residential buildings, or around 50% of the buildings in the district. The authors evaluate four different intervention scenarios in the district considering possible envelope interventions to reduce carbon emissions: (1) demolishing and reconstructing all the buildings, (2) an advanced retrofit of all the buildings, plus (3) and (4) with 12% of buildings replaced and the remaining refurbished, but with different priority sequences for the refurbishment. They performed a GHG calculation over 34 years (2016–2050) over the entire life cycle of the district (production stage, use stage, end-of-life stage), and conclude that the 80% reduction target of the German federal government in primary energy demand cannot be achieved with envelope refurbishment alone. Furthermore, 60% of GHG emissions during use stage can be avoided, but this figure is reduced when accounting for embodied emissions in refurbishment scenarios.

In another work evaluating retrofit scenarios, [47] ranked four intervention alternatives comprising increasingly high-performance solutions (status quo, envelope upgrades, low-carbon design and low-carbon materials, and low-carbon strategies combined with PV-panels) against three parameters: Embodied CO_2 emissions, Operational CO_2 emissions, Whole life cycle emissions at 1, 10, and 50 years after calculation.

[32] evaluate the energy consumption of material production of new residential construction, energy use for the operation and demolition of buildings, and the disposal of demolition waste. They combine LCA with a System Dynamics Model (SDM) to predict the newly built and demolished residences over the calculation period. The authors conclude that the majority of the energy consumption occurs in the operational stage (60% of the total energy consumption), with an increasing trend over the years. They note the possibility of reducing this figure by 6.6%-13.2% by lowering energy-intensive activities, such as heating, air conditioning, lighting, electric devices.

Another group of studies includes other sectors beyond the built environment, such as transport and mobility [26, 38, 39, 50], and infrastructure [14, 20, 57]. In their analysis of a suburban precinct in Adelaide (Australia), [50] include the total energy consumption embodied in the construction and maintenance of precinct objects, the total energy required for the operation of precinct objects and the total energy related to occupant travel, including commuting for work, school, and leisure. They propose two transportation scenarios: one assuming current modes of transportation; and another one assuming 30% of occupants switch to public transport. They found out that operational energy accounts for 32% of the total (of which HVAC accounts for 48.8%, appliances for 24%, and lighting 13.1%), while travelling energy reached 55% of the total, being the largest use of annual energy. A second transport scenario analyzed (30% of residents shifting to public transport) reduced precinct energy consumption by 6.3%.

Related to the previous study, [39] evaluate the two precincts depending on their geographical location and socio-economical composition, highlighting the significance of embodied carbon (both initial and recurrent) and travel related carbon, together accounting for 49.9% and 58% of the total. They also calculate carbon reductions in a scenario with increased public transport (15.1% and 30.4% in the inner and outer precinct respectively) and a scenario with a 90% increase in residential PV installation (81.7% and 75.7% in the outer and inner precincts respectively, with a 1.1% and 0.7% increase in embodied carbon).

With an approach including infrastructure, [14] apply the LCA method to capture the effect of Urban Heat Island (UHI) and climate change in cities considering the mutual relationship among buildings, vehicles and pavements.

[57] analyze five "synthetic" cities (Orlando, Phoenix, Austin, Seattle, and a fictitious "Maximum-Density Case"), studying embodied and operational energy for buildings, infrastructure (freshwater, wastewater, lighting) and transport (fuel use, parking, sidewalks, streets), and calculate energy performance per-capita. Furthermore, [20] evaluate different scenario for a pilot project in a neighborhood in Elverum, Norway. The parameters considered were mobility energy use in operation, area of PV panels, embodied emissions in building materials, emissions associated with vehicle production, travel distance per inhabitant and year, and the emission intensity of electricity. In this study, mobility is the largest GHG emission contributor (61% of the total), while PV panels are responsible for only 4% of total emissions.

In the evaluation of the LCA, several studies have highlighted the high percentage contribution of the operational energy consumption on the total environmental impacts [31, 32, 36, 39, 50, 53]. Indeed, several studies focus solely on Energy Simulation (ES) [12, 21, 29, 40, 44]. For instance, [21] analyze a neighborhood in Seville, Spain, proposing two intervention scenarios combining PV panel installation, substitution of heating and cooling systems, and implementation of specific energy efficiency measures, to prioritize possible areas of energy intensity reduction intervention. In [29], researchers use local weather station data to drive an ES, calculating energy consumption of a typical 30-storey building in Hong Kong and the resulting effect of UHI and Urban Moisture Island (UMI). They highlight a 96% increase in latent cooling demand due to UMI effect and UHI impact in a range of 45.7% - 104.2% increase in sensible cooling demand in urban areas compared to rural ones. In [40], the study combines data from a survey (resident questionnaire) and simulation models to evaluate tenants' behavior on energy consumption in a residential neighborhood to evaluate the impact of possible retrofit intervention on different socio-economically defined occupants.

Further combining methods from Industrial Ecology, some analogies can be drawn between Environmentally Extended Input-Output Analysis (EEIOA) and Material Flow Analysis (MFA) and UM. In particular, the first aims at including all monetary transaction in an economy to quantify the environmental impact of a product or service; the second has its goal in describing the input and output flows of materials [63].

With an approach focused on the urban scale, [30] combine LCA and UM to calculate construction materials, fossil fuels, energy, food beverages, as well as other flows in both Bilbao and Seville, Spain, estimating their impacts in terms of global warming, stratospheric ozone depletion, terrestrial acidification, freshwater eutrophication, marine eutrophication, fossil resource scarcity, human carcinogenic toxicity drawing specific insights related to different characteristics of the two cities. [45] use UM to combine

Environmental Input-Output (EIO) and LCA on the evaluation of flows in Los Angeles County, USA, quantifying GHG emissions related to electricity consumption, embodied energy due to buildings and roadways, water use, and waste flows. [41] calculate the impact of two recycling scenarios in Jakarta and Bandung, Indonesia, to compare the estimated flows of demolition materials during the time span of the calculation and the stocking capacity of two newly planned landfills. Table 1 provides a summary of LCA and related DM tools, including KPIs.

Table 1: Summary of LCA and related DM tools.

DM tool	KPIs most frequently observed in the literature	KPIs less frequently observed in the literature
Life Cycle Assessment (LCA)	• Carbon emissions ($kgCO_2$) • Energy consumption (kWh/GJ) *(Both of the above may include Embodied or Operational carbon / energy)*	• Eutrophication – Freshwater (kg_{PO4eq}) and Marine (kg_{Neq}) • Acidification of soil and water (kg_{SO2eq}) • Stratospheric ozone depletion ($kg_{CFC11eq}$) • Photochemical ozone creation ($kg_{ethyleneeq}$) • Water use (m^3) • Human toxicity ($kg_{1.4DCB}$) • Aquatic eco-toxicity (m^3)
Energy Simulation (ES)	• Operational energy consumption (kWh/GJ) • Operational carbon emissions ($kgCO_2$)	*n/a*
Urban Metabolism (UM)	• Embodied carbon ($kgCO_2$) and energy (PJ) • Disposed material (tonnes)	*n/a*

3.3 Cost-Based, Multi-criteria, and Other Tools for DMs

While LCA is the most widely used method to support decision making in district-wide energy upgrading, the literature review shows that other quantitative and qualitative evaluative methods are also common. In particular, quantitative economic evaluation methods found are Life Cycle Costing (LCC), Cost-Benefit Analysis (CBA), and Cost-Optimal Analysis (COA), whereas a range of methods falling under the umbrella term Multi-Criteria Analysis (MCA) include both quantitative and qualitative approaches.

Based on the literature review, it has emerged that the LCC method is the most widely used after the LCA method. This method of monetization, focusing on "global costs", is also used alongside LCA, as it estimates all costs related to the life cycle of the materials used in construction [9, 60]. Calculation of LCC of a building is based on adding up the investment, energy, maintenance and replacements costs minus the RV (Residual Value), and applying a discount rate to costs incurred in the future [69].

In the context of district-level energy retrofitting, LCC can be used to analyze potential scenarios to find the best energy solution from an economic standpoint. [28, 32]. In the redevelopment of a historic district in Visby, Sweden, [28] supported LCC using OPERA-MILP software (Optimal Energy Retrofit Advisory-Mixed Integer Linear Program), thus analyzing multiple strategies in terms of costs for each type of intervention.

Similar to a combination of LCA and LCC is Life-Cycle Performance and Design (LCPD), also used to evaluate the performance of an asset over its lifetime. The approach uses indicators of two main scopes – economic and environmental – and within each, develops specific KPIs for buildings, local energy systems, and other sectors [33].

Another method used to evaluate and support energy regeneration is Cost-Benefit Analysis (CBA). This method, unlike other financial methods such as Cost-Optimal Analysis, which calculates the investment cost, energy price, inflation, maintenance cost, and uses the discount rate [18], also considers the environmental and social co-benefits arising from the intervention [13, 22, 23, 56]. In a study analyzing installation of green roofs in Seoul [42], costs and benefits were calculated to find the optimal building locations for green roof installation, including socio-economic, energy, and environmental aspects, including bee habitats. The results show that 100 buildings were selected for the installation of green roofs, satisfying 92% of the demand imposed by existing green spaces [42].

A group of methods falls under the umbrella term Multi-Criteria Analysis (MCA), which can also be combined with cost-based methods. In one example, in a case study in Greece regarding the expansion of the electrical system where both methods are used to evaluate different scenarios to support the decision-maker [69]. MCA may consider not only quantitative but also qualitative aspects. In the article [34], the authors have classified four principal classes of MCA methods: (i) value measurement models (e.g., AHP, MAUT); (ii) goal, aspiration and reference level models (e.g., TOPSIS); (iii) outranking models (e.g., ELECTRE, PROMETHEE); and (iv) combination of models [34]. An example of the first type, Analytical Network Process (ANP) was used in Qingdao, China, to weight and score values of priorities related to architecture, planning, and design as well as construction management, including indicators related to building orientation, energy saving design, and building materials, among others [64].

The outranking method has been re-encountered in our bibliographic analysis. In detail, the study presented an application of the PROMETHEE multi-criteria method to outrank the different building energy retrofit alternatives at both the building and district levels, considering the citizen and municipality perspectives respectively [34]. In detail, different quantitative and qualitative criteria have been identified at the district and building level, moreover, alternatives have been defined. By performing sensitivity analysis and varying the weights of the various criteria, particularly the socio-economic ones, the preferential order of the alternatives is modified. The method demonstrates that the socio-economic part influences decision-making choices.

Another multi-criteria decision-making tool falling under the MCA umbrella, Multi-Objective Optimization (MOO) was used in studies [23, 55, 61]. MOO is a data-driven tool which can use computing power to process exponential possible outcomes. For example, [61] used MOO to maximize total fuel cycle efficiency, minimize life cycle cost, and minimize annual CO_2 emissions, finding tens of thousands of solutions that met their target criteria. Table 2 provides a summary of the other DM tools from the literature review, including KPIs.

Table 2: Summary of other DM tools commonly featured in the literature review.

DM tool	KPIs most frequently observed in the literature	KPIs less frequently observed in the literature
Life Cycle Costing (LCC)	• Investment cost (currency/ m^2) • Operations & maintenance cost (currency/ m^2)	• Payback period (years) • Net Present Value (currency)
Cost-Benefit Analysis (CBA)	Includes all KPIs as LCC, plus added co-benefits include: • Economic savings from energy reduction (currency/m^2)	*n/a*
Cost-Optimal Analysis (COA)	• Global cost (currency) • Carbon emissions ($kgCO_2$) • Payback period (years) • Energy savings compared to baseline (%)	• Net Present Value (currency)
Multi-Criteria Analysis (MCA), including Analytic Network Process (ANP)	• Energy savings (%) • Internal comfort / temperature (%)	• Costs – Investment, Replacement, Maintenance (currency) • Tax detraction (%) • Reliability / satisfaction with retrofit (%) • Social image & awareness (%)
Multi-Objective Optimization (MOO)	• Life cycle cost (currency) • Carbon emissions ($kgCO_2$)	• Total Fuel Cycle Efficiency (%) • Loss of Power Supply Probably (%)

4 Conclusions

Human activities are responsible for vast environmental impacts, with carbon emissions and climate change being chief among them. The urban environment is a main source of many of these impacts, and accordingly, the European Union has launched the "100 climate-neutral cites" mission to operationalize a carbon-free urban future.

While climate-neutral cities may be part of the solution to the climate problems we are experiencing, as Huovila et al. [59] note, cities require support to develop and evaluate action plans to transform into climate-neutral cities. Thus, this paper seeks to provide such assistance by reviewing the decision-making support and evaluation tools that facilitate this transition.

This paper employed a Scopus database search for key words in the macro groups Building Sector, Climate Neutrality, and Decision-Making Tools, and searching title for terms related to our target Scale of Intervention. This macro group approach allowed us to quickly narrow the results to articles within the scope of this review, excluding many irrelevant articles studies and providing a manageable quantity of articles to review. However, as a possible downside, relevant articles could have been excluded.

The review study shows that the most prevalent method among research in the built environment at the urban scale is LCA, which aims at quantifying the environmental impacts of a product from beginning of life (BoL) to End of Life (EoL) [65]. While we began this review with dozens of decision-making tools in mind, it is surprising to find that LCA is so dominant in the literature. However, this can be explained perhaps by the idea of searching for tools addressing carbon- and climate-neutral cities, as LCA seeks to quantify energy consumption and carbon emissions, and has been shown to work well in comparing pre- and post-intervention scenarios. While LCA provides a clear picture of energy, carbon, and several other environmental indicators, potential shortcomings of this tool are that it does not consider costs, nor co-benefits in the social domain. In theory, the extension of LCA to include social indicators, namely the complete life cycle sustainability assessment (LCSA) [65], would overcome this limitation, however we did not encounter any such applied case studies in this literature review.

We addressed scale in this review so that policy makers could contextualize decision-making at different scales, from the building to the district, ultimately extending to the climate-neutral city. The literature reveals challenges in measuring KPIs at scale, and notes numerous methods, both geospatial and non-geospatial, to address this. Previous work has referred to the two most common upscaling methods as the "building-by-building" and "archetype" approaches, noting that the former leads to more refined modelling of the building, at the cost of higher input data requirements and computational burdens [67]. We chose to classify these two methods as geospatial and non-geospatial archetypes, as both approaches begin with reference buildings, then upscaling based on building geometry from GIS in the former approach, or using statistical data in the latter. In either case, such a study uses averages based on construction eras and typologies, which necessitates simplification and thus some error. The geospatial methods reduce uncertainty by modeling with actual building parameters, such as surface area and volume. Other recent work attempts to further improve certainty with actual window to wall ratios, extracted automatically across urban areas from street view imagery using machine learning [73]. When aggregated at the city scale, archetype methods have been shown to provide overall results within acceptable error ranges [66].

While the research presented in this paper specifically focuses on the built environment, some of the studies analyzed also consider other aspects of the urban fabric, including the transport sector, infrastructure, water management and other material and energy flows. Our focus on the built environment might explain the finding that CO_2 emissions and energy-related indicators as the most common KPIs. Considering the

LCA studies reviewed, a minor number of these included other impact categories such as eutrophication and acidification of soil and water.

Additionally, if we consider wider criteria to evaluate urban interventions (such as in the framework of the triple bottom-line approach), neglecting some aspects of the evaluation could lead to distorted or suboptimal results as discussed in Sect. 3.3, where assigning a different weighing system to different social, economic and environmental criteria altered the ranking of urban scale retrofit intervention scenarios [34].

For future analysis, an in-depth exploration of methodologies related to a comprehensive framing of decision-making could be valuable, including social, environmental, and economic domains. Such an approach would focus on a deeper literature analysis of applications in the urban environment at different scales and on application in other fields, such as energy production, environmental risk and scenario analysis, and cultural heritage. Furthermore, the increasing availability of real-time data from monitoring systems and smart devices within the Internet of Things (IoT) paradigm could represent an untapped resource to develop realistic scenarios and support data-informed and holistic decision making [1, 71].

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