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Environmental benchmarking of building typologies through BIM-based combinatorial case studies

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ABSTRACT

Integrated life-cycle assessment (LCA) tools have emerged as decision-making support for BIM practitioners during the design stage of sustainable projects. However, differences between methodologies applied for determining the environmental impact of buildings produce significant variations in the results obtained, making them difficult to be compared. In this study, a methodology is defined for generating environmental benchmarks for building typologies through a combination of BIM-based LCA tools and machine learning techniques. When applied to an 11-story residential building typology with 92 dwellings by varying the constructive solutions of façades, partitions, roof and thermal insulation materials, results fall within a range from 360 to 430 $kgCO_2eq/m^2$. The Random Forest (RF) algorithm is successfully applied for identifying the most decisive variables in the analysis (partitions and façades), and shows signs of being useful for predicting the environmental impact of future constructions and to be applied to the analysis of greater scale urban zones.

1. Introduction

The study of the environmental impact of buildings has been a mainstream research topic in recent years, promoted by new international directives for the reduction of energy consumption, CO_2 emissions, and waste generation of this industrial sector [1]. Frequently, 30–40% of the environmental impact of humans on the Earth is attributed to buildings, which has drawn the attention of architects and engineers to the design of more sustainable buildings, with lower energy and resources consumption [2]. Numerous studies have focused on the development of tools and calculation models to determine this environmental impact, whether using single issue indicators, such as the embodied energy, carbon footprint [3] or emergy [4,5], or more complex ones, such as the ecological footprint [6–8], CML or Eco-indicator, also known as multi-variable indicators.

However, while appropriate calculation models were being developed to estimate the environmental impact of buildings, technology has made significant advances with the introduction of new tools based on the Building Information Modelling (BIM) methodology [9]. The European Union Public Procurement Directive (Directive 2014/25/EU) [10] states that all the 28 European Member States may encourage, specify or mandate the use of BIM for publicly funded construction and building projects in the European Union by 2016. This has already become mandatory in several countries such as UK, Netherlands, Denmark, Finland and Norway [11]. This fact, along with the trend of the architecture, engineering and construction (AEC) sector toward sustainability make it necessary to provide designers with reliable tools that combine BIM with life-cycle assessment (LCA), which would allow the latter to

Abbreviations: A, Air chamber; AC, Aerated concrete; AEC, Architecture, engineering and construction; AI, Acoustic insulation; AP, Acidification potential; BIM, Building Information Modelling; CB, Cored brick; CEC, Constructive Elements Catalogue; CHB, Concrete hollow-core block; CM, Cement mortar; CS, Concrete slab; CT, Ceramic tile; DBL, Default to building life; DHB, Double-hollow brick; DT, Decision tree; EDA, Exploratory data analysis; EIFS, External insulation finish system; EP, Eutrophication potential; EPD, Environmental product declaration; GHG, Greenhouse gas; GP, Gypsum plaster; GW, Glass wool; GWP, Global warming potential; LCA, Life-cycle assessment; LCB, Light-weight clay block; LCI, Life cycle inventory; MAE, Mean absolute error; NRED, Non-renewable energy demand; ODP, Ozone depletion potential; OOB, Out-of-bag; PB, Gypsum plasterboard; PED, Primary energy demand; PUR, Polyurethane rigid foam; RED, Renewable energy demand; RF, Random forest; RMSE, Root-mean-square error; SFP, Smog formation potential; SHB, Single hollow brick; TI, Thermal insulation; TT, Terracotta tile; VB, Vapor barrier; WL, Waterproof layer; XPS, Extruded polystyrene.

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follow the advance that BIM is imposing.

BIM environments add a main information layer to building projects such that the designer now draws constructive elements and populates them with characteristics or parameters, which are defined with a level of detail according to the current life cycle stage of the project [12]. Therefore, this technology allows introducing information of different natures, including those data necessary for carrying out an early LCA study of projects from the design stage, which can be useful for decision-making before it is actually built [13–16]. Such analysis would allow designing more sustainable buildings by determining with anticipation the environmental impact that these will produce through the consumption of materials and energy, as well as greenhouse gas (GHG) emissions and waste generation [17].

Few developers have worked on this topic, since the implementation of LCA in BIM environments requires programming skills, turning it into a multidisciplinary issue which needs involving environmentalists, architects, engineers, and programmers in order to develop tools that behave properly and be useful for these purposes [18]. One of the main problems detected is the lack of consistency of the results obtained through these tools in comparison with pure LCA tools such as SimaPro, Umberto or GaBi, probably due to the need for simplifying the analysis and make it accessible to professionals in the AEC industry, who are not specialized in environmental impact assessment [19]. Similarly, the inclusion of primary materials as part of a same material or family constitutes a limitation for a detailed LCA [20], unless the life-cycle inventory includes aggregated materials. This problem relates to the difficulties in defining a framework of necessary parameters to carry out a correct LCA in BIM for the various stages of the life cycle of buildings, which has already been approached in some studies [21,22].

Among the scarce tools currently available, a set of external applications are able to import and work with data from BIM files (Elodie, eTool LCA, GBAT, Impact Compliant Suite, and Lesosai), and few examples of tools have been completely integrated in BIM environments through plugins, such as LCA Design, Ecotect, Green Building Studio, One Click LCA, and Tally [19].

BIM-LCA integration tools allow automating the connection between the information contained in the BIM model, concretely materials quantity take-off, and LCA databases, thus considerably accelerating the environmental impact assessment of architectural projects in early stages. However, a state of the art and a reference baseline are required in order to provide practitioners not only with results, but also with benchmarks that allow them to evaluate if their projects are sustainable or not [23]. Moreover, the aforementioned integration makes it possible to automate the generation and evaluation of multiple project's design variations or alternatives by modifying the necessary parameters within the BIM model. The analysis of a significant quantity of variations generated for an architectural project can be useful to provide the required environmental benchmarks for its specific building typology. It is worth noticing that the analysis of results from these variations can become unmanageable and not very intuitive through simple observation given the great amount of data generated. Machine learning algorithms can be of help to carry out this analysis and provide objective answers and explanations for the results obtained. In addition, machine learning models trained with this data can make better predictions of the environmental impact of buildings.

The present study aims at defining a methodology for generating environmental benchmarks for building typologies using a combination of BIM-based LCA tools and machine learning algorithms. The methodology is subsequently tested by means of an actual example of residential building typology as case study for which a set of environmental impact indicators derived from combinatorial variations of its constructive solutions are calculated. These benchmarks will be useful in the short term for promoting a continuous improvement of the sustainability of buildings.

In the next section, a state-of-the-art on BIM-LCA integration and environmental benchmarking for buildings is provided. In Section 3, a case study of an 11-story building is presented as a basis for the subsequent combinatorial analysis, along with the research methodology that will be applied in this study. This methodology consists of working with the case study and data in several environments, concretely comprising Autodesk Revit as BIM software for modelling, Tally as integrated LCA plugin, and finally Microsoft Excel for spreadsheets and Python's Scikit-Learn library for data analysis. In Section 4, the results obtained from applying the described methodology to the case study are analyzed through a combination of exploratory data analysis and machine learning techniques. In Section 5, these results are discussed in comparison to those from similar studies. Finally, in Section 6, the conclusions drawn from this study are presented.

2. State-of-the-art

2.1. BIM-LCA integration

A general overview of BIM-based tools for environmental impact assessment showed that most of them need to combine BIM software with other applications to obtain quantification of environmental indicators. Various approaches have been followed, which were classified by Santos et al. [22]: using external tools [24]; connecting quantity take-off and an external LCA database with integrated tools in proprietary software [25]; and including LCA information in BIM models [22]. The main advantage of this last approach is that it automatically updates results when the project is modified, thus taking advantage of the full potential of BIM tools, while the others require to re-export the information and re-link it to the external databases, besides needing extra licenses for the external software involved.

Regarding the first approach, Jrade and Jalaei [26] developed an integration between Autodesk Revit, Microsoft Excel, and Athena Impact Estimator to analyze the environmental impact and the EE of constructive solutions. Marzouk et al. [27] proposed a combination of several software tools (i.e., Autodesk Revit, Revit DB Link, Microsoft Access, and Athena Impact Estimator) for measuring direct and indirect CE in construction projects. Chen and Pan [28] presented a multi-criteria decision making on low carbon construction measures by combining Revit, eQuest, and Promethee [29]. Ajayi et al. [30] explored a combination of Revit Architecture, Green Building Studio (GBS), and ATHENA complement for global warming potential (GWP) and health impact assessment. Crippa et al. [31] integrated data extracted from Ecoinvent with Excel and ArchiCad for the analysis of the carbon footprint of wall systems in Brazil. Finally, the authors also suggest the development of an automation module (a plugin) within the BIM environment through its application programming interface. However, these integration models frequently require some manual steps to be taken by the user, which is somehow opposite to the pursued automation of the analysis.

As examples of application of the second approach, Najjar et al. [32] analyzed a case study with the Tally plugin to evaluate the entire life cycle of buildings, aiming to provide recommendations such as carefully reviewing the manufacturing process and technological advances of the construction materials selected for an architectural project in order to reduce the environmental impact of both the manufacturing and operation phases. Schultz et al. [33] studied the differences in the LCA results obtained from Tally and Athena Impact Estimator, those of general use in USA, getting similar results, but identifying significant differences in the impact categories they presented. Basbagill et al. [24] developed a BIM model using DProfiler linked to eQuest within a BIM environment. Subsequently, the results were manually loaded into SimaPro and Athena EcoCalculator to obtain the CF. Azhar et al. [34] combined Revit with IES Virtual Environment to calculate CE and incorporated energy to convert them into LEED credits. Also, Ilhan and Yaman [18] developed a green building evaluation tool using Graphisoft ArchiCAD® linked to the BREEAM material database.

Regarding the third approach, some authors reviewed the existing research on BIM-LCA integration and its possibilities for simplification in terms of input-output data and LCA results [14], and pointed out that the best solution would be to remain within the BIM environment to facilitate the interaction between design and environmental performance assessment [2]. Gan et al. [35] developed a holistic approach to evaluate built-in and operational carbon in high-rise buildings using Revit and a parametric complement, Dynamo. These researchers also evaluated the reduction of the CF by replacing steel and cement with recycled materials [36]. Other environmental evaluation tools and models were defined by Inyim et al. [37], who presented a BIM extension named Simulation of Environmental Impact of Construction (SimulEICon), which was designed to assist in decision-making during the design stage of construction projects. Finally, Yang et al. [38] deployed a unidirectional workflow to calculate the operation and energy of materials and CO_2eq.

2.2. Environmental benchmarking of buildings

As mentioned before, some researchers highlight the need for benchmarks that provide designers with references to evaluate the environmental performance of their projects [23]. These benchmarks would also allow the establishment of policies with sustainability requirements for new buildings [39].

Recently, Trigaux et al. [40] analyzed 23 different systems to generate environmental benchmarks based on five categories comprising 16 sub-aspects that can vary between systems, which produced different results depending on the system used. For example, Alghamdi et al. [41] used fuzzy clustering to group educational building typologies by energy and water consumption and CO_2 emissions. This allowed them to identify those needing more urgent refurbishment in order to reduce the environmental impact of the built environment. Ji et al. [42] established baselines for the environmental impact of educational buildings referred to 8 indicators and economic cost. To that end, case studies where classified into two clusters, obtaining carbon footprint reference values of 2530 and 3700 $kgCO_2eq/m^2$ for them. Moschetti et al. [43] analyzed four residential building typologies introducing variations in their constructive solutions based on the results from the European project TABULA, and locating them in three climatic zones in Italy aiming at establishing reference values in terms of economic cost and environmental impact indicators.

As can be seen, although some initial approaches to this topic have been carried out by researchers, environmental benchmarking of buildings remains a scarcely explored research field, and robust methodologies to establish these benchmarks must arise to provide practitioners and policy-makers with reference baselines. The present study defines a method to automate the benchmarking of building typologies through a sequence of generation of combinatorial variations of constructive solutions in BIM, quantity take-off and LCA, followed by a data selection and sorting process based on spreadsheet macros, and finally data analysis with standard machine learning algorithms. This method is not only capable of providing an environmental benchmark for any building typology, but also allows identifying the most influencing variables in order to support efficient decision-making during the design process.

3. Materials and methods

3.1. Description of the case study

The selected case study, located in the north sector of Seville (Spain, 37° 22′ 58" N 5° 58′ 23" W, 16 m.a.s.l.), is an 11-story residential building with 92 dwellings, commercial premises in the ground floor, and two underground floors containing the parking lot and storage rooms. It is a detached building with 13,367.93 m^2 of built-up surface, which was built in 2002 and, for the purposes of this study, a service life of 100 years is assumed (according to Spanish Regulations [44]). It has an almost rectangular shape with two small wings, and a front yard where pedestrian and vehicular accesses are located (see Fig. 1). The building's typology is a representative case of social dwellings built in Spain in the latest decades [45–47], which allows results to be extrapolated to a significant amount of existing buildings in that region.

The building's structure consists of a 70 cm-thick reinforced concrete slab foundation, retaining walls in the underground levels, and columns and waffle slabs in the rest of floors. There are three staircases and four elevators distributed in three main structurally independent blocks. Each block contains four dwellings per floor, except for the last two floors, where four dwellings in total share the space with an accessible rooftop.

The original envelope is built with 9 cm-thick masonry walls. This brick façade system offers mostly a facing brick finish and cement mortar lining in some areas, with polyurethane foam insulation plus an air chamber and self-supporting plasterboard partitions in the inner side. The floorings are generally covered with terrazzo, and ceilings with gypsum plasterboard. In the kitchens and bathrooms, ceramic tiles fully cover walls and floors. The underground floors use cement mortar-based covering in floors. Given that technical services will not suffer variations in this study, in addition to not being included in Tally, these are not taken into consideration in the system boundaries, and therefore do not need to be described.

3.2. Research methodology

In order to ease understanding of the following sections, an overview of the research methodology applied in the present study is provided in Fig. 2, where the various steps to be taken and the environments or tools with which these are carried out are specified. As a first step, it is necessary to make a selection of the constructive solutions to be included in the study as variations for the building elements. Then, types of BIM elements are generated for each constructive solution, and entries from the LCA database are assigned to the materials involved in these solutions, thus defining what is called a template file. Once the template file is ready, the building typology is modeled, and BIM types can be assigned to the elements in the model in order to generate all the different combinations that will become case studies. Subsequently, the various combinations are analyzed with the LCA plugin, generating a report file for each case. The information in these reports is then automatically structured as desired through macros that read the source files and organize the data in a new spreadsheet. In the next step, exploratory data analysis (EDA) is applied to these data through Excel and Python's Scikit-Learn library in order to identify outliers, correlations, and the impact of each variable in the results obtained. Finally, some of the findings from EDA are double-checked by using a Random Forest (RF) regression algorithm, which aims to predict results for future combinations or case studies that match this building typology.

3.2.1. LCA software, database, and assessment methodology

For the purposes of this study, the Tally plugin for Autodesk Revit (ver. 2019.06.27.01) [48] has been selected as the tool for the environmental impact assessment of the building. This plugin uses the GaBi database as LCA data source, which was identified as one of the most complete and comprehensive databases for LCA of construction materials [49]. First, it scans the BIM model and identifies all the elements and materials in the project. Subsequently, entries from the LCA database must be assigned to each material. Parameters such as density, service life or transportation means and distances must be specified to better describe them.

After the analysis is performed, several indicators are reported, including materials mass, potentials of acidification, eutrophication, global warming, ozone depletion and smog formation, and primary, non-renewable and renewable energy demands. The presentation and analysis of results in this study considers all these indicators. However, for a richer comparison to other studies, the discussion section is focused

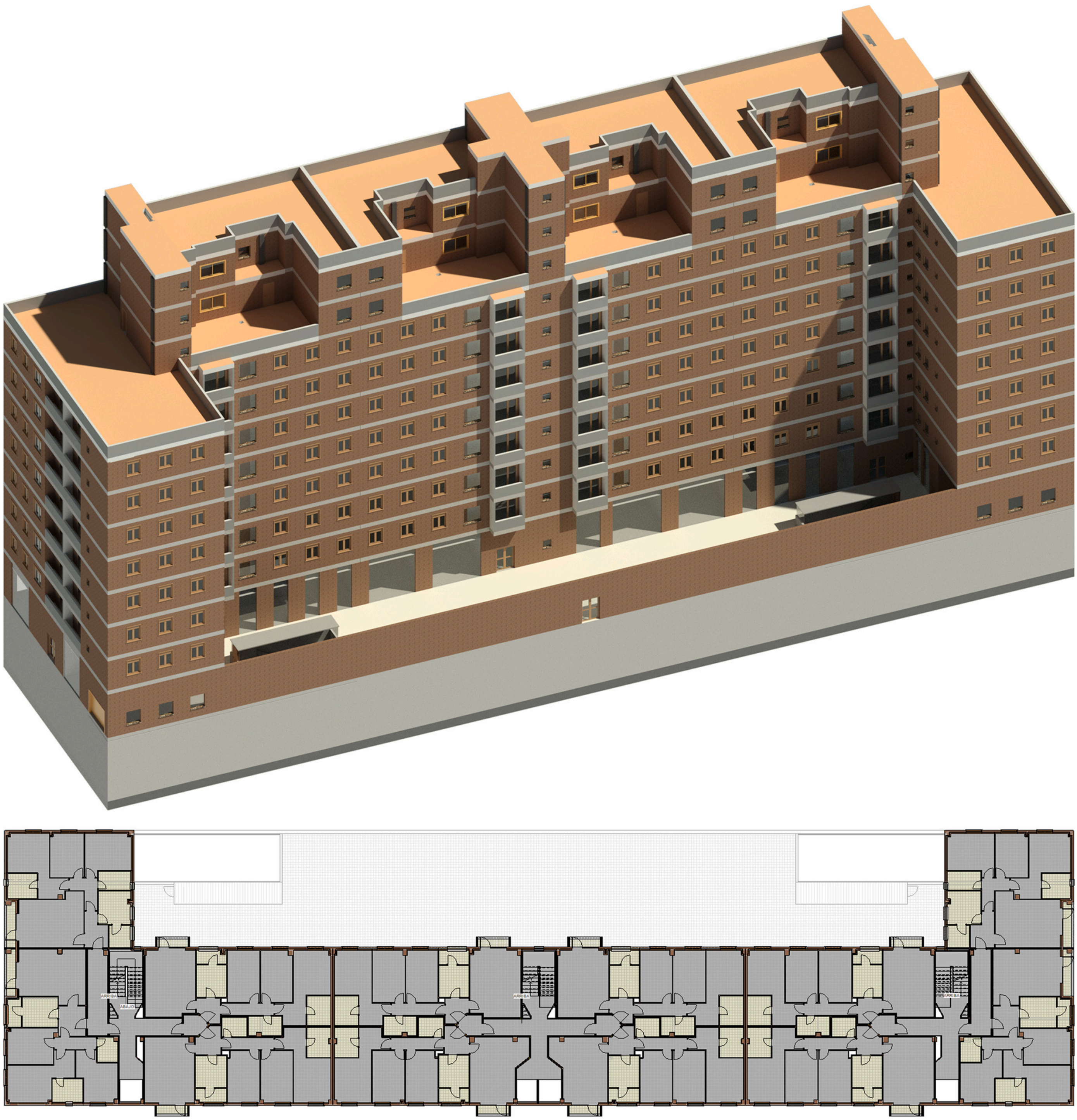

Fig. 1. Case study of a 10-story residential building in Seville.

on the carbon footprint indicator, that is, global warming potential, which consists of determining the emissions of GHG produced by a specific process [50]. While other indicators are of great importance, carbon footprint stands out for its strong relation to the main aims of the Kyoto Protocol, and the ease to communicate results to non-specialized audiences [51].

Regarding the system boundaries, all the life-cycle stages of construction materials, A1 to C4 and D according to UNE-EN 15978:2012 [52] will be considered in this analysis, with the use stage being blocked for all the cases product of the combinatorial assessment by adjusting the thermal insulation thickness in order to produce equal thermal transmittances for each one of the selected envelope solutions. Therefore, only maintenance (B2) and replacement (B4) of materials are included regarding stage B of the life cycle. While the building's structure is not affected by these variations of constructive solutions, it has been included in the analysis since it usually produces a significant share of the total environmental impact of building materials, and the influence of the variations here proposed in the overall result of the building is worth being studied. As mentioned before, Tally still does not consider technical services in its analysis, and therefore these cannot be included in the assessment.

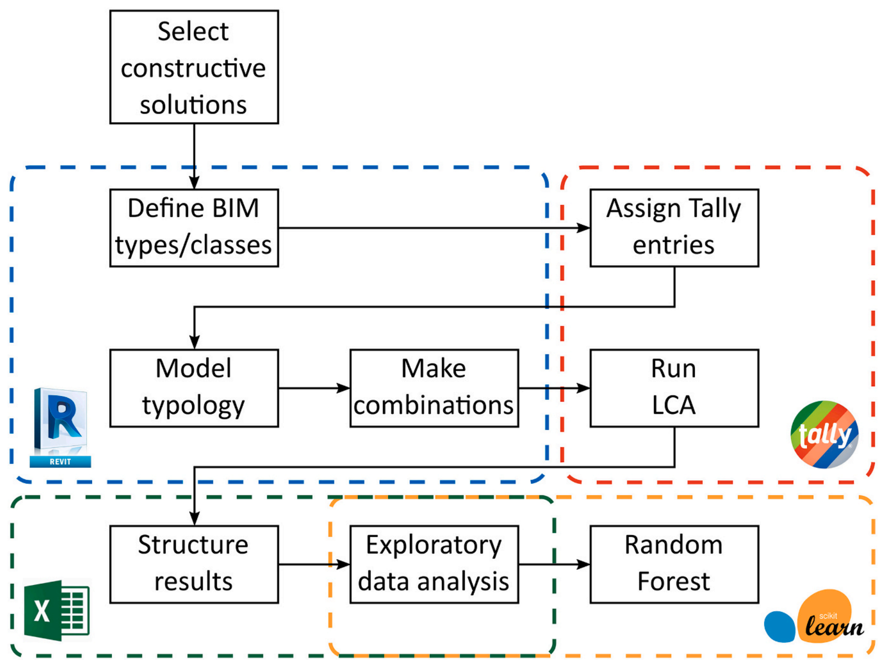

Fig. 2. Methodology flowchart.

3.2.2. Selection of constructive solutions and assignment of LCA data entries

In order to generate populated distributions with the results obtained, a selection of constructive solutions was made that will be considered for the multiple variations of the case study. These solutions were obtained from the Constructive Elements Catalogue (CEC) of the Technical Code of Buildings Construction in Spain [53], which contains a comprehensive list of solutions for façades, partitions and rooftops. As shown in Table 1, this selection considers 13 different façade solutions, including options with external insulation finish systems (EIFS), 4 types of internal partitions, and 3 rooftop solutions which are the most widespread constructive solutions in Spain [45–47,54]. Façades, partitions and rooftop and their finishes have been identified as decisive constructive elements for the environmental impact of buildings [55]. Additionally, variations of these are considered regarding the type of thermal insulation material used and the need for ceramic tile coverings for wet rooms in one or both sides, according to their location in the building.

Thus, according to the solutions presented in this table, it will be possible to generate 240 ($39 \times 4 \times 5$) different versions of the case study by modifying the family types assigned to the façades, partitions and rooftops in the model, with side walls being modified according to the solution applied to partitions. To that end, it is necessary to first generate a template file containing the family types and the assignment of their materials to specific entries of the LCA database. Given that this study aims to provide a methodology for generating environmental benchmarks for building typologies, this pairing between BIM materials and LCA database entries becomes crucial for the traceability and reproducibility of results by future researchers, since different methodologies and pairings could produce significantly different results [56]. Therefore, in Appendix 1, Table A.1 shows the assignment of LCA database entries to the materials of the various constructive solutions considered in the combinatorial case study, as well as extra parameters specified for each assignment, and Table A.2 presents the transportation distances by truck applied to each material considering the case study's location.

3.2.3. Data processing and analysis

The results from each generated design option will be obtained in individual spreadsheets where the contribution of each item to the total environmental impact is specified by life cycle stage, division (e.g. concrete, masonry, openings and glazing, finishes, etc.), and category (e.g. doors, floors, roofs, walls, structure, etc.), thus allowing a detailed analysis of the source for each impact. Given the great amount of combinations (240), and therefore result files, along with the fact that the corresponding BIM models will have to be manually generated, the processing of results will be automated through a macro which will read every file in the folder and will combine the data in a single spreadsheet in order to allow a comparative analysis.

Finally, an exploratory data analysis (EDA) methodology will be applied for analyzing the distributions of overall results for the 240 cases regarding each environmental impact indicator, to subsequently search for the specific causes for the identified differences. Additionally, a massive analysis of combinations will allow determining reference ranges of results for this building typology as a baseline for the evaluation of the sustainability of design options for new buildings. The analysis will be supported by the design of a RF regression model which, among other functionalities, allows identifying the most important features that determine the results.

3.2.4. Random forest algorithm

As mentioned before, while the application of EDA to the results obtained can be descriptive for the 240 variations generated in this study, this could be less intuitive for a greater set of combinations that involved variations in windows, doors, floor slabs, floorings, paints, and technical services elements, among others. Machine learning algorithms can provide a consistent analysis for a massive amount of data and help in obtaining objective findings based on statistics.

Decision trees (DT) are tree-based machine learning algorithms that allow executing both classification and regression tasks. In decision trees, every node is a condition on how to split values in a single feature so that similar values of the dependent variable end up in the same set after the split [57]. The features for internal nodes are selected with some criterion, which for classification tasks can be Gini impurity or information gain, and for regression tasks is variance reduction [58].

DTs allow computing how much each feature contributes to decreasing the weighted impurity or, in the case of regression tasks, to reducing variance. In other terms, this reduction of variance indicates which features are more decisive for obtaining the final result in the

Table 1
Selection of constructive solutions for a combinatorial case study.

Code	Base layers, outer to inner (thickness (cm))	Thermal insulation	
Façades		Material	Thickness (cm)
F1.1	CB (11.5) + CM (1.5) + TI + DHB (7.0) + GP (1.5)	Glass fiber PUR foam EPS	2.0 1.8 2.1
F1.3	CB (11.5) + CM (1.5) + TI + PB (1.1)	Glass fiber PUR foam EPS	2.4 2.2 2.6
F1.9	CHB (14.0) + CM (1.5) + TI + DHB (7.0) + GP (1.5)	Glass fiber PUR foam EPS	2.1 1.9 2.3
F1.12	CHB (14.0) + CM (1.5) + TI + PB (1.1)	Glass fiber PUR foam EPS	2.5 2.3 2.8
F3.1	CM (1.5) + CB (11.5) + TI + DHB (7.0) + GP (1.5)	Glass fiber PUR foam EPS	2.0 1.8 2.1
F3.3	CM (1.5) + CB (11.5) + TI + PB (1.1)	Glass fiber PUR foam EPS	2.4 2.2 2.6
F3.9	CM (1.5) + CHB (14.0) + TI + DHB (7.0) + GP (1.5)	Glass fiber PUR foam EPS	2.1 1.9 2.3
F3.13	CM (1.5) + CHB (14.0) + TI + PB (1.1)	Glass fiber PUR foam EPS	2.5 2.3 2.8
F3.21	CM (1.5) + LCB (14.0) + TI + DHB (7.0) + GP (1.5)	Glass fiber PUR foam EPS	1.7 1.5 1.8
F3.23	CM (1.5) + LCB (14.0) + TI + PB (1.1)	Glass fiber PUR foam EPS	2.1 1.9 2.3
F4.1	CM (1.5) + TI + CB (11.5) + GP (1.5)	Glass fiber PUR foam XPS	2.5 2.3 2.8
F4.3	CM (1.5) + TI + CHB (14.0) + GP (1.5)	Glass fiber PUR foam XPS	2.5 2.3 2.8
F4.5	CM (1.5) + TI + LCB (14.0) + GP (1.5)	Glass fiber PUR foam XPS	2.1 1.9 2.3
Partitions			
P1.1	GP (1.5) + SHB (4.0) + GP (1.5)	–	–
P2.1	GP (1.5) + SHB (4.0) + AI + SHB (4.0) + GP (1.5)	Mineral wool	3.0
P4.1	PB (1.1) + A + PB (1.1)	–	–
P4.2	PB (1.1) + PB (1.1) + AI + PB (1.1) + PB (1.1)	Mineral wool	3.0
Rooftops			
C1.6	TT (1.2) + CM (1.5) + WL + TI + VB + AC + CS (30.0)	PUR foam XPS Glass wool	5.7 6.9 6.3
C1.6i	TT (1.2) + CM (1.5) + TI + WL + AC + CS (30.0)	XPS	6.9
C4.6	CT (1.2) + A + CM (1.5) + TI + WL + AC + CS (30.0)	XPS	6.9
Side walls			
P2.3	GP (1.5) + CB (11.5) + TI + CB (11.5) + GP (1.5)	EPS	3.0
P2.5	GP (1.5) + CHB (14.0) + TI + CHB (14.0) + GP (1.5)	EPS	3.0
P2.4	GP (1.5) + LCB (14.0) + TI + LCB (14.0) + GP (1.5)	EPS	3.0

CB: Cored brick; DHB: Double hollow brick; SHB: Single hollow brick; CHB: Concrete hollow-core block; LCB: Light-weight clay block; CM: Cement mortar; GP: Gypsum plaster; PB: Gypsum plasterboard; TI: Thermal insulation; AI: Acoustic insulation; A: Air chamber; WL: Waterproof layer; VB: Vapor barrier; TT: Terracotta tile; CT: Ceramic tile; AC: Aerated concrete; CS: Concrete slab.

regression task and thus, in our case, which features can produce greater reductions in the building's environmental impact. In the case of RFs, the importance of features is measured by averaging the reduction in variance over trees [57]. The relative importance of features can also be obtained for other machine learning algorithms such as neural networks by calculating permutation importance, although this requires further manipulation of the dataset [59]. RF automatically provides an easily accessible 'feature importance' variable that is calculated after training, which makes this machine learning algorithm especially useful for the present study's purposes.

RF is one of the most frequently used machine learning algorithms nowadays, and it has been successfully applied before in classification and regression tasks related to the construction sector [60–62]. It consists of an ensemble of DTs, each one generated with a random subset of the same training set. These subsets can be obtained whether applying bootstrap sampling, i.e. sampled with replacement, or not. As an ensemble method, its results are subsequently determined by aggregating the results obtained in the various DTs as a mean value. If bootstrap sampling is applied, the RF behaves as a bagging (bootstrap aggregating) algorithm. Otherwise it is called a pasting algorithm [63].

Bagging implies that, probabilistically speaking, around one third of the samples in the training set will not be sampled in each decision tree, being these known as 'out-of-bag' (OOB) samples. In an ideal case, about 36.8% of the total training data forms the OOB sample in each tree [64], but it is worth noting that this subset of samples will not be identical for all the decision trees in the RF. OOB samples allow determining the so-called OOB score, which is the mean coefficient of determination (R^2) for all the OOB samples, which are evaluated in the DTs that did not sample them for training. This means only a subset of DTs can be used for determining the coefficient of determination for each OOB sample. In general, validation on a full ensemble of DTs is better than a subset of DTs for estimating the score. However, occasionally the dataset is not big enough, and hence setting aside a part of it for validation is unaffordable. Consequently, in cases where a large dataset is not available and it must be all consumed as the training dataset, the OOB score provides a good trade-off [64] and insights on how the model could behave with a larger dataset that allowed splitting into training and validation sets.

4. Results

4.1. Overall environmental impact of combinatorial case studies

As a first approach to analyze the results of the environmental impact assessment performed with Tally, the scatter plots of the total results obtained for the various ecological indicators are presented with the case number, i.e. combination of constructive solutions, in the horizontal axis (Fig. 3). These results show an apparent similarity among them, which can indicate a strong correlation, except for those regarding Ozone Depletion Potential (ODP). This is double-checked through a correlation matrix generated with Python's numpy, seaborn and matplotlib libraries (Fig. 4), where all indicators except ODP show values close to 1, thus confirming that strong correlation between them.

As can be observed, combinations in the first half (1−120) produce higher environmental impacts than those of the second half (121–240). By analyzing the variations introduced as input variables between these two subsets of combinations, the cause of this difference in results seems to be the constructive solution assigned to partitions. Cases 1 to 120 use P1.1 and P2.1 from the solutions described in Table 1 (represented as blue points in Fig. 3), that is, single hollow bricks covered with gypsum plaster and paint, while cases 121 to 240 use P4.1 and P4.2 from Table 1, i.e. plasterboard-based solutions (represented as orange points in Fig. 3).

Another observable difference in results is detected between each set of 15 combinations or cases, which are highlighted with different gradients of colors in Fig. 3. The variation introduced in these subsets corresponds to the façade solution, with higher environmental impacts

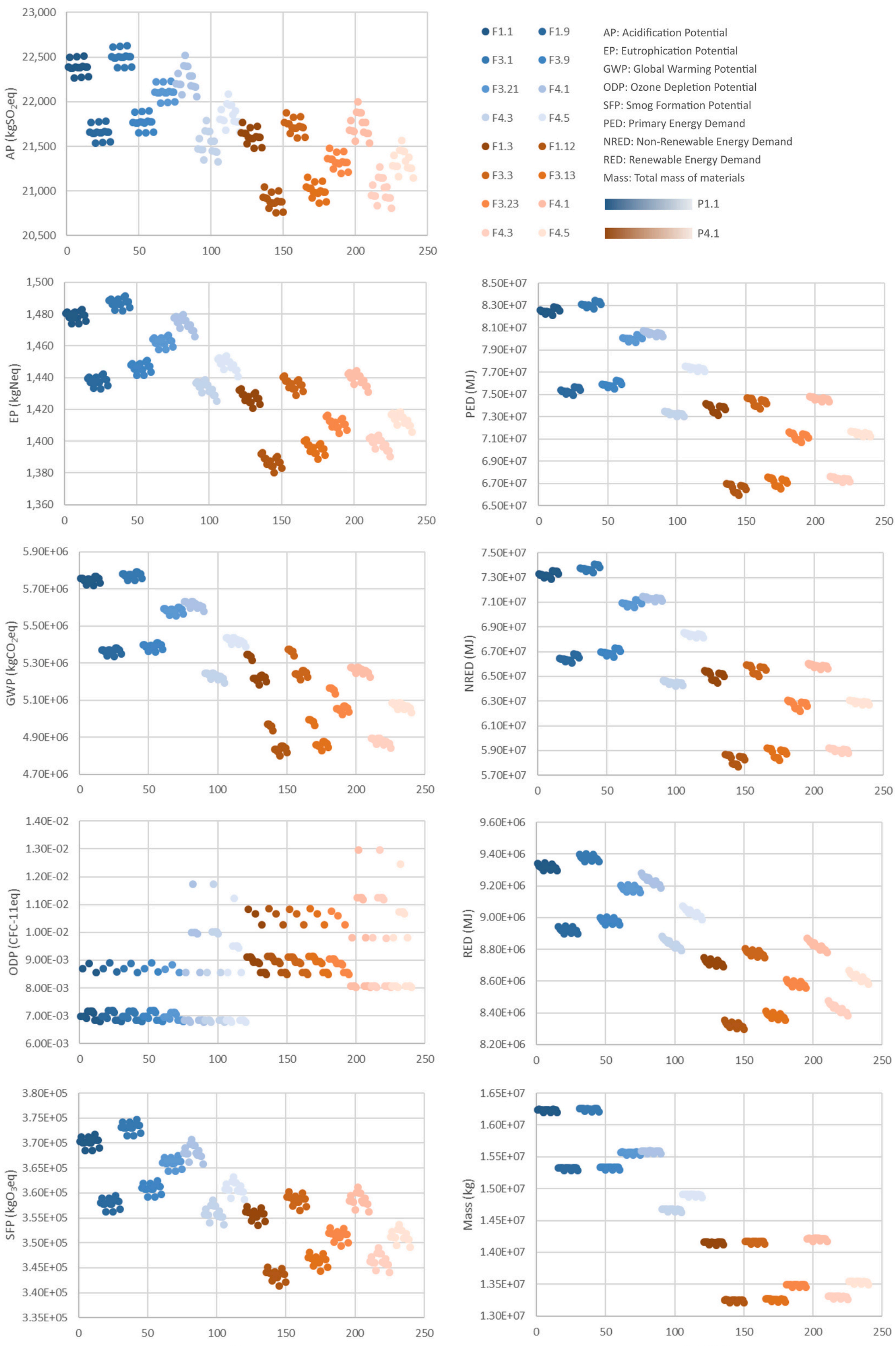

Fig. 3. Environmental impact of the 240 combinations for the case study expressed in terms of the ecological indicators included in Tally.

in cases 1–15, 31–45 and 61–75, while cases 16–30, 46–60 and 91–105 show lower results in the first half. Those with a higher impact have in common the use of ceramic bricks in both the outer and inner layers, while the latter use concrete hollow-core blocks (CHB) in one of their layers. Concretely, cases 31–45, which have cored bricks in the outer layer and double hollow bricks in the inner layer, the most common configuration in the project location, produce the highest environmental impact of all the analyzed combinations and of those in each half, and cases 91–105, with an EIFS solution as outer layer and CHB as inner layer, show the lowest impact in this first half of combinations.

Regarding the second half, that is, those using P4.1 and P4.2 as partitions, those variations of the façade solution with higher

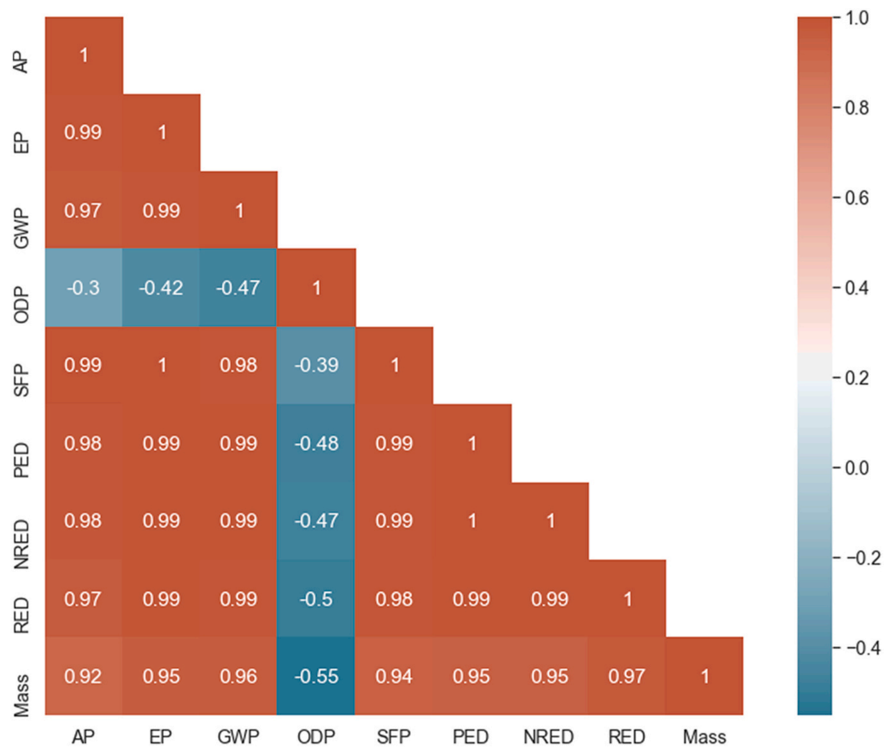

Fig. 4. Correlation matrix of output variables in the study.

environmental impact coincide with those in the first half. However, the combinations causing the lowest impacts differ. Specifically, cases 136–150, 166–180 and 211–225 again share the use of CHB as support layer instead of ceramic bricks. This difference in the lowest impacting solutions between the first and the second half of combinations is due to the fact that, in the configuration of cases, when plasterboard partitions are assigned, plasterboard inner layers are also assigned to façades as in fact occurs in construction, thus generating a lower environmental impact than brick-based inner layers. Consequently, cases 136–150, i.e. those using P4.1 and P4.2 for partitions and F1.12 for façades, cause the lowest environmental impact of all the analyzed combinations.

As mentioned before, variations in ODP results follow a different pattern, with those cases using glass wool (GW) as thermal insulation material in roofs showing the highest impact in this category. According to consulted Environmental Product Declarations (EPDs) of GW [65], expanded polystyrene (XPS) [66] and polyurethane rigid foam (PUR) [67], PUR should produce a higher ODP than XPS and GW due to the use of CFC-11 gas as inflating agent, which points out the possibility of a mistake in the calculations of this version of Tally for that indicator. For that reason, it is decided to neglect the ODP impact category in this study.

Apparently, the partitions and façade solutions are the most decisive variables in defining the building's environmental impact since they cause the greatest differences. This might be somehow easy to perceive from the scatter plots in Fig. 3. However, if there were a greater quantity of variables involved in the design process decision-making, as there should be in order to determine environmental benchmarks for building typologies, this analysis would become less viable. To that end, in the next subsection a regression model based on the RF algorithm is applied with two main aims: first, to corroborate the aforementioned findings about the importance of each variable in determining the final results; and second, to prove the usefulness and feasibility of the methodology here described to analyze and predict the environmental impact of a larger set of building typologies by using artificial intelligence techniques such as RF.

4.2. Random forest regression

As mentioned in subsection 3.2.4, when applying RF to design a prediction model with a reduced dataset, setting aside a part of it for validation becomes unaffordable. In these cases, it is usually preferred to use the entire dataset as training set and use OOB evaluation to validate the model, bearing in mind that OOB evaluation is much less reliable than using a validation set [64].

The RF model was trained using five features as input variables, corresponding to the constructive solutions specified in Table 1 for: façade, façade's thermal insulation material, partitions, roof, and roof's thermal insulation material. The output variables were the 8 indicators, once ODP was discarded. The number of estimators, i.e. DTs, generated during the training process was determined by studying configurations from 1 to 50 trees for each environmental impact indicator. Bootstrap and oob_score parameters were set to true. These configurations were evaluated using three of the most usual statistical parameters, the coefficient of determination (R^2), the mean absolute error (MAE), and the root mean squared error (RMSE) [63]. Additionally, the potential of the model to make accurate estimations with new data was taken into account based on the OOB score. Despite Fig. 5 only shows this evaluation for the GWP indicator, given the strong correlation between them (see Fig. 4), the result obtained was the same for all the output variables.

As can be seen, R^2 soon reaches values close to 1, and the OOB score starts from 0.998 with 10 trees and then slightly increases. MAE and RMSE are soon reduced to less than 2000 and 3500, respectively, reaching a minimum with 43 trees. At this point, also a maximum is reached by the OOB score, thus making it the best option among the evaluated variations. Considering that results for GWP in the dataset vary from $4.8 \cdot 10^6$ to $5.8 \cdot 10^6$ $kgCO_2eq$, 2000 $kgCO_2eq$ represent an error of 0.00038% in the estimations. It is worth bearing in mind that this error rate corresponds to a validation based on the OOB-score and not a separate validation set evaluated on all the DTs in the RF, which could be higher. In future developments of this research, including a wider set of variations, the number of observations would allow splitting the dataset into training and validation sets, thereby obtaining more

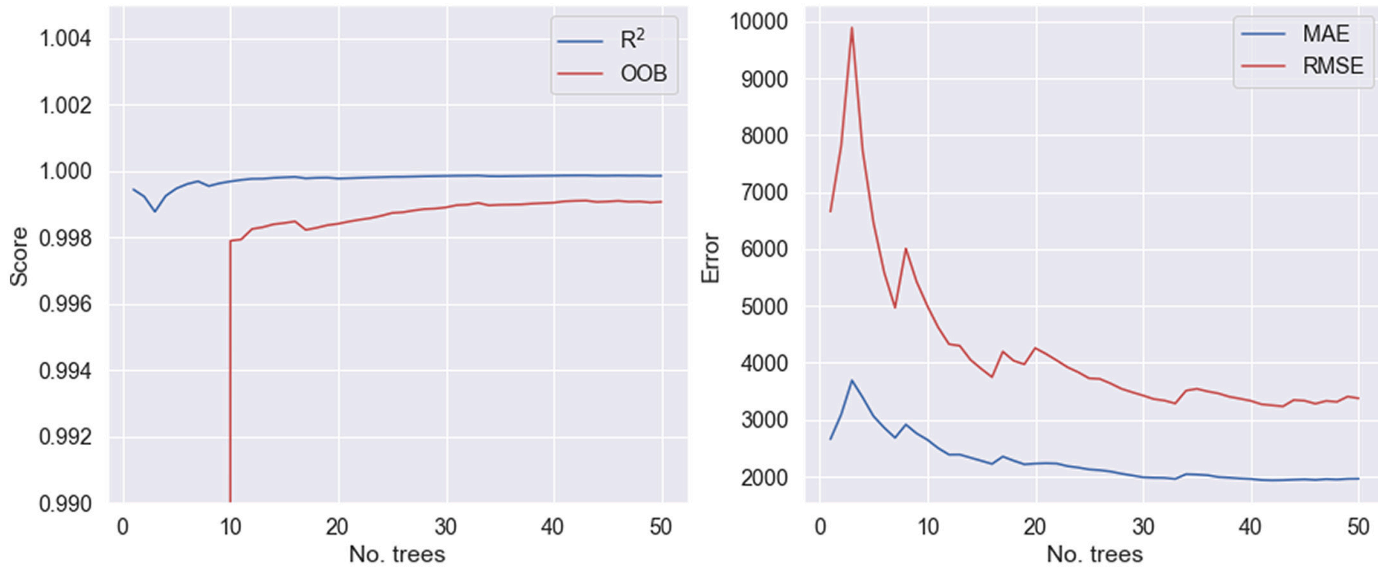

Fig. 5. Statistical parameters in the RF regression model training to estimate GWP with variations in the number of trees.

accurate evaluation results.

Once the number of trees was decided, the RF algorithm was applied to each output variable to analyze the importance of each feature or input variable for determining the estimations. As shown in Table 2, the constructive solutions for partitions and façades are the two most important variables for all the environmental impact indicators, thus confirming the findings from the previous subsection. Also the OOB score obtained for each output variable provides insights on the performance that the RF models could have on new data, thereby proving the feasibility of defining environmental impact prediction models using a set of input variables that can be controlled within the BIM environment.

4.3. Detailed environmental impact

When studying the environmental impact according to the three classification modalities Tally has to offer, now focusing on GWP (see Fig. 6), it can be seen that the product and maintenance stages account for a high portion of the emissions, with ~3000–4000 and ~ 1750 tCO_2eq, respectively. In combinations using brick walls as partitions and inner layers of façades, concrete (~1800 tCO_2eq), masonry (~1000 tCO_2eq) and finishes (~860 tCO_2eq) account for 96% of the GWP during the product stage, which is logical as these products represent most of the mass of construction materials in the building and, as stated before, GWP (and the rest of indicators) has a strong correlation with mass. In cases where the partitions and the façade's inner layer is solved with plasterboard, masonry is relegated to third place with ~430 tCO_2eq, but still the sum of concrete, masonry and finishes account for 93% of the product stage GWP. Regarding the maintenance and replacement stage, finishes of floors, walls and ceilings, along with doors and windows, produce 94.5% of this stage's GWP, which is logical given that these elements have shorter service lives (see Table A.1) and therefore must be replaced at least once during the building's service life. In contrast, the difference between the GWP of brick walls and plasterboard during this stage is not significant.

When observing the results by division, it is observed that the building's overall GWP is mainly caused by finishes (~2400 tCO_2eq), concrete (~1800 tCO_2eq) and masonry (~150–1250 tCO_2eq), with 97% of the former being explained by the use of terrazzo and ceramic tiles for flooring, plasterboard for ceilings, and cement stucco for exterior finishes, while the importance of concrete and masonry was expected given their high presence in the building's structure and walls. Again, the high variability of the masonry's GWP is due to changes in the materials used for partitions and the inner layer of façades, obtaining lower environmental impacts when using plasterboard instead of bricks.

Regarding GWP by Revit category, Tally provides slightly misleading results, since by default it includes the structural layer of floors, roofs and walls within these categories instead of separating and including them in the structure category, where only columns are originally considered. Therefore, a corrected version of this last graph was

Table 2
Feature importance and statistical parameters of each input variable for the prediction of the environmental impact indicators using RF regression with 43 trees.

	Environmental impact indicator							
	AP	EP	GWP	SFP	PED	NRED	RED	Mass
Feature	Importance (%)							
Partitions	49.76	59.50	60.69	55.44	58.27	57.54	68.20	78.84
Façade	46.41	39.32	37.99	43.06	41.50	42.23	31.44	21.13
TI Façade	1.40	0.40	1.09	0.41	0.17	0.18	0.15	0.00
Roof	1.31	0.45	0.19	0.79	0.05	0.05	0.09	0.03
TI Roof	1.12	0.33	0.04	0.30	0.01	0.00	0.12	0.00
Statistical parameters								
Mean	21,667.78	1435.98	$5.29 \cdot 10^6$	$3.58 \cdot 10^5$	$7.47 \cdot 10^7$	$6.58 \cdot 10^7$	$8.85 \cdot 10^6$	$1.46 \cdot 10^7$
SD	480.50	29.31	$2.83 \cdot 10^5$	8508.10	$5.04 \cdot 10^6$	$4.72 \cdot 10^6$	$3.20 \cdot 10^5$	$1.02 \cdot 10^6$
R^2	0.9990	0.9997	0.9999	0.9995	0.9999	0.9999	0.9999	1.0000
OOB	0.9928	0.9975	0.9991	0.9966	0.9995	0.9995	0.9992	1.0000
MAE	9.83	0.41	1937.96	135.53	30,772.45	26,910.65	2525.31	898.52
RMSE	14.78	0.54	3235.19	184.78	41,966.87	38,443.10	3441.80	1452.25

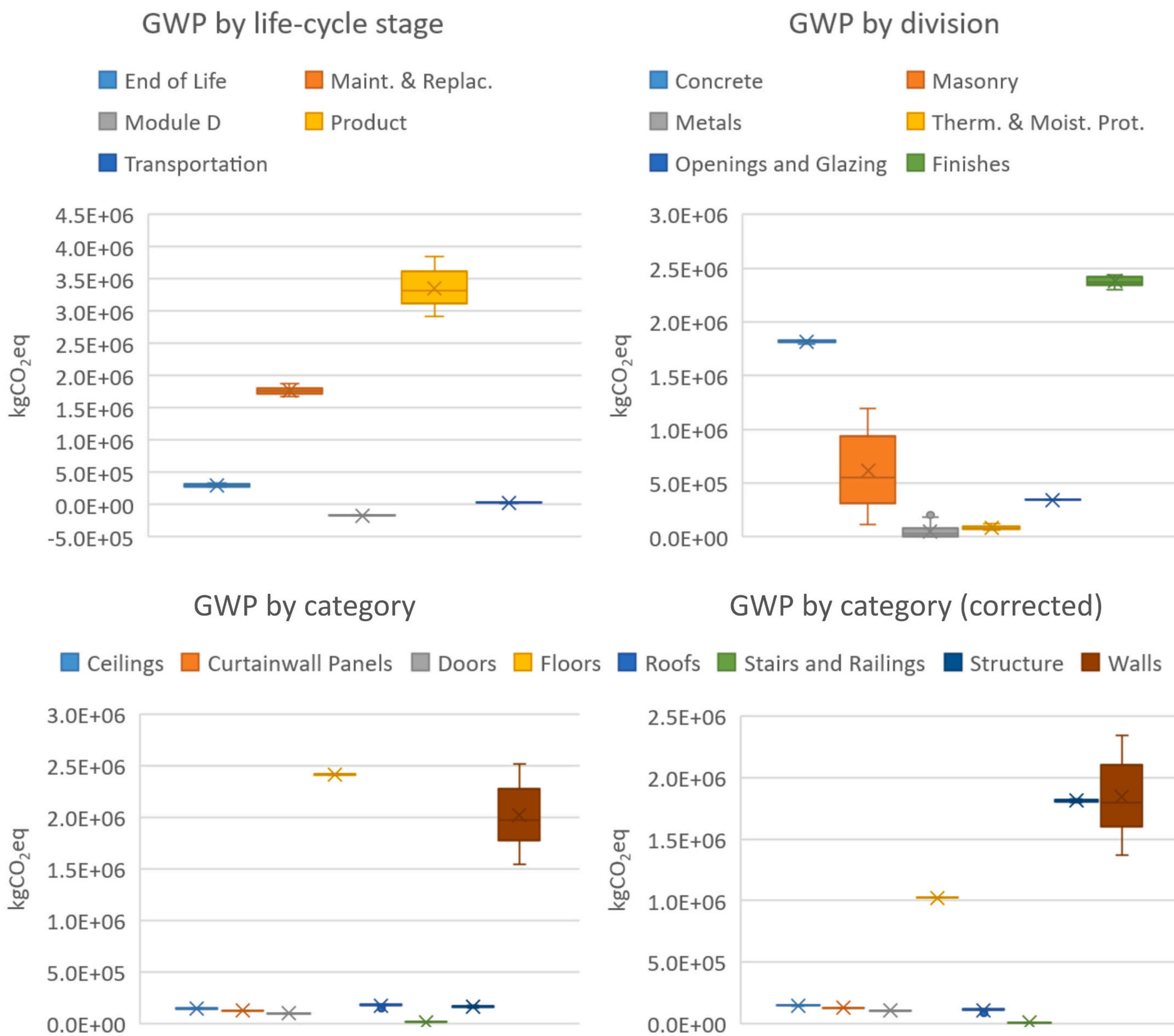

Fig. 6. Ranges of GWP by life-cycle stage, division and category.

calculated in order to gain better understanding on the distribution of the environmental impact among the various categories. As can be observed, walls, structure and floors are responsible for most of the building's GWP, thus confirming the priorities of elements in these categories for possible modifications aimed at reducing the building's CF. The high variability of the walls category is explained by the nature of the variations introduced among the 240 cases, which mostly affect the material layers of walls, being partitions also included in this category.

As stated in Section 3.2, being partitions and façades identified as the most decisive variables and in view of the findings from this analysis, it can be inferred that using plasterboard in partitions and the inner layer of façades would be a good strategy to reduce the environmental impact of this building typology. Let aside the reinforced concrete structure, which is the most common solution in this typology, two more recommendations for reducing the building's CF stem from the detailed analysis: first, it would be advisable to use a more sustainable material for flooring, perhaps wooden materials that do not require cement mortar underlayment [55]; and second, selecting constructive solutions for façades that do not require to be covered with cement stucco, such as exposed bricks.

Given the aforementioned limitations of this classification system, it becomes necessary to restructure them into equivalent categories to those from other studies not using Tally in order to make them comparable. In the next section, two different redistributions of the environmental impacts are carried out to be able to establish a discussion with reference to similar studies.

5. Discussion

By analyzing how overall results compare to those from similar studies (see Fig. 7), it can be observed that, while all these studies keep results within the same magnitude order, differences stem from the high quantity of factors involved in the analysis. For instance, the difference between the results from this study (~360–430 $kgCO_2eq/m^2$) and those from Solís-Guzmán et al. [68] (~570–880 $kgCO_2eq/m^2$) is mainly due to the inclusion of technical services, manpower and machinery within the system boundaries of their study. In contrast, De Wolf [69] reports lower impacts (~180–320 $kgCO_2eq/m^2$) than those here obtained –with some

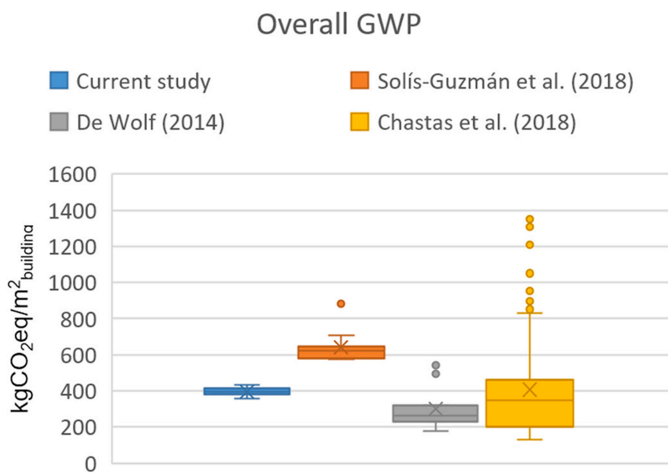

Fig. 7. Comparison of overall results (GWP per m^2 of building) between similar studies.

outliers- as a consequence of the building typologies considered in her analysis which, in the case of residential buildings, include dwellings with timber structure. Finally, the results from the current study fall within the upper half of the range defined by Chastas et al. [70] (~130–1350 kgCO_2eq/m^2), which is logical given the great variety of building typologies included in their review and the environmental load that tall buildings tend to generate.

Differences in methodologies among studies make their results difficult to compare to each other, thereby making it necessary to establish a common method for the environmental impact assessment. This would also promote the development of environmental benchmarks and, as a consequence, a continuous improvement of the sustainability of buildings.

After redistributing the environmental impacts of the various elements from the BIM model according to the categories studied by Hollberg et al. [23] and expressing them by m^2 of the corresponding element (see Fig. 8), it is observed that the results obtained fall within the ranges determined in their study for most categories. Exceptions are identified regarding foundation (base slab in both cases) and external wall below the ground level, both of which, given the selected reference unit (m^2 of the element), must be influenced by differences in the third dimension (thickness) to produce such variations.

A similar comparison is presented in Fig. 9 using the study by González-Vallejo et al. [71] as reference. In this case, the categories for building elements are organized according to the budget sections defined in the Andalusian Construction Cost Database (ACCD) [72], and their GWP is calculated per m^2 of building. As can be seen, most of the categories present small variability because only one building typology is considered in the present study, while González-Vallejo et al. include 24 buildings of different typologies, which present more diversity in their constructive solutions and bills of quantities. Significant differences between these two studies are detected in the masonry and finishes categories. The former is due to the total mass of materials for masonry. While façades in the typologies studied in González-Vallejo et al. are built with one-foot CB in the outer layer and DHB for the inner layer and partitions, façades in the building typology presented in this study use a half-foot outer layer and, in some cases, CHB which, as mentioned before, produces lower environmental impacts. Also the partitions in their study always consist of brick walls, thereby increasing the mass of masonry materials. Regarding the finishes category, the breach is produced due to substantial differences in the emission factors considered for certain materials, such as cement mortar, to which Tally assigns 0.564 kgCO_2eq/kg versus 0.191 kgCO_2eq/kg applied by González-Vallejo et al., or 0.781 kgCO_2eq/kg corresponding to stone tile (in absence of terrazzo in Tally's database), versus 0.002 kgCO_2eq/kg in the reference study.

The uncertainty of LCA results is a usual concern in this type of analysis since it can stem from numerous sources, such as the quantity take-off method, assumptions regarding the energy mix applied in materials manufacturing, their transportation, service life, the assessment method to translate the LCI into environmental impact indicators, or the system boundaries defined by LCA practitioners, among others [73]. As mentioned in Section 2, Tally uses the GaBi database, which has been employed in LCA models worldwide in both industrial and scientific applications and has undergone internal and critical reviews in published studies that allow reducing uncertainty stemming from its data [48]. This issue has been approached in recent studies through probabilistic and stochastic methods [74–77], and service life and replacement assumptions have been identified as important sources of uncertainty [74,78]. Additional methods to evaluate the reliability of

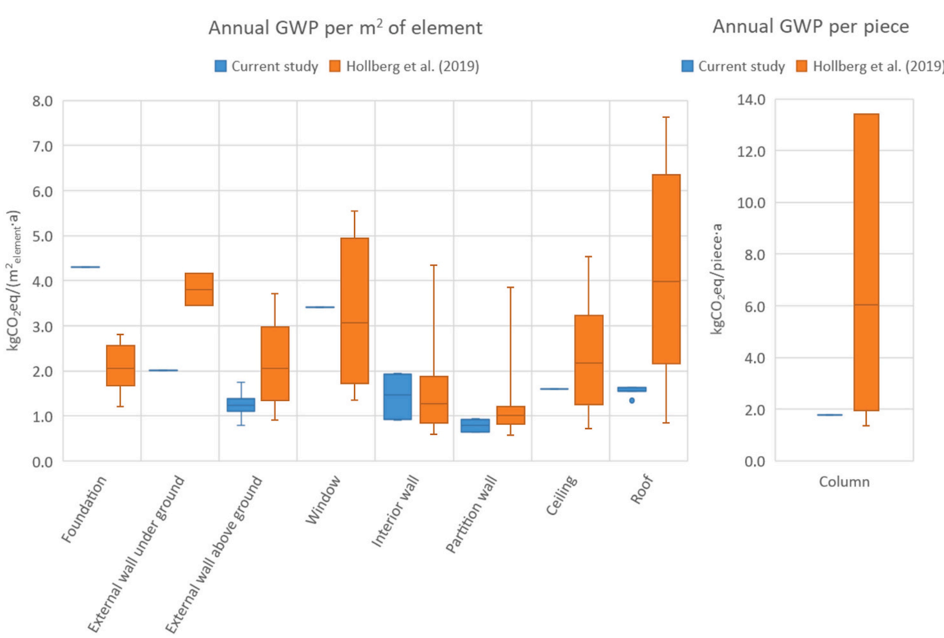

Fig. 8. Comparison of annual GWP by building element between the current study and Hollberg et al. [23].

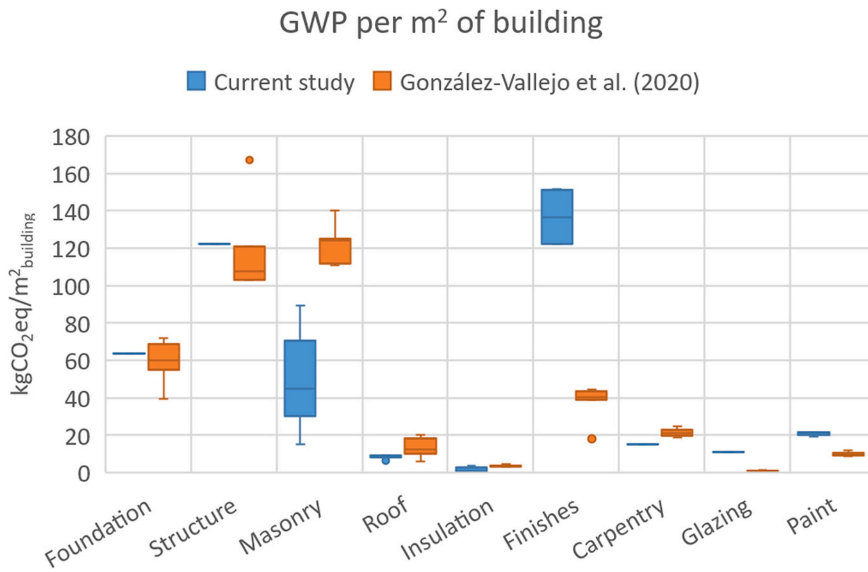

Fig. 9. Comparison of GWP by budget section between the current study and González-Vallejo et al. [71].

results could be based on double-checking with the accuracy of the budget, partial cost estimations or the quantity of concrete in the structure, which are parameters with a lower uncertainty, to be used as reference values to validate overall estimations for an accurately defined building typology.

6. Conclusions

In the present work a methodology has been defined for the environmental benchmarking of building typologies. For this, different constructive solutions are assessed using a combination of BIM-based LCA tools and machine learning algorithms. A case study of a social housing project in Spain has been evaluated and ranges for its environmental impact indicators have been derived from combinatorial variations of its constructive solutions. The workflow here described allows automating the obtention of environmental benchmarks thanks to the full integration of BIM and LCA and to the automatic generation a variety of combinations of constructive solutions for a case study. Subsequently, a data structuring process through spreadsheet macros organizes the results obtained in the previous step in order to analyze them by means of standard machine learning algorithms such as RF regression. In addition, the latter provide useful information about the importance of each variable for determining the environmental impact of the analyzed building typology, thereby easing decision-making during the design stage of projects.

In the case study, consisting in an 11-story residential building with 92 dwellings, the constructive solutions for partitions and façades are the two most important variables for all the environmental impact indicators, which present a strong correlation. The product and maintenance stages of its life cycle account for a high portion of the emissions, with ~3000–4000 and ~ 1750 tCO_2eq, respectively. In combinations using brick walls in partitions and façades' inner layer, masonry and finishes account for 96% of the GWP during the product stage. In cases where these are solved with plasterboard, masonry is relegated to third place with ~430 tCO_2eq, but the sum of concrete, masonry and finishes is still high and accounts for 93% GWP of the product stage. Regarding the maintenance and replacement stage, finishes of floors, walls and ceilings, along with doors and windows, produce 94.5% of its GWP. The difference between brick walls and plasterboard during this stage is not significant.

RF machine learning algorithm has been successfully applied for identifying the most decisive variables in the case study's building typology, as well as for predicting the environmental impact of new buildings complying with this typology. Once the number of trees was decided, the RF algorithm was applied to each output variable to analyze the importance of each feature or input variable for estimating results for each environmental impact indicator with a negligible error. For example, considering the results for GWP, a mean absolute error of 0.00038% in the estimations has been reached. With an increase in the number of building typologies analyzed and in the variations of constructive solutions considered for each element in the building, the developed regression model shows signs of being useful for predicting the environmental impact of future constructions and to be applied to the analysis of greater scale urban zones.

Benchmarking will be useful in promoting the sustainability of buildings, but limitations have also been identified, such as the uncertainties that rise, mainly from the LCA data source reliability and the quantity take-off method, as well as the combination of both when defining BIM objects and matching them to LCA data from Tally. The existing diversity in the environmental impact assessment methodologies applied to buildings in the different studies poses a challenge to be tackled in order to be able to establish environmental benchmarks and make results comparable between studies. Two main limitations were detected in this research specifically regarding the use of the Tally plugin, although these could be overcome in future versions of the plugin. First, it is not possible to modify LCA data in Tally, for example to use more reliable and local data from EPDs by manufacturers. And second, technical services have been excluded in this study because they are not detected by the plugin during the BIM model scan process. An additional limitation was identified related to the number of combinations generated, which was reduced and therefore did not allow to split the dataset for validation purposes.

Nevertheless, and considering that the methodology here described could be applied not necessarily using the specific software employed in this study, the validity of this tool as support for a first approach in decision-making among a variety of constructive solutions during the design process has been proved, leading to reductions of up to 70 $kgCO_2eq/m^2$ in dwellings for the analyzed case study only considering construction materials involved in the solutions that were varied among the explored design options. Thus, the true value of this methodology relies on the automation potential of BIM for linking the information contained in the model, especially quantity take-off, to LCA databases, which allows generating a variety of combinations of constructive solutions for a case study, thereby offering the possibility of establishing environmental benchmarks for building typologies.

Given the aforementioned limitations, forthcoming research should aim at solving these issues in order to allow a complete LCA of buildings. First, flexibility regarding LCA data should be provided, whether through data modification or selection among different LCA databases. And second, both the combinatorial case study and the calculation model should consider the entire variety of elements included in a building in order to gain understanding on their relative importance with respect to the total environmental impact of the project. To that end, not only the architectural view of the project should be analyzed, but also those regarding technical services and structural elements, which are usually designed in independent BIM files. Once these aspects have been approached, research should aim at establishing a set of environmental benchmarks for different building typologies by following the methodology described in this study, thus providing practitioners and policy-makers with reference baselines for future architectural projects and sustainability requirements.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A.1
Tally database entries assigned to construction materials in the BIM model.

Material	Tally entry	Service life (years)	Takeoff method
Structural elements			
Concrete floor slabs	Structural concrete, 3001–4000 psi, 0–19% fly ash and/or slag	DBL	33% by volume
	Steel, reinforcing rod	DBL	35.6 kg/m^3
Foundation slab	Structural concrete, 3001–4000 psi, 0–19% fly ash and/or slag	DBL	100% by volume
	Steel, reinforcing rod	DBL	50 kg/m^3
Retaining walls	Structural concrete, 3001–4000 psi, 0–19% fly ash and/or slag	DBL	100% by volume
	Steel, reinforcing rod	DBL	60 kg/m^3
Reinforced concrete columns	Structural concrete, 4001–5000 psi, 0–19% fly ash and/or slag	DBL	100% by volume
	Steel, reinforcing rod	DBL	125 kg/m^3
Stairs	Structural concrete, 3001–4000 psi, 0–19% fly ash and/or slag	DBL	100% by volume
	Steel, reinforcing rod	DBL	40 kg/m^3
	Galvanized steel railings	75	0.641 kg/m
Aerated concrete	Structural concrete, 0–2500 psi, 0–19% fly ash and/or slag	DBL	300 kg/m^3
	No reinforcement	–	–
Floorings			
Ceramic tile flooring	Ceramic tile, unglazed	60	10 mm thickness
	Cement mortar, TCNA - EPD	60	3 cm thickness
	Cement grout, TCNA - EPD	60	0.212 kg/m^2
Terrazzo tile flooring	Stone tile, generic	50	2 cm thickness
	Cement mortar, TCNA - EPD	60	2 cm thickness
	Cement grout, TCNA - EPD	60	0.212 kg/m^2
Underground cement flooring	Self-leveling underlayment	60	7 mm thickness
Ceilings			
Standard gypsum plasterboard	Wall board, gypsum, natural	30	10 mm thickness
	Paint, interior acrylic latex	7	1 coat plus primer
	No foil facing	–	–
Moisture-resistant gypsum plasterboard	Wall board, gypsum, moisture- and mold-resistant	30	12.5 mm thickness
	Paint, interior acrylic latex	7	1 coat plus primer
	No foil facing	–	–
Roofing			
Terracotta tile flooring	Terracotta	75	12 mm thickness
	Cement mortar, TCNA - EPD	60	19 mm thickness
	Cement grout, TCNA - EPD	60	0.212 kg/m^2
Ceramic tile flooring over plots	Ceramic tile, unglazed	60	12 mm thickness
	No mortar, no grout	–	–
Insulated metal roof	Steel, sheet, by gauge	45	5 mm thickness
	Fluoropolymer coating, metal stock	75	0.3225 kg/m^2
	Spray polyurethane foam insulation, closed cell roofing (HFC blowing agent), SPFA - EPD	50	70 mm thickness
	Steel, sheet	45	5 mm thickness
	Fasteners, stainless steel, with clip	40	0.88 kg/m^2
Thermal insulations and moisture protections			
Foundations moisture protection	Polyethylene sheet vapor barrier (HDPE)	DBL	0.2 mm thickness
	No attachment	–	–
Extruded polystyrene	Polystyrene board (XPS), Pentane foaming agent	50	Various thicknesses
Polyurethane board	Polyurethane foam (PUR) rigid board	50	Various thicknesses
Spray polyurethane foam	Spray polyurethane foam (PUR) insulation, closed cell (HFC blowing agent), SPFA - EPD	50	Various thicknesses
Glass fiber (rooftop)	Glass fiber board, NAIMA - EPD	60	Various thicknesses
HDPE vapor barrier	Polyethylene sheet vapor barrier (HDPE)	DBL	0.2 mm thickness
	No attachment	–	–
Asphaltic reinforced membrane	APP modified bitumen, assembly, (base & cap), ARMA - EPD	40	9.77 kg/m^2

(continued on next page)

Table A.1 (*continued*)

Material	Tally entry	Service life (years)	Takeoff method
Glass fiber (walls)	Fiberglass blanket insulation, unfaced	60	Various thicknesses
	No foil facing		
Expanded polystyrene	Expanded polystyrene (EPS), board	50	Various thicknesses
Mineral wool	Mineral wool, Knauf, TP 115 - EPD	50	Various thicknesses
Doors			
Parking lot doors	Door frame, metal, galvanized, no door	45	0.3032 kg/m
	Fasteners, galvanized steel	40	0.021 kg/m
	Hollow door, exterior, steel, powder-coated	30	21.25 kg/m^2
	Hardware, stainless steel	DBL	2.32 kg/m^2
	No hinges	–	–
	Overhead door closer, cast iron	30	2.857 kg/m^2
Rooftop exterior doors	Hollow door, exterior, steel, powder-coated	30	21.25 kg/m^2
	Hardware, stainless steel	DBL	2.32 kg/m^2
	Stainless steel door hinge	30	1.25 kg/m^2
	No closer	–	–
Interior doors	Door, interior, wood, particle board core, flush	30	28.38 kg/m^2
	Wood stain, water based finish	10	0.11 kg/m^2
	Hardware, aluminum	DBL	1.00 kg/m^2
	Steel door hinge	30	0.933 kg/m^2
	No closer	–	–
Fire-rated interior doors	Hollow door, interior, steel, fire-rated	50	20.97 kg/m^2
	Hardware, aluminum	DBL	1.00 kg/m^2
	Steel door hinge	30	0.933 kg/m^2
	Overhead door closer, aluminum	30	1.20 kg/m^2
Dwelling entrance doors	Door, exterior, wood, solid core	30	28.9 kg/m^2
	Wood stain, water based finish	10	0.11 kg/m^2
	Hardware, stainless steel	DBL	2.32 kg/m^2
	Stainless steel door hinge	30	1.25 kg/m^2
	No closer	–	–
Building entrance doors	Hollow door, exterior, aluminum, anodized	30	13.25 kg/m^2
	Glazing, monolithic sheet, tempered	40	4 mm thickness
	Hardware, stainless steel	DBL	2.32 kg/m^2
	Stainless steel door hinge	30	1.25 kg/m^2
	Overhead door closer, aluminum	30	1.20 kg/m^2
Windows			
Fixed + operable frame (balcony)	Window frame, aluminum, powder-coated, operable, insulated	45	0.98 kg/m
Double slider frame	Window frame, aluminum, powder-coated, divided operable, insulated	45	1.02 kg/m
Single window frame	Window frame, aluminum, powder-coated, operable, insulated	45	0.98 kg/m
Glazing	Glazing, double, insulated (air)	40	21.4 kg/m^2
Hardware	Hardware, aluminum window fitting	20	0.656 kg/m^2
Walls and partitions			
Clay block	Brick, generic	150	127.4 kg/m^2
	Mortar type N	60	8% by volume
	Paint, exterior acrylic latex	10	1 coat plus primer
	No grout, no reinforcement	–	–
Concrete block	Concrete masonry unit (CMU), hollow-core	100	703 kg/m^3
	Mortar type N	60	7.12% by volume
	Paint, exterior acrylic latex	10	1 coat plus primer
	No grout, no reinforcement	–	–
Double hollow brick	Brick, generic	150	7 cm thickness
	Mortar type N	60	11.68% by volume
	No grout, reinforcement and finish	–	–
Perforated brick	Brick, generic	150	11.5 cm thickness
	Mortar type N	60	16% by volume
	No grout, reinforcement and finish	–	–
Ceramic tile finish	Ceramic tile, glazed	60	4 mm thickness
	Cement mortar, TCNA - EPD	60	2 cm thickness
	Cement grout, TCNA - EPD	60	0.212 kg/m^2
Gypsum plaster finish	Wall board, gypsum, natural	30	15 mm thickness
	Paint, interior acrylic latex	7	1 coat plus primer
	No foil facing	–	–
Partition metal framing with insulation	Galvanized steel, C-stud metal framing with insulation	75	48 S 50–60 cm
	Insulation (see Thermal insulations and moisture protections section)	–	–
Partition metal framing	Galvanized steel, C-stud metal framing	75	48 S 50–60 cm
Curtain wall	Curtain wall system, Kawneer, 1600 Wall System – EPD	60	35.6 kg/m^2

DBL: Default to building life.

Table A.2
Transportation distances by truck assigned to each material in the analysis of the case study with Tally.

Material	Distance (km)
APP modified bitumen, assembly, (base & cap), ARMA - EPD	555
Brick, generic	80
Cement grout, TCNA - EPD	10
Cement mortar, TCNA - EPD	10
Ceramic tile, glazed	660
Ceramic tile, unglazed	240
Concrete masonry unit (CMU), hollow-core	18
Curtain wall system, Kawneer, 1600 Wall System - EPD	535
Door frame, metal, galvanized, no door	320
Door, exterior, wood, solid core	475
Door, interior, wood, particle board core	475
Expanded polystyrene (EPS), board	130
Fasteners, galvanized steel	530
Fasteners, stainless steel	530
Fiberglass blanket insulation, unfaced	530
Fluoropolymer coating, metal stock	530
Galvanized steel	35
Glass fiber board, NAIMA - EPD	555
Glazing, double, insulated (air)	140
Glazing, monolothic sheet, tempered	140
Hardware, aluminum	20
Hardware, stainless steel	185
Hollow door, exterior, aluminum, anodized	20
Hollow door, exterior, steel, galvanized	20
Hollow door, exterior, steel, powder-coated	20
Hollow door, interior, steel, fire-rated	20
Light-weight clay block	240
Mineral wool, Knauf, TP 115 - EPD	530
Mortar type N	10
Overhead door closer, aluminum	10
Overhead door closer, cast iron	20
Paint, exterior acrylic latex	40
Paint, interior acrylic latex	40
Polyethylene sheet vapor barrier (HDPE)	530
Polystyrene board (XPS), Pentane foaming agent	530
Polyurethane foam (PUR) rigid board	20
Self-leveling underlayment	10
Spray polyurethane foam insulation, closed cell (HFC blowing agent), SPFA - EPD	475
Spray polyurethane foam insulation, closed cell roofing (HFC blowing agent), SPFA - EPD	475
Spray polyurethane foam insulation, open cell, SPFA - EPD	475
Stainless steel door hinge	185
Steel door hinge	185
Steel, reinforcing rod	185
Steel, sheet	185
Stone tile	250
Structural concrete, 0–2500 psi, 0–19% fly ash and/or slag	10
Structural concrete, 3001–4000 psi, 0–19% fly ash and/or slag	10
Structural concrete, 4001–5000 psi, 0–19% fly ash and/or slag	10
Stucco, Portland cement	10
Terracotta	240
Thickset mortar	10
Wall board, gypsum, moisture- and mold-resistant	229
Wall board, gypsum, natural	229
Window frame, aluminum, powder-coated, divided operable, insulated	10
Window frame, aluminum, powder-coated, operable, insulated	10
Wood stain, water based	40

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