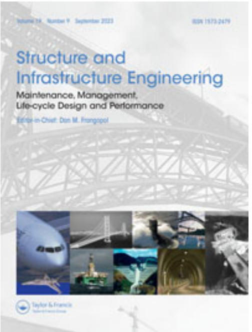


Structure and Infrastructure Engineering

Maintenance, Management, Life-Cycle Design and Performance

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/nsie20

A decision-making framework for school infrastructure improvement programs

Rafael Fernández, Juan Francisco Correal, Dina D'Ayala & Andrés L. Medaglia

To cite this article: Rafael Fernández, Juan Francisco Correal, Dina D'Ayala & Andrés L. Medaglia (2023): A decision-making framework for school infrastructure improvement programs, Structure and Infrastructure Engineering, DOI: 10.1080/15732479.2023.2199361

To link to this article: https://doi.org/10.1080/15732479.2023.2199361

STRUCTURE AND INFRASTRUCTURE ENGINEERING
https://doi.org/10.1080/15732479.2023.2199361

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

A decision-making framework for school infrastructure improvement programs

Rafael Fernández[a], Juan Francisco Correal[a], Dina D'Ayala[b] and Andrés L. Medaglia[c]

[a]Centro de Investigación en Materiales y Obras Civiles (CIMOC), Department of Civil and Environmental Engineering, Universidad de los Andes, Bogotá, Colombia; [b]Department of Civil, Environmental & Geomatic Engineering, University College London, United Kingdom; [c]Centro para la Optimización y Probabilidad Aplicada (COPA), Department of Industrial Engineering, Universidad de los Andes, Bogotá, Colombia

ABSTRACT
School infrastructure affects the quality of education and the performance of children and youth. Natural hazards such as earthquakes, hurricanes, floods, and landslides, threaten critical infrastructure such as school facilities. Additionally, problems related to the functionality of these facilities are common in the region, such as an inadequate number of classrooms, poor lighting, and insufficient ventilation, among others. At a national level, the decision-making process to prioritize schools' interventions becomes even more challenging due to limited resources and lack of information. Furthermore, there is a lack of a systematic approach to address the need of improving existing infrastructure taking into consideration limited resources. Considering this, a novel decision-making framework is proposed that prioritizes school infrastructure investment with limited budgets, using clustering procedures, a multi-criteria utility function, and an optimization component. This framework allows better public policy decisions and benefits students in terms of buildings quality with a multi-criteria perspective, improving both safety and functional conditions. The framework is illustrated with a case study applied to the public-school infrastructure in the Dominican Republic.

ARTICLE HISTORY
Received 30 August 2022
Revised 11 January 2023
Accepted 17 January 2023

KEYWORDS
Budget allocation; clustering; decision-making; disaster risk reduction; multi-criteria; optimization; public-school infrastructure; school's functionality

1. Introduction

Quality education is a necessary condition to close inequality gaps, as it is stated in the Universal Declaration of Human Rights by The United Nations (1948). Quality education is also a priority of the Sustainable Development Goals (SDG), as the fourth goal states: *Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all* (The United Nations, 2020). Additionally, education contributes to many SDGs by reducing poverty, driving economic growth, and preventing inequality and injustice, among others (UNICEF, 2019). Although there are national and international efforts to improve education in low- and middle-income countries (L&MICs), more cooperative, structured, systematic, and coordinated efforts are required from governments and multilateral agencies to enhance quality education and reduce inequality gaps.

The United Nations showed that in L&MICs: 57 million primary-aged children remain out of school; one out of four girls do not have access to school; 50 percent of out-of-school children live in conflict-affected areas; 103 million adolescents (from which at least 60 percent are women) lack of necessary literacy skills; and six out of ten children and adolescents are not achieving a minimum level of proficiency in reading and math (The United Nations, 2015). In addition, the education level and quality among countries have large differences, for example L&MICs have lower completion rates in all levels compared to high-income countries (UNESCO, 2020).

Several factors affect the quality of education and account for the existing gap between L&MICs and High-Income Countries (HICs). In particular, the Non-Governmental Organization (NGO) *Educate a Child* establishes the following list of barriers to better quality education: poverty; challenging geographies; conflict, insecurity, and instability; refugees; gender; infrastructure; human, material, and financial resources; teachers, contents, and academic procedures quality; and climate change (Educate a Child, 2020). Likewise, the World Bank argues that quality education should be achieved through five pillars: learners, teachers, learning resources, schools (infrastructure), and systems management (human resources and internal procedures) (The World Bank, 2020). Both sources acknowledge the critical role that infrastructure plays in the quality of education; the role has become evident with the COVID-19 crisis (The World Bank, 2020). Also, this situation differs considerably between Low-Income Countries (LICs) and Middle-Income Countries (MICs), since the latter usually have more technical and financial capacity than the former (Huss & Keudel, 2020). In MICs, in contrast to LICs,

CONTACT Andrés L. Medaglia andres.medaglia@uniandes.edu.co Centro para la Optimización y Probabilidad Aplicada (COPA), Department of Industrial Engineering, Universidad de los Andes, Bogotá, Colombia.

Supplemental data for this article can be accessed online at https://doi.org/10.1080/15732479.2023.2199361.

institutions are strong enough to address this problem at the country level. Therefore, improving school infrastructure in MICs could have an impact on the education quality in these countries, which account for 71% of the world's population.

In essence, school infrastructure in MICs is in general insufficient and the demand/capacity ratio to serve students is unevenly distributed; both socio-economically and geographically (The World Bank, 2020). In addition, this infrastructure usually presents significant functional and safety limitations. Buildings typically do not meet minimum functional learning conditions (e.g. students' density, bathroom facilities quality, and ventilation, among others), construction quality, and safety standards. It is also common that government educational agencies require technical orientation to support strategic decisions on how to invest the limited resources available to improve and maintain the institutional capacity and education quality. However, these efforts usually lack of a systematic approach to address the need of improving existing infrastructure considering limited resources. This has been demonstrated for the Latin America and the Caribbean context by Muñoz et al. (2020) and in Lebanon by Naja and Baytiyeh (2014). For these reasons, this gap is addressed by proposing a decision-making framework to prioritize school infrastructure interventions to develop large-scale improvement programs.

The rest of the paper is organized as follows: Section 2 presents the literature review. Section 3 outlines the decision-making framework. Section 4 illustrates the framework in a case study in the Dominican Republic. Finally, Section 5 presents some concluding remarks.

2. Literature review

Before defining the methodological approach, it is important to understand how this problem has been approached in the existing literature. This section presents the relevant studies and initiatives that have been conducted to address each step needed to improve school infrastructure. First, the role that multilateral agencies, development banks, and national governments have in the process of improving infrastructure in developing countries is discussed. Then, how school infrastructure can be measured, classified, and organized to understand the impacts of the previously mentioned efforts in infrastructure improvement programs is presented. This will give a better understanding of the current efforts and how they can be considered and improved.

In the first place, multilateral agencies promote infrastructure development programs for the educational sector. UNICEF, the United Nations International Children's Emergency Fund, works to guarantee access, improve learning skills, and help emergencies in 190 countries through the UNICEF education strategy 2015–2030 (UNICEF, 2019). UNESCO (the United Nations Educational, Scientific, and Cultural Organization), focuses on the school sector through the World Education Agenda 2030 and the Global Education Monitoring Report (GEM) (UNESCO, 2020). UNESCO has also emphasized infrastructure safety by developing different tools such as VISUS (UNESCO, 2019), a methodology for assessing safety attributes in school facilities in El Salvador, Laos, Indonesia, and Peru. Related to safety in school facilities, the UNDRR (the United Nations Office for Disaster Risk Reduction), in collaboration with the Global Alliance for Disaster Risk Reduction & Resilience in Education Sector (GADRRRES), has developed initiatives such as the Comprehensive School Safety program and the Worldwide Initiative for Safe Schools (UNDRR & GADRRRES, 2017). These two initiatives provide a global framework to support activities related to safe learning facilities, school disaster risk management, and risk reduction and resilience education. In addition, several NGOs have worked together with these institutions to improve education quality in MICs such as Educate a Child and Save the Children.

Development banks have also played a vital role in technical support, training, capacity building, and loans. In the Latin American and the Caribbean (LAC) region, the Inter-American Development Bank (IADB) conducted a project named *Learning in twenty-first-century schools* (IADB., 2014) in which they established the architectural and functional characteristics to ensure a quality learning environment for public schools in LAC countries. They produced 11 documents addressing different quality considerations such as environmental impact, comfort, normative and costs, maintenance, disaster risk management, and their applications to the region. In 2014, the World Bank launched the Global Program for Safer Schools to invest in and improve school infrastructure around the world. The program's purpose is to boost large-scale investments to enhance the safety and resilience of school infrastructure at risk from natural hazards and to improve the quality of learning environments for children (The World Bank, 2020).

Regardless of the international efforts to improve infrastructure at the country level, most of these initiatives depend on the short-term policies of the current government, as identified by Huss and Keudel (2020). In MICs, school infrastructure management lacks a well-structured long-term strategy, usually due to the frequent changes in government policies. In terms of budget allocation, the education ministry at the national level often works with a tight annual budget that shall be split on the maintenance of existing infrastructure and the development of new facilities (Huss & Keudel, 2020). The allocated budget is often not enough to maintain the current infrastructure under the right conditions, yet it is even harder to find resources to develop new infrastructure or improve the existing one. This situation is even more critical considering that the school facilities portfolio is usually composed of different construction typologies, financed and built through disparate national programs, and executed by local governments, generally lacking reasonable quality control and standards enforcement. These contextual factors contribute to inefficient school infrastructure investment strategies in developing countries, as seen in the LAC context (IADB., 2014). In other L&MICs countries, such as Nigeria, there is no consistent and coordinated political effort related to maintenance, improvement, and development of the school infrastructure while simultaneously considering social, economic, and political aspects (Osaro & Wokekoro, 2018).

However, before implementing any school infrastructure intervention, it is important to understand what constitutes good quality infrastructure and how this can be measured. This question has been addressed by Barrett, Treves, Shmis, Ambasz, and Ustinova (2019), who highlight that quality school infrastructure should be characterized by being accessible, providing a safe and healthy environment, and offering optimal space for learning. These characteristics can be grouped into two main categories: *functionality* and *safety*. While functionality focuses on an optimal learning environment and health conditions; safety focuses on the structural stability of buildings in the case of natural hazards.

The functionality of school buildings relates to multiple aspects, from water and sanitation hygiene (e.g. bathroom facilities quality and occurrence), students' density, access to the sewer system, security fences, ventilation, lighting, and CO_2 levels, among others. In HICs, one of the most recognized and accepted standards is the Building Handbook developed by the Department of Education of the United Kingdom (UK Department of Education, 2011), which several countries follow. In MICs, although there are national guides with varying standards, as is the case for Colombia (Icontec; Ministerio de Educación Nacional, 2017) and Dominican Republic (SEOPC, 2006) according to UNESCO these can vary as much as tenfold among them (Beynon, 1997). For example, student density is addressed in the UK, Colombia, and the Dominican Republic, varying its requirement from 2.0, 1.8, and 1.4 square meters built per student, respectively. Concerning the bathroom facilities density, the maximum number of students per toilet, urinals, and sinks, ranges from 15, 25, to 30 students per element, respectively. These differences show how students' conditions vary from HICs to MICs, and among countries.

Aside from being functional, the infrastructure must also be safe for students and the school community. Natural hazards such as earthquakes, cyclones, floods, wildfires, and landslides can affect to various degrees the stability and integrity of school infrastructure, as documented in D'Ayala et al. D'Ayala et al., (2020). Indeed, the Earthquake Engineering Research Institute (EERI) identified collapses and extensive damages to school infrastructure in India, Indonesia, Peru, Turkey, the United States, and Haiti, among other countries (EERI., 2019). The Geotechnical Extreme Events Reconnaissance (GEER) reported collapses due to the Muisne earthquake in Manta, Pedernales, and Portoviejo regions in Ecuador in 2016 (GEER, 2016); and reported more than 280 damaged school facilities and around 30 students fatalities due to the Puebla earthquake in Mexico in 2017 (GEER, 2017).

Disaster risk mitigation has been a difficult task due to the large number of buildings, their vulnerability, and the uncertainty related to the natural hazards (Yamin, Ghesquiere, Cardona, & Ordaz, 2013). To assess the problem of large portfolios of buildings, several authors had proposed clustering techniques. Clustering is a technique to find groups of similar elements in a dataset, for example, infrastructure. Indeed, Aleskerov, Say, Toker, Akin, and Altay (2005) developed a decision support system for disaster management centered on clusters of buildings based on their characteristics, to predict damages and losses in seismic scenarios, in Turkey. Likewise, Prasad, Singh, Kaynia, and Lindholm (2009) identified residential building clusters based on the socioeconomic level of the occupants in the city of Dehradun in India to develop a risk assessment, in which they conclude that poorer people are subject to higher seismic risk. A more global approach was developed by Gunasekera et al. (2015) in which they developed a global exposure model based on clustering of satellite images using 1 km^2 resolution to support the generation of country disaster risk profiles.

Several algorithms implement different clustering procedures, like the most common K-means, and its variation for categorical data, K-modes. In these two algorithms, the clusters are identified by an iterative process based on a central statistical measure (mean and mode respectively). There are other algorithms considering a different type of data distribution such as the Mixture Models, or different approaches in the iterative process such as Hierarchical clustering that can consider different types of distance metrics between elements (Casella, Fienberg, & Olkin, 2013). Each of these algorithms has its advantages and limitations. The clustering analysis output should be interpreted through the expert's lens to develop sound intervention strategies.

Apart from the classification and clustering of school buildings, it is important to measure the current condition to develop common strategies for improvement. It is important to consider a multi-criteria approach to holistically assess the current condition and the impact on the quality that intervention strategies can have. This approach allows for the inclusion of characteristics such as functionality and safety of buildings, as well as for several sub-criteria. Some of the methodologies that allow to express criteria on different scales and conveniently transform them into a single-utility scale are the Multi-Attribute Utility Theory (MAUT) (Joint Research Centre - European Comission, 2008), the Analytic Hierarchy Process (AHP) (Castillo, 2011; Saaty, 1990), and the Optimal Scoring Method (OSM) (Castro-Lacouture, Medaglia, & Skibniewski, 2007; Sefair, Castro-Lacouture, & Medaglia, 2009) among others.

In particular, the OSM is a methodology based on optimization, that includes constraints to indicate the preferences among criteria for a particular decision maker (Sefair et al., 2009). In this method, the user does not need to explicitly indicate the level of importance of one criterion related to another, avoiding the need to implement pairwise comparisons as in AHP. OSM is linked to the principles behind data envelopment analysis (Castro-Lacouture et al., 2007), a methodology that ranks decision-making elements, like persons or institutions, with multiple inputs and outputs (i.e. multiple criteria) based on a single efficiency score.

After having assessed the quality of the infrastructure accounting for multiple criteria, it is necessary to define the best intervention programs to optimize the resource investment. The latter has been applied extensively in residential buildings and bridge infrastructure management using multi-criteria decision-making (MCDM) (Kabir, Sadiq, & Tesfamariam, 2014; National Academies of Sciences, Engineerinng and Medicine, 2007; Salem, Miller, Deshpande, & Arurkar, 2013). Asadi, Salman, and Li (2019) presented a methodological approach for decision making of seismic resilience in diagrid buildings, which includes a multi-attribute utility valuation based on an AHP analysis and TOPSIS. Specifically, for school facilities, Anelli, Santa-Cruz, Vona, Tarque, and Laterza (2019) developed a framework for prioritizing seismic retrofitting interventions and tested it in the public-school buildings infrastructure of Lima (Peru). The authors proposed the framework considering engineering, organizational, socio-economic, and political criteria to retrofit buildings, but did not consider broader functional aspects such as ventilation, lighting, bathrooms conditions and quality, or students' density among others.

To the best of the authors' knowledge, there is not a unified, comprehensive, and systematic methodology in the literature that specifically integrates school infrastructure assessment with multiple functional and safety criteria, a clustering procedure that identifies groups of buildings to apply common interventions, and an optimization strategy that prioritizes interventions for school infrastructure improvement programs. The purpose of this paper is to fill this gap.

3. Proposed methodology

To prioritize school infrastructure investment and maintenance the following methodological framework is proposed, comprising the following modules: 0) Data preparation; 1) quality assessment through the Building Quality Index (BQI); 2) buildings' and schools' cluster formation; 3) interventions design; and 4) optimal allocation of resources. As data needs to be prepared and pre-processed, the first module is referred to as module zero. Figure 1 summarizes the proposed methodology and shows the relation of its modules.

For the portfolio characterization (module 0), a comprehensive set of taxonomies identifies each building's characteristics (Adhikari, D'Ayala, Ferreira, & Ramirez, 2018; D'Ayala et al., 2020; The World Bank, 2019). The taxonomies include the essential information related to the functional characteristics (such as bathroom quality, bathroom density, and students' density) of each school facility and the structural vulnerability due to natural hazards (such as earthquakes and hurricanes). Also, in this module, general characteristics of the infrastructure are gathered to assign a quantitative valuation to the buildings in their functional and safety criteria. Once the portfolio database is fully characterized, (in module 1) a quality measurement is calculated, namely, the Building Quality Index (BQI). This assessment includes two of the most important school building quality conditions: functionality and safety. Each one of these criteria includes all relevant sub-criteria. In parallel, in module 2, for the same set of buildings and the set of school facilities, a clustering algorithm identifies the buildings' main typologies.

These typologies denote a specific combination of attributes representing a group of building assets (The World Bank, 2020). Construction experts identify the most critical conditions for each typology and propose potential improvements by identifying structural, non-structural, and functional interventions (like structural retrofitting, replacement, or refurbishment) at the building or school level. The costs and the benefit of each intervention are estimated based on the unitary costs and their impact on the BQI (module 3). Finally, in module 4, an optimization component evaluates an action plan of intervention strategies. It is important to highlight the fact that the application of this method relies on experts' judgment in each step to ensure the quality of the results and to make them truly applicable. The following sections present the technical details of each module.

3.1. Module 0: Data preparation

The first step in this module is to characterize the school building's portfolio. Information needs to be gathered so the quality of each building can be measured. This information should be gathered to characterize quantitatively the conditions of the school infrastructure. For instance, to characterize the functionality it is necessary to obtain geometric information on the openings, conditions of the lighting systems, and the student's density, among others. Similarly, for the safety characterization, it is relevant to obtain information related to the risk level of each building in terms, for example, of the average annual losses obtained from a probabilistic risk assessment. This information is used in module 1 to characterize the Building Quality Index (BQI).

In addition, a characterization should be done through a taxonomy system common to all school buildings considered, and encompassing relevant attributes related to safety and functionality. For example, if the methodology is to be applied in the Caribbean, it would be necessary to characterize the buildings in terms of their structural response related to seismic and to hurricane-wind actions. Therefore, as the vulnerability to the two hazards is related to different structural components and their behavior, two taxonomies will be needed to analyze the buildings' safety. In case additional natural hazards are relevant, each one of these hazards should have its proper taxonomy. In relation to seismic vulnerability, the seismic taxonomy developed in the Global Library for School Infrastructure (GLOSI) could be included in this framework (Adhikari et al., 2018; D'Ayala et al., 2020; The World Bank, 2019, Adhikari et al., 2023). In addition to safety, functional taxonomies shall be developed considering the building and school-complex levels, separately. The result of this step will be the characterization of each building of the portfolio according to the taxonomies.

Table 1 presents four indicative general taxonomies that could be considered in this step of the module. The seismic taxonomy was developed in the context of GLOSI and the hurricane taxonomy was developed in a previous project funded by the World Bank (2020). The functional taxonomies were proposed herein by the authors based on expert criteria. Other taxonomies might also be included depending on each case study. The taxonomies might need to be tailored to the geographic context and its attributes depend on data availability. Each taxonomic parameter has several attributes. For instance, the main structural system in the seismic taxonomy can be classified as reinforced concrete frames, masonry load-bearing walls, steel frames, or other additional subclassification. This fact generates many possible combinations of taxonomic attributes in a portfolio.

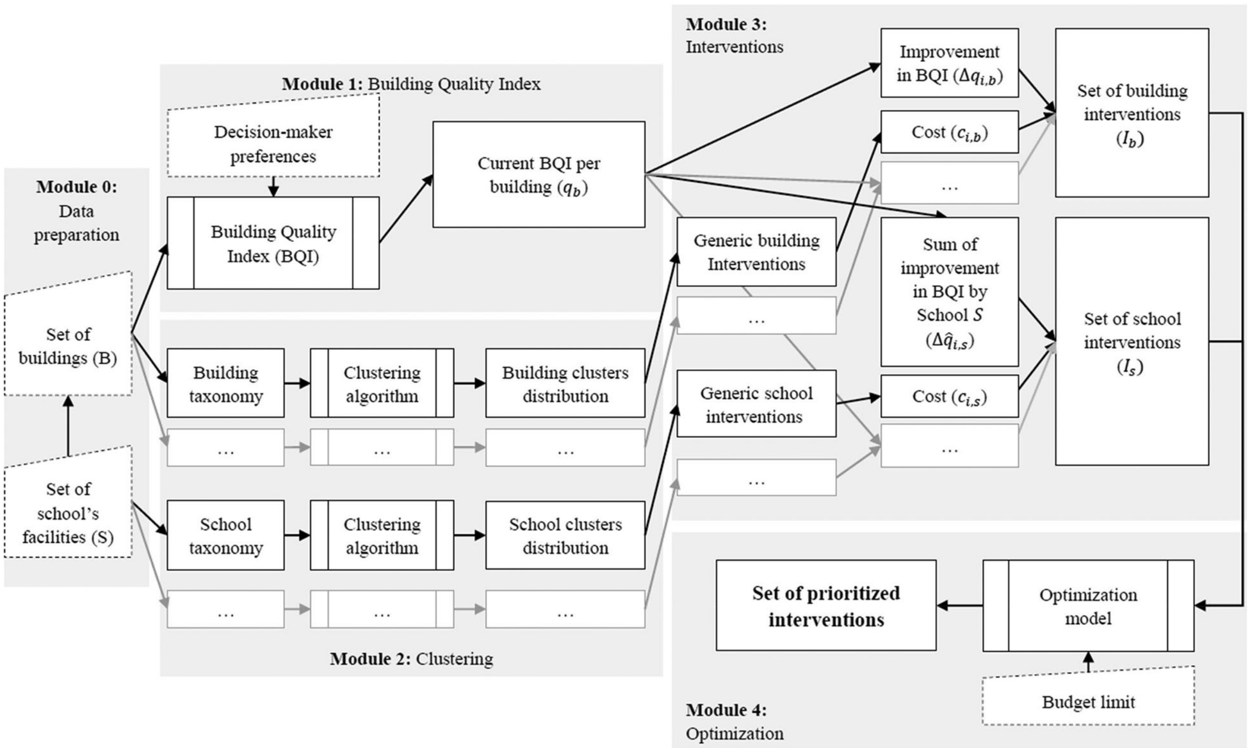


Figure 1. Proposed decision-making framework for prioritizing school infrastructure investment.

Table 1. Taxonomy systems for seismic, hurricane-wind, functional at the building level, and functional at the school level.

	Taxonomy			
	Seismic (GLOSI)	Hurricane	Functional– building level	Functional– school level
Parameters	Main structural system	Main structural system	Main structural system	Functionality design level
	Height range	Height range	Height range	Student density
	Seismic design level	Hurricane wind design level	Functionality design level	Bathroom density
	Diaphragm type	Roof shape	Ventilation	Bathroom quality
	Structural irregularity	Roof structure type	Illumination	Accessibility provisions
	Span length/Wall panel length	Roof to wall/frame connection	IT provisions	Water supply system
	Pier type/Wall openings	Roof covering type	Energy efficiency (HVAC)	Sewerage system
	Foundation type	Roof covering to roof structure	Building Age	Enclosure and access control points
	Seismic pounding risk	Roof health condition		
	Effective seismic retrofitting	Roof projection length		
	Structural health condition	Presence of bracing in roof structure		
	Non-structural components	Wall typology		
		Wall openings		
		Typical opening size		
		Opening's type		
		Shutter provision		
		Structural health condition		
		Specific wind vulnerable elements		

Hence, there is a need to create clusters so that one can develop generic interventions to all members of a given clustered group (see module 2).

There are several methods to gather this information, such as field surveys or reports of existing building programs. However, as important as these procedures are, they are beyond the scope of this paper and will not be discussed in detail henceforth.

3.2. Module 1: Building quality index

The main objective of this module is to define a holistic Building Quality Index (BQI) to assess and understand the quality aspects of the educational infrastructure for each building in its current condition. This index considers functionality and safety criteria. Figure 2 presents the hierarchical representation of the possible criteria (and sub-criteria). For example, functionality can include quantitative sub-criteria such as the bathroom facilities density, the level of natural lighting (ratio between built area and windows area), or the student's density. Conversely, for safety sub-criteria, such as the earthquakes or hurricanes safety level, the average annual losses can be considered from a probabilistic risk assessment. All these scores should be normalized between 0 and 1, where 1 is the best condition and 0 is the worst. For this task, a direct rating technique is proposed as follows:

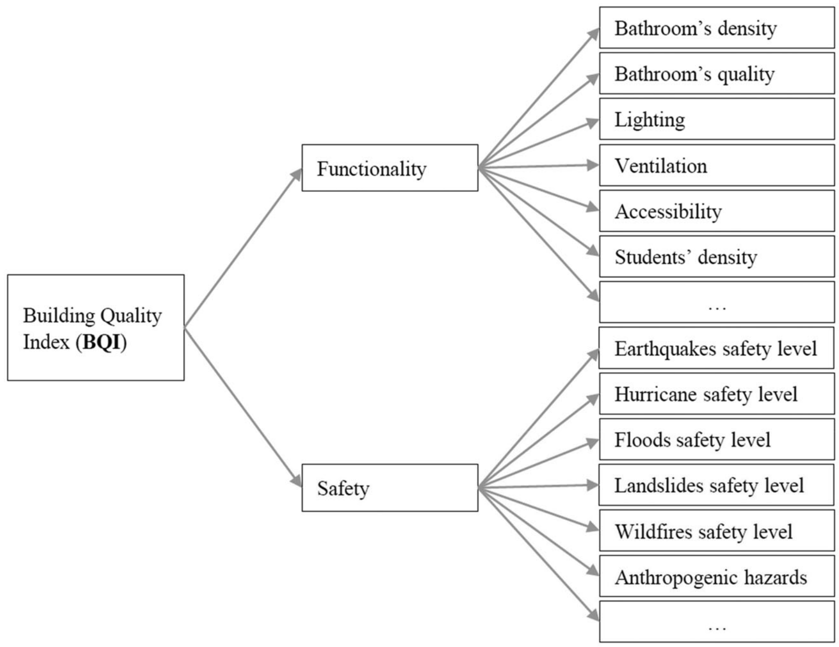


Figure 2. Attributes hierarchic representation.

$$s_{b,c} = \frac{\hat{s}_{b,c} - \hat{s}_c^{worst}}{\hat{s}_c^{best} - \hat{s}_c^{worst}} \quad (1)$$

where $s_{b,c}$ is the normalized score of a particular building b in the criterion c; $\hat{s}_{b,c}$ is the score of a particular building b in the criterion c; $\hat{s}_c^{worst}$ is the worst value in criterion c; and $\hat{s}_c^{best}$ is the best value in the criterion c. These criterion and sub-criterion ratings, combined with selected specific weights, give a combined measure that allows the comparison of different school buildings and facilities.

The BQI, also referred hereafter as q, is used to measure the impact on the quality of each possible intervention (e.g. retrofitting, functional intervention, or maintenance) for each building. Therefore, the impact or change on BQI due to an intervention will be referred as to Δq. The Δq for each intervention in each building, will create the basis for a comprehensive decision framework that looks for optimal decisions concerning future investment in maintenance and development of the infrastructure, as will be presented in module 3.

The BQI ranges from 0 to 1, where 0 and 1 denotes the worst and best quality in a school building, respectively. The BQI of a building b (q_b) is defined as a weighted sum of the normalized score in each criterion, as follows:

$$q_b = \sum_{c \in C} s_{b,c} \cdot w_c \quad (2)$$

where C is the set of criteria; $s_{b,c}$ is the normalized score of a particular building b in the criterion c; and w_c is the weight associated with the criterion c. This weight accounts for the decision-maker profile and the sum of all weights should add up to one (i.e. $\sum_{c \in C} w_c = 1$). To determine the weights, the decision theory literature provides several methods (Bradley, 2018; Hansson, 1990, 2005; Joint Research Centre - European Comission, 2008), such as the Analytic Hierarchy Process (AHP) (Saaty, 1990) or the Optimal Scoring Method (OSM) (Sefair et al., 2009), among others. Any of these methods could be used to obtain the weights and the selection should be based on the available information and possible interactions with the stakeholders.

3.3. Module 2: Clustering

After coding each building according to the parameters of each taxonomy (data obtained from field visits, virtual surveys, and geo-databases, among others) and calculating the BQI for all buildings, the next step of the module uses an algorithm to find buildings that show sufficient similarity so that they can be clustered in groups. This clustering component has been designed to scale up interventions in school risk-reduction programs (Fernández, Correal, D'Ayala, & Medaglia, 2023). This clustering is done using the taxonomy as descriptor (i.e. categorical variables) and converting the strings into binary vectors using one-hot encoding (Zheng & Casari, 2018). As most of the variables are categorical, data compression (e.g. using categories instead of the exact number of stories), allowed us to encode the data easily to be used in the clustering method. Note that buildings with the same taxonomy string are not necessarily identical buildings, since intrinsic characteristics are expected to be different, such as the exact number of stories or total built area. Also, buildings with different taxonomy strings may result in the same cluster, since the clustering algorithm may consider them to be close enough to be grouped together.

Due to the taxonomic encoding (categorical variables), and after trying multiple clustering algorithms, the Expectation-Maximization clustering algorithm using a Bernoulli Mixture Model was selected as a good choice for this application. This selection is mainly because of its stability and reliability dealing with categorical data, as it has been reported in the literature (Govaert & Nadif, 2008; Saeed, Javed, & Atique Babri, 2013). After applying the clustering algorithm, each building is classified into a single cluster for every taxonomy. The clustering assignment depends on the attributes of each building. Buildings that are similar from a taxonomical point of view, will be included within the same cluster; yet buildings far away from a taxonomical point of view will be in separate clusters.

The final output of this module is the ensemble of the building clusters for each taxonomy. In summary, for each cluster obtained in each taxonomy, the following should be identified: the representative combination of attributes; representative building type; cluster name (based on the characteristics of each cluster); structural or functional deficiencies. The analysis and validation of the clustering output requires expert knowledge and human intervention to find the correct number of clusters for each taxonomy; it is by no means, automatic.

3.4. Module 3: Interventions

This module is divided into two steps: the first one, is the development of generic interventions by cluster (group of schools or buildings); and the second one, is the implementation of the generic intervention in each specific element (particular school or building). As presented in Figure 3, in the Step A (generic intervention design) one interprets and identifies the common characteristics of each cluster, to propose interventions that could be applied to all elements belonging to the cluster. These interventions should be identified together with technical experts in each field (i.e. structural, architectural, functional) with deep understanding of the construction characteristics. For each intervention, it is important to define the objective, the strategy to achieve the objective, and the unitary cost of the intervention. This can be done by designing a particular intervention for a representative building or school for the cluster and then specifying the general characteristics of the intervention and the normalizing cost.

Step B (specific intervention implementation) calculates the cost and the quality improvement by implementing the generic cluster intervention in each specific building or school. This is needed since elements with the same taxonomic string may have different intrinsic characteristics, for example the built area. This intervention considers the unitary cost obtained from the previous step and the increase in quality generated by the intervention. With this information, it is possible to calculate the Δq for the interventions in each building in the portfolio. When the intervention is at the school level, the Δq assigned to the intervention will be the sum over all buildings in the facility. Therefore, the final output of this module is a database of interventions by each taxonomy implemented in each building and each school. Considering this, the maximum number of interventions should be the number of school building taxonomies times the number of buildings, plus the number of school facilities taxonomies times the number of schools. Each one of the interventions shall be characterized by its total cost and its corresponding Δq. This database will be the input for the optimization component presented in the next module.

3.5. Module 4: Optimization component

This module uses the database of interventions generated in the previous module and additional decision inputs and rules, such as the budget limit and minimum level of quality, to maximize the increase of quality using an optimization model. In this model, the following sets are defined. Let B be the set of buildings in the portfolio; S, the set of school facilities; B_s, the set of buildings in school $s \in S$; I, the set of all interventions; I_b, the set of possible interventions to building $b \in B$. I_s, the set of possible interventions to school $s \in S$. Let $s(b)$ be a function that returns the school $s \in S$ of building $b \in B$. Figure 4 shows a schematic representation of the schools, buildings, and intervention sets and their relations.

The parameters of the optimization model are the following: $c_{i,b}$, the cost of intervention $i \in I_b$ in building $b \in B$; $c_{i,s}$, the cost of intervention $i \in I_s$ in school $s \in S$; $\Delta q_{i,b}$, the BQI improvement in building $b \in B$ due to intervention $i \in I_b$; $\Delta\hat{q}_{i,s}$, the BQI improvement in school $s \in S$ due to intervention $i \in I_s$ accounted as the sum of the BQI improvement of all the buildings in the school ($\Delta\hat{q}_{i,s} \stackrel{\text{def}}{=} \sum_{b \in B_s} \Delta q_{i,b}$); q_b, the current BQI of building $b \in B$;

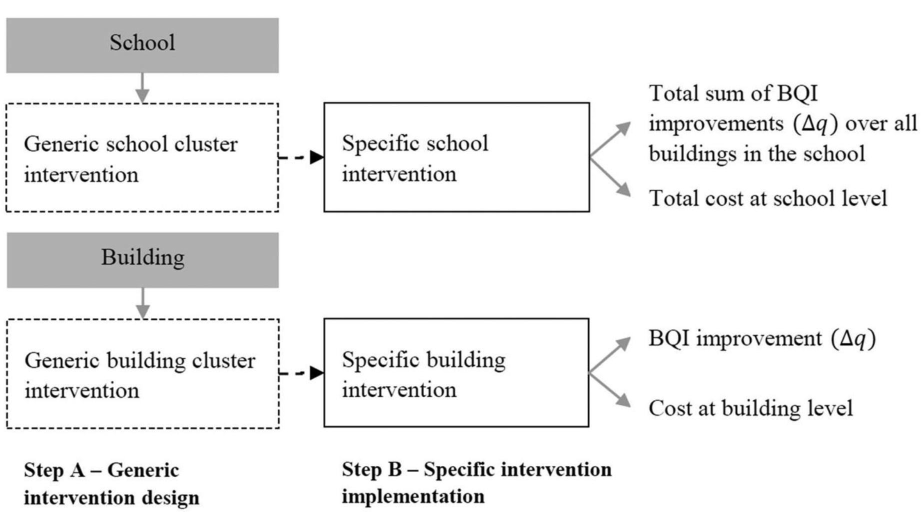


Figure 3. Steps to identify specific interventions at the school and building levels.

$\underline{q}_b$, the minimum *BQI* required for building $b \in B$; and $\overline{M}$, the budget limit for the investment plan.

The decision variables considered in the formulation are: $x_{i,b}$, a binary variable that takes the value of 1 if building $b \in B$ is subject to intervention $i \in I_b$, and it takes the value of 0, otherwise; $y_{i,s}$, a binary variable that takes the value of 1 if school $s \in S$ is subject to intervention $i \in I_s$, and it takes the value of 0, otherwise; and δ_b, deviation variable that guarantees that every building $b \in B$ meets the quality threshold $\underline{q}_b$. The School Infrastructure Investment Optimization (SIIO) problem follows:

$$\max \sum_{b\in B}\sum_{i\in I_b} \Delta q_{i,b}\cdot x_{i,b} + \sum_{s\in S}\sum_{i\in I_s} \Delta\hat{q}_{i,s}\cdot y_{i,s} - \sum_{b\in B}\delta_b \tag{3}$$

subject to:

$$\sum_{b\in B}\sum_{i\in I_b} c_{i,b}\cdot x_{i,b} + \sum_{s\in S}\sum_{i\in I_s} c_{i,s}\cdot y_{i,s} \le M \tag{4}$$

$$q_b + \sum_{i\in I_b} \Delta q_{i,b}\cdot x_{i,b} + \sum\nolimits_{i\in I_{s(b)}} \frac{\Delta\hat{q}_{i,s(b)}}{\left|B_{s(b)}\right|}\, y_{i,s(b)} + \delta_b \ge \underline{q}_b, \quad \forall\ b \in B, \tag{5}$$

$$x_{i,b} \in \{0,1\}, \quad \forall\ b \in B,\ \forall\ i \in I_b \tag{6}$$

$$y_{i,s} \in \{0,1\}, \quad \forall\ s \in S,\ \forall\ i \in I_s \tag{7}$$

$$\delta_b \ge 0, \quad \forall\ b \in B \tag{8}$$

The objective function (3) maximizes the total *BQI* improvement due to the implementation of the selected interventions at the building (first term) and school (second term) levels over the whole portfolio. The third term, as it is commonly used in goal programming (Rardin, 1998), minimizes the sum of deviations against the quality targets set for the buildings included in the soft constraint (5). Constraint (4) assures that the total cost of the interventions does not exceed the available budget. The set of constraints in (5) aims that every building achieves a minimum BQI improvement defined by the decision maker. These constraints can also be seen as soft constraints or as minimum quality goals; if the quality targets cannot be met, the deviation variables δ activate to satisfy the corresponding constraints. The last constraints in (6) to (8) define the nature of the decision variables.

The result of module 4, and therefore, of the proposed methodology, is the set of optimal interventions to be implemented in the school buildings portfolio. These interventions account for a total cost, which satisfies the budget limit, and a total (per building) quality improvement. The proposed method provides a novel decision-making framework for school infrastructure improvement, that provides a technical orientation to support strategic decisions on how to invest the limited resources to improve education quality. This method is intended to maximize the quality of the school infrastructure by allocating a budget wisely. However, it is important to state that this is not a purely data-driven process. The method aids the decision-making process but requires valuable input from experts and decision-makers. It relies on experts' judgment to ensure the quality of the results and to make them truly applicable.

4. Case study

The proposed methodology is applied to the public-school building portfolio for the Dominican Republic. The following sections present the details of the implementation of each module.

4.1. Database

The portfolio is comprised of 6,087 schools that serve approximately 1.5 million students (data gathered in 2020). These school facilities comprise 18,280 buildings, for an average of three school buildings per facility. The total built area covers 4.3 million square meters, rendering a density of 2.86 square meters per student. The exposure model was developed using basic information of all the schools provided by the Ministry of Education, high resolution satellite images of 300 schools located in Santo Domingo, information from field visits of around 950 schools' facilities distributed across the country, and virtual surveys to school

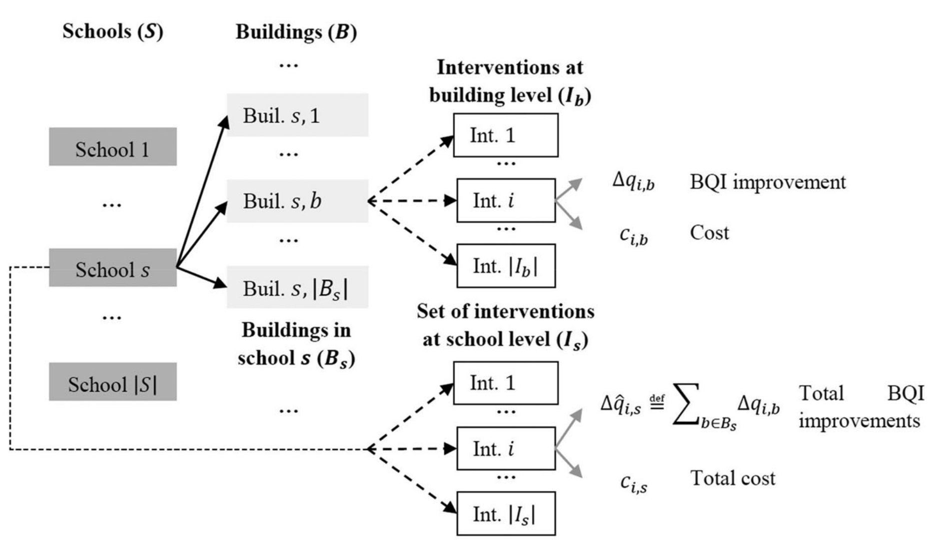


Figure 4. Illustrative sets considered in the optimization model formulation.

directors of approximately 2,800 schools. For the schools without information, a proxy model using the geographic and demographic characteristics to assign the missing data was developed. Figure 5 depicts the geographic distribution of the school facilities in the country.

In this case study, four taxonomies to characterize all buildings in the portfolio were used. These taxonomies include the seismic taxonomy (GLOSI seismic taxonomy (The World Bank, 2019)); a hurricane-wind taxonomy (The World Bank, 2020); and two functional taxonomies, one at the building level and the other at the school level. The latter functional taxonomies were developed for this case study, based on information gathered in the field and by online surveys filled by school principals in 2020 (The World Bank, 2020). Table 2 summarizes the four taxonomies with their parameters and attributes (for more information see Appendix A).

Figure 6 presents the 17 combinations of attributes that describe the Dominican Republic school building portfolio for the seismic taxonomy; Figure 7 presents the nine combinations for the hurricane taxonomy; Figure 8 presents the 14 combinations for the functional taxonomy at the building level, and Figure 9 shows the 15 combinations for the functional taxonomy at the school level. To understand the taxonomy string shown in Figures 6–9 the reader is referred to Appendix A.

The information gathered from the virtual surveys to school directors (number of bathrooms, fraction of bathrooms in good quality, year of construction) and structural and architectural drawings provided by the Ministry of Education (for example, to obtain the ratio between built to openings area) was used to define the quantitative scores for the functional criteria.

For the safety criterion, the results were obtained from the probabilistic risk assessments of CAPRA-GIS. The probabilistic model includes three main modules: the exposure, hazard, and vulnerability modules. The exposure model contains all the school buildings and its replacement value is approximately US$2,300 million. The hazard model included 8,710 earthquakes scenarios (ground acceleration)

Table 2. Taxonomies considered in the Dominican Republic case study.

Taxonomy	No.	Parameter
Seismic taxonomy	1	Main structural system
	2	Height range
	3	Seismic design level
	4	Diaphragm type
	5	Structural irregularity
	6	Span length/Wall panel length
	7	Pier type/Wall openings
	8	Foundation type
	9	Seismic pounding risk
	10	Effective seismic retrofitting
	11	Structural health condition
	12	Non-structural components
Hurricane taxonomy	1	Main structural system
	2	Height range
	3	Hurricane wind design level
	4	Roof shape
	5	Roof structure type
	6	Roof to wall/frame connection
	7	Roof covering type
	8	Roof covering to roof structure
	9	Roof health condition
	10	Roof projection length
	11	Presence of bracing in roof structure
	12	Wall typology
	13	Wall openings
	14	Typical opening size
	15	Opening's type
	16	Shutter provision
	17	Structural health condition
	18	Specific wind vulnerable elements
Functional taxonomy – building level	1	Main structural system
	2	Height range
	3	Functionality design level
	4	Ventilation
	5	Illumination
Functional taxonomy – school level	1	Functionality design level
	2	Student density
	3	Bathroom density
	4	Bathroom quality

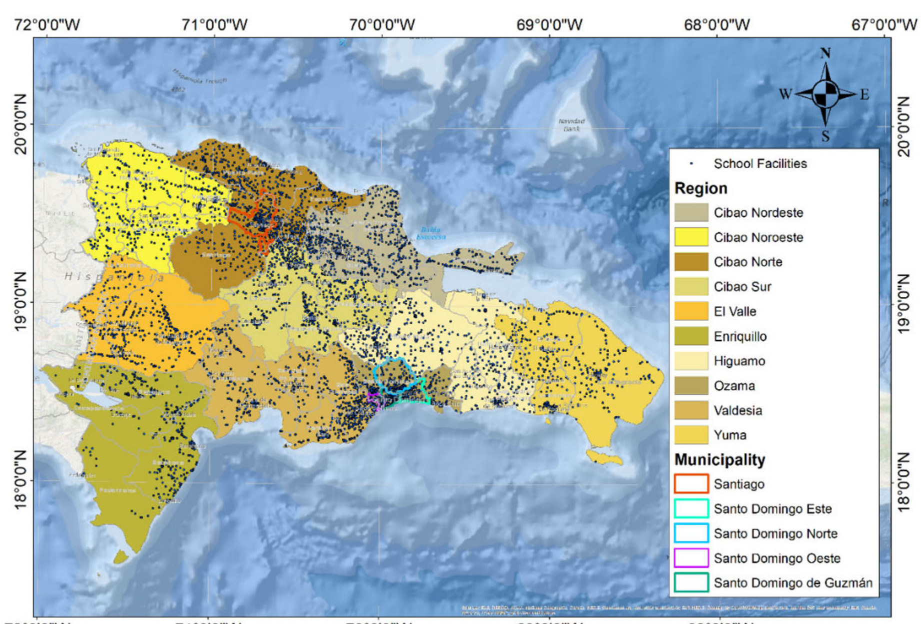


Figure 5. Distribution of school facilities in the Dominican Republic.

and 11,200 hurricanes (wind velocity), each characterized with its frequency and magnitude. The vulnerability models are based on the structural characteristics of the buildings and their behavior in terms of ground acceleration and wind pressure. One of the main results of this analysis is the average annual losses (AAL) per building. The sum of the seismic AAL is estimated in US$13.6 million while the sum of AAL for hurricane hazard is US$3.6 million for the current condition (The World Bank, 2020). For this implementation, the safety score was calculated with the relative average annual losses by building using an inverse direct rating technique, so the worst value is 0 and the best is 1, being consistent with the scores of the other criteria. To avoid the effect of extreme values (around 1%) in the process of normalization, we propose a maximum value of AAL of 15‰, which is usually consider as a high risk. Table 3 summarizes the source of the scores and the normalization method used at the building level.

Figure 10 presents the current valuation for the normalized criteria graphically. Each criterion has its specific distribution since they are measured independently from each other. This information is calculated at the building level and shows the current condition of the buildings and the improvement opportunities for each rating. As the mean values of *lighting*, *ventilation*, *student density*, *building age*, and *hurricane safety level* are close to 1.0, it shows that the current conditions of these criteria are better than those of the *bathroom's density*, *bathroom quality*, and *earthquake safety level*, which are not as high. Also, it is possible to see that the best condition in terms of the mean is related to the student's density, while the worst is the bathroom facilities density. This low density shows the importance of considering the Water and Sanitation Hygiene (WASH) aspects in the decision-making framework. Finally, in the case of student's density, the values are concentrated near the mean possibly because in developing countries usually the demand exceeds the supply. Therefore, existing schools are commonly used at its full capacity. These scores are the input for the BQI calculation described in the following section.

4.2. Building quality Index

With the database in place, the next step is to calculate the 4.2 Building Quality Index, BQI (q), for the entire portfolio as presented in Section 3.2. Figure 11 shows the attributes hierarchy for the BQI calculation in this case study.

To obtain the BQI in the current conditions, the first step is to determine the relative importance of each criterion, and

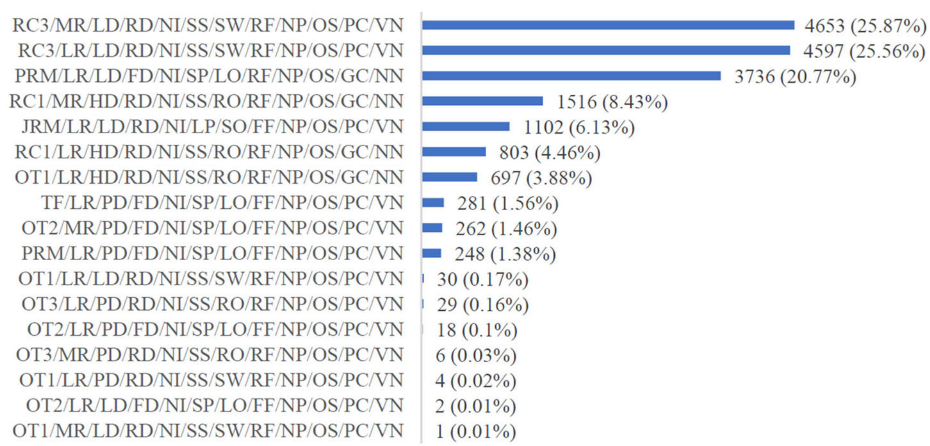


Figure 6. Seismic taxonomy attributes combination frequencies. Each bar contains to the right its frequency (number of buildings) and relative frequency (in parentheses).

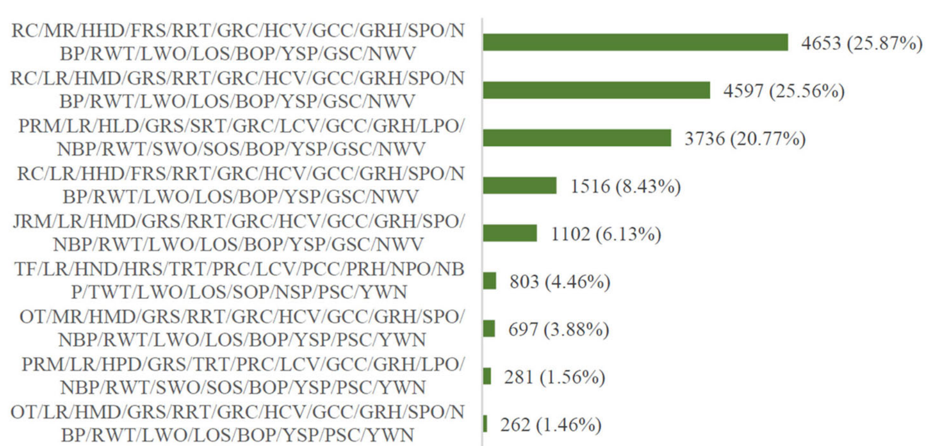


Figure 7. Hurricane taxonomy attributes combination frequencies. Each bar contains to the right its frequency (number of buildings) and relative frequency (in parentheses).

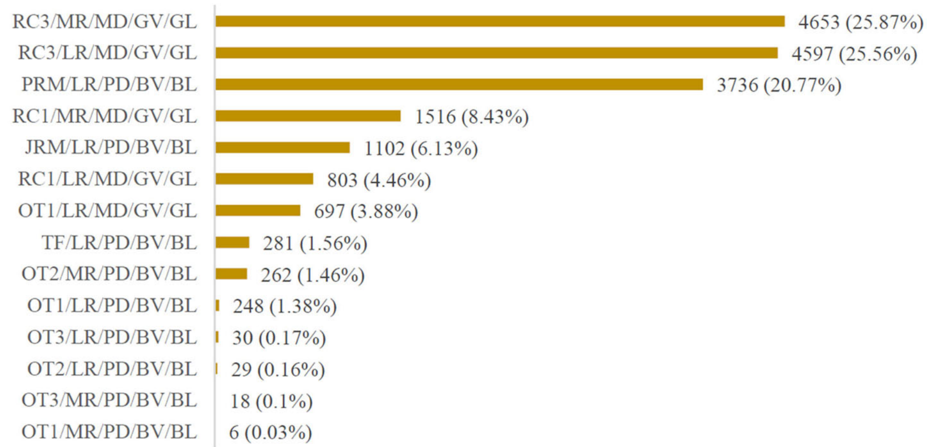


Figure 8. Functional building-level taxonomy attributes combination frequencies. Each bar contains to the right its frequency (number of buildings) and relative frequency (in parentheses).

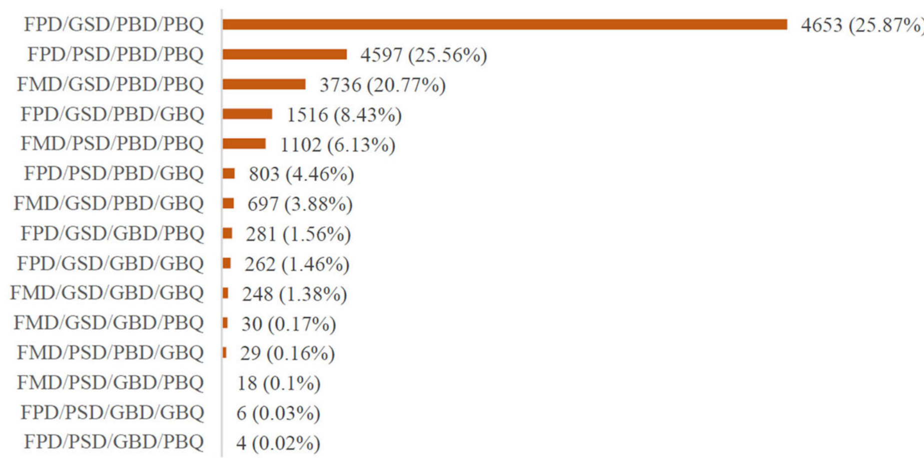


Figure 9. Functional school-level taxonomy attributes combination frequencies. Each bar contains to the right its frequency (number of buildings) and relative frequency (in parentheses).

Table 3. Score assignment method per school building.

Criterion	Sub-criterion	Source	Normalization method [0-1]
Functionality	Bathroom density	Number of bathrooms reported by school principals and number of students by school facility	Direct rating technique
	Bathroom quality	Quality level defined by school principals on a numerical scale	Direct rating technique
	Lighting (natural)	Open windows area relation to building area	Direct rating technique
	Ventilation (natural)	Open windows area relation to building area	Direct rating technique
	Student density	Number of students by school facility and total built area	Direct rating technique
	Building age	Year of construction	Direct rating technique
Safety	Earthquakes safety level	Relative average annual losses (AAL) from seismic risk assessment	Inverse direct rating technique. If AAL is greater than 15‰, a value of 0 is assigned in the normalization (worst value)
	Hurricane wind safety level	Relative average annual losses (AAL) from hurricane-wind risk assessment	Inverse direct rating technique. If AAL is greater than 15‰, a value of 0 is assigned in the normalization (worst value)

therefore their corresponding weighting. For this case study, the Optimal Scoring Method (OSM) was used to find the weights that maximize the total sum of BQI for the school buildings portfolio. This method was selected for simplicity, since other methods, such as the Analytic Hierarchy Process (AHP), require interviewing the decision makers to capture their preferences. The technical details of the OSM model can be found in detail in the literature (Sefair et al., 2009). For the OSM model, let C be the set of criteria; $s_{b,c}$ the normalized score valuation for building $b \in B$ in criterion $c \in C$; and w_c the weight for criterion $c \in C$. Specifically, for the case study, the weights w_c are obtained such that they comply with the following OSM model:

$$\max \sum_{b \in B} \sum_{c \in C} s_{b,c} \cdot w_c \tag{7}$$

subject to:

$$\sum_{c \in C} w_c = 1 \tag{8}$$

$$0.10 \leq w_c \leq 1.0 \quad \forall\ c\ \in C \tag{9}$$

$$w_{Earthquakes} \geq w_{Hurricane\ \ wind} \tag{10}$$

$$w_{Hurricane\ \ wind} \geq w_{Student\ \ density} \tag{11}$$

$$w_c \geq 0 \quad \forall\ c\ \in C \tag{12}$$

The objective function (7) maximizes the total *BQI* sum over the entire portfolio by calibrating the weights. This maximization means that more importance is given to the criteria that are in better condition. The rationale behind this logic is that the effort needed to improve these criteria is not as demanding, so they become more relevant in the implementation. Certainly, this can be modified to a minimization model to obtain the opposite result (as will be discussed in Section 4.6). Constraint (8) assures that the sum of weights is equal to one. The set of constraints in (9) guarantees that every weight will have at least 0.1 as the lower bound and the full value of 1.0 as the upper bound. The constraint (10) indicates that the weight associated with the earthquake's safety level criterion should be greater than or equal to the hurricane weight (considering hurricanes can be anticipated while earthquakes do not). Constraint (11) enforces that the weight associated with the hurricane criterion should be greater than or equal to the student density's weight (to give more importance to safety in general than students density). It is important to note that constraints (10) and (11) are subjective rules and should convey a global consensus of the decision makers' preferences, yet not at the granularity of giving a priori weights to each criterion, which is cumbersome in most situations. As part of a sensitivity analysis, other weight combinations are explored in Section 4.6. Finally, constraints (12) assure that all weights are non-negative (which in this case is redundant with (9) but is added for consistency with the original formulation of the model).

The result of the OSM model yields the optimal weights for the preferences expressed in the formulation (as raw rules). In this case, a weight of 10% is assigned to the *bathroom's density*, the *bathroom quality*, the *illumination*, the *ventilation*, and *building age* criteria; and a weight of 16.7% to *earthquake safety*, *hurricane wind safety*, and *student's density*. With these weights, it is possible to calculate the BQI for each school building in the current state, as it is summarized in Table 4. From these results, it is possible to conclude that no building is in its best or worst condition, therefore there is room for improvement.

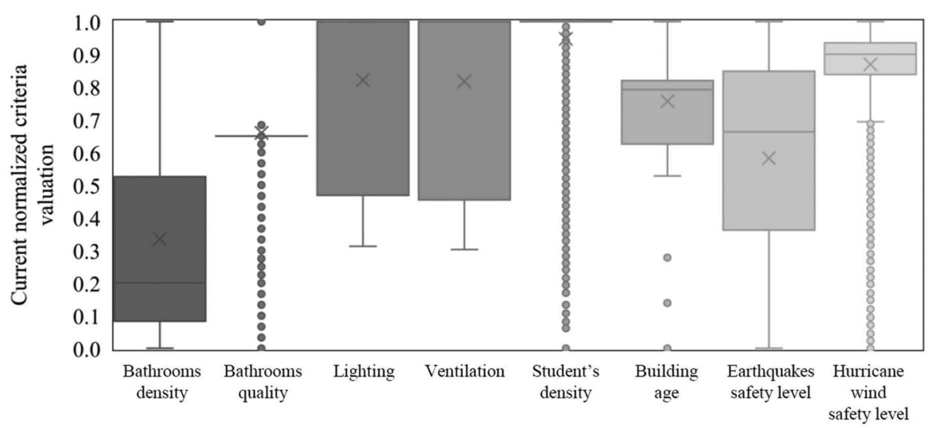


Figure 10. Summary of the current normalized criteria valuation.

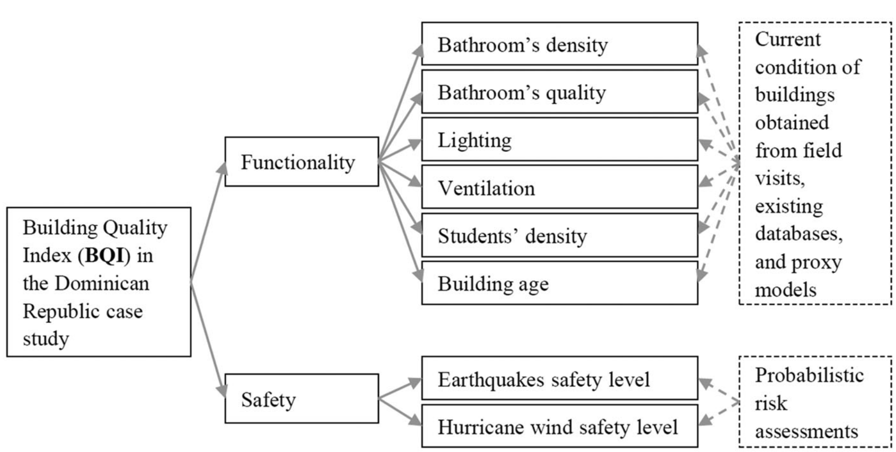


Figure 11. Attributes hierarchy for the case study.

4.3. Clustering

The clustering algorithm described in Section 3.3 is applied to each one of the taxonomies in the Dominican Republic public-school portfolio. The different number of clusters (henceforth referred as to parameter K) was fine-tuned and analyzed from an expert perspective to find the best distribution of clusters. For each cluster, the combination of the attributes that characterize a representative building (or index building) was identified to analyze and establish an intervention alternative.

Table 5 presents the seismic clusters. For this taxonomy, buildings were grouped into seven clusters, based on their seismic vulnerability. Through clustering it is possible to arrange the 17 combinations (from Figure 6) into only seven groups of buildings. In particular, note that the reinforced masonry buildings with flexible roof (PRM/LR/LD) are included in cluster 1; the reinforced masonry buildings with rigid roof (JRM/LR/LD) are part of cluster 2; the reinforced concrete short-column one-story buildings (RC3/LR/LD) are located in cluster 3; high-design reinforced concrete buildings are part of cluster 4; the non-engineered oldest buildings are part of cluster 5; a group of buildings with variable characteristics forms cluster 6; and the reinforced concrete short-column two-story buildings, RC3/MR/LD, are part of cluster 7. This distribution of buildings is logical from an engineering point of view. The interventions for these clusters could include replacements of buildings; extensive, moderate, and minor retrofitting; or doing nothing, as is the case for low vulnerability buildings and for high variability buildings where no large-scale intervention can be planned.

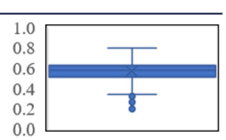
Table 6 illustrates the five hurricane wind taxonomy clusters (in contrast to the nine possible attribute combinations of Figure 7). Cluster 1 contains the timber buildings. These buildings are the most vulnerable in the portfolio and therefore a replacement should be considered. All the reinforced buildings have similar wind vulnerability and are part of cluster 2. For this type of building, no intervention is required. Reinforced masonry (RM) buildings are divided into two clusters since the oldest ones have a higher vulnerability (cluster 3) than the newer ones (cluster 4). Finally, cluster 5 includes buildings with high variability of characteristics and therefore no large-scale intervention can be planned.

Similarly, Table 7 presents the building level functional taxonomy clustering results. The clustering algorithm is able to classify all 14 attribute combinations in two main groups. The first cluster includes almost all the masonry buildings, which are the oldest and hence have poor internal conditions. The second cluster includes almost all the reinforced concrete buildings, which were built recently and their internal conditions are better. Functional deficiencies concerning ventilation and illumination were identified in cluster 1, while cluster 2 does not present these problems. Consequently, the intervention for cluster 1 is the installation of a new ventilation and illumination system.

Finally, Table 8 summarizes the four clusters that group the 15 attribute combinations in the school-level functional taxonomy. The first cluster includes school facilities with the poorest building conditions; therefore, the proposed intervention is the construction of new buildings. The second cluster includes the school facilities where bathroom facilities are insufficient and low quality, so the intervention is targeted to build new bathrooms and to maintain the existing ones. The third cluster includes schools with good quality bathrooms, but insufficient in number. In this cluster, the intervention is designed to build new bathroom batteries. Lastly, the fourth cluster includes school facilities with good conditions in relation to density and bathrooms. It is important to note that in these clusters, the interventions are targeted to improve the school facility and the improvement will affect all school buildings at the facility.

Table 4. Current BQI statistics in the Dominican Republic Portfolio.

Statistic	BQI current condition
Mean	0.570
Median	0.583
Maximum	0.790
Minimum	0.197
Standard deviation	0.091



4.4. Interventions

Once the deficiencies are identified in the previous step, it is possible to design the intervention strategies and quantify the corresponding BQI improvement and unitary cost in a given building. Table 9 presents the summary of generic interventions, unitary cost (as of 2021), and quality improvement for each cluster (step A). To calculate the total cost of the intervention in a building, the unitary cost and the building's area is used. The BQI improvement (Δq) is also building dependent, as it depends on its location and base risk metric. Note that the same seismic intervention of two buildings in the same cluster may end up having different costs and BQI improvements.

As the goal is to illustrate the decision-making methodology with a holistic perspective, the technical details of each intervention are out of the scope of this paper and therefore are not presented. The different interventions in this case study might not be generally applicable to other countries or case studies. Each intervention should be assessed and devised by experts in each one of the domains (i.e. structural or functional experts) in the application setting. Also, the unitary costs are representative rather than real costs and they just provide a relative scale for the illustrative application of the methodology.

Table 10 presents a sample of a database produced by applying the interventions of Table 9 to every specific building (step B). One intervention per cluster was selected, thus the database includes four interventions for each building (as every building belongs to one cluster per taxonomy). This database is the output of module 3, and input for the optimization model of module 4.

4.5. Optimization component

The database of interventions (see Table 10) feeds the optimization component. Assuming a limitless budget, the cost of

Table 5. Seismic clusters description.

ID	Taxonomy attributes combination	Cluster name	Percentage of buildings	Structural deficiencies
1	RM/LR(1)/LD/FD/NI/SP/LO/RF/NP/OS/PC/VN	Reinforced masonry with flexible roof	21%	Lack of rigid diaphragm Low shear capacity Weak connections Out-of-plane failure Low material quality
2	RM/LR(1)/LD/RD/NI/SP/LO/RF/NP/OS/PC/NN	Reinforced masonry with rigid roof	6%	Low shear capacity Weak connections Out-of-plane failure Low material quality
3	C3/LR(1)/LD/RD/NI/SS/SW/RF/NP/OS/PC/VN	Reinforced concrete short-column one story	26%	Short column Weak story
4	RC1/MR/HD/RD/NI/SS/RO/RF/NP/OS/GC/VN	High design	17%	No structural deficiencies
5	RM/LR(1)/LD/PD/NI/SP/LO/RF/NP/OS/PC/VN	Non-engineered	5%	High seismic vulnerability
6	Other	Other	~0%	No Information.
7	RC3/MR/LD/RD/NI/SS/SW/RF/NP/OS/GC/VN	Reinforced concrete short-column one story	26%	Short column Low stiffness Weak story Strong beam weak column

Table 6. Hurricane-wind clusters description.

ID	Taxonomy attributes combination	Cluster name	Percentage of buildings	Structural deficiencies
1	TF/LR/HPD/HRS/TRT/PRC/LCV/PCC/PRH/SPO/NBP/RWT/SWO/SOS/BOP/YSP/PSC/YWN	Timber	2%	High hurricane wind vulnerability
2	FRS/RRT/GRC/HCV/GCC/GRH/SPO/NBP/RWT/LWO/LOS/BOP/YSP/GSC/YWN	RC	43%	No deficiencies
3	RM/LR/HLD/ GRS/SRT/PRC/LCV/PCC/PRH/SPO/NBP/RWT/LWO/LOS/BOP/YSP/PSC/YWN	RM Low	21%	Roof coverings
4	RM/LR/HPD/ GRS/TRT/PRC/LCV/PCC/PRH/SPO/NBP/RWT/LWO/LOS/BOP/YSP/PSC/YWN	RM Poor	1%	Roof coverings Roof structure
5	–	Other	34%	No Information

Table 7. Functional building-level clusters description.

ID	Taxonomy attributes combination	Cluster name	Percentage of buildings	Deficiencies
1	RM/MR/PD/PD/PV/PI	Poor classroom conditions	32%	No natural ventilation No natural illumination
2	RC/MR/GD/GD/GV/GI	Good classroom conditions	68%	No deficiencies

Table 8. Functional school-level clusters description.

ID	Taxonomy attributes combination	Cluster name	Percentage of buildings	Deficiencies
1	PSD/PBD/PBQ	Poor condition	18%	Poor student density Poor bathroom density Poor bathroom quality
2	GSD/PBD/PBQ	Poor bathroom condition	70%	Poor bathroom density Poor bathroom quality
3	GSD/PBD/GBQ	Poor bathroom density	7%	Poor bathroom density
4	Other	Good condition	5%	No information

implementing all the interventions identified in module 4 for all the schools in the database adds up to US\$1,023,489,100 (an average spending by school building of around US\$56,000). The maximum improvement of *BQI*, $\Delta q = 4{,}121$ points. These reference values allow the comparison of different scenarios.

As a first illustrative scenario, a budget limit of US\$100,000,000, value of M in the budget constraint, is defined (an average spending of US\$5,500 per school building). The criteria weights according to the output of the OSM model in Section 4.2 are fixed and a minimum $\underline{q}_b = 0.5$ is defined for all buildings. The optimization model reaches a solution with a total spending of \$99,999,970 with a Δq of 1,334 points. The optimization component carefully chooses the right interventions and obtains 32.4% of the total quality improvement by just investing 9.8% of the cost of the limitless budget scenario. In other words, the optimization model finds the best quality improvement with a given budget.

Following the same logic, a parametric analysis was conducted to understand how the BQI improvement varies at different budget levels. Figure 12 shows the optimized interventions frontier, resulting from varying the budget limit M from 0% to 100% of the cost of all interventions. The *ideal* point is the one with 0% budget and 100%

Δq, which is clearly utopian, but acts as a magnet for unveiling a frontier of optimal interventions in the buildings' portfolio. Note that the first scenario, with an approximate 10% budget constraint and 32.4% of the maximum Δq, lies on this frontier. This is just one of many scenarios with varying budget levels.

This result is also helpful to compare the Δq improvement by implementing targeted programs, such as implementing at the same time *all* the interventions belonging to only one category (seismic, hurricane, functional at the building level, and functional at school-level interventions),

Table 9. Unitary cost and BQI improvement by cluster intervention.

Taxonomy	ID	Cluster name	Generic intervention	Unitary cost (2021)	BQI improvement (Δq)
Seismic	1	Reinforced masonry with flexible roof	Concrete confinement elements Ring beam	180 US$/m^2	Reduction in the average annual losses (AAL) due to the implementation of the retrofitting
	2	Reinforced masonry with rigid roof	Concrete confinement elements Foundation's retrofitting	80 US$/m^2	
	3	Reinforced concrete short-column one story	Masonry walls isolation Lateral stiffness elements	25 US$/m^2	
	4	High design	No intervention	0	
	5	Non-engineered	Replacement	535 US$/m^2	
	6	Other	No Intervention	0	–
	7	Reinforced concrete short-column one story	Masonry walls isolation Steel diagonals in both stories	140 US$/m^2	Reduction in the average annual losses (AAL) due to the implementation of the retrofitting
Hurricane	1	Timber	Replacement of the building	535 US$/m^2	Reduction in the average annual losses (AAL) due to the implementation of the retrofitting
	2	RC	No intervention	0	–
	3	RM Low	Change of covering and retrofitting of connections	75 US$/m^2	Reduction in the average annual losses (AAL) due to the implementation of the retrofitting
	4	RM Poor	Replacement of roof structure Change of covering and retrofitting of connections	110 US$/m^2	
	5	Other	No intervention	0	–
Functional at building level	1	Poor classroom conditions	Installation of a new artificial ventilation system Installation of a new artificial illumination system	65 US$/m^2	Maximum value (1.0) minus current rating in Illumination and Ventilation score
	2	Good classroom conditions	No intervention	0	0
Functional at school level	1	Poor condition	Construction of new buildings including new bathrooms	535 US$/m^2	Maximum value (1.0) minus current rating in Bathroom's density and quality and in Student score
	2	Poor bathrooms condition	Construction of new bathrooms Maintenance of existing bathrooms	1200 US$/New Unit 320 US$/ Existing Unit	Maximum value (1.0) minus current rating in Bathroom's density and quality score
	3	Poor bathrooms density	Construction of new bathrooms	1200 US$/New Unit	Maximum value (1.0) minus current rating in Bathroom's quality score
	4	Good condition	No intervention	0	–

instead of implementing a mix of different types. These interventions are represented in Table 11 and in Figure 12 as one point, relating the total cost of implementing the set of interventions and the sum of the benefits. The results presented in Figure 12, show that for the same budget (vertical projection to the optimized frontier), the optimization component will lead to up to a 3.54-fold Δq increment compared to the targeted programs. Similarly, for the same Δq improvement (horizontal projection to the optimized frontier), with the implementation of the optimization model, the investment could be reduced from 39% up to 65%.

These results show how relevant is to apply a consistent and technically robust methodology in the decision-making process for the prioritization and implementation of interventions in the existing infrastructure. On the contrary, not doing so could lead to the loss of economic resources or the loss of quality, which as shown before, have a direct impact on infrastructure's long-term resilience and hence education quality.

4.6. Sensitivity analysis with different decision profiles

In the budget parametric analysis presented above, the criteria weights were fixed according to the optimal scoring model presented in Section 4.2. However, if the optimization in the OSM changes to minimization instead of maximization, it will prioritize bathrooms density, above all other criteria. Furthermore, a different decision maker could

Table 10. Illustrative example of interventions database.

ID	Seismic interventions – building level			Hurricane interventions – building level			Functional interventions – building level			Functional interventions – school level		
	Type	Total cost (US$)	Δq	Type	Total cost (US$)	Δq	Type	Total cost (US$)	Δq	Type	Total cost (US$)	Δq
1	Minor retrofitting	$ 4,200	0.049	No intervention	$ 0	0.000	No intervention	$ 0	0.000	New building	$ 44,160	0.125
2	Minor retrofitting	$ 4,200	0.049	No intervention	$ 0	0.000	No intervention	$ 0	0.000	New building	$ 44,160	0.125
3	Replacement	$ 374,500	0.095	No intervention	$ 0	0.000	artificial Vent. and Light	$ 45,500	0.138	New building	$ 78,720	0.136
	…	…	…	…	…	…	…	…	…	…	…	…
18279	Minor retrofitting	$ 4,200	0.029	No intervention	$ 0	0.000	No intervention	$ 0	0.000	New bathrooms and maintenance	$ 9,920	0.115
18280	Minor retrofitting	$ 4,200	0.029	No intervention	$ 0	0.000	No intervention	$ 0	0.000	New bathrooms and maintenance	$ 9,920	0.115

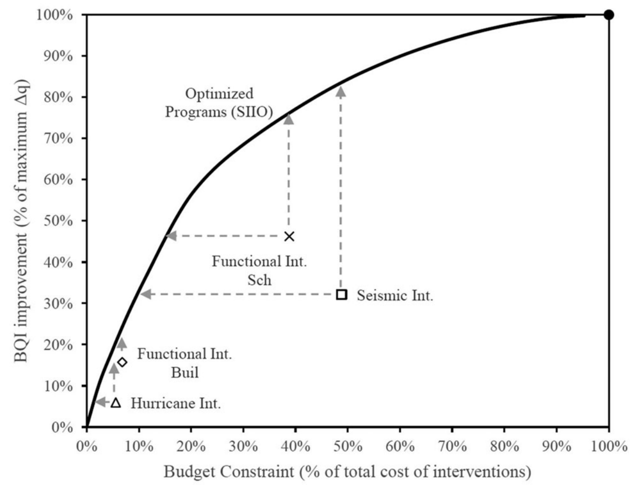


Figure 12. Optimal investments frontier with the optimal-scoring decision profile.

have different preferences and specify other types of restrictions in the model. Therefore, one may ask: if the decision profile changes (i.e. criteria weights), how much impact will it have on the optimization investments frontier? To address this question, a thorough sensitivity analysis is conducted, including the results presented for the OSM with maximization, the OSM with minimization, and five parametric decision profiles. In these parametric profiles, different weights were given to the first level of the hierarchy, namely, the functionality and safety criteria. For the second level of the hierarchy, the weights were evenly distributed across all sub-criteria. The first two parametric profiles are biased toward the functionality criterion (100% and 75%); a balanced profile (same weight for functionality and safety); and two decision profiles with a bias toward the safety criterion (75% and 100%). Table 12 shows the final weights included in the seven decision-maker profiles.

Since each profile represents a different measure of quality, the direct results are not comparable to each other since they measure quality with a different index (different weights). Therefore, the results should be analyzed and presented in terms of the balanced profile $\Delta q_{Profile\,3-Balanced}$. That is, resulting interventions are obtained with the Δq obtained for each profile, but the resulting Δq improvement was converted with the weights of the balanced profile (Profile 3) to make the curves comparable. Also, note that cost is the same in each profile since it is not dependent on the weights assigned in each decision profile. Therefore, Figure 13 displays the optimal investment frontiers for each decision profile in terms of the $\Delta q_{Profile\,3-Balanced}$.

Considering the weights presented above, it is worth noting that OSM-min is farther away from the balanced frontier, which can be expected considering the strong bias given to the functionality in this profile (i.e. functionality accounts for 80% of the total weight). In relation to the five parametric profiles, the less biased profiles (2 and 4) are the ones nearest to the balanced results, while the more biased ones (1 and 5) are the farthest. Results for Profiles 2 and 4 are near to the ones of Profile 3 but are not equal since they were designed to fulfill other objectives by selecting

Table 11. Targeted programs characteristics.

Interventions set	Total cost (US$ million [%])	Total BQI improvement (Δq [%])	Optimized program BQI-improvement for the same budget (*n*-fold)	Optimized program cost reduction for the same BQI improvement
All seismic	$ 500 [49%]	1,322 [32%]	2.60	65%
All hurricane	$ 57 [6%]	247 [6%]	3.54	75%
All functional at building level	$ 70 [7%]	648 [16%]	1.54	39%
All functional at school level	$ 397 [39%]	1,904 [46%]	1.65	62%

Table 12. Criteria weights for the decision-maker profiles.

Hierarchy	Criterion weight	OSM Max	OSM Min	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
First level	Functionality	67%	80%	100%	75%	50%	25%	0%
	Safety	33%	20%	0%	25%	50%	75%	100%
Second level	Bathrooms density	10.0%	30.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Bathrooms quality	10.0%	10.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Lighting	10.0%	10.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Ventilation	10.0%	10.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Student's Density	16.7%	10.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Building Age	10.0%	10.0%	16.7%	12.5%	8.3%	4.2%	0.0%
	Earthquakes safety level	16.7%	10.0%	0.0%	12.5%	25.0%	37.5%	50.0%
	Hurricane wind safety level	16.7%	10.0%	0.0%	12.5%	25.0%	37.5%	50.0%

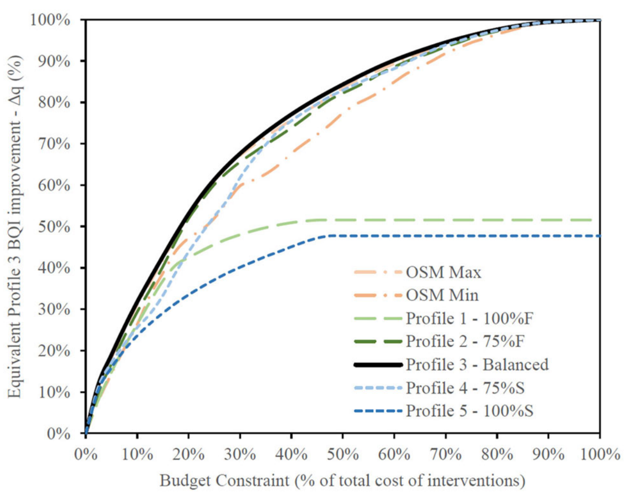


Figure 13. Optimal frontiers for different decision profiles.

different weights. Furthermore, in the 100% biased profiles (1 and 5), the BQI improvement reaches barely 40% of the total benefits and not 100% as the others. The flattened part of the curves occurs since in these two profiles a weight of 0% is selected for either the functional or safety criteria, therefore, the optimization model does not select any interventions that are targeted to improve these criteria. These results show that, in terms of the balanced profile, it is not recommended to bias any criterion by assigning 100% of the weight. The biased profiles neglect the possible benefits obtained in a subset of interventions that are logical from a holistic perspective. Finally, the methodology presented in this paper can be adapted to different decision-maker profiles, making it robust to implement in contexts with multiple stakeholders with different interests.

4.7. Comparison with single-policy programs

The question of how the optimized intervention program compares to simplified programs remains. For example, government officials might want to assign resources –and therefore conduct interventions– prioritizing the number of students, the cost, or the level of quality, until the whole budget is allocated. These rule-of-thumb programs can be much simpler to design than optimize the whole set of interventions. To see how these simplified programs compare to the proposed optimized interventions, six single-policy programs were designed based on the sum of the intervention's costs and the sum of the BQI improvement (over the buildings). These programs are based on sorting the building's interventions based on three criteria: number of students, intervention costs, and BQI improvement. Each of these criteria was sorted in descending and ascending order, leading to six intervention programs, as presented in Figure 14.

Figure 15 depicts the optimized program in comparison to the single-policy programs (using the weights identified with the OSM-max presented in Section 4.2 in all cases). The first conclusion that can be drawn from this comparison is that the optimization results obtained from the implementation of the proposed methods are efficient in terms of the unveiled frontier (i.e. best quality, for a given budget). In that sense, all simplified programs are less efficient in terms of prioritizing interventions that improve the overall quality of the infrastructure system.

To quantify the differences between the programs, the relative efficiency of the program compares the area under the curve for each program with respect to the area under the curve of the optimized program (efficient frontier). This is generalized in multi-objective optimization for more dimensions as the hypervolume metric (Guerreiro, Fonseca, & Paquete, 2020; Zitzler, Thiele, Laumanns, Fonseca, & Da Fonseca, 2003). Table 13 shows that the *cost* program (*ascending* order) has a relative efficiency of 91%, whereas the *cost* program (*descending* order) has a relative efficiency of just 50.7%. With scarce information, other simplified programs can be designed and evaluated in terms of their efficiency.

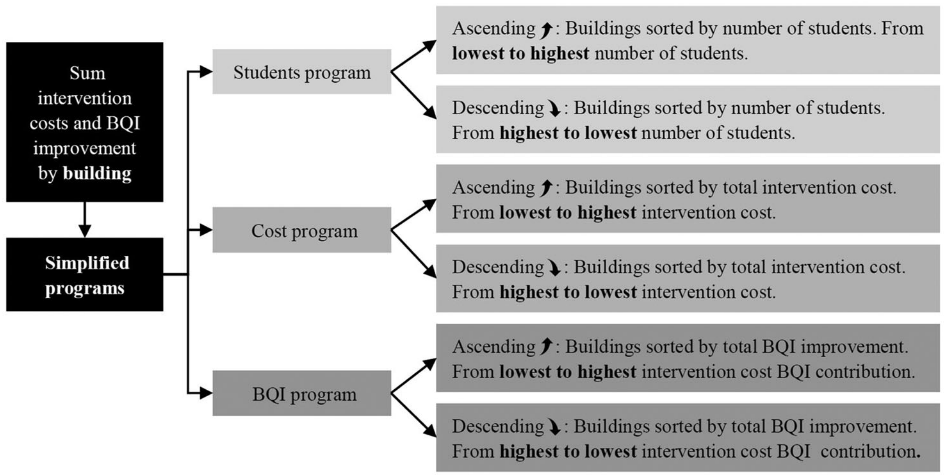


Figure 14. Single-policy interventions programs.

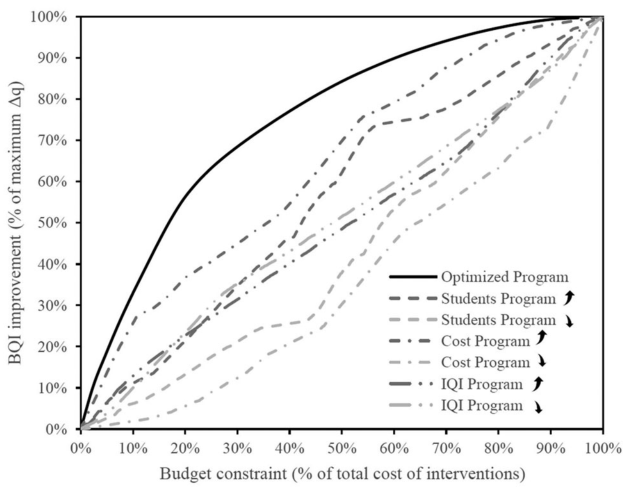


Figure 15. Comparison of optimal investment with simplified programs.

Table 13. Optimized program efficiency related to simplified programs.

Program	Relative efficiency
Optimized program	**100.0**%
Students program ascending	79.2%
Students program descending	61.1%
Cost program ascending	91.0%
Cost program descending	50.7%
BQI program ascending	70.0%
BQI program descending	71.7%

5. Conclusions

The main contribution of this paper is the decision-making framework for the holistic improvement of school infrastructure in terms of functionality and safety. The objective of the proposed framework is to maximize the quality of the school infrastructure by allocating a budget wisely. The method consists of four modules: data collection, building quality index, clustering, intervention definition, and the optimization component. The application of the methodology leads to the selection of an optimal set of interventions to implement for a school building's portfolio. Even though the framework is supported by quantitative data and analytics models in several modules, it is important to note that it is not a purely data-driven process. The application of this method relies on experts' judgment to ensure the quality of the results and to make them truly applicable. The method aids the decision-making process but requires valuable input from experts and decision makers.

A case study of the school buildings portfolio of the Dominican Republic was implemented to illustrate the decision-making framework. This implementation showed that the methodology leads to a quality improvement up to 3.54 times that of targeted programs with a given budget and can potentially save up to 65% of the budget with a given quality improvement threshold. The method also excels in terms of relative efficiency in comparison to single-policy allocation programs, showing inefficiencies ranging from 9% to 50% in the implementation of the simplified programs. The flexibility of the method and how it can adapt to multiple decision-maker profiles was illustrated by conducting a sensitivity analysis, showing the effect of emphasizing certain criteria on the final results.

The proposed methodology can be applied in any context where school infrastructure needs to be improved holistically. Even though the method has significant value in middle-income countries where the school systems are usually in bad condition, it can also be adapted to high-income countries where information may be better and other criteria become available. Indeed, characteristics such as the quality of the leisure spaces and accessibility can be included in the decision-making process to target other types of interventions. At the other end of the spectrum, the method could also be adapted to low-income countries, where information is scarce and other proxy socio-economic and geographical variables may be derived. The implementation of the methodology in low-income countries could help to answer questions such as if safety might be prioritized given the quality of construction and hazard exposure, or if it is better to invest in functionality to retain students in school and therefore improve the country's education and build capacity for economic development. Aside from school infrastructure, a similar decision-making framework could be designed to prioritize other types of infrastructure investment such as in bridges or hospitals, among others.

However, despite the strengths of the method, there is still room for improvement. Research currently underway involves considering other non-additive utility functions in the decision-making framework. For example, the user may want to consider criteria that may not be added linearly since there could be some complementarity or correlations among them. This can be required in other types of contexts such as bridges, where the infrastructure is interconnected. Furthermore, additional taxonomies with other types of variables can also be considered in the clustering procedure. Another area of improvement is to add the time dimension to the prioritization process (Medaglia, Hueth, Mendieta, & Sefair, 2008). As it stands right now, the decision-making framework is static in the sense that it decides the investments at a given moment in time. An extension of the optimization model could consider time to schedule the interventions over time.

Acknowledgments

This study was developed under a project in the Dominican Republic funded by the Global Program for Safer Schools (GPSS) of The World Bank. The authors are thankful to the World Bank and the entire GPSS technical team and to the Dominican Republic Ministry of Education who facilitated the information for the project and were always keen to help. Prof. Dina D'Ayala and Dr. Rafael Fernández gladly acknowledge the support of the UNESCO Chair in Disaster Risk Reduction and Resilience Engineering, which funds some of their time. The authors would also like to thank the Vice Presidency of Research & Creation's Publication Fund at Universidad de los Andes for its financial support. Last, but not least, this paper is dedicated to the memory of Professor Luis E. Yamin, team leader of CIMOC at Universidad de Los Andes for over 30 years, who led this research at an early stage and was deeply involved with the design of the methodology.

ORCID

Rafael Fernández http://orcid.org/0000-0002-2585-1958
Juan Francisco Correal http://orcid.org/0000-0002-6904-0081
Dina D'Ayala http://orcid.org/0000-0003-3864-2052
Andrés L. Medaglia http://orcid.org/0000-0003-1529-0322

References

Adhikari, R., D'Ayala, D., Fernández, R., Yamin, L., Narssipour, A., P Vatteri, A., … Ramírez, F. (2023). GLOSI taxonomy: A tool for 'seismic risk assessment' oriented classification of school buildings. *International Journal of Disaster Risk Reduction*, *87*, 103594. doi:10.1016/j.ijdrr.2023.103594.

Adhikari, R., D'Ayala, D., Ferreira, C., & Ramirez, F. (2018, June 18–21). Structural classification system for load bearing masonry school buildings. In *16th European Conference on Earthquake Engineering*, Thessaloniki, Greece.

Aleskerov, F., Say, A., Toker, A., Akin, H., & Altay, G. (2005). A cluster-based decision support system for estimating earthquake damage and casualties. *Disasters*, *29*(3), 255–276. doi:10.1111/j.0361-3666.2005.00290.x

Anelli, A., Santa-Cruz, S., Vona, M., Tarque, N., & Laterza, M. (2019). A proactive and resilient seismic risk mitigation strategy for existing school buildings. *Structure and Infrastructure Engineering*, *15*(2), 137–151. doi:10.1080/15732479.2018.1527373

Asadi, A., Salman, A., & Li, Y. (2019). Multi-criteria decision-making for seismic resilience and sustainability of diagrid buildings. *Engineering Structures*, *191*, 229–246. doi:10.1016/j.engstruct.2019.04.049

Barrett, P., Treves, A., Shmis, T., Ambasz, D., & Ustinova, M. (2019). The impact of school infrastructure on learning: A synthesis of the evidence.

Beynon, J. (1997). *Physical facilities for education: What planners need to know*. Unesco, International Institute for Educational Planning.

Bradley, R. (2018). Decision theory: A formal philosophical introduction. In S. Hansson & V. Hendrick (Eds.), *Introduction to formal philosophy* (pp. 611–655). Cham: Springer. doi:10.1007/978-3-319-77434-3_34

Casella, G., Fienberg, S., & Olkin, I. (2013). *An introduction to statistical learning*. Springer texts in statistics (p. 618). New York, NY: Springer. Retrieved from http://books.google.com/books?id=9tv0taI8l6YC.

Castillo, M. (2011). *Toma de decisiones en las empresas* (Ediciones Uniandes). Bogotá.

Castro-Lacouture, D., Medaglia, A. L., & Skibniewski, M. J. (2007). Supply chain optimization tool for purchasing decisions in B2B construction marketplaces. *Automation in Construction*, *16*(5), 569–575. doi:10.1016/j.autcon.2006.08.005

D'Ayala, D., Galasso, C., Nassirpour, A., Adhikari, R. K., Yamin, L., Fernandez, R., … Oreta, A. (2020). Resilient communities through safer schools. *International Journal of Disaster Risk Reduction*, *45*, 101446. doi:10.1016/j.ijdrr.2019.101446

Educate a Child. (2020). Barriers to education. Retrieved from https://educateachild.org/explore/barriers-to-education.

EERI. (2019). Concrete buildings damaged in earthquakes. Retrieved from http://db.concretecoalition.org/list?submit=Search&q=&occupancy=Education.

Fernández, R., Correal, J. F., D'Ayala, D., & Medaglia, A. L. (2023). Towards disaster risk mitigation on large-scale school intervention programs. *International Journal of Disaster Risk Reduction*, *90*, 103655. doi:10.1016/j.ijdrr.2023.103655

GEER. (2016). *GEER-ATC earthquake reconnaissance April 16th 2016*. Muisne, Ecuador.

GEER. (2017). *Geotechnical engineering reconnaissance of the 19 September 2017 Mw 7.1 Puebla-Mexico City Earthquake Version 1.0*.

Govaert, G., & Nadif, M. (2008). Block clustering with Bernoulli mixture models: Comparison of different approaches. *Computational Statistics & Data Analysis*, *52*(6), 3233–3245. doi:10.1016/j.csda.2007.09.007

Guerreiro, A., Fonseca, C., & Paquete, L. (2020). The hypervolume indicator: Problems and algorithms. Retrieved from http://arxiv.org/abs/2005.00515.

Gunasekera, R., Ishizawa, O., Aubrecht, C., Blankespoor, B., Murray, S., Pomonis, A., & Daniell, J. (2015). Developing an adaptive global exposure model to support the generation of country disaster risk profiles. *Earth-Science Reviews*, *150*, 594–608. doi:10.1016/j.earscirev.2015.08.012

Hansson, S. O. (1990). *An overview of decision theory*. Stockholm: Uppsala University.

Hansson, S. O. (2005). *Decision theory: A brief introduction*. Stockholm: Royal Institute of Technology.

Huss, O., & Keudel, O. (2020). *Open government in education: Clarifying concepts and mapping initiatives*. UNESCO.

IADB. (2014). *Learning in twenty-first century schools*. Retrieved from http://idbdocs.iadb.org/wsdocs/getdocument.aspx?docnum=36894958.

Icontec; Ministerio de Educación Nacional. (2017). *Planeamiento y diseño de ambientes para la educación inicial en el marco de la atención integral*. Retrieved from https://www.mineducacion.gov.co/1759/articles-355996_recurso_1.pdf.

Joint Research Centre - European Comission. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. Paris: OCDE Publishing.

Kabir, G., Sadiq, R., & Tesfamariam, S. (2014). A review of multi-criteria decision-making methods for infrastructure management. *Structure and Infrastructure Engineering*, *10*(9), 1176–1210. doi:10.1080/15732479.2013.795978

Medaglia, A. L., Hueth, D., Mendieta, J. C., & Sefair, J. A. (2008). Multiobjective model for the selection and timing of public enterprise projects. *Socio-Economic Planning Sciences*, *42*(1), 31–45. doi:10.1016/j.seps.2006.06.009

Muñoz, V. A., Carby, B., Abella, E. C., Cardona, O. D., López-Marrero, T., Marchezini, V., … Wisner, B. (2020). Success, innovation and challenge: School safety and disaster education in South America and the Caribbean. *International Journal of Disaster Risk Reduction*, *44*(November 2019), 101395. doi:10.1016/j.ijdrr.2019.101395

Naja, M., & Baytiyeh, H. (2014). Towards safer public school buildings in Lebanon: An advocacy for seismic retrofitting initiative. *International Journal of Disaster Risk Reduction*, *8*, 158–165. doi:10.1016/j.ijdrr.2014.03.005

National Academies of Sciences, Engineerinng and Medicine. (2007). *Multi-objective optimization for bridge management*. Washington DC: National Academies Press.

Osaro, N., & Wokekoro, E. (2018). Stakeholders roles in improving the current state of public secondary schools infrastructure in Rivers State, Nigeria. *International Journal of Social Sciences and Humanities Invention*, *5*(3), 4503–4508.

Prasad, J., Singh, Y., Kaynia, A., & Lindholm, C. (2009). Socioeconomic clustering in seismic risk assessment of urban housing stock. *Earthquake Spectra*, *25*(3), 619–641. doi:10.1193/1.3158547

Rardin, R. (1998). *Optimization in operations research*. Hoboken, NJ: Pearson.

Saaty, T. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26. doi:10.1016/0377-2217(90)90057-I

Saeed, M., Javed, K., & Atique Babri, H. (2013). Machine learning using Bernoulli mixture models: Clustering, rule extraction and dimensionality reduction. *Neurocomputing*, *119*, 366–374. doi:10.1016/j.neucom.2013.03.021

Salem, O., Miller, R., Deshpande, A., & Arurkar, T. (2013). Multi-criteria decision-making system for selecting an effective plan for bridge rehabilitation. *Structure and Infrastructure Engineering*, *9*(8), 806–816. doi:10.1080/15732479.2011.615843

Sefair, J., Castro-Lacouture, D., & Medaglia, A. (2009). Material selection in building construction using Optimal Scoring Method (OSM). In Construction Research Congress 2009: Building a Sustainable Future (pp. 1079–1086). ASCE. doi:10.1061/41020(339)109

SEOPC. (2006). *R-023 Reglamento para el diseño de plantas fisicas escolares*. Santo Domingo: República Dominicana.

The United Nations. (1948). *Universal declaration of human rights*. Retrieved from https://www.un.org/en/about-us/universal-declaration-of-human-rights.

The United Nations. (2015). *Sustainable development goals*. Retrieved from https://sdgs.un.org/es/goals.

The United Nations. (2020). *Goal 4: Quality education*. Retrieved from https://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-4-quality-education.html.

The World Bank. (2019). *Global library of school infrastructure - taxonomy*. Washington DC: The World Bank Report. Retrieved from https://gpss.worldbank.org/sites/gpss/files/2019-10/GLOSI%20taxonomy%20guide.pdf.

The World Bank. (2020). *Evaluación del riesgo por sismo y viento huracanado y planes de reducción del riesgo para la infraestructura educativa pública de República Dominicana*. Washington DC: The Global Program for Safer Schools.

The World Bank. (2020). *Global library of school infrastructure*. Washington, DC: Global Program for Safer School. Retrieved from https://gpss.worldbank.org/index.php/en/about-us.

The World Bank. (2020). *Realizing the future of learning*. Washington, DC. Retrieved from http://documents.worldbank.org/curated/en/250981606928190510/Realizing-the-Future-of-Learning-From-Learning-Poverty-to-Learning-for-Everyone-Everywhere.

UK Department of Education. (2011). *Building hanbook*. Retrieved from https://www.education-ni.gov.uk/building-handbook.

UNDRR & GADRRRES (2017). *Comprehensive school safety*. Retrieved from https://www.undrr.org/publication/comprehensive-school-safety.

UNESCO. (2019). *UNESCO guidelines for assessing learning facilities in the context of disaster risk reduction and climate change adaptation - VISUS* (Vol. 1). Paris.

UNESCO. (2020). *Global Education Monitoring Report Summary 2020: Inclusion and education: All means all*. Paris. Retrieved from https://unesdoc.unesco.org/ark:/48223/pf0000373718.

UNICEF. (2019). *Every child learns: UNICEF Education Strategy 2019–2030*. Retrieved from https://www.unicef.org/media/59856/file/UNICEF-education-strategy-2019-2030.pdf.

Yamin, L., Ghesquiere, F., Cardona, O., & Ordaz, M. (2013). *Modelación probabilista para la gestión del riesgo de desastre, El caso de Bogotá, Colombia*. Bogotá: Banco Mundial, Universidad de los Andes.

Zheng, A., & Casari, A. (2018). *Feature engineering for machine learning*. Sebastopol, CA: O'Reilly.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C., & Da Fonseca, V. (2003). Performance assessment of multiobjective optimizers: An analysis and review. *IEEE Transactions on Evolutionary Computation*, *7*(2), 117–132