APPLICATION OF MACHINE LEARNING MODELS TO SELECT QUARRY LIMESTONE FOR HERITAGE RESTORATION

Manuel Saba[*]
Faculty of Engineering, Universidad de Cartagena, Colombia

Óscar E. Coronado-Hernández, Alfonso Arrieta-Pastrana
Institute of Hydraulics and Environmental Sanitation, Universidad de Cartagena, Colombia

Keywords: ML-driven heritage restoration, machine learning for UNESCO, cultural heritage conservation

1. Introduction

Cultural heritage sites represent invaluable historical and architectural assets, requiring meticulous conservation efforts to preserve their integrity over time [1-3]. Environmental factors are crucial in heritage degradation [4-7]. The fortress of Nueva Tabarca in Spain, constructed with porous limestone, has accelerated decay due to salt crystallisation, wind erosion, and fluctuating humidity. The study introduced the concept of Equivalent Years (Yeq) to quantify the extent of natural versus artificial ageing, providing a framework for predicting long-term deterioration processes [8]. Likewise, research on Angkor sandstone monuments demonstrated that increased porosity and capillary water retention facilitated microbial colonization, ultimately exacerbating stone degradation [1].

Non-destructive testing methods have further improved the assessment of stone deterioration in heritage structures. Techniques such as Schmidt hammer rebound and ultrasound velocity measurements have been successfully applied to evaluate granite decay in historic buildings, providing valuable understanding into material weathering through a non-destructive approach [9]. Moreover, studies on the Fontvieille limestone used in Algerian coastal architecture have illustrated how microclimatic conditions, particularly salt exposure and wet-dry cycles, accelerate the decay of soft-porous stones, necessitating more durable alternatives for restoration efforts [10].

Among the challenges in heritage restoration, selecting suitable replacement materials is critical to ensuring compatibility with original buildings [11]. In this context, limestone has been widely used in historical constructions due to its availability, workability, and aesthetic properties [12]. However, identifying limestone with mechanical properties that match those existing structures remains a complex task. Traditionally, this selection process has relied on petrographic analysis [13-14], laboratory testing [12, 15-16], and expert judgment, which can be time-consuming and resource-intensive.

Several studies have explored the importance of selecting replacement stones with appropriate physical and mechanical properties to prevent further deterioration of historical structures [17-18]. For instance, research on the Acropolis circuit wall in Athens evaluated different porous stones from active quarries in Greece to identify materials

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[*] Corresponding author: msaba@unicrtagena.edu.co

compatible with the original Aktitis stone [19]. The study emphasized the necessity of considering both mechanical strength and durability, concluding that a combination of high-strength and softer stones could best mimic the construction techniques of classical walls. Similarly, an analysis of Baroque monuments in southeastern Sicily highlighted the risks associated with unregulated replacement, demonstrating that significant variations in physico-mechanical parameters could lead to structural instability [20]. Their findings revealed a substantial variation in physico-mechanical properties, suggesting that improper replacements could contribute to further structural deterioration without a systematic selection approach. Similarly, Forestieri et al. [21] examined four quarry limestones to propose suitable restoration strategies for historical structures in Calabria, Italy. In another study, Concu et al. [18] investigated the performance of replacement stones in heritage buildings in northwestern Belgium, demonstrating that these materials exhibited increased porosity, greater capillary water absorption, and lower mechanical strength. Such discrepancies could lead to unforeseen structural implications, including compromised durability and accelerated degradation of the original masonry [22-23].

On the other hand, recent advancements in machine learning (ML) have demonstrated significant potential in optimizing material selection. For instance, a rock compressive strength prediction study incorporated eight supervised learning algorithms, with AdaBoost emerging as the most effective model, achieving a high coefficient of determination ($R^2 = 0.995$) [24]. Similarly, a comparative analysis of statistical and machine learning methods for estimating rock tensile strength found that support vector regression outperformed other models, achieving an R^2 of 0.99 and minimal error rates [25].

Further reinforcing this trend, machine learning models have been employed to upscale meso-mechanical parameters for predicting macroscopic rock properties [26]. This study demonstrated the capability of optimized models such as kernel ridge regression and Gaussian process regression, to predict uniaxial compressive strength and elastic modulus with high accuracy, emphasizing the importance of advanced computational techniques in rock mechanics.

Additionally, deep learning approaches have been successfully applied to predict geomechanical indices of marlstone, achieving high precision and low error rates [27].

Regarding cultural heritage applications, a methodology for identifying suitable replacement stones in heritage restoration was developed using geochemical fingerprinting and statistical modelling. The approach, applied to Finnish rapakivi stones, combined XRF surface analysis with multivariate statistics and machine learning [28]. Results demonstrated its potential for matching quarry stones to historical buildings, ensuring structural and aesthetic compatibility. Despite the increasing application of machine learning techniques in geotechnical engineering, their use in cultural heritage restoration remains mainly unexplored [29]. Bridging this gap could revolutionize conservation strategies by enabling a data-driven selection of compatible restoration materials, thus preserving structural integrity and historical authenticity.

The restoration of historical structures is a complex, multi-step process that involves assessing deterioration, removing surface contaminants, consolidating the stone material, repairing structural damage with appropriate restoration mortars and replacement stones, applying protective treatments, and establishing maintenance strategies. Among these stages, selecting suitable replacement stones is particularly critical, as improper material choices can accelerate degradation rather than ensure long-term preservation. Traditional methods for determining the compatibility of replacement stones rely on extensive laboratory testing, which, while effective, can be time-consuming and resource-intensive.

Building on recent advancements, this study integrates ML techniques to optimize the selection process for quarry limestones intended to restore Cartagena's UNESCO-listed heritage walls (Figure *1*). By developing predictive models, this research enhances the accuracy and efficiency of material selection, ensuring that replacement stones possess mechanical and physical properties comparable to those of the original construction material. Key parameters, including ultrasonic wave velocity, compressive strength, mass and porosity, were analysed through experimental testing. The findings contribute to a systematic methodology for guiding restoration professionals and authorities in selecting appropriate replacement materials, mitigating the risk of further structural degradation (Figure *2*). Although tailored to Cartagena's fortifications, this approach can be adapted to other heritage structures, promoting more sustainable and scientifically grounded conservation strategies.

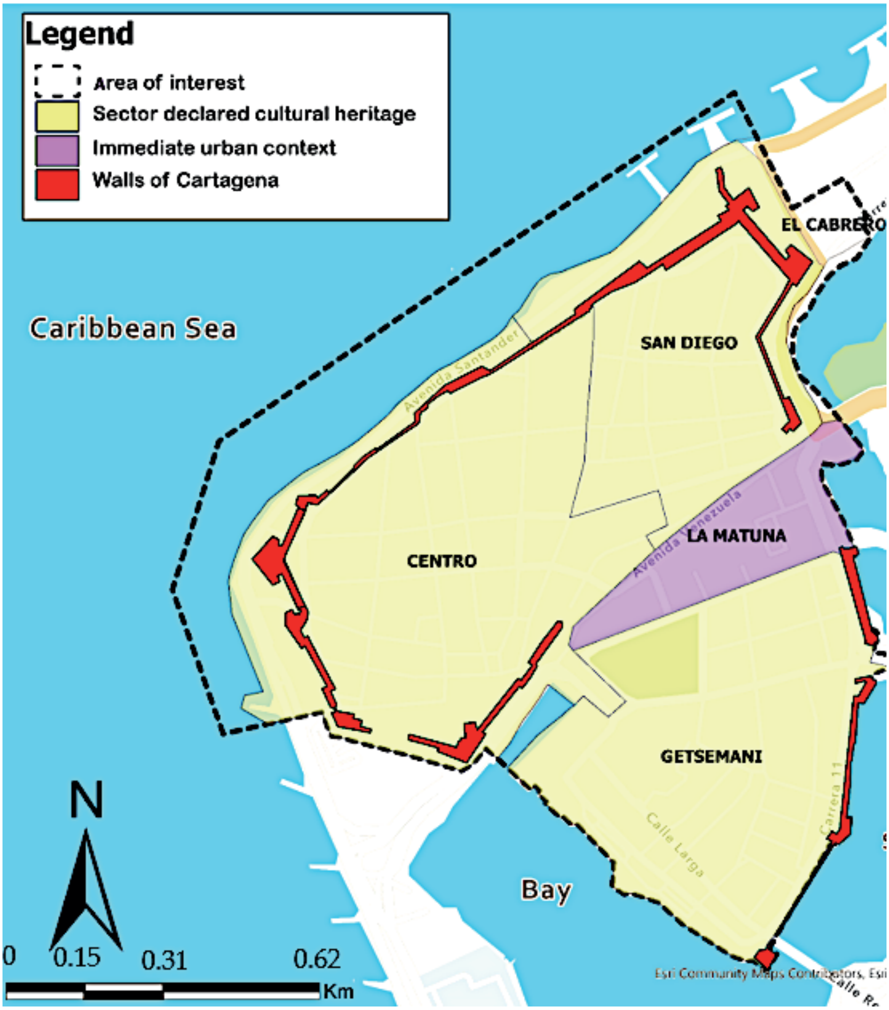


Figure 1. Cartagena de Indias City Centre.

Figure 2. An example of deterioration on the city walls of Cartagena de Indias. a) and b) widespread rising damp on the walls; c) widespread deterioration of mortar; d) rising damp at the cornerstone of the Santo Domingo Bastion.

2. Materials and methods

This study employed a combined experimental and computational methodology to develop a predictive framework for Uniaxial Compressive Strength (UCS) in limestone (Figure 3). Physical and mechanical properties were assessed through standardized laboratory procedures, including non-destructive ultrasonic testing and compressive strength analysis under different moisture conditions. Machine learning techniques were then applied to model UCS, evaluating multiple regression algorithms to determine the most accurate predictive approach. Statistical metrics ensured robust model validation, providing a data-driven tool for optimizing material selection in heritage restoration projects.

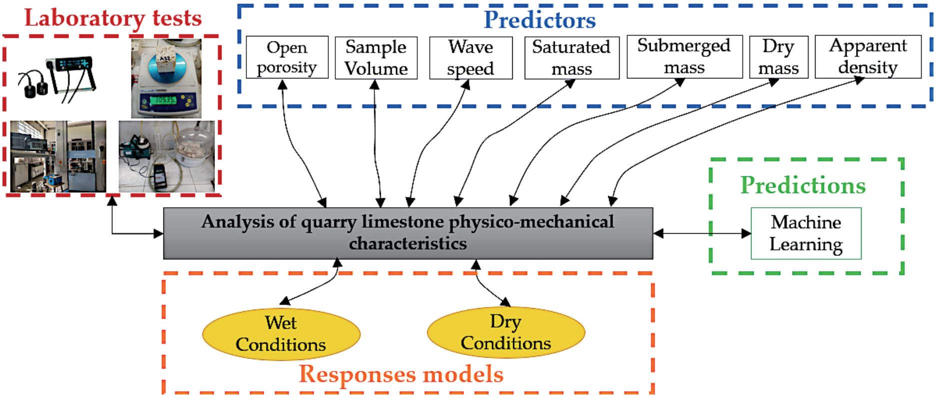


Figure 3. Methodology workflow.

2.1. Material

Limestones sourced from five quarry excavation fronts close to the city were analysed, revealing noticeable variations in colour, weight, and porosity, as depicted in Figure 4. These stones are typically utilised in the restoration efforts of Cartagena's fortifications. For each lithotype of stone, forty cubes measuring 5.0 x 5.0 x 5.0 cm were prepared, resulting in a total of approximately 200 samples for physical and mechanical characterisation. The specimens were dried at 70.0 ± 5.0 °C until they reached a constant weight according to UNI EN 1936 [30]. Weights (g) were measured for Dry (MDry), Saturated (MSat), and water immersion (MWet), enabling the calculation of Real Volume V (m^3), Open Porosity (Po in %), and Apparent Density (ρb in kg m^{-3}).

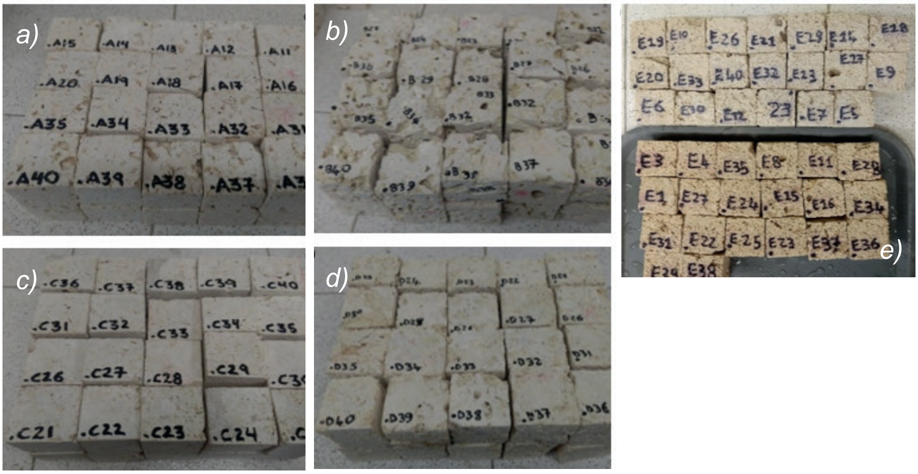


Figure 4. Quarry Limestones: a) Lithotype A; b) Lithotype B; c) Lithotype C; d) Lithotype D; e) Lithotype E.

Non-destructive testing was conducted using 500 kHz ultrasonic transducers to measure the P-wave velocity (Vp) in $m \cdot s^{-1}$, following the methodology described in Fort et al. [9]. Subsequently, UCS tests were carried out on the quarry materials using a Shimadzu AGX Plus universal testing machine with a maximum capacity of 300 kN, applying a constant loading rate of 1 $mm \cdot min^{-1}$. The specimens were categorised into 100 dry and 100 saturated with distilled water. Care was taken to ensure that both groups exhibited comparable average porosity and standard deviation, minimising variability due to pore structure differences.

2.2. Machine Learning

A total of 26 Machine Learning (ML) regression models were implemented, including eight general algorithmic approaches and several variants: Ensemble Methods (EM) [31], Gaussian Process Regression (GPR) [32], Kernel-based Regression (KR) [33], Linear Regression (LR) [34], Neural Networks (NN), Stepwise Linear Regression (SLR) [35], Support Vector Machines (SVM) [36], and Tree-based regression (TR) [37] (Figure 5). Given the extensive literature detailing the fundamental principles of machine learning algorithms, the main parameters of each model are reported in Table 1. The data analysis was conducted using MATLAB R2025 (The MathWorks Inc., Natick, MA, USA), incorporating the Statistics and Machine Learning Toolbox. All statistical evaluations were conducted under a 95% confidence interval, corresponding to a significance threshold of $\alpha = 0.05$. (See Figure 3). R-squared (R^2) [38-39], Root Mean Square (RMSE) [40-41], Mean Square (MS) [42], and Mean Absolute Error (MAE) [43] were determined to provide crucial insights into how well each model performs.

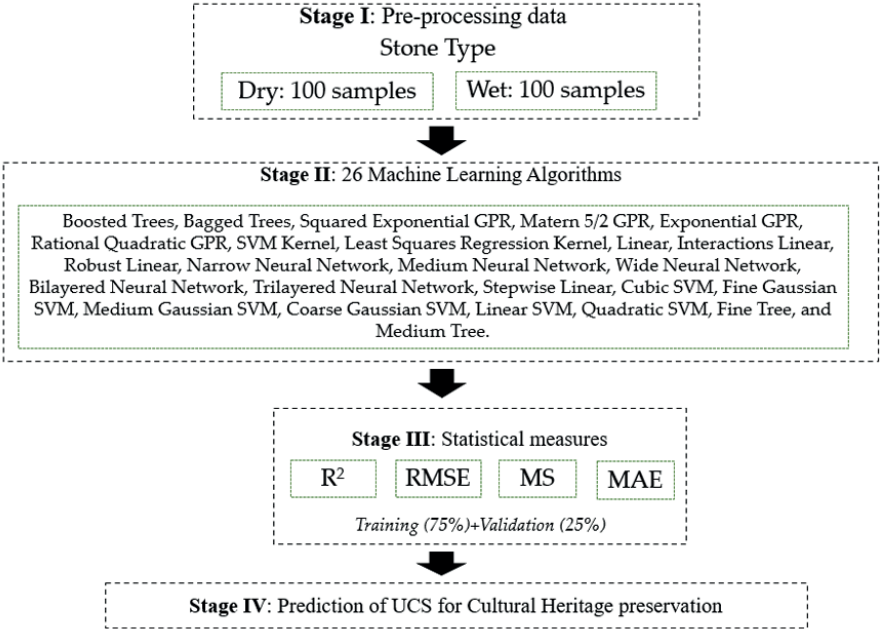


Figure 5. Machine learning methodology

Table 1. Machine learning models and description of the parameters used

N.	***Status***	***Present***
1	*Ensemble*	*Boosted Trees*
2	*Ensemble*	*Bagged Trees*
3	*Gaussian Process Regression*	*Squared Exponential GPR*
4	*Gaussian Process Regression*	*Matern 5/2 GPR*
5	*Gaussian Process Regression*	*Exponential GPR*
6	*Gaussian Process Regression*	*Rational Quadratic GPR*
7	*Kernel*	*SVM Kernel*
8	*Kernel*	*Least Squares Regression Kernel*
9	*Linear Regression*	*Linear*
10	*Linear Regression*	*Interactions Linear*
11	*Linear Regression*	*Robust Linear*
12	*Neural Network*	*Narrow Neural Network*
13	*Neural Network*	*Medium Neural Network*
14	*Neural Network*	*Wide Neural Network*
15	*Neural Network*	*Bilayered Neural Network*
16	*Neural Network*	*Trilayered Neural Network*
17	*Stepwise Linear Regression*	*Stepwise Linear*
18	*SVM*	*Cubic SVM*
19	*SVM*	*Fine Gaussian SVM*
20	*SVM*	*Medium Gaussian SVM*
21	*SVM*	*Coarse Gaussian SVM*
22	*SVM*	*Linear SVM*
23	*SVM*	*Quadratic SVM*
24	*Tree*	*Fine Tree*
25	*Tree*	*Fine Tree*
26	*Tree*	*Medium Tree*

3. Results and discussion

Table 2 presents a comparative analysis of five distinct quarry limestone lithotypes, detailing their average physical and mechanical properties alongside standard deviations. The observed inter-lithotype variability is substantial, particularly concerning mass and porosity. Lithotype E exhibits a significantly lower mass, ranging from 25% to 45% less than other lithotypes, and a 2.23 to 4.4 times greater porosity. Furthermore, the Uniaxial Compressive Strength (UCS) of lithotype E is markedly reduced, showing a 91% decrease compared to lithotype A and a 47% decrease compared to lithotype B. These findings underscore the critical necessity for comprehensive physico-mechanical characterisation before material selection in heritage restoration projects, exemplified by the fortifications of Cartagena de Indias.

The structural integrity and long-term stability of these fortifications hinge upon applying rigorous restoration standards, including the precise selection of replacement stone with mechanical properties commensurate with the existing historic fabric. In developing nations, where access to universal testing machines for UCS determination may be limited, material selection often relies on subjective professional judgment, prioritising economic and logistical factors over technical suitability. This practice poses a significant risk to the preservation of cultural heritage, potentially leading to accelerated deterioration and structural compromise.

Current restoration practices at the Cartagena Walls, which frequently involve indiscriminate substitution of deteriorated stone blocks with locally sourced limestone, disregard critical technical criteria. This approach can lead to severe conservation issues. For instance, using low-porosity replacement stone can disrupt the natural capillary moisture transport, accelerating the degradation of non-hydraulic mortars (see Figure 2a and b). This disruption forces moisture to seek alternative pathways, primarily through the more permeable mortars, leading to their rapid deterioration. Subsequent replacement with hydraulic mortars further impedes moisture flow, exacerbating stone decay and potentially increasing hydrostatic pressure behind the walls due to trapped moisture.

Incorporating replacement blocks characterised by elevated porosity may result in reduced load-bearing capacity, thereby adversely affecting the overall stability of the structure and heightening its vulnerability to both gravitational and seismic forces. Therefore, a scientifically informed approach to material selection, based on comprehensive physico-mechanical characterisation and predictive modelling, is essential to sustain Cartagena's cultural heritage.

Table 2. Quarry stone physical-mechanical properties

	Stone Lithotypes				
Characteristic	***A***	***B***	***C***	***D***	***E***
MDry (g x10^2)	*3.1 ± 0.2*	*2.4 ± 0.3*	*3.2 ± 0.2*	*2.7 ± 0.3*	*1.8 ± 0.1*
MSat (g x10^2)	*3.2 ± 0.2*	*2.6 ± 0.3*	*3.3 ± 0.2*	*3.0 ± 0.3*	*2.3 ± 0.2*
MWet (g x10^2)	*1.8 ± 0.1*	*1.4 ± 0.2*	*1.9 ± 0.1*	*1.6 ± 0.2*	*1.0 ± 0.1*
VR (mm^3 x10^5)	*1.5 ± 0.1*	*1.6 ± 0.2*	*1.5 ± 0.1*	*1.5 ± 0.1*	*1.4 ± 0.1*
P_0 (%)	*9.4 ± 1.3*	*14.9 ± 2.7*	*11.8 ± 2.4*	*18.4 ± 3.1*	*41.3 ± 1.6*
ρb (kg/m^3)	*2192.0 ± 37.0*	*2064.0 ± 106.0*	*2135.0 ± 70.0*	*1922.0 ± 110.0*	*1380.0 ± 35.0*
Vp (m/s)	*5000.0 ± 147.0*	*4616.0 ± 168.0*	*4978.0 ± 231.0*	*3793.0 ± 366.0*	*3406.0 ± 133.0*
UCSDry (MPa)	*21.0 ± 4.7*	*3.6 ± 1.3*	*20.9 ± 6.9*	*5.4 ± 2.0*	*1.9 ± 0.4*
UCSWet (MPa)	*13.5 ± 4.4*	*2.2 ± 0.6*	*13.7 ± 5.0*	*3.0 ± 1.5*	*1.5 ± 0.3*

Machine learning (ML) models were implemented to predict UCS based on physical properties to address this challenge. Among the eight models evaluated (Table 3, Figure 6, Figure 7 and Figure 8), Stepwise Linear Regression demonstrated superior performance both in Dry and Wet conditions, achieving an R^2 of 87% for Dry and 85 % for Wet, and an RMSE of 3.42 and 2.44, respectively. These metrics indicate a robust predictive capability, particularly considering the inherent heterogeneity of natural stone. Ensemble, Gaussian Process Regression, and Quadratic SVM models exhibited commendable performance in both dry and wet conditions, showing a 5% improvement in R^2 compared to the optimal Linear Regression model (Figure 6).

Establishing direct correlations between measured parameters can be challenging given limestone's anisotropic nature, irregular pore distribution, microfractures, crystallographic orientation, and sedimentary structures. However, the R² values presented in Table 3 suggest a discernible relationship between physical and mechanical properties. These findings align with recent studies [20, 44-46] that have explored the mutual correlation of these properties, often observing exponential or potential relationships (Table 4).

Table 3. ML methods and performance indicators for dry samples; the best values are highlighted in gray

Status	***Present***	***Rsquared (validation)***	***RMSE (validation)***	***MSE (validation)***	***MAE (Validation)***	***MAE (Test)***
Ensemble	*Boosted Trees*	*0.85*	*3.68*	*13.54*	*2.48*	*27.25*
Ensemble	*Bagged Trees*	*0.86*	*3.55*	*12.58*	*2.46*	*30.53*
Gaussian Process Regression	*Squared Exponential GPR*	*0.86*	*3.49*	*12.17*	*2.29*	*25.93*
Gaussian Process Regression	*Matern 5/2 GPR*	*0.86*	*3.49*	*12.17*	*2.23*	*24.03*
Gaussian Process Regression	*Exponential GPR*	*0.86*	*3.51*	*12.34*	*2.27*	*26.62*
Gaussian Process Regression	*Rational Quadratic GPR*	*0.86*	*3.49*	*12.17*	*2.29*	*25.92*
Kernel	*SVM Kernel*	*0.52*	*6.48*	*41.93*	*4.53*	*66.07*
Kernel	*Least Squares Regr.Kernel*	*0.73*	*4.83*	*23.30*	*3.32*	*58.33*
Linear Regression	*Linear*	*0.81*	*4.12*	*16.95*	*2.81*	*37.93*
Linear Regression	*Interactions Linear*	*0.26*	*8.04*	*64.58*	*4.60*	*98.00*
Linear Regression	*Robust Linear*	*0.81*	*4.10*	*16.80*	*2.78*	*33.52*
Neural Network	*Narrow Neural Network*	*0.53*	*6.41*	*41.06*	*4.12*	*54.79*
Neural Network	*Medium Neural Network*	*0.22*	*8.27*	*68.41*	*5.09*	*69.48*
Neural Network	*Wide Neural Network*	*0.61*	*5.82*	*33.88*	*4.38*	*83.71*
Neural Network	*Bilayered Neural Network*	*0.26*	*8.06*	*65.02*	*4.87*	*50.94*
Neural Network	*Trilayered Neural Network*	*0.58*	*6.05*	*36.63*	*3.81*	*47.31*
Stepwise Linear Regression	*Stepwise Linear*	*0.87*	*3.42*	*11.70*	*2.45*	*37.25*
SVM	*Cubic SVM*	*0.50*	*6.62*	*43.82*	*4.27*	*74.79*
SVM	*Fine Gaussian SVM*	*0.69*	*5.25*	*27.52*	*3.72*	*71.18*
SVM	*Medium Gaussian SVM*	*0.83*	*3.83*	*14.65*	*2.57*	*33.22*
SVM	*Coarse Gaussian SVM*	*0.78*	*4.39*	*19.31*	*3.01*	*40.89*
SVM	*Linear SVM*	*0.82*	*4.00*	*16.00*	*2.71*	*34.29*

Status	*Present*	*Rsquared (validation)*	*RMSE (validation)*	*MSE (validation)*	*MAE (Validation)*	*MAE (Test)*
SVM	*Quadratic SVM*	*0.86*	*3.56*	*12.65*	*2.54*	*36.90*
Tree	*Fine Tree*	*0.79*	*4.33*	*18.73*	*2.99*	*36.94*
Tree	*Fine Tree*	*0.79*	*4.33*	*18.73*	*2.99*	*36.94*
Tree	*Medium Tree*	*0.81*	*4.11*	*16.91*	*2.81*	*37.57*

Table 4. UCS Correlation models found in the literature

Parameters	*R2*	*Reference*
Vp - UCSDry	*0.84*	[20]
Vp - UCSDry	*0.86*	[44]
Vp - UCSDry	*0.73*	[45]
Vp - UCSDry	*0.63*	[13]
Vp - UCSWet	*0.63*	[13]
P0 - UCSWet	*0.70*	[13]
P0 - UCSDry	*0.73*	[13]
P0 - UCSDry	*0.85*	[20]

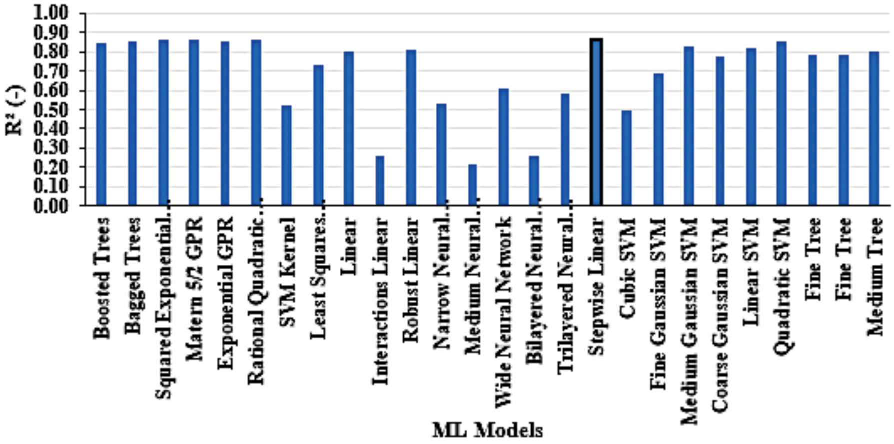


Figure 6. Coefficient of determination (R2) for each ML model. The highest value is highlighted.

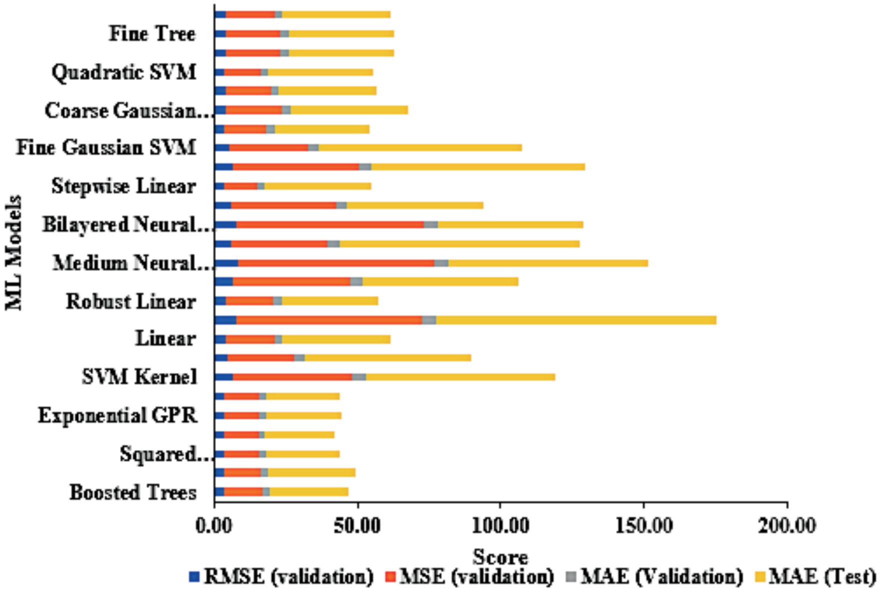
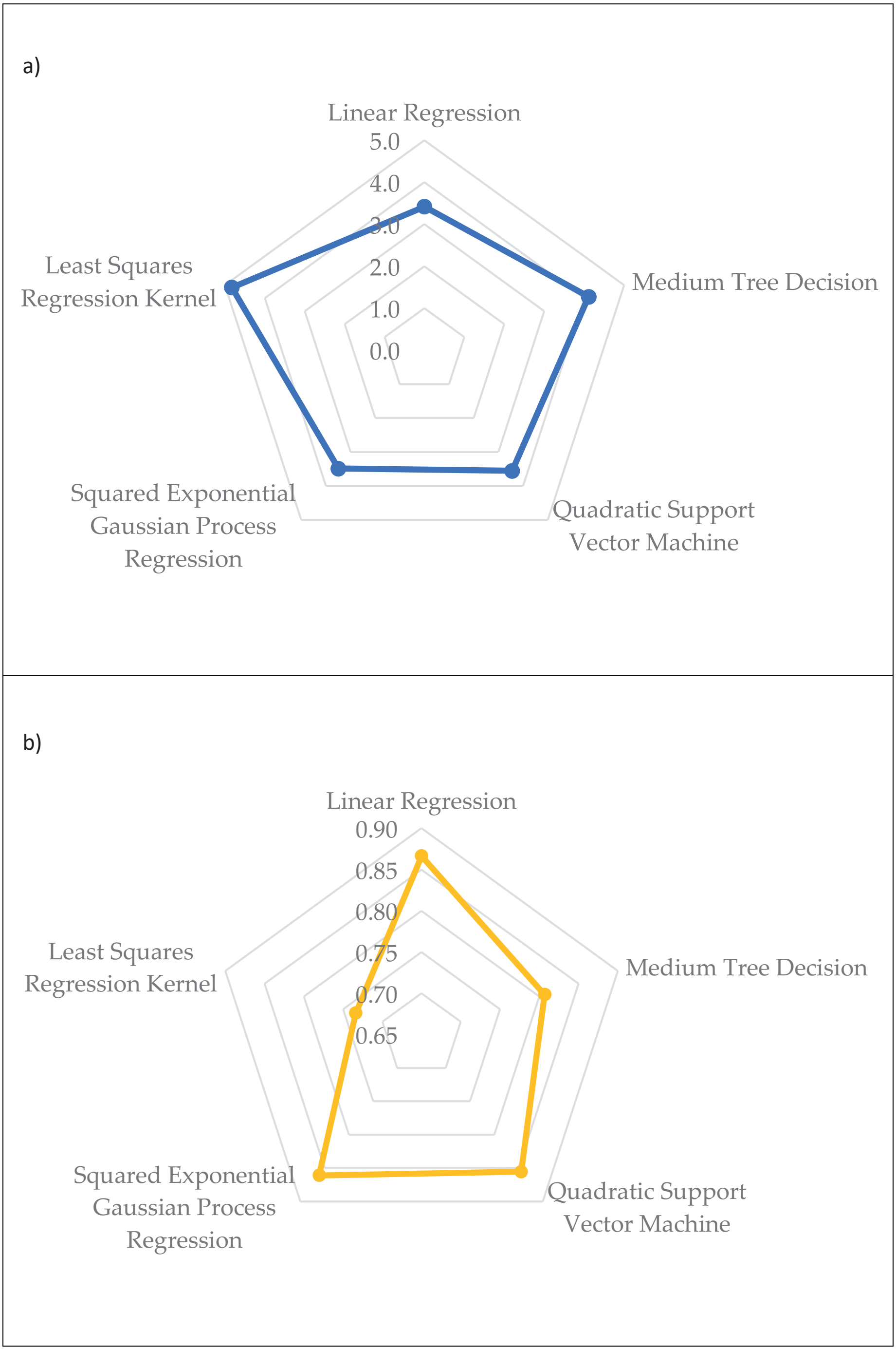


Figure 7. Score ranking chart of ML models.

Notably, the material's properties, such as porosity, mass measurements, and density, are critical in influencing UCS. The inherent complexity of the relationships among these variables may necessitate the use of models capable of capturing non-linear interactions and higher-dimensional correlations. While Neural Networks (NN) and Kernel methods theoretically offer the flexibility required for such tasks, our empirical results suggest that these models struggle to generalise effectively, potentially due to their susceptibility to overfitting in the presence of noise or limited data points.

In contrast, Ensemble Methods (EM) and Gaussian Process Regression (GPR) demonstrated superior performance, likely due to their ability to aggregate multiple models while offsetting individual weaknesses, thus enhancing predictive accuracy. Methods like Support Vector Machines (SVM) and Tree-based regression (TR) also outperformed NN, suggesting that these algorithms, which focus on partitioning the feature space or maximising margin between classes, are more adept at handling the intricacies of the dataset we employed. The performance differences may be attributed to the predictive capabilities of these models in capturing the underlying data structures more effectively, providing a more reliable estimate of UCS, which is essential for the safe replacement and conservation of heritage structures.


a)
Linear Regression
5.0
4.0
3.0
2.0
1.0
0.0
Medium Tree Decision
Quadratic Support Vector Machine
Squared Exponential Gaussian Process Regression
Least Squares Regression Kernel
b)
Linear Regression
0.90
0.85
0.80
0.75
0.70
0.65
Medium Tree Decision
Quadratic Support Vector Machine
Squared Exponential Gaussian Process Regression
Least Squares Regression Kernel

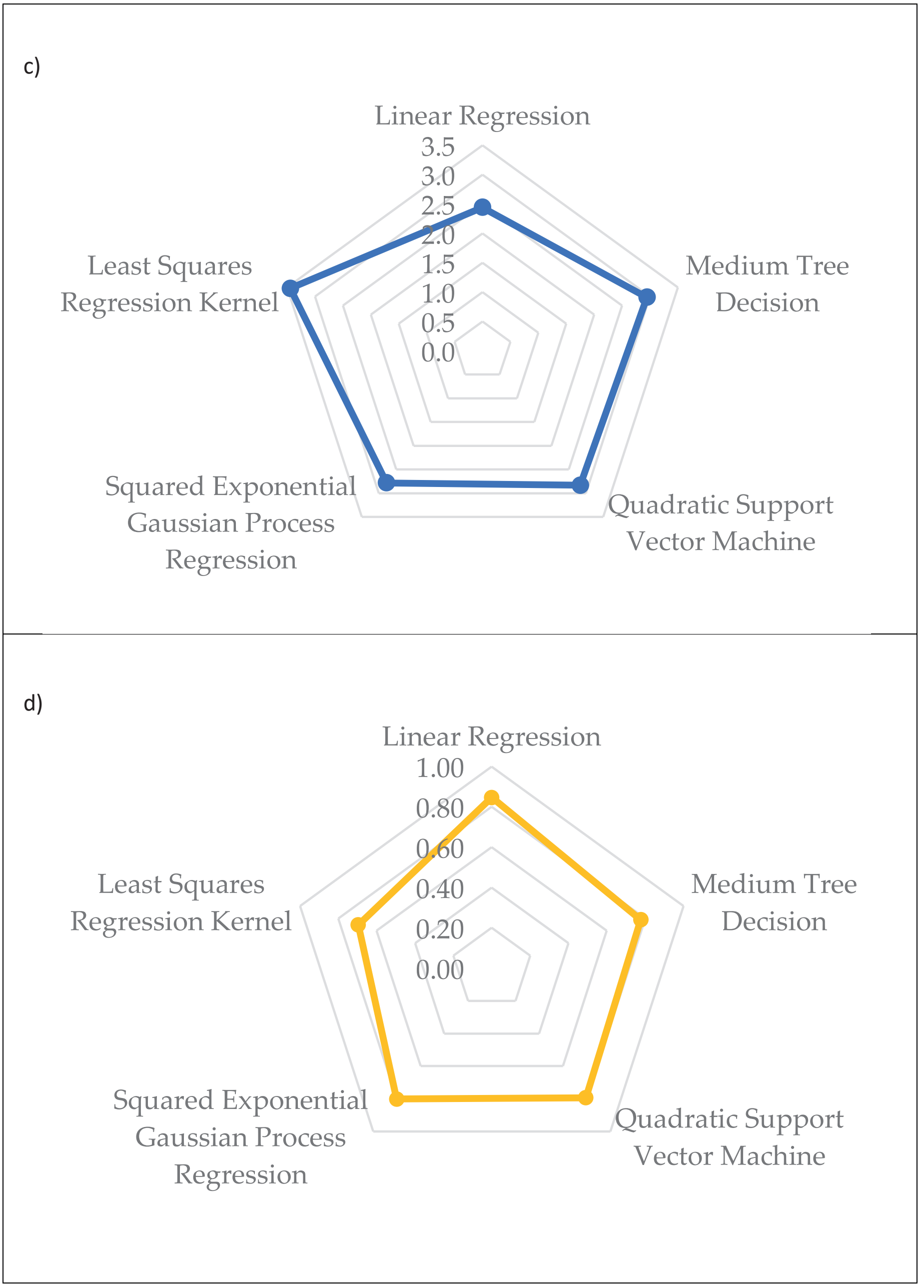


Figure 8. Statistical measure for dry conditions: (a) Root Mean Square Error (MPa), and (b) Coefficient of Determination (R2); Statistical measure for wet conditions: (c) Root Mean Square Error (MPa), and (d) Coefficient of Determination (R2).

The present study distinguishes itself through the comprehensive application of 26 distinct machine learning models to predict Uniaxial Compressive Strength (UCS) in limestone, a methodological breadth unparalleled in existing literature. This extensive comparative analysis demonstrates a streamlined, non-destructive approach to accurately estimating UCS by leveraging easily obtainable physical parameters such as mass, volume, and ultrasonic velocity. Such an approach significantly mitigates the reliance on costly and time-consuming destructive testing, thereby offering a practical and efficient solution for selecting suitable replacement stone in cultural heritage restoration.

In comparison to the study by Ding et al. [24], which utilised a dataset of 1,774 rock compressive strength tests and identified AdaBoost as the optimal model with an impressive R^2 of 0.995 and a MAPE of 3.61%, the present research, while focused on limestone and employing a broader range of models, underscores the general efficacy of machine learning in geotechnical predictions. While the former study emphasised efficiency gains and accuracy improvements over traditional methods, our approach explicitly targets the preservation of cultural heritage by facilitating non-destructive material selection.

The research by Wu et al. [26] explored the correlation between meso- and macro-mechanical properties, achieving notable prediction accuracies for UCS and elastic modulus using optimised Gaussian Process Regression (GPR) and Kernel Ridge Regression (KRR). This study, focusing on understanding underlying meso-mechanical parameters, achieved average errors of 4.9% for UCS and 1.1% for elastic modulus, highlighting the potential for enhancing predictive accuracy through detailed parametric analysis. In contrast, our study demonstrates that robust UCS predictions are achievable even with readily measurable physical parameters, simplifying material selection in restoration contexts.

Furthermore, Azarafza et al. [27] demonstrated the efficacy of a deep neural network (DNN) model in predicting the geomechanical properties of marlstone, achieving an R^2 of 0.933 for UCS. While earning significant accuracy through deep learning, this study focused on a specific rock lithotype and a narrower set of predictive models. Our research, by contrast, evaluates a diverse array of machine learning techniques across multiple limestone lithotypes, providing a more generalised and broadly applicable framework for material selection in heritage restoration.

3.1. Criteria for limestone compatibility in restoration

While previous studies collectively demonstrate the potential of machine learning (ML) in predicting the mechanical properties of rocks, our approach provides a distinct contribution by evaluating the applicability of multiple models to limestone, specifically within the framework of cultural heritage conservation. The capability to accurately estimate uniaxial compressive strength (UCS) using readily available physical parameters, without relying on destructive testing, represents a significant advancement.

This section presents a proposed approach to evaluate the compatibility of limestone for restoration purposes, with a specific focus on the historic walls of Cartagena de Indias. Earlier research has analysed the open porosity of the limestone material in these structures by examining petrographic thin sections [13], reporting values ranging from 18% to 25%. This parameter serves as an initial criterion for selecting regional quarry stones. However, porosity alone is insufficient; UCS must also be considered (see Figure 9).

This study introduces an ML-based approach to predict UCS without a universal testing machine, which is often difficult to access in developing countries, and without in situ compressive strength data for the structural blocks. Instead, UCS reference values were derived from quarry rock samples, focusing exclusively on specimens with 18% and 25% porosity values. The estimated UCS ranges were 4.90±2.02 MPa for dry conditions (UCSDry) and 2.40±1.41 MPa for wet conditions (UCSWet). These estimates provide decision-making authorities with a valuable tool for selecting appropriate restoration materials.

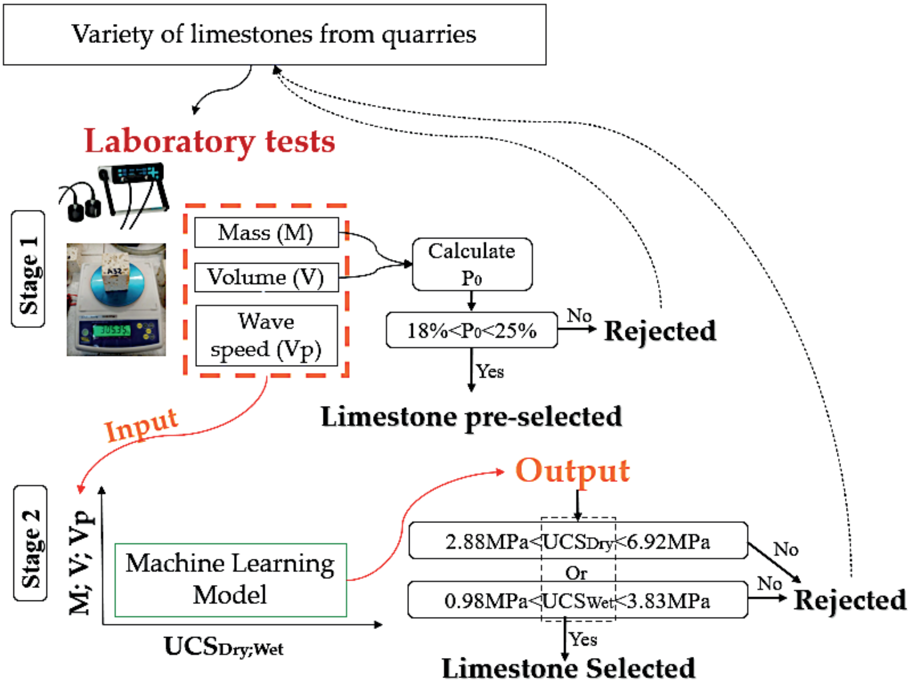


Figure 9. Stone replacement criteria.

However, it is crucial to recognise that the accuracy and reliability of our models may be influenced by the specific geological characteristics of the limestone formations in the Cartagena region, as it is for other areas of the world. Future research could enhance predictive accuracy by incorporating additional parameters such as colour, texture, and mineralogical composition. Furthermore, validating these models across different limestone lithotypes and heritage contexts would strengthen their robustness and broader applicability.

4. Conclusions

This study aimed to develop a predictive framework for UCS in limestone using ML algorithms, facilitating informed material selection for restoring cultural heritage sites.

This is a novelty in the literature, since the research focused on limestones from quarries surrounding Cartagena, Colombia, revealing substantial variability in their physico-mechanical properties, and underscoring the need for precise material characterisation. A key finding was the effectiveness of non-destructive measurements, such as ultrasonic velocity, volume, and mass, in predicting UCS, even in inherent material heterogeneity. Implementing and evaluating 26 model variants across seven machine learning algorithms provided critical insights, with Stepwise Linear Regression (SLR) emerging as the most accurate predictor for dry and wet UCS conditions. The superior performance of SLR, characterised by high R^2 values and low RMSE, highlights its suitability for limestone selection in restoration projects. Ensemble methods, Gaussian Process Regression, and Quadratic Support Vector Machines also demonstrated robust predictive capabilities, offering viable alternatives for UCS estimation.

To support informed decision-making in heritage conservation, this study presents a comprehensive set of criteria for evaluating limestone compatibility in restoration projects. These criteria are designed for adaptability across various cultural heritage contexts and offer a standardised yet flexible approach. By introducing a reliable, non-destructive method for estimating UCS, this research provides a data-driven tool that enables restoration authorities to safeguard both the structural integrity and aesthetic authenticity of heritage sites over the long term.

Finally, the investigation revealed a significant inverse correlation between moisture content and UCS, underscoring the critical importance of effective drainage systems in minimising mechanical degradation of limestone structures.

Acknowledgements

This research was supported by the Universidad de Cartagena, Colombia, under Commitment Deed No. 046 of 2023, as part of the ESCONPAT research group capacity-building initiative. Additional financial support was provided by the European Commission through Grant Agreement No. 2014-0873/001-001. The authors also gratefully acknowledge the financial assistance of the Universidad Nacional de Colombia through funding initiative DIB 34835. Special thanks are extended to Professor J. Lizarazo-Marriaga from the Department of Civil and Agricultural Engineering at Universidad Nacional de Colombia, and to Professor E. Quiñones-Bolaños, head of the Environmental Modelling Research Group at Universidad de Cartagena, for their valuable contributions to the development of this study.

References

[1] D. Buragohain, Y. Meng, C. Deng, Q. Li, and S. Chaudhary, “Digitalizing cultural heritage through metaverse applications: challenges, opportunities, and strategies,” *Herit. Sci.*, vol. 12, no. 1, p. 295, 2024, doi: 10.1186/s40494-024-01403-1.

[2] P. Moya-Olmedo, “De ciudades y de hombres: primer urbanismo americano del siglo XVI,” *Quiroga. Rev. Patrim. Iberoam.*, vol. 2023, no. 22, pp. 126–143, Oct. 2023, doi: 10.30827/quiroga.v0i22.0010.

[3] K. García-baltodano, D. Méndez-álvarez, A. Varela-fonseca, and A. Porras-alfaro, “Biodeterioration of heritage buildings representative of Costa Rican Caribbean architecture,” *Conserv. Sci. Cult. Herit.*, vol. 23, no. 1, p. Conserv. Sci. Cult. Herit., 2023.

[4] O. J. Esteban-Cantillo, B. Menendez, and B. Quesada, “Climate change and air pollution impacts on cultural heritage building materials in Europe and Mexico,” *Sci. Total Environ.*, vol. 921, p. 170945, 2024, doi: https://doi.org/10.1016/j.scitotenv.2024.170945.

[5] K. Athanasiou, “The Rise and Decline of Settlement Sites and Traditional Rural Architecture on Therasia Island and Their Reciprocal Interaction with the Environment,” *Heritage*, vol. 7, no. 10, pp. 5660-5686, 2024, doi: 10.3390/heritage7100267.

[6] R. P. Lilyam, “La edificación y el abandono del Castillo de San Francisco, siglos XVII-XVIII,” *Quiroga. Rev. Patrim. Iberoam.*, vol. 1, no. 21, pp. 256–266, Oct. 2022, doi: 10.30827/quiroga.v0i21.0020.

[7] S. Paris, V. Gattulli, A. Landa, and C. Vannini, “Protecting and redeveloping industrial archaeological heritage through design strategies driven by digital modelling,” *Conserv. Sci. Cult. Herit.*, vol. 23, no. 1, pp. 331-348, 2023, doi: 10.6092/issn.1973-9494/20083.

[8] J. Martínez-Martínez, D. Benavente, S. Jiménez Gutiérrez, M. A. García-del-Cura, and S. Ordóñez, “Stone weathering under Mediterranean semiarid climate in the fortress of Nueva Tabarca island (Spain),” *Build. Environ.*, vol. 121, pp. 262-276, 2017, doi: 10.1016/j.buildenv.2017.05.034.

[9] R. Fort, M. Alvarez de Buergo, and E. M. Perez-Monserrat, “Non-destructive testing for the assessment of granite decay in heritage structures compared to quarry stone,” *Int. J. Rock Mech. Min. Sci.*, vol. 61, pp. 296-305, 2013, doi: 10.1016/j.ijrmms.2012.12.048.

[10] N. Rabahi Touloum and A. Brara, “Advanced decay of the Fontvieille porous limestone used in the construction of Pouillon’s housing estates in Algiers (Algeria),” *J. Archaeol. Sci. Reports*, vol. 47, p. 103804, 2023, doi: https://doi.org/10.1016/j.jasrep.2022.103804.

[11] M. P. Lapuente Mercadal, J. A. Cuchí Oterino, and L. F. Auqué Sanz, “Compatibility Assessment in the Replacement of Damaged Sandstone Used in the Cathedral of Huesca (Spain),” *Heritage*, vol. 7, no. 2, pp. 896–912, 2024, doi: 10.3390/heritage7020043.

[12] C. Lisci, F. Sitzia, V. Pires, and J. Mirão, “Aging of Limestones and Silane–Siloxane-Based Protective Hydrophobics: The Impact of Heating–Cooling and Freeze–Thaw Cycles,” *Heritage*, vol. 7, no. 12, pp. 6657–6682, 2024, doi: 10.3390/heritage7120308.

[13] M. Saba, N. Hernandez-Romero, E. Quiñones-Bolaños, and J. Lizarazo-Marriaga, “Petrographic of Limestone Cultural Heritage as the Basis of a Methodology to Rock Replacement and Masonry Assessment: Cartagena de Indias Case of Study,” *Case Stud. Constr. Mater.*, 2019.

[14] C. Ciantelli, S. I. Arroyo Duarte, C. Vaccaro, and A. Bonazza, “Characterization of the Stone Masonries and Evaluation of the Environmental Impact in Panamá Viejo: A Contribution for the Conservation of the Monumental Complex,” *Heritage*, vol. 6, no. 10, pp. 6526–6546, 2023, doi: 10.3390/heritage6100341.

[15] U. S. Jayawardena, “Laboratory studies of Miocene limestone in Sri Lanka,” *Q. J. Eng. Geol. Hydrogeol.*, vol. 50, no. 4, pp. 422–425, 2017, doi: 10.1144/qjegh2016-106.

[16] G. Concu, B. De Nicolo, and M. Valdes, “Prediction of building limestone physical

and mechanical properties by means of ultrasonic P-wave velocity,” *Sci. World J.*, vol. 2014, 2014, doi: 10.1155/2014/508073.

[17] M. Korkanç, “Deterioration of different stones used in historical buildings within Nigde province, Cappadocia,” *Constr. Build. Mater.*, vol. 48, pp. 789-803, 2013, doi: 10.1016/j.conbuildmat.2013.07.033.

[18] T. De Kock *et al.*, “Replacement stones for Lede stone in Belgian historical monuments,” *Geol. Soc. Lond. Spec. Publ.*, vol. 391, no. 2011, pp. 31–46, 2013, doi: 10.1144/SP391.9.

[19] E. Ksinopoulou, E. Aggelakopoulou, and V. Eleftheriou, “Investigation of a suitable porous stone for the restoration work on the Acropolis circuit wall,” *Constr. Build. Mater.*, vol. 335, p. 127522, 2022, doi: https://doi.org/10.1016/j.conbuildmat.2022.127522.

[20] G. Pappalardo, S. Mineo, and C. Monaco, “Geotechnical characterization of limestones employed for the reconstruction of a UNESCO world heritage Baroque monument in southeastern Sicily (Italy),” *Eng. Geol.*, vol. 212, pp. 86–97, 2016, doi: https://doi.org/10.1016/j.enggeo.2016.08.004.

[21] G. Forestieri, M. De Buergo, and M. Ponte, “Estudio y Conservación del Patrimonio Cultural – 2015 (ECPC – 2015),” in *Idoneidad de rocas como material constructivo y restauración idoneidad de rocas como material constructivo y restauración mediante la evaluación de su comportamiento hídrico y físico – mecánico*, 2015, no. November, pp. 1–5.

[22] M. F. La Russa *et al.*, “The behaviour to weathering of the hyblean limestone in the baroque architecture of the val di Noto (SE Sicily): an experimental study on the ‘calcare a lumachella’ stone, Construction and building Materials,” *Constr. Build. Mater.*, vol. 7, pp. 7-19, 2015, doi: http://dx.doi.org/10.1016/j.conbuildmat.2014.11.073.

[23] L. Anania *et al.*, “The stones in monumental masonry buildings of the ‘“Val di Noto”’ area : New data on the relationships between petrographic characters and physical – mechanical properties,” *Constr. Build. Mater.*, vol. 33, pp. 122-132, 2012, doi: 10.1016/j.conbuildmat.2011.12.076.

[24] X. Ding, M. Dong, and W. Shen, “Research on rock strength prediction model based on machine learning algorithm,” *Discov. Appl. Sci.*, vol. 7, no. 1, p. 16, 2024, doi: 10.1007/s42452-024-06387-y.

[25] Z. Fang, J. Cheng, C. Xu, X. Xu, J. Qajar, and A. Rastegarnia, “Comparison of machine learning and statistical approaches to estimate rock tensile strength,” *Case Stud. Constr. Mater.*, vol. 20, p. e02890, 2024, doi: https://doi.org/10.1016/j.cscm.2024.e02890.

[26] Z. Wu, Y. Wu, L. Weng, M. Li, Z. Wang, and Z. Chu, “Machine learning approach to predicting the macro-mechanical properties of rock from the meso-mechanical parameters,” *Comput. Geotech.*, vol. 166, p. 105933, 2024, doi: https://doi.org/10.1016/j.compgeo.2023.105933.

[27] M. Azarafza, M. Hajialilue Bonab, and R. Derakhshani, “A Deep Learning Method for the Prediction of the Index Mechanical Properties and Strength Parameters of Marlstone,” *Materials (Basel).*, vol. 15, no. 19, 2022, doi: 10.3390/ma15196899.

[28] Z.-S. Duma, A. Surakka, P. Härmä, H. Laxström, T. Sihvonen, and S.-P. Reinikainen, “Tool for similarity identification of rapakivi granites in heritage buildings,” *J. Cult. Herit.*, vol. 58, pp. 229-236, 2022, doi: https://doi.org/10.1016/j.culher.2022.10.013.

[29] Scopus, “Scopus ‘stone AND cultural AND heritage AND machine AND learning,’” 2025. https://www.scopus.com/results/results.uri?st1=urban+planning&st2=military+

history&s=%28TITLE-ABS-KEY%28stone+cultural+heritage%29+AND+TITLE-ABS-KEY%28machine+AND+learning%29%29&limit=10&origin=searchbasic&sort=plf-f&src=s&sot=b&sdt=b&sessionSearchId=fc44 (accessed Mar. 22, 2025).

[30] European Committee for Standardization, *1936:2007 Natural stone test methods – Determination of real density and apparent density, and of total and open porosity*. European Union, 2007, pp. 1-14.

[31] The MathWorks Inc., “Ensemble Algorithms.” https://la.mathworks.com/help/stats/ensemble-algorithms.html (accessed Mar. 27, 2025).

[32] The MathWorks Inc., “Gaussian Process Regression Models.” https://la.mathworks.com/help/stats/gaussian-process-regression-models.html (accessed Mar. 27, 2025).

[33] The MathWorks Inc., “Regression Kernel.” https://la.mathworks.com/help/stats/regressionkernel.html (accessed Mar. 27, 2025).

[34] The MathWorks Inc., “Linear Regression.” https://la.mathworks.com/help/stats/linear-regression-model-workflow.html (accessed Mar. 27, 2025).

[35] The MathWorks Inc., “Stepwise Regression.” https://la.mathworks.com/help/stats/stepwise-regression.html (accessed Mar. 27, 2025).

[36] I. The MathWorks, “Support Vector Machine Regression.” https://ch.mathworks.com/help/stats/support-vector-machine-regression.html (accessed Mar. 27, 2025).

[37] The MathWorks Inc., “Regression Trees.” https://ch.mathworks.com/help/stats/regression-trees.html (accessed Mar. 27, 2025).

[38] The MathWorks Inc., “Coefficient of Determination (R-Squared).” https://ch.mathworks.com/help/stats/coefficient-of-determination-r-squared.html (accessed Mar. 27, 2025).

[39] A. Dodge, “Coefficient of Determination,” in *The Concise Encyclopedia of Statistics*, New York, NY: Springer New York, 2008, pp. 88–91.

[40] The MathWorks Inc., “Root mean squared error.” https://ch.mathworks.com/help/matlab/ref/rmse.html (accessed Mar. 27, 2025).

[41] T. Chai and R. R. Draxler, “Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature,” *Geosci. Model Dev.*, vol. 7, no. 3, pp. 1247-1250, Jun. 2014, doi: 10.5194/GMD-7-1247-2014.

[42] The MathWorks Inc., “Mean squared error.” https://ch.mathworks.com/help/deeplearning/ref/dlarray.mse.html (accessed Mar. 27, 2025).

[43] The MathWorks Inc., “Mean absolute error.” https://ch.mathworks.com/help/deeplearning/ref/mae.html (accessed Mar. 27, 2025).

[44] T. Parent, N. Domede, A. Sellier, and L. Mouatt, “Mechanical characterization of limestone from sound velociy measurement,” *Int. J. Rock Mech. Min. Sci.*, vol. 79, no. October 2017, pp. 149–156, 2015, doi: 10.1016/j.ijrmms.2015.08.009.

[45] E. Vasanelli, D. Colangiuli, A. Calia, M. Sileo, and A. Aiello, “Ultrasonic pulse velocity for the evaluation of physical and mechanical properties of a highly porous building limestone,” *Ultrasonics*, vol. 60, no. February, pp. 33–40, 2015, doi: 10.1016/j.ultras.2015.02.010.

[46] M. Saba, J. Lizarazo-Marriaga, N. Hernandez-Romero, and E. Quiñones-Bolaños, “Physico-mechanical characterization of the limestone used in Cartagena walls and a proposal for their restoration process.,” *Constr. Build. Mater.*, vol. 214, pp. 420–429, 2019, doi: 10.1016/j.conbuildmat.2019.04.170.

Biographical notes

Manuel Saba is a Civil Engineer holding a Master's degree in Structural Engineering (*cum laude*) from the University of Cagliari, Italy, and a Ph.D. (*cum laude*) in Engineering with a specialization in Materials Science and Technology. He currently serves as a full-time professor at the University of Cartagena, where he also leads the Research Group on Structures, Construction, and Heritage (ESCONPAT) and coordinates the Master's Program in Civil Engineering.

Over the past five years, he has authored more than 50 scientific papers published in high-impact international journals, accumulating over 200 citations, as well as two research books. His research spans a broad range of topics, including cultural heritage, characterization of construction materials, nanotechnological materials, particulate matter dispersion in urban environments, asbestos-related issues, and remote sensing analysis. Notably, Manuel Saba leads the most significant research project on asbestos in Latin America.

Óscar E. Coronado-Hernández holds an International Ph.D. in Water and Environmental Engineering from the Polytechnic University of Valencia (Spain), a Bachelor's degree in Civil Engineering from the University of Cartagena (Colombia), and a Master's degree in Civil Engineering with an emphasis on Sustainable Water Resources Management and Hydroinformatics from the University of Los Andes (Colombia). He has carried out research stays at the Instituto Superior Técnico of the University of Lisbon (Portugal).

He has an extensive background in research, consulting, and teaching within the field of civil and environmental engineering. He has published more than 65 scientific articles in high-impact journals indexed in the first and second quartiles of the WoS/Scopus databases. His main areas of expertise include water systems analysis, sustainable urban drainage management, and hydrology. He currently serves as a full-time professor at the Institute of Hydraulics and Environmental Sanitation of the University of Cartagena.

Alfonso Arrieta-Pastrana is a Civil Engineer from the University of Cartagena. He holds a Master's degree in Hydraulic Resources from the National University of Colombia, Faculty of Mines, and a Ph.D. in Marine Sciences from the University of Cádiz, Spain. He currently serves as the Director of the Institute of Hydraulics and Environmental Sanitation at the University of Cartagena.

Dr. Arrieta has over 20 years of professional and academic experience in the fields of hydraulic engineering, water resources management, and environmental sanitation. His expertise encompasses the design and optimization of hydraulic systems, as well as water supply and sewer networks, with a strong focus on sustainable infrastructure planning and environmental protection. Throughout his career, he has contributed to numerous research and consulting projects aimed at improving urban water systems and advancing the understanding of coastal and marine hydrodynamics in tropical environments.

Summary

The fortification system of Cartagena de Indias, designated as a UNESCO World Heritage Site in 1984, represents a fundamental element of the city's cultural heritage and historical legacy. However, significant portions of these structures have undergone severe degradation due to environmental and anthropogenic factors, requiring continuous restoration efforts. Currently, the selection of replacement limestone blocks is conducted without a standardised technical criterion, potentially compromising the structural integrity and breathability of the walls. Stones with high porosity exhibit low mechanical resistance, making them susceptible to failure under static and seismic loads. In contrast, those with low porosity hinder moisture exchange, leading to overpressures and biodeterioration. This study introduces a machine learning-based (ML) approach to predict the Uniaxial Mechanical Strength (UCS) both in dry and wet conditions of quarry limestone intended for restoration, utilising key physical parameters such as real volume, average wave speed, saturated mass, submerged mass, and dry mass. Seven predictive models were evaluated: Ensemble Methods (EM), Gaussian Process Regression (GPR), Kernel-based Regression (KR), Linear Regression (LR), Neural Networks (NN), Stepwise Linear Regression (SLR), Support Vector Machines (SVM), and Tree-based regression (TR). The novelty lies in applying these models to improve material selection for restoration, ensuring the structural and aesthetic integrity of the restored limestone structures, while minimising the need for destructive testing. The findings reveal that SLR has the highest predictive accuracy across both dry and wet conditions, achieving an R^2 of 87% with an RMSE of 3.42 for dry UCS, and an R^2 of 85% with an RMSE of 2.44 for wet UCS. Furthermore, Ensemble, Gaussian Process Regression, and Quadratic SVM models demonstrated significant performance, achieving a 5% improvement in R^2 compared to standard LR models. Finally, an original criterion for limestone selection as a replacement for cultural heritage restoration is proposed as a tool for competent authorities.

Riassunto

Il sistema di fortificazioni di Cartagena de Indias, dichiarato Patrimonio Mondiale dell'UNESCO nel 1984, rappresenta un elemento imprescindibile del patrimonio culturale e della memoria storica della città. Tuttavia, ampie porzioni di tali strutture hanno subito un grave degrado a causa di fattori ambientali e antropici, rendendo necessari interventi di restauro continui. Attualmente, la selezione dei blocchi di calcare sostitutivi avviene in assenza di criteri tecnici standardizzati, con il rischio di compromettere l'integrità strutturale e la traspirabilità delle murature. Le pietre con elevata porosità presentano una bassa resistenza meccanica, risultando vulnerabili a collassi sotto carichi statici e sismici. Al contrario, materiali a bassa porosità ostacolano lo scambio di umidità, favorendo fenomeni di sovrapressione e biodeterioramento. Il presente studio propone un approccio innovativo basato su tecniche di machine learning (ML) per la previsione della Resistenza Meccanica a Compressione Uniassiale (UCS), in condizioni sia asciutte sia sature, di calcari di cava destinati al restauro, utilizzando parametri fisici chiave quali volume reale, velocità media delle onde, massa satura, massa immersa e massa secca. Sono stati valutati sette modelli predittivi: metodi Ensemble (EM), Regressione a Processi Gaussiani (GPR), Regressione basata su Kernel (KR), Regressione Lineare (LR), Reti Neurali (NN), Regressione Lineare Stepwise (SLR), Support Vector Machines (SVM) e Regressione ad albero decisionale (TR).

La novità risiede nell'applicazione di tali modelli al fine di migliorare la selezione dei materiali per il restauro, garantendo l'integrità strutturale ed estetica delle strutture in calcare restaurate e riducendo al minimo la necessità di prove distruttive. I risultati ottenuti confermano che il modello SLR presenta la maggiore accuratezza predittiva sia in condizioni di asciuttezza sia in condizioni di saturazione, con un valore di R^2 pari all'87% e un RMSE di 3,42 per l'UCS a secco, e un R^2 dell'85% con un RMSE di 2,44 per l'UCS a umido. Inoltre, i modelli Ensemble, GPR e SVM quadratico hanno mostrato prestazioni significative, ottenendo un miglioramento del coefficiente R^2 pari al 5% rispetto ai modelli di regressione lineare standard. Infine, viene proposto un criterio innovativo per la selezione del calcare come materiale sostitutivo negli interventi di restauro del patrimonio culturale, concepito come strumento di supporto per le autorità competenti.