



School of Applied Arts and Sustainable Design
M.Sc. Protection of Cultural Heritage and Monuments
of Nature from the Effects of Climate Change

Postgraduate Dissertation

“Database Development for Cultural Heritage Building Materials
Deterioration and Performance: From Physico-Chemical
Characterization to Predictive Conservation.”

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Alexandroupolis, Greece, June 2026

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With sincere gratitude to my supervisor, Dr. Anno Hein, and Dr. Kontogianni from N.C.S.R. Demokritos for their guidance, and to the pioneers of relational database systems in archaeometry, whose work inspired the digital architecture of this study.

Abstract

The preservation of global Cultural Heritage (CH) depends critically on understanding the long-term performance and susceptibility of historic building materials to environmental stressors, particularly those exacerbated by climate change. This thesis addresses this need by establishing a comprehensive, machine learning (ML)-ready database that systematically links material properties to observed deterioration.

The purpose of the thesis is two-fold; it involves a thorough literature survey concerning studies of cultural heritage building materials, including their physico-chemical and thermo-mechanical properties, and their performance, both in their present state and under accelerating weathering tests, such as salt crystallization or freeze-thaw cycles. The scope of this survey is to develop a database for heritage materials such as ancient stone, ceramics, mortars, and ultimately enrich and incorporate additional features to the database development efforts of the Ceramics and Composite Materials Research Laboratory (CCM) at N.C.S.R. "Demokritos". The key expected result is for this database to be able to be used for training machine learning models in future projects in order to adjust and complement missing features and ultimately predict the performance and deterioration of heritage building and conservation materials in different climate scenarios. The prediction of performance and deterioration ultimately aims for the most suitable preservation measures to be employed in order to mitigate the critical effects of climate change on the world's heritage fabric.

The methodology begins with a literature survey for collecting data on CH building materials performance and deterioration under specific environmental conditions by collecting data from accelerating weathering tests. The overall methodology involves the creation or "buildup" of a database which comprises both existing and newly collected literature data. This database structure then facilitates the subsequent methodological step: using the collected data to train machine learning models for predictive purposes.

Keywords

heritage material characterization, database development, deterioration assessment, accelerated weathering, freeze-thaw, salt crystallisation, climate change, predictive modelling

“Ανάπτυξη βάσης δεδομένων για την απόδοση και τη διάβρωση των δομικών υλικών πολιτιστικής κληρονομιάς: Από τον φυσικοχημικό χαρακτηρισμό έως την προληπτική συντήρηση.”

Χρυσοβαλάντου Αναστασία Γονιοπούλου

Περίληψη

Η διατήρηση της παγκόσμιας πολιτιστικής κληρονομιάς (CH) εξαρτάται σε μεγάλο βαθμό από την κατανόηση της μακροπρόθεσμης απόδοσης και ευαισθησίας των ιστορικών δομικών υλικών σε ακραίους περιβαλλοντικούς παράγοντες, ιδίως εκείνων που επιδεινώνονται λόγω της κλιματικής αλλαγής. Η παρούσα διατριβή ανταποκρίνεται σε αυτή την ανάγκη δημιουργώντας μια ολοκληρωμένη βάση δεδομένων, έτοιμη για μηχανική μάθηση (machine learning), η οποία συνδέει συστηματικά τις ιδιότητες των υλικών με την παρατηρούμενη φθορά.

Η παρούσα διατριβή είναι δισυπόστατη. Αφενός, περιλαμβάνει μια βιβλιογραφική έρευνα μελετών για τα δομικά υλικά πολιτιστικής κληρονομιάς, συμπεριλαμβανομένων των φυσικοχημικών ιδιοτήτων τους και της δοκιμής της θερμομηχανικής τους απόδοσης, τόσο στην υφιστάμενη κατάστασή τους όσο και υπό συνθήκες επιταχυνόμενων δοκιμών διάβρωσης, όπως κύκλοι κρυστάλλωσης αλάτων ή κύκλοι ψύξης-απόψυξης. Σκοπός της έρευνας είναι η επέκταση της υπάρχουσας βάσης δεδομένων σε υλικά όπως αρχαίες πέτρες, κεραμικά, κονιάματα, και τελικά ο εμπλουτισμός και η ενσωμάτωση πρόσθετων χαρακτηριστικών στις προσπάθειες ανάπτυξης βάσεων δεδομένων του Εργαστηρίου Έρευνας Κεραμικών και Σύνθετων Υλικών (CCM) του ΕΚΕΦΕ «Δημόκριτος». Το βασικό αναμενόμενο αποτέλεσμα είναι η δυνατότητα χρήσης αυτής της βάσης δεδομένων για την εκπαίδευση μοντέλων μηχανικής μάθησης σε μελλοντικά έργα, με σκοπό την προσαρμογή και τη συμπλήρωση των ελλειπόντων χαρακτηριστικών και, τελικά, την πρόβλεψη της

απόδοσης και της φθοράς των κτιρίων πολιτιστικής κληρονομιάς και των υλικών συντήρησης σε διαφορετικά κλιματικά σενάρια. Η πρόβλεψη της απόδοσης και της φθοράς στοχεύει τελικά στην εφαρμογή των καταλληλότερων μέτρων διατήρησης, προκειμένου να μετριαστούν οι κρίσιμες επιπτώσεις της κλιματικής αλλαγής στο παγκόσμιο κληρονομικό ιστό.

Η μεθοδολογία ξεκινά με μια εκτενή βιβλιογραφική έρευνα για τη συλλογή δεδομένων σχετικά με την απόδοση και τη φθορά των δομικών υλικών πολιτιστικής κληρονομιάς υπό συγκεκριμένες περιβαλλοντικές συνθήκες, μέσω της συλλογής δεδομένων από δοκιμές επιταχυνόμενης διάβρωσης. Η συνολική μεθοδολογία περιλαμβάνει τη δημιουργία ή την «οικοδόμηση» μιας βάσης δεδομένων που περιλαμβάνει τόσο υπάρχοντα όσο και νεοσυλλεγμένα βιβλιογραφικά δεδομένα. Αυτή η δομή της βάσης δεδομένων διευκολύνει στη συνέχεια το επόμενο μεθοδολογικό βήμα: τη χρήση των συλλεγμένων δεδομένων για την εκπαίδευση μοντέλων μηχανικής μάθησης για σκοπούς πρόβλεψης.

Λέξεις – Κλειδιά

χαρακτηρισμός υλικών πολιτιστικής κληρονομιάς, ανάπτυξη βάσης δεδομένων, αξιολόγηση φθοράς, επιταχυνόμενη διάβρωση, κύκλοι ψύξης-απόψυξης, κρυστάλλωση αλατιού, κλιματική αλλαγή, προγνωστική μοντελοποίηση

Table of Contents

Abstract	v
Περίληψη.....	vi
Table of Contents	viii
List of Figures	xi
List of Tables.....	xiv
List of Abbreviations & Acronyms	xv
Introduction	1
CHAPTER 1: CULTURAL HERITAGE BUILDING MATERIALS TYPOLOGIES, PHYSICO-CHEMICAL & THERMO-MECHANICAL CHARACTERIZATION WITHIN THE DATABASE SCOPE.....	4
1.1 Typologies of cultural heritage building materials in the database scope	5
1.1.1 Stone lithologies and heritage contexts	6
1.1.2 Ancient ceramics (bricks, clay and earthenware)	23
1.1.3 Ancient mortars and plasters	29
1.2 Conservation and repair material typologies.....	35
1.2.1 Inorganic and organic consolidants.....	35
1.2.2 Protective coatings and water repellents	36
1.2.3 Compatibility criteria for repair mortars	36
1.3 Analytical methods for physico-chemical and thermo-mechanical characterisation of CH materials	37
1.3.1 Bulk chemical composition & provenance tracing – Crystalline phase identification & transformations	41
1.3.2 Microstructural and textural analysis	46
1.3.3 Mechanical performance testing	52
1.3.4 Thermal and hygric properties	53
CHAPTER 2: ACCELERATED WEATHERING TESTING PROTOCOLS AND QUANTITATIVE ASSESSMENT OF MATERIAL PERFORMANCE AND DETERIORATION DATA	57
2.1 Mechanisms of moisture-driven decay	57
2.1.1. Capillary Transport and Pore Network Dynamics	57

2.1.2	Hydraulic Pressure and Cryo-static Stress	58
2.1.3	Chemical Weathering and Dissolution-Precipitation Cycles	59
2.1.4	Hygric Swelling and Differential Expansion	59
2.2	Accelerated weathering testing protocols (AWTP)	60
2.2.1	Freeze-thaw damage: test modes, cycles & moisture influence	70
2.2.2	Wetting-Drying cycles (Slake Durability) protocols	75
2.2.3	Chemical dissolution and acid rain simulation	75
2.2.4	Thermal Shock and UV-A photo-oxidative aging	76
2.2.5	Salt crystallization: salt type, concentration & temperature effects.....	78
2.2.6	Synergistic AWTP: coupled salt and frost damage.....	79
2.3	Deterioration and Dynamic Performance Metrics (DPM)	80
2.3.1	Quantification of damage: mass loss, strength reduction, porosity increase	81
2.3.2	Microstructural damage indicators.....	82
2.3.3	Durability of protective layers under UV and salt stress	83
2.3.4	Evaluation of “compatibility metrics” as Database features.....	84
CHAPTER 3:	DATABASE METHODOLOGY, STRUCTURE, AND IMPLEMENTATION	86
3.1	Data acquisition and standardization	88
3.1.1	Data collection and digitization methodology	89
3.1.2	Standardizing units: Resolving data heterogeneity	91
3.2	Relational database design and structure	93
3.2.1	Defining and enforcing primary and foreign key relationships	93
3.2.2	Conceptual model and entity-relationship diagram (ERD).....	94
3.3	Data quality control and documentation	97
3.3.1	Procedures for data validation and missing data handling.....	97
3.3.2	Documentation of database schema	98
CHAPTER 4:	MACHINE LEARNING FEATURE ENGINEERING AND DATA VALIDATION FOR PREDICTIVE CONSERVATION.....	114
4.1	Defining the predictive model framework	115
4.1.1	Identification of ML input features (PCC, TMP, AWTP) and target variables (DPM)	116
4.1.2	The role of the database in training future ML models.....	118

4.2 Data transformation and feature selection.....	120
4.2.1 Creating ML-ready datasets using database queries	121
4.2.2 Feature selection based on physical relevance and statistical metrics.	122
4.3 Data validation and foundational relationships.....	124
4.3.1 Correlation Analysis to validate data utility.....	125
4.3.2 Potential for Multivariate Analysis and Material Grouping	133
CHAPTER 5: CONCLUSIONS OF THIS RESEARCH’S EFFORT OF A HERITAGE MATERIAL DATABASE DEVELOPMENT	147
5.1 Summary of research findings and Database development	147
5.2 Contribution to the field of predictive conservation diagnostics	148
5.3 Difficulties encountered	148
5.4 Future research directions	149
References	151
Appendix A: Material Database Open Access Repository Link.....	166

List of Figures

<i>Figure 1. Classification of stones geologically, chemically and physically. (Source: Jain, 2017, URL: wixsite.com/stone-classification).....</i>	<i>7</i>
<i>Figure 2. Cubic specimen of the stones and their relative photomicrographs of representative thin sections observed under crossed polarized light (Coletti et al., 2025).</i>	<i>17</i>
<i>Figure 3. Schematic representation of the XRF principle (a) and EDXRF instrument (b) (Magdy, 2023).</i>	<i>42</i>
<i>Figure 4. Schematic illustration of the different information that is typically obtained from an XRD mapping experiment (Gonzalez et al., 2020).</i>	<i>44</i>
<i>Figure 5. Schematic diagram of the three freeze–thaw methods test by Peng et al. (2022) where; (a) represents the Immersion freeze–thaw method; (b) the capillary freeze–thaw; and (c) the capillary freeze–thaw method (Source: Peng et al. (2022)).</i>	<i>70</i>
<i>Figure 6. Variation characteristics of macroscopic morphology of rock samples under different freeze–thaw modes by Peng et al. (2022), where: (a) Immersion freeze–thaw after 60 cycles; (b) immersion freeze–thaw after 60 cycles; and (c) immersion freeze–thaw after 60 cycles (Source: Peng et al. (2022)).</i>	<i>71</i>
<i>Figure 7. Heavy vulnerability of the Sfouggaria Stone against freeze-thaw action as shown in this deterioration evolution of samples after ageing tests at 20 cycle steps (Source: Coletti et al. 2025)).</i>	<i>72</i>
<i>Figure 8. Three-dimensional representation of the examined ceramic specimen by Porfido et al. (2020) (Post 10 cycles) and visualisation of the three parts chosen for fracture investigation (Porfido et al., 2020).</i>	<i>73</i>
<i>Figure 9. Experimental limestone samples exposed to the UV irradiation in conservation efforts of ancient Egyptian outdoor carved limestone sculpture (Source: Aldosari et al. (2019)).</i>	<i>77</i>
<i>Figure 10. Three orthogonal sections captioned from the micro-CT pre and post several frost cycles (Source: Porfido et al., 2020).</i>	<i>83</i>
<i>Figure 11. Schematic breakdown of the FAIR Data Principles guiding the development of the cultural heritage materials database architecture (‘FAIR Principles What Are They And Why Are They Important?’, 2020).</i>	<i>87</i>

Figure 12. Relational structure of the heritage materials database illustrating the connectivity between material characterization and weathering protocols (Source: original).....	96
Figure 13. Correlation analysis for data validation between bulk density and total porosity of the database's heritage stone samples (Source: original).	125
Figure 14. Correlation analysis for data validation between UCS and UPV of the database's heritage stone samples (Source: original).	126
Figure 15. Correlation analysis for data validation between UCS and UPV of the database's heritage mortar samples (Source: original).	126
Figure 16. Correlation analysis for data validation between total porosity and water absorption of the database's heritage stone samples (Source: original).	127
Figure 17. Correlation analysis for data validation between total porosity and water absorption of the database's heritage ceramic samples (Source: original).....	128
Figure 18. Correlation analysis for data validation between total porosity and water absorption of the database's heritage mortar samples (Source: original).	128
Figure 19. Highly scattered mass change kinetics in heritage stone samples, indicating complex sub-florescence and localized spalling mechanisms (Source: original).	130
Figure 20. Threshold-dependent mass loss in ancient ceramic samples showing sudden structural failure (Source: original).	131
Figure 21. Bimodal durability behavior in various ancient mortar samples, highlighting severe degradation versus high-survival samples (Source: original).....	132
Figure 22. Aesthetic decay prediction of heritage stone samples (Source: original).....	135
Figure 23. Multiparametric non-destructive estimation of heritage stone samples' strength (Source: original).	136
Figure 24. Heritage stone samples' mechanical behaviour under cycles of accelerated weathering (Source: original).....	138
Figure 25. Technological characterisation of heritage ceramic samples based on their firing temperature (Source: Original).	140
Figure 26. Mechanical behaviour of heritage ceramic and brick samples under accelerated weathering conditions (Source: original).	142
Figure 27. Correlation of the database's ancient and restoration mortar samples' total porosity to uniaxial compressive strength (Source: original).....	143

Figure 28. Heritage and restoration mortar, plaster and composite database samples’ mechanical behaviour under accelerated weathering conditions (Source: original).145

List of Tables

Table 1. Query of some Stone samples included in the database (Source: original).	18
Table 2. Query of some Ceramics/ Bricks samples included in the database (Source: original).....	27
Table 3. Query of some Mortars and Plasters samples included in the database (Source: original).....	31
Table 4. Some non-destructive characterisation methods applied to cultural heritage materials (Source: Aucouturier & Darque-Ceretti, 2007).	40
Table 5. Query of some Accelerated Weathering Test Protocols from the literature survey included in the database (Source: original).....	62
Table 6. Internal model for the Sites entity of the database (Source: original).....	100
Table 7. Internal model for the Samples entity of the database (Source: original).....	102
Table 8. Internal model for the physicochemical entity of the database (Source: original).	103
Table 9. Internal model for the accelerated weathering test protocols (AWTP) entity of the database (Source: original).	106
Table 10. Internal model for the auxiliary table of the database linking samples and tests (Source: original).....	107
Table 11. Internal model for the Dynamic Performance Metrics (DPM) entity (performance and deterioration tracking) of the database (Source: original).....	108
Table 12. . Internal model for the References entity of the database (Source: original)..	111

List of Abbreviations & Acronyms

A

Alb: Albite

APD: Average Pore Diameter

APR: Average Pore Radius

Arg: Aragonite

AWTP: Accelerated Weathering Testing Protocols

B

B/A: Binder-to-Aggregate Ratio

Bt: Biotite

BTS: Brazilian Tensile Strength

C

C.I.: Cementation Index

Cc: Calcite

CCM: Ceramics and Composite Materials Research Laboratory

CH: Cultural Heritage

CSH / C-S-H: Calcium-Silicate-Hydrate

D

DAP: Diammonium Hydrogen Phosphate

DHL: Dry Hydrated Lime

DIA: Digital Image Analysis

Dol: Dolomite

DPM: Dynamic Performance Metrics

E

ERD: Entity-Relationship Diagram

F

F-T: Freezing-Thawing / Freeze-Thaw

Fe-Dol: Iron-rich Dolomite (Ferroan Dolomite)

FK: Foreign Key

Fs: Feldspar

FTIR: Fourier-Transform Infrared Spectroscopy

G

GIS: Geographic Information System

H

HAP: Hydroxyapatite

HBIM: Historic Building Information Modeling

Hem: Hematite

HISKP: Helmholtz-Institute of Nuclear Physics at the University of Bonn

HL: Leeb Rebound Hardness

HOU: Hellenic Open University

I

ICP-AES: Inductively Coupled Plasma Atomic Emission Spectroscopy

Ill: Illite

IMS-DEMO: Institute of Materials Science at N.C.S.R. "Demokritos"

IO: Iron Oxide

IR: Insoluble Residue / Insoluble fraction (e.g., IR < 2 μ m)

K

Kao: Kaolinite

L

LOI: Loss on Ignition

M

MgCal: Magnesium-rich Calcite

Mgs: Magnesite

MIP: Mercury Intrusion Porosimetry

MK: Metakaolin

ML: Machine Learning

Mnn: Manganite

Ms: Muscovite

N

N.C.S.R.: National Centre for Scientific Research ("Demokritos")

NAA: Neutron Activation Analysis

NDT: Non-Destructive Testing

NHL / NHL5: Natural Hydraulic Lime

NMK: Nano-metakaolin

O

OM: Organic Matter

OPC: Ordinary Portland Cement

P

PCA: Principal Component Analysis

PCC: Physicochemical Characterization

PK: Primary Key

Pl: Plagioclase

PSD: Pore-Size Distribution

Q

QC: Quality Control

Qtz / Qz: Quartz

R

RDBMS: Relational Database Management System

RH: Relative Humidity

S

Sa: Sanidine

SEM-EDS: Scanning Electron Microscopy – Energy Dispersive X-ray Spectroscopy

SiAlFe: Silicon, Aluminum, and Iron oxides combination ($\text{SiO}_2 + \text{Al}_2\text{O}_3 + \text{Fe}_2\text{O}_3$)

Sme: Smectite

SQL: Structured Query Language

SSA: Specific Surface Area

T

TMP: Thermo-Mechanical Performance

U

UCS: Uniaxial Compressive Strength

UPV: Ultrasonic Pulse Velocity

UV: Ultra-Violet

V

v/v: Volume to volume ratio

W

WAC: Water Absorption Coefficient

WWA: Wide Wheel Abrasion

X

XRD: X-Ray Diffraction

XRF: X-Ray Fluorescence

Introduction

Cultural heritage building materials and structures embody the intrinsic cultural, traditional, and architectural value of past civilizations, serving as tangible evidence of human ingenuity and identity, thus rendering their preservation critical and essential for transferring our history for generations to come. Unfortunately, recurring degradation processes inevitably threaten the diverse nature and composition of this heritage building materials, causing their erosion and, oftentimes irreversible weathering, necessitating a targeted conservation approach. This deterioration is often driven by a number of combined factors that are an outcome of extreme environmental conditions, like freezing-thawing cycles (F-T), thermal shocks, salt crystallization, or exposure to acidic conditions. In order to understand these decay processes and, in the future, predict the impending risks on cultural heritage building materials, it is fundamental to try and quantify their intrinsic properties and their responses to environmental stressors.

This is where material science plays a crucial role; Conservation strategies require a comprehensive pre-examination of the original materials to ensure that any intervention preserves cultural value and maintains material compatibility. Therefore, advanced scientific investigation is required to understand ancient material composition, production techniques, and the associated processes of deterioration. Characterizing materials such as stone, clay/ceramic-based materials, and mortars, involves detailed analyses of chemical, mineralogical, microstructural, and mechanical properties. Sophisticated methods, such as Scanning Electron Microscopy (SEM-EDXA), X-ray Diffraction (XRD), Mercury Intrusion Porosimetry (MIP), and X-ray Fluorescence (XRF), are routinely employed to define composition, pore structure, and chemical makeup.

An interesting challenge in the heritage material science field is the scarcity and fragmentation of gathered reliable data. Even when individual research focuses on certain performance indicators or thoroughly documents material deterioration, the resulting datasets are frequently divided by material type or property focus. Furthermore, assessing parameters like rock strength often requires Destructive Testing (DT), which is typically avoided in protected heritage sites. This constraint necessitates relying on correlations derived from Non-Destructive Testing (NDT) indices (such as surface hardness or ultrasonic pulse velocity) to assess mechanical performance and evaluate the overall deterioration

degree of stone artifacts. The successful prediction of deterioration depends on bridging this gap by systematically integrating diverse material properties—such as porosity, thermal conductivity, and compressive strength—into a unified quantitative framework.

Thus, the objective of this current research, is two-fold; Firstly, to conduct a comprehensive literature survey concerning cultural heritage building materials, focusing on stone, clay/ceramic-based materials, and mortars, while gathering data on their physico-chemical properties, thermo-mechanical performance, and resilience under accelerating weathering tests (specifically salt crystallization cycles and freeze-thaw cycles). This process includes extending and incorporating additional features into the database in progress of the Ceramics and Composite Materials Research Laboratory (CCM). While another crucial objective of the thesis is to establish an optimized database structure that can be utilized for training machine learning models in future research projects.

The expected outcome is a database capable of providing the necessary features to predict the performance and deterioration of CH materials under various climate scenarios. This predictive capability will ultimately inform the selection of suitable preservation measures, offering a robust foundation for non-invasive heritage diagnostics and risk assessment. The methodology begins with the extensive literature survey and internal data collection, followed by the systematic creation and structuring of the database to facilitate the subsequent methodological step: training predictive models through the rigorous application of statistical methods (e.g., correlation, regression, and multivariate analysis) on integrated datasets.

The present dissertation is organized into five main chapters, transitioning from the literature survey and theoretical assessment of heritage material decay to the technical implementation of a digital repository. Chapter One establishes the fundamental necessity for characterizing Cultural Heritage (CH) building materials by outlining their physico-chemical and thermo-mechanical properties, while defining the material typologies—such as stone, mortars, and ceramics—within the database scope. Chapter Two systematically evaluates the environmental stressors and accelerated weathering testing protocols (AWTP) utilized in literature to quantify material failure, serving as the dynamic foundation for the relational database. Chapter Three details the core methodology of the study, describing the systematic data mining of academic literature, the standardization of heterogeneous datasets, and the technical development of the relational database structure using Microsoft Access.

Chapter Four focuses on machine learning feature engineering and data validation, identifying specific input features and target variables to create ML-ready datasets for predictive conservation. Finally, Chapter Five, the Conclusions, summarizes the research findings, evaluates the database's contribution to predictive diagnostics, and outlines future research directions for integrating digital heritage workflows.

This organizational framework moves beyond traditional descriptive cataloging toward an objective, predictive conservation methodology. Ultimately, the development of this unified relational repository provides heritage professionals, scientists, and decision-makers with a robust, data-driven diagnostic pipeline. In an era where cultural assets face unprecedented threats from global climate dynamics, transforming fragmented literature into a standardized, machine-learning-ready platform establishes a crucial stepping stone toward proactively safeguarding tangible human history for generations to come.

CHAPTER 1: CULTURAL HERITAGE BUILDING MATERIALS TYPOLOGIES, PHYSICO-CHEMICAL & THERMO-MECHANICAL CHARACTERIZATION WITHIN THE DATABASE SCOPE

This research began with the conduction of a comprehensive literature review on material characterisation and testings under accelerated weathering conditions. As it was expected, there is an extensive number of papers concerned with cultural heritage material characterisation; numerous studies that begin by describing the history of the particular monument under study, then providing the physical and mechanical properties of the materials involved; Petrological descriptions, mineralogy, coupled with measurements of capillarity, porosity and pore size distribution, surface hardness, mechanical strength, and so on and so forth. This information is undoubtedly of immense value. However, when the field moves beyond material characterisation and onto a better understanding of their performance through the lens of various environmental stressors or climate change conditions, the research becomes even more significant. To take it a step further, when qualitative and quantitative results of studies of cultural heritage material decay and performance can be carefully gathered into a database that will comprise datasets, widely accessible and robust, technology can work miracles; Machine learning models could be trained, by virtue of this database, to predict material performance and deterioration in future climate extremes and environmental conditions, thus aiding conservation efforts.

Therefore, the systematic characterization of cultural heritage (CH) building materials forms the fundamental basis of this research, serving as the necessary input data for predicting material performance and deterioration in future machine learning models. For effective conservation work, especially when substitution materials are required, simple analytical methods may suffice for matching basic properties of conservation mortars with ancient masonry. However, detailed analyses are required when the aim is to understand the original traditional forms of materials of construction or to precisely characterize the degradation processes. By defining the physico-chemical, microstructural, and thermo-mechanical properties of these materials is crucial for generating a unified predictive framework applicable to heritage risk assessment and conservation planning. This chapter

is the beginning of an extensive literature survey, through which, the typologies of materials targeted by this research are established and the methods for determining their fundamental identity and structure are outlined, therefore creating the necessary core of the dataset, for subsequent predictive modelling.

1.1 Typologies of cultural heritage building materials in the database scope

The scope of this thesis involves not only extending an existing database to comprehensively incorporate material types crucial for CH buildings but also develop one that is robust and machine-learning ready. Ancient stone, clay and ceramic-based materials, as well as ancient mortars or plasters are the heritage materials of interest in this current database development. These materials exhibit high variability influenced by local resources, ancient techniques, and environmental exposure. While the primary digital architecture and feature sets of this current study focus heavily on these dominant inorganic geomaterials, a comprehensive understanding of historical built heritage requires acknowledging the symbiotic presence of organic structural elements. In historical monuments, wood beams, timber frameworks, and tie-rods play an integral structural role, often acting as the flexible tensile counterparts to rigid masonry elements. Although wood decay mechanisms (such as fungal rot or insect infestation) operate on a different biochemical plane than salt crystallization or frost fatigue (Vintzileou, 2008), future expansions of heritage repositories must eventually integrate these organic features.

To establish the foundational context for the database, this section delineates these primary material categories that constitute the architectural fabric of cultural heritage sites. The selection of these materials is not arbitrary but is based on their historical prevalence and the critical need to quantify their unique responses to environmental stressors. By categorizing materials into distinct typologies, specifically stone, mortars and plasters, and clay and ceramic-based materials, as well as restoration materials, a database can systematically organize high-dimensional data, ranging from mineralogical composition to advanced mechanical indices.

This categorization is essential for developing a unified quantitative framework that can bridge the gap between fragmented datasets often divided by material type. In a predictive conservation context, these typologies serve as primary categorical variables that allow future machine learning models to adjust for inherent material differences when predicting failure or deterioration levels under various climate scenarios. The following subsections further define these materials, focusing on the specific physico-chemical, thermo-mechanical, and structural attributes that define their identity within the database.

1.1.1 Stone lithologies and heritage contexts

Stone has become renowned for being a versatile and sustainable building material with a low intrinsic carbon signature, while also representing a substantial portion of the tangible heritage of the world (Smith et al., 2008). Building stones are generally classified as igneous, sedimentary, and metamorphic in nature, with a history of being utilised for construction and adornment, as well as for fill material, crushed stone, and coarse-grained grit material. These rocks are in fact separated into what are known as hard and soft rocks. Granite, rhyolite, and basalt are some examples of hard rocks that are challenging to mechanically process. Sandstones, tuffs, limestones, and serpentinites are examples of soft rocks that are typically easily handled. Natural building stones are among the most used building materials in construction and cultural heritage (Galanaki et al., 2022) and are often characterised by their physical properties, including water absorption, porosity, flexural strength, compressive strength, by their colour, as well as their aesthetics (Siegesmund & Snethlage, 2011). Within the scope of a predictive database, the preservation of these materials requires moving beyond simple qualitative descriptions, to also establishing strict, numerical feature sets based on their distinct petrophysical, mineralogical, and thermo-mechanical properties (Coletti et al., 2025). Because a stone's specific lithology dictates its intrinsic vulnerabilities, capturing its specific response to Accelerated Weathering Testing Protocols (AWTP), such as salt crystallization, freeze-thaw cycles, and thermal fatigue, is essential for training machine learning algorithms (Galanaki et al., 2022).

Many of the stone artifacts included in the database are made of sandstone, marble, and granite, representing sedimentary, metamorphic, and igneous rock, respectively. The

stone lithologies integrated into this database represent a wide spectrum of natural materials whose inherent properties—such as mineralogy, texture, and pore structure—dictate their long-term performance in heritage contexts. The selection of the surveyed literature reflects a global diversity of heritage sites, from Mediterranean monuments to rock-hewn sites in Asia. Consequently, the literature survey of this current research begins by determining as many lithologies from the gathered bibliography as possible.

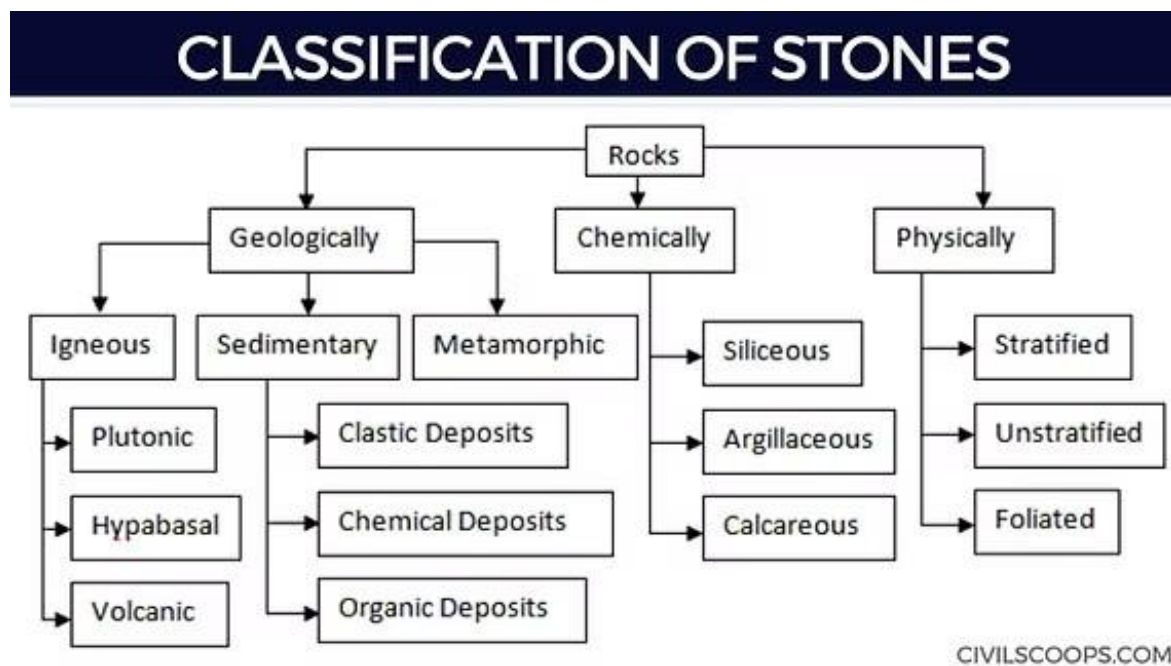


Figure 1. Classification of stones geologically, chemically and physically. (Source: Jain, 2017, URL: wixsite.com/stone-classification).

For instance, Zhang et al. (2023) provide adequate data material on sandstone, marble, and granite from the stone artifacts mined in Shandong Province, China, both from their initial undamaged state, as well as data from the influence of freeze-thaw weathering on their thermal properties. Cappai et al. (2024) experimented on various facies of limestones used in cultural heritage sites. Specifically, six different facies of Miocene limestone originating from Santa Caterina di Pittinuri (central-western Sardinia, Italy) were analysed for material characterisation and subjected to salt crystallisation testing for decay resistance determination. *Miocene limestone* refers to a sedimentary rock formed during the Miocene Epoch (approximately 23 to 5.3 million years ago). These limestones are often "bioclastic", meaning they are composed of fragments of shells, coral, and algae, while their texture

typically ranges from calcarenites (sand-sized grains) to grainstones or packstones. Miocene limestones are frequently characterized by high primary porosity (spaces between the original fragments) and secondary porosity (dissolution holes formed later), making them highly susceptible to salt and frost. Additionally, Zhang et al. (2025), added to this research’s data gathering on sandstone characterisation, after exploring the influences of various salts and temperature on salt weathering of sandstone in the Nankan Grotto. Peng et al. (2022) also investigated the freeze-thaw damage on sandstone, testing samples of yellow sandstone from the Qingyang North Grottoes in the Gansu Province of China. Their research included the analysis of sandstone’s macroscopic and microscopic morphologies under different freeze-thaw cycles, testing porosity, surface hardness, and uniaxial compressive strength, as well as wave velocity and water content, further adding to the sandstone’s datasets for the purposes of this research.

Coletti et al. (2025) selected to investigate six limestones (Botticino, Red Verona, Costozza, Istrian, Santa Pudica and Sfouggaria stones), two white marbles (Carrara and Macael), two volcanic rocks (Euganean and Tønsberg), one carbonate-dominated sandstone (Lartios stone), and one intrusive igneous rock (Tønsbergite) (Coletti et al., 2025). The literature regarding the characterisation and broad use of these stones in cultural heritage is abundant, thus aiding in the population of the stone heritage building materials dataset of this research’s database. However, there are still some stones, namely the Sfouggaria and Tønsberg stones or the Tønsbergite, that have not yet been extensively studied upon (Coletti et al., 2025), therefore including as much literature of their characterisation as possible, would be an important representation of these lithologies for the development of this database.

Galanaki et al. (2022) studied the susceptibility to salt crystallisation of five different stones quarried from the Mediterranean basin, following their characterisation conducted by Apostolopoulou et al. (2019). Sfouggaria Stones (Sa and Sb) are two *biocalcarenes* sourced from the Stegna quarry in Rhodes. *Sfouggaria A (Sa)* contains silicate minerals like ilvaite and kaolinite, it is denser, and characterised by lower porosity and smaller pores, while *Sfouggaria B (Sb)* contains cristobalite and possesses a significantly more open structure, with an average pore radius and compressive strength nearly double that of Sa. *Albamiel (Alb)* is a Spanish stone from Murcia, also a biocalcarene, that mimics the

materials used during the Italian restoration period (1937–38). It exhibits the lowest mechanical strength among the group. *Cyprus Stone (K)* is a biocalcarenite that contains lithic and crystalline fragments. While its porosity matches Albamiel, its pores are much smaller, contributing to a compressive strength that is twice as high. Lastly, unlike the carbonate-dominated stones, the *Daskalakis lithotype* from Achaia is a *calcitic sandstone (litharenite)*. Dominated by quartz rather than bioclasts, it displays the highest cohesion, the lowest porosity, and the greatest compressive strength of the five stones studied.

Capasso et al. (2024) also contributed to the population of this research’s heritage stone dataset by their raw and consolidated Vincenza stone testing. *Vincenza stone* is a historically significant calcareous limestone, renowned for its aesthetic appeal and extensively used in historical monuments and pieces of art in the Veneto Region of Italy. It is mainly composed of dolomite and calcite, with low clay and silica contents, originating from the Oligocene backreef zone bioapatite formations (Capasso et al., 2024), as already mentioned above. Capasso et al. overviewed the main properties of Vincenza Stone (VS) stone samples and then assessed its durability by means of accelerate weathering tests, namely salt crystallisation, freeze-thaw testing, and acid rain simulation, thus offering helpful data for the population of original and weathered samples dataset.

1.1.1.1. Sedimentary Rocks: Limestones, Calcareenites, and Sandstones

Sedimentary rocks are frequently shown up as layered deposits that form bed structures or strata. They represent a major component of the cultural heritage database due to their historical prevalence in construction and their complex, often porous structures that dictate their susceptibility to environmental decay. Within the context of this research, sedimentary siliciclastic rocks (sandstones) and carbonate sedimentary rocks (limestones) are prioritized for their diverse responses to stressors like salt crystallization and freeze-thaw cycles.

The archaeometric literature provides vital data on how the interplay between compressive strength and pore size distribution dictates a stone’s decay pathway. For example:

- a) Pore size distribution ($>10\ \mu\text{m}$) plays a critical role; Accelerated salt crystallization tests on Mediterranean biocalcarenites (such as the *Sfouggaria* stone from Rhodes,

Greece, and *Albamiel* from Spain) versus the *Daskalakis* calcitic sandstone reveal counter-intuitive performance metrics. The *Daskalakis* sandstone exhibits extremely high uniaxial compressive strength (132.1 MPa) and very low total porosity (1.89%). However, because it contains very few coarse pores ($>10\text{ }\mu\text{m}$), it is highly susceptible to severe salt decay, failing through multiple flaking. Conversely, the *Sfougaria* and *Albamiel* stones, despite having much lower compressive strengths (10.8 to 30.18 MPa) and higher porosities (13% to 16.7%), possess high percentages of coarse pores. These macro-pores act as safe reservoirs for salt crystallization, leading to a less destructive "granular disintegration" rather than catastrophic flaking (Galanaki et al., 2022).

- b) Stones with highly porous facies like heritage limestones such as the Miocene Pietra Cantone from Sardinia (Colombu et al., 2017) and the Carovigno stone from Apulia, Italy, exhibit exceptionally high open porosities (ranging from 28% to 37%). Interestingly, in the Carovigno stone, this massive void volume creates a "pillow effect," granting the stone high resistance to thermal shocks by providing internal space for calcite crystals to expand without generating macro-cracks (Fioretti et al., 2018).
- c) Structural heterogeneity is also vital as proven by the many researches executed on widely used European limestones, such as Costozza stone (a highly porous Vicenza stone used in Palladian architecture) and Santa Pudia stone (Granada, Spain), exhibit low compressive strengths (10–22 MPa) and high moisture absorption, rendering them highly vulnerable to freeze-thaw degradation (Coletti et al., 2025).

Botticino Stone is a partially dolomitised micritic limestone of the Corna Formation, from the early Jurassic era. Wackestone, mudstone, and floatstone, along with fossil assemblages like red algae, oncolites, and other bioclasts, are part of this formation. Quarry areas are located in Brescia, northern Italy, like Botticino, Mazzano, and Rezzato. Some relevant monuments of this stone are namely, the Vespasian Temple, Theatre, Forum and Baths (Roman), Santa Maria dei Miracoli, and Palazzo della Loggia (Coletti et al., 2025). In terms of database engineering and research, Botticino stone serves as a significant case study for the behavior of partially dolomitized micritic limestones. The transition from a calcium-rich wackestone or mudstone to a dolomitic composition introduces mineralogical heterogeneity that directly affects its long-term durability. Integrating this stone into the database allows for a detailed analysis of how micro-fossil assemblages—such as red algae and bioclasts—

influence the distribution of its internal pore network. Furthermore, the extensive use of Botticino stone in monuments spanning from Roman bathhouses to Renaissance palaces provides a robust longitudinal dataset, enabling researchers to correlate specific quarry origins (Botticino, Mazzano, or Rezzato) with the varying rates of chemical and physical decay observed across different historical periods.

Red Verona Stone, or *Rosso di Verona*, is an ammonite-containing limestone from the Rosso Ammonitico Veronese Formation, a late Bajocian to Thitonian compacted sedimentary sequence deposited on the distal Trento Plateau. In terms of petrography, it comprises mudstone and floatstone with a variety of colours, ranging from yellow and white to reddish-brown or reddish orange, depending on the concentration of iron oxides and clay minerals. Since the Roman era, this formation has been heavily utilised in the Venetian Prealps as dimension stone, especially in northeastern Italy. The majority of the Roman theatre's components, including the Ponte Pietra (Stone Bridge) in Verona and the Roman amphitheatre "Arena," are composed of this stone. The many historical applications of Red Verona stone include the cathedrals of Bologna, Parma, and Cremona, as well as the lions at the entrance of the Basilica of Santa Maria Maggiore in Bergamo (Coletti et al., 2025). Red Verona stone provides a vital dataset for studying the influence of mineral impurities on the durability of sedimentary sequences. Its complex petrography—varying from mudstones to floatstones—is highly dependent on the concentrations of iron oxides and clay minerals, which not only dictate its iconic colour palette but also function as primary variables in its hygric behavior and sensitivity to moisture. By documenting its extensive use in landmark structures like the Verona Arena and the Ponte Pietra, the database can link these internal chemical features to specific macroscopic decay patterns observed over two millennia of exposure.

Costozza stone is an ivory variation of *Vicenza Stone*, an ornamental stone extracted from the Berici Hills of north-eastern Italy and represents lithofacies of lower Oligocene Castelvetro formation. Since the Roman era, Vicenza stone has been extracted from more than a hundred subterranean locations for use in statues, headstones, and architectural components. Its most famous use is in the construction of churches, private villas, and public palaces in Vicenza and the surrounding areas, all of which are included in the UNESCO World Heritage Site "City of Vicenza and the Palladian Villas of the Veneto." Vicenza stone

is also used to create the seventy-eight statues in Padova's Prato della Valle square, as well as the Modena Cathedral and Ghirlandina, which are included in the UNESCO World Heritage Site "Cathedral, Torre Civica and Piazza Grande, Modena." Because of this, Vicenza Stone and Red Verona Stone have both been suggested for IUGS Global Heritage Stone Resource (GHSR) recognition (Coletti et al., 2025). Costozza stone serves as a vital case study for high porosity lithofacies within a UNESCO World Heritage context. As an ivory variation of the broader Vicenza Stone, its data-engineering value lies in its extensive subterranean quarrying history and its role as a primary material for Palladian architecture. Thus, though this database, it can provide the necessary framework to correlate its specific microstructural "ivory" characteristics with the salt crystallization and weathering patterns typical of the Berici Hills lithotypes, facilitating predictive maintenance for some of Italy's most culturally significant monuments.

Istrian stone is a widely extracted and exploited stone from the late Jurassic to Eocene age, with thousands of quarries, the most important of which are located in Rovinj and in the Vrsar (Orsera) area. Dunda and Kujundžić (2004) have estimated that around 80% of the stones used in Venice from the 14th century onward originated from Istria. The stone is of significantly low porosity (often below 1%), and was also often used for cladding, as seen in the Rialto Bridge, or the Bridge of Sights. Istrian stone has also been used in façades for the Basilica of San Pietro di Castello, and San Giorgio Maggiore. Aside from Venetian architecture, the stone has been used in heritage monuments in Thessaloniki (Greece), in Dubrovnik (Croatia), as well as in the Euphrasian Basilica in Poreč, Croatia (Coletti et al., 2025).

Sfouggaria stone is a critical lithotype used extensively in the Mediterranean heritage context. It is a biocalcarenite (specifically grainstone, rudstone, or floatstone) belonging to the Cape Arkhangelos Calcarenite of the Rhodes Formation. It is composed of fossiliferous marine sediments, including diverse mollusc assemblages. Since 408 BCE, this stone has been the primary building material for the City of Rhodes, a UNESCO World Heritage Site. It was used for fortifications and buildings throughout the Byzantine period, the period of the Knights, and during the Italian occupation (Coletti et al., 2025).

Santa Pudia stone is a porous, yellowish-white limestone of the Tortonian age, primarily sourced from the Escuzar region near Granada, Spain. Due to its manageable

softness and local availability, it has served as a foundational material for iconic Andalusian architecture, including the Granada Cathedral and the Palace of Carlos V, and has been utilized in major restoration works like those for the Mosque of Córdoba. Scientific interest in this stone is significant because its durability is heavily influenced by its internal pore system and clay content, which make it particularly vulnerable to atmospheric pollution and salt crystallization. Because of its historical prominence, researchers have extensively documented its mechanical properties, creep behavior, and specific weathering patterns to develop comprehensive degradation models and evaluate the efficacy of various conservation treatments (Coletti et al., 2025).

1.1.1.2. Metamorphic rocks: marbles

Metamorphic rocks represent a critical category in the cultural heritage database due to their extensive use in ornamental elements and structural veneers. Within this research framework, the analysis of metamorphic stones focuses on how their unique anisotropic structures and mineralogical stability respond to environmental stressors like thermal stress and salt-induced crystallization. In heritage contexts, predominantly calcitic and dolomitic marbles (e.g., *Carrara* marble from Italy, *Macle* marble from Spain, and *Makrana* marble from India), are generally characterized by low initial open porosity (often <0.5%) and dense, interlocking crystalline textures.

The primary degradation mechanism for marbles is thermal weathering (Ghimire & Manohar, 2025; Martínez-Martínez et al., 2013). Calcite crystals exhibit highly anisotropic thermal dilation: they expand significantly along the *c*-axis while simultaneously contracting along the *a* and *b* axes upon heating (Mahmutoğlu, 2017; Martínez-Martínez et al., 2013). Over repeated diurnal heating and cooling cycles, this competing expansion and contraction generates severe inter-granular stress, leading to "thermal fatigue," micro-cracking, and a phenomenon known as "sugaring" (granular disaggregation) (Martínez-Martínez et al., 2013). Thermal Effusivity and UPV are essential decay proxies in metamorphic rocks, hence their inclusion to this database effort. As thermal weathering opens the grain boundaries, the marble's open porosity increases, which subsequently invites moisture and salt ingress. This microstructural deterioration can be quantified non-

destructively. Studies on weathered marbles (Ghimire & Manohar, 2025; Martínez-Martínez et al., 2013) show a direct correlation between the proliferation of micro-cracks and a significant reduction in Ultrasonic Pulse Velocity (UPV). Furthermore, changes in thermal properties—specifically reductions in thermal effusivity and thermal conductivity—serve as highly sensitive, quantitative indicators of the aging degree in these stones (Zhang et al., 2023).

Carrara marble is a globally renowned stone from the Apuan Alps in Tuscany, Italy, celebrated for its exceptional quality and deep historical roots dating back to pre-Roman times. Geologically, it originates from Mesozoic carbonate sequences that underwent low-grade metamorphism during continental plate collisions between the Eocene and early Miocene. This process resulted in a fine- to medium-grained calcitic marble, primarily known in its classical ivory-white form, though it also appears in veined and brecciated varieties. Its architectural and sculptural legacy is unparalleled, featuring in ancient Roman monuments like the Pantheon and Trajan’s Column, as well as Renaissance masterpieces such as Michelangelo’s David and Pietà. The stone's prestige persisted into modern eras, being utilized in international landmarks ranging from London's Marble Arch to the Sheikh Zayed Grand Mosque in Abu Dhabi. Recognizing this immense cultural and geological value, Carrara marble was officially designated as an IUGS Heritage Stone in 2017 (Coletti et al., 2025).

Macael marble is a significant metamorphic stone designated as an IUGS Heritage Stone in 2019 due to its extensive cultural and historical legacy. Originating from the town of Macael in Almería, Spain, this stone is characterized as a coarse-grained, purely calcitic white marble. Certain varieties feature grey banding caused by the presence of micas, quartz, and opaque minerals. The marble is part of the Nevado-Filábride Complex, which represents the deepest tectonic layer of the Betic Cordillera's Internal Zone. Macael marble has been utilized in some of the most iconic architectural landmarks in Spain, many of which are UNESCO World Heritage Sites; it was used for statues, inscriptions, and architectural components in cities like Itálica and Sagunto, the Mosque-Cathedral of Córdoba and the Madinat al-Zahra palace-city, while it also featured prominently in the Hall of the Two Sisters and the famous Court of the Lions in Granada (Coletti et al., 2025).

1.1.1.3. *Igneous Rocks: Granites, Trachytes, and Tuffs*

Igneous Rocks (comprising both volcanic/extrusive and intrusive types) are integrated into the database to provide a critical comparative durability profile against sedimentary and metamorphic lithologies. While often perceived as exceptionally durable, their complex mineralogy—rich in feldspars, micas, and pyroxenes—makes them susceptible to specific chemical and thermal degradation pathways, particularly when exposed to salt mixtures and frost action. Because quartz has a thermal expansion coefficient significantly higher than that of feldspar, severe temperature fluctuations induce intra-granular and inter-granular micro-cracking due to thermal expansion mismatch (Hale, 2003). Additionally, certain highly porous volcanic tuffs are highly vulnerable to chemical alteration and salt crystallization, where acidic water attacks silico-aluminate minerals, transforming them into soluble sulphates that drastically weaken the rock matrix (Barbero-Barrera et al., 2019; Çelik & Sert, 2020).

Euganean trachyte is an early Oligocene subvolcanic porphyritic rock sourced from the Euganean Hills in northeastern Italy. Its use in cultural heritage is remarkably long-lived, spanning from the Neolithic period through the Roman era and into the Renaissance. Due to its durability and specific mechanical properties, it was historically employed for various functional and structural purposes, including millstones, sarcophagi, paving stones, and maritime infrastructure like harbour elements (Coletti et al., 2025).

Tønsberg and Tønsbergite are two igneous stones sourced from the Tønsberg region of Norway, which serves as a primary pilot site for the Hyperion Project. These rocks were formed during the late Carboniferous period as part of the magmatic activity within the Oslo Graben, a rift system that penetrated the ancient Fennoscandian Shield. Tønsberg Latite is a reddish-pink volcanic (extrusive) rock. It is visually defined by large, characteristic rhomb-shaped anorthoclase crystals (phenocrysts) set within its matrix. Tønsbergite on the other hand, is a red, quartz-bearing intrusive rock. It is a specific variety of larvikite (classified as syenite or monzonite) and contains a complex mineral assembly including Ti-augite, biotite, and ternary feldspars. Both lithotypes have an established history in Norwegian architecture. Notable examples include the Slottsfjell tower in Tønsberg and the Norwegian Order of Freemasons lodge in Oslo (Coletti et al., 2025). Their inclusion in your

database provides essential data on the performance of high-durability, crystalline igneous rocks within Northern European heritage contexts.

Lartios stone (or *lithos lartios*) is a distinctive grey-blue carbonate rock native to the island of Rhodes, primarily sourced from the village of Lardos. Geologically, it belongs to the lower Oligocene sequences of the Kattavia Flysch, specifically within the Kalathos Member. This formation is characterized by a complex alternation of grey limestones, lithic turbiditic sandstones, and sandy nummulitic detrital limestones that have undergone weak metamorphism. During the Hellenistic period, it was frequently used alongside marble for portrait statues, pedestals, and decorative moldings found at the Lindos Acropolis. While primarily for local use, its prestige is evidenced by its use in the base of the iconic Nike of Samothrace (the Winged Victory) in the form of a ship's bow (Coletti et al., 2025). From a data-engineering and conservation standpoint, Lartios stone offers unique research variables due to its high degree of provenance variability. While often grouped under a single name, the stone originates from three distinct quarrying districts—Lardos, Kymissala, and Lyros—each displaying subtle differences in colour and texture. For database population, these variations are resolved through high-resolution analytical fingerprinting using EPR spectroscopy and stable isotope analysis. Furthermore, its geological transition from grey limestone to sandy detrital limestone introduces mineral heterogeneity and complex pore structures, making Lartios stone an ideal subject for multivariate analysis of shifting decay patterns.

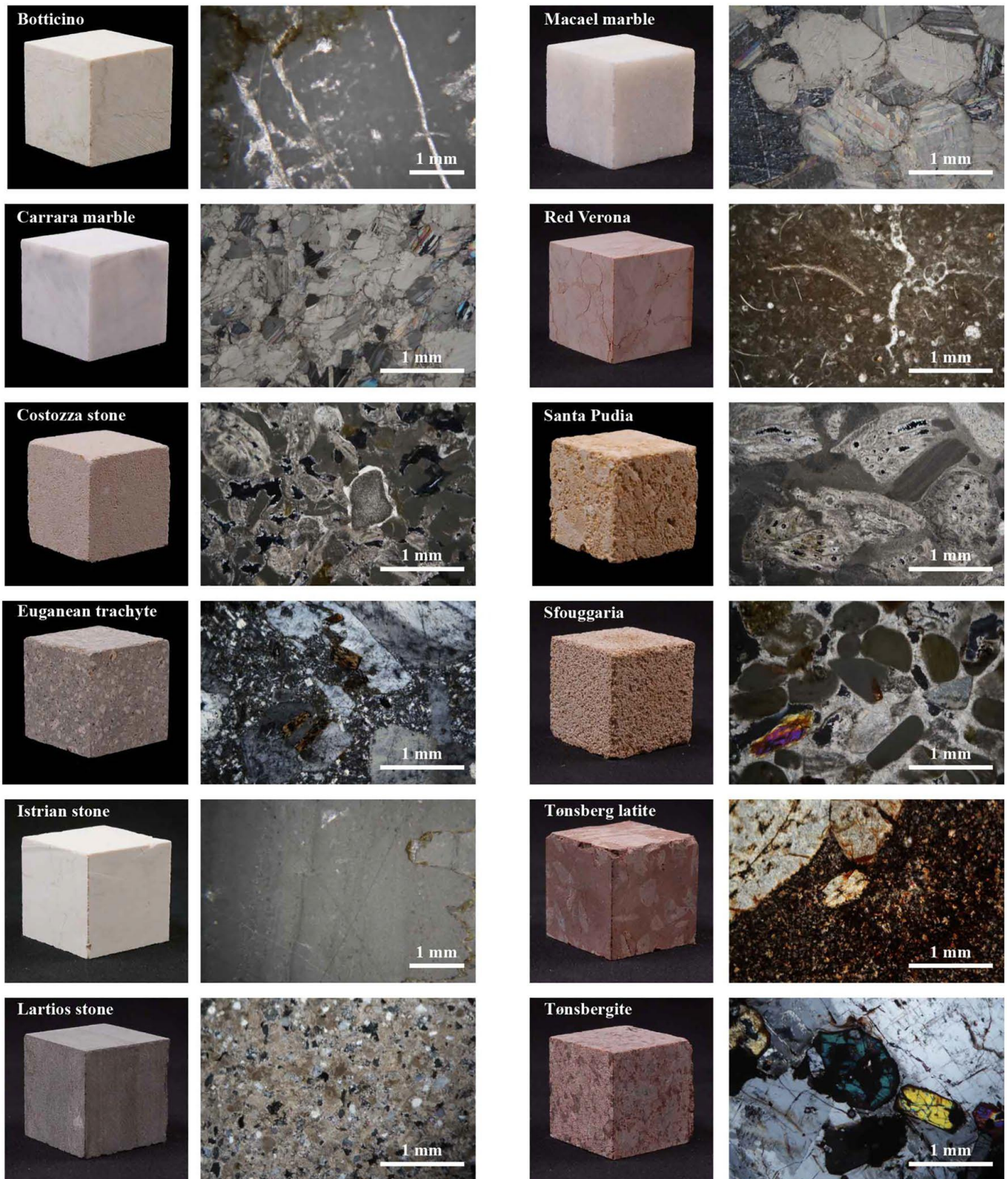


Figure 2. Cubic specimen of the stones and their relative photomicrographs of representative thin sections observed under crossed polarized light (Coletti et al., 2025).

Table 1. Query of some Stone samples included in the database (Source: original).

Sample_Code	Material_Subtype_&_Description	Mineralogy*	Chemical_Composition	Reference
MLN-SP	Santa Pudia Tortonian bioclastic calcarenite limestone	Cc, Sme, Ill	Carbonates: 97%, IR<2μm: 1.5%	Molina et al. (2013)
MLN-TA	Pleistocene travertine	Cc, Paragonite	Carbonates: 98%, IR<2μm: 0.5%	Molina et al. (2013)
MLN-DB	Upper Cretaceous Boñar dolostone	Dol, Cc, Ill	Carbonates: 80%, IR<2μm: 0.8%	Molina et al. (2013)
MLN-CF	Fraga Miocene bioclastic wackstone, limestone	Cc, Ill, Sme, OM	Carbonates: 94%, IR<2μm: 0.2%	Molina et al. (2013)
MLN-AU	Uncastillo sandstone: Lower Miocene litharenite	Cc, Qtz, Ill, Sme	Carbonates: 44%, IR>2μm: 54.1%	Molina et al. (2013)
MLN-AV	Villaviciosa sandstone: Upper Jurassic grey sandstone	Qtz, Fs, Ill	Carbonates: 0%, IR>2μm: 98.9%	Molina et al. (2013)
FIO-CAR	Fine-grained, pure white, medium-soft calcarenite (packstone)	Cc (almost exclusively), rare iron hydroxides	Pure or nearly pure calcium carbonate	Fioretti et al. (2018)
CEL-S-AND	Fine-grained, porphyritic volcanic rock	Pl (oligoclase, andesine, Sa), pyroxene, hornblende, Bt, montmorillonite, tridymite, Qtz	SiO ₂ 56.70%, Al ₂ O ₃ 16.10%, K ₂ O 7.09%, Fe ₂ O ₃ 5.39%, CaO 5.40%, Na ₂ O 2.80%, MgO 2.10%, TiO ₂ 1.19%, P ₂ O ₅ 1.00%	Çelik & Sert (2020)
GH-M-WMM	Marble	Cc, Bt, actinolite, iron impurities	Calcium carbonate	Ghimire & Manohar (2025)
WN-LGL	Limestone	Cc (84.3%), Dol (15.4%)	Site surface ions (mg/L): Chloride 265.4, Sulfate 208.7, Sodium 112.3, Potassium 74.9,	Wang et al. (2026)

			Carbonate 70.5, Calcium 37.9, Magnesium 11.6	
SH-M-s	Tertiary purplish-red and brick-red glutenite rock cemented with mud, iron, and calcium	Qtz (30%), Fs (23%), Cc (15%), Black mica (9%), White mica (5%), Clay minerals (18%)	Site surface ions (mg/l): SO ₄ (927.62), Na ⁺ (237.30), Ca ²⁺ (172.51), Mg ²⁺ (131.36), NO ₃ ⁻ (71.70), K ⁺ (26.37), Cl ⁻ (18.39)	Sheng et al. (2024)
SH-N-s	Tertiary purplish-red and brick-red glutenite rock	Qtz (30%), Fs (23%), Cc (15%), Black mica (9%), White mica (5%), Clay minerals (18%)	Site surface ions (mg/l): SO ₄ (927.62), Na ⁺ (237.30), Ca ²⁺ (172.51), Mg ²⁺ (131.36), NO ₃ ⁻ (71.70), K ⁺ (26.37), Cl ⁻ (18.39)	Sheng et al. (2024)
RB-PO-T	Porous laminated facies	Cc (95.02%), Siderite (1.54%), Mnn (1.49%), IO (1.41%), Anhydrite (0.54%)	Calcium carbonate, IOs/manganese	Romero Bastidas (2022)
RB-YO-T	Porous laminated facies	Cc (65.50%), Arg (23.91%), Mgs (9.69%), Strontianite (<0.5%), IO (<0.5%)	Calcium carbonate	Romero Bastidas (2022)
APO-IR	Calcarenite	Cc, Qtz, halite, Arg	CaCO ₃ , SiO ₂	Apostolopoulou et al. (2019)
ZH-NS	Sandstone	Qtz (69.2%), Fs (21.4%), Cc (4.9%), Clay (4.5%)	SiO ₂ (76.06%), Al ₂ O ₃ (7.57%), CaO (4.62%)	Zhang et al. (2025)
HO-LS	Sandstone	Qtz (46–55%), Alb (18–25%), Cc (13–19%), Microcline (7–12%)	SiO ₂ (73.21%), Al ₂ O ₃ (12.45%), Fe ₂ O ₃ (3.82%), CaO (4.15%)	Hong et al. (2023)

HO-SL	Paleozoic Cambrian limestone	Cc (58–75%), Dol (15–30%), small amounts of Qtz/clay	CaO (52.14%), MgO (18.32%), CO ₂ (28.54%), Fe ₂ O ₃ (0.55%)	Hong et al. (2023)
PE-YS	Sandstone	Qtz, Fs, Cc, Dol	Argillaceous cement: Montmorillonite, Ill, Kao	Peng et al. (2022)
COL-BS	Floatstone/Crystalline carbonate, Corna Formation	Cc, Dol	CaCO ₃ , CaMg(CO ₃) ₂	Coletti et al. (2025)
COL-CM	Marble, Tuscan Nappe formation	Cc, Dol, Qz	CaCO ₃	Coletti et al. (2025)
COL-CS	Grainstone/Rudstone, Castelgomberto Limestone Formation, Oligocene era	Cc	CaCO ₃	Coletti et al. (2025)
COL-ET	Trachyte, Venetian Volcanic Province	Qz, Pl, K-Fs, Anorthoclase, Bt, Clinopyroxene, Amphibole	Silicates	Coletti et al. (2025)
COL-IS	Mudstone, Kirmenjak Unit formation	Cc	CaCO ₃	Coletti et al. (2025)
COL-LS	Carbonate-dominated sandstone, Kattavia Flysch formation	Cc, Qtz, Pl, Chlorite, White mica	CaCO ₃ , SiO ₂	Coletti et al. (2025)
COL-MM	Marble, Nevado-Filábride Complex	Cc, MgCal, White mica	CaCO ₃	Coletti et al. (2025)
COL-RV	Mudstone/Floatstone, Rosso Ammonitico Veronese Formation	Cc, Qtz	CaCO ₃ , Fe ₂ O ₃	Coletti et al. (2025)
COL-SP	Grainstone/Rudstone, Granada basin formation	Cc, Qtz	CaCO ₃	Coletti et al. (2025)

COL-SFS	Grainstone/Rudstone, Rhodes Formation	Cc, Qtz	CaCO ₃	Coletti et al. (2025)
COL-TONS-L	Latite, Oslo graben formation	Pl, K-Fs, Bt, Clinopyroxene	Silicates	Coletti et al. (2025)
COL-TONS	Larvikite (variety of syenite), Oslo graben formation	Pl, K-Fs, Bt, Clinopyroxene	Silicates	Coletti et al. (2025)
WZ-YM	Permian Limestone	Cc, Calcium magnesium carbonate	CaCO ₃ , CaMg(CO ₃) ₂	Wang and Zhang (2023)
WZ-LA	Sinian Flint	Qz, Ms, Siderite	SiO ₂ , KAl ₂ (AlSi ₃ O ₁₀)(OH) ₂ , FeCO ₃	Wang and Zhang (2023)
WZ-FL	Carboniferous Limestone	Cc, High-Mg Cc	CaCO ₃ , CaMg(CO ₃) ₂	Wang and Zhang (2023)
WZ-LQ	Sinian Dolostone	Fe-Dol, Dol	Ca(Mg,Fe)(CO ₃) ₂ , CaMg(CO ₃) ₂	Wang and Zhang (2023)
WZ-GM	Jurassic Tuff; pink, porphyritic texture	Qtz, Orthoclase, Ms	SiO ₂ , KAlSi ₃ O ₈ , KAl ₂ (AlSi ₃ O ₁₀)(OH) ₂ +1	Wang and Zhang (2023)
HEI-ANH	Tectonized limestone; Wackestone	Cc, Qtz	87% CaCO ₃	Heidari et al. (2017)
HEI-ANO	Bioclastic wackestone	Cc, Qtz	90% CaCO ₃	Heidari et al. (2017)
HEI-ESH	Bioclastic wackestone	Cc, Dol, Ms	82% CaCO ₃	Heidari et al. (2017)
ALDO-PB-72	Limestone	Cc, Qtz	C (Polymer)	Aldosari et al. (2019)
ALDO-CAOH2	Limestone	Cc, Qtz, Portlandite	Ca (Enhanced)	Aldosari et al. (2019)
ALDO-KAO	Limestone	Cc, Qtz, Kao	Al, Si (Enhanced)	Aldosari et al. (2019)
CEL-S-DT	Volcanic tuff	Fs (Alb, Sa), Qtz, Ill, pyroxene, hornblende, volcanic glass	SiO ₂ 70.36%, Al ₂ O ₃ 13.53%, Fe ₂ O ₃ 1.43%, MgO 0.15%, CaO 1.65%, Na ₂ O 2.34%, K ₂ O 6.85%, TiO ₂ 0.05%, P ₂ O ₅ 0.01%, SrO 0.006%, LOI 3.18%	Çelik & Sert (2021)

AO-YT-A	Travertine, yellow, sedimentary rock with porosity <5%	Cc (95%), Dolomitic admixture (5%)	CaO (52.70), Fe ₂ O ₃ (1.22), SiO ₂ (1.22), MgO (1.00), Al ₂ O ₃ (0.23), Na ₂ O (0.08), K ₂ O (0.05)	Akin & Özsan (2011)
AO-YT-B	Travertine, yellow, sedimentary rock with porosity ≥5%	Cc (95%), Dolomitic admixture (5%)	CaO (52.70), Fe ₂ O ₃ (1.22), SiO ₂ (1.22), MgO (1.00), Al ₂ O ₃ (0.23), Na ₂ O (0.08), K ₂ O (0.05)	Akin & Özsan (2011)
WLB-LS	Creamy white oolitic limestone (packstone)	Cc (>99%), Impurities (<1%)	Calcium carbonate	Walbert et al. (2015)
WLB-MS	White oolitic limestone (packstone)	Cc (>99%), Impurities (<1%)	Calcium carbonate	Walbert et al. (2015)
WLB-SS-59	Light beige oolitic and coquina stone (grainstone)	Cc (>99%), Impurities (<1%)	Calcium carbonate	Walbert et al. (2015)
WLB-SS-73	Light beige oolitic grainstone	Cc (>99%), Impurities (<1%)	Calcium carbonate	Walbert et al. (2015)
BB-WD-T	Salic trachytic phonolitic tuff	Chabazite (34%), Alb (18%), Sa (16%), Tremolite (15%), Kao (7%), Hem (6%), Diopside (5%)	SiO ₂ (59.06), Al ₂ O ₃ (19.52), P ₂ O ₅ (7.85), K ₂ O (5.21), Fe ₂ O ₃ (3.70), Na ₂ O (3.05), TiO ₂ (0.69), CaO (0.28), MnO (0.23), MgO (0.19)	Barbero-Barrera et al. (2019)
BB-B-T	Breccia tuff	Chabazite (41%), Alb (16%), Sa (15%), Tremolite (13%), Kao (6%), Diopside (5%), Qtz (3%), Hem (1%)	SiO ₂ (40.51), MgO (12.08), CaO (11.74), Al ₂ O ₃ (10.93), Na ₂ O (4.55), TiO ₂ (3.96), Fe ₂ O ₃ (3.60), K ₂ O (1.33), P ₂ O ₅ (1.15), MnO (0.18)	Barbero-Barrera et al. (2019)

*Abbreviations of minerals are all mentioned in the [List of Abbreviations & Acronyms](#).

1.1.2 Ancient ceramics (bricks, clay and earthenware)

Ancient ceramics, comprising historical bricks, clay-based materials, and earthen structures, represent a critical typology within the database due to their historical prevalence and complex degradation pathways. These materials are characterized by high variability influenced by local resource availability, traditional manufacturing techniques, and centuries of environmental exposure. The scientific study of archaeological ceramics, including provenance and manufacturing technology, has been a central focus of archaeometry since the late 19th century. Originally centered on technological questions, research has evolved to address the origin, production, and distribution of specific ware types and entire ceramic assemblages. Unlike other ancient materials such as metals, ceramics can not be recycled after use; while some fragments can be reused to a limited extent in building or as grog, the vast majority of produced pottery is eventually discarded (Hein & Kilikoglou, 2012).

Ceramic materials are particularly valuable for long-term study because they are barely affected by alteration or deterioration during burial, meaning they generally preserve their original material properties and chemical composition. In this context, the chemical elemental composition serves as a "chemical fingerprint," providing a reliable basis for classifying assemblages and determining their provenance. This characteristic composition arises from the geochemical diversity of raw material sources and variations in the pottery manufacturing process. When identifying the origin of these materials, researchers typically rely on two types of reference materials: (a) established ceramics: items of well-known provenance based on stylistic or archaeological evidence, and (b) extant clay sources: natural clay deposits used as a direct material reference. However, using raw clays as a reference involves certain complexities, as processes such as clay mixing, purification, or tempering during the original manufacturing stage can complicate the direct comparison between archaeological ceramics and modern clay sources. Since the 1950s, the systematic determination of these chemical profiles has utilized various analytical techniques—most notably neutron activation analysis (NAA) and optical emission spectrometry (OES)—to build extensive digital databases that allow for sophisticated classifications and comparisons across different laboratories and regions (Hein & Kilikoglou, 2012).

Within the database scope, the systematic categorization of these materials begins with historical and archaeological bricks, which are sourced from geographically diverse contexts such as the 17th-century Baroque monuments of Poland (Misiewicz et al., 2025), traditional heritage residential buildings in China (Tang et al., 2018), and historical masonry units from Slovenia used to quantify the evolution of mechanical degradation (Uranjek and Bokan-Bosiljkov, 2015). The database also integrates standardized structural units like those from the Capidava Fortress in Romania (Ion et al., 2016) and alkali-damaged ancient bricks that exhibit specific weathering traces such as alkali-silica reactions (Lopez-Arce and Garcia-Guinea, 2005).

The ceramic category is further expanded to include artistic and utilitarian pottery, which provides essential data on firing technologies and material refinement. This includes prehistoric Gumelnița ceramics and Schneckenberg culture pottery from the Early Bronze Age (Ion et al., 2016), as well as antique Dutch ceramic tiles, which are analysed specifically for the salt weathering resilience of the brittle interface between the porous ceramic body and the lead-tin glaze (Chekai et al., 2025). Furthermore, the database accounts for specialized materials like pre-Columbian pottery from the Hualfin Valley in Argentina, characterized by its distinct pore-size distribution as determined by mercury intrusion porosimetry (Volzone and Zagorodny, 2014). Earthen and raw clay materials form the final pillar of this subsection, incorporating fine grey clay with micrometric particle size (ENSMR, 2025), silty clay subjected to freeze-thaw cycles (Cui et al., 2014), and salt-contaminated earthen sites where the cooling rate significantly influences the intensity of mechanical damage (Liang et al., 2025).

The durability and microstructural characteristics of historical bricks and earthenware are fundamentally dictated by the mineralogical composition of the raw clays used and the firing technologies applied during their manufacture. A primary distinction in archaeometric classification is based on the calcium oxide (CaO) content, categorizing raw materials into calcareous (Ca-rich, generally >6% CaO) and non-calcareous (Ca-poor) clays (Çam & Sağın, 2023; Elert et al., 2003). This compositional divide directly influences the required firing temperatures and the subsequent formation of the ceramic's internal pore network. Calcareous clays fired at lower temperatures (700–900 °C) often display a higher initial degree of vitrification and compressive strength than their non-calcareous

counterparts. To produce highly durable bricks unaltered by weathering, ancient builders needed to reach firing temperatures of approximately 1100 °C for calcareous clays and 1000 °C for non-calcareous clays, which significantly reduces total porosity and fosters a more favorable pore-size distribution (Elert et al., 2003).

Macroscopic colorimetric data (*Lab** coordinates) can serve as an effective, non-destructive proxy for deducing these internal firing dynamics and raw material compositions. For example, in the 16th-century Renaissance walls of Padua, Italy, yellow and beige bricks were manufactured using Mg- and Ca-rich illitic clays fired at temperatures of 900 °C or higher, which led to the formation of high-temperature phases such as diopside and gehlenite. Conversely, pale red bricks from the same structures were produced using Ca- and Fe-rich illitic clays fired at lower temperatures (850–900 °C), where the increased red hue correlates directly with higher silicate inclusions and a lower degree of reaction rim development around grains (Pérez-Monserrat et al., 2021). Similar archaeometric patterns are observed in Byzantine building bricks from the Anaia Church in Western Anatolia (5th–14th centuries). These bricks were manufactured from Ca-rich calcareous clays and fired at temperatures between 800 and 900 °C during the earlier construction periods, and below 850 °C in later periods. Consequently, they exhibit brown-beige colors, high total porosity ranging from 24.25% to 51.47%, low apparent densities (1.22–1.73 g/cm³), and relatively low uniaxial compressive strengths of 4.8 to 24.5 MPa. These high porosities highlight the fact that the survival of ancient ceramics does not rely solely on mechanical strength, but on the complex interplay between the ceramic's pore network and its surrounding environment (Çam & Sağın, 2023).

Environmental interactions, particularly moisture ingress and freeze-thaw (F-T) cycles, actively alter the microstructural integrity of historical bricks over time. A study on Baroque bricks from the 18th and 19th centuries demonstrated that F-T cycles induce pore coalescence, resulting in a significant decrease in fine, non-harmful pores (<1.0 µm) and a drastic increase in larger voids (3.0–10.0 µm). This transformation of the pore architecture promotes the initiation of microcracks and degrades the mechanical properties of the masonry (Misiewicz et al., 2025). The severity of this degradation is highly dependent on the degree of moisture saturation. Research on unsaturated F-T cycles in 19th-century bricks from China's Shanxi Province revealed that at low saturation levels, freeze-thaw actions can

marginally improve material strength, whereas at high saturation levels, the volumetric expansion of frozen water immediately causes cracking and structural failure (Tang et al., 2018). Furthermore, studies on the ancient clay bricks of the Ekur Ziggurat in Nippur, Mesopotamia, underscore how high-temperature firing processes and long-term environmental exposure yield bricks with lower densities and distinct thermal conductivity compared to modern equivalents, allowing them to endure millennia of weathering (Al-Sibahy & Edwards, 2017).

For the purposes integration of machine learning feature engineering with the aid of this predictive database, the diverse variables extracted from these typologies—such as exact calcium oxide percentages, categorical clay types (calcareous vs. non-calcareous), firing temperatures (°C), *Lab** colorimetric coordinates, total open porosity (%), specific pore-size distribution ranges (e.g., % of pores <2 µm vs >3 µm), and uniaxial compressive strength (MPa)—will be structured as numerical and categorical features. By feeding these quantified historical weathering pathways into the machine learning algorithms, the model will be able to correlate specific compositional fingerprints with distinct failure thresholds under simulated environmental loads like salt crystallization and frost damage.

Table 2. Query of some Ceramics/ Bricks samples included in the database (Source: original).

Sample_Code	Material_Subtype_&_Description	Mineralogy	Chemical_Composition	Reference
AN-WJ-GB	Ancient Grey Brick	Qtz (55%), Cc (22%), Alb (17%), Clay Mineral (4%), Cypsum (2%)	Cations and Anions (mg/L): Li ⁺ (27.66), K ⁺ (164.31), Ca ²⁺ (221.27), Na ⁺ (194.84), F ⁻ (44.84), Cl ⁻ (229.29), Br ⁻ (31.77), SO ₄ ²⁺ (302.19)	An et al. (2024)
AS-BRK	Class 5 burnt clay brick	Alumina, feldspar, quartz, magnetite	SiO ₂ 62.72%, Al ₂ O ₃ 17.28%, Fe ₂ O ₃ 9.61%, K ₂ O 3.95%, CaO 2.79%, TiO ₂ 1.06%	Anupama & Santhanam (2024)
PM-M1-4.8-A	Petro-fabric A1. Fired at ≥900 °C from Mg- and Ca-rich illitic clays.	Anorthite, diopside, calcite, gehlenite, forsterite	SiO ₂ 43.6, CaO 20.9, Al ₂ O ₃ 11.2, MgO 9.59, Fe ₂ O ₃ 4.54	Pérez-Monserrat et al. (2021)
PM-M2-1.1-A	Petro-fabric A1. Fired at ≥900 °C. Contains clay lumps with porous rims	Anorthite, diopside, calcite, gehlenite, forsterite	SiO ₂ 48.7, CaO 13.9, Al ₂ O ₃ 15.9, MgO 7.08, Fe ₂ O ₃ 5.61	Pérez-Monserrat et al. (2021)
PM-M2-4.6-A	Petro-fabric A1. Fired at ≥900 °C. Dark and light clayey materials shaping flux textures	Anorthite, diopside, aragonite, gehlenite, forsterite	SiO ₂ 42.8, CaO 17.3, Al ₂ O ₃ 14.4, MgO 7.32, Fe ₂ O ₃ 5.42	Pérez-Monserrat et al. (2021)
PM-M4-4.1-A	Petro-fabric A2. Fired at ≥900 °C. Displays a more friable texture	Anorthite, diopside, calcite, gehlenite	SiO ₂ 45.9, CaO 18.5, Al ₂ O ₃ 11.8, MgO 5.92, Fe ₂ O ₃ 3.98	Pérez-Monserrat et al. (2021)
PM-M4-4.3-B	Petro-fabric B1. Fired at 850–900 °C from Fe-rich calcareous clays. Flux textures evident	Quartz, K-feldspar, albite, calcite, hematite	SiO ₂ 52.5, Al ₂ O ₃ 12.5, CaO 12.1, MgO 5.43, Fe ₂ O ₃ 4.36	Pérez-Monserrat et al. (2021)

PM-M1-4.7-B	Petro-fabric B1. Fired at 850–900 °C. Moderate compact appearance	Quartz, K-feldspar, albite, calcite, hematite	SiO ₂ 52.5, Al ₂ O ₃ 12.5, CaO 12.1, MgO 5.43, Fe ₂ O ₃ 4.36	Pérez-Monserrat et al. (2021)
MSW-H-SM	Historical brick from 18th century, Calcareous clay origin (CaO > 6%)	Quartz 44.8%, Hematite 4.1%, Albite 10.0%, Geothite 15.5%, Amorphous 28.1%	SiO ₂ 53.8, Fe ₂ O ₃ 29.8, K ₂ O 7.3, CaO 6.3, TiO ₂ 2.1	Misiewicz et al. (2025)
MSW-H-OR	Historical brick from 16th-18th century, Non-calcareous clay origin (CaO < 6%)	Quartz 48.5%, Hematite 11.5%, Albite 21.0%, Amorphous 18.9%	SiO ₂ 55.9, Fe ₂ O ₃ 30.9, K ₂ O 7.1, CaO 2.7, TiO ₂ 2.2	Misiewicz et al. (2025)
MSW-H-ML	Historical brick from 18th century, Non-calcareous clay origin	Quartz 44.8%, Hematite 3.9%, Illite 17.6%, Albite 11.7%, Geothite 1.9%, Amorphous 20.2%	SiO ₂ 60.6, Fe ₂ O ₃ 24.0, K ₂ O 8.3, CaO 3.8, TiO ₂ 2.2	Misiewicz et al. (2025)
MSW-H-SB	Historical brick from 19th century, Calcareous clay origin	Quartz 42.2%, Illite 11.5%, Albite 14.2%, Calcite 7.7%, Amorphous 25.7%	SiO ₂ 53.4, Fe ₂ O ₃ 26.0, K ₂ O 6.9, CaO 10.4, TiO ₂ 2.4	Misiewicz et al. (2025)

*Abbreviations of minerals are all mentioned in the [List of Abbreviations & Acronyms](#).

1.1.3 Ancient mortars and plasters

Historical mortars and plasters represent highly engineered composite materials whose long-term performance heavily relies on their binder-to-aggregate ratios (traditional binders including aerial lime, hydraulic lime, and gypsum, as well as the diverse volcanic or ceramic pozzolanic additives) and the induction of "hydraulicity"; the capacity to set and remain stable in moisture-rich environments (Veiga et al., 2009; Brunello et al., 2021). In Roman, Byzantine, and Ottoman baths and cisterns across Greece, ancient builders utilized a mixed binding system of hydrated lime combined with natural pozzolans or crushed brick dust (artificial pozzolans) to meet the strict requirements for impermeability and durability. The aggregates varied from fine brick fragments (<2 mm) in plasters to coarse siliceous aggregates and brick fragments (up to 8 mm or even 2 cm) in structural bedding mortars. Interestingly, the humid and hot service environments of these baths favored the dilution of primary calcite, which subsequently underwent secondary crystallization within empty voids. This process densified the mortar matrix over time without causing fractures. As a result, these historical hydraulic mortars present a highly compact structure, with open porosities ranging from 11.8% to 28.2%, compressive strengths between 1.02 and 4.65 MPa, and binder-to-aggregate volumetric ratios between 1:1 and 1:3 (Stefanidou et al., 2014). Historical mortars and plasters constitute a vital component of a predictive database, acting as the sacrificial and binding media that determine the overall structural coherence and durability of masonry systems. The database categorizes these materials starting with original ancient mortars, such as the lime-based hydraulic mortars from Sagalassos, Turkey, which utilize local volcanic trass as pozzolana (Degryse et al., 2002), and various Turkish archaeological mortars evaluated through both simple acid-loss methods and sophisticated mineralogical identification (Gulec and Ersen, 1998). Furthermore, the scope encompasses restoration-grade materials, including mortars with pozzolanic additions designed for compatibility with historical substrates (Veiga et al., 2009) and standardized mock-ups of aerial and hydraulic lime mixtures used to calibrate microstructural imaging techniques (Brunello et al., 2021).

The integration of local volcanic aggregates further exemplifies the sophisticated adaptation of historical mortars to environmental challenges. Experimental testing has shown that the combination of limestone and volcanic aggregates produced mortars with

excellent frost resistance against freeze-thaw weathering, far outperforming mortars that relied solely on crushed ceramics (Degryse et al. 2002). Similarly, in the historic built heritage of Catania, Eastern Sicily, traditional lime mortars were formulated using a 1:2 binder-to-aggregate ratio combined with two distinct local volcanic aggregates: *azolo* (crushed dark-gray basalt) and *ghiara* (a reddish, thermally altered paleo-soil). While the *ghiara* aggregate is chemically reactive—forming hydrated silicates that provide better early mechanical performance—its physical microstructure renders it highly vulnerable to environmental decay. Specifically, *ghiara* mortars exhibit a higher open porosity (46.6%) and specific surface area compared to the *azolo* mortars (38.5%). Consequently, under accelerated salt crystallization testing (15 cycles), the *ghiara* mortars absorb water much more rapidly by capillarity and suffer mass losses nearly double those of the *azolo* mortars (63.55% vs. 38.40%) due to crystallization pressures within their higher microporosity network (Belfiore et al., 2023).

For the predictive database, the quantitative metrics extracted from these diverse mortar and plaster typologies must be standardized into specific feature sets. Numerical variables such as binder-to-aggregate ratios (e.g., 1:1 to 1:3), total open porosity (%), specific surface area (m^2/g), uniaxial compressive strength (MPa), will be coupled with categorical features like aggregate type (siliceous, crushed brick, volcanic tuff) and binder composition. Additionally, dynamic performance metrics from Accelerated Weathering Testing Protocols, such as the exact percentage of mass loss under salt crystallization, will serve as critical target variables. By structuring this archaeometric data, the machine learning algorithms will be equipped to model the non-linear relationships between a mortar's original recipe, its internal microstructural evolution (such as secondary calcite crystallization), and its ultimate failure thresholds under simulated weathering load.

Table 3. Query of some Mortars and Plasters samples included in the database (Source: original).

Sample_Code	Material_Subtype_&_Description	Mineralogy	Chemical_Composition	Ref_Code
L-M10.5	Lime-Metakaolin Mortar (10.5% MK)	Portlandite, Cc, CSH	Ca(OH) ₂ , Al ₂ Si ₂ O ₅ (OH) ₄	Apostolopoulou et al. (2019)
L-NP12.5	Lime-Natural Pozzolan Mortar	Portlandite, Cc, Qtz	Ca(OH) ₂	Apostolopoulou et al. (2019)
STF-NEW	Structural mortar; lime and pozzolan (B/A ratio 1:3); siliceous and reddish local stone aggregates (0–8 mm)	Lime, Pozzolan, Siliceous	CaO: 33.0%, SiAlFe: 36.2%, C.I.: 2.43	Stefanidou et al. (2014)
STF-NNW	Structural mortar; lime and pozzolan (B/A ratio 1:3); siliceous aggregates (0–8 mm)	Lime, Pozzolan, Siliceous	CaO: 41.1%, SiAlFe: 26.2%, C.I.: 2.63	Stefanidou et al. (2014)
AS-L-AC-28	Lime mortar (100% Dry Hydrated Lime). Binder-to-aggregate ratio 1:3. Accelerated carbonation for 28 days	Portlandite, Cc, Qtz (sand aggregate)	(DHL) CaO 94.37%, MgO 2.99%, SiO ₂ 1.17%, SO ₃ 0.74%	Anupama & Santhanam (2024)
AS-L-NC-365	Lime mortar (100% Dry Hydrated Lime). Binder-to-aggregate ratio 1:3. Natural carbonation for 365 days	Portlandite, Cc, Qtz	(DHL) CaO 94.37%, MgO 2.99%, SiO ₂ 1.17%	Anupama & Santhanam (2024)
AS-OL-NC-365	OPC-Lime mortar (50% OPC, 50% Lime). Binder-to-aggregate ratio 1:3. Natural carbonation for 365 days	Cc, C-S-H, Qtz	(OPC) CaO 66.21%, SiO ₂ 19.42%, Al ₂ O ₃ 5.04%, Fe ₂ O ₃ 4.58%, SO ₃ 2.67%	Anupama & Santhanam (2024)

GBL-UT	Mortar from slaked lime (CL 70-S) and calcareous aggregates (max size 4 mm, 95% CaCO ₃). Binder-to-aggregate ratio 1:2 v/v.	Cc, slaked lime	CaCO ₃ (aggregate), Ca(OH) ₂ (binder)	Gabrielli et al. (2024)
GBL-DAP	Lime mortar was treated with a 3M (396 g/L) aqueous solution of diammonium hydrogen phosphate (DAP) by brushing until apparent refusal, followed by a limewater poultice. Cured for 1 month.	Cc, Hydroxyapatite (HAP)	CaCO ₃ , Ca ₁₀ (PO ₄) ₆ (OH) ₂	Gabrielli et al. (2024)
GBL-NL	Lime mortar was treated with a 5 g/L dispersion of nanolimes (Ca(OH) ₂ nanoparticles in ethanol) by brushing until apparent refusal, followed by a water poultice. Cured for 1 month.	Cc, slaked lime	CaCO ₃ , Ca(OH) ₂	Gabrielli et al. (2024)
JI-NMK-0	NHL-based mortar composed of 100% natural hydraulic lime (NHL5) and 0% nano-metakaolin. Water-to-solid ratio: 0.5	Qtz, Cc, Portlandite, Larnite, Alb, C-S-H	(NHL5 Raw) CaO 77.9%, SiO ₂ 16.89%, Al ₂ O ₃ 1.92%, MgO 1.58%, Fe ₂ O ₃ 0.785%	Ji et al. (2025)
JI-NMK-20	Composite mortar: 80% NHL5, 20% NMK	Qtz, Cc, Larnite, Alb, Dense C-S-H Network (Portlandite mostly consumed)	(NMK Raw) SiO ₂ 51.59%, Al ₂ O ₃ 44.70%, TiO ₂ 1.53%, MgO 0.72%, Fe ₂ O ₃ 0.67%	Ji et al. (2025)
STF-DH	Structural mortar; lime and pozzolan (B/A ratio 1:2); siliceous and calcitic aggregates (0–8 mm)	Lime, Pozzolan, Siliceous, Calcitic	CaO: 32.4%, SiAlFe: 10.5%, C.I.: 1.51	Stefanidou et al. (2014)

STF-BBD	Structural mortar; lime and pozzolan (B/A ratio 1:2); angular siliceous aggregates (0–4 mm) with few fine brick fragments	Lime, Pozzolan, Siliceous, Brick	CaO: 24.8%, SiAlFe: 48.1%, C.I.: 4.14	Stefanidou et al. (2014)
STF-BBW	Structural mortar; lime and pozzolan (B/A ratio 1:2); angular siliceous aggregates (0–4 mm)	Lime, Pozzolan, Siliceous	CaO: 24.0%, SiAlFe: 51.4%, C.I.: 4.63	Stefanidou et al. (2014)
STF-BBA	Structural mortar; lime and pozzolan (B/A ratio 1:2); angular siliceous aggregates (0–4 mm)	Lime, Pozzolan, Siliceous	CaO: 28.7%, SiAlFe: 44.0%, C.I.: 3.35	Stefanidou et al. (2014)
STF-BBC	Structural mortar; lime and pozzolan (B/A ratio 1:2); angular siliceous aggregates (0–2.5 mm)	Lime, Pozzolan, Siliceous	CaO: 20.7%, SiAlFe: 45.3%, C.I.: 0.15	Stefanidou et al. (2014)
STF-SC	Structural mortar; lime, pozzolan, and brick dust (B/A ratio 1:1); siliceous and coarse brick aggregates (0–8 mm)	Lime, Pozzolan, Siliceous, Brick	CaO: 27.5%, SiAlFe: 47.6%, C.I.: 2.26	Stefanidou et al. (2014)
STF-HP	Structural mortar; lime and pozzolan (B/A ratio 1:2); siliceous and coarse brick aggregates (0–8 mm)	Lime, Pozzolan, Siliceous, Brick	CaO: 39.1%, SiAlFe: 26.1%, C.I.: 1.26	Stefanidou et al. (2014)
STF-HC-1	Structural mortar; lime and pozzolan (B/A ratio 1:2); siliceous and brick aggregates (0–8 mm)	Lime, Pozzolan, Siliceous, Brick	CaO: 41.0%, SiAlFe: 22.1%, C.I.: 0.88	Stefanidou et al. (2014)
STF-HC-2	Structural mortar; lime and pozzolan (B/A ratio 1:1.5); siliceous and coarse brick aggregates (0–8 mm)	Lime, Pozzolan, Siliceous, Brick	CaO: 34.7%, SiAlFe: 33.2%, C.I.: 2.26	Stefanidou et al. (2014)

STF-DCP	Plaster (1 layer, 4cm); lime, pozzolan, and brick dust (B/A 1:1.5); mainly brick aggregates (0–4 mm)	Lime, Pozzolan, Brick, Siliceous	CaO: 16.4%, SiAlFe: 54.0%, C.I.: 4.77	Stefanidou et al. (2014)
STF-DHP	Plaster (1 layer, 3.5cm); lime, pozzolan, and brick dust (B/A 1:2); mainly brick aggregates (0–4 mm)	Lime, Pozzolan, Brick, Siliceous	CaO: 17.2%, SiAlFe: 50.4%, C.I.: 4.11	Stefanidou et al. (2014)
STF-SP	Plaster; lime, pozzolan, and brick dust (B/A 1:1); mainly brick aggregates (0–4 mm)	Lime, Pozzolan, Brick, Siliceous	CaO: 31.0%, SiAlFe: 40.8%, C.I.: 4.16	Stefanidou et al. (2014)
BE-MOR-NHL5	Natural hydraulic lime (NHL5) mortar mixed with soft sand at a 1:3 binder-to-aggregate ratio	Silicates, calcium aluminates, calcium hydroxide	Free lime $\text{Ca(OH)}_2 > 15\%$, sulphates $< 2\%$	Bompa & Elghazouli (2020)

*Abbreviations of minerals are all mentioned in the [List of Abbreviations & Acronyms](#).

1.2 Conservation and repair material typologies

The effective preservation of cultural heritage necessitates a systematic approach to the selection of intervention materials. The primary objective of any conservation action is to restore structural or superficial cohesion and mitigate future decay while adhering to the principles of reversibility, retreatability, and compatibility. Within the scope of this database, repair and conservation materials are categorized based on their chemical nature and their functional interaction with the original substrate. As highlighted by Doehne and Price (2011), the field has transitioned from simply applying available industrial products to developing specialized formulations tailored to the specific physico-chemical properties of the host material. This section reviews the typologies of consolidants, protective coatings, and mortars that form the restorative data layer of the research.

1.2.1 Inorganic and organic consolidants

Consolidation aims to improve the mechanical properties of weathered substrates by re-establishing the grain-to-grain contact lost through chemical leaching or mechanical fracturing (Aucouturier & Darque-Ceretti, 2007). These materials are generally divided into inorganic and organic categories:

- Inorganic Consolidants: These are often favored for their superior chemical affinity with stone and masonry. Traditional methods include the use of limewater, while modern advancements have introduced nanomaterials, such as nanolimes, which offer deeper penetration into the micro-pore network compared to conventional binders. Inorganic treatments are valued for their thermal stability and resistance to UV radiation (Weththimuni & Licchelli, 2023). Recent studies, such as those conducted on Vicenza Stone, have demonstrated that inorganic consolidants can effectively restore mechanical integrity, though their efficacy is heavily dependent on the initial weathering state of the substrate (Capasso et al., 2024).
- Organic Consolidants: This category primarily includes synthetic resins (e.g., acrylics, epoxies, and silanes). Among these, Ethyl Silicates (TEOS) remain the most widely used organic-inorganic hybrids for silicate stones. They work by depositing a silica gel within the pores, providing structural reinforcement while

maintaining a degree of vapor permeability. However, as noted in general stone conservation research, organic treatments can be prone to yellowing or becoming brittle over time, necessitating careful monitoring of their aging characteristics (Doehne & Price, 2011).

1.2.2 Protective coatings and water repellents

The primary vehicle for most decay mechanisms—including salt crystallization and freeze-thaw cycles—is moisture transport. Protective treatments are applied to create a hydrophobic barrier that prevents the ingress of liquid water while allowing the egress of water vapor (Guo et al., 2022).

For example, water repellents are typically based on silanes or siloxanes, which alter the surface tension of the material, causing water to bead. The success of these treatments is quantified by the reduction in the capillary water absorption coefficient and the increase in the static contact angle. Additionally, recent research has focused on incorporating nanoparticles – nanocomposite coatings into protective matrices to improve durability and provide self-cleaning properties. However, the application of such coatings requires a deep understanding of the substrate's surface chemistry to avoid trapping moisture behind the treated layer, which can lead to catastrophic spalling—a risk particularly prevalent in materials like sandstones subjected to capillary salt weathering (Zhang et al., 2025).

1.2.3 Compatibility criteria for repair mortars

Repair mortars must fulfill structural and aesthetic roles without inducing secondary decay in the original masonry. The database emphasizes the documentation of compatibility criteria, which are evaluated through a comparative analysis of original and restoration binders.

Specifically, restoration binders should possess physico-chemical compatibility, meaning the mineralogical composition of the mortar should ideally mirror the original binder. For instance, the study of ancient mortars from Sagalassos revealed that the use of local pozzolanic trass contributed to the long-term resilience of the structure, providing a blueprint for modern restoration mixtures (Degryse et al., 2002). Modern restoration efforts

often utilize pozzolanic additions to lime mortars to enhance hydraulic properties and mechanical strength without reaching the extreme rigidity of Portland cement, which is often chemically incompatible with historical substrates (Veiga et al., 2009).

Simultaneously, thermo-mechanical and microstructural compatibility is a critical criterion for repair mortars; they should possess a lower compressive strength and higher porosity than the surrounding bricks or stones to ensure that moisture and salts accumulate in the mortar rather than the structural units (Anupama & Santhanam, 2024). As established by Brunello et al. (2021) and Apostolopoulou et al. (2019), the use of X-ray CT and MIP is essential for ensuring that the pore network of the new mortar facilitates the safe passage of moisture, preventing "stress shielding" and localized mechanical failure. Finally, mechanical diagnostics, such as the Equotip hardness tester, provide a non-destructive means to verify that the mortar strength is appropriate for the maintenance and conservation of historical facades (Mammoliti et al., 2021; Grazzini et al., 2019).

1.3 Analytical methods for physico-chemical and thermo-mechanical characterisation of CH materials

The accurate prediction of material decay within a machine learning framework necessitates a robust transition from qualitative description to quantitative "fingerprinting." This section details the multi-scale analytical protocol used to define the Physico-Chemical Characterization (PCC) and Thermo-Mechanical Performance (TMP) of the heritage building materials in the database by focusing on the mineralogical, elemental, and microstructural identification of CH materials including natural stone, ancient mortars, and ceramics.

According to Aucouturier and Darque-Ceretti, the specific nature of cultural heritage objects dictates that analytical methods must be carefully selected and clearly classified based on their invasive character. They are broadly grouped into three categories:

- a) Non-destructive methods which are highly preferred for heritage assets as they preserve the artefact's integrity without requiring sample extraction. Over the past decades Non-Destructive Testings (NDTs) have allowed for precise in-situ analyses of monuments directly in their natural environment. Some examples include portable X-Ray

Fluorescence (pXRF), micro-Raman spectrometry, Fourier Transform Infrared (FTIR) spectroscopy, colorimetry, Ultrasonic Pulse Velocity (UPV), and Infrared Thermography (IRT).

- b) Micro-destructive methods in which the physical intervention on the object is of a very small amplitude, rendering it barely visible to the naked eye or easy to hide. It involves micro-sampling, such as extracting minute chips (e.g., ~10 mg of material) via micro-drilling or superficial scratching. Highly accurate chemical analyses are then performed on these small volumes using techniques like Inductively Coupled Plasma Atomic Emission Spectrometry (ICP-AES), Mass Spectrometry (ICP-MS), or Laser Ablation ICP-MS (LA-ICP-MS).
- c) Destructive methods which require a considerable amount of matter to be sampled, pulverized, or cut into specific test geometries, resulting in large-scale specimen destruction. Techniques such as Transmission Electron Microscopy (TEM), Mercury Intrusion Porosimetry (MIP), and standard mechanical tests (e.g., Uniaxial Compressive Strength) fall into this category. Due to their highly invasive nature, their application is strictly limited in protected heritage contexts, often necessitating a reliance on non-destructive proxies or comparable fresh quarry stones (Aucouturier & Darque-Ceretti, 2007).

By integrating mineralogical identification with high-resolution chemical mapping, we establish a primary "feature set" for each material type. These mineralogical fingerprints are not merely descriptive; they serve as the foundational inputs that dictate a heritage material's intrinsic vulnerability. For instance, the presence of specific clays or silicate minerals (as seen in the Sfouggaria and Daskalakis heritage stone samples) significantly alters the hygric expansion and chemical stability of the carbonate matrix. By quantifying these mineral phases alongside microstructural data—specifically pore-size distribution and total porosity—the database provides the high-fidelity data required for algorithms to identify non-linear correlations between a material's internal chemistry and its macroscopic failure thresholds.

Traditional CH materials' thermo-mechanical performance is dependent on a number of intrinsic and extrinsic factors, including the raw materials used, which may be tempered or mixed, the design and construction of the objects or structures, processing that

uses heat, and environmental factors that affect deterioration. The assessment of thermo-mechanical properties is fundamental to understanding the structural resilience and long-term durability of cultural heritage materials. While physico-chemical fingerprinting identifies the material's composition, this phase focuses on the macroscopic response of the substrate to physical loads and environmental stressors. By quantifying mechanical integrity through parameters such as Uniaxial Compressive Strength (UCS) and surface hardness, and evaluating thermal behaviour through dilatometry or thermal conductivity, we can map the thresholds at which internal stresses exceed the material's cohesive strength. This characterization is especially critical for heritage assets exposed to fluctuating climates, where the synergistic effects of cyclic thermal expansion and moisture-driven mechanical strain often lead to irreversible structural decay, such as micro-cracking, scaling, or granular disintegration.

The integration of these methods allows for the creation of a Dynamic Performance Metric (DPM). By correlating the PCC (Physico-Chemical properties) data with Thermo-Mechanical (TMP) results, researchers can develop digital twins and Machine Learning models. For example, a model can be trained to recognize that a limestone with high clay content (from XRD) and a bimodal pore distribution (from MIP) will show a specific loss of compressive strength (Mechanical) after 50 cycles of salt-frost weathering.

Table 4. Some non-destructive characterisation methods applied to cultural heritage materials (Source: Aucoeur & Darque-Ceretti, 2007).

Method ^a	Incident radiation or item	Detection	Information	Analysed depth	Depth resolution	Lateral resolution
Eye examination ^b	Light	Light	Shape, colour, topography	First layer	First layer	mm
Optical microscopy ^b	Light	Light	Shape, colour, topography	First layer	First layer	μm
SEM, ESEM, EM-EDS, EPMA	e-	e-, X-ray	Topography and elemental analysis	μm	μm	100nm (structure), μm (analysis)
XRD, μXRD ^c	X-Ray	X-Ray	Compound crystallography	>10 μm	μm	mm to μmc
GXRD ^c	X-Ray	X-Ray	Compound crystallography	<100nm	nm	cm
XRF, ^b μXRF	X-Ray	X-Ray	Elemental analysis	>10 μm	>10 μm	mm to μmc
TXRF	X-Ray	X-Ray	Elemental analysis	<100nm	<100nm	cm
XANES, EXAFS ^c	X-Ray	X-Ray	Atomic environment	—	—	μm
Profilometry	Tip or light	Height	Surface topography	Roughness	μm to nm	mm to μmc
AFM ^b	Micro tip	Height	Surface topography	First layer	<nm	<nm
FTIR	Infrared	Infrared	Compound and bonds	μm	μm	mm to μmc
Raman, μRaman ^b	Light	Raman emission	Compound and bonds	μm	μm	mm to μmc
PIXE	MeV ions	X-Ray	Elemental analysis	>10 μm	>10 μm	mm to μmc
RBS, NRA, ERDA	MeV ions	Ions	Elemental in-depth analysis	>10 μm	10–100 nm	mm to μmc
Spectrophotometry ^b	Light	Light	Colorimetry	First layer	First layer	mm

^a Acronyms are defined in [List of Abbreviations & Acronyms](#). ^b Portable equipment available. ^c Techniques available under synchrotron radiation.

1.3.1 Bulk chemical composition & provenance tracing – Crystalline phase identification & transformations

Since the mid-20th century, particularly in recent decades, analytical methods employed in experimental sciences have increasingly been applied to the study of materials in the field of Cultural Heritage, thereby enhancing scientific and historical-archaeological knowledge and progress. This experimental technology has been used to address a number of issues, including composition, chronology, provenance, and production technology. These analytical techniques even enable us to set conservation and restoration protocols as necessary (Martín et al., 2020). To establish a "fingerprint" of the materials under study, researchers each time employ a multi-scale approach to identify mineral phases, elemental composition, and microstructural arrangements.

A group of analytical methods, X-ray techniques, are employed for mineralogical identification and physico-chemical composition analysis and depend on subjecting a sample to an onslaught of primary X-rays. X-ray fluorescence, X-ray diffraction, X-ray photoelectron spectroscopy, and X-ray imaging are among the X-ray techniques used in cultural heritage material analyses. The primary goal of X-ray applications is to characterise and interpret the chemical composition of artefacts that are the focus of legacy study, including the elemental content, molecular structure, chemical environment, and crystalline phases (Magdy, 2023).

1.3.1.1 X-ray fluorescence (XRF)

The XRF technique's fundamental concept is to subject materials (heritage material samples) to an X-ray beam. An XRF is known as the first powerful, commercial, fast, non-destructive, and relatively accurate technique for qualitative as well as semiquantitative chemical analysis for heritage materials (Ion et al, 2016). The energy of the X-rays is transmitted to the atoms in the sample when they are absorbed. Ionisation, in which electrons are expelled from their inner shells and produce positively charged ions, is brought on by this energy transfer. Depending on the X-ray wavelength, this reaction might occur at different energy levels. Following excitation, the electrons release distinctive X-rays or a certain amount of energy as they fall from the outer shell into the inner shell. The difference

in binding energy between the two shells involved in the electron transition is reflected in the photon energy that is released. The different elements in the sample are represented by distinct energy in fluorescent photons.

Energy dispersive systems (EDXRF) and wavelength dispersive systems (WDXRF) are the two primary categories of XRF detectors. Since all energies are captured simultaneously, the EDXRF offers simultaneous multi-elemental analysis. Because the detector is near the sample, the measurement time is shortened and good brightness is achieved. Therefore, in the analysis, the lower excitation intensity is adequate. The elements in the sample are identified (qualitative analysis) and their relative abundance for the materials utilised is determined (semi-quantitative analysis) by the EDXRF readings. The WDXRF approach, on the other hand, contains more optical components (such as collimators and diffracting crystals) and a finer spectral resolution. (Magdy, 2023).

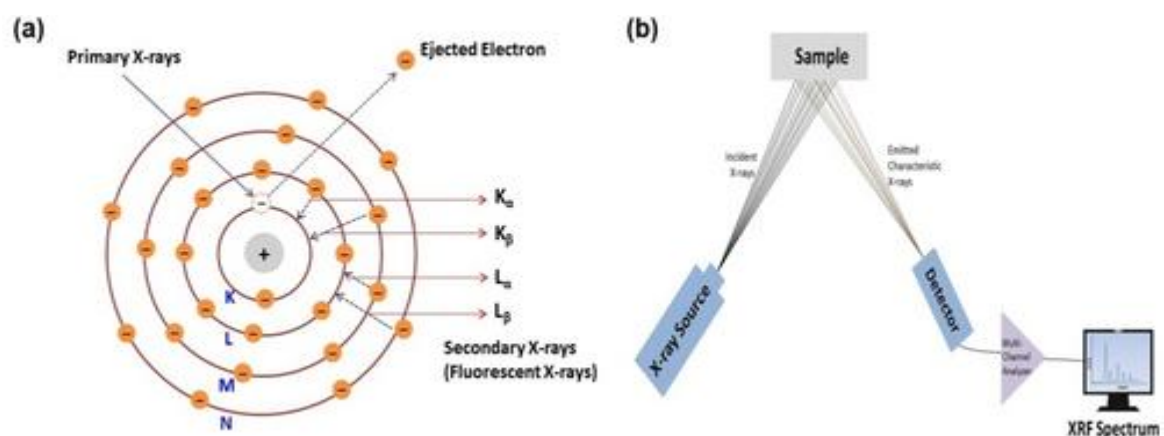


Figure 3. Schematic representation of the XRF principle (a) and EDXRF instrument (b) (Magdy, 2023).

For instance, Zhang et al. (2025) used X-ray fluorescence spectroscopy to determine the major element composition of sandstone samples from the Nankan Grotto in Bazhong City. Marrocchino et al. (2021) also used XRF analysis to characterise the chemical and mineralogical composition of raw materials, like bricks, cotto, mortars and plasters, used in the medieval Renaissance buildings of Ferrara, in Emilia Romagna, Italy. Overall, the XRF technique allows for major elements to be determined and expressed as a percentage of oxide weight (i.e. SiO_2 , TiO_2 , Al_2O_3 , Fe_2O_3 , MnO , MgO , CaO , Na_2O , K_2O , P_2O_5), while trace elements can be expressed in parts per million (ppm) (i.e. Cr, Ni, Cu, Zn, Ga, Rb, Sr, Zr, Ba, La, Ce, Pb, Sc, Co, Th, Y, Nd, S), offering an important amount of data for this

current research's database development. Ion et al. (2016) performed EDXRF for the analysis of Romanian ceramics with an PW4025 apparatus, type Minipal PANalytical, with a Si(PIN)-detector and an Rh tube with an acceleration voltage of 30 kV, on both sides of the inhomogeneous samples, calculating the mean value, when the analysis must remain non-destructive.

1.3.1.2 X-ray diffraction (XRD)

The X-ray diffraction (XRD) method relies on the elastic (coherent) scattering of X-rays by crystalline substances exhibiting long-range order (Magdy, 2023). Both single-crystal and polycrystalline materials can be characterised using XRD techniques. The key requirement for observing a diffraction pattern is that, when X-rays interact with a collection of non-oriented crystallites, a sufficient quantity of those crystallites must possess appropriate orientation for the diffraction phenomenon to occur at the reflection angle 2θ . The diffraction pattern seen is made up of what are known as Debye-Scherrer rings if the crystallites are randomly orientated and the beam size is significantly more than the crystallite size. The method is known as X-ray powder diffraction (XRPD) in these circumstances (Gonzalez et al., 2020).

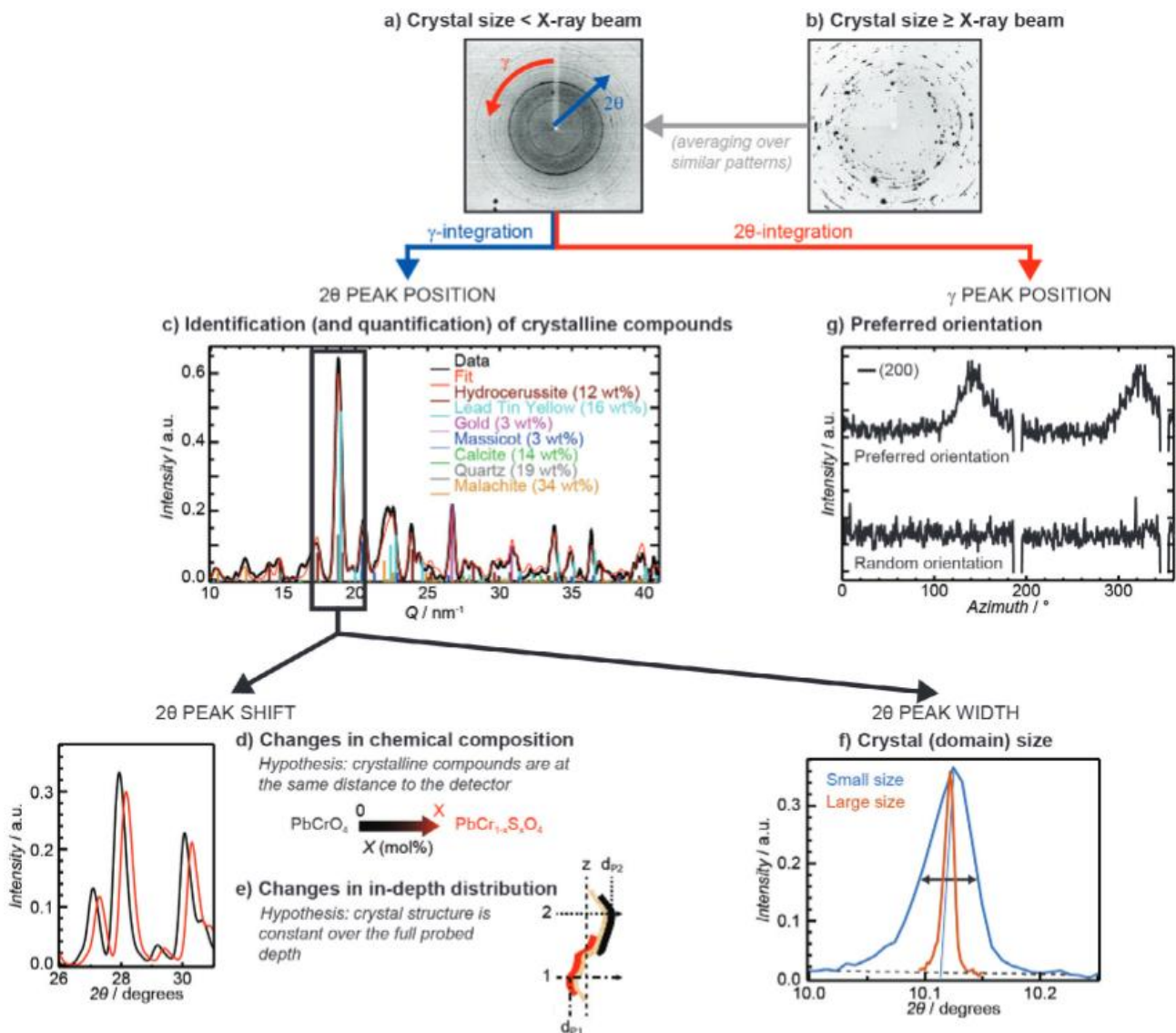


Figure 4. Schematic illustration of the different information that is typically obtained from an XRD mapping experiment (Gonzalez et al., 2020).

Coletti et al. (2025) performed XRPD analyses on limestones, marbles, carbonate-dominated sandstone, and volcanic rocks samples using a Panalytical Empyrean diffractometer in Bragg–Brentano reflection geometry, with Cu K α radiation (operating at 40 kV and 40 mA) and an X'Celerator detector. Similarly, Cappai et al. (2024) had employed tests using Cu K α radiation, scanning over a range of scattering angles (2θ) from 5° to 80° , with a step size of 0.05° and an acquisition time of 15 s per angle to obtain the mineralogical phases that constituted the Miocene limestones samples.

Zhang et al. (2023) obtained the mineral composition of several sandstone, marble and granite samples mined from the Shandong Province of China, using an Olympus TERRA II portable XRD Analyser. Moreover, Marrocchino et al. (2021), investigated the mineralogical compounds of Renaissance brick, mortar, and plasters by x-ray diffractometer from powders (XRPD) by means of a PW1860/MM with a graphite filtered and a Cu K α radiation also. Diffraction patterns were collected in the 2 θ angular range 3–50°, with a 5 s/step. Likewise, Ion et al (2016), recorded patterns of Romanian ceramics on a a DRON UM1 diffractometer, operating at 32 kV and 25 mA, using Co K α radiation and an iron filter, collecting useful data of material characterisation.

1.3.1.3 Scanning electron microscopy with energy dispersive X-ray spectroscopy (SEM-EDS)

The scanning electron microscope (SEM) is a crucial elemental and surface analytical instrument in these study domains; it is rare to encounter a publication that lacks SEM analysis. Scanning electron microscopy is most frequently used to determine the size, shape, and related composition of samples. It is typically used in conjunction with energy dispersive X-ray analysis (EDS). Because SEM-EDS makes it possible to identify the mineral phases based on their stoichiometry, shape and texture, stratigraphic section sequences, sizes, and other parameters, the most recent developments in these systems and the calibre of the chemical quantification data they generate have increased their relevance upstream in the field of mineral characterisation (Martín et al., 2020). The use of a Scanning Electron Microscope (SEM) equipped with Energy Dispersive X-ray Spectroscopy (EDS) offers significant advantages for heritage material analysis, as it allows for the examination of unprepared fragments or varied sample sizes up to 100 mm x 100 mm while providing detailed surface and point mapping. Furthermore, the system provides high sensitivity to low-energy light elements and quantifies the weight percentage concentration of oxide elements, facilitating a precise chemical and mineralogical characterization of the material's surface (Falcone et al., 2024).

As highlighted in studies of volcanic and sedimentary stones (e.g., Apostolopoulou et al., 2019), SEM provides direct visual evidence of the micro-texture, allowing researchers to observe intergranular voids, fossil-derived cavities, and the morphology of binding

cements (micritic vs. sparitic). Overall, the material characterisation of heritage building materials of artistic and archaeological significance has made considerable use of scanning electron microscopy, particularly when combined with energy dispersive X-ray spectroscopy (SEM-EDS), offering helpful data to be added in the database prototype.

1.3.1.4 Inductively coupled plasma atomic emission spectrometry (ICP-AES)

The use of inductively coupled plasma atomic emission spectrometry (ICP-AES) for elemental analysis of archaeological samples has increased in appeal. Excellent analytical features like high precision, high selectivity, and high sensitivity, along with low limits of detection, a large linear dynamic range, and low matrix effects, can account for ICP-AES's widespread appeal (Paama et al., 2000). Elements such as Na, Cu, Al, Pb, Si, Ca, Mn, Mg, Fe, Zn, Ti, and K can be scanned and identified from ancient ceramics and pottery using this method. Ion et al (2006) have used ICP-AES with multielement matrix-matched standards to quantify minor and trace elements of samples powdered in an agate mortar and mineralized with a microwave-assisted digestion oven with the use of high pressure closed Teflon PFA vessels. A detection limit was set for major ones under the ppm level, with the analytical precision calculated from replicate analysis at $\pm 1\%$.

Paama et al (2000) conducted spectrochemical and thermal examination of clay minerals and archaeological samples in order to provide important insights into the 700-year period of St. John Church construction, restoration, and reconstruction. A portion of the bricks used in the pottery were produced in Uhlenstorf, Germany, and Riga, Latvia. The elemental composition of archaeological samples has been examined in order to identify clay with a composition that is extremely similar to the original in order to restore the bricks and terracotta figures. These kinds of studies provided excellent amount of data for the population of the ceramics dataset of this current research.

1.3.2 Microstructural and textural analysis

Micro-scale examination of heritage construction materials may yield critical insights into their structural, physical, and mechanical characteristics. Microstructure and porosity can be assessed by indirect methods, like mercury intrusion porosimetry (MIP) or water

absorption tests (Brunello et al., 2021). Textural properties of the heritage materials involve, among others, pore volume, specific surface area, pore surface, and pore size (Volzone & Zagorodny, 2014), therefore these methods can be coupled with Digital Image Analysis (DIA) in order to provide precise data on grain size and areal distribution of the different textures of the materials (Coletti et al., 2025).

1.3.2.1 Mercury Intrusion Porosimetry (MIP)

Mercury Intrusion Porosimetry is a technique that utilizes mercury to probe the surface accessible pores of a solid or powder material. Mercury is an ideal probe chemical because it is a non-wetting liquid that requires external pressure to fill voids in the surface of a sample. By volumetrically measuring the quantity of mercury forced into the pores of a sample at a given pressure, we can determine the pore size, pore volume, and porosity of your sample. Pore size is inversely proportional to the amount of pressure required to force the mercury into the sample pore. Large pores require less pressure to fill with mercury than smaller pores.

Mercury porosimetry determines larger pores that are not within the detection range of nitrogen adsorption (Gregg et al., 1967; Volzone & Zagorodny, 2014), able to characterize pore diameters in the size range of 4nm to 200μm. This makes the MIP technique an ideal candidate for samples with larger pore structures. These pores must be open pores, meaning they are surface accessible.

As noted in the literature, MIP is the most common technique to investigate the porosity of cultural heritage building materials. The Washburn equation is the base principle of MIP analysis and describes the relationship between the pressure and capillary diameter as:

$$P = \frac{-4\gamma \cos \theta}{d}$$

This equation relates the contact angle (θ) formed by a non-wetting liquid (Hg) and a surface of the material under study, with the surface tension (γ) of the liquid itself, and the diameter (d) of the capillary. All these parameters are connected to the pressure (P) applied in order to obtain the measurement of the equivalent pore radii (r): $r = -2\gamma \cos \theta / P$ (Brunello et al., 2021).

Mercury must be compelled through pressure into the pores of a material. The volume intruded at each pressure increment is used to calculate the pore size distribution. The total volume intruded is used to calculate the overall porosity. There are certain limits to this method that have been noted in various research. The "ink-bottle effect" is one of the most well-known biases (Nichols et al., 1999; Volzone & Zagorodny, 2014); when large internal pores can only be accessed by narrower pore throats, the intruded volume that determines the pore size distribution misrepresents the size of these large internal pores due to the size of their (smaller) throats. However, because of the high pressures utilised in MIP studies, samples may occasionally be altered by the production of difficult-to-identify cracks and ruptures. Furthermore, the samples are completely filled with mercury following the examination, making it impossible to perform additional studies on the same sample (Brunello et al., 2021).

For instance, Coletti et al. (2025) used MIP to measure the open porosity, pore-size distribution, bulk density, and matrix density of several limestones, volcanic rocks, marbles, carbonate dominated sandstones and igneous rocks by means of a Thermo Scientific Pascal 140–240 porosimeter, covering a pore radius range of 0.003–100 μm , on three samples of each lithotype with a volume of about 1.5 cm^3 . Cappai et al. (2024) also employed Mercury Intrusion Porosimetry for their Miocene limestone studies, while Zhang et al. (2023) used MIP to evaluate the modification of sandstone, granite, and marble samples after freeze-thaw cycles. Brunello et al. (2021) used MIP as a primary quantitative technique to characterize the pore structure of different heritage-style mortar mock-ups (lime, gypsum, hydraulic lime, and cement), providing high-resolution numerical data for the smallest pores that are invisible to X-ray imaging.

1.3.2.2 X-ray Computed Tomography (μCT)

Characterising the material properties of heritage construction materials, including porosity and water absorption rate, is crucial for comprehending their environmental interactions and temporal transformations. Although these characteristics are typically understood in "bulk," μCT can be used in conjunction with image analysis to provide more detailed information about the water movement and pore structure.

X-ray computed tomography (μ CT) is a method that can contribute to the interpretation of MIP results of heritage materials. μ CT enables non-destructive material analysis with many benefits, such as the ability to conduct dynamic experiments or many (complementary) investigations on the same sample. The literature reports some examples of the use of X-ray μ CT analysis on building materials and on the analysis of cement porosity; Arandigoyen et al. thoroughly examined the use of this technique for the investigation of porosity and the mechanical properties of cement and lime-based mortars; Plessis et al. used cement samples to compare various μ CT analysis resolutions. However, the study of mortar porosity in the context of heritage studies, which is the primary topic of this work, has been covered in a few papers. The spatial resolution of this method is physically constrained by instrumental characteristics, including the spot size of the X-ray source, the geometrical magnification, and the detector pixel size. The majority of research on stone or cementitious materials is conducted with a voxel size of 100–102 μ m, however laboratory systems are often limited to a minimum voxel size somewhat below 1 μ m (Brunello et al., 2021). μ CT can also be used to study the processes of freeze-thaw weathering (ice crystallisation in pores), gypsum crust formation and development, and dissolution, crystallisation, as well as mobilisation, of soluble salts based on relative humidity fluctuations in materials and environments that are representative of real heritage buildings and scenarios. This way suitable replacement materials can be determined, while the relative risk posed by different scenarios and/or various materials can be assessed.

1.3.2.3 Digital Image Analysis (DIA)

Digital Image Analysis (DIA) serves as a quantitative bridge between traditional qualitative petrography and high-resolution petrophysical modeling, offering a means to overcome the limitations of invasive techniques. While Mercury Intrusion Porosimetry (MIP) is a standard for quantifying interconnected pore networks, it is frequently restricted by the "ink-bottle effect" and the inability to visualize the spatial arrangement of the solid matrix (Coletti et al., 2025). DIA addresses these gaps by utilizing high-resolution imagery—typically obtained from polarizing optical microscopy (POM) or Scanning Electron Microscopy (SEM)—to extract objective numerical data from the rock's fabric (Hong et al., 2023). In the context of cultural heritage, this technique allows for the precise characterization of a

material's "birth properties" and provides the geometric variables necessary for predicting how decay will propagate through a specific micro-texture.

The theoretical strength of DIA lies in its ability to isolate and quantify specific phases within a material through image segmentation and thresholding. By converting high-resolution images into binary maps, researchers can distinguish between the solid mineral matrix and the pore space, specifically identifying macroporosity and micro-cracks that are often beyond the detection limits of pressure-based intrusion methods (Capasso et al., 2024). This allows for the calculation of critical textural parameters such as grain size distribution, crystal shape factors (e.g., aspect ratios and circularity), and the degree of sorting. For instance, in the study of complex sedimentary and metamorphic stones, DIA is utilized to distinguish between the solid mineral matrix and the pore space, providing objective data on areal and geometric information that dictates a material's mechanical durability (Apostolopoulou et al., 2019).

Beyond simple two-dimensional measurements, DIA algorithms facilitate the extraction of advanced structural metrics, such as Feret diameters and the spatial distribution of micritic or sparitic phases. These observations are vital for understanding the hydric behavior of a stone, as the connectivity and tortuosity of the pore space—parameters often estimated through stereological principles in DIA—determine the resistance to environmental stresses like salt crystallization and freeze-thaw cycles (Peng et al., 2022). Furthermore, DIA provides a quantitative method for assessing damage patterns that are difficult to measure through traditional mechanical testing, such as the development of micro-fissures or the loss of binder in weathered mortars (Apostolopoulou et al., 2019).

When integrated into a relational database, these DIA-derived metrics—such as the percentage of macroporosity or specific grain dimensions—become the primary structural variables for mathematical models. These models can then simulate the distribution of stresses within the stone fabric, ultimately allowing for a more accurate prediction of the material's long-term durability and the effectiveness of conservation treatments in their specific environmental context (Coletti et al., 2025).

1.3.2.4 Colorimetry

Establishing a quantitative aesthetic "fingerprint" through Colorimetry is a fundamental component of material characterization in cultural heritage, providing a non-destructive method to objectively measure appearance and monitor physical-chemical alterations. While microstructural techniques like Mercury Intrusion Porosimetry (MIP) quantify internal pore networks and textural analyses like Digital Image Analysis (DIA) define the solid matrix fabric, colorimetry bridges the gap between these internal properties and the external surface state of the material. In the context of stone and mortar characterization, this method is essential for two primary reasons: evaluating the compatibility of potential restoration materials and quantifying the progression of decay during accelerated weathering. The theoretical framework for these measurements is predominantly based on the CIE $L^*a^*b^*$ color space, an international standard that defines color through a three-dimensional coordinate system. In this space, the L^* axis represents lightness, ranging from 0 (absolute black) to 100 (absolute white). The chromatic components are defined by the a^* coordinate, where positive values indicate red and negative values indicate green, and the b^* coordinate, where positive values indicate yellow and negative values indicate blue. By recording these numerical parameters, researchers can create a stable reference for a material's initial state, which is far more precise than qualitative visual descriptions (Capasso et al., 2024).

A critical metric derived from these coordinates is the Total Color Difference (ΔE) which calculates the Euclidean distance between two color points in the $L^*a^*b^*$ space. This value serves as a quantitative indicator of "damage" or "change" over time. In conservation science, a $\Delta E < 3$ is generally considered the threshold below which variations are not perceptible to the human eye, while a $\Delta E = 5$ is often established as the maximum acceptable threshold for chromatic alteration after a restoration treatment or weathering event. However, standard ΔE calculations can sometimes be inadequate when comparing materials with significantly different surface textures, such as an irregular historical stone fragment and a smooth quarry specimen. In such cases, adjusted parameters like ΔE_{94} or specific evaluations of saturation (ΔC^*) and hue (ΔH^*) are utilized to ensure the aesthetic characterization remains scientifically valid despite physical surface variations.

Methodologically, these assessments are often conducted following rigorous international standards, such as UNI EN 15886. Standardized measurements typically employ spectrophotometers with specific experimental parameters, including an 8.0 mm-diameter viewing aperture, the inclusion of the specular component (SCI) to account for surface gloss, a D65 illuminant to simulate natural daylight, and a 10° observer angle. By maintaining these consistent conditions, colorimetry data becomes highly queryable within a database, allowing researchers to correlate surface color shifts with internal structural changes, such as the moderate lightening (ΔL^*) observed when acidic weathering removes the darkening effects of previous consolidation treatments in carbonate stones (Capasso et al., 2024).

1.3.3 Mechanical performance testing

When characterising heritage materials’ mechanical performance, the following properties are studied:

- a. compressive strength
- b. flexural strength
- c. toughness
- d. impact strength
- e. Young's modulus

The evaluation of mechanical integrity and surface resilience is a decisive factor in determining the structural stability and remaining service life of architectural heritage. According to Özmen and Sayın (2023), the assessment of cultural heritage materials often necessitates a hybrid approach where destructive testing is minimized in favor of high-fidelity non-destructive techniques (NDT). Among these, *Ultrasonic Pulse Velocity (UPV)* is frequently implemented to detect internal structural discontinuities, as a decrease in pulse velocity directly correlates with the proliferation of micro-cracks and voids induced by environmental weathering (Mammoliti et al., 2024). Mammoliti et al. (2024) utilized UPV to establish a correlation between wave speed and the deterioration degree of historical

sandstones, noting that lower velocities serve as a reliable indicator of internal micro-cracking and void expansion that are invisible to the naked eye.

For surface-level resilience, *Equotip or Leeb hardness testing* provides a quantitative measure of superficial cohesion, allowing researchers to map deterioration gradients across a monument's facade without causing visible damage (Heidari et al., 2017). Salvatici et al. (2023) applied Equotip diagnostics to the Florentine Pietra Serena, mapping how surface hardness decreases in areas of high exposure to urban pollutants. Furthermore, Mammoliti et al. (2021) refined this approach by defining a specific methodology to correlate Equotip rebound values directly with the mechanical strength of historical mortars, allowing for a quantitative structural assessment of masonry joints without removing samples.

When sampling is permissible, *Uniaxial Compressive Strength (UCS)* serves as the fundamental metric for quantifying the load-bearing capacity of historical masonry and ancient bricks, particularly when they are subjected to the weakening effects of salt contamination or unsaturated freeze-thaw conditions (Tang et al., 2018). Furthermore, Uranjek and Bokan-Bosiljkov (2015) highlight that the mechanical response of historical brickwork is not static; it evolves significantly under cyclic environmental stress, where the loss of compressive strength often serves as the primary indicator of advanced material fatigue. By integrating these mechanical datasets, the research can establish "damage performance thresholds," effectively bridging the gap between microscopic pore-scale decay and macroscopic structural failure. Additionally, for sandstones, which often exhibit thin-bedded structures, Huang et al. (2022) demonstrated that the orientation of the bedding planes relative to the load significantly affects UCS values, a critical consideration when evaluating the stability of historical sandstone facades or "dimension stones" in architecture.

1.3.4 Thermal and hygric properties

Thermal and hygric characterization identifies how Cultural Heritage (CH) materials respond to temperature fluctuations and moisture transport, factors that are fundamental for understanding "thermal fatigue" and hygric stress. These properties represent the material's dynamic interaction with its environment and serve as the primary precursors to the macroscopic mechanical breakdowns—such as cracking, spalling, and granular disintegration—discussed in subsequent chapters.

1.3.4.1 Anisotropic expansion & thermal conductivity

Thermal characterization quantifies the volumetric response of a material to heat and its ability to transmit thermal energy. In the context of heritage conservation, the coefficient of thermal expansion is not merely a single value, but a complex variable influenced by the material's mineralogical heterogeneity.

In poly-mineralic materials such as Red Verona stone or Granite, anisotropic expansion occurs because different mineral species (e.g., quartz, feldspar, calcite) expand at different rates and along different crystallographic axes. As established by Lobarinhas et al. (2024), this differential movement induces significant internal inter-granular stresses. Over repeated diurnal or seasonal cycles, these stresses lead to a process known as "thermal fatigue," where the mineral bonds are weakened, resulting in micro-cracking or "sugaring." This effect is particularly pronounced in stones with a high quartz content, as quartz exhibits a sharp increase in expansion at specific temperature thresholds.

Furthermore, thermal conductivity and thermal diffusivity dictate the speed and depth of heat penetration. Research by Zhang et al. (2023) has demonstrated that thermal properties are not static; as freeze-thaw weathering progresses, the resulting increase in porosity leads to a significant reduction in thermal conductivity. This reduction creates steeper thermal gradients between the sun-exposed exterior and the cooler core of the artifact. These steep gradients concentrate mechanical stress in the outer few millimetres of the material, which—when coupled with the aforementioned anisotropic expansion—accelerates surface exfoliation and delamination.

1.3.4.2 Capillary water absorption

Capillary water absorption measures the rate and capacity of liquid uptake through the material's surface-accessible pore network. This "hygric" behavior is perhaps the most decisive indicator of heritage resilience, as liquid water serves as the primary vehicle for the most destructive decay mechanisms, including the salt crystallization and frost damage investigated by Peng et al. (2022).

The rate of absorption is governed by the bimodal or trimodal pore-size distribution of the substrate. In highly porous materials like biocalcarenes or historical bricks (e.g., those from the Baroque monuments studied by Misiewicz et al., 2025), high capillary sorptivity

allows for the deep penetration of salt-laden water or rain. This creates a reservoir of moisture that, upon freezing, exerts significant cryo-static pressure on the pore walls.

The interaction between hygric behaviour and the environment is further complicated by "multi-field coupling." As demonstrated by Anupama and Santhanam (2024), wind-induced drying variations significantly alter the moisture profile within masonry. If the drying rate is high, the evaporation plane sits at the surface, resulting in relatively harmless efflorescence. However, if the drying rate is slowed by environmental factors or incompatible coatings, the evaporation plane moves deep into the pores, leading to destructive subflorescence (internal crystallization). By documenting water absorption coefficients alongside Mercury Intrusion Porosimetry (MIP) data, the database allows for the prediction of these crystallization zones, a critical factor for the long-term survival of both original substrates and repair mortars (Brunello et al., 2021; Volzone & Zagorodny, 2014). Similarly, in clay-based systems like the silty clays studied by Cui et al. (2014), the hygric state modulates the mechanical behaviour, where saturation levels directly dictate the material's vulnerability to seasonal frost heave.

1.3.4.3 Differential Scanning Calorimetry and Thermogravimetry (DSC/TGA)

Thermal analysis compares the sample to an inert reference material and allows for the detection of exothermic and endothermic peaks (effects resulting from gain or loss of enthalpy) that occur during controlled heating (Ion et al., 2016).

For mortars and ancient ceramics, thermal analysis through Differential Scanning Calorimetry (DSC) and Thermogravimetry (TGA) provides a "thermal history." Ion et al. (2016) used these techniques to identify the firing temperatures of historical ceramics by observing phase transitions and weight loss associated with the dihydroxylation of clay minerals. Similarly, Rahman et al. (2024) utilized thermal analysis to distinguish between different types of historical binders, identifying the presence of organic additives (like oils or proteins) that were historically used to enhance the mechanical flexibility of mortars.

1.3.4.4 FTIR analysis

Characteristic processes like dehydration, dihydroxylation, and breakdown linked to the heating process can be studied using TG analysis and FTIR techniques. The infrared spectra of gases produced during thermogravimetric analysis are obtained using the TG–IR system (Paama et al., 2000).

Ion et al (2016) collected standard spectra of Romanian ancient ceramics using a PerkinElmer Spectrum GX spectrometer, for a range of 400–4000 scans and a spectral resolution of 4 cm^{-1} , while Paama et al (2000) used the Fourier Transform Infrared Spectrometry (FTIR) technique for Evolved Gas Analysis (EGA) to investigate the thermal decomposition of archaeological materials like bricks, terra-cotta, and local clays. The FTIR was coupled with thermal analysis; The FTIR spectrometer was connected to a Thermogravimetric (TG) analyser. As the samples were heated in a dynamic nitrogen atmosphere from 25°C to 900°C , the gaseous products released during characteristic chemical reactions were funnelled into the FTIR for real-time identification.

By analysing the gases evolved during reheating, one could infer information about the original production process. For example, the absence or presence of specific dihydroxylation peaks in the FTIR data can help determine whether the archaeological samples have been fired at high temperatures in antiquity or if they contained raw, unreacted clay minerals.

CHAPTER 2: ACCELERATED WEATHERING TESTING PROTOCOLS AND QUANTITATIVE ASSESSMENT OF MATERIAL PERFORMANCE AND DETERIORATION DATA

The transition from static material characterization to predictive modeling requires a deep understanding of the "environmental load" acting upon Cultural Heritage (CH) substrates. In the context of climate change, the frequency and intensity of extreme weather events—such as rapid freeze-thaw cycles and increased saline aerosol deposition—necessitate a shift from qualitative decay descriptions to digitized, high-frequency performance data (Grossi et al., 2007; Sahyoun et al., 2024). This chapter systematically evaluates the environmental stressors and the experimental protocols (AWTP) utilized in recent literature that was gathered and studied, to quantify material failure, serving as the dynamic foundation for the relational database.

2.1 Mechanisms of moisture-driven decay

The interaction between liquid water and the porous matrix of Cultural Heritage (CH) materials represents the most significant catalyst for physical and chemical deterioration. Moisture does not merely act as a passive occupant of the pore space; it functions as the primary vehicle for the transport of exogenous pollutants, the medium for phase transitions, and the activator of mechanical stress through hydraulic and crystallization pressures. In the context of your database, this section establishes why hygric metrics—such as the Water Absorption Coefficient (WAC) and capillary sorptivity—are the decisive "input features" for predicting material failure (Capasso et al., 2024; Vasanelli et al., 2019).

2.1.1. Capillary Transport and Pore Network Dynamics

The movement of water within stones, bricks, and mortars is governed by the principles of capillary suction, where the pore-size distribution (PSD) identified in Chapter 1 dictates the

velocity and height of the rising damp. According to the research of Netinger Grubeša et al. (2020) and Brunello et al. (2021), the "active" pores for capillary transport are typically those in the range of 0.1 to 10 μm . Pores smaller than this (micropores) often remain inaccessible or lead to trapped moisture, while larger pores (macropores) identified through Digital Image Analysis (DIA) facilitate rapid ingress but also offer "safe" spaces for volumetric expansion (Nichols et al., 1999).

For materials like the Vicenza stone, which exhibits a high open porosity (approx. 28–30%), capillary transport ensures that moisture reaches deep into the core of the masonry. This creates a "moisture reservoir" that maintains a high degree of saturation, a critical variable in the severity of subsequent freeze-thaw or salt crystallization events. As moisture migrates toward the surface during drying phases, it carries dissolved ions, concentrating them at the evaporation front and initiating the transition from harmless surface efflorescence to destructive subflorescence (Zhang et al., 2025; Galanaki et al., 2022).

2.1.2 Hydraulic Pressure and Cryo-static Stress

When moisture-saturated materials are subjected to temperature drops, the phase transition of water to ice involves a volumetric expansion of approximately 9%. If the pore network is near "critical saturation"—typically defined as 91% of the total pore volume—the expanding ice exerts cryo-static pressure directly onto the mineral walls. Peng et al. (2022) and Liang et al. (2025) demonstrate that in sandstones and earthen materials, this pressure exceeds the splitting tensile strength of the stone, leading to the development of micro-cracks and a progressive reduction in Ultrasonic Pulse Velocity (UPV).

Furthermore, the "trapped water" mechanism exacerbates this damage. If the surface pores freeze first, they create an impermeable seal that prevents excess liquid water from escaping to the exterior. This results in hydraulic pressure build-up within the interior pores, often leading to deep structural fracturing or "scaling" rather than simple surface powdering (Tang et al., 2018; Uranjek & Bokan-Bosiljkov, 2015).

2.1.3 Chemical Weathering and Dissolution-Precipitation Cycles

Beyond mechanical stress, moisture facilitates chemical alteration through the dissolution of carbonate binders and the oxidation of mineral phases. In calcareous stones, the presence of water—especially when acidified by atmospheric CO₂ or SO₂—leads to the dissolution of calcite (CaCO₃). This increases the total porosity of the material over time, creating a "feedback loop" where the weathered stone becomes even more susceptible to moisture ingress (Smith et al., 2008).

In ceramics and bricks, moisture triggers the mobilization of internal salts and the hydration of clay minerals. The study by An et al. (2024) on ancient bricks highlights that moisture-driven hydration leads to the loss of the ceramic bond, particularly in materials fired at lower temperatures where the vitrification process was incomplete. This chemical instability results in a loss of mass and a reduction in surface hardness, which the database records as a primary deterioration index (An et al., 2024; Allegretta et al., 2017).

2.1.4 Hygric Swelling and Differential Expansion

Certain clay-bearing materials and sandstones exhibit "hygric swelling," where the absorption of water into the lattice of clay minerals (such as smectite or kaolinite) causes significant volumetric expansion. This expansion is often anisotropic, meaning it occurs at different rates in different directions based on the material's fabric. When this swelling is coupled with the anisotropic thermal expansion discussed by Siegesmund & Snethlage (2011), the resulting internal strain can detach surface layers (delamination) or cause the detachment of protective consolidant layers.

By digitizing these mechanisms, the database provides a clear link between the static "Characterization" data and the "Dynamic" weathering results. The moisture content at any given cycle acts as the trigger for mechanical rupture, making hygric behavior the most critical performance variable in your predictive framework.

2.2 Accelerated weathering testing protocols (AWTP)

Due to climate change, scholars have increasingly concentrated on measuring the deterioration of historical sites. Despite these attempts, further research is necessary due to the severity of the climate catastrophe and the difficulty of creating predictive models for stone decay that are relevant to all situations (Coletti et al., 2025). Numerous cultural heritage structures face various environmental threats, including salt deterioration, biological assault, and atmospheric contamination (Grossi et al., 2007). Climate change and the extreme fluctuations in climatic conditions may exacerbate the biological, chemical, and physical processes that lead to degradation by altering the composition and/or structure of the impacted historical materials. For example, frost damage is a significant physical factor contributing to the deterioration of ancient or restoration building materials (Grossi et al., 2007); water trapped in porous materials expands in volume during freezing, resulting in internal stress. While most of Europe is expected to see a decrease in the frequency of the freezing-thawing mechanism due to climate change, certain parts may see an increase. A warmer climate in Europe's far north would enable temperatures to fluctuate above and below freezing, putting porous materials in historical structures and archaeological sites at risk. Stone, brick, and ceramic materials – all material types included in this database development effort – may disintegrate and sustain structural damage as a result of the mechanical weathering that follows (Sesana et al., 2021).

To transform static material properties into a dynamic predictive model, the database incorporates standardized data from Accelerated Weathering Testing Protocols (AWTP). These protocols aim to compress decadal or centurial environmental exposure into manageable laboratory timeframes by intensifying the frequency and magnitude of stress cycles. In the context of the current database development, AWTP data serves as the "temporal" dimension, providing the essential failure points and rate-of-decay metrics required to train machine learning algorithms (Coletti et al., 2025; Wang & Zhang, 2023).

Unfortunately, the majority of test methods are criticised for their unrealistic parameters, which produce damage processes that differ from those seen on-site. These tests are used to compare the weathering ability of various materials, despite their artificial circumstances. The freezing and thawing temperatures and duration, the type of salt, the size and shape of the specimen, the length of the test, and even the contamination process, which

usually entails either partial or total immersion of the specimen in the water or salt solution/deposition, all contribute to the variation in observation. Therefore, any attempt to compare across different research is complicated by the absence of a globally standardised test protocol and specimen type (Anupama & Santhanam, 2024).

Table 5 below includes some of the Accelerated Weathering Test Protocols (AWTP) that were gathered from the surveyed literature of this research.

Table 5. Query of some Accelerated Weathering Test Protocols from the literature survey included in the database (Source: original).

Test_Protocol	Standard	Total_Cycles	Ref_Code
Synergic Salt & Freeze-Thaw	Custom Laboratory Procedure	25	Wang and Zhang (2023)
Freeze-Thaw (UNI EN 12371)	UNI EN 12371	35	Capasso et al. (2024)
Salt Crystallisation (UNI EN 12370)	UNI EN 12370	15	Capasso et al. (2024)
Acid Rain Simulation (HNO₃)	Custom Laboratory Procedure	5	Capasso et al. (2024)
Acid Rain Simulation (H₂SO₄)	Custom Laboratory Procedure	5	Capasso et al. (2024)
Thermal Shock artificial accelerated ageing test	BS EN 1406	40	Heidari et al. (2017)
Salt Crystallisation artificial accelerated ageing test	BS EN 12370	16	Heidari et al. (2017)
Thermal Aging	Custom Laboratory Procedure	30	Aldosari et al. (2019)
NaCl Weathering	Custom Laboratory Procedure	3	Chekai et al. (2025)
Na₂SO₄ Weathering	Custom Laboratory Procedure	3	Chekai et al. (2025)
Salt Crystallisation (Na₂SO₄·10H₂O)	UNI-EN 12370:2020	15	Belfiore et al. (2023)
Salt Crystallisation (NaCl)	Custom Laboratory Procedure	60	Galanaki et al. (2022)

Sulfate Weathering	Custom Laboratory Procedure	25	Hong et al. (2023)
Capillary Freeze-Thaw	Custom Laboratory Procedure	80	Peng et al. (2022)
Periodic Saturation F-T	Custom Laboratory Procedure	80	Peng et al. (2022)
Salt Crystallisation (EN 12370)	EN 12370 (1999)	100	Coletti et al. (2025)
Freeze-Thaw (EN 12371)	EN 12371 (2001)	100	Coletti et al. (2025)
Salt Crystallisation	Custom (based on Flatt et al.)	15	Cappai et al. (2024)
Freeze-Thaw Resistance Test	UNI EN 12371	25	Török et al. (2019)
Salt Crystallisation Test	EN 12370 (1999)	15	Stefanidou & Karozou (2016)
Freeze-Thaw Deterioration Test	EN 12390-2:2002	40	Stefanidou & Karozou (2016)
"JUS" Freeze-Thaw Test	JUS B. D8. 011	25	Uranjek & Bokan-Bosiljkov (2015)
"EN" Freeze-Thaw Test	SIST-TS CEN/TS 722-22:2006	50 and 150	Uranjek & Bokan-Bosiljkov (2015)
Freeze-Thaw Test	UNE-EN 12371 (2003)	25	Molina et al. (2013)
Salt Crystallisation	UNE-EN 12370 (2001)	15 + Wash	Molina et al. (2013)

Salt Attack	TS EN 1925	1 Cycle (Continuous 4320 min imbibition + subsequent drying)	Çelik & Sert (2021)
Accelerated salt weathering (w/ wind)	Custom Laboratory Procedure	Up to 25 Cycles	Anupama & Santhanam (2024)
Accelerated salt weathering (w/o wind)	Custom Laboratory Procedure	Up to 25 Cycles	Anupama & Santhanam (2024)
Freezing-thawing	TS 699	20	Yavuz et al. (2006)
Thermal shock	TS EN 14066	20	Yavuz et al. (2006)
Wet-Dry	ASTM D5313	80	Akin & Özsan (2011)
Freeze-Thaw	TS EN 12371	50	Akin & Özsan (2011)
Salt Crystallization Na₂SO₄	RILEM (1980)	25	Akin & Özsan (2011)
Salt Crystallization MgSO₄	RILEM (1980)	25	Akin & Özsan (2011)
Freeze-thaw Weathering	EN 12371	96	Martínez-Martínez et al. (2013)
Freezing-Thawing (F-T)	ISRM Methods	300	Momeni et al. (2015)
Heating-Cooling (H-C)	ISRM Methods	600	Momeni et al. (2015)
Salt Weathering (Na₂SO₄)	ISRM Methods	35	Momeni et al. (2015)
Salt Weathering (MgSO₄)	ISRM Methods	50	Momeni et al. (2015)
Freeze-thaw	ASTM (2013)	40	Heidari et al. (2016)

Salt crystallization-Na₂SO₄	EN 12370 (1999)	16	Heidari et al. (2016)
Salt crystallization-MgSO₄	EN 12370 (1999)	16	Heidari et al. (2016)
Freeze-thaw cycles (FT)	Combo of EN 12371, EN 14617-5, UNI11186	10	Gabrielli et al. (2024)
Salt crystallization (EN)	Modified EN 12370:2001	10	Gabrielli et al. (2024)
Salt crystallization (RILEM)	RILEM TC 271-ASC	10	Gabrielli et al. (2024)
Freeze-Thaw	UNI EN 12371	20	Pérez-Monserrat et al. (2021)
Salt Crystallization	UNI EN 12370	15	Pérez-Monserrat et al. (2021)
Fire Exposure	Evaluated against EN 13501-1 for fire reaction	1 exposure per temperature tier	Al-Sibahy et al. (2017)
Wet-state saturation	Custom Laboratory Procedure	1 Cycle (Static Submersion)	Bompa & Elghazouli (2020)
Sodium sulphate crystallisation	EN 12370	10	Pápay et al. (2021)
Freeze–thaw durability	EN 12370	10	Pápay et al. (2021)
Accelerated Thermo-hygrometric Ageing & Solar Radiation	Custom Regional Simulation	180 days	Sitzia et al. (2021)

In-Situ Environmental Ageing	Custom / In Situ (EN 1015-12 for adhesion and Rilem Pipe Method for permeability)	14 Weeks (Evaluated at 6 and 14 weeks)	Veiga et al. (2009)
Unsaturated Freeze-Thaw Test	Custom procedure (using GB/T 50129-2011, GB/T 2542-2012, and ASTM C1314-14 for mechanical evaluations)	35	Tang et al. (2018)
Freeze-Thaw Cycles	Custom Laboratory Procedure	6	Zhang et al. (2023)
Thermal Ageing	Custom Laboratory Procedure	5	Ban et al. (2016)
Freeze-Thaw Ageing	Custom Laboratory Procedure	25	Ban et al. (2016)
Salt Crystallization	Custom Laboratory Procedure	25	Ban et al. (2016)
Wetting & Drying	Custom Laboratory Procedure	80	Ban et al. (2016)
Acid Attack	Custom Laboratory Procedure	1-3	Ban et al. (2016)
Freeze-Thaw Weathering Test	UNE 67-028-84 specifications	30	Elert et al. (2003)
Salt Crystallisation Test	UNE 7136 specifications	10	Elert et al. (2003)

Accelerated Climate Ageing	Custom (Based on regional meteorological data)	60	Pavlendova et al. (2014)
High-Temperature Fire and Water Cooling	Custom (Fire Simulation). Mechanical tests followed EN 1926:2006, EN 1936:2006, EN 14579:2004	3 Target Temperatures (Tested independently at 200 °C, 400 °C, and 600 °C)	Pires et al. (2024)
Freeze-Thaw Resistance	PN-B-12012:2022-07	25	Misiewicz et al. (2025)
Weathering Study (WS)	Custom (Sanyo-FE 300H/MP/R20 chamber)	30	Arizzi et al. (2012)
WS + Rain (WS+R)	Custom Laboratory Procedure	30	Arizzi et al. (2012)
WS + Salt Capillary Absorption (WS+SS)	Custom Laboratory Procedure	10	Arizzi et al. (2012)
WS + Salt Surface Deposition (WS+SD)	Custom Laboratory Procedure	30	Arizzi et al. (2012)
Freeze–Thaw Weathering	ASTM D5312 M-12	40	Torabi-Kaveh et al. (2019)
Salt Crystallization (Sodium Sulfate)	BS EN 12370	40	Torabi-Kaveh et al. (2019)
Salt Crystallization (Magnesium Sulfate)	BS EN 12370	40	Torabi-Kaveh et al. (2019)
Thermal Shock	BS EN UNI (2013)	40	Torabi-Kaveh et al. (2019)
Dry - Wet Cycle Test	Custom Laboratory Procedure	10	Ji et al. (2025)

Freeze-Thaw Cycle Test	Custom Laboratory Procedure	10	Ji et al. (2025)
Freeze-Thaw Weathering (HRN)	HRN B.D8.011 (comparable to SFS 2803 RIL 85)	25	Netinger Grubeša et al. (2020)
Thermal Treatment (High Temp)	Custom Laboratory Procedure	8	Fioretti et al. (2018)
Thermal Shock (Heating-Cooling)	Custom Laboratory Procedure	80	Fioretti et al. (2018)
Salt Crystallization (Sodium Sulphate)	UNI EN 12370:2001 (Modified timeframe)	12	Fioretti et al. (2018)
Salt Crystallization (Sodium Chloride)	UNI EN 12370:2001 (Modified timeframe)	24	Fioretti et al. (2018)
Salt Crystallization Test	TS EN 12370	15	Çelik & Sert (2020)
Freezing–Thawing Test	TS EN 12371	56	Çelik & Sert (2020)
Thermal Shock Test	TS EN 14066	20	Çelik & Sert (2020)
SO2 Action in presence of humidity	TS EN 13919	1	Çelik & Sert (2020)
Capillary Water Absorption	TS EN 1925		Çelik & Sert (2020)
Dry-Wet Cycles (Sodium Sulfate)	Custom / ISRM Sample prep guidelines	7	Lv et al. (2025)
Accelerated Thermal Weathering	Custom simulation (Porosity followed NBN EN 1936; Compressive strength followed IS: 1121 Part I-1974)	Varies per set (Max 25 cycles overall per sample series)	Ghimire & Manohar (2025)

Salt Crystallization-Freeze-Thaw (SCFT)	Custom (calibrated using local 10-year meteorological data)	90	Wang et al. (2026)
Soaking & Temp/Humidity Cycling	Custom (based on 2022 site environmental monitoring)	18	Sun et al. (2023)
Salt Crystallization Cyclic Test	Custom Laboratory Procedure	Up to 9 Cycles (M-Series); Up to 6 Cycles (N-Series)	Sheng et al. (2024)
Freeze-Thaw (F-T)	UNE-EN 12371	80	Romero Bastidas (2022)
Thermal Shock (T-S)	UNE-EN 14066	80	Romero Bastidas (2022)
Salt Crystallization (NaCl)	Modified UNE-EN 12370	50	Romero Bastidas (2022)
Salt Crystallization (Na₂SO₄)	Modified UNE-EN 12370	50	Romero Bastidas (2022)
Acid Attack (A-A)	UNE-EN 13919	1 (21 days)	Romero Bastidas (2022)
Freeze-Thaw Treatment	GB/T 50266–2013	60	Yu et al. (2023)

2.2.1 Freeze-thaw damage: test modes, cycles & moisture influence

Freeze-thaw (F-T) cycles represent one of the most significant mechanical stressors for building materials in temperate and cold climates. The database standardizes diverse F-T protocols by documenting three critical variables: the number of cycles (often ranging from 15 to 100), the temperature range (typically -20°C to $+40^{\circ}\text{C}$), and the degree of saturation.

Research by Peng et al. (2022) and Liang et al. (2025) indicates that the "test mode", specifically the cooling rate, is a decisive factor in damage intensity. Rapid cooling prevents water from migrating to larger "safe" macropores, forcing ice crystals to grow within restricted capillaries and leading to the catastrophic micro-fracturing of the mineral matrix, as can be seen in *Figure 6*. Their study introduces a sophisticated categorization of environmental simulation by identifying that the specific "pathway" of moisture ingress during temperature oscillations determines the velocity and nature of material failure. The research evaluates sandstone deterioration across three distinct freeze-thaw (F-T) modes as presented in *Figure 5*: Immersion Freeze-Thaw, where the sample is fully submerged; Capillary Freeze-Thaw, where moisture ingress is limited to capillary suction; and Periodic Saturation Freeze-Thaw, which simulates alternating cycles of saturation and drying. Their findings reveal that while the immersion mode provides the most extreme laboratory stress, capillary and periodic saturation modes often mirror the heterogeneous damage patterns seen in situ, such as the differential scaling observed at the base of monuments due to rising damp versus the more uniform surface recession of fully exposed elements. The digitization of these three modes in this database, was essential for transforming the relational database into a high-fidelity tool for future performance prediction and machine learning.

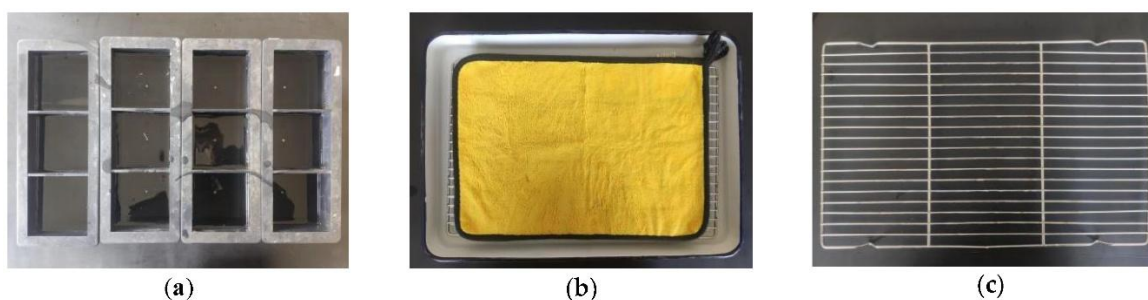


Figure 5. Schematic diagram of the three freeze-thaw methods test by Peng et al. (2022) where; (a) represents the Immersion freeze-thaw method; (b) the capillary freeze-thaw; and (c) the capillary freeze-thaw method (Source: Peng et al. (2022)).

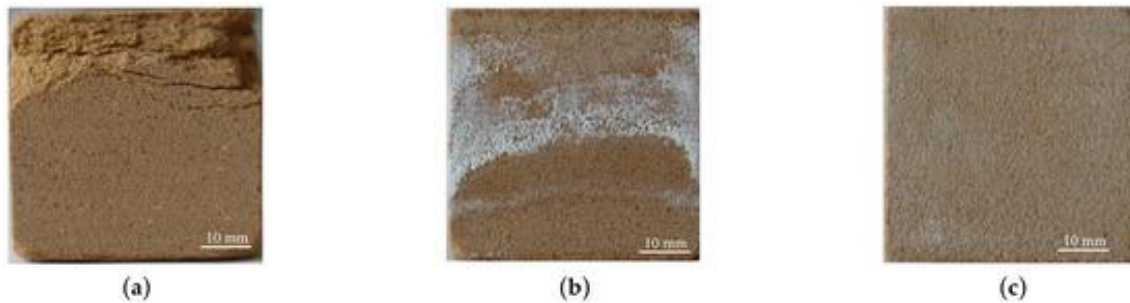


Figure 6. Variation characteristics of macroscopic morphology of rock samples under different freeze–thaw modes by Peng et al. (2022), where: (a) Immersion freeze–thaw after 60 cycles; (b) immersion freeze–thaw after 60 cycles; and (c) immersion freeze–thaw after 60 cycles (Source: Peng et al. (2022)).

Furthermore, the "moisture influence" is non-linear; damage only becomes significant once a material exceeds its "critical degree of saturation," usually defined around 91% of total pore volume. The database records these saturation levels to differentiate between materials that exhibit frost resilience and those that suffer rapid granular disintegration or scaling (Uranjek & Bokan-Bosiljkov, 2015; Zhang et al., 2023).

In their study of diverse European stone materials which were included in this database effort, Coletti et al. (2025) utilized accelerated freeze-thaw testing following the EN 12371 (2001) standard to simulate the stress caused by cryo-static pressure in monumental structures. The experimental protocol consisted of 100 cycles, where each individual cycle comprised a 6-hour freezing phase in air at -20°C followed by a 6-hour thawing phase in water at room temperature. Throughout these cycles, researchers systematically monitored the specimens for macroscopic damage, changes in sample mass, and variations in P-wave and S-wave velocities to quantify internal structural fatigue. By recording the standardized parameters, the database transforms raw laboratory observations into structured "stressor" features.

The researchers observed that the intensity of freeze-thaw decay was primarily determined by a stone's pore abundance and size distribution, rather than its broad lithological classification. Stones categorized in the high-porosity group—specifically Costozza stone (28.60% porosity), Santa Pudia stone (19.65%), and Sfougaria stone (17.04%)—were found to be the most vulnerable to these tests, as seen in *Figure 7* below. For instance, Costozza and Santa Pudia stones underwent rapid and substantial decay

between the 15th and 30th cycles, characterized by pervasive fracturing and sudden large detachments. In contrast, Sfouggaria stone remained relatively stable for a longer period, with significant detachments commencing only around the 70th cycle. The study further highlights that moisture interaction, particularly capillary water absorption, acts as a critical precursor to freeze-thaw damage. Stones with an abundance of capillary pores (ranging from 0.1 to 1000 μm) showed enhanced water absorption capacity, which negatively influenced their ability to resist frost action. While compact materials such as Carrara marble and Istrian stone sustained no major weight loss, ultrasonic measurements still detected subtle internal decay, such as a 15% decrease in P-wave velocity for Carrara marble, attributed to a minor increase in porosity from microcracking.



Figure 7. Heavy vulnerability of the Sfouggaria Stone against freeze-thaw action as shown in this deterioration evolution of samples after ageing tests at 20 cycle steps (Source: Coletti et al. 2025)).

Collectively, the correlation between the rapid decay of high-porosity stones (e.g., Costozza) and the stability of compact lithotypes (e.g., Istrian stone) provides the high-fidelity training data necessary for machine learning. This allows the database to categorize materials not just by mineralogy, but by "behavioral clusters," where initial petrophysical metrics like the Water Absorption Coefficient serve as the primary predictors for the percentage mass loss and UPV reduction recorded during the weathering phase.

Regarding clay based ceramics of this database, having reviewed multiple research publications, like ones from Grossi et al., 2007; Netinger Grubeša et al., 2020; Sahyoun et al., 2025; Uranjek & Bokan-Bosiljkov, 2015, the study by Porfido et al. (2020) also provides

a much sophisticated high-resolution perspective on the internal mechanics of freeze-thaw damage. By employing X-ray micro-computed tomography (micro-CT) coupled with a specialized thermal stage to maintain samples in a frozen state during analysis, the researchers were able to visualize the "in situ" behavior of fully water-saturated specimens. Their experimental protocol focused on the evolution of fractures over repeated cycles, demonstrating that damage is not merely a surface phenomenon but a complex 3D network of internal failures. A critical finding was the role of inclusions; in quartz-tempered ceramics, the interface between the clay matrix and the temper grains acts as a primary site for stress concentration, as presented in *Figure 8*. The mismatched thermal and mechanical properties between these phases facilitate fracture initiation and propagation, eventually leading to the detachment of ceramic fragments and a measurable increase in fracture intensity and density. The integration of the Porfido et al. study into the database provides a vital link between 2D textural analysis (DIA) and 3D structural failure;

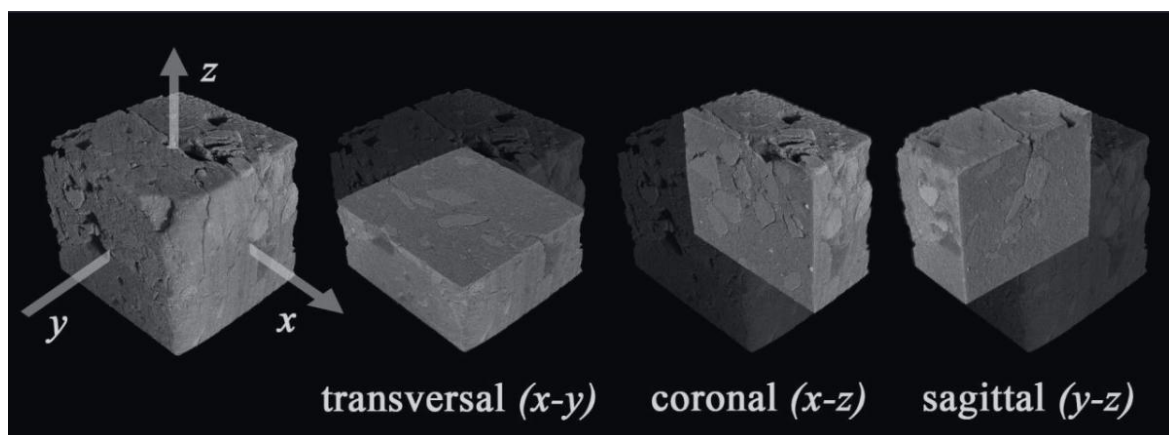


Figure 8. Three-dimensional representation of the examined ceramic specimen by Porfido et al. (2020) (Post 10 cycles) and visualisation of the three parts chosen for fracture investigation (Porfido et al., 2020).

(a) the study introduces "fracture intensity" and "connectivity" as high-fidelity features: these metrics allow the database to track "internal fatigue" long before physical disintegration occurs, (b) by identifying the "temper-matrix interface" as a critical vulnerability, the database can now include "inclusion-to-matrix ratio" and/ or "grain distribution" s primary predictive variables for ceramic durability, (c) the 3D renderings and 2D micrographs analyzed via FracPaQ provide the "ground truth" labels for machine learning models. These models can be trained to recognize the specific digital signatures of fracture initiation, allowing the database to predict the "remaining useful life" of a ceramic

material based on its initial micro-CT or high-resolution imaging profile, and (d) the use of a thermal stage to analyze frozen, saturated samples validates the "Test Protocol" variables in this database's AWTP dataset table, emphasizing that the state of water during the frozen phase is as critical as the number of cycles themselves.

Meanwhile, the research conducted by Apostolopoulou et al. (2019) regarding the restoration of the Apollo Pythios Temple in Rhodes provides significant data for frost resistance of high-performance restoration mortars. The researchers designed and evaluated various mortar compositions—specifically natural hydraulic lime (NHL) and lime-metakaolin (LM) based mixtures—to replace degraded historical materials. The freeze-thaw testing protocol employed also followed the EN 12371 standard, consisting of 30 cycles where samples were subjected to a freezing phase in air at -15°C and a thawing phase via total immersion in water at 20°C. This protocol once again emphasizes the "moisture influence" variable, as the periodic transition from dry freezing to total saturation simulates the severe environmental stresses characteristic of Mediterranean coastal archaeological sites.

The findings highlight that the frost durability of restoration mortars is fundamentally linked to their hydraulic properties and pore structure development. The NHL-based mortars, which develop a more robust hydraulic network, exhibited superior resistance compared to traditional lime-putty mixtures. Specifically, after 30 cycles, these hydraulic mortars maintained high mechanical integrity, showing minimal mass loss and effectively resisting the expansive pressures of ice crystallization. The researchers noted that the incorporation of metakaolin in the LM mixtures further refined the pore network, potentially enhancing frost resistance by increasing the tortuosity of the capillary system and reducing the overall volume of "active" pores susceptible to cryo-static pressure. Integrating these results into the database facilitates a comprehensive "performance prediction" for restoration mortars and conservation interventions. For machine learning applications, these data points serve as "compatibility features," allowing models to predict the durability of a specific restoration mortar based on its hydraulic binder-to-aggregate ratio and its initial water absorption coefficient. This ensures that conservation practitioners can select restoration materials that not only match the aesthetic and chemical profile of the historical substrate but also possess the requisite frost resilience to withstand site-specific climatic stressors.

2.2.2. Wetting-Drying cycles (Slake Durability) protocols

The periodic transition between total saturation and dehydration represents a fundamental fatigue mechanism for building materials, particularly for stones with significant clay content or weak cementitious matrices where expansion-contraction cycles lead to micro-fissuring. Heidari et al. (2017) introduce a quantitative approach to this phenomenon through the implementation of the Slake Durability Index (Id_2), following standardized ASTM D4644 procedures. In this rigorous protocol, ten spherical rock specimens, each weighing between 40 and 60 grams, are placed inside a standardized rotating drum with a 2.00 mm mesh. The drum is rotated at 20 revolutions per minute for a duration of 10 minutes while partially submerged in a water trough at 20°C. Following this mechanical agitation, the samples are oven-dried at 105°C for a full 24-hour period to achieve constant mass.

Complementing this standardized index, Aldosari (2019) utilizes a wetting-drying simulation designed to mimic the rapid climatic shifts of outdoor environments, such as the transition from intense solar radiation to heavy rain. This protocol consists of 30 cycles, where each cycle involves a prolonged 18-hour immersion in distilled water to ensure deep capillary saturation, immediately followed by a 4-hour forced drying phase in an oven at 105°C. The high temperature of the drying phase accelerates the internal vapor pressure, which, when coupled with the previous hydration state, triggers the "slaking" behavior and surface granular disintegration typical of weathered Egyptian limestones. By digitizing these specific immersion times and drying temperatures, the database can effectively model the surface recession rates of outdoor sculptures and architectural elements exposed to seasonal precipitation, providing a high-fidelity "slake resistance" variable for predictive machine learning models.

2.2.3. Chemical dissolution and acid rain simulation

To address the chemical vulnerability of calcareous heritage materials in polluted or urban environments, the database incorporates specialized protocols for simulating acidic dissolution and the resulting leached material loss. Heidari et al. (2017) describe a sophisticated laboratory dissolution apparatus that maintains a constant environmental stress through a continuous water flow system. In this protocol, water is circulated at a rate of 3.5 liters per minute through a chamber where CO₂ gas is continuously pumped in to maintain

a stable pH of 6, effectively replicating the natural acidity of unpolluted rainwater. Samples are subjected to 9 consecutive cycles of this acidic flow, allowing for the precise measurement of mass loss and the quantification of "chemical fatigue." This protocol is essential for the database as it provides a benchmark for the baseline dissolution rate of carbonate stones like travertine and limestone, which can then be correlated with the material's initial porosity and mineralogical purity.

This simulation of chemical decay is further intensified in the research of Aldosari (2019), who proposes a coupled protocol to evaluate the synergistic impact of salts and atmospheric pollutants, specifically targeting the formation of "black crusts" and surface erosion. In this methodology, limestone specimens are first subjected to a salt stress phase involving immersion in a saturated sodium sulfate (Na_2SO_4) solution for 4 hours. Following this, the samples are sprayed with a 3% carbonic acid (H_2CO_3) solution to simulate the aggressive chemical environment of industrial zones. This "acidic salt stress" protocol is vital for the database because it simulates the realistic "multi-field" conditions where chemical dissolution and mechanical crystallization pressure act simultaneously. By recording the pH levels, acid concentrations, and spraying durations, the database provides the specific chemical-mechanical failure points required to model the accelerated deterioration of carved architectural elements and reliefs in highly polluted urban contexts.

2.2.4. Thermal Shock and UV-A photo-oxidative aging

Thermal shock and ultra-violet (UV) radiation represent high-frequency surface stressors that primarily degrade the mechanical coherence of the stone fabric and the chemical stability of conservation treatments. Heidari et al. (2017) implement a thermal shock protocol in accordance with BS EN 14066, designed to simulate the extreme temperature gradients experienced by monuments in arid or desert climates. This protocol involves 40 rigorous cycles where samples are first heated in an oven to 105°C for 18 hours to induce maximum mineral expansion, and are then immediately plunged into a water bath at 20°C for 6 hours. The resulting rapid contraction triggers intense micro-fissuring and "thermal stress fatigue," which the database records as a progressive reduction in P-wave velocity and a loss of effective elastic modulus. These data points allow for the prediction of

"scaling" and "spalling" in stones with high coefficients of thermal expansion, such as travertines and certain sandstones.

Furthermore, the database addresses the longevity of modern conservation materials through the UV-A photo-oxidative aging protocols detailed by Aldosari (2019). To evaluate the stability of polymeric nanocomposites and traditional consolidants like Paraloid B72, samples are exposed to two 100 W UV-A fluorescent tubes placed at a fixed distance of 20 cm, as shown in *Figure 9* below. This exposure continues for a duration of 45 days, providing a simulated timeframe of several years of natural solar radiation.

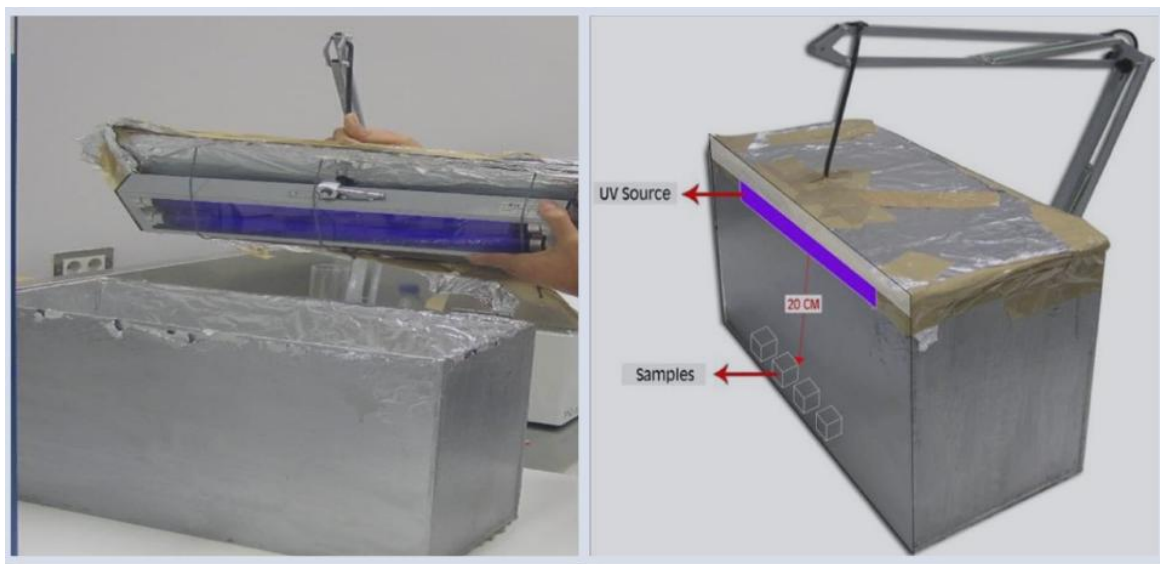


Figure 9. *Experimental limestone samples exposed to the UV irradiation in conservation efforts of ancient Egyptian outdoor carved limestone sculpture (Source: Aldosari et al. (2019)).*

This protocol allows the database to quantify the photo-stability of the consolidant's chemical bond by measuring the resulting shifts in Total Color Difference (ΔE) and the subsequent reduction in Wide Wheel Abrasion (WWA) resistance. By digitizing these UV intensities and exposure durations, the database enables a holistic evaluation of a treatment's "life expectancy," ensuring that future predictive models can account for the degradation of protective layers over time when exposed to high-UV environments.

2.2.5. Salt crystallization: salt type, concentration & temperature effects

In an effort to replicate realistic deterioration patterns, accelerated weathering studies are used to investigate salt crystallisation mechanisms and their impact on building materials. To hasten the damage, these tests usually use harsh, exacerbated circumstances. To accelerate the deterioration, frequent alternating wetting-drying cycles, a higher temperature, a lower relative humidity, and a greater salt concentration than the practical conditions are used (Anupama & Santhanam, 2024). Salt crystallization is widely regarded as one of the most destructive environmental stressors affecting the durability of Cultural Heritage building materials. The magnitude of the resulting damage is not a fixed variable but rather a dynamic outcome influenced by the chemical nature of the salt, its concentration within the pore solution, and the fluctuating temperature regimes of the micro-environment. As highlighted by Zhang et al. (2025), the crystallization characteristics, such as the crystallization position and the resulting pressure, are heavily dependent on the interplay between salt properties and ambient thermal conditions. In the specific case of historical ceramics, Chekai et al. (2025) demonstrate that the internal distribution of salt and the subsequent mechanical breakdown are intrinsically linked to the material's firing history and resulting microstructure, which govern the transport of saline solutions and the location of the drying front.

The chemical identity of the salt significantly dictates the severity of the decay. Sodium sulfate (Na_2SO_4) and sodium chloride (NaCl) are among the most frequently cited agents in literature due to their high solubility and prevalence in coastal and polluted urban environments. Sodium sulfate is particularly lethal to porous substrates like limestone and sandstone because of its ability to exist in multiple hydration states; the phase transition from thenardite (Na_2SO_4) to mirabilite ($\text{Na}_2\text{SO}_4 \cdot 10\text{H}_2\text{O}$) involves a substantial volume expansion that exerts internal stresses exceeding the tensile strength of many historical materials (Galanaki et al., 2022; Cappai et al., 2024). Comparative studies suggest that while NaCl often leads to surface efflorescence and granular disintegration, Na_2SO_4 typically promotes more severe structural flaking and subflorescence within the deeper pore network (Galanaki et al., 2022). Furthermore, Chekai et al. (2025) highlight that for antique Dutch ceramic tiles, the damage induced by sodium sulfate is exacerbated by the presence of a

glaze layer, which acts as a vapor barrier, forcing crystallization to occur at the interface between the glaze and the porous ceramic body, ultimately leading to delamination.

Concentration levels further modulate this "condition-response" relationship. Higher saline concentrations generally lead to a more rapid accumulation of crystals within the capillary pores, thereby accelerating the frequency of crystallization-dissolution cycles. However, the damage is not always linear. Zhang et al. (2025) observed that in capillary salt weathering tests, the concentration of the solution alters the height of the capillary rise and the subsequent "evaporation front," effectively shifting the zone of maximum damage. Furthermore, the presence of salt mixtures—common in real-world heritage sites—can create synergistic effects where the solubility of one salt is altered by the presence of another, complicating the prediction of crystallization pressures (Wang & Zhang, 2023).

Lastly, temperature plays a dual role in this process by influencing both the solubility of the salts and the kinetics of evaporation. For hydrated salts like sodium sulfate, temperature fluctuations dictate the transition points between different mineral phases. Liang et al. (2025) noted that the cooling rate significantly affects the freeze-thaw deterioration of salt-contaminated materials, suggesting that thermal gradients can exacerbate the mechanical fatigue induced by salt expansion. Additionally, elevated temperatures during the drying phase of accelerated weathering protocols can lead to rapid supersaturation of the pore solution, causing crystals to precipitate in narrower pores where the resulting pressure is most disruptive (Anupama & Santhanam, 2024). This synergy between thermal stress and saline concentration underscores the necessity of the "multi-field coupling" approach proposed by Guo et al. (2022), which recognizes that salt weathering in heritage materials must be evaluated as a complex interaction of chemical, thermal, and hydraulic variables.

2.2.6. Synergistic AWTP: coupled salt and frost damage

In real-world environmental scenarios, Cultural Heritage materials are rarely subjected to isolated weathering agents; rather, they face the concurrent action of multiple stressors. The database prioritizes the digitization of "synergistic" data, where the coupled effects of salt crystallization and freeze-thaw (F-T) cycles create a destructive feedback loop. Research by Wang and Zhang (2023) demonstrates that the presence of salts fundamentally alters the

thermodynamics of the pore network. Specifically, saline solutions lower the freezing point of water, which paradoxically extends the duration of the liquid-to-solid phase transition and increases the cryo-static pressure exerted during the freezing process. This synergy is particularly aggressive in rock-hewn heritages, where the coexistence of sulfate salts and frost leads to a more rapid reduction in mechanical strength and P-wave velocity than single-agent tests would suggest.

The intensity of this coupled decay is also heavily influenced by the cooling rate and the concentration of the salt mixture. Liang et al. (2025) and Guo et al. (2022) highlight that salt-contaminated materials (such as those at earthen sites) exhibit enhanced hygroscopicity, maintaining higher degrees of moisture saturation than uncontaminated samples. This increased saturation exacerbates the volumetric expansion during frost cycles, while the subsequent drying phases drive the concentration of salts at the micro-fractures initiated by ice crystallization. By recording these "multi-field coupling" parameters, the database moves beyond simplistic modeling to account for the complex chemical-mechanical interactions that drive the granular disintegration of historic masonry and archaeological substrates.

The current database developed in the context of this thesis work, aims to provide the high-fidelity features required for machine learning models to identify "worst-case" environmental profiles by integrating these synergistic findings into the database is essential for the refinement of future performance predictions. For conservation practitioners, this data-driven approach facilitates the identification of high-risk zones on a monument, where the simultaneous presence of rising damp and sub-zero temperatures necessitates urgent, targeted intervention to prevent catastrophic structural fatigue.

2.3 Deterioration and Dynamic Performance Metrics (DPM)

The final phase of the data collection framework involves the systematic quantification of material alteration following exposure to environmental stressors. Deterioration and Dynamic Performance Metrics (DPM) represent the "output features" of the database, providing the objective measurements of decay required to validate predictive models. Unlike initial characterization, which describes a material's potential vulnerability, DPM captures the realized fatigue of the substrate, typically expressed through changes in

physical, mechanical, and microstructural properties (Coletti et al., 2025; Wang & Zhang, 2023). By digitizing these metrics, the database establishes a clear correlation between specific weathering protocols and the resulting loss of functional performance.

2.3.1 Quantification of damage: mass loss, strength reduction, porosity increase

The most fundamental indicator of macroscopic decay in the database is the percentage mass loss (ΔM %) This metric is particularly critical in salt crystallization and freeze-thaw studies, where it serves as a direct measure of surface recession and granular disintegration. As demonstrated by Coletti et al. (2025), high-porosity stones like Costozza can undergo catastrophic mass loss in a non-linear fashion, often exhibiting "plateaus" followed by sudden structural failure. When mass loss is tracked over consecutive cycles, it allows for the calculation of a Damage Index, which represents the velocity of material loss and provides a standardized target for machine learning classification (Chen et al., 2023).

However, structural failure often initiates internally before mass loss becomes evident. To capture this "hidden" decay, the database integrates mechanical strength reduction and porosity increase. In sandstone and historical bricks, weathering cycles induce micro-fractures that significantly lower the Uniaxial Compressive Strength (UCS) and P-wave velocity (Peng et al., 2022; An et al., 2024). Simultaneously, the rupture of internal pore walls—quantified through Mercury Intrusion Porosimetry (MIP)—leads to a shift in the pore-size distribution toward larger, more vulnerable diameters. This increase in "active" porosity further exacerbates the material's susceptibility to moisture ingress, creating a destructive feedback loop that is recorded in the database as a progressive reduction in the material's structural coherence (Netinger Grubeša et al., 2020).

2.3.1.1 Efficacy of consolidants in reducing mass loss and porosity increase

A specialized subset of the DPM module evaluates the performance of conservation interventions by comparing weathered raw samples against consolidated specimens. The efficacy of consolidants—such as ethyl silicates, nano-silica, or lime-based mixtures—is primarily measured by their ability to inhibit mass loss and stabilize the pore network. Research by Capasso et al. (2024) on Vicenza stone demonstrates that successful

consolidation significantly delays the onset of granular disintegration during salt crystallization tests by strengthening the mineral grain boundaries.

The database tracks the "Consolidation Efficacy" as the percentage reduction in mass loss compared to the untreated control. Furthermore, the impact on porosity is critical; while a consolidant must reduce the volume of macropores to increase mechanical strength, it must not completely block the pore network, as this would reduce water vapor permeability and lead to sub-surface spalling (Weththimuni & Licchelli, 2023). By recording these deltas in porosity and mass loss for treated materials, the database provides a comparative framework for "Predictive Conservation," allowing practitioners to select treatments that offer the highest durability with the lowest risk of secondary structural incompatibility (Doehne & Price, 2011; Apostolopoulou et al., 2019).

2.3.2 Microstructural damage indicators

The internal structural fatigue of Cultural Heritage (CH) materials is often captured through microstructural indicators long before macroscopic failure is visible. The database primarily utilizes Mercury Intrusion Porosimetry (MIP) and Ultrasonic P-wave velocity to quantify these shifts. Research by Brunello et al. (2021) and Volzone & Zagorodny (2014) demonstrates that weathering cycles—particularly salt crystallization and freeze-thaw—induce a measurable "pore structure shift," where the rupture of micro-pore walls leads to an increase in the average pore diameter and total porosity. These changes directly impact the material's mechanical stability; for example, the evolution of internal fractures in clay-based ceramics during frost cycles has been visualized through 3D X-ray micro-CT (, showing how inclusion-matrix interfaces act as primary sites for damage initiation (Porfido et al., 2020).

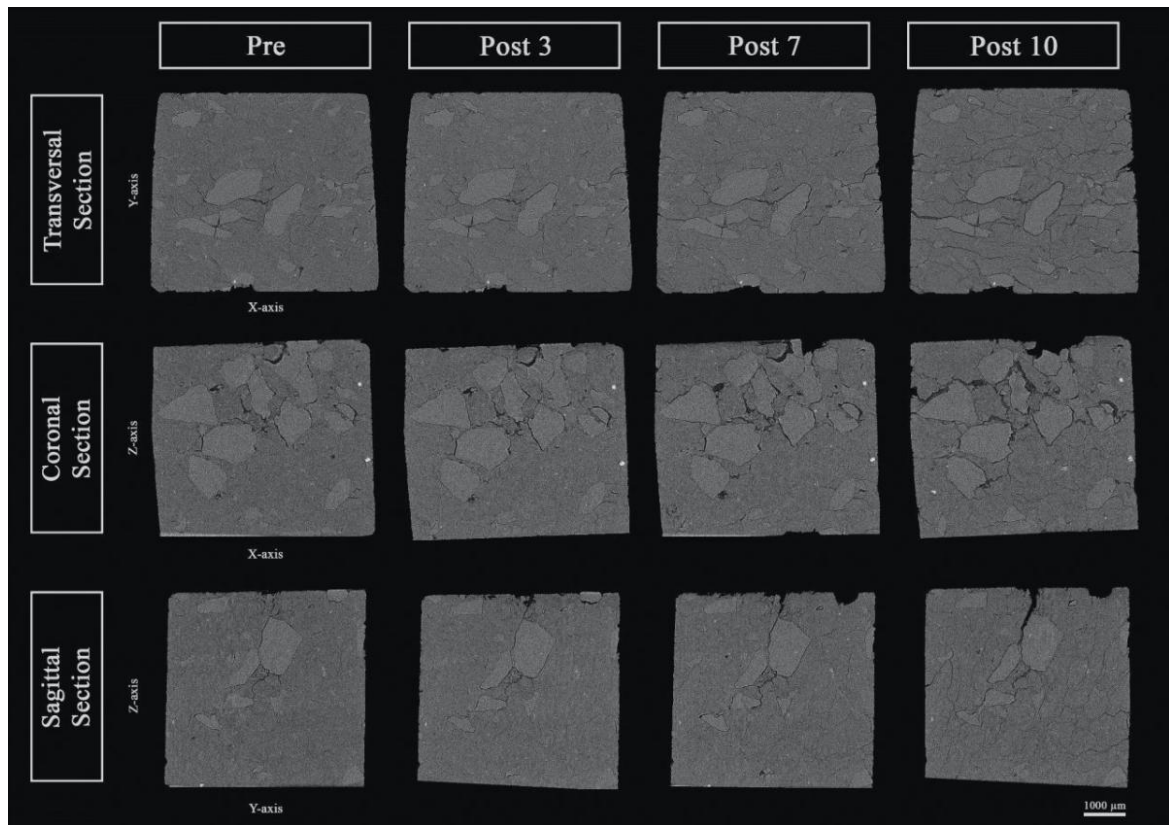


Figure 10. Three orthogonal sections captioned from the micro-CT pre and post several frost cycles (Source: Porfido et al., 2020).

Complementing these invasive techniques, the reduction in P-wave velocity (UPV) serves as a critical non-destructive proxy for internal decay. As micro-cracks propagate and binder cohesion is lost, the velocity of ultrasonic pulses through the material decreases significantly (Apostolopoulou et al., 2019). Mammoliti et al. (2024) and Wang & Zhang (2023) highlight that this reduction in UPV can be correlated with the "weathering degree" of the substrate, allowing the database to track the "velocity of decay" across different lithotypes. By recording these P-wave shifts alongside micro-CT and MIP data, the database establishes the multi-scale structural features necessary for training predictive models to recognize the early stages of material fatigue.

2.3.3 Durability of protective layers under UV and salt stress

The long-term performance of conservation interventions is a vital component of the database, specifically regarding the durability of consolidants and water-repellents. Research focuses on how these protective layers withstand the synergistic effects of UV

radiation and salt stress. According to Weththimuni & Licchelli (2023) and Capasso et al. (2024), the efficacy of treatments—such as nano-silica or ethyl silicates—is evaluated by monitoring changes in surface hydrophobicity (contact angle) and color stability over time. UV exposure often leads to the photo-degradation of organic binders within consolidants, resulting in yellowing and the loss of protective properties, which the database records as a "performance reduction index."

Salt stress poses an even greater challenge, as the crystallization of salts beneath or within the treated layer can lead to the "detachment of the consolidated crust" if the treatment significantly reduces the material's breathability (water vapor permeability). Anupama & Santhanam (2024) and Galanaki et al. (2022) emphasize that the durability of these layers is dictated by their ability to accommodate internal crystallization pressures without facilitating the delamination of the original substrate. By digitizing these "after-treatment" weathering results, the database provides a comparative framework for selecting conservation materials that maintain their protective efficacy under site-specific climatic stressors.

2.3.4 Evaluation of “compatibility metrics” as Database features

The selection of restoration materials is governed by "Compatibility Metrics," which ensure that interventions do not induce secondary decay or aesthetic scarring. The database treats these metrics as primary features, focusing on chromatic, mechanical, and hygric compatibility. Chromatic compatibility is quantified via Colorimetry, where the Total Color Difference (ΔE) between the original substrate and the restoration material (or treated surface) is measured. Capasso et al. (2024) and Hamza et al. (2017) suggest that ΔE values above a threshold of 5 signify unacceptable aesthetic alteration, a critical "binary target" for predictive modeling.

Beyond aesthetics, mechanical and hygric compatibility are essential for structural longevity. The database integrates the binder-to-aggregate ratio and the Water Absorption Coefficient (WAC) of restoration mortars to ensure they do not create "moisture traps" within the historical masonry (Apostolopoulou et al., 2019; Veiga et al., 2009). If a restoration mortar is significantly less porous or harder than the original brick or stone, it can exacerbate the weathering of the historical material at the interface. By recording these

"compatibility deltas" as digitized features, the database allows researchers to evaluate the holistic success of conservation treatments, ensuring that the "restored" state is as durable and physically coherent as the original fabric (Doehne & Price, 2011).

CHAPTER 3: DATABASE METHODOLOGY, STRUCTURE, AND IMPLEMENTATION

Global knowledge of the composition and properties of building materials, as well as the causes underlying their deterioration and ageing, has grown over the past few decades. The goal of the current research is to develop an instrument for recording and maintaining the qualities, performance, and history of these heritage materials. The samples repository is required as a foundation for future innovation and development in addition to the preservation of materials with educational and historical value. The preservation and restoration of architectural history depend on this important information. The methodology for constructing this database centers on the transition from traditional, analog-based material science to a digitized, relational framework capable of supporting advanced performance analytics. Unlike static repositories, this research follows a "condition-response" methodology, where the primary objective is to link the intrinsic petrophysical properties of a material to its measured response under specific environmental stressors.

In order for this architectural and experimental data to transcend isolated lab environments, its infrastructure must be aligned with the FAIR data principles (Findable, Accessible, Interoperable, and Reusable). While data sharing and standardized data exchange formats are deeply established, common practices in other analytical research areas, CH studies have historically suffered from data fragmentation and localized storage paradigms. The ultimate long-term scope of this database effort is to transition toward either a centralized heritage repository, where multi-laboratory experimental datasets can be uploaded seamlessly, or a federated network of data repositories that are linked securely among each other via standardized APIs (Wilkinson et al., 2016).

Flexibility in the data format should be a primary feature of a heritage materials database, such as the one this current thesis is developing. The database should be extendable to include information other than chemical composition so that various methodologies may be compared and multidisciplinary studies can be implemented (Hein & Kilikoglou, 2012). The current study was motivated by an inter-laboratory calibration exercise conducted as part of a large-scale inter-comparison analytical program between the NAA laboratories at the Institute of Materials Science at N.C.S.R. "Demokritos" (IMS-

DEMO) and the Helmholtz-Institute of Nuclear Physics at the University of Bonn (HISKP) through which several thousand chemical compositions of ceramics from the Mediterranean region, spanning the Neolithic to the Byzantine periods, have been examined at both labs. In terms of the geographical areas and time periods covered, the data are largely complementary. It was therefore anticipated that the combining of the various databases, following the application of calibration factors and the use of a uniform data format, would yield a useful set of reference data for the ceramic groups they represent (Hein & Kilikoglou, 2012).

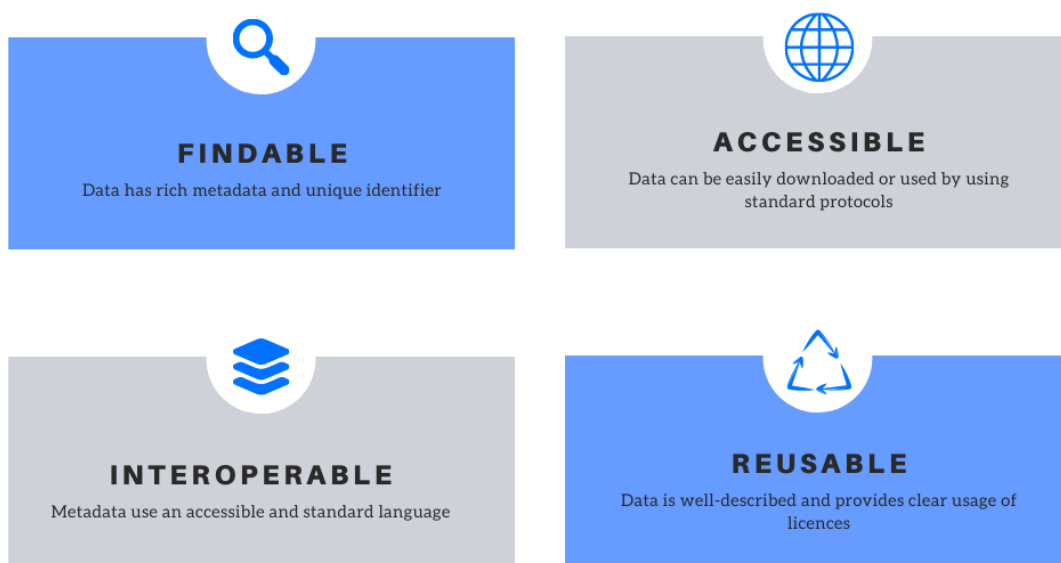


Figure 11. Schematic breakdown of the FAIR Data Principles guiding the development of the cultural heritage materials database architecture ('FAIR Principles | What Are They And Why Are They Important?', 2020).

In a similar manner, this current study's database development efforts, were conducted using Microsoft Access (MS Access), leveraging its robust relational engine to integrate the multifaceted data extracted from a broad and diverse bibliography. While the ceraDAT prototype (Hein & Kilikoglou, 2012) demonstrated the power of a centralized repository for elemental compositions via Neutron Activation Analysis (NAA), this thesis extends that logic to the physical and mechanical resilience of several types of heritage materials. Choosing the appropriate software environment requires a careful balance between commercial desktop management systems and open-source database engines. Commercial software such as MS Access provides a highly accessible, localized graphical

interface that is ideal for schema prototyping and standalone query validation within the scope of an MSc thesis under a personal license framework. However, proprietary desktop software introduces inherent limitations regarding user access, scalability, and web integration. In contrast, open-source relational database management systems (RDBMS) like MySQL or PostgreSQL operate on robust, server-based SQL protocols that are natively built for multi-user concurrency and open-access web deployment. Consequently, while MS Access serves as an excellent localized incubation environment for this research, publishing the database as an open, publicly accessible repository will necessitate migrating the entire schema and its relational key hierarchy into a server-hosted SQL ecosystem (Salunke & Ouda, 2024).

The implementation phase began with the identification of a core data structure that could accommodate the high degree of variability found in heritage science research. The idea of a *relational database management system (RDBMS)* was deemed appropriate in light of wider interconnection and the potential to incorporate other data types in the future. The benefits of establishing a platform for managing historical materials, both past and future, are substantial. These are useful for research to extend the life of historic building materials by promoting their appropriate selection and use as well as by postponing deterioration.

3.1 Data acquisition and standardization

The transition from scattered, multidisciplinary experimental data into an organised digital environment is the fundamental stage of this study. There are few cohesive datasets that follow a material from its perfect state to its eventual breakdown in the field of Cultural Heritage (CH) science since data is frequently generated in groups, ranging from strictly mineralogical investigations to engineering-focused durability testing. The methodical approach utilised to find, extract, and harmonise high-fidelity data from various scientific sources, case studies and publications in order to close these gaps is described in this section.

The conservation and restoration of architectural heritage necessitate an understanding of the condition of its constituent materials to formulate suggestions for the intervention plan, including the materials and techniques to be employed. When available, information about the mechanical, chemical, and physical characteristics of materials is typically shared between various actors but is not typically available to the general public

(Santos Silva et al., 2017). Since the early 1970s, a growing amount of reference data has been kept in digital databases due to advances in computer applications. It is clear that a wide range of methods with fluctuating performance throughout time were used to gather all of this analytical data. As a result, it has become challenging to simply compare data from various studies. Even while analytical methods have gradually improved in terms of precision and accuracy, it is still difficult to compare data directly between various laboratories.

In addition to technical issues, that comparison has been hampered by the different database formats employed in each laboratory. Hence, rather than obtaining analytical data on the identical material produced by another institute, it has been preferred in many case studies to perform repetitive fresh measurements of reference materials. In the early phases, exchanging data tables in hard copy was the most popular way for laboratories to share data. The Archaeometry Laboratory at the University of Missouri Research Reactor (<http://archaeometry.missouri.edu/datasets/datasets.html>) and the Helmholtz-Institute of Nuclear Physics at the University of Bonn (<http://www.hiskp.uni-bonn.de/gruppen/mommsen/data.html>) are two examples of research groups that have only recently begun to make some data tables of ancient ceramics available online in electronic format (Hein & Kilikoglou, 2012).

3.1.1 Data collection and digitization methodology

The data collection strategy was designed as a "Literature Mining" operation, targeted at capturing the full experimental lifecycle of stone, brick, mortar, and some restoration specimens. As already mentioned, this approach was heavily informed by the ceraDAT prototype (Hein & Kilikoglou, 2012), which demonstrates the necessity of storing not only primary analytical results (such as NAA or XRF) but also the critical metadata concerning provenance and methodology.

The methodology for constructing this database follows a "Condition-Response" framework, aimed at linking the intrinsic properties of materials to their measured decay under stress. To ensure the database could support future predictive modeling, a selective acquisition process was employed: sources were filtered based on the presence of "linked data." Specifically, a study was digitized when it provided a clear trajectory between the

material's baseline petrophysical/ physicochemical properties and its response to controlled environmental stressors. For instance, recent advances highlight the critical need to compile multi-weathering databases (incorporating acid, alkali, salt, and freeze-thaw cycles) to train models like Artificial Neural Networks (ANN) or Support Vector Regression (SVR). These models can predict variables that cannot be easily measured in situ (like bulk porosity and static elastic modulus) using non-destructive field indicators such as Leeb hardness and P-wave velocity (Zhang et al., 2024). Additionally, integrating Digital Image Analysis (DIA) paired with non-destructive rebound-based devices (Equotip) offers quantitative tracking of surface and in-depth hardness variations associated with grain size, significantly augmenting the reliability and depth of the collected data points (Mammoliti et al., 2024).

As highlighted by Zhao et al. (2015), the digitization of building materials often suffers from a "scarcity of comprehensive data," where researchers must often piece together information from multiple, non-standardized sources. In this research, the digitization process involved manual extraction of quantitative data from the reviewed literature's technical tables and the recovery of values from graphical plots, such as pore-size distribution curves and mass-loss gradients.

The objective was to evaluate the extent of scientific research on heritage and restoration materials and interpret quantitative findings, especially with regard to the effects of accelerated weathering techniques used on their testing, in order to simulate the ongoing global climate change and extreme environmental fluctuations' effect on these materials. This was accomplished through a systematic analysis of the articles obtained from the SCOPUS, Springer, MDPI, npj Heritage Science, and Google Scholar search. To identify academic papers that mostly adhered to the "linked data" criteria, the search was executed using specific combinations of keywords, such as: "heritage stones," "historical bricks," "restoration mortars," "petrophysical characterization," "accelerated weathering," "freeze-thaw cycles," "salt crystallization cycles," "pore structure," "durability metrics", etc. These terms ensured the retrieval of publications that provided a holistic view of the material's mineralogical state alongside its subsequent mechanical and physical degradation. Microsoft Excel was used for the initial organization and preprocessing of the collected material. Subsequently, MS Access was then utilised for a more sophisticated organization and visualisation, allowing for a thorough analysis of the dataset's relationships. This

integrated approach made it possible to explore and categorise the data in a thorough and detailed manner.

Initially, in order to ascertain whether a sizable number of studies would have been eliminated from the analyses because of the use of different names, it was deemed crucial to examine whether the publication referred to distinct denominations of the typologies. Afterwards, in an attempt to determine the degree to which the composition of the materials sparked interest in the scientific community, it was decided to investigate whether any references to each material's composition were made. It was considered necessary to determine whether mechanical and/or physical characteristics were also stated, and lastly, determining whether the examined publications had information on how these materials behaved under accelerated weathering testing was also key. Regarding other terminology/*Nomenclature* used for material typologies, the objective was to ascertain whether the material typology is frequently referred to by other names, since it can make it more difficult to locate all pertinent scientific articles. Terminology variations might result from varied facies of the lithotype or material in general, each of which may be linked to different qualities and behaviours, or from different commercial names (typically when referring to mortar products).

Meanwhile, regarding composition, the goal was to ascertain how much attention the scientific community paid to their importance, since the mineralogical and chemical composition of the materials are essential in comprehending their behaviour. Lastly, the goal was also to obtain an overview of the extent of investigation being conducted on the effects of environmental factors, such as freeze thaw cycles or salt crystallisation on heritage materials, given its importance in this study for the development of this database. Each publication and research was only taken into consideration for inclusion in the designated category of this database if it contained data that satisfied (at an accepted extent) these predetermined standards.

3.1.2 Standardizing units: Resolving data heterogeneity

A primary obstacle in the meta-analysis of Cultural Heritage materials is the lack of a unified reporting language across international research groups. Data heterogeneity arises from two main sources: the use of different measurement systems (e.g., metric vs. imperial or non-SI

units) and the utilization of varying experimental methodologies to describe the same physical phenomenon. Zhao et al. (2015) emphasize that for a database to be useful for performance simulation, the "transferability of parameters" must be ensured. This was achieved here by standardizing qualitative descriptions into quantitative intervals.

To resolve these discrepancies, a comprehensive "Normalization Layer" was integrated into the data entry workflow. This process involved the manual conversion of all physical and mechanical properties into a standardized internal metric system. For instance, hydric properties, which are notoriously fragmented in literature, were harmonized: moisture transport coefficients reported in varying units such as $\text{kg/m}^2\text{h}^{0.5}$ or $\text{cm/min}^{0.5}$ were converted to a consistent base unit to ensure parity during querying. Similarly, all porosity data was standardized to volume percentage (%), and mechanical strength metrics, such as Uniaxial Compressive Strength (UCS), were normalized to Mega-Pascals (MPa). This mathematical harmonization aligns with the inter-laboratory calibration methodology discussed by Hein and Kilikoglou (2012) in the ceraDAT project, ensuring that the combined datasets yield a reliable set of reference values. Furthermore, standardization was applied to the qualitative and categorical descriptions of material states and experimental conditions. One of the most significant challenges is the "sharp boundary problem," where different authors use subjective terms like "moderately weathered" or "highly durable" to describe materials with overlapping quantitative values. Following the logic of the Fuzzy Inference System proposed by Heidari et al. (2017), these qualitative labels were cross-referenced with the reported physical data (e.g., P-wave velocity or mass loss) to map them into standardized quantitative intervals.

Experimental "Testing Modes" were also subjected to this normalization. For example, the diverse freeze-thaw protocols described in the bibliography, ranging from the three sandstone-specific modes in Peng et al. (2022) (Immersion, Capillary, and Periodic Saturation) to the standardized EN-based cycles in Coletti et al. (2025), were assigned unique categorical IDs within *tbl_4_Weathering_Test_Protocols*. This systematic categorization allows the database to resolve the "scarcity of comprehensive data" noted by Zhao et al. (2015) by enabling the software to treat disparate studies as a single, multi-variant experimental population. The database becomes a reliable instrument for statistical analysis and machine learning by "levelling the field of play" through this strict unit and mode

standardisation, where each characteristic is represented by a logically consistent and mathematically similar value.

3.2 Relational database design and structure

The purpose of this database was to store and present trustworthy information about the performance of materials. As a result, the database was designed in accordance with the primary elements that affect the performance of materials, which include material qualities, environmental parameters, and historical data pertaining to activities made during service life.

The general data for each case study can include information about the project, samples tested and accelerated testing protocols details. This dynamic definition of attributes gives data management flexibility in this area as well as all others. Each case study's unique defined levels may contain various data regarding the material characterisation, as well as the historical context. The database was structured to make updating and analysing data easier. In addition to the ability to export data in several formats, it incorporates some streamlined tools like maps, images, and filters. Additionally, the hierarchical description of the artwork can be filtered to obtain only the elements that meet the user-selected criteria.

The form of the database that was developed aimed to make it easier for a regular user to import and amend data. This tool should be fully accessible since it is being evaluated with an overview of new case studies. The database makes it possible to categorise the materials based on their nature and purpose. In order to incorporate the pertinent data in the historical context of the building materials, a dedicated interface is being designed. Additionally, a module to oversee the physical archive of a sample of historical materials is being developed.

3.2.1 Defining and enforcing primary and foreign key relationships

The backbone of the database's scientific reliability is the enforcement of a rigorous Primary Key (PK) and Foreign Key (FK) hierarchy. At the apex of this hierarchy is *tbl_1_Sites*, where each geographic location is assigned a unique Site_ID. This ID migrates as a Foreign

Key to *tbl_2_Samples*, establishing a permanent link between the material and its geological or architectural provenance. Every unique specimen in *tbl_2_Samples* is assigned its own *Samples_ID*, which acts as the "Universal Identifier" for that material's entire digital lifecycle.

Relational integrity is strictly enforced to prevent "data drifting." For instance, a record in *tbl_3_Characterization* cannot exist without a valid *Sample_ID* from the parent table, ensuring that high-resolution mineralogy and porosity data are always tied to a verified material identity. This strictly enforced key hierarchy is particularly critical when preparing datasets for supervised machine learning approaches. A well-defined relation between the sample identity (PK) and its performance metrics (FK) ensures that input variables (e.g., initial UPV, hardness, mineralogy) are flawlessly matched with their corresponding output target variables (e.g., post-weathering porosity or strength loss). Such structural consistency guarantees that the 70% training and 30% testing data splits required for algorithmic validation remain contextually accurate and free of relational orphans (Zhang et al., 2024).

A critical technical innovation in this thesis is the implementation of *tbl_5_Sample_Test_Link*. This junction table facilitates a many-to-many relationship between materials and tests, allowing a single heritage sample to be linked to multiple records in *tbl_4_Weathering_Test_Protocols* (e.g., separate links for freeze-thaw and salt crystallization). Furthermore, the introduction of *tbl_7_References* as a top-level anchor ensures that every data point across the entire database is traceable to its bibliographic source. By linking the *Citation_ID* to each record, the methodology provides a complete audit trail. This ensures that when the database is queried for machine learning training, the "Stressor" features (from *tbl_4*) and "Performance" targets (from *tbl_6_Deterioration_Metrics*) are logically and scientifically synchronized through their shared relationship with the material identity.

3.2.2 Conceptual model and entity-relationship diagram (ERD)

The structural logic of the database, as presented in *Figure 12*, was developed using a relational model to ensure data integrity and to eliminate the multidimensional redundancy inherent in flat-file spreadsheets. Traditional spreadsheets often struggle with the "one-to-

many" nature of heritage science data—where a single lithotype might be subjected to ten different weathering protocols—leading to data entry errors and fragmentation. To resolve this, the database architecture follows a modular "Event-Response" design. This design separates the material's intrinsic properties (static data) from the experimental loads (stressor data) and the resulting material fatigue (dynamic data).

The conceptual framework is divided into three primary clusters: the Material Cluster, the Stressor Cluster, and the Performance Cluster. The Material Cluster, comprising tables for Site Identity, Material Samples, and Physicochemical Baseline, defines the pristine state of the object. The Stressor Cluster, anchored by `tbl_4_Weathering_Test_Protocols`, documents the precise standards and environmental variables such as salt concentration, freezing and thawing temperatures, or cycle count used in each research paper. Finally, the Performance Cluster records the output features, such as mass loss, P-wave velocity reduction or color changes. This modularity allows the database to scale horizontally, meaning new testing protocols or material categories can be added without restructuring the existing data. By explicitly linking the Material Cluster (input features) with the Stressor Cluster (environmental loads) to produce the Performance Cluster (output targets), the Entity-Relationship Diagram inherently mimics the feed-propagation pathways of Artificial Neural Networks. Consequently, researchers can efficiently query the database to extract multi-dimensional arrays, predicting how specific intrinsic features—like the relative composition of specific minerals—directly influence the non-linear deterioration curves under diverse, simulated weathering scenarios (Zhang et al., 2024).

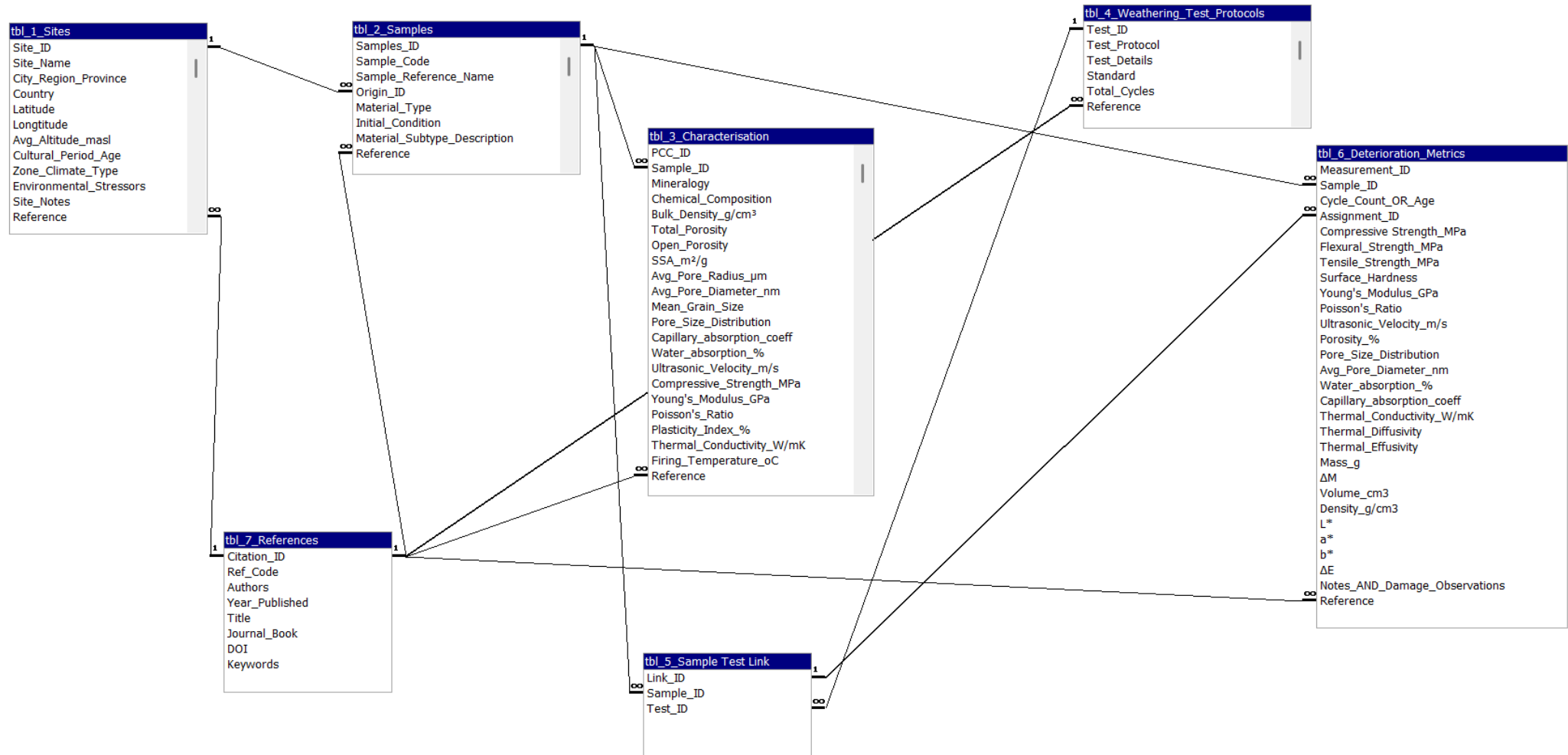


Figure 12. Relational structure of the heritage materials database illustrating the connectivity between material characterization and weathering protocols (Source: original).

3.3 Data quality control and documentation

Quality control (QC) is the critical final phase of the methodology, ensuring that the database functions as a reliable scientific instrument rather than a mere repository of raw values. Given that the data originated from disparate bibliographic sources—often spanning different decades and experimental standards—a systematic QC framework was necessary to identify "data noise" and prevent errors from propagating into future predictive models. This phase focused on three pillars of data integrity: source verification, logical consistency, and structural transparency. The necessity of this framework stems from the "Stochastic Material" reality described by Zhao et al. (2015); since heritage materials are naturally aged and heterogeneous, the "quality" of data is often as much about the context of the measurement as the measurement itself. In this study, QC was treated as an active filtering process that evaluated the "Data Provenance" of each entry. This involved ensuring that every record was not only numerically accurate but also contextually complete. By anchoring the data structure in a relational model, the QC phase allowed for the detection of "relational orphans", meaning data points that lacked a clear link between their mineralogical origin and their weathered state, which were subsequently removed to maintain the high fidelity of the dataset.

3.3.1 Procedures for data validation and missing data handling

The data validation process was designed as a multi-tier verification system. Initially, a "Scientific Range Check" was implemented; for every numerical field (e.g., Porosity, UPV, etc.), the database enforced boundaries based on established material science norms. For example, entries for compact stones like Carrara marble were flagged for manual re-verification if extracted literature values showed porosity exceeding 2%, ensuring that digitization errors or extreme experimental outliers did not skew the dataset. Similarly, a "Compositional Balance Check" was applied to `tbl_2_Characterisation`, requiring that the sum of mineral phases or chemical oxides documented via XRD and XRF did not exceed 100%—a validation step crucial for maintaining the geochemical accuracy prioritized in the `ceraDAT` project (Hein & Kilikoglou, 2012).

Handling missing data represented a significant challenge, as literature mining frequently reveals "incomplete experimental chains" (e.g., a study reporting mass loss but

omitting ultrasonic pulse velocity). Again, following the "stochastic data" logic proposed by Zhao et al. (2015), this database strictly differentiates between a value of *zero* and a missing value. Rather than populating empty fields with zeros, which would introduce catastrophic bias into machine learning algorithms—the database utilizes NULL values, meaning leaving the cells empty instead. This strict protocol for missing data is indispensable for advanced statistical evaluations such as Principal Component Analysis (PCA) and regression models. If algorithms such as Multiple Linear Regression (MLR) or Gaussian Process Regression (GPR) encounter zero-filled gaps, they artificially interpret them as true physical baselines, heavily distorting error metrics like Root Mean Square Error (RMSE) and the coefficient of determination (R^2) (Zhang et al., 2024).

By preserving NULL states, the database enables data scientists to accurately deploy imputation algorithms or correctly exclude incomplete datasets without compromising the physical reliability of the weathering simulations. This ensures that when the data is exported for performance simulation or statistical clustering, the algorithms recognize the lack of data as a "missing feature" rather than an absence of physical response. This distinction is vital for maintaining the statistical power of the dataset when performing cross-comparisons between high-resolution studies, such as the micro-CT fracture analysis of Porfido et al. (2020) and the macroscopic scaling tests of Coletti et al. (2025).

3.3.2 Documentation of database schema

The documentation of the database schema serves as the "Technical Manual" for the research, ensuring that the relational logic is transparent, reproducible, and extendable. This documentation is materialized through a comprehensive Data Dictionary, which defines the specific attributes of every field across the seven tables of the MS Access framework. Each entry in the dictionary specifies the data type (e.g., Double, Short Text, Long Integer, etc.), the standardized unit of measurement (e.g., MPa, m/s), and the specific bibliographic link to tbl_7_References. This metadata-centric approach follows the ceraDAT methodology, where the ultimate goal is to provide a "uniform data format" that allows for the integration of future inter-laboratory studies (Hein & Kilikoglou, 2012).

The schema documentation details the SQL (Structured Query Language) logic used to create the "Joined Views" that link the Material Identity to the Weathering Protocols and

Performance results. By documenting these relational paths, the research provides a clear audit trail from the raw PDF source to the final digitized entry. This documentation also includes a "Reliability Index" for specific data fields, distinguishing between high-precision laboratory measurements (e.g., MIP or micro-CT) and estimated properties derived from qualitative descriptions. As noted by Zhao et al. (2015), such documentation is essential for the "transferability of parameters" in building performance simulation, allowing other researchers to verify the dataset's integrity or expand the schema to include new deterioration mechanisms or emerging conservation technologies. Furthermore, the schema documentation clarifies which data fields can act as viable non-destructive in-situ indicators (e.g., rebound hardness, acoustic emission-based wave velocity) versus those requiring laboratory extraction. Mapping this distinction directly in the schema allows future database users to easily filter and deploy specific input arrays tailored for on-site predictive diagnostics, ultimately streamlining the decision-making process for cultural heritage conservators (Zhang et al., 2024; Mammoliti et al., 2024).

Table 6. Internal model for the Sites entity of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_1_Sites	Site_ID	Primary Key (PK) ; A unique numerical identifier for each specific site or monument. This is the master key that migrates to all other tables (Samples, PCC, etc.) to ensure that every material property is linked to a specific geographic location.	AutoNumber – Long Integer
	Site_Name	The official or primary name of the monument, archaeological site, or historical building.	Short Text
	City_Region_Province	Provides granular geographic data, which is essential for correlating material deterioration with specific regional micro-climates.	Short Text
	Country	Identifies the nation-state where the site is located. This is a vital field for high-level spatial queries and for identifying regional patterns in material decay.	Short Text
	Latitude	Spatial Metadata; Stores the exact latitude and longitude of the site in Decimal Degrees. This field is critical for mapping the database entries into GIS software, allowing researchers to visualize the spatial distribution of material decay and correlate it with satellite-derived climate data	Number – Double
	Longitude		
	Avg_Altitude_masl	Altitude in meters above sea level (masl)	Number – Double
	Cultural_Period_Age	A text field identifying the historical or archaeological period (e.g., Roman, Byzantine, Bronze Age) to provide chronological context.	Short Text
	Zone_Climate_Type	A categorical field designating the regional climate in the Köppen climate classification order (e.g., Mediterranean, Arid, Temperate) to help correlate macro-climatic conditions with material degradation rates.	Short Text

	Environmental_Stressors	A descriptive field capturing site-specific weathering agents such as acid rain, marine aerosol exposure, or heavy freeze-thaw cycles.	Short Text
	Site_Notes	General notes about the environmental context and climatic zone, a descriptive field identifying the primary natural threats reported in the literature for that specific site. This allows for the analysis of how external macro-climatic factors influence the rate of salt crystallization and frost damage.	Short Text
	Reference	Foreign Key (FK); Links the site information to its bibliographic source in tbl_7_References. This ensures that the description of the site and its environmental context is scientifically traceable to the reviewed literature.	Number – Long Integer

Table 7. Internal model for the Samples entity of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_2_Samples	Samples_ID	Primary Key (PK) ; A unique numerical identifier for each specific site or monument. This ID is the "Universal Identifier" used to link the sample to its chemical composition, petrophysics, and performance results across all subsequent tables.	AutoNumber – Long Integer
	Sample_Code	Name code given for the sample(s) tested.	Short Text
	Sample_Reference_Name	Original name of the sample, exactly as mentioned in each case study.	Short Text
	Origin_ID	Foreign Key (FK) ; Links the sample to its geographic origin in tbl_1_Sites.	Number – Long Integer
	Material_Type	A categorical field identifying the broad class of the material (e.g., Stone, Brick, Mortar) and more granular classification providing the specific variety or lithotype (e.g., Biocalcarenite, Tuff, Lime Mortar).	Short Text
	Material_Subtype_Description	A detailed text description providing the specific petrographic or fabric classification (e.g., bioclastic wackestone, calcareous brick) and any observable textural features.	Short Text
	Initial_Condition	Records the macroscopic state of preservation of the sample at the time of collection (e.g., fresh/intact sample vs. highly weathered historical core).	Short Text
	Reference	Foreign Key (FK) ; Links the site information to its bibliographic source in tbl_7_References. This ensures that the description of the site and its environmental context is scientifically traceable to the reviewed literature.	Number – Long Integer

Table 8. Internal model for the physicochemical entity of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_3_Characterisation	PCC_ID	Primary Key (PK) ; A unique numerical identifier for each specific physicochemical characterization (PCC) and thermomechanical record.	AutoNumber – Long Integer
	Sample_ID	Foreign Key (FK) ; Relates the characterization data to a specific specimen in tbl_2_Samples.	Number – Long Integer
	Mineralogy	Records the qualitative and semi-quantitative mineral phases usually identified via X-ray Diffraction (e.g., Calcite, Quartz, Albite).	Long Text
	Chemical_Composition	Stores the chemical or oxide analysis (e.g., CaCO ₃ , SiO ₂) usually extracted from X-ray Fluorescence data.	Long Text
	Bulk_Density_g/cm ³	A numerical value representing the mass per unit volume of the specimen, including its pore system.	Number – Double
	Total_Porosity	The volume percentage of the bulk material occupied by pores, serving as a primary indicator of weathering vulnerability.	Number – Double
	Open_Porosity	The volume percentage of interconnected pores accessible to fluids, critical for understanding capillary water absorption and salt ingress.	Number – Double
	SSA_m ² /g	Specific Surface Area; records the total surface area of the material per unit of mass, often used to predict reactivity and salt accumulation.	Number – Double
	Avg_Pore_Radius_μm	Quantitative parameter derived from MIP defining the dominant pore radius.	Number – Double
	Avg_Pore_Diameter_nm	Quantitative parameter defining the dominant pore diameter, dictating susceptibility to crystallization pressures.	Number – Double

Mean_Grain_Size	The average dimension of the mineral grains or clasts, often obtained via optical microscopy or Digital Image Analysis, affecting the mechanical strength.	Short Text
Pore_Size_Distribution	Categorical or percentage-based breakdown of pore sizes (e.g., micro, meso, macro pores), influencing frost and salt weathering resilience.	Short Text
Capillary_absorption_coeff	Quantifies the rate of water uptake by capillary action, standardized to $\text{g/m}^2 \cdot \text{s}^{0.5}$.	Number – Double
Water_absorption_%	The percentage of weight increase of the heritage material sample when fully saturated with water.	Number – Double
Ultrasonic_Velocity_m/s	P-wave velocity measured in m/s, serving as a non-destructive index of internal compactness and micro-cracking.	Number – Double
Compressive_Strength_MPa	The Uniaxial Compressive Strength (UCS) of the unweathered sample in MPa, providing the baseline load-bearing capacity.	Number – Double
Young's_Modulus_GPa	The static or dynamic elastic modulus in GPa, representing the material's stiffness.	Number – Double
Poisson's_Ratio	The ratio of transverse to axial strain, a key mechanical property for modeling structural deformation.	Number – Double
Plasticity_Index_%	A measure of the plasticity of clay-based raw materials, derived from Atterberg limits, critical for ceramic manufacturing analysis.	Number – Double
Thermal_Conductivity_W/mK	Measures the material's ability to conduct heat, a vital parameter for hygrothermal building performance simulation.	Number – Double
Firing_Temperature_oC	The estimated temperature at which a historical ceramic or brick was fired, deduced from mineralogical markers.	Number – Double

	Reference	Foreign Key (FK); Links the site information to its bibliographic source in tbl_7_References. This ensures that the description of the site and its environmental context is scientifically traceable to the reviewed literature.	Number – Long Integer
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Table 9. Internal model for the accelerated weathering test protocols (AWTP) entity of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_4_Weathering_Test_Protocols	Test_ID	Primary Key (PK) ; A unique numerical identifier for each distinct weathering protocol. It serves as the relational anchor to link laboratory "stressors" to material "responses."	AutoNumber – Long Integer
	Test Protocol	Categorical name of the experimental procedure (e.g., Salt Crystallization, Freeze-Thaw, Thermal Shock). This field facilitates high-level sorting of aging mechanisms.	Short Text
	Test_Details	A comprehensive text field documenting the specific laboratory parameters, such as cycle duration, chemical concentrations (e.g., 14%w/w Na ₂ SO ₄), temperature ranges, etc.	Long Text
	Standard	The referenced international standards (e.g., EN 12370) followed by each case study included in the database.	Short Text
	Total_Cycles	The total cycles run for each test.	Short Text
	Reference	Foreign Key (FK) ; Links the site information to its bibliographic source in tbl_7_References. This ensures that the description of the site and its environmental context is scientifically traceable to the reviewed literature.	Number – Long Integer

Table 10. Internal model for the auxiliary table of the database linking samples and tests (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_5_Sample Test Link	Link_ID	Primary Key (PK); A unique identifier for each specific connection made between a material sample and an experimental protocol. The "bridge" that connects the Samples to Weathering Protocols.	AutoNumber – Long Integer
	Sample_ID	Foreign Key (FK); Relates the link to a specific specimen in tbl_2_Samples. This identifies which material is being tested.	Number – Long Integer
	Test_ID	Foreign Key (FK); Relates the link to a specific weathering protocol in tbl_4_AWTP. This identifies which stressor is being applied.	Number – Long Integer

Table 11. Internal model for the Dynamic Performance Metrics (DPM) entity (performance and deterioration tracking) of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_6_Deterioration_Metrics	Measurement_ID	Primary Key (PK); A unique identifier for every individual measurement event recorded in the database.	AutoNumber – Long Integer
	Sample_ID	Foreign Key (FK); Relates the measurement to a specific specimen in tbl_2_Samples.	Number – Long Integer
	Cycle_Count_OR_Age	Records the specific point in time or cycle number when the measurement was taken (e.g., "Cycle 0", "Cycle 40", or "28 days").	Short Text
	Assignment_ID	Foreign Key (FK); Links the measurement to the specific test/link record to identify which weathering protocol produced this result.	Number – Long Integer
	Compressive_Strength_MPa	Uniaxial Compressive Strength; the maximum axial compressive stress the material can withstand before failure.	Number – Double
	Flexural_Strength_MPa	Flexural strength; measures the material's ability to resist deformation under load.	Number – Double
	Tensile_Strength_MPa	The Brazilian Tensile Strength (BTS) or direct tensile strength in MPa, measuring the material's resistance to pulling forces.	Number – Double
	Surface_Hardness	Surface hardness, usually determined by Leeb hardness (equotip) testing.	Number – Double
	Young's_Modulus_GPa	The elastic modulus recorded at this specific cycle, tracking the loss of stiffness due to weathering.	Number – Double

Poisson's_Ratio	The Poisson's ratio evaluated at a specific cycle.	Number – Double
Ultrasonic_Velocity_m/s	Ultrasonic Pulse Velocity/ <i>p-wave velocity</i> ; used to assess the internal integrity and detect cracks or voids developed during weathering.	Number – Double
Porosity_%	The volume of pores measured at that specific cycle/age, showing how the internal structure opens up during decay.	Number – Double
Pore_Size_Distribution	The altered distribution of pore sizes due to internal microstructural damage and coalescing of pores.	Short Text
Avg_Pore_Diameter_nm	The new average pore diameter following the destructive weathering cycles.	Number – Double
Water_absorption_%	Measures the increase in mass due to water uptake, indicating changes in hydric behavior over time.	Number – Double
Capillary_absorption_coeff	Capillary absorption coefficient; Quantifies the rate of water uptake by capillary action (standardized to $\text{g/m}^2 \cdot \text{s}^{-0.5}$).	Number – Double
Thermal_Conductivity_W/mK	Records changes in heat transfer properties as the material deteriorates or becomes saturated.	Number – Double
Thermal_Diffusivity	The rate of heat transfer through the material which often decreases as porosity increases, standardised in mm^2/s	Number – Double
Thermal_Effusivity	The material's ability to exchange thermal energy with its surroundings in $\text{W} \cdot \text{s}^{0.5}/\text{m}^2 \cdot \text{K}$, highly sensitive to weathering deterioration.	Number – Double
Mass_g	The dry weight of the sample at the specific cycle count, used to calculate "Mass Loss %."	Number – Double
Volume_cm ³	The physical volume of the specimen, used for density and swelling calculations.	Number – Double

	Density_g/cm ³	The bulk density at the specific measurement interval.	Number – Double
	L*, a*, b*, ΔE	Colorimetry coordinates and total color difference; used to quantify surface staining, oxidation, or bio-growth. (L*=Lightness: from 0 (Black) to 100 (White), a*= Red/Green: Positive = Red, Negative = Green, b*= Yellow/Blue: Positive = Yellow, Negative = Blue, ΔE= Total Color Difference: Calculated from the L*, a* and b* properties.)	Number – Double
	Notes_AND_Damage_Observations	A text field for qualitative findings, such as "Visual scaling," "Cracking observed," or "Complete disintegration."	Short Text
	Reference	Foreign Key (FK); Links the site information to its bibliographic source in tbl_7_References. This ensures that the description of the site and its environmental context is scientifically traceable to the reviewed literature.	Number – Long Integer

Table 12. . Internal model for the References entity of the database (Source: original).

	a. Field Name	b. Description	c. Field Typology
tbl_7_References	Citation_ID	Primary Key (PK); A unique numerical identifier for each bibliographic source. This ID migrates to all other tables as a Foreign Key to ensure every data point is traceable.	AutoNumber – Long Integer
	Ref_Code	A short-hand citation key (e.g., "Apostolopoulou et al., 2019") used for quick identification within the database interface.	Short Text
	Authors	The full list of authors associated with the publication, ensuring proper academic credit and facilitating literature searches.	Short Text
	Year	The year of publication, allowing for the analysis of data based on the chronological evolution of experimental standards.	Short Text
	Title	The full title of the research paper, article, or book chapter from which the data was extracted.	Short Text
	Journal_Book	The name of the scientific journal or book, including volume and page numbers, providing the context of the publication.	Short Text
	DOI	Digital Object Identifier; a permanent link to the original source, ensuring the long-term verifiability of the digitized data.	Hyperlink
	Keywords	A list of descriptors extracted from the paper (e.g., "Rhodes," "Biocalcarenite," "Mortars"). This field is used for multi-criteria filtering and metadata analysis.	Short Text

The tables above are descriptive of this research's database tables that were created in this effort; Initially, tbl_1_Sites was created to provide more detailed information about the exact geographical position (altitude, latitude) of the samples tested, which some can be linked to a map, while tbl_2_Samples identifies the actual pieces of material (Stone, Brick, Mortar) taken from that place and represents the central physical inventory of this database.

Additionally, tbl_3_Characterisation captures the 'static' physicochemical and thermomechanical state of heritage materials. By integrating high-resolution data such as the materials' mineralogy, composition, or micropore description, the database establishes the necessary baseline to correlate a sample's inherent structure with its dynamic performance during accelerated weathering tests. Consequently, tbl_4_Weathering_Test_Protocols, functions as the 'Stressor Cluster' of the database. Unlike a flat-file system, this table isolates the experimental parameters within the Details field, allowing for a systematic categorization of the 'testing modes' (e.g., immersion vs. capillary rise) which are critical for determining the intensity of accelerated weathering, such as it is discussed by Zhao et al. (2015) and Coletti et al. (2025).

Most importantly, tbl_5_Sample_Test_Link functions as a junction table designed to manage the complex many-to-many relationships inherent in heritage science. This structure resolves the technical challenge where a single material specimen (e.g., a specific limestone) may undergo multiple, distinct weathering protocols—such as salt crystallization followed by freeze-thaw cycles. By isolating these connections in a dedicated link table, the database maintains strict relational integrity and eliminates the data redundancy typically found in traditional flat-file spreadsheets. After the materials gathered from each case study have undergone weathering testings, the resulting data from the literature is gathered in tbl_6_Deterioration_Metrics, created to represent the 'Performance Cluster' of the database. By recording variables such as Porosity, Pore Size Distribution, p-wave velocity, Compressive, Flexural or Tensile strength, mass changes, Thermal or Colour properties across varying Cycle Counts, the database enables the transition from static observation to dynamic decay modeling. This multi-variant structure is designed to support machine learning algorithms that require both the physical 'target' (e.g., mass loss) and the microstructural 'features' (e.g., change in porosity) to predict future material failure.

Lastly, tbl_7_References acts as the foundational anchor for the entire relational system. By assigning a unique Citation_ID to every source and linking it to each individual sample and measurement, the database satisfies the requirements for 'Structural Transparency' and 'Information Provenance,' allowing for the complete reproducibility of the dataset as emphasized by Hein & Kilikoglou (2012).

CHAPTER 4: MACHINE LEARNING FEATURE ENGINEERING AND DATA VALIDATION FOR PREDICTIVE CONSERVATION

The successful implementation of a digital repository, as detailed in Chapter 3 above, is not an end in itself; rather, it serves as the foundational architecture for predictive conservation. To accurately evaluate weathered heritage materials, such as the stone lithologies, ceramics, and mortars cataloged in this database, it is critical to use efficient algorithms to forecast typical micro and macro indicators, thus avoiding the high computational costs and slow efficiency of refined numerical models (Zhang et al., 2024). By employing advanced ML algorithms, researchers can rapidly and non-destructively estimate critical deterioration indicators, allowing conservators to forecast material failure with a high level of accuracy without subjecting valuable heritage samples to endless laboratory testing cycles. This chapter outlines how the data extracted from the Accelerated Weathering Testing Protocols (AWTP) and Physico-Chemical Characterization (PCC) are transformed into structured feature sets to train regression-based Machine Learning (ML) algorithms.

As emphasized by recent bibliometric and task-oriented reviews of AI in cultural heritage, the successful integration of machine learning relies on a tightly interconnected "*data + technology + task*" framework (Li et al., 2026). Within the context of this thesis, the "data" consists of the multimodal physicochemical and thermomechanical metrics structured in the database; the "technology" comprises regression and classification algorithms; and the "task" is predicting specific material failure thresholds under environmental stressors (Li et al., 2026)..

The application of ML methods to analytical chemistry and material science typically follows a rigorous standard sequence: data acquisition, data preprocessing, feature selection, model training, and performance verification (Towarek et al., 2024). The database tables compiled in this research directly map to this workflow. By strictly enforcing relationships between the physicochemical baselines, the environmental stressors, and the resulting dynamic performance metrics, the database provides the exact "Condition-Response" data pairs required for supervised machine learning. Because ML models require standardized, scaled inputs to avoid computational biases, the relational design ensures that

highly heterogeneous experimental data, ranging from mineralogical ratios and total porosity to ultrasonic pulse velocity and mass loss, are harmonized into ML-ready numerical arrays (Towarek et al., 2024). The application of these models must adhere to the principles of Trustworthy AI, ensuring that algorithms are not only highly accurate but also interpretable, fair, and free from historical or contextual biases that could distort heritage conservation decision-making (Paolanti et al., 2026).

In conclusion, by addressing data heterogeneity, scaling inconsistencies, and inherent biases, the relational database elevates raw heritage data into a *mathematically sound*, interpretable, and ethically aligned training environment. This empowers surrogate ML models to provide reliable, high-fidelity predictions that can safely inform real-world conservation strategies.

This chapter details the framework for transforming the compiled database into a training ground for predictive conservation. It outlines the precise identification of key input features and target variables, the procedures for data transformation, and the statistical methodologies employed to validate the predictive power and generalization capabilities of the engineered datasets.

4.1 Defining the predictive model framework

The predictive model framework acts as a computational bridge between static material characterization data and dynamic environmental stressors. The application of ML methods to analytical chemistry and material science typically follows a rigorous standard sequence: data acquisition, data preprocessing, feature selection, model training, and performance verification (Towarek et al., 2024). By employing machine learning (ML) algorithms, such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Multiple Linear Regression (MLR), this framework can learn the complex, non-linear relationships between a material's intrinsic properties and its subsequent deterioration. Ultimately, the framework aims to provide a "surrogate model" that can estimate destructive parameters non-destructively and quickly, allowing conservators to predict future material failure with a high level of accuracy without needing to run endless laboratory cycles (Zhang et al., 2024).

However, developing a predictive framework in Cultural Heritage (CH) requires moving beyond traditional "black-box" approaches. It necessitates the integration of multidimensional explainability—ensuring that heritage professionals understand how specific input features influence predictions. By mapping the database's "Condition-Response" data pairs to interpretable algorithmic pathways, the framework ensures that ML outputs are scientifically valid, contextually grounded, and practically actionable for conservation workflows (Paolanti et al., 2026).

4.1.1 Identification of ML input features (PCC, TMP, AWTP) and target variables (DPM)

Predictive modeling in cultural heritage requires the precise identification of independent variables (input features) that can accurately forecast dependent variables (target outputs). Because destructive testing, such as extracting large core samples for compressive strength tests, is strictly limited or entirely prohibited in protected heritage sites, the selected input features must rely heavily on Non-Destructive Testing (NDT) proxies or easily obtainable micro-samples (Jamshidi, 2024; Zhang et al., 2024). So, based on recent ML implementations for heritage stone, the input features can be divided into macroscopic NDT parameters and microscopic chemical/mineralogical parameters. Some critical macro inputs that have been included in this current database build-up effort, include compression wave velocity (V_p), mass change variations (M), and surface hardness. These are coupled with micro-chemical features obtained via XRF and XRD, such as the ratio of silicon to aluminum (S-A), the ratio of the sum of calcium and potassium to aluminum (Ca+K-A), and the relative content of specific minerals like kaolinite (Kln) and feldspar (Kfs).

Specifically, the *Input features* fed into the ML algorithms are extracted directly from the database's defined entities;

Regarding Physico-Chemical Characterization (PCC), due to macroscopic decay usually being accompanied by complex chemical reactions (e.g., the dissolution of calcite or the transformation of feldspar into clay minerals), relying solely on mechanical inputs is insufficient. Microscopic chemical and mineralogical parameters obtained via X-Ray Fluorescence (XRF) and X-Ray Diffraction (XRD), anchored in *tbl_3_Characterisation* of this database, are essential. For example, in predicting the weathering of historical

sandstones, researchers utilize chemical ratios such as the ratio of silicon to aluminum (S-A) and the ratio of the sum of calcium and potassium to aluminum (Ca+K-A). Furthermore, because changes in mineral composition directly alter the internal pore size distribution, the relative content of specific minerals like kaolinite (Kln) and feldspar (Kfs) serve as highly relevant statistical features for representing the true degree of weathering (Zhang et al., 2024). At the same time, critical macroscopic NDT parameters also serve as the primary mechanical inputs. These include compression P-wave velocity (V_p) and S-wave velocity (V_s), which are highly sensitive to internal micro-cracking, as well as surface Leeb rebound hardness (HRC) or Schmidt hardness (SH). Other innovative NDT inputs that have proven highly effective for ML training include mass change variations (M), which can be measured rapidly in situ. Lastly, the environmental loads (extracted from *tbl_4_Weathering_Test_Protocols* table which is dynamically linked to the samples via the junction table *tbl_5_Sample_Test_Link*) such as the accelerated weathering methods (e.g., salt crystallization, freeze-thaw, acid/alkali soaking) gathered from the surveyed literature, act as the "temporal" or stressor inputs. For the algorithms to accurately predict decay, they must be fed the exact parameters of the simulated environment, including the number of freeze-thaw or salt crystallization cycles, the duration of each cycle, the specific temperature ranges, or the type of salt solutions used.

Target variables (Dynamic Performance Metrics – DPM) in this case are the output predictions that mathematically quantify the structural fatigue of the material. These are extracted directly from the records in the *tbl_6_Deterioration_Metrics* table.;

To accurately evaluate a weathered material, surrogate models frequently target input characteristics such as the material's porosity (P) or static elastic modulus (Es). Predicting these types of parameters non-destructively is vital. For example, porosity is a micro-indicator that perfectly reflects microscopic weathering characteristics and the opening of the internal pore structure, while the static elastic modulus is a macro-indicator that accurately reflects the uniaxial compressive strength (UCS) and the material's overall macroscopic deformation ability.

Alternatively, depending on the algorithm used (such as Fuzzy Inference Systems), models can be trained to predict the overarching "Weathering Degree" (categorized on a scale from fresh to completely weathered), or target specific destructive metrics like the

exact percentage of mass loss, Brazilian Tensile Strength (BTS), or the Slake Durability Index (Id2) after a specified number of environmental cycles.

4.1.2 The role of the database in training future ML models

The relational database designed in this thesis functions as much more than a digital archive; it serves as the structured training ground essential for predictive machine learning algorithms. As highlighted by Towarek et al. (2024), the quantity and quality of the data employed are the primary determinants governing the performance of any ML algorithm. To effectively map the non-linear relationships between initial material properties and their subsequent deterioration, the training dataset must be consistent, complete, unbiased, and representative of the problem (Towarek et al., 2024). The architecture of this database directly addresses these prerequisites by enforcing a rigorous "Condition-Response" framework.

4.1.2.1 Data preprocessing, normalization, and standardization

Before quantitative predictions can be made, the raw experimental data collected in the database must undergo a rigorous preprocessing workflow. Cultural heritage data is notoriously heterogeneous, combining multi-scale microstructural data, macro-mechanical test results, and temporal weathering variables (Towarek et al., 2024). Because predictive algorithms calculate complex mathematical weights, feeding raw data directly into a model can cause severe scaling issues. For instance, ultrasonic wave velocities (often exceeding 2000 m/s) and total porosity measurements (represented as small percentages, e.g., 7–14%) operate on vastly different numerical scales (Zhang et al., 2024).

To resolve this, the database facilitates automated queries that normalize and standardize these diverse features into unified arrays. Furthermore, outliers caused by human error or improper experimental operations must be systematically filtered out to improve the accuracy of subsequent ML predictions. In cases of missing data which is common when literature mining yields incomplete experimental chains, the database's strict adherence to NULL values instead of zero-filling ensures that algorithms do not artificially misinterpret gaps as true physical baselines. If algorithms encountered zero-filled gaps, they

would heavily distort error metrics like Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2) (Zhang et al., 2024; Towarek et al., 2024).

4.1.2.2 Data splitting for algorithmic validation

To verify a model's performance and ensure it does not suffer from "overfitting", a scenario where an algorithm learns the training data perfectly but fails to adapt to new, unseen heritage samples, the unified datasets extracted from the database must be split. Following standard data science protocols in analytical chemistry and archaeometry, the structured datasets are routinely partitioned: typically, 70% to 80% of the data is allocated as a training set to teach the algorithms the deterioration patterns, with the remaining 20% to 30% reserved as an isolated testing set for objective validation (Towarek et al., 2024; Zhang et al., 2024).

By utilizing the strict relational integrity enforced between *tbl_2_Samples*, *tbl_4_Weathering_Test_Protocols*, and *tbl_6_Deterioration_Metrics* (connected via the junction table *tbl_5_Sample_Test_Link*), the database ensures that input variables are flawlessly matched with their corresponding output target variables across all stages of testing. This architectural consistency guarantees that the datasets required for algorithmic validation remain contextually accurate and free of relational orphans.

4.1.2.3 Overcoming Data Scarcity and Biases

A prominent challenge in cultural heritage AI is the lack of large-scale, standardized benchmark datasets compared to general computer science fields. Given the strict conservation principles that limit destructive testing, collecting thousands of physical samples is impossible. When authentic data is scarce, the database can serve as a foundation for advanced ML strategies such as Transfer Learning. When the available dataset is insufficient to produce reliable predictions from scratch, models can be pre-trained on broader material science datasets and subsequently "fine-tuned" using the specific, domain-restricted data housed within this heritage database (Towarek et al., 2024).

Simultaneously, the database plays a critical role in establishing "Trustworthy AI." If a database contains severe historical or contextual biases, the resulting machine learning

models will inevitably produce skewed heritage interpretations. To ensure fairness and accuracy, the database architecture proactively mitigates several recognized AI biases (Paolanti et al., 2026).

When omitted variable bias arises and historical records or characterizations are incomplete, it leads to models missing critical contextual factors. This is mitigated by the data acquisition parameters defined in *tbl_3_Characterisation*, which demand multi-modal physical and chemical profiles rather than relying on a single metric (Paolanti et al., 2026). Whereas, historical and contextual bias could occur if models fail to account for regional climate variations or rely on past dominant cultural perspectives. By linking every sample to precise geographic, climatic, and temporal metadata in *tbl_1_Sites*, the database ensures that algorithms interpret decay relative to its specific local environment (e.g., distinguishing marine aerosol decay from freeze-thaw damage) (Paolanti et al., 2026).

Lastly, with the rise of "Big Data", algorithms often over-represent canonical Western architectural styles while ignoring underdocumented or non-Western cultures. A rigorously curated relational database combats this population target bias by ensuring equitable representation across diverse lithotypes, ceramics, and historical mortars globally (Paolanti et al., 2026).

4.2 Data transformation and feature selection

Transitioning an archival, relational database infrastructure into an actionable predictive environment requires meticulous data transformation and targeted feature selection. Raw data harvested from heterogeneous literature sources frequently exhibit variances in measurement units, missing fields, and structural differences across testing methodologies. Within the context of heritage science and material conservation, data preprocessing serves as a vital bridge between structural cataloging and numerical prediction (Li et al., 2026; Towarek et al., 2024).

Feature selection was guided by key engineering principles in material degradation, specifically identifying intrinsic "cause" attributes and pairing them with cyclic "effect" indicators. For this study, parameters describing a material's baseline pore network architecture, such as open porosity (X_1) and capillary absorption coefficients (X_2), were

isolated as the primary independent variables (predictors). Conversely, dynamic indicators representing structural and mechanical integrity, namely, Ultrasonic Pulse Velocity (UPV) and Compressive Strength (UCS), were selected as dependent target variables (Y).

To make the raw database matrices suitable for mathematical regression modeling, values were standardized, categorical records (such as lithotype classifications or weathering agents) were structurally indexed, and non-numeric artifacts (e.g., text-based placeholders or ranges) were sanitized. This rigorous preprocessing structure mitigates systemic data bias and ensures structural alignment, laying a transparent foundation for trustworthy and explainable analytical outcomes (Paolanti et al., 2026).

4.2.1 Creating ML-ready datasets using database queries

Before executing regression models or predictive computations, unstructured and scattered rows must be reconstructed into a flat, contiguous tabular matrix. In this study, this was achieved by developing structured SQL (Structured Query Language) queries within Microsoft Access. These custom queries extract disparate data fragments across relational tables and compile them into standardized, ML-ready datasets.

Rather than relying on manual file manipulation, which risks human error and compromises data integrity, relational constraints were enforced upstream. The queries execute precise table joins by matching unique primary keys (e.g., Sample_ID) across the baseline characterization inventory (tbl_3_Characterisation) and the dynamic performance tracker (tbl_6_Deterioration_Metrics).

For instance, to evaluate the progression of material decay under accelerated ageing, a dedicated query isolated specific material subsets (such as fired clay bricks versus biocalcarenites) alongside explicit environmental stressors (such as sodium sulfate crystallization or freeze-thaw regimes). The core mathematical operations performed by these automated database queries include:

1. **Relational Synchronization:** Aligning each sample's unaged, baseline physical fingerprint directly alongside its multi-cycle weathered metrics into a single row.
2. **Dynamic Decay Tracking:** Automatically calculating exact degradation deltas, such as the Strength Loss Percentage (Δ UCS %), computed via the formula:

$$\Delta UCS\% = \frac{UCS_{baseline} - UCS_{weathered}}{UCS_{baseline}} \times 100$$

3. **Contiguous Range Filtering:** Systematically filtering out records with missing target fields or incompatible cross-study metrics, ensuring that Excel can process the exported dataset without triggering contiguous range errors.

4.2.2 Feature selection based on physical relevance and statistical metrics.

A critical challenge in applying predictive workflows to cultural heritage conservation is avoiding the "black-box" dilemma, where algorithms identify purely mathematical correlations that lack structural or physical meaning (Paolanti et al., 2026). To ensure that the subsequent regression models are both scientifically valid and interpretably trustworthy, a dual-gate feature selection strategy was executed. Features extracted via the Microsoft Access database queries were strictly filtered based on: (1) their thermodynamic and mechanical relevance to stone, brick, and mortar decay, and (2) standard statistical health metrics.

From a material science perspective, building material deterioration—whether driven by cyclic freeze-thaw sub-florescence or salt crystallization pressure—is fundamentally governed by a material's internal fluid transport properties and pore network layout (Degryse et al., 2002; An et al., 2024). Therefore, parameters were categorized into structural predictors and degradation indicators rather than pooling all database variables indiscriminately:

1. **Intrinsic Microstructural Predictors (X):** Variables such as *Open Porosity* and *Capillary Absorption Coefficients* were selected due to their active role in weathering kinetics. Porosity dictates the maximum volumetric capacity available for salt crystallization or ice formation, while capillary coefficients govern the velocity of moisture intake and chemical transport into the core matrix.
2. **Dynamic Target Indicators (Y):** Variables such as *Ultrasonic Pulse Velocity (UPV)* and *Compressive Strength (UCS)* were isolated as the targets. These metrics represent the macro-scale structural response to microstructural damage. As micro-cracking and salt-shattering expand internal voids, sound waves slow down and load-bearing capacities decline, providing a measurable proxy for decay.

By focusing on these causally linked variables, the models maintain physical explainability, meeting the ethical and practical criteria for trustworthy artificial intelligence in cultural heritage management (Paolanti et al., 2026).

Now, following the validation of physical relevance, the candidate features underwent a statistical screening process to ensure computational compatibility with ordinary least squares (OLS) linear regression modeling within an Excel environment. This involved analyzing the quality, consistency, and alignment of data distribution across multi-author studies: To address data completeness and facilitate pairwise filtering, the extraction workflow accounted for systemic *structural* gaps common in historical and laboratory data matrices retrieved from the literature review. For instance, several studies frequently record macro-mechanical decay parameters while completely omitting non-destructive ultrasonic monitoring, or vice versa. To resolve this, candidate features with an excessive abundance of NULL placeholders or mismatched records were systematically excluded from the modeling pipeline. Pairwise filtering was strictly enforced via custom database queries, ensuring that every record in the finalized analytical subset contained a non-zero, contiguous pair of matching baseline (X) and weathered (Y) inputs required to run structurally sound models.

At the same time, the elimination of multi-collinearity was vital to safeguard model interpretability and mathematical validity. Highly redundant features that capture identical physical or geometric phenomena, such as incorporating both *Total Porosity* and *Open Porosity*, or *Bulk Density* and *Apparent Density* simultaneously within a single regression model, were deliberately avoided. Because the inclusion of highly collinear variables destabilizes regression coefficients in ordinary least squares (OLS) estimation, features displaying near-perfect linear relationships in initial correlation matrices were streamlined. This reduction process retained only the specific metric exhibiting the highest cross-paper reporting rate, thereby prioritizing parameters like *Open Porosity* due to their wider availability and standardization across the compiled historical bibliography. Finally, scale stabilization was executed to ensure computational compatibility and numerical readability within the Excel analytics environment. Because the isolated variables naturally exist across vastly different numerical scales—with porosity expressed as minor percentages (~0-40%), strength spanning megapascals (1-150MPa), and ultrasonic pulse velocity extending across

thousands of meters per second (500–5000 m/s), features were explicitly defined by standardized SI units during the database query export stage.

This dual-layered validation framework directly addresses the data preprocessing and feature optimization criteria emphasized in recent heritage science reviews (Li et al., 2026; Towarek et al., 2024), proving that empirical material physics coupled with structured data cleansing, results in the compiled datasets being optimally configured for executing stable, mathematically valid linear regressions.

4.3 Data validation and foundational relationships

Before deploying complex machine learning algorithms, the utility, contextual alignment, and physical integrity of the compiled database must be mathematically validated. As highlighted by Towarek et al., exploring analytical data through preliminary statistical methods and feature selection is a critical preprocessing step to ensure the selected datasets hold a high signal-to-noise ratio. In the context of heritage science, correlation and regression analyses act as deterministic benchmarks that mathematically map the connections between a material's intrinsic features and its dynamic weathering targets, confirming that the "Condition-Response" data pairs extracted from the literature are statistically sound and free of relational orphans (Zhang et al., 2024).

Regression models are essential to prove that non-destructive proxies, such as ultrasonic pulse velocity (V_p) or rebound surface hardness, can accurately predict critical structural load capacities, such as Uniaxial Compressive Strength (UCS) and static elastic modulus (E_s). For example, studies on weathered grotto sandstones heavily utilize correlation matrices to validate the strong linear and non-linear relationships between non-destructive macro-indicators and actual bulk porosity before feeding this data into Artificial Neural Network (Zhang et al., 2024).

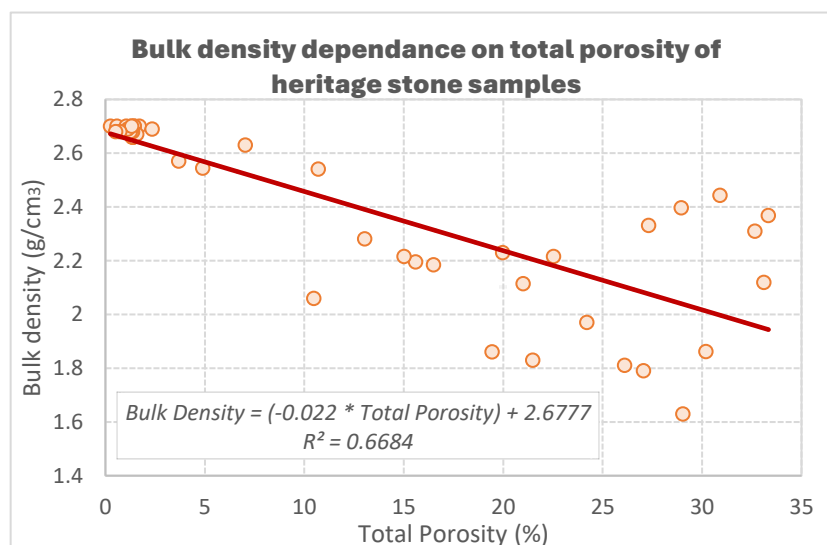
Heritage material deterioration is inherently complex and frequently behaves as a non-linear system, meaning decay rates may suddenly accelerate once specific stress thresholds are crossed (Martínez-Martínez et al., 2013). To quantify these deterioration kinetics, regression analysis is widely utilized in archaeometry to establish "decay function models". By applying exponential or linear regression equations to the progressive loss of

mechanical properties over simulated freeze-thaw or salt crystallization cycles, researchers can calculate two vital predictive parameters: the decay constant (λ), which quantifies the average integrity loss per single weathering cycle, and the half-life ($N_{1/2}$), which predicts the exact number of cycles required to reduce the material's strength to half of its initial value (Altindag et al., 2004). Consequently, evaluating cultural heritage materials within the scope of *predictive conservation* requires this multi-scale analytical progression. By transitioning from a static microstructural baseline to a dynamic, multiparametric failure forecasting model, the following Figures provide specific regression configurations. These models visually and mathematically validate the digital repository's condition-response framework, confirming its readiness for training future, highly interpretable artificial intelligence systems.

4.3.1 Correlation Analysis to validate data utility

As a fundamental check of volumetric and mass consistency across the dataset, the relationship between apparent density (ρ_b , g/cm³) and open/total porosity (ϕ , %) was analysed, as shown in *Figure 13*.

The regression reveals a strong, statistically significant negative linear correlation ($R^2 = 0.6684$). This perfectly aligns with petrophysical expectations: as the internal pore volume of a stone matrix increases, the bulk mass per unit volume systematically decreases. The intercept (2.677) closely approximates the average solid grain density of common silicate and carbonate minerals (such as quartz and calcite) that typically comprise cultural heritage building substrates. This confirms the baseline integrity of the mass and volume metrics recorded in the database.



To also evaluate the feasibility and **Figure 13. Correlation analysis for data validation between bulk density and total porosity of the database's heritage stone samples (Source: original).**

reliability of using non-destructive testing (NDT) data within the heritage material database, linear regression analyses were conducted between Ultrasonic Pulse Velocity (UPV) and Uniaxial Compressive Strength (UCS). Establishing robust correlations

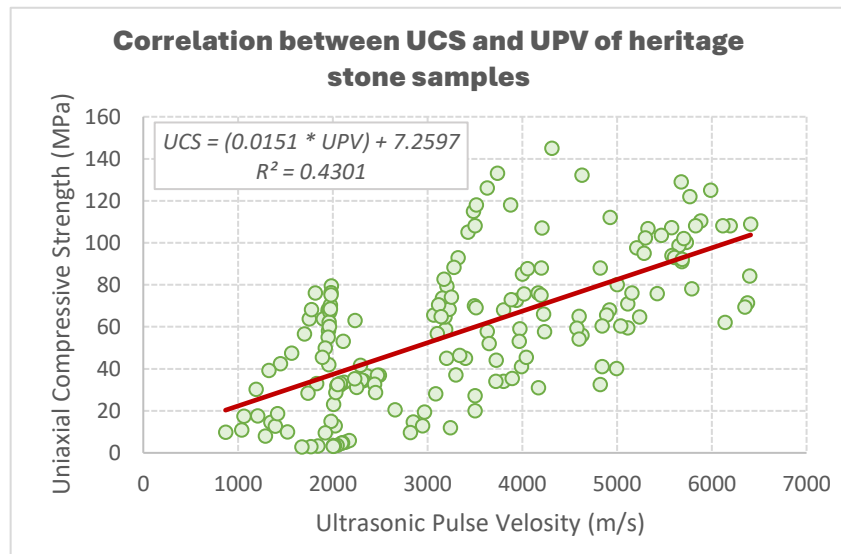


Figure 14. Correlation analysis for data validation between UCS and UPV of the database's heritage stone samples (Source: original).

between these two parameters is critical, as it allows for the estimation of mechanical strength (UCS) directly from less invasive, field-deployable acoustic measurements (UPV).

The correlation models were developed separately for two distinct material categories within this database: heritage stone samples and ancient mortar samples derived from numerous case studies of the literature review. For the heritage

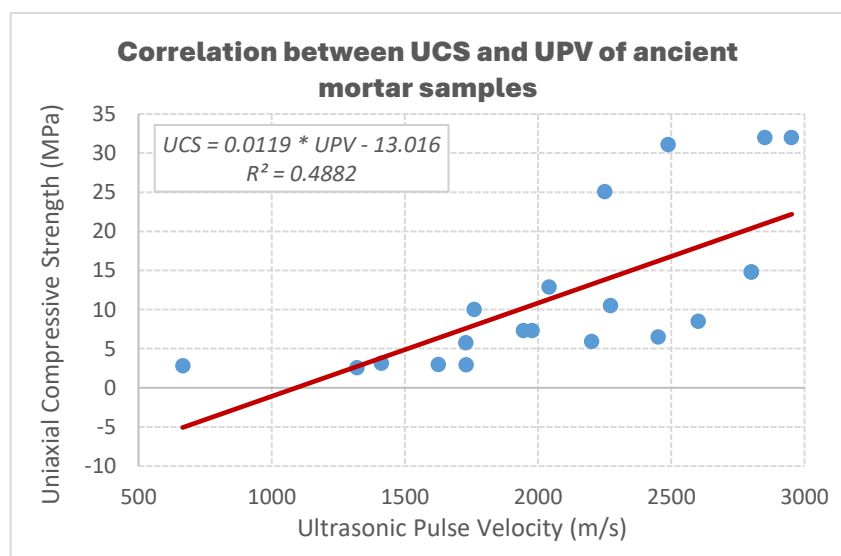


Figure 15. Correlation analysis for data validation between UCS and UPV of the database's heritage mortar samples (Source: original).

stone dataset, the relationship between UCS and UPV, as shown in Figure 14, is defined by a strong coefficient of determination of $R^2 = 0.4301$. While this indicates a statistically significant positive linear trend, where higher acoustic velocities generally correspond to superior compressive strength, the data exhibits a high degree of dispersion, particularly within the 3000 to 4500 m/s UPV range.

This scatter is highly characteristic of heritage geomaterials, reflecting inherent lithological heterogeneities, varying degrees of historical weathering, macro-porosity, and micro-fissuring across the collected samples. For the ancient mortar dataset, the model shown in *Figure 15*, achieves a slightly higher coefficient of determination of $R^2 = 0.4882$. The regression line successfully captures the upward trajectory of strength relative to pulse velocity. However, the model yields negative theoretical UCS values at ultra-low pulse velocities (below approximately 1100 m/s), highlighting the mathematical limitations of applying a purely linear model to highly porous or degraded binder matrices.

To further validate the internal consistency and physical accuracy of the database, linear regression analyses were performed between total porosity (%) and water absorption (%) across three material categories from the literature's samples: heritage stone, ancient ceramics, and ancient mortars. Understanding the correlation between these two hydric and physical parameters is essential for database quality control, as both metrics directly influence a historic material's vulnerability to environmental degradation (e.g., freeze-thaw cycles, salt crystallization).

The relationship between total porosity and water absorption for the heritage stone dataset as shown in *Figure 16* demonstrates a strong positive correlation, with a coefficient

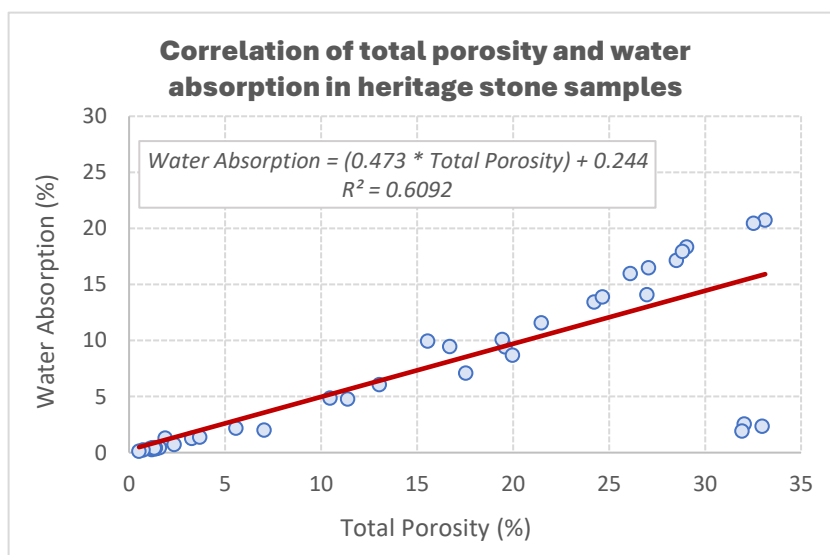


Figure 16. Correlation analysis for data validation between total porosity and water absorption of the database's heritage stone samples (Source: original).

of determination of $R^2 = 0.6092$. The majority of the data tightly tracks the regression line, confirming a highly predictable relationship between the total volume of voids and the material's capacity for water intake. However, a distinct cluster of outliers is observable at high total porosities

(around 32–33%), where water absorption drops sharply to near-zero values (approx. 2–3%). This phenomenon points to an important physical distinction within the database: these

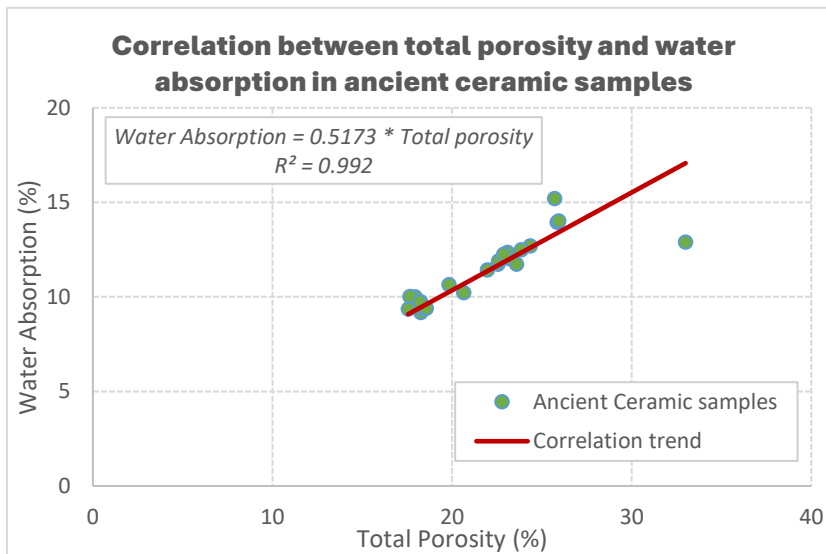


Figure 17. Correlation analysis for data validation between total porosity and water absorption of the database's heritage ceramic samples (Source: original).

coefficient of $R^2 = 0.992$ is encountered. The data points are predominantly tightly grouped in the lower-left quadrant (17–25% porosity), reflecting standard historical firing and manufacturing techniques that limit extreme void variations. A few isolated outliers exist at higher water absorption levels near 26% porosity, which may represent either local structural defects (such as micro-cracking from weathering) or variations in historical kiln temperatures that altered the vitrification process.

The mortar samples display the highest coefficient of determination among the three datasets, at $R^2 = 0.9621$, as shown in Figure 18. This strong linear alignment suggests that the porosity in these historic mortars is overwhelmingly open and interconnected,

specific stones likely possess high closed/isolated porosity rather than interconnected networks of open pores, preventing capillary water intake despite a high total void volume.

For the ancient ceramic dataset, as shown in Figure 17, a robust correlation

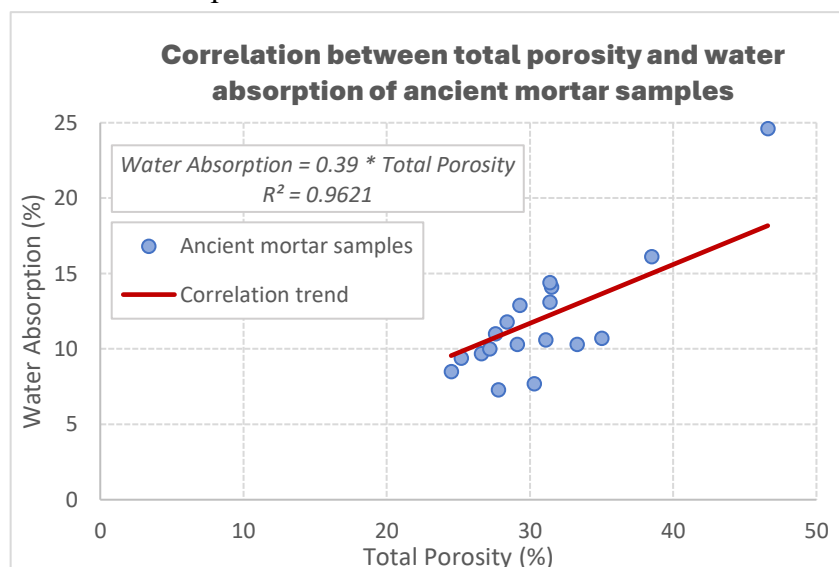


Figure 18. Correlation analysis for data validation between total porosity and water absorption of the database's heritage mortar samples (Source: original).

allowing water absorption to scale predictably with the overall void space. The data is shifted toward significantly higher porosity ranges (25–47%) compared to the stones and ceramics, which is highly consistent with the typical carbonation and binder-to-aggregate ratios found in weathered historic lime mortars.

To evaluate how durability metrics operate within the database architecture, linear regression analyses were conducted between the number of accelerated weathering cycles and the corresponding percentage mass change (ΔM %). Tracking mass loss kinetics is a standard method for quantifying material decay (e.g., salt crystallization, frost action, or thermal fatigue). However, applying linear regression across highly heterogeneous historic substrates yields distinct mathematical challenges that directly impact data interpretation and database design. The relationship between weathering cycles and mass change for the heritage stone dataset, for each stone subtype is presented in *Figure 19*. The chart plots the mass variation (ΔM %) of different lithotypes against the number of accelerated weathering cycles. However, the most striking feature of this chart is the extremely low Coefficient of Determination (R^2) for almost all the stones—such as Limestone ($R^2=0.0075$), Sandstone ($R^2=0.0158$), and Dolostone ($R^2=0.0004$). These near-zero values prove that the data points are highly scattered.

The "weight gain vs. weight loss" paradox in the chart, such as the data points scattering above the 0-line (indicating mass gain, up to +15%) and plummeting far below it (indicating mass loss, down to -45% or -55%), may occur because these mechanisms are happening:

- Stage 1 (salt/water accumulation): During the initial cycles, porous stones actually gain weight because salt crystals (or water) accumulate inside their pore networks without causing immediate material detachment (Arizzi et al., 2012). For example, sandstone and highly porous limestone will show a mass increase early on due to this salt uptake (Hong, et al., 2023; Huang et al., 2025).
- Stage 2 (meta-stable state): The rock reaches a balance where salt deposition compensates for any minor loss of mineral grains (Akin & Özsan, 2011), and
- Stage 3 (accelerated disintegration): Once the internal crystallization or frost pressure exceeds the stone's tensile strength, the pore walls rupture, leading to a sudden and massive drop in weight as fragments fall off (Akin & Özsan, 2011; Hong, et al., 2023).

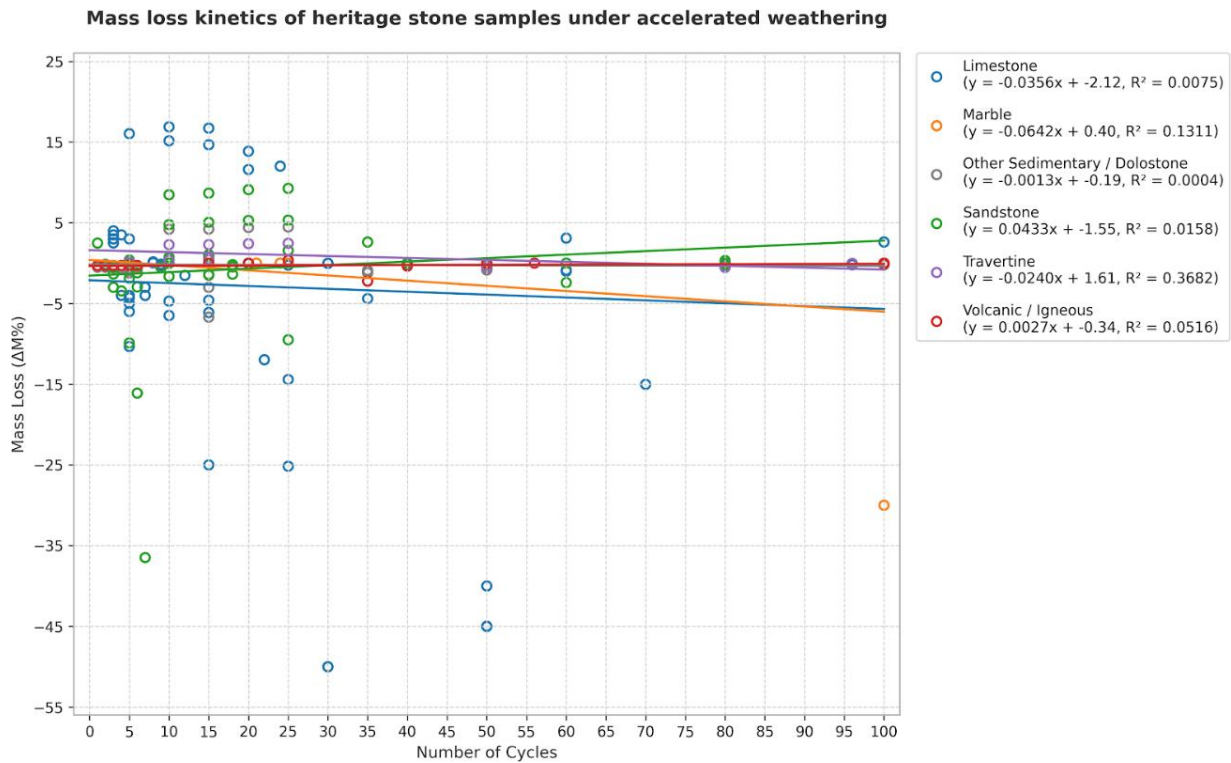


Figure 19. *Highly scattered mass change kinetics in heritage stone samples, indicating complex sub-florescence and localized spalling mechanisms (Source: original).*

The varying slopes of the regression lines effectively reflect the fundamental microstructural differences between the tested lithotypes. Denser rocks with low overall porosity restrict fluid ingress. Consequently, they absorb minimal salt and moisture, resulting in very flat linear slopes with minor mass fluctuations prior to their ultimate failure. Conversely, highly porous materials like sandstone exhibit profound data scatter and can even display a uniquely positive linear slope during early weathering stages (Hong, et al., 2023; Huang et al., 2025). This indicates that their vast and interconnected pore networks have the capacity to retain massive amounts of expansive salts for extended periods before finally crumbling (Molina, et al., 2013). Given these chaotic variations, the literature strongly advises against relying solely on linear mass-loss tracking to assess long-term durability. To accurately model deterioration kinetics, advanced predictive frameworks must employ non-linear decay function models, such as exponential decay equations ($M_N = M_0 \cdot e^{-\lambda N}$). The decay constant (λ) and the half-life parameter, can now successfully map

how physical integrity is proportionally lost over time, providing a mathematically sound baseline for forecasting future material behavior regardless of erratic mass fluctuations.

For the ceramic dataset, the regression analysis that's presented in *Figure 20* yields a noticeably higher fit than the other durability datasets, with an $R^2 = 0.31$. While a general downward trend in mass is visible as weathering cycles progress to 30, the dataset remains constrained by localized clustering at specific cycle intervals (e.g., 10 and 30 cycles) and a

significant outlier dropping below -55% mass change at 20 cycles. This reflects a threshold-dependent decay mechanism typical of ancient ceramics, where substantial damage remains hidden until a sudden, catastrophic structural failure occurs.

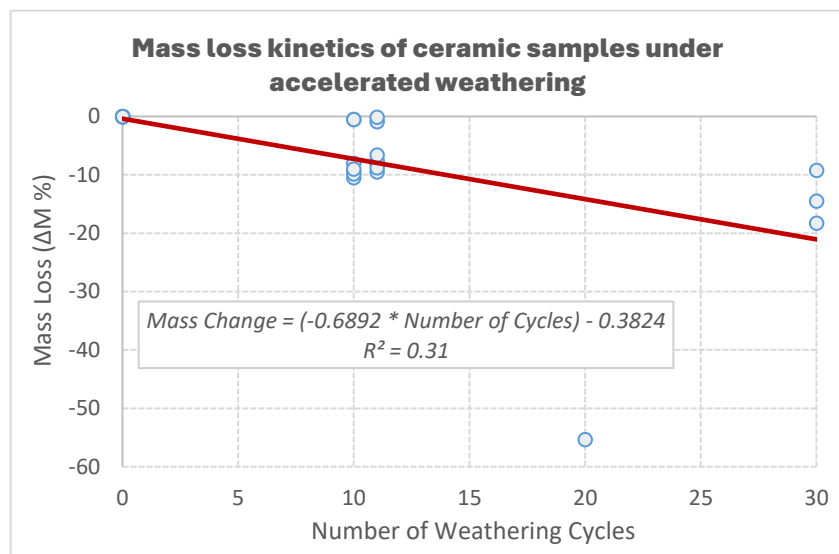


Figure 20. Threshold-dependent mass loss in ancient ceramic samples showing sudden structural failure (Source: original).

Lastly, similar to the stone dataset, the model for various heritage mortar and composite samples in *Figure 21* exhibits a negligible fit with an $R^2 = 0.0053$. The data is heavily concentrated below 30 cycles, showing extreme scatter where some samples completely disintegrate (dropping past -60% mass change) in under 20 cycles, while others survive up to 150 cycles with virtually zero mass loss.

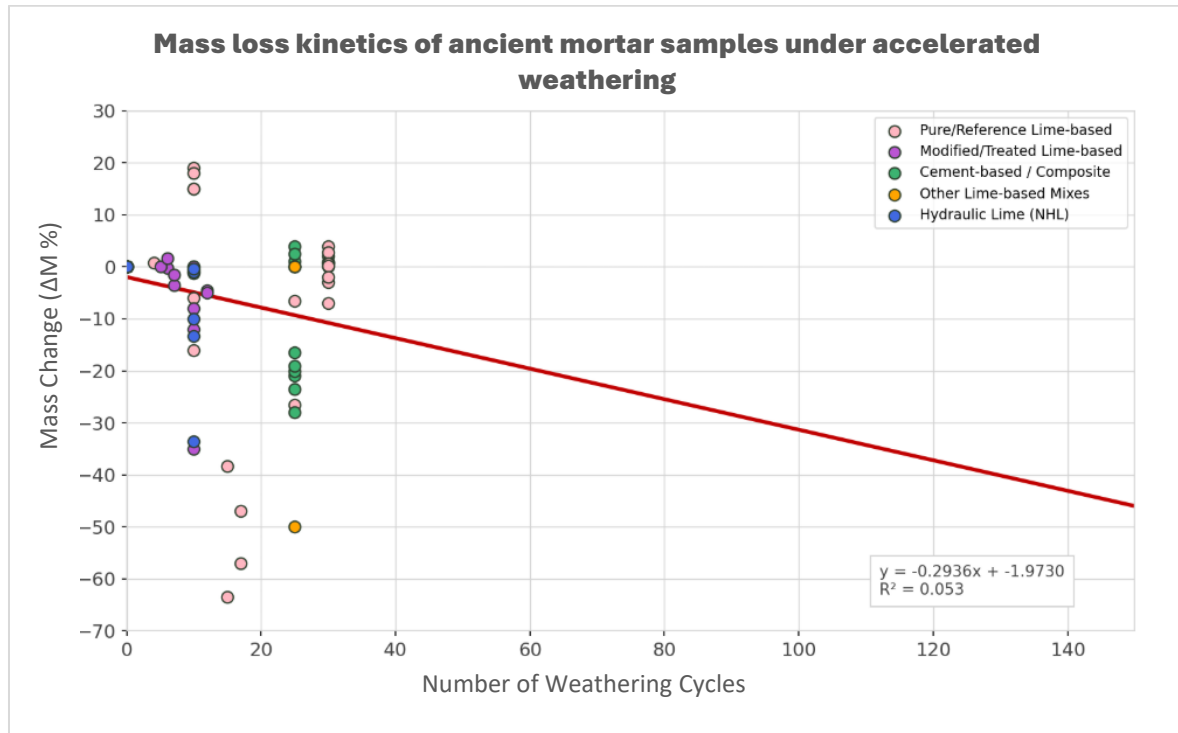


Figure 21. Bimodal durability behavior in various ancient mortar samples, highlighting severe degradation versus high-survival samples (Source: original).

Much like in Figure 19 with heritage stone samples, during the initial stages of weathering, highly porous mortars absorb moisture and saline solutions. As the water evaporates, salts crystallize within the pore network, temporarily increasing the specimen's weight without immediate material loss (Anupama & Santhanam, 2024). However, once the internal crystallization pressure exceeds the mortar's tensile strength, the pore walls violently rupture, leading to sudden, catastrophic material detachment and a drastic plunge in mass (Anupama & Santhanam, 2024; Martínez-Martínez, Benavente, Gomez-Heras, Marco-Castaño, & García-del-Cura, 2013).

This erratic deterioration pattern is strongly influenced by the specific mortar typology. Pure lime mortars, which possess higher porosity and lower mechanical strength, are highly vulnerable to rapid deterioration and powdering under crystallization stress. Conversely, modified hydraulic limes (NHL) or cement-based composites feature denser microstructures that resist these stresses for longer periods. Consequently, the literature strongly advises against relying on linear mass-loss tracking to assess long-term mortar durability, recommending instead the use of non-linear exponential decay models or

structural metrics like compressive strength (Anupama & Santhanam, 2024; Martínez-Martínez, Benavente, Gomez-Heras, Marco-Castaño, & García-del-Cura, 2013).

4.3.2 Potential for Multivariate Analysis and Material Grouping

While ordinary least squares (OLS) bivariate regressions establish basic mathematical relationships between isolated physical traits and degradation rates, they inherently oversimplify the multifaceted nature of geo-material weathering. The physical reality of stone, brick, and mortar decay is rarely governed by a single attribute. Instead, it is dictated by the complex, simultaneous interactions of chemical composition, physical structure, and ambient microclimatological parameters. The consolidated relational database developed in this study provides an ideal platform for expanding beyond simple two-variable plots and venturing into multivariate statistical modeling and algorithmic material grouping. Consistent with contemporary reviews of artificial intelligence in heritage science, transitioning from simple linear relationships to multi-predictor configurations significantly enhances both model accuracy and explainability (Li et al., 2026; Towarek et al., 2024).

The structure of the compiled data matrix holds profound potential for executing multiple linear regressions (MLR), where a target deterioration variable, such as the percentage of mechanical strength loss, can be modeled against a combination of predictors ($Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$) (Zhang et al., 2024). Rather than evaluating open porosity in isolation, an MLR model could simultaneously assess porosity, capillary absorption coefficients, and the total count of environmental weathering cycles. This approach allows researchers to calculate the partial regression coefficients of each variable, effectively isolating the exact contribution of internal pore geometry versus external environmental fatigue. Such multi-variable workflows protect against the omitted-variable bias that frequently weakens single-factor assessments, thereby generating highly resilient equations capable of predicting asset decay across highly disparate historic sites.

Beyond regression modeling, the dataset exhibits strong compatibility with unsupervised machine learning algorithms aimed at material grouping and classification, such as K-Means Clustering and Principal Component Analysis (PCA). In cross-study bibliographies, historical materials are often cataloged using inconsistent nomenclature. By subjecting the unified characterization table (*tbl_3_Characterisation*) to PCA, high-

dimensional datasets containing mineralogical data, bulk density, and initial ultrasonic velocities can be compressed into principal components. This mathematical reduction reveals hidden structural patterns and clusters across the literature, effectively grouping materials based on their actual physical behavior and durability fingerprints rather than their nominal classifications.

Implementing these advanced multivariate techniques directly addresses the core requirements for developing trustworthy AI in cultural heritage preservation (Paolanti et al., 2026). By feeding multi-layered, pre-filtered data streams into classification and regression pipelines, heritage professionals can mitigate algorithmic bias stemming from localized or narrow datasets. The relational architecture constructed in Microsoft Access establishes a data "pipeline", ensuring that as new material profiles and multi-variable weathering records are integrated from future literature, the predictive framework becomes increasingly robust, moving monument conservation closer to an objective, data-driven methodology.

4.3.2.1 Model 1: Stone aesthetic degradation and surface weathering tracking

The dynamic interaction between atmospheric exposure and natural stone lithologies manifests as a progressive alteration of surface characteristics. To map this evolutionary decay pathway non-destructively, a simple linear regression model was established using the total number of accelerated weathering cycles as the independent input variable (x) and the colorimetry metric, Total Color Difference (ΔE), extracted from *tbl_6_Deterioration_Metrics* as the target variable (y):

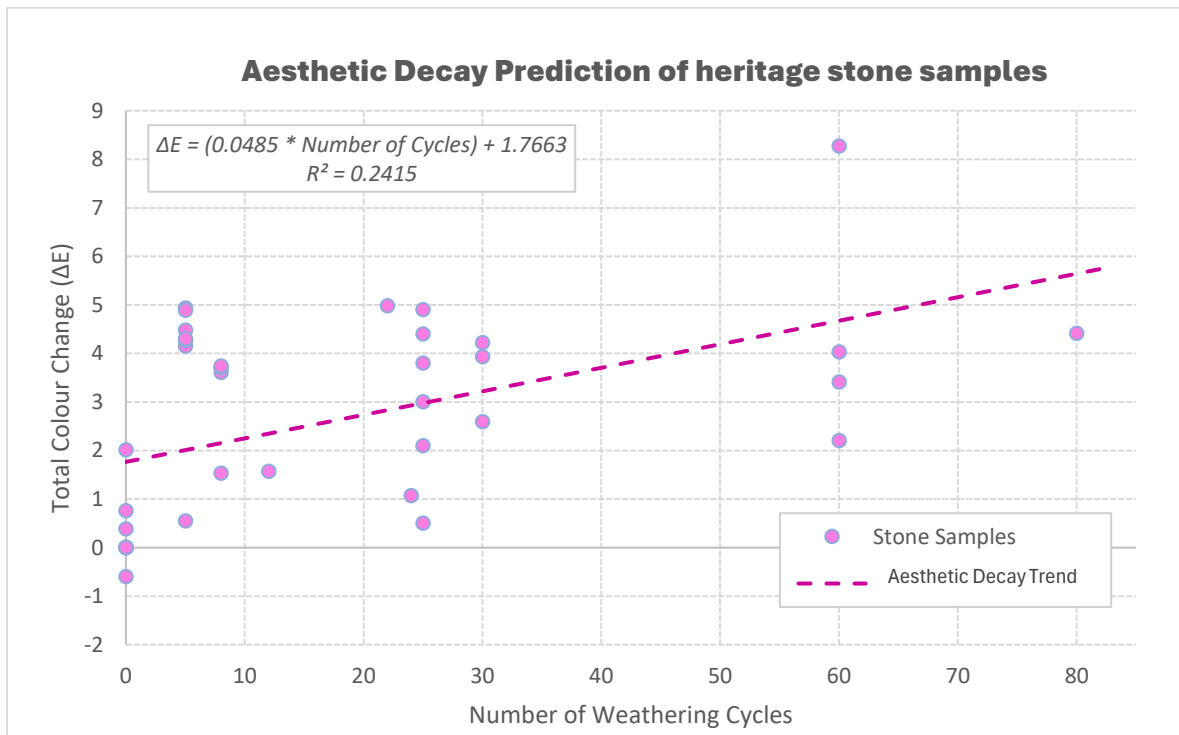


Figure 22. Aesthetic decay prediction of heritage stone samples (Source: original).

This predictive model in Figure 22 yields a coefficient of determination (R^2) of 0.241. The positive slope parameter (0.0485) mathematically models the velocity of surface discoloration per environmental cycle.

In a predictive conservation framework, this baseline relationship demonstrates that *nearly a quarter of all aesthetic variance can be predicted by a single time-series metric*. By establishing this foundational trend line, the database provides a clear baseline configuration that more advanced, non-linear machine learning models can build upon to forecast surface recession thresholds and optimize treatment schedules relative to regional microclimates.

4.3.2.2 Model 2: Multiparametric non-destructive estimation of heritage stone strength and estimation of heritage stone samples behaviour under accelerated weathering conditions

Since extracting large core samples to measure Uniaxial Compressive Strength (UCS) is strictly prohibited on protected monuments, establishing non-destructive proxies is paramount. To achieve this, the data distribution was evaluated using an Ordinary Least

Squares (OLS) Multiple Linear Regression (MLR) framework, trained using fundamental microstructural attributes as simultaneous input features. Open Porosity (%) and Bulk Density (g/cm^3) from *tbl_3_Characterisation* were configured as predictors to map the baseline unweathered load-bearing performance as shown in *Figure 23*.

The calculated coefficient of determination ($R^2 = 0.558$) establishes that 55.8% of the mechanical resistance variance across the heterogeneous stone dataset is successfully explained by this multiparametric combination of baseline physical properties. The negative coefficient for open porosity (-2.28) explicitly quantifies the severe mechanical compromise introduced by internal void volumes. For every 1% increase in open porosity, the structural matrix suffers a direct compressive strength loss of 2.28MPa, highlighting its role as a primary driver of material weakness. The positive coefficient for bulk density (26.58) demonstrates that denser mineral matrices strongly counteract destructive compressive stresses. When porosity is held constant, a tighter, more compact crystalline packing structure contributes significantly to a higher structural baseline. The solid red line illustrates the regression trajectory plotted specifically at the mean bulk density of the dataset (2.44 g/cm^3), showing the direct downward strength path as porosity expands.

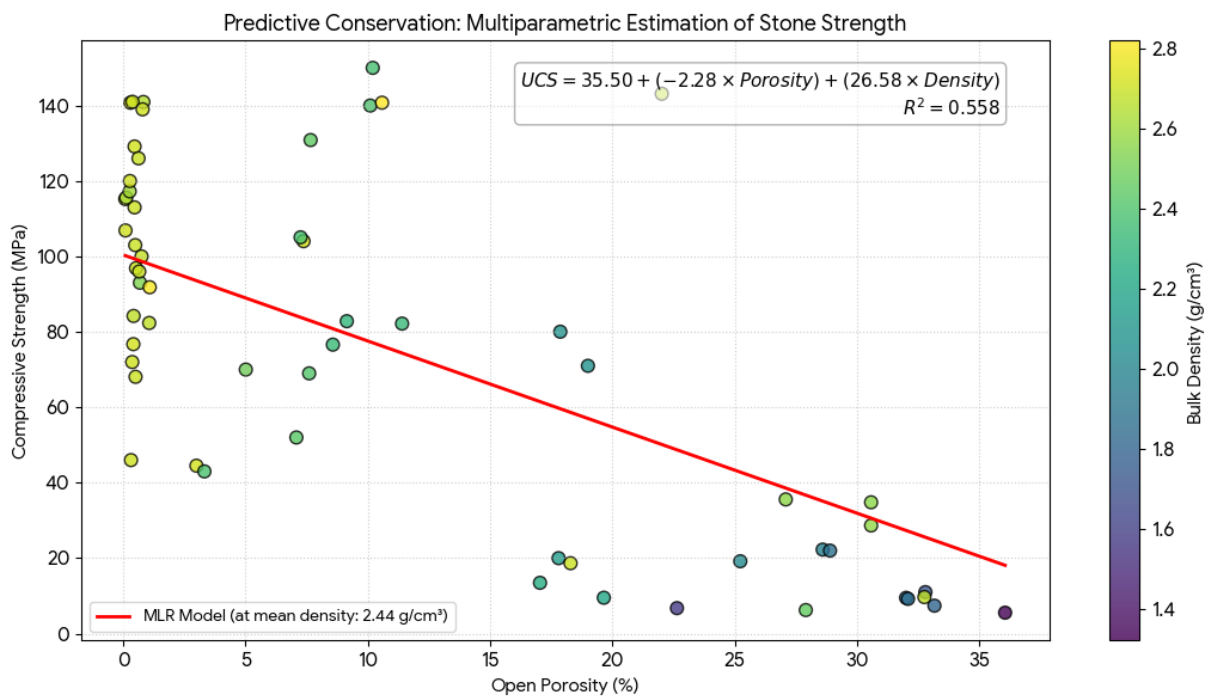


Figure 23. Multiparametric non-destructive estimation of heritage stone samples' strength (Source: original).

This configuration serves as a key benchmark for validating your database's utility in training future Machine Learning surrogate pipelines. As mentioned, extracting stone cores for destructive crushing is heavily restricted on cultural heritage monuments, this model proves that feeding non-destructive or micro-sampled physical parameters (porosity and density) into an empirical pipeline can predict structural load capacities (UCS) with strong statistical power ($R^2 = 0.558$), safely informing real-world conservation and risk assessment workflows. When replacing degraded historical elements, restoration stones must match the original fabric's breathability without introducing extreme structural rigidities. This model allows practitioners to pre-screen replacement quarry options by plotting their porosity and density values against the regression line, ensuring the selected restoration materials possess appropriate mechanical compatibility.

In addition to this thesis' research, bridging the material database with machine learning applications, the plot in *Figure 24* illustrates the mechanical behavior of stone samples by exploring the relationship between a non-destructive testing (NDT) proxy (UPV), an environmental stressor variable (number of cycles after accelerated weathering testings), and a destructive macro-mechanical property (UCS).

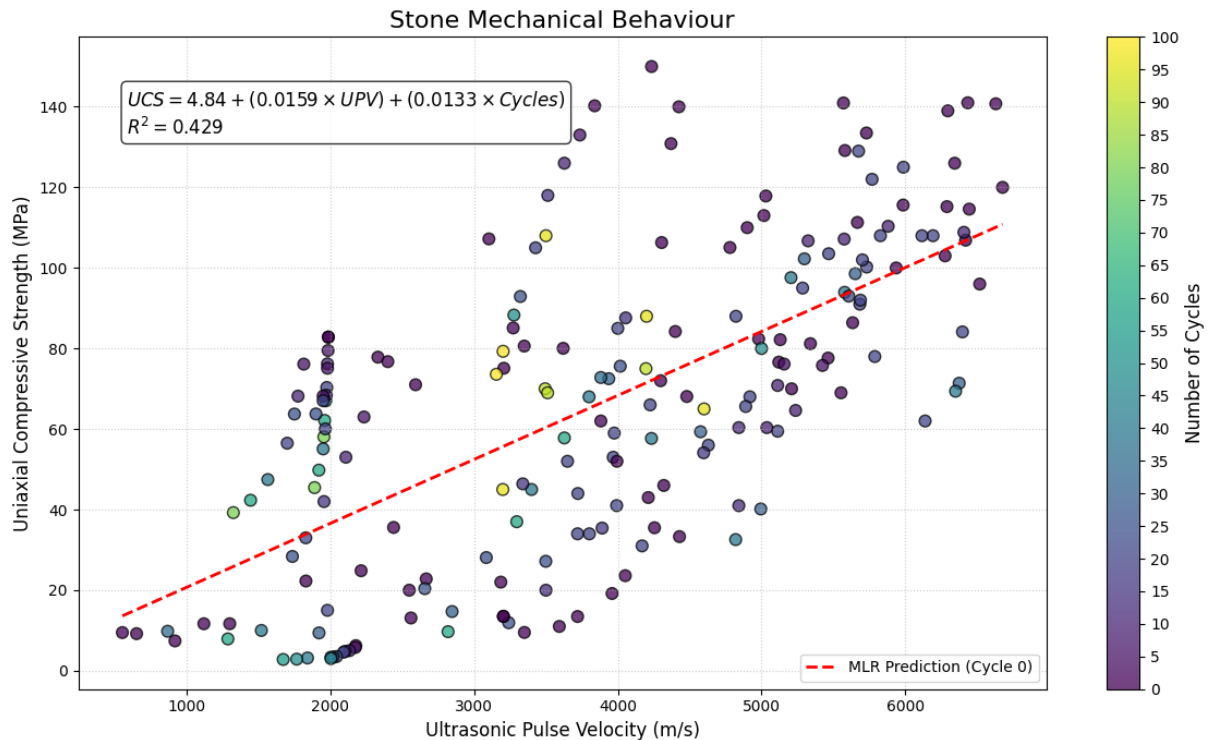


Figure 24. Heritage stone samples' mechanical behaviour under cycles of accelerated weathering (Source: original).

Each circular point represents a specific measurement instance. The points are color-coded according to a third variable, Number of Cycles (the color bar on the right ranging from 0 to 100), which serves as the "temporal" or environmental weathering stressor input feature. The coefficient of determination (R^2) is 0.429, indicating that 42.9% of the variance in the stone's compressive strength is explained by the joint linear changes in UPV and weathering cycles. The dashed red line illustrates the regression trajectory plotted specifically at Cycle 0 (unweathered baseline condition). It highlights a clear, direct upward trajectory: higher wave velocities strongly correlate with greater baseline compressive strength.

This plot demonstrates that by feeding an easily obtainable, completely non-destructive field indicator (UPV) paired with known exposure tracking (Cycles) into an empirical pipeline, you can estimate structural load capacities safely without physical intervention. This Condition – Response temporal mapping allows the underlying model to factor in environmental fatigue. It explicitly demonstrates how an original "birth property", like ultrasonic pulse velocity, evolves under simulated climate strains. Even when high-

porosity or complex stones undergo severe microstructural fracturing that is invisible to the eye, the combination of dropping UPV values and advancing cycles allows the model to map the progression toward catastrophic structural failure.

This MLR model behaves as an important, highly interpretable deterministic benchmark. While simple linear setups cannot fully map the non-linear realities of severe stone weathering (such as sudden flaking plateaus), this $R^2 = 0.429$ output sets a clear baseline configuration. It proves that this thesis' database tables successfully maintain a healthy signal-to-noise ratio, offering a mathematically sound foundation upon which advanced, non-linear algorithms (like Support Vector Regression or Artificial Neural Networks) can build to achieve higher predictive accuracies.

4.3.2.3 Model 3: Technological characterization and vitrification quality control of ancient ceramic samples as well as their behaviour under accelerated weathering conditions

The performance profiles of ancient clay bricks and ceramic assemblages are bound to their thermodynamic manufacturing histories. To decode these internal dynamics, a linear model shown in *Figure 25* was deployed utilizing the historical Firing Temperature (°C) as the input variable (x) to predict the resulting microstructural Open Porosity (%) (y).

This technological configuration demonstrates a strong correlation, yielding an R^2 of 0.5351. The negative directional slope directly quantifies the physics of ceramic vitrification: as kiln temperatures scale upward, high-temperature mineral phases precipitate, systematically shrinking and closing the capillary void networks. Meaning, for every 100°C increase in kiln temperature, open porosity systematically shrinks by 5.05 %. This tracks the exact rate at which partial vitrification occurs, indicating the point where structural clay channels fuse together to restrict water transport spaces. In antiquity, matching clay source chemistry with the optimal firing threshold was crucial. Firing calcareous clays between 700-900°C creates safe, highly vitrified structures with balanced pore networks. This model serves as an analytical standard against which historic bricks can be evaluated to determine whether ancient bricklayers reached appropriate temperatures, or if structural defects stem from under-fired, unstable manufacturing batches.

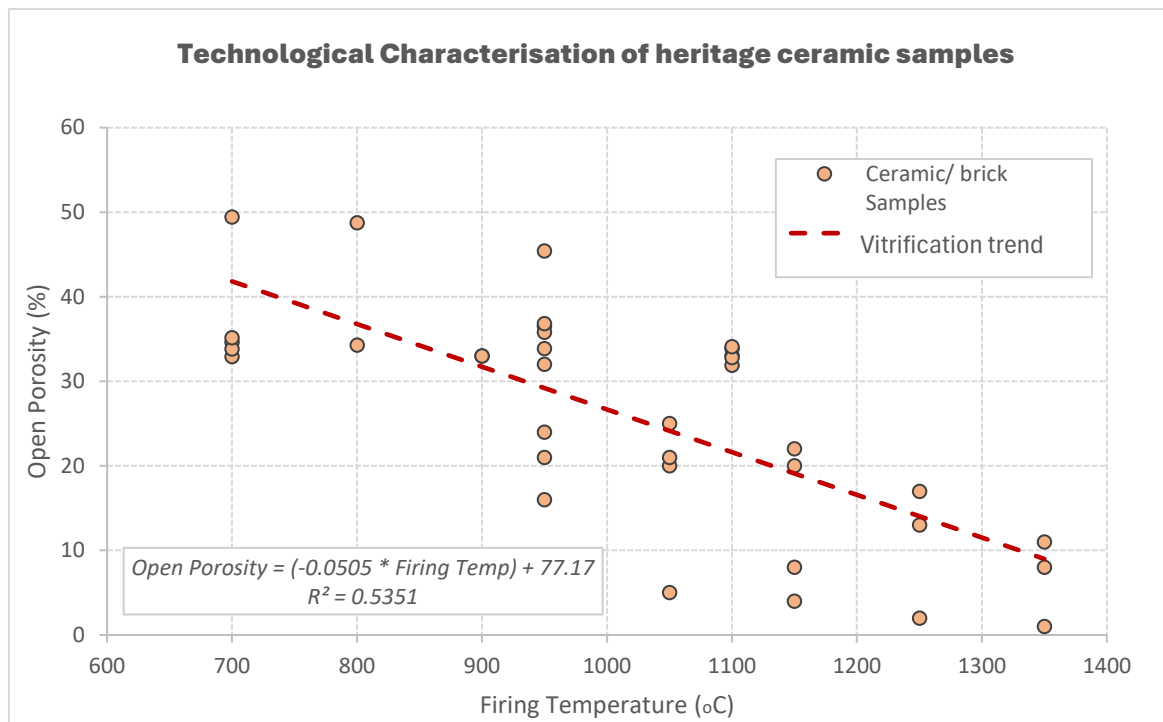


Figure 25. Technological characterisation of heritage ceramic samples based on their firing temperature (Source: Original).

For machine learning applications, this high-fidelity correlation proves that elemental and physical database features can accurately train classification networks to retrospectively infer undocumented archaeological manufacturing conditions or locate clay provenance markers based on fundamental laboratory porosimetry data. For example, a major obstacle when compiling historical literature datasets is data fragmentation, where specific properties like micro-porosity are omitted. Because this linear baseline achieves high statistical confidence ($R^2 = 0.5351$), it acts as a reliable feature generator. Future machine learning classifiers can utilize this model to infer missing open porosity metrics using confirmed firing estimates.

This model also provides strategic utility in predictive conservation diagnostics, since in predictive conservation, moisture ingress remains the primary driver of masonry weathering, salt crystallisation, and frost-driven fracturing. Since total open porosity dictates a brick's initial water capacity, this model allows researchers to predict a brick's foundational baseline vulnerability.

Environmental stress like freeze-thaw cycles alters the internal microstructure of ancient bricks by expanding fine pores into larger, dangerous void networks over time. Knowing a historical brick assembly's estimated firing temperature allows for a safe, calculated approximation of its baseline porosity network. This estimated porosity can then be fed into deterioration algorithms to forecast macroscopic structural failure points across different climate change scenarios without requiring invasive sampling. To fully transition from basic characterization to active degradation tracking, this relationship is extended by analyzing the multi-parameter interaction of non-destructive proxies and progressive environmental loads.

In material informatics and machine learning database design, a dataset is highly valuable if it can connect a material's entire lifecycle. While the above technological characterisation maps how the ancient manufacturing process dictates a brick's internal framework, this following multi-parameter regression model completes the engineering loop by mapping how that material structure degrades mechanically over time under environmental loading. *Figure 26* establishes that firing histories directly govern open porosity distributions. This extension model takes that logic to the field by using Ultrasonic Pulse Velocity (UPV), which drops as weathering micro-cracks open up, to estimate real-time Uniaxial Compressive Strength (UCS) non-destructively.

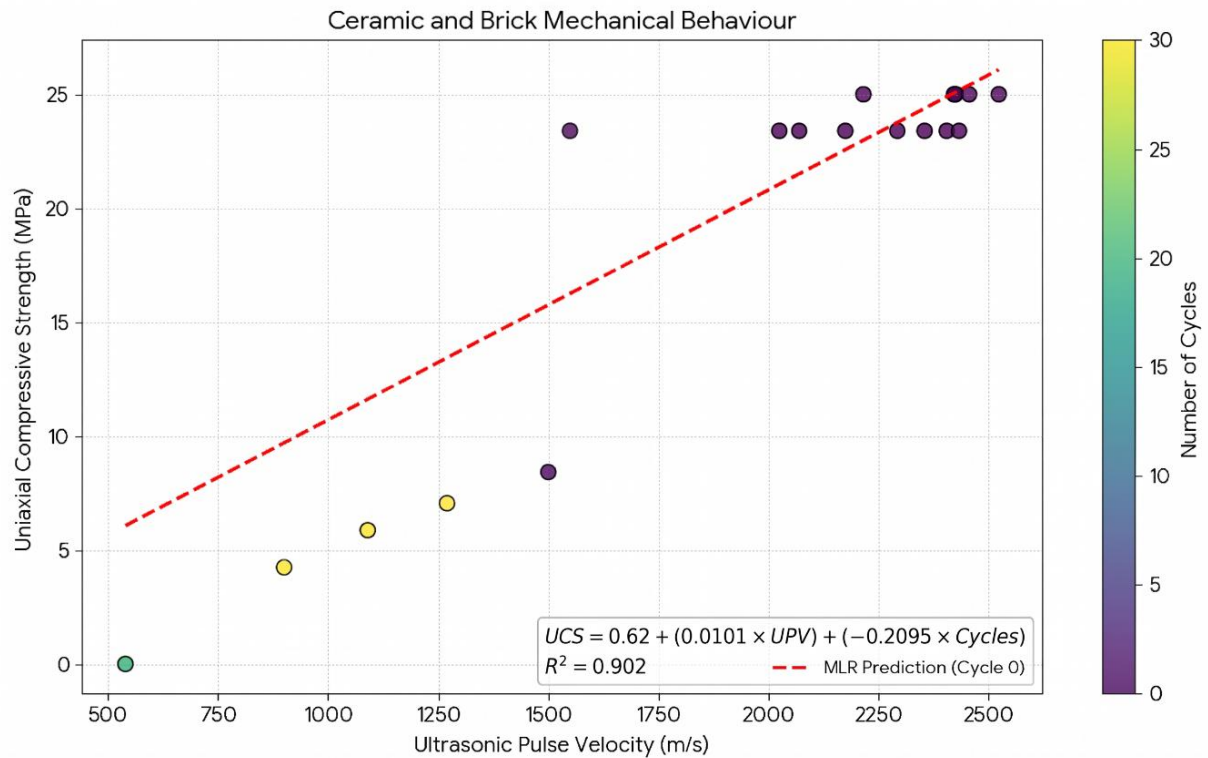


Figure 26. Mechanical behaviour of heritage ceramic and brick samples under accelerated weathering conditions (Source: original).

With a high predictive fit ($R^2 = 0.902$), this MLR proves that nearly the entire structural performance variance across your heterogeneous historic brick dataset is accurately captured by these two predictors, and provides a solid foundation to justify training more complex, non-linear machine learning models (like Neural Networks or Random Forests) to simulate heritage brick stability across different climate change scenarios.

Together, this multi-stage analytical track proves that the relational database architecture captures the engineering sequence necessary to model structural failure non-destructively within predictive conservation workflows.

4.3.2.4 Model 4: Mechanical resilience and porosity-driven decay trends in ancient mortars: from microstructural baselines to dynamic weathering performance

Historical mortars act as the sacrificial, flexible binding media within structural load paths, meaning their microstructural evolution dictates overall masonry resilience. This model

cross-examines the direct, empirical toll of internal porosity values (%) against the Uniaxial Compressive Strength (UCS, MPa) recorded across ancient and restoration formulations:

Within the scope of predictive conservation, evaluating these materials requires a multi-scale analytical progression, establishing that predictive workflow by transitioning from a static microstructural baseline to a dynamic, multiparametric failure forecasting simulation model.

To identify the fundamental physical constraints governing binder performance, a simple linear regression model shown in *Figure 27* was established using the initial, unweathered and weathered Total Porosity (%) from *tbl_6_Deterioration_Metrics* as the independent variable (x) and the ultimate baseline Uniaxial Compressive Strength (UCS, MPa) as the dependent target output (y). Operating with a coefficient of determination (R^2) of 0.1737, this model establishes an inverse mechanical trajectory. The calculated negative slope parameter (-0.2468) explicitly quantifies the structural compromise introduced by internal void volumes: for every 1% increase in initial matrix porosity, the baseline compressive resilience decreases by approximately 0.25 MPa.

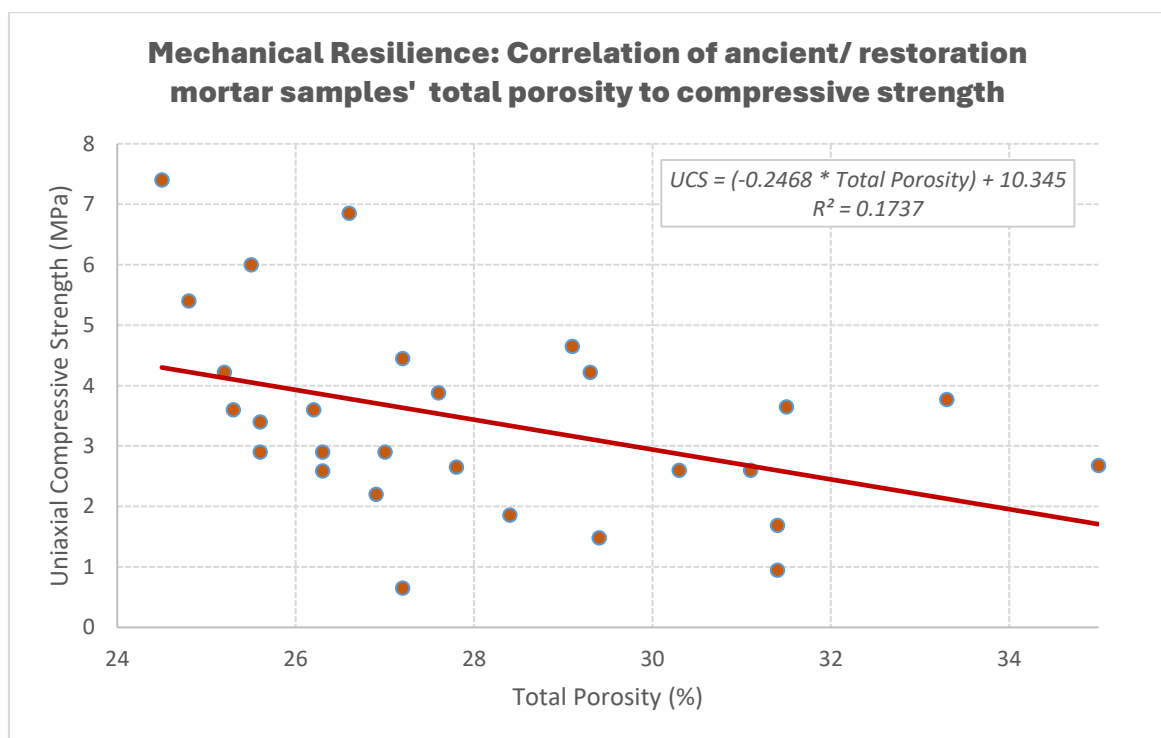


Figure 27. Correlation of the database's ancient and restoration mortar samples' total porosity to uniaxial compressive strength (Source: original).

This empirical trend reflects the core material characteristics of historical binders stored within the dataset. Mortars with higher open voids absorb fluids more rapidly by capillary suction, lowering their overall resistance threshold against subsequent crystallization or environmental pressures. In restoration engineering, this regression equation provides a critical screening index. By charting the initial microstructural footprint, conservation practitioners can mathematically evaluate potential repair mortars, predicting their baseline performance to ensure they do not introduce severe rigidities or physical incompatibilities when paired with a historical substrate.

While the total porosity baseline provides an essential physical profile, it remains a static indicator. To transition your repository into an active predictive diagnostic engine, this analytical track is expanded into a time-series weathering environment. An Ordinary Least Squares (OLS) Multiple Linear Regression (MLR) configuration was deployed using combined metrics from *tbl_6_Deterioration_Metrics*. This configuration evaluates how Ultrasonic Pulse Velocity (UPV, m/s) and the progressive Number of Weathering Cycles simultaneously predict real-time variations in Uniaxial Compressive Strength (UCS, MPa). This multi-parameter configuration shown in *Figure 28* achieves a solid coefficient of determination ($R^2 = 0.521$), successfully capturing more than half (52.1%) of the complex mechanical variance across a highly heterogeneous mix of ancient mortars, plasters, and structural composites.

The positive UPV parameter (0.0147) quantifies the high sensitivity of historical matrices to density alterations. For every 1,000 m/s increase in wave transmission speed, the estimated mechanical resistance scales upward by 14.7 MPa. This strong correlation mathematically validates the deployment of non-destructive acoustic pulse velocity as a dependable virtual proxy for structural integrity checks, allowing field conservators to assess crumbling joint cohesion *in situ* without removing physical core specimens. Meanwhile, the positive directional slope for the cycle count isolates a specific, well-documented technological phenomenon recorded within this database. In hydraulic binding systems or formulations subjected to long-term curing intervals (such as natural carbonation sequences extending up to 365 days), early moisture and ambient exposure actively drive the dissolution of primary components and trigger secondary calcite crystallization within empty micro-voids. This secondary precipitation process densifies the internal pore structure over time, generating minor mechanical strength gains in the earlier weathering

cycles before late-stage fracture propagation and macrostructural fatigue set in. The trend line displays the model's deterministic path calculated specifically at Cycle 0 (the initial, unweathered state), providing a clear baseline trend line from which progressive degradation behavior can be forecasted (Anupama & Santhanam, 2024; Jamshidi, 2024; Stefanidou, et al., 2014).

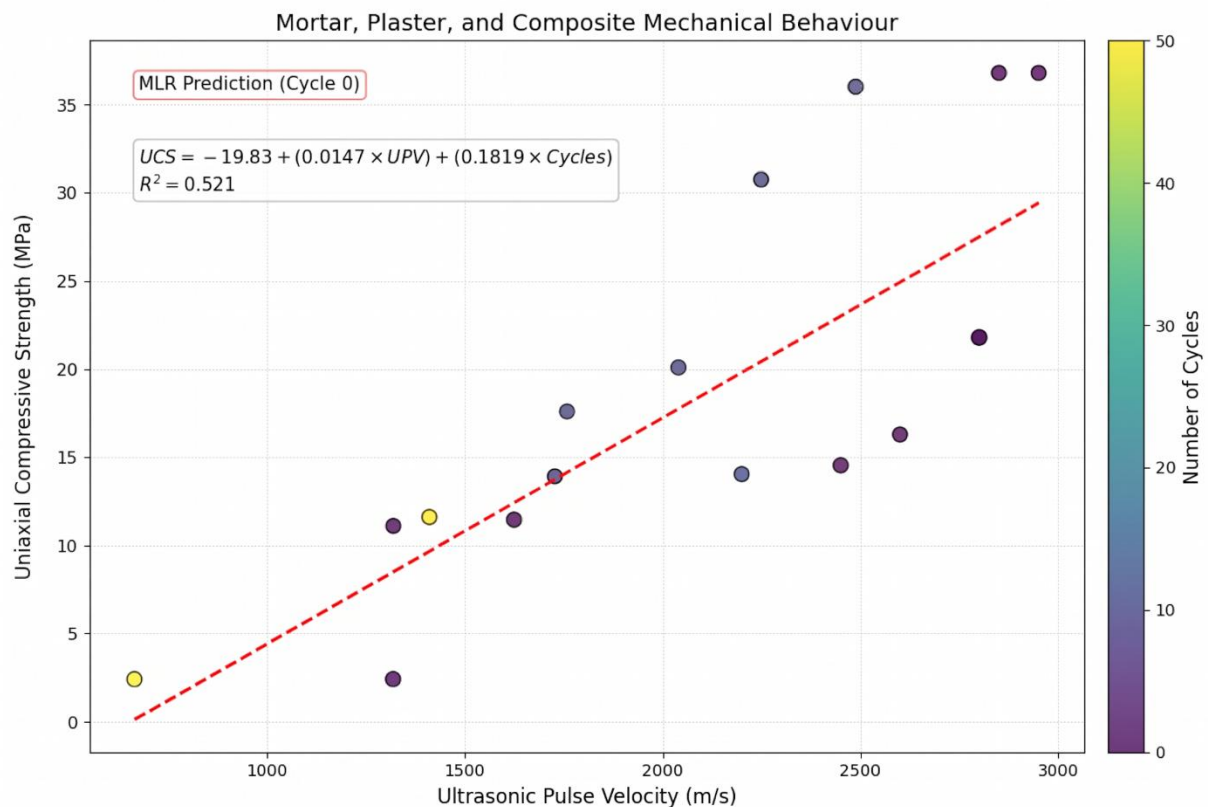


Figure 28. Heritage and restoration mortar, plaster and composite database samples’ mechanical behaviour under accelerated weathering conditions (Source: original).

Achieving an $R^2 = 0.521$ across highly disparate bibliographic sources proves that this research’s database columns capture a high enough signal-to-noise ratio to move past basic statistical summaries. This provides the mathematically sound, reliable Condition-Response training pairs required to train more advanced machine learning algorithms and enables the development of digital twins capable of non-destructively estimating structural remaining useful life, safely informing long-term preservation planning and climate risk assessments. Combined, these two plots demonstrate a core utility of this developed relational database for predictive conservation diagnostics and machine learning feature

engineering. The static total porosity regression serves as a necessary microstructural filter, while the multi-parameter MLR model provides a structured, multi-field training environment.

CHAPTER 5: CONCLUSIONS OF THIS RESEARCH'S EFFORT OF A HERITAGE MATERIAL DATABASE DEVELOPMENT

5.1 Summary of research findings and Database development

The primary objective of this dissertation was to address the critical need for a structured, quantitative approach to understanding the long-term performance and susceptibility of historic building materials to environmental stressors exacerbated by climate change. To achieve this, an extensive literature survey was conducted covering a diverse spectrum of cultural heritage (CH) building materials, specifically natural stone lithologies, ancient ceramics and bricks, and historical mortars. The research identified that traditional material science in heritage conservation frequently produces fragmented data, separating static material characterization from dynamic engineering-focused durability testing. To resolve this, the central outcome of this research was the technical implementation of a relational digital repository using Microsoft Access. This database was engineered upon a rigorous "Condition-Response" framework, directly linking a material's intrinsic petrophysical and physicochemical baseline (the "Condition") to its dynamic mechanical and structural degradation under Accelerated Weathering Testing Protocols (the "Response").

This research transitioned traditional, analog-based material science into a digitised, machine-learning-ready framework by enforcing a strict relational hierarchy through the connection of geographic provenance (tbl_1_Sites), material identity (tbl_2_Samples), and static baselines (tbl_3_Characterisation) with environmental stressors (tbl_4_Weathering_Test_Protocols) and their resulting failures (tbl_6_Deterioration_Metrics). Furthermore, rigorous quality control measures, such as the explicit use of NULL values to handle missing data rather than zero-filling, were implemented to ensure the datasets maintain high statistical power and remain free of algorithmic bias.

5.2 Contribution to the field of predictive conservation diagnostics

A major challenge in heritage science has been the scarcity of comprehensive, unified data, as different laboratories historically utilize varied database formats, making the direct comparison of analytical data exceedingly difficult. This research contributes significantly to the field of predictive conservation diagnostics by actively unifying multidimensional, heterogeneous datasets into a standardized mathematical format.

This research ensures the "transferability of parameters" essential for complex performance simulations by standardizing diverse measurement units and categorizing qualitative descriptions into quantitative intervals. In doing so, this thesis actively aids in extending the database development efforts of the Ceramics and Composite Materials Research Laboratory (CCM) at N.C.S.R. "Demokritos". While pioneering prototypes like *ceraDAT* demonstrated the power of centralized repositories for elemental compositions and provenance tracing, this current database broadens that logic to include the thermo-mechanical resilience and physical decay of heritage materials.

Ultimately, this unified architecture provides the high-fidelity "Condition-Response" data pairs necessary to train advanced machine learning (ML) surrogate models. This empowers algorithms, such as Artificial Neural Networks or Multiple Linear Regression models, to accurately predict destructive parameters entirely non-destructively, thus supporting early-warning heritage risk assessments without compromising the physical integrity of monuments.

5.3 Difficulties encountered

Throughout the literature mining and data structuring phases, several distinct difficulties were encountered. Data heterogeneity posed a primary obstacle, stemming from the lack of globally standardized testing protocols across the scientific community. For instance, accelerated weathering tests frequently feature highly variable parameters, such as different cooling rates in freeze-thaw cycles, varying salt solution concentrations, and varying exposure times, making cross-study comparisons challenging. Additionally, literature mining frequently revealed "incomplete experimental chains," where studies recorded

macroscopic decay parameters but omitted essential non-destructive monitoring metrics, resulting in missing data that required careful handling to avoid introducing omitted variable bias into the database.

Furthermore, the research highlighted inherent limitations in Non-Destructive Testing (NDT). While NDTs like Ultrasonic Pulse Velocity (UPV) are invaluable for assessing internal integrity without invasive sampling, their predictive capability diminishes at advanced stages of material deterioration. For example, once a material surpasses a specific porosity threshold due to severe micro-cracking, UPV values tend to stabilize or decrease only marginally, limiting the method's sensitivity for continuous long-term degradation assessment. Similarly, techniques like Mercury Intrusion Porosimetry (MIP) are often constrained by the "ink-bottle effect," where the presence of large pores connected by narrow throats can lead to an underestimation of macroporosity, complicating the precise correlation of pore-size distributions with mechanical failure.

5.4 Future research directions

This relational database creates structured matrices that provide a solid basis for future integration into sophisticated digital heritage workflows, especially Heritage Building Information Modelling (HBIM) (Li et al., 2026). Recent developments in artificial intelligence for cultural heritage demonstrate how machine learning may greatly speed up the process of converting raw three-dimensional survey data into semantic HBIM representations. In order to automate 3D point cloud semantic segmentation and architectural component classification, future research should concentrate on using the unified categorical and numerical features found in this database to train deep learning architectures, such as Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) (Li et al., 2026; Paolanti et al., 2026). Researchers can produce dynamic "digital twins" of historical structures by connecting the predictive degradation models obtained from this database with scanned geometric data (Li et al., 2026). This integration will enable conservators to chart particular architectural features, like vaults, columns, and ancient masonry joints, and visually model how their petrophysical characteristics might deteriorate

over time based on local climate scenarios, fully automating the shift from static 3D surveys to predictive, life-cycle HBIM models (Li et al., 2026; Silva & Oliveira, 2024).

Alongside structural and geometric modeling, the database possesses significant potential for creating machine learning models aimed at enhancing conservation methods and material choices. Future algorithms may be developed by utilizing the compatibility metrics, consolidation efficiencies, and accelerated weathering information consistently recorded in the repository. Through the examination of multi-parameter associations, these predictive models will be able to suggest the most suitable repair materials—like particular restoration mortars, inorganic consolidants, or water repellents—tailored to a monument's distinct lithology and specific environmental risk factors. For example, upcoming machine learning frameworks might anticipate the photo-oxidative breakdown of protective coatings subjected to intense ultraviolet exposure or accurately estimate a new consolidant's durability against particular synergistic salt-frost weathering cycles (Li et al., 2026).

Ultimately, utilizing this data-informed strategy will transform cultural heritage conservation from a responsive, symptom-focused practice into a precisely aimed, proactive method that reduces climate-induced risks prior to permanent structural failure.

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Appendix A: Material Database Open Access Repository Link

This current Dissertation’s Material Database effort can be accessed and downloaded for viewing through the following link:

https://drive.google.com/file/d/1yy4RHY9zITeU_jVAEcuNAPxcplXK1igh/view?usp=sharing

This Dissertation’s *Material Database* will be uploaded as an *.accdb* file (MS Access format) and available in open access once accepted for the award of a Master’s degree, as part of the Hellenic Open University’s Library’s collection through this webpage <https://apothesis.eap.gr/> , in the sector of ‘School of Applied Arts and Sustainable Design’ for the M.Sc. ‘Protection of Cultural Heritage and Monuments of Nature from the Effects of Climate Change (CCC)’.

Author’s Statement:

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