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Developing a Resilience Assessment Matrix for Cultural Heritage Buildings

Dang Thi Huyen

Department of Civil Engineering, University of Minho, ISISE, ARISE, Portugal. E-mail: danghuyen02101998@gmail.com

Jose C. Matos

Department of Civil Engineering, University of Minho, ISISE, ARISE, Portugal. E-mail: jmatos@civil.uminho.pt

Hélder S. Sousa

Department of Civil Engineering, University of Minho, ISISE, ARISE,, Portugal. E-mail: hssousa@civil.uminho.pt

Monica Santamaria-Ariza

Department of Civil Engineering, University of Minho, ISISE, ARISE,, Portugal. E-mail: msantamaria@civil.uminho.pt

Luca Urciuoli

KTH, Royal Institute of Technology, , Sweden. E-mail: luca.urciuoli@indek.kth.se

Climate change has been related to an increase of the frequency and severity of extreme weather events, posing significant threats to cultural heritage (CH) buildings. Traditional conservation approaches are increasingly inadequate in the face of these escalating risks. Current policies focus primarily on post-disaster responses rather than proactive adaptation, highlighting the urgent need for robust assessment tools to measure the impact of preventive measures. This study presents a Resilience Assessment Matrix (RAM) specifically designed for CH buildings, integrating key performance indicators (KPIs): reliability, agility, sustainability and recovery. By combining multivariate regression and time-dependent differential equations, the framework captures both static and dynamic aspects of resilience. The RAM enables a systematic evaluation of how each KPI influences the resilience trajectory over time, providing both quantitative insights and practical implications. This integrated model supports heritage managers in scenario analysis, intervention planning, and resource prioritization. Moreover, the study links supply chain performance with heritage conservation, offering a scalable, data-driven tool to enhance resilience against climate and logistical challenges.

Keywords: Resilience, Climate change, Cultural Heritage Conservation, Assessment Matrix, Agility Supply Chain

1. Introduction and Background

Cultural heritage (CH) buildings are valuable treasures containing historic, artistic and social values, and at the same time contribute greatly to tourism and local economies [1][2]. However, extreme weather events are increasing in intensity, frequency, and duration also due to climate change. These events pose serious threats to the integrity and resilience of CH structures [3][4][5][6]. Moreover, heritage conservation projects face complex logistical challenges such as timely delivery of specialised materials, skilled labour, specialised equipment and ensuring optimised operational processes [7][8]. These supply chains are frequently disrupted by environmental events, resulting in extended recovery times and increased costs [9]. In addition, poor coordination among stakeholders also makes conservation work more complicated and costly [10][11]. In modern construction, supply chain management (SCM) has been applied to reduce fragmentation and improve efficiency [12]. Yet, its application in heritage conservation remains limited and underdeveloped. Existing SCM models are typically designed for repetitive, contemporary construction projects and are ill-suited to the unique demands of heritage conservation, which must ensure historical authenticity and comply with strict technical and regulatory standards [13][14][15]. Moreover, while SCM can be formulated for both multi-period and single-period settings, heritage conservation is predominantly single-period and case-specific. This is more challenging because each intervention differs in constraints and resource configurations, often requiring ad-hoc supply and restoration solutions. This makes the application of common supply chain Key Performance Indicators (KPIs) such as reliability, agility, and sustainability particularly challenging in heritage contexts. Additionally, recovery - a critical post-event performance metric - remains underrepresented in traditional supply chain performance assessment frameworks, even though it is well established as a core dimension in most resilience assessment models. Despite advances in disaster risk management and supply chain optimization, there is still a lack of quantitative models that clearly link supply chain performance to heritage resilience capacity. Current studies either focus on engineering resilience or general disaster preparedness, or aim to optimize supply chains in conventional construction. Very few address the dynamic, multi-dimensional relationship between SCM and resilience in heritage buildings. To fill this gap, this study proposes the development of a Resilience Assessment Matrix (RAM). This conceptual model integrates key performance indicators: reliability, agility, sustainability, and recovery to assess their collective impact on the resilience of heritage buildings. The core research question is: How can key performance indicators of supply chains be integrated into a conceptual model to assess the resilience of CH buildings?

By focusing on resilience as a quantifiable and actionable KPI, this study aims to support heritage managers in prioritizing interventions and improving preparedness, ultimately enhancing the resilience of CH assets in the face of climate-induced disruptions.

2. Research Framework

This study develops a Resilience Assessment Matrix (RAM) for cultural heritage buildings (Figure 1). Figure 1 presents the complete workflow, starting from the collection and analysis of multi-source heritage-related data, including structural conditions, environmental factors, material characteristics, energy and financial performance, risk preparedness plans, and supply chain related information such as material availability, transport accessibility, and the capacity to mobilize skilled labour during disruptive events. Based on these inputs, four key performance indicators (KPIs): reliability, agility, sustainability, and recovery are selected. The selected KPIs are then identified, prepared, and used to construct the RAM, which serves as a decision-support output to inform appropriate intervention strategies for enhancing heritage resilience.

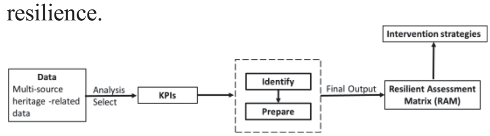

Fig 1: Development process of the Resilience Assessment Matrix (RAM) for cultural heritage buildings

Figure 2 presents an integrated system framework that clarifies the interrelationships among the key factors influencing the resilience of cultural heritage buildings. In this model, Nature represents the environmental dimension, including both positive heritage-related conditions and climate-related hazards. Together with data inputs such as structural assessments, material inventories, environmental and financial information, and preparedness plans, these factors feed RAM, which operationalises four KPIs: reliability, agility, sustainability, and recovery. The RAM provides analytical guidance for heritage managers, enabling the optimisation of conservation and risk-management strategies. The resulting management decisions generate feedback to the broader Society and Economy and Governance domains, shaping community engagement, policy development, and long-term investment priorities. Conversely, these domains also influence the resilience of heritage buildings, creating reciprocal feedback loops. Overall, the figure illustrates a dynamic system in which environmental conditions, data availability, assessment processes, management practices, and governance decisions collectively shape cultural heritage resilience.

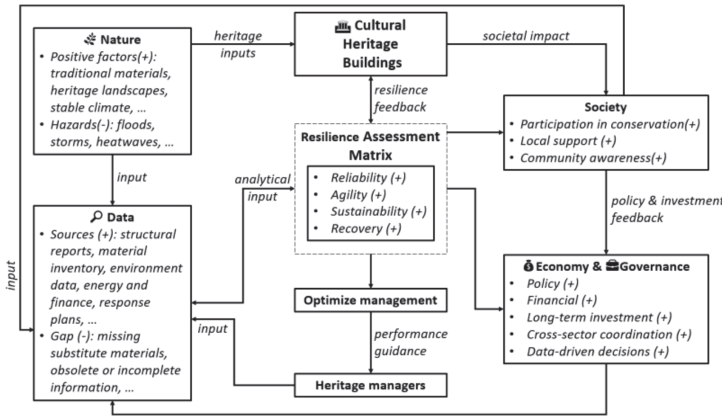

Fig 2: Integrated System Framework for Heritage Resilience Assessment and Management

The four selected KPIs in the RAM framework serve as the core analytical foundation and are specified operationally in Table 1. Table 1 summarises the KPI definitions (independent variables), their measurement criteria and units, and the data sources used to compute the derived resilience index (dependent variable). These indicators are operationalized through multivariate regression models and time-dependent differential equations to estimate resilience levels across heritage scenarios.

Table 1: Variables for the Resilience Assessment Matrix (RAM)

Variable	Operational description	Specific measurement criteria	Definition/computation (how quantified)	Measurement method/protocol	Data sources
Independent variables (KPI)					
Reliability X_i	The degree of consistency and ability to maintain the structural integrity of the building during conservation and recovery processes.	-Percentage of operational time without major damage (%)	(Time in service without major damage)/(Total operational time)×100 Define "major damage" using the project's damage classification threshold	Periodic structural inspection + condition assessment. Record downtime/service interruption attributable to major damage. Standardise damage classification criteria across inspections.	Structural inspection reports; structural survey data. Update: after each inspection cycle and after incidents.
		-Average lifespan of restored materials (years)	Mean expected/observed service life of restored/replaced materials used in the intervention, aggregated across components/material types.	Materials inventory review + verification from technical datasheets/as-built records; cross-check with maintenance/repair history where available.	List of materials and their origin; maintenance/material records (as available); structural survey data. Update: at completion of restoration and during scheduled reviews
Agility Y_i	The ability to quickly adapt recovery strategies when facing changing	-Percentage of adjusted restoration methods (%)	(Number of restoration method changes approved/implemented)/(Total restoration methods or planned activities)×100	Document-based audit of method statements: compare baseline plan and revised method statements and site instructions; count approved deviations	Analysis records of changing environmental conditions; restoration method change logs. Update: per project

	environmental factors.		"Adjusted" = deviation from the baseline method statement due to changing conditions.	and reasons (environmental constraints/material change).	phase / monthly during works.
		-Number of alternative solutions in case of material change	Count of feasible, pre-qualified alternatives (materials/techniques/suppliers) that meet heritage requirements and compatibility constraints.	Options registry/procurement review: compile validated alternatives from supplier lists, technical approvals, and heritage authority acceptance (if required). Maintain a documented list of equivalence criteria.	Records of alternative materials used; procurement/supplier qualification records (if available). Update: when supply conditions change / quarterly.
Sustainability Z_i	Ensures that the restoration process maintains the long-term integrity of the heritage asset.	-Proportion of sustainable materials used in restoration (%)	(Quantity (or cost) of materials meeting "sustainable" criteria)/(Total materials quantity (or cost))x100 Sustainable criteria must be explicitly defined (certified/EPD/low-impact/local sourcing).	Bill of quantities (BoQ) + material verification: classify each material against the defined sustainability criteria; compute proportion using quantity/area/cost.	Environmental and material restoration reports; list of sustainable materials. Update: at procurement batches and at end of works.
		-Energy consumption during restoration (kWh)	Total energy used by restoration activities over the reporting period (site electricity + fuel where applicable), aggregated to project total.	Metering/utility-bill method: read site meters/utility invoices; allocate shared energy use to restoration activities using equipment logs if needed.	Energy usage during restoration (meter/bills); environmental restoration reports. Update: monthly (or per billing cycle).
Recovery W_i	The ability to recover quickly and effectively after an incident, preserving cultural and historical values.	-Time to complete restoration after an incident (months)	Duration from incident occurrence (or safe access granted) to completion of restoration/return-to-service milestone.	Schedule/records-based tracking: use incident reports and project schedule milestones; define a consistent "completion" criterion (practical completion or functional reopening).	Financial recovery reports; incident and project schedule records (if available). Update: per incident and at project close-out.
		-Percentage of mobilized restoration funding (%)	(Funding secured and available for restoration)/(Total required recovery budget)×100	Financial audit: verify allocated vs. required funds using approved budgets, contracts, grants, and disbursement records; document funding accessibility constraints (timing/conditions).	Investment records and recovery budgets; financial recovery reports. Update: monthly during recovery financing phase and after major funding changes.
Dependent variable					
Resilience R_i	Overall index representing the heritage asset's ability to withstand and recover from external impacts	-Calculated resilience index -Based on mathematical models using KPI data	Resilience index computed from the KPI dataset using the proposed mathematical model	Model-based computation: compile KPI values from defined methods above; run model to obtain resilience output; apply normalisation/aggregation steps consistently across cases.	KPI data analysis results from multiple case studies. Update: whenever KPI dataset is updated/ new case added.

3. Resilience Assessment Matrix Construction

The construction of the RAM relies on a two-stage modelling structure. First, a multivariate regression model is calibrated to determine the contribution of each KPI to the composite resilience index. The regression coefficients α are estimated in advance using a separate training dataset, which may consist of expert-defined scenarios or representative heritage cases. Once these coefficients are obtained, they remain fixed and can be applied to any individual cultural heritage building. This allows the resilience value R_i to be computed even when only a single observation of the four KPIs is available, which represents an operational advantage in data-scarce heritage contexts. In the second stage, the computed resilience values serve as inputs to a differential equation model that characterizes how resilience evolves under different resilience conditions.

3.1. *Multivariate Regression Model*

The multivariate regression model quantifies how each KPI contributes to the resilience of the building. This helps identify the main factors affecting the resilience and recovery of heritage buildings and proposes effective improvement measures. The general form of the regression model is:

$$R = \alpha_0 + \alpha_1 X + \alpha_2 Y + \alpha_3 Z + \alpha_4 W + \varepsilon \quad (1)$$

- R represents the resilience of cultural heritage buildings under the impact of external factors.
- X, Y, Z, W are the KPIs that assess the reliability, agility, sustainability and recovery of the supply chain in the context of heritage conservation, respectively.
- α_0 is the intercept coefficient that shows that in the absence of the impact of the KPI factors, the basic resilience of the process is still maintained at a certain level.
- $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the regression coefficients for each KPI that indicate their level of influence on the overall resilience.
- ε is the error term, representing the remaining unexplained part in the model.

To estimate the regression coefficients, a dataset containing observations of the KPIs and the corresponding resilience values is required. For each observation i, the regression equation can be written as:

$$R_i = \widehat{R_i} + e_i = \hat{\alpha}_1 X_i + \hat{\alpha}_2 Y_i + \hat{\alpha}_3 Z_i + \hat{\alpha}_4 W_i + e_i \quad (2)$$

The coefficients $\hat{\alpha}_j$ $(j = 1,2,3,4)$ are determined using the Ordinary Least Squares (OLS) method, which estimates the set of coefficients that minimises the sum of squared residuals between the observed and predicted resilience values . Formally, the following condition must be satisfied for each coefficient:

$$\frac{\partial \sum e_i^2}{\partial \hat{\alpha}_j} = 0 \quad (3)$$

This condition leads to a system of equations, which can be solved simultaneously to obtain the regression coefficients:

$$\begin{cases} \dfrac{\partial \sum e_i^2}{\partial \hat{\alpha}_1} = 0 \\ \vdots \\ \dfrac{\partial \sum e_i^2}{\partial \hat{\alpha}_4} = 0 \end{cases} \quad (4)$$

$$\begin{cases} \sum 2(R_i - \hat{\alpha}_1 X_i - \hat{\alpha}_2 Y_i - \hat{\alpha}_3 Z_i - \hat{\alpha}_4 W_i)(-1) = 0 \\ \vdots \\ \sum 2(R_i - \hat{\alpha}_1 X_i - \hat{\alpha}_2 Y_i - \hat{\alpha}_3 Z_i - \hat{\alpha}_4 W_i)(-W_i) = 0 \end{cases} \quad (5)$$

The system of equations can be expressed in a matrix form as:

$$(X^T X)\,\hat{\alpha} = X^T R \Rightarrow \hat{\alpha} = (X^T X)^{-1}(X^T R) \quad (6)$$

where:

$$\hat{\alpha} = \begin{bmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \\ \hat{\alpha}_4 \end{bmatrix} \quad X = \begin{bmatrix} 1 X_1 Y_1 Z_1 W_1 \\ 1 X_2 Y_2 Z_2 W_2 \\ \vdots \; \vdots \; \vdots \; \vdots \; \vdots \\ 1 X_n Y_n Z_n W_n \end{bmatrix} \quad (7)$$

$$X^T R = \begin{bmatrix} \sum R_i \\ \sum X_i R_i \\ \vdots \\ \sum W_i R_i \end{bmatrix} \quad (8)$$

$$X^TX = \begin{bmatrix} n & \sum X_i & \sum Y_i & \sum Z_i & \sum W_i \\ \sum X_i & \sum X_i^2 & \sum X_i Y_i & \sum X_i Z_i & \sum X_i W_i \\ \sum Y_i & \sum Y_i X_i & \sum Y_i^2 & \sum Y_i Z_i & \sum Y_i W_i \\ \sum Z_i & \sum Z_i X_i & \sum Z_i Y_i & \sum Z_i^2 & \sum Z_i W_i \\ \sum W_i & \sum W_i X_i & \sum W_i Y_i & \sum W_i Z_i & \sum W_i^2 \end{bmatrix} \quad (9)$$

Figure 3 is used to visualize the relationship between the independent variables and the dependent variable R_i. Due to the limitation of three-dimensional space, the diagram only displays three axes R_i, X_i, Y_i. Therefore, the effects of the two additional variables Z_i, W_i on R_i cannot be directly illustrated. The plane in the figure represents α linear regression model between R_i and the two variables X_i, Y_i. The black dots represent actual observations from the collected dataset. Points that lie close to the regression plane indicate that the model predicts R_i well using X_i, Y_i, whereas points far from the plane suggest residual errors, reflecting portions of the variability in R_i that are not fully explained by the model.

From the graph, the following key observations can be drawn:

- Trend analysis: When the values of independent variables reach certain thresholds, the regression results may change according to non-linear models.
- Variable influence: The slope of the regression plane reflects the degree of impact of each variable; the larger the slope, the stronger the influence.
- Model fit: The distance between the data points and the regression plane represents the error ε_i, which helps to evaluate the accuracy of the model.

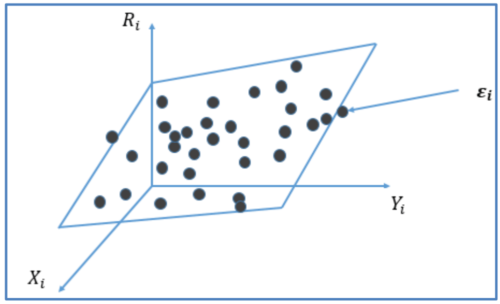

Fig 3: 3D multivariate regression plot assessing resilience

Table 2 summarizes the regression matrix derived from the multivariate model, illustrating the impact of each KPI on resilience R. Each KPI plays a distinct role. The regression coefficients α_1 to α_4 reflect the influence level of each KPI, offering both quantitative insight and practical guidance for improving heritage resilience.

Table 2: Matrix from the results of the multivariate regression model

KPI	**Regression coefficient α**	**Quantitative interpretation**	**Practical implications for heritage conservation**
X (reliability)	α_1	An increase of 1% in X leads to an α_1% rise in R	Ensuring material quality and technical integrity should be prioritized throughout the restoration process.
Y (agility)	α_2	An increase of 1% in Y_i leads to an α_2% rise in R	It is necessary to develop agile response strategies to cope with disruptions.
Z(sustainability)	α_3	An increase of 1% in Z leads to an α_3% rise in R	Emphasis should be placed on sustainable materials and techniques to achieve long-term improvement.
W (recovery)	α_4	An increase of 1% in W leads to an α_4% rise in R	Rapid allocation of recovery resources is crucial for improving recovery efficiency.

3.2. *Differential Equation Model for Resilience over Time*

The resilience model $R(t)$ describes the time-dependent evolution of system resilience after a disaster. By using a differential equation, the resilience process is represented continuously over time, capturing the simultaneous influence of key input variables: X, Y, Z, W - the main KPIs identified from the regression analysis. Based on this, a generalized differential equation can be formulated to simulate resilience over time:

$$\frac{d\,R(t)}{dt} = \alpha_1 X\,(t) + \alpha_2 Y(t) + \alpha_3 Z(t) + \alpha_4 W(t) - \beta\,R(t) \qquad (10)$$

In which the variables and coefficients are defined as follows:

- $\frac{d\,R(t)}{dt}$ is the rate of change in resilience over time.
- $\alpha_1, \alpha_2, \alpha_3, \alpha_4$: It represents the influence level of that KPI on the resilience rate. These values are taken directly from the results of the multivariate regression model, indicating how much the rate of change in $R(t)$ will vary with a one-unit increase in the KPI. The larger the absolute value of α (positive or negative), the stronger the quantitative impact of that KPI on $R(t)$. A positive α indicates a positive effect that accelerates resilience, while a negative α implies a negative influence that hinders it.
- β: a non-negative adjustment (damping) parameter governing how quickly the system approaches its steady resilience level, larger β implies faster convergence (stronger pull toward equilibrium).
- $X(t), Y(t), Z(t), W(t)$: The independent variables representing key aspects of resilience. Their values serve as input factors that determine the rate of change of $R(t)$.

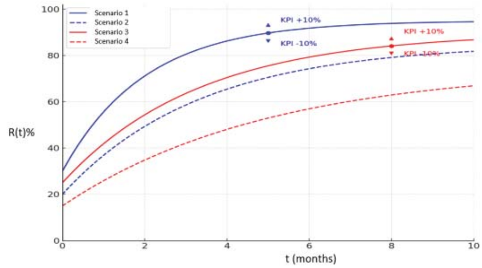

Fig 4: Graph simulating the resilience $R(t)$over time

Figure 4 illustrates the resilience curves $R(t)$for four hypothetical scenarios (conditions improve after an initial response period, leading to changes in resilience speed and trajectories). Scenario 1 represents the baseline (nominal KPI values); Scenario 2 assumes reduced reliability (supply continuity constraints), Scenario 3 assumes enhanced agility (greater adaptive capacity in sourcing/logistics), and Scenario 4 assumes constrained recovery capability (slower restoration due to limited resources). Each scenario modifies only one dimension relative to the baseline while the others are kept constant, allowing its influence on the curve shape to be interpreted. In all scenarios, only the stated KPI condition is varied while the remaining inputs and modelling settings are held constant.

The time axis is defined such that t=0 represents the end of the disruptive event and the beginning of the resilience phase. The vertical axis $R(t)\%$, expressed as a percentage (%), represents the system's level of resilience relative to its pre-disaster state (100% indicates full resilience). To express resilience in percentage terms, the model output is normalised with respect to the reference target state R_{ref} (assumed to equal the pre-disaster level in this study). The resilience percentage is defined as:

$$R(t)\% = \frac{R(t)}{R_{ref}} \qquad (11)$$

For decision-making, $R(t)\%$ is used as the resilience index at time *t* and is mapped to the five RAM classes in Figure 5.

The triangle markers labelled "KPI+10%" and "KPI-10%" indicate the results of a local sensitivity analysis conducted at a specific time point. In this analysis, only one KPI at a time is increased or decreased by 10%, while all other KPIs remain unchanged. The small displacement of the triangle points from the main curve shows that a modest change in a single KPI produces a correspondingly small change in $R(t)$. This demonstrates that the model response around that operating point is locally stable and only weakly sensitive to small variations in individual KPI inputs. Future work will extend this analysis toward multi-factor scenario stress-testing that combines simultaneous KPI shifts and hazard intensity assumptions

Resilience level	Very low	Low	Medium	High	Very high
R(t)	<50%	50-60%	60-70%	70-85%	>85%

Fig 5: Resilience Assessment Matrix (RAM) with five qualitative levels and threshold mapping from the continuous resilience index

The quantitative results obtained from the time-dependent differential equation can be expressed as a continuous resilience index $R(t)$between 0% and 100%. However, for practical decision-making, it is often more useful to work with a limited number of qualitative classes rather than raw numerical values. To this end, the model outputs are mapped onto five resilience levels: very low, low, medium, high, and very high using the thresholds shown in Figure 5. This five-level structure is consistent with ordinal scales commonly employed in risk and resilience assessment frameworks [16] [17]. In operational terms, for each heritage building and for each time step of interest, the four KPIs (reliability, agility, sustainability, and recovery) are first evaluated and used to compute $R(t)$ through the calibrated regression and differential-equation models. The resulting values are then classified according to Figure 5, so that both the KPIs and the composite resilience index can be expressed as categorical levels (very low to very high) and visualised using a consistent colour code. This procedure effectively constitutes the Resilience Assessment Matrix (RAM): a structured, colour-graded representation of resilience performance over time that facilitates comparison between assets and highlights where interventions should be prioritised.

4. Conclusion

This study proposes a Resilience Assessment Matrix (RAM) framework to analyse the impact of supply chains on the resilience of cultural heritage buildings. By integrating key performance indicators (reliability, agility, recovery, and sustainability), the research develops a hybrid assessment model combining both static and dynamic analyses. RAM enables heritage managers to identify which factors have the most significant influence on resilience under varying conditions. Future studies will apply RAM to real-world cases, using empirical data to calibrate model parameters and validate the framework, thereby enhancing the model's accuracy. A key next step is to integrate RAM into decision-support systems for scenario analysis and conservation planning optimization. Overall, this research lays an important foundation for bridging supply chain resilience theory with practical heritage conservation, providing a valuable tool to address future challenges posed by climate change and logistical disruptions.

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