D6.7- Financial strategies selection tool

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Revision table

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V 0.1	Simona Denaro (RED)	24/06/2024	First draft
V 0.2	Gianbattista Bussi (RED), Paola Ceresa (RED)	24/06/2024	Updated draft internally reviewed
V 0.4	Simona Denaro (RED), Paola Ceresa (RED)	28/06/2024	Updated draft internally reviewed
V 1.0	Iulia Anton (ATU), Salem Gharbia (ATU)	30/06/2024	Final version
V 1.1	Simona Denaro (RED), Gianbattista Bussi (RED), Paola Ceresa (RED)	29/08/2024	Updated version
V1.2	Iulia Anton (ATU), Salem Gharbia (ATU)	30/08/2024	Final version

LIST OF ACRONYMS AND ABBREVIATIONS

Acronym / Abbreviation	Meaning / Full text
AAL	Average Annual Loss
RAAL	Residual Average Annual Loss
AAP	Average Annual Affected Population
CCLL	Coastal City Living Lab
EBA	Ecosystem-Based Approach
JRC	European Commission's Joint Research Centre
RCP	Representative Concentration Pathways
DSS	Decision Support System

BACKGROUND: ABOUT THE SCORE PROJECT

SCORE is a four-year EU-funded project aiming to increase climate resilience in European coastal cities.

The intensification of extreme weather events, coastal erosion and sea-level rise are major challenges to be urgently addressed by European coastal cities. The science behind these disruptive phenomena is complex, and advancing climate resilience requires progress in data acquisition, forecasting, and understanding of the potential risks and impacts for real-scenario interventions. The Ecosystem-Based Approach (EBA) supported by smart technologies has potential to increase climate resilience of European coastal cities; however, it is not yet adequately understood and coordinated at European level.

SCORE outlines a co-creation strategy, developed via a network of 10 coastal city 'living labs' (CCLLs), to rapidly, equitably and sustainably enhance coastal city climate resilience through EBAs and sophisticated digital technologies.

The 10 coastal city living labs involved in the project are: Sligo and Dublin, Ireland; Barcelona/Vilanova i la Geltrú, Benidorm and Basque Country, Spain; Oeiras, Portugal; Massa, Italy; Koper, Slovenia; Gdansk, Poland; Samsun, Turkey.

SCORE will establish an integrated coastal zone management framework for strengthening EBA and smart coastal city policies, creating European leadership in coastal city climate change adaptation in line with The Paris Agreement. It will provide innovative platforms to empower stakeholders' deployment of EBAs to increase climate resilience, business opportunities and financial sustainability of coastal cities.

The SCORE interdisciplinary team consists of 28 world-leading organisations from academia, local authorities, RPOs, and SMEs encompassing a wide range of skills including environmental science and policy, climate modelling, citizen and social science, data management, coastal management and engineering, security and technological aspects of smart sensing research.

EXECUTIVE SUMMARY

In the context of the project activities of WP6, entitled "Strategies to increase the financial resilience of coastal cities", this document briefly describes the contents of D6.7 "Financial strategies selection tool". The tool is intended as a Decision Support System (DSS) for decision makers in Massa, Vilanova i la Geltrú, and Oarsoaldea CCLLs to help them evaluate and choose among different financial resilience strategies to manage flood related financial risk.

LINKS WITH OTHER PROJECT ACTIVITIES

The present Financial Strategies Selection Tool demonstrator (D6.7), together with the accompanying cash flow diagrams (D6.6), were developed concurrently in the context of WP6's Task 6.4. Task 6.4 develops financial resilience strategies aimed at managing the financial risk related to floods (both fluvial and coastal) for the three frontrunner CCLLs. This task will provide input to Task 6.5, which will produce a set of risk management decision support guidelines for policymakers. Task 6.4 is linked to the previous Task 6.3 and the results previously produced by WP6, namely the flood risk and residual flood risk profiles.

The flood risk model used to estimate both losses and residual losses, utilized initial information on the elements and exposure characteristics of the CCLL frontrunners provided by WP2 and derived from their "CCLL questionnaires". The hazard maps used to estimate losses were provided by WP3. Additionally, the development of the Ecosystem-Based Approaches (EBAs) was a collaborative effort involving the frontrunner CCLLs and WP7.

CONTENT OF DELIVERABLE D6.7

The files in this demonstrator compose D6.7 of the SCORE project, entitled "Financial strategies selection tool". The D6.7 file is located on Zenodo, under, D6.7, SCORE community, link.

1.1. INTRODUCTION

The Historical as-if cash flow for all strategies, as well as the methodologies adopted in their development, are described in D6.6, "Historical 'as-if' cash flow diagrams according to all strategies developed". All climate and temporal scenarios considered in the development of the risk profiles were described and presented in D6.4 "Residual risk assessment report for the frontrunner CCLLs ", and D6.5 "Risk profiles for the frontrunner CCLLs" both delivered in June 2024. A more comprehensive description of the methods and results obtained in Task 6.4 will be provided in Report D6.8 Financial strategy and guidelines for CCLLs, due M44.

In this context, the present document, entitled "Financial strategies selection tool", briefly describes the DSS and outlines its potential applications and interpretation. Task 6.4 involved the development of layered financial risk management strategies. These strategies consist of multiple components designed to address different types of risk: risk retention mechanisms, such as a reserve fund for managing high-frequency, low-impact risks (low-risk layer), and risk transfer mechanisms, such as insurance or parametric insurance, for covering low-frequency, high-impact losses.

Several parameters define these strategies. For instance, determining the optimal size of the reserve fund is crucial to ensure it effectively covers high-frequency losses while remaining economically viable in terms of opportunity cost and political feasibility. Additionally, decisions regarding the extent of insurance coverage, which involves determining how much risk should be transferred to an insurance company, are essential. This decision-making process is complex, as it involves not only the monetary costs associated with the strategy but also its socio-economic impact. For example, the unavailability of critical infrastructure following a flood event can significantly affect economic activities and social well-being. Ensuring financial coverage for prompt repairs and assistance extends beyond mere financial considerations and has substantial implications for the overall resilience and functionality of the city. Therefore, considering the socio-economic and political dimensions is crucial for city officials when selecting the most appropriate strategy. For this reason, the strategies were designed to optimize two different objectives: minimizing the total cost of the strategy and minimizing the Residual (uncovered) Average Annual Losses (RAAL). The result is a set of Pareto optimal alternatives. In this context, a Pareto optimal solution refers to a scenario where no objective can be improved without worsening another. The following section illustrates the methodology that was implemented to design the optimal strategies.

1.2. METHODOLOGY

To derive a set of Pareto optimal alternatives, we conducted a simulation-based Multi-Objective (MO) optimization using a 20,000-year Monte Carlo simulation. This method employs random sampling to model and analyze the impact of uncertainty across different scenarios, allowing for a thorough evaluation of each strategy's performance. In this context, the Monte Carlo simulation helps identify the best strategies by simulating thousands of potential outcomes and balancing multiple objectives. The process was organized as follows:

1.2.1. Dataset Preparation:

We generated a Monte Carlo dataset, comprising 20,000 years of stochastically independent and identically distributed realizations.

The first step involved fitting the simulated loss data points, which delineate the risk curve from Task 6.3, to an appropriate distribution. Several potential distributions were tested (see Figure 1), and the best-performing one, the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), was selected. Using this distribution, we generated 20,000 years of synthetic data to ensure a comprehensive and robust dataset for the Monte Carlo simulation.

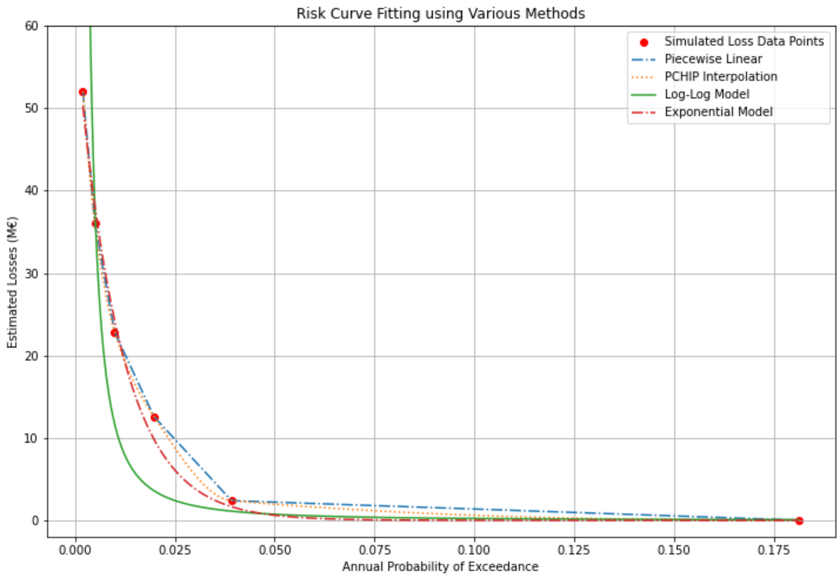

Figure 1. Risk Curve Fitting

This dataset is the historical as-if cash flow data from the "business as usual" scenario (scenario before the implementation of any financial strategy) and it provides the baseline financial losses that the strategies are intended to manage.

This dataset serves as input to the optimization and was organized into 1,000 realizations, each spanning 20 years, enabling us to assess the performance of strategies over short to medium-term horizons.

1.2.2. Optimization Objectives:

The optimization aimed to minimize two primary objectives:

1. **Total Financial Strategy Cost**: This includes the insurance loading (the actual cost of insurance policies) and the opportunity cost of the strategy. Opportunity cost refers to the value of the best alternative use of resources, such as investments, that are forgone by allocating liquidity to the reserve fund or insurance premiums.
2. **Average Annual Residual Loss (AARL)**: This measures the losses that remain uncovered after the implementation of the strategy, which has significant socio-economic and political implications. Minimizing AARL is crucial to ensuring the strategy effectively mitigates residual risks.

1.2.3. Optimization Variables:

The key decision variables optimized in this process included:

1. The allocation of the yearly budget between reserve fund intake and insurance premiums.
2. The percentage of risk transferred to a third party through insurance (insurance ceding).

3. The thresholds such as insurance deductibles and exhaustion points. These variables define the layered financial risk management strategy, determining the balance between immediate liquidity and long-term financial stability.

1.2.4. Constraints:

The optimization was constrained by the total yearly budget allocated for the strategy. This constraint ensures that the strategies are financially feasible within the available resources.

1.2.5. Optimization:

The simulation based multi-objective optimization (MO) problem was solved using an evolutionary algorithm (NSGAII). In solving MO problems, evolutionary algorithms are highly effective, drawing inspiration from natural evolution processes like selection, crossover, and mutation. These algorithms begin with a diverse set of potential solutions, each representing different combinations of decision variables such as budget allocation between reserve funds and insurance premiums.

To assess each solution, the algorithm evaluates its performance 1,000 times across a 20-year horizon, focusing on minimizing the total financial strategy cost and the Average Annual Residual Loss (AARL) in each scenario. The best-performing solutions are selected to form the next generation, mimicking natural selection. Through crossover, parts of selected solutions are combined to create new ones, mixing and matching traits to potentially produce better outcomes. Mutation introduces small random changes to maintain diversity and explore new areas in the solution space.

This process of selection, crossover, and mutation is repeated over many generations, with the population of solutions gradually improving. The algorithm converges towards the Pareto front, representing a set of optimal solutions where no single objective can be improved without worsening the other. For our problem, this means finding the best trade-offs between minimizing financial costs and residual losses.

Evolutionary algorithms excel in handling complex, nonlinear relationships between variables and provide a diverse set of high-quality solutions. This allows us to identify the most effective financial risk management strategies, making informed, robust decisions in the face of uncertain future scenarios.

1.2.6. Pareto Optimal Solutions:

Solutions on the Pareto front (see Figure 2) represent optimal trade-offs between minimizing the total strategy costs and AARL. Ideally, the most favourable solutions are positioned in the lower-left corner of the Pareto front, indicating strategies with both low insurance costs and minimal residual losses. Solutions above the Pareto front are considered suboptimal within our defined criteria, while those below are deemed unfeasible or beyond computational limits or the problem definition. A number of solutions (20) were homogeneously sampled from the optimal front for further analysis and comparison. Cashflow diagrams and attributes/parameters of each sampled strategy are included in the deliverables and can be interactively explored via the DSS tool (D6.7).

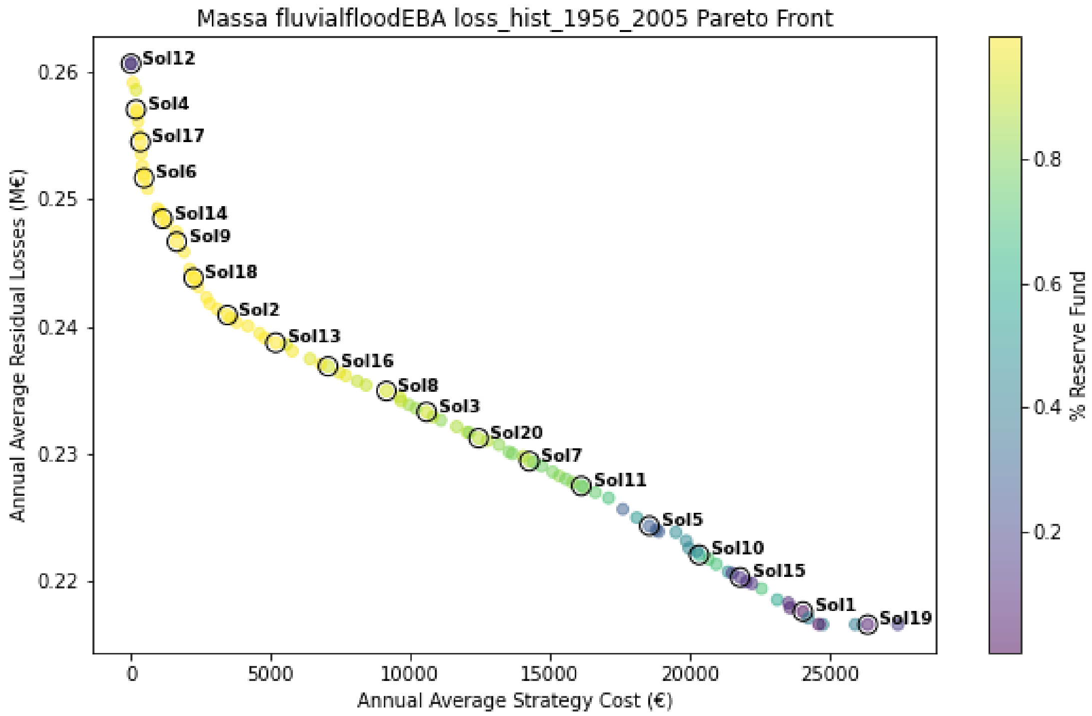

Figure 2. Example of Pareto Front and sampled solutions

1.3. DECISION SUPPORT SYSTEM (DSS)

The Decision Support System (DSS) is a specialized software developed in Python, designed to assist users in visualizing and selecting optimal financial risk management strategies. The DSS operates as follows:

1.3.1. Scenario Selection:

Users are first prompted to select a city and a scenario from the various available climate and temporal ones to be explored. This allows the DSS to tailor the visualization and analysis to the specific context of the chosen scenario.

1.3.2. Pareto Front Visualization:

Once a scenario is selected, the DSS displays the Pareto front showing the optimal solutions (see Figure 2). Each point on the Pareto front represents a layered strategy that combines reserve funds and insurance policies to achieve the best balance between minimizing costs and residual losses. Twenty strategies were homogeneously sampled from each Pareto front for further analysis. A table next to the Pareto displays attributes and parameters that define each sampled strategy.

1.3.3. Interactive Exploration:

Users can interact with the Pareto front by hovering over each point to visualize the value of the objectives and the budget distribution of each layered strategy. The figure can be zoomed in, the sampled solutions can be turned off. This feature allows users to explore different strategies and understand the trade-offs involved.

The user can also visualize the attributes of each sampled strategy and interact with them in a parallel coordinate plot which gives an idea of where each sampled solution stands in the attribute space. By selecting a solution, the corresponding line on the parallel plot is highlighted. This enables a deeper analysis of the selected strategies' implications and performance metrics.

Figure 3 shows screenshot of the tool. A video tutorial showing its potential use can be found in the deliverable folder (DSS_tutorial.mp4).

1.3.4. Detailed Analysis:

For the sampled solutions, the DSS provides detailed objective values, such as the total financial strategy cost and AARL and further metrics/attributes and graphs to fully explore and compare each optimal solution. This information helps users to make informed decisions based on quantifiable metrics.

The DSS also provides guidance to the full cash-flow data folder (D6.6) and presents comprehensive graphical representations of the strategies' performance. These visual aids enhance the understanding of the strategies' impact and help to communicate the results effectively.

By combining these elements, the DSS facilitates informed decision-making for city officials, ensuring that financial risk management strategies are both effective and feasible within the given constraints.

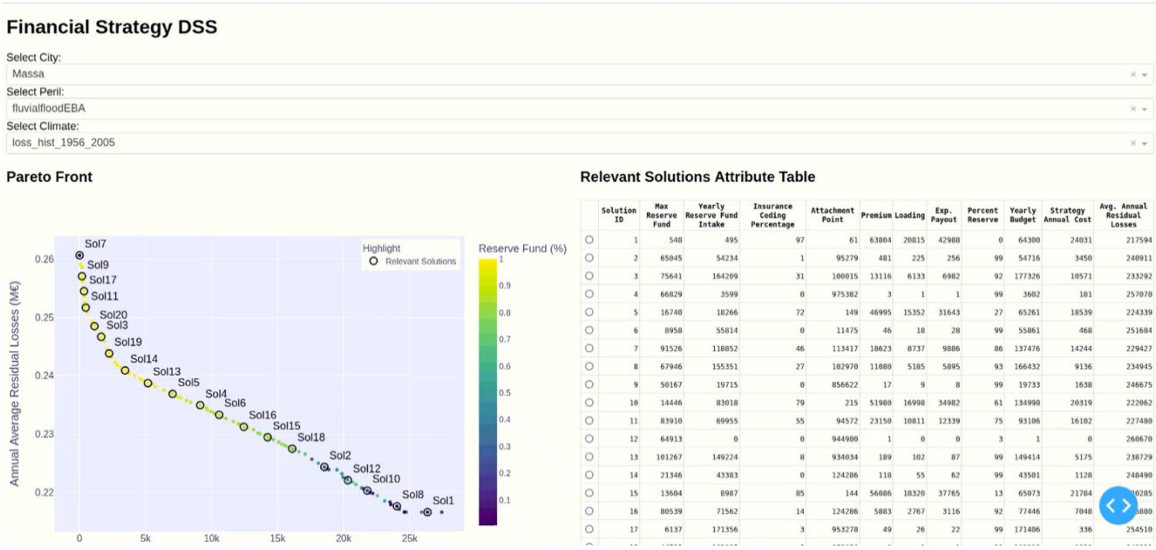

Figure 3. DSS tool demonstration

1.3.5. Contents of the deliverable folder

The D6.7 folder contains the following files and subfolders:

- app_DSS_Tool.py: This is the Python script that, when executed, generates the tool's web interface, allowing users to interact with the Decision Support System (DSS).
- DSS_tutorial.mp4: A video tutorial demonstrating the capabilities and functionalities of the DSS tool, guiding users on how to effectively use it.
- Pareto_solutions_figs: This subfolder contains .png figures of Pareto fronts for all city and scenario combinations, visualizing the trade-offs between the optimization objectives for different strategies.
- Pareto_solutions_attributes: For each city and scenario combination, this subfolder contains two files:
  - .csv file: A table listing all major attributes of the 20 sampled Pareto optimal solutions.
  - .pkl file: A structure file containing the same information for all Pareto solutions in a compressed format, readable in Python (pickle file).

The attribute values listed for each solution are as follows:

- **Max Reserve Fund (€)**: The maximum amount allocated to the reserve fund.
- **Yearly Reserve Fund Intake (€/year)**: The annual contribution to the reserve fund.
- **Insurance Ceding Percentage (%)**: The proportion of risk transferred to the insurance provider.
- **Attachment Point (€)**: The loss threshold above which the insurance coverage begins.
- **Exhaustion Point (€)**: The upper limit of the loss coverage provided by the insurance.
- **Premium (€/year)**: The annual payment for the insurance coverage.
- **Loading (€)**: The cost portion of the premium, reflecting administrative costs and profit margins.
- **Expected Payout (€/year)**: The average annual payout expected from the insurance policy.
- **Percent Reserve (%)**: The proportion of the yearly budget allocated to the reserve fund.
- **Yearly Budget (€/year)**: The total budget available annually for implementing the financial strategy.
- **Strategy Annual Cost (€/year)**: The total annual cost of the strategy, including both the opportunity cost (of both the reserve fund and insurance premium) and the loading
- **Average Annual Residual Losses (€/year)**: The average annual losses that remain uncovered after the strategy is implemented.