AI-Driven Tool for Climate Change Risk Assessment: An Application on Airports Adaptation.

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Abstract

In this study, we present an AI-powered Multi-Agent System (MAS) designed to assess climate risks through a structured, semi-quantitative framework based on the IPCC risk concept. The system is composed of thematic agents specialized in analyzing Exposure, Vulnerability, and Hazard. Each agent leverages specific data sources and tools, ranging from digital elevation models and land cover datasets to online research capabilities and gridded climate projections from CMIP6 models. We apply this framework to a case study involving seven Italian airports and four different climate hazards, demonstrating the potential of LLM-driven agents in supporting climate risk assessments for critical infrastructure.

Introduction

In the sixth Assessment Report (AR6), the Intergovernmental Panel on Climate Change (IPCC) has underlined how the concept of risk can serve as framework for understanding Climate Change, and its relationship with impacts and adaptation measures[1].

Risk is defined as the "result of the dynamic interactions between climate-related hazards [potential occurrence of a physical event] with the exposure [the presence of people or infrastructure that could be adversely affected] and vulnerability [the propensity to be adversely affected] of the affected human or ecological system to the hazards"[2].

This definition expands beyond the conventional view of risk as the product of likelihood and consequences of an event. It allows for a more comprehensive assessment of climate risk, which can also account for complex risks[3,4] and include physical hazards that are difficult to define in terms of probability, either because of their chronic nature or due to insufficient scientific understanding.

Concurrently, Climate Services[5], which are meant to provide the decision makers with the appropriate information and knowledge to address climate risks[6], still fall short of their potential and face numerous challenges, including relevance, interdisciplinarity, scalability, and the ability to meet the needs of decision-makers[7–9]. To address these challenges, Climate Services are increasingly integrating emerging technologies, particularly Machine Learning (ML) and Artificial Intelligence (AI), to enhance key components of their value chain, including data assimilation, predictive modeling, uncertainty quantification, and knowledge synthesis[10–13].

As Large Language Models (LLMs) gain prominence, the climate scientific community has commenced to investigate their potential within Climate Services applications[14]. With the rapid advancement of LLMs and the introduction of concepts such as Artificial Intelligence Autonomous Agents and Augmented Language Models (ALMs)[15], it has become evident that LLMs can be effectively instructed to perform highly specialized tasks with remarkable precision. In some instances, their performance surpasses that of highly educated humans.

However, intricate tasks frequently demand multidisciplinary expertise and surpass the capabilities of a single AI agent. Consequently, Multi-Agent Systems (MAS)[16] have emerged, wherein multiple autonomous agents collaborate within a structured framework to solve complex problems. When powered by AI, MAS can replicate human-like collaboration, enabling distributed reasoning, task delegation, and dynamic problem-solving.

Here, we present an AI-driven Multi-Agent System (MAS) designed to perform climate change risk assessments in alignment with the conceptual framework defined by the IPCC AR6. The proposed system leverages the coordinated interaction of specialized AI agents within a modular and extensible architecture.

With this work we aim to demonstrate the feasibility of applying AI-powered MAS to highly specific and multidisciplinary contexts, such as climate change risk assessment, where diverse expertise and heterogeneous data sources must be integrated coherently. Moreover, it lays the groundwork for the operational use of such systems in Climate Services, highlighting their potential to evolve alongside the rapid advancements in Large Language Models (LLMs) and domain-specialized AI agents.

We conducted a case study of seven selected Italian airports to assess the risk associated with four distinct climate hazards: heatwaves, cold waves, extreme rainfall, and droughts. As many other critical infrastructure, airports are expected to face significant material impacts related to Climate Change[17–21].

Methods

Architecture

The proposed tool is based on a Large Language Model (LLM) driven Multi-Agent System. The architecture consists of three main thematic agents, each responsible for conducting an analysis related to Exposure, Vulnerability, and Hazard, respectively. Each agent is equipped with a distinct set of capabilities tailored to its specific task. These agents generate detailed technical reports outlining the analytical procedures and key findings.

Subsequently, the risk is defined using a semi-quantitative approach, which mathematically formalizes the approach of the so-called risk matrices[22,23].

A Risk Synthesis Agent assigns standardized scores for Exposure (0–5), Vulnerability (1–5), and Hazard (1–5), along with a rationale justifying each score. The overall risk score is then computed with the following procedure: i) the three scores are multiplied to obtain a preliminary risk score (r), ii) the final risk score is obtained as:

$$R = 5\left(1 + e^{-k(r-r_0)}\right)^{-1} \qquad Eq.1$$

This normalization step is based on a logistic function and serves to mitigate the disproportionate compression of intermediate-to-high risk combinations that arises from the direct multiplication of the three scores. We set $k = 0.8$ to assure a moderate slope, and $r_0 = 30$ to assure that a combination of medium hazard, exposure and vulnerability (≈ 3) results in a medium risk. The final risk R is thus a numerical decimal value in the range 0 to 5.

Once this procedure has been executed for each combination of airport and climate hazard defined, a Review Agent assesses the consistency of the entire analysis and identifies potential concerns. This also serves as evaluation method for the tool, following the concept of 'LLM as a judge'[24,25], based on the evidence that LLMs have some ability to express their internal confidence level when generating content[26]. The combinations of climate hazard-airport that are flagged are subsequently reviewed by thematic agents, who are specifically instructed to repeat the analysis while incorporating the observations made by the Review Agent.

Thematic agents

Each thematic agent has been augmented with the capability to interact with a set of tools suitable for the given task:

- The Exposure Agent can retrieve key environmental factors.
- The Vulnerability Agent can conduct online research on the internet and provide a concise summary of the findings.
- The Hazard Agent has the capability to access a large dataset of gridded climate indicators at high resolution (0.25°x0.25° latitude x longitude), derived from an ensemble of CMIP6 models and distributed by the World Bank Climate Change Knowledge Portal[27].

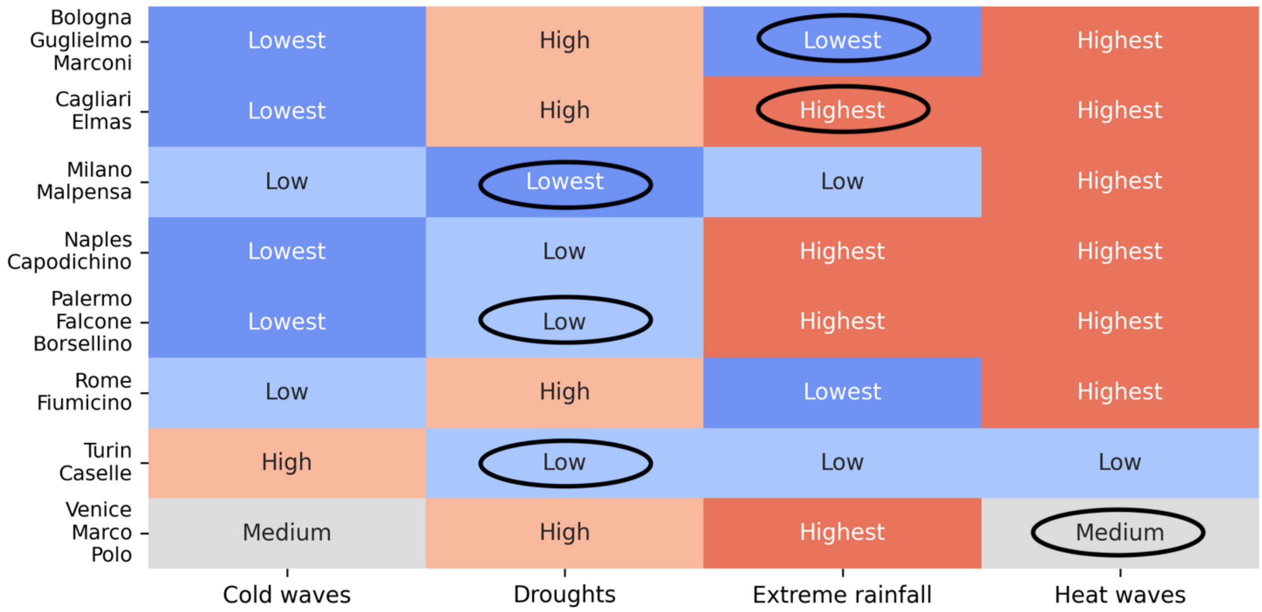

Figure 1 *- Risks Identified in the Initial Analysis. To enhance the representation, the final risk has been categorized into five classes (Lowest, Low, Medium, High, and Highest) based on the numerical risk result, which was previously on a scale of 0 to 5. Black circles indicate the results that were flagged by the Review Age*

Case study

We applied the tool to a set of seven Italian Airports: Milano Malpensa, Torino Caselle, Venezia Marco Polo, Bologna Marconi, Roma Fiumicino, Cagliari Elmas, Napoli Capodichino, and Palermo Falcone-Borsellino. We extended the analysis on four climate hazards: heat waves, cold waves, drought and extreme rainfall. Additionally, we specifically requested the Hazard Agent to focus the analysis on the scenario SSP 2-4.5 for the year 2050.

The initial iteration of the tool engages all thematic agents for each combination of Airport and Climate Hazard. Subsequently, the Risk Synthesis Agent assigns scores to each determinant (Hazard, Exposure, and Vulnerability), and the final risk is computed based on Eq. 1. Finally, the Review Agent identifies critical analysis that necessitates control (***Figure 1***).

The Review Agent identified six analysis areas that required revision. Five of these areas resulted in an escalation of the overall risk score, while one area led to a reduction (**Figure 2**).

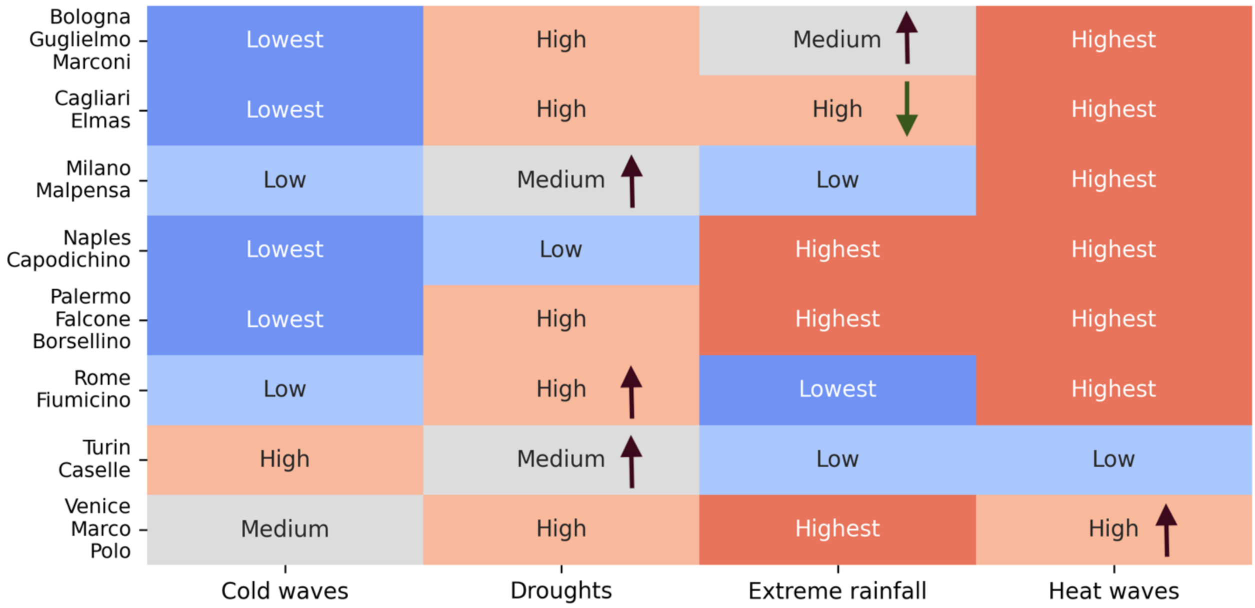

Figure 2 *- Final Risks after the reanalysis triggered by the Review Agent. Arrows quantifies the changes in the Final Risk after the reanalysis.*

Conclusion

Addressing climate-related risks is a multifaceted subject that necessitates an initial analysis, commonly referred to as a Climate Change Risk Assessment. This analysis demands multidisciplinary expertise and the delineation of an analysis context that presents substantial challenges to Climate Services providers.

In this research, we developed an AI-powered MAS based on LLMs to conduct this type of analysis. Our approach is grounded in the risk framework outlined by IPCC-AR6. We have incorporated three distinct thematic agents, each with specialized capabilities for assessing Exposure, Vulnerability, and Hazard. These assessments serve as the basis for semi-quantitative evaluation of the overall risk.

This approach has facilitated the integration of diverse data sources, including a substantial repository of climate indicators' projections and unstructured information obtained through web research, into a seamless workflow. Leveraging the textual capabilities of LLMs, each stage of the process is accessible to a human reviewer, thereby mitigating the black box phenomenon.

It is noteworthy that this aspect is not a secondary consideration. Climate Change Risk, particularly within the context outlined by the IPCC AR6, is a highly subjective and context-dependent process. In such a scenario, the comprehension of the underlying factors that influence the outcomes holds greater significance than the outcomes themselves.

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