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# Making Climate AI Systems Past and Future Aware to Better Evaluate Climate Change Policies

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## Abstract

Addressing the issues faced by climate change necessitates appropriate methodologies for evaluating climate policies, particularly when discussing long-term and real-world scenarios. While large language models (LLMs) have altered artificial intelligence, they ultimately fall short of connecting historical data with future estimates. We propose an agentic LLM system that would address this gap by considering and analyzing the probable outcomes of the user-specified climate policy inside the practical settings. Further, we propose using knowledge graphs to model the existing data about the impact of climate policies along with allowing our system to access the data about future climate predictions. Done this way, the model can peek into the past (previous policies) and the future (climate scenarios forecast), paving the way for agencies to evaluate and design strategies and plans for climate change more effectively.

## 1 Introduction

Climate change’s growing urgency has motivated a variety of stakeholders, including governments, non-governmental organizations (NGOs), and researchers, to develop and implement climate policies aimed at lowering greenhouse gas emissions and strengthening resilience to climate effects [1]. However, these regulations usually emphasize short-term effectiveness and regulatory compliance, frequently overlooking long-term consequences and the intricate interdependencies that characterize climate systems [2].

Current Large Language Models (LLMs) represent tremendous advances in artificial intelligence in recent years [3], but they have limits for assessing climate policy. Specifically, these models [4] fall short of integrating the extensive diversity of information required for measuring policy success [5], risking missing out on crucial aspects of a program’s influence [6]. Furthermore, many LLMs must be trained to predict future climatic conditions precisely, complicating their capacity to produce dependable long-term projections [7].

To address these difficulties we suggest using an agentic LLM system that can access and integrate many sources of information, such as databases containing comprehensive future climate projections, past policy data, and their results. This methodology seeks to bridge the significant gap in current methodologies: inadequate integration of historical data with predictive climate modelling. While current frameworks thoroughly examine previous policies [8], there is a noteworthy paucity of instruments for accurately forecasting the impacts of future policies in the context of changing climatic circumstances. Our suggested method bridges this gap, enabling agencies to make more informed and effective climate policy decisions.

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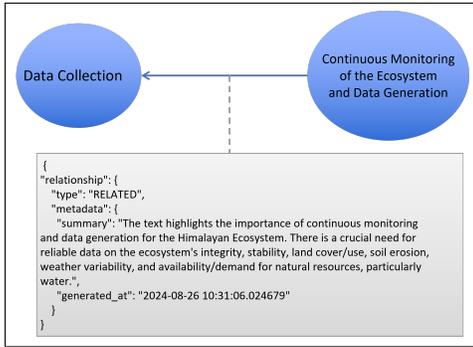


Figure 1: Node of Knowledge Graph

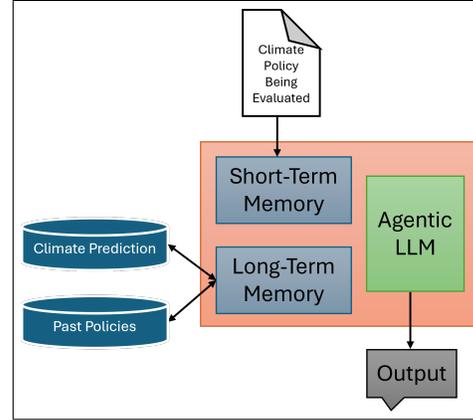


Figure 2: Proposed Agentic LLM

## 2 Proposed Solution

### 2.1 Knowledge Graphs

Our method will build Knowledge Graphs (KGs) [9] to produce a structured representation of past climate policies, reports, and associated data. The LLM agent can better comprehend the links between different policies, the conditions under which they were executed, and their subsequent influence on climate variables if they can access a KG that captures all of this historical background. This contextual awareness enables a more informed appraisal of future policy design, ensuring that the LLM agent considers lessons from earlier endeavours.

Figure 1 depicts a KG node for "Continuous Monitoring of the Ecosystem and Data Generation" in the Himalayan Ecosystem, with further information offered in a "summary" field created using NMSHE Mission document<sup>2</sup>. This graph was generated using Graph Maker<sup>3</sup>. Integrating such nodes into our KG improves the LLM's capacity to analyze and anticipate the impact of new climate policies.

### 2.2 Accessing Climate Forecasting Data

In addition to being able to access past data, we propose that our system should be able to access a curated summary of data from climate forecasting models to evaluate the possible long-term effects of the policies being evaluated. Our motivation for this is an open-source example of such an LLM agent based system - climate-change-assistant<sup>4</sup>. It provides a summary of the climate data for any geographic location worldwide for conditions such as heat, humidity, drought, precipitation, and storms under various warming scenarios. Building on that idea, our system could potentially have access to a diverse set of sources, such as ocean currents, air currents and any other geological data relevant to the policy being evaluated.

### 2.3 Putting it all together

Integrating KGs (having information about past policies and future prediction) into the LLM agent [10] provides a promising framework for assessing climate policy. This method allows for the simultaneous examination of historical outcomes and future forecasts, resulting in more relevant and successful evaluations of currently active climate policies. This tool allows policymakers to investigate various policy alternatives, understand their possible consequences, and make educated decisions that balance urgent requirements with long-term sustainability. The proposed LLM agent promises a big step forward in climate policy evaluation by combining the capabilities of historical data, predictive modelling, and sophisticated natural language processing.

<sup>2</sup>NMSHE Mission document

<sup>3</sup>Graph Maker

<sup>4</sup>climate-change-assistant

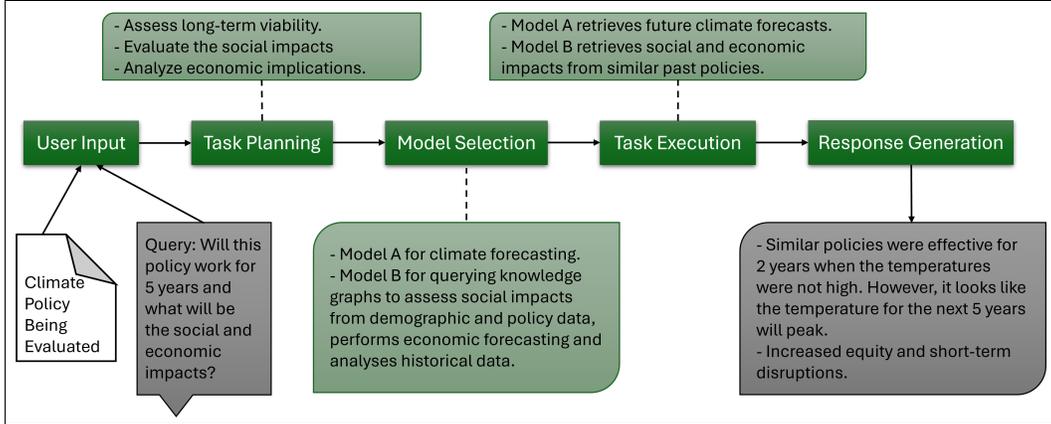


Figure 3: Workflow of the proposed Agentic LLM system for evaluating climate policy

Figure 2 depicts our proposed agentic LLM system that uses short-term and long-term memory [11] to evaluate climate policy. Short-term memory stores the policy being assessed, and long-term memory keeps data from climate predictions and prior policies.

Figure 3 illustrates the system’s process [12], which begins with user inquiries concerning a policy’s long-term implications. The system next performs task planning, analyzing the query, followed by model selection, which selects a model for each task. Finally, during execution, the system obtains climatic projections and historical data to assess the policy’s efficacy.

### 3 Impact of the Proposed Solution

Integrating LLMs and KGs into the proposed framework has multiple advantages, including improved analytical skills, the capacity to handle and process massive volumes of data, and the flexibility to adapt to various policy circumstances. However, the computing resources required to maintain and run such models are enormous, raising questions about their environmental impact. The suggested LLM agent addresses these difficulties in two ways. First, the KG creation is a one-time process and further, its structure could be standardized by allowing multiple sources of data to be combined in a centralized open-source data repository. Second, since the creation of the KG already takes care of building appropriate relationships in the past data, the LLM agent can attend to the most relevant pieces in the data, do tailored analyses and ensure that computing resources are used efficiently while maintaining assessment quality.

### 4 Conclusion

Our proposed agentic LLM system substantially contributes to climate policy evaluation by bridging the gap between historical data and future estimates. By combining past policy reports with the future using Knowledge Graph, the system provides a complete framework for evaluating the possible long-term effects of climate policy. This technique helps policymakers make better judgments by offering a more sophisticated knowledge of previous policy effects and projected future situations. As a result, our system promises improvements in the accuracy and relevance of climate policy assessments. It could help develop strategies that balance immediate goals with long-term sustainability, resulting in more effective climate change mitigation and adaptation efforts.

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