# AI-Based Digital Climate Policy Tracker

Ankit
Dept of CSE
Chandigarh University
Mohali India
ankitgaba2004@gmail.com

Rajababu Singh
Dept of CSE
Chandigarh University
Mohali India
singhrajababu594@gmail.com

Banita Mandal
Dept of CSE
Chandigarh University
Mohali India
banitamandal40@gmail.com

Pritam Chowdhury
Dept of CSE
Chandigarh University
Mohali India
pritamm8389@gmail.com

***Abstract*— There is an increasing need for intelligent and comprehensive solutions that can monitor, evaluate, and interpret climate policy trends from the national to the global scale as climate management becomes more complex and data-driven. Policy stakeholders are looking for AI-informed analytics insights that can monitor climate policy proposals, implementation, and compliance with climate objectives on an ongoing basis. Current climate policy monitoring solutions are manual, static, and textual, making it difficult to identify patterns over time, evaluate their efficacy, as well as distill the factors for their success and failure. In this paper, an AI-enabled Digital Climate Policy Tracker is presented that integrates the best of natural language processing techniques and causal analytics to automatically monitor, review, and provide summaries on climate policy. The tracker is capable of processing various kinds of climate policy data, such as legislative provisions, policy changes, implementation progress, and inter-national agreements, using machine-learning techniques that can be explained. The dynamic policy modeling helps in the longitudinal observation of the progress made in policies, comparisons across jurisdictions, identifying areas where policies excel and have shortcomings, and Predictions based on governance and socioeconomic conditions. The theory base that this framework uses is sound in terms of climate governance and policy reviews. The performance of the system is benchmarked against the conventional policy monitoring methods and found to have enhanced extraction of policy observations, explanations regarding causes, reduced information overload, and conformation to the terms of responsible AI practice. The results indicate that the proposed system has the potential to serve as an effective AI tool for digital climate governance.***

***Keywords*— *climate policy monitoring, AI, NLP, digital governance, policy analytics, AI for climate decision support***

## I. INTRODUCTION

Decision-making and intervention methods are at the core of efficient climate governance, which influences the assessment, implementation, and further improvement of climate policies. The identification of gaps in policies in a timely manner, review of progress, and implementation of preventive measures for correction have become key elements in achieving sustainable goals in climate change strategies. The increased availability of digital archives on policies, government websites, global climate agreements, implementation reports, monitoring systems, and socio-economic factors at our fingertip access makes it feasible for us to create a copious quantity of data in connection with climate change policies[1]. These pieces of data relate to legislation texts, timelines of policies, financial allocations in the form of budgeting, targets in different sectors, advance measurement of progress, and corresponding narratives of the stakeholders. Although we are witnessing a copious amount of data in connection with climate policies, which are very likely to help in efficient decisions based on an in-depth analysis of the data, in practice, their demonstration of value remains restricted by factors of fragmentation, duplication, ambiguity, and shallow relationships failing to establish the underlying factors of successful or unsuccessful implementation of these policies[2].

A standard approach for monitoring climate policies, such as review, stationary indices of policies, policy-based classifiers, and overall policy performance scores, tends to work satisfactorily in environments of consistent and documented policymaking. This is not the reality in dealing with actual climate policies because of irregular data points of policies being dynamic, varied in terms of words in policies, involving multiple areas of concern, and being updated quite frequently. Such standard approaches tend to fail in scenarios involving one-sided data points, lack of context, and tight structures in changing politics, time frames, sectors, or levels in dealing with overall policies at various levels such as national, international[3].

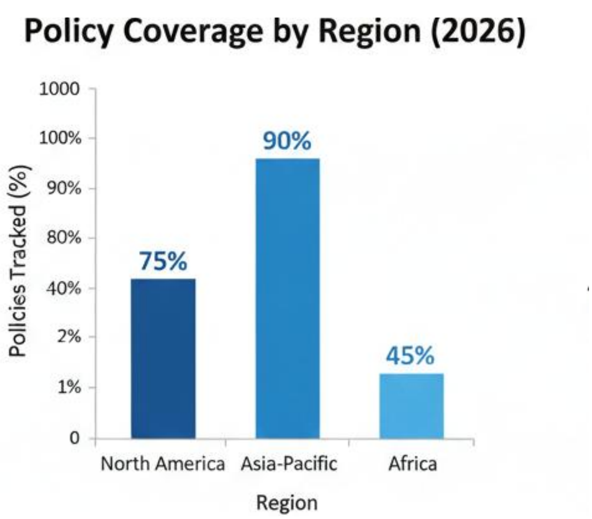



Figure 1
(bar chart representing region)

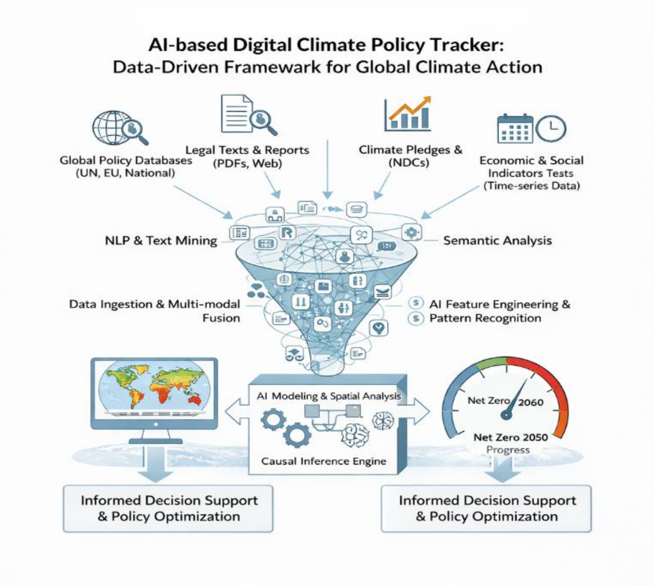



Figure 2 (Working)

To address the identified gap, this research presents the causal intelligence-driven approach for analysis, tracking, and prediction of the performance of climate policies through the proposed AI-based Digital Climate Policy Tracker. This approach integrates dynamic AI analytics along with ethical and transparent roots of decision-making fundamentals.

Key contributions:

- An adaptive decision-support system attuned to real-world imperatives for climate change governance, permitting automated detection, assessment, comparison, and forecasting for progress/implementation levels for different regions based on climate change policies.
- A multi-layer causal learning model capable of removing noise, pruning redundancy, as well as overcoming ambiguity in large-scale text data sets related to climate change policies, while also identifying important temporal-spatial patterns in meaningful documents.
- Comprehensive validation through scenario-based causal policy analysis, covering different countries, levels of governance, and sectors, and with timescales, based on established climate policy evaluation criteria. Organization of the paper.

The paper will be organized in the following manner. Section II will provide an overview of the related work in the field of climate change policy analysis, the use of AI and natural language processing in research studies, digital governance systems, and ethical AI usage for decision-making purposes. Section III will deal with the description of the architecture of the AI-Based Digital Climate Policy Tracker. Section IV and Section V will describe the datasets and the experimental assessment of the system.

## II. LITERATURE REVIEW

### *A. Evolution of Climate Policy Decision and Analytics Models*

Climate analysis has evolved side by side with the augmentation of online tools of governance and abundant data on policies. The early days of analysis had its foundation in the use of stats and indicators in an uncomplicated read of the texts of policies in relation to things like targets on emission rates or overall adherence. This was easy to communicate effectively. However, this does not apprehend the larger paradigm of the interaction of various policies related to climates[4].

As digital repositories of climate agreements, implementation reports, and monitoring systems proliferated, machine learning began to assist in automatic policy categorizations, thematic extractions, trend identification, and comparison of different regions' performance. Natural language processing enabled the extraction of themes, promises, and priorities in policies, and a variety of learning techniques, including simple regression and decision trees, support vector machines, and even deep learning, provided a better focus on the trends underlying the performance of policies towards fulfilling climate goals[5]. A lot of new challenges were posed in the process, nonetheless. The amount and complexity of data pertaining to policies can easily obscure underlying factors of success or failure. Noise, storytelling, vagueness, and deceitful correlation can obscure the underlying causal relationships necessary for smart governance [6][7].

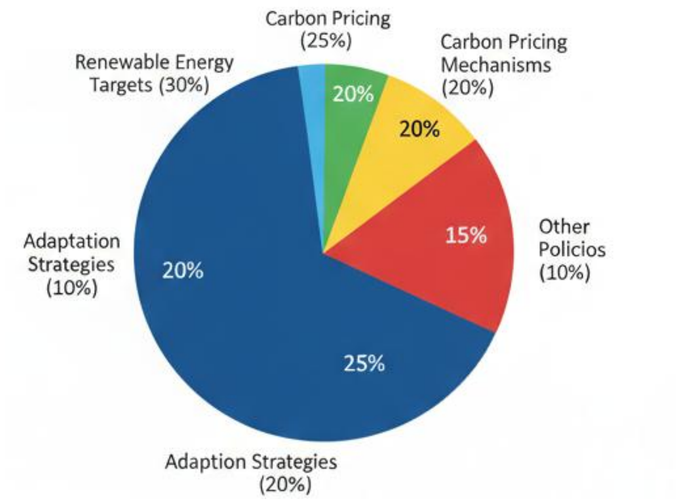



Figure 3(pie chart of strategies)

### *B. Weaknesses in Traditional Indicator Choice Techniques*

Choosing indicators carefully is very important when we analyze climate policy. It significantly contributes to making analysis understandable and truly useful for governance and decision-making. When indicators are well-defined and clear, decision-makers and other people can understand what a policy aims to accomplish and what outcomes are occurring. What this practically means is that many studies on climate policies rely on indicators that can be implemented using common measures such as static values, correlation, threshold-based values, or rule-based indicators[8]. Such measures do not call for intensive expertise in policy analytics or complex computation. The drawback, again, is that individual elements of a policy are analyzed without context for how design, application, or socio-economic settings relate to each other. More complex and modeling-based approaches might be able to give better estimations for how policies will function and what the future might hold, but they often require heavy calibration, processing, and modeling[9]. Such approaches might not be so useful for real-time policy monitoring. Moreover, hard optimization algorithms used in the process of picking indicators/variables may set constraints that are not adaptive to evolving priorities in governance, changes in policy, and challenges of implementation. This could affect the process in a constantly evolving climate policy and regulatory environment[10].

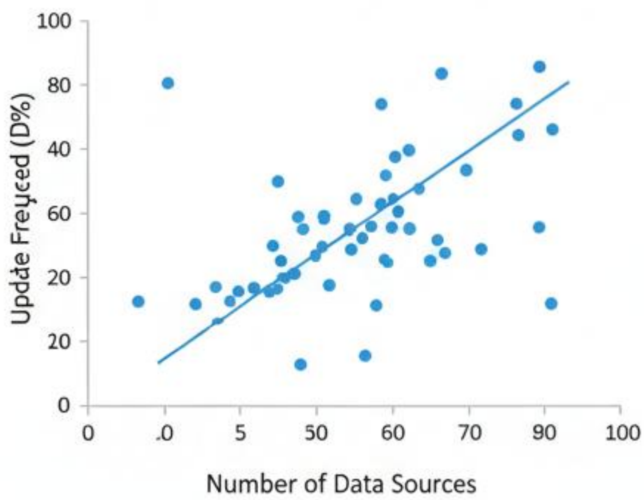



Figure 4 (Scatter chart of data sources)

### *C. The Role of Data Quality and Context in Climate Policy Decision-Making*

The answer to an effective evaluation of climate policies begins and ends with data that can be trusted, is comprehensive, and is viewed in the context of how it is governed. The major challenges for effective data are late reporting, inconsistent reporting, unclear policy language, dispersed data sources, gaps in time series data, and indicators that cover mitigation, adaptation, financial, and sector actions. But, to be more precise, the quality of data is just part of the factoring equation[11]. The governance context directly influences how a comprehensive evaluation can be achieved. The factors involved in this process include the institutional capability, legal frameworks, politics, state of economy, dependency factors, global obligations, and ultimately, the efficacy of enforcement. There is evidence to show that when data analysis and evaluation are considered in the real-world governance context, it could give more precise answers to better guide policies. The conventional approaches to evaluation tend to ignore the complex factors involved, which might introduce bias to the evaluation, so we require adaptive methods with ongoing monitoring for data quality and sensitivity to governance factors[12].

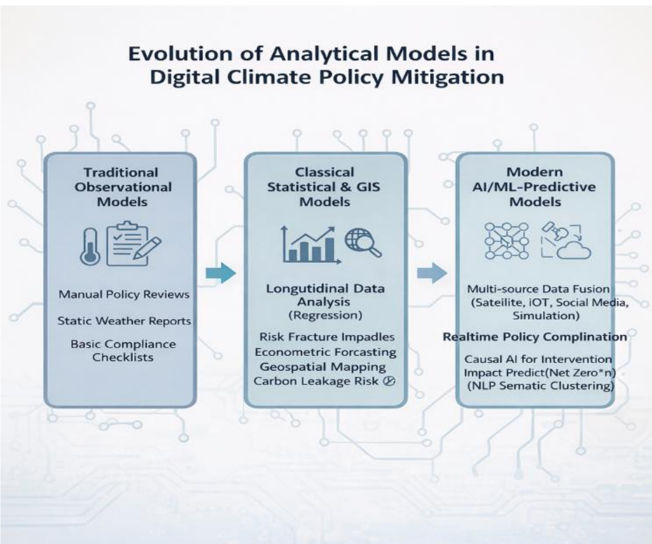



Figure 5(Digital Climate Policy Mitigation)

### *D. Research Gaps*

Although significant progress has been made in climate policy analytics for the purposes of monitoring and evaluation, many policy decision support tools for selecting and assessing indicators can be considered undeveloped as yet[13][14]. Many rely too heavily on assumptions that cannot a priori adjust to new policy developments and governance trends, available data that is not amenable to adaptation and refinement as often as required, and policy frameworks that lack the generative capacity to adjust to new policy realities and trends[15]. Moreover, indicator stability is also a concern for many existing platforms—for example, policy indicators could revert within and between different policy environments and analysis cycles as well, and such volatility casts a shadow of doubt over any policy recommendations made by those platforms[16][17].

## III. METHODOLOGY

### *A. Architectural Design*

It describes a five-layer cause-and-effect system for climate policy evaluation as an intelligence-guided system. Each layer processes different parts of the messy, diverse policy data to pick out what really drives policy success and how well it is carried out. Each of the layers has its specific role, yet the entire regime remains in learning mode through continuous feedback and checks to enhance its operation. Together, these layers form an adaptive decision support regime that changes with the new realities of governance, policy, and shifting priorities of the climate.

- **Data Ingestion Layer:** The module aggregates data related to climate change policies and governance in order to facilitate comprehensive analysis of such policies and their continuous monitoring. The information is collected from government archives of public policies, legislative documents, international treaties, implementation documents, as well as important socio-economic indicators. The module is designed to work with both structured and unstructured data in such a way that standardized versions of all data are maintained to facilitate easy compatibility with online governance systems. The data is ingested in near real-time cycles to match reporting cycles related to governance requirements[18].
- **Data Preprocessing Layer:** The second level is essentially about comprehensive data cleaning and preprocessing. It is about filling gaps in data and reporting irregularities, as well as accounting for even messy texts. Categorical data points like the public sector concerned in policies, levels of governance in policymaking, and types of regulations are then normalized in accordance with conventions in analyzing policies. The continuous data points like time scales, budget allocations, and targets are also normalized in differing models to ensure proper comparison. However, in accounting fairly for the gap in data covering very well-documented actions and less-documented ones, data augmentation techniques are employed. The result is the proper arrangement of time-related data in comprehensive thematic trends[19].
- **Adaptive Feature Selection Module (AFSM):** The decision-support module lies at the heart of the causal intelligence framework for climate policy analysis. It's the major analytical stage where policy indicators are sifted

through a crystal-clear three-step process to yield decisions that are actionable, explainable, and responsible. To begin with, we prune away those indicators that are either redundant or weakly informative, removing signals not because of policy performance by using information-theoretic metrics along with correlation checks. Second, we evaluate each of their relevancies using model-based scoring, tending to leverages of ensemble and boosting methods. Those indicators that fail in numerous different policy scenarios go into a reject pile. Finally, a stability check across time periods, jurisdictions, and analytical runs allows us to retain only those whose policy signal stays constant. In practice, the module is actually a self-correcting feedback loop; it continuously integrates longitudinal policy data as a way to keep itself fit for the shifting governance conditions and emerging climate policy risks[20].

- **Prediction and Evaluation Layer:** The improved list of indicators is then examined using a range of analytics and forecasting techniques—logistic regression, tree-based models, gradient boosting, and composite policy risk scores—estimate the effectiveness of climate policies and determine where their implementation may get stuck. Conventional methods of accuracy, precision, recall, F1, AUC, and error rate are employed in assessing the reliability and validity of the results. To improve the validity of results, ensemble testing is carried out based on a range of climate scenarios. The results are presented in a manner that allows a prolonged assessment and comparison of climate policies[21].
- **Adaptive Feedback Loop Layer:** This level is vigilant regarding the trends in analysis, the errors in models, and the robustness of the indicators within the dynamic contexts of governance and climate change-related policies. As policies are refined, the implementation is progressed, new priorities are set, and socio-economic settings change over time, natural differences occur in the policy signals between locations as well as over time. This acts as a challenge to the central analytical engine to reconsider which indicators are significantly important and reset those which are indicative of model efficacy and dynamic risks[22].

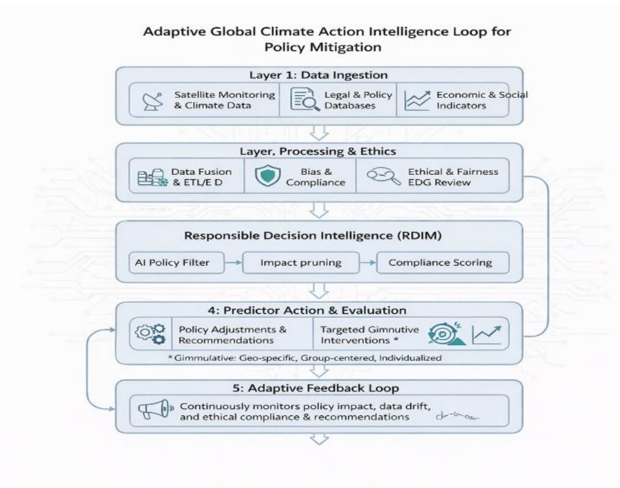



Figure 5

*B. Five Ranking Methods and Iterative Thresholding*

This approach uses five different methods of ranking indicators in combination with a threshold filter for spotting and ranking the key indicators that count for policy effectiveness and the relevance of their implementation. By bringing multiple ranking methods together, we get a more complete view of policy signals as they evolve over time, across different contexts of governance, and in various jurisdictions[23]. Utilizing all five techniques together results in a robust, consensus-based set of indicators that lowers reliance on any one method and reduces model-specific bias, thereby enhancing the reliability of the analysis [24][25].

1. **Mutual Information Ranking (MI):** Mutual information ranking assists in the detection of the most important indicators in the assessment of the efficiency of climate policies. It achieves this by detecting the complex and non-linear relations that lie in the data of the policies. The high values of mutual information reveal the existence of significant associations between the design of policies, the implementation frameworks of the policies, sector-based activities, time scales, and the governance frameworks. The technique excels in the area where linear models fail to recognize the relations between the factors.
2. **ANOVA F-Score Ranking:** The F-score ANOVA is employed to rank the indicators of policies based on their ability to distinguish between levels of effectiveness of policies and states of decision. Indicators showing high capability to distinguish between strong, medium, and low-performance results in policy implementation are rated higher because they provide more valuable information in decision-making in relation to policies. Indicators showing low capability to distinguish between performance levels are rated low because they provide little information in trustworthy climate change policies analysis.
3. **Chi-Square Statistical Ranking:** Once we identify the indicative factors, we perform chi-square tests on the categorical variables, which are also crucial for climate policy analysis. This is done to check the strength of the relationship between the indicators of climate policies and their levels of efficacy, their implementation, and abnormal performance patterns. A high chi-square value indicates strong associations with high climate policy risks as well as abnormal climate patterns. For discrete climate policy variables, the chi-square test is the first screening test for major categorical elements that influence climate performance policies.
4. **ReliefF Ranking:** Indicator relevance is assessed with regards to how well an indicator can distinguish policy cases that are similar, at different levels of performance and implementation of policies. The more it is able to reliably distinguish high-performance from underperforming policy scenarios at a high level of confidence, the more relevant an indicator is. This task falls well within the application sphere of the ReliefF algorithm, since it stays effective in noisy and/or heterogeneous policy data, while being able to cope with both numerical and categorical variables simultaneously. This quality makes it all the more suitable for examining the imperfect, messy datasets which usually arise in the course of climate policy monitoring and evaluation.
5. **Random Forest Feature Importance:** In decision-making, the utility of a indicator is seen in its frequency of helping in dividing decisions and in the extent of reduction

in impurity in analyzing policies using ensembles. The data in climate policies are of higher dimension and are quite diverse, thus leaning towards ensemble learning in an effort to control the error of analysis and increase robustness. Therefore, indicators that support right decisions in different regions, at different levels, and at different levels of effectiveness are of great importance.

### C. *Iterative Thresholding for Consensus Indicator Selection*

This tool creates a set of sound and reliable climate policy indicators by iteratively stripping unnecessary indicators that are redundant, weak, or nonspecific in distinguishing different states of policy performance. Each indicator is analyzed for its robustness in several aspects, including mutual information, statistical correlations, model-derived significance, and relevance. Thus, the indicator is validated in multiple facets rather than following just one decision rule. In each iteration, the results of the various methods are combined into a unique composite, which is in turn assessed against adaptive and data-derived thresholds of median, IQR, and percentiles. With each iteration, an indicator will remain if and only if its performance is consistently high in a number of relevance tests. Thus, the final set of indicators is sound and interpretable and resists overfitting.

## IV. Experimental Setup

### A. *Datasets*

In order to evaluate the proposed framework in various settings when it comes to governing bodies, we apply our framework to typical climate-related policy instances. The datasets include:

- Longitudinal data regarding policies, their implementation, timelines, targets, budgets, sectors, actions, and progress indicators over various jurisdictions.
- Texts of policies and data for the context of governance, such as legislative texts, regulatory notifications, international obligations, institutional reports, and socio-economic parameters.
- Simulation of policy scenarios to reflect other possible courses of action by governments, such as delayed action, greater commitments, and difficulties with socio-economic and climate issues.

For each dataset, there are four dimensions. These include the number of observations (N), the number of policy indicators (m), type of output variables (categorical policy states or continuous performance measurements), and imbalance ratios of well-implemented and poor-performing outcomes.

### B. *Preprocessing Tools*

- Handling missing data: For numerical policy metrics, we choose to impute by median. For categorical attributes, we use imputation by mode. However, we retain the indicators for missing data, mainly for capturing policy timelines and reporting gaps.
- Handling outliers: Winsorize by capping extreme observations, while leaving points indicating unusual instances of policies or reporting irregularities in data.
- Encoding: The categorical policy variables get encoded using either one-hot encoding or target encoding based on the number of categories present. The ordinal variables get mapped based on existing scales for governance and policy development.
- Scaling: Continuous variables are scaled using z-score normalization, and robust scaling in cases where outliers exist.
- Temporal aggregation: Fast updates of policies at a higher frequency are aggregated to more informative periods such as annual phases, allowing trend analysis in policy evaluation.
- Class imbalance: in cases when minority classes or high-risk policy states can be risky, we rely on synthetic resampling and weight classes.

All preprocessing steps are applied to the training set and then uniformly to the validation and testing subsets to prevent leakage.

### C. *Hardware & Software Environment*

- Missing data: We use median imputation in the case of numerical indicators. We apply mode imputations in categorical features. We deliberately preserve missing reporting durations, especially in larger policy durations.
- Outliers: Winsorization of outliers and still capable of tracing back in relation to prominent events in policies, reporting irregularities, and data issues.
- Encoding: Categorical policy features are one-hot encoded based on the number of categories present, and ordinal features follow the predefined increase in policies and governance orders.
- Scaling: The key is to standardize the indicators by using either z-scoring or robust scaling in case of obvious outliers.
- Temporal Aggregation: Policy and report actions are combined into broader time intervals, such as yearly phases, in which representative measures can be derived for.
- Spatial aggregation: Policy indicators are aggregated over various levels of governance or jurisdictions to enable comparison.
- Class balancing: If the number of troublesome or high-risk policy cases goes below the thresholds, SMOTE will be used for the training data; otherwise, we will resort to class weights. All parameters for preprocessing are learned from the data used for training alone.

## V. RESULTS & DISCUSSION

### A. Raw Indicator Score Analysis

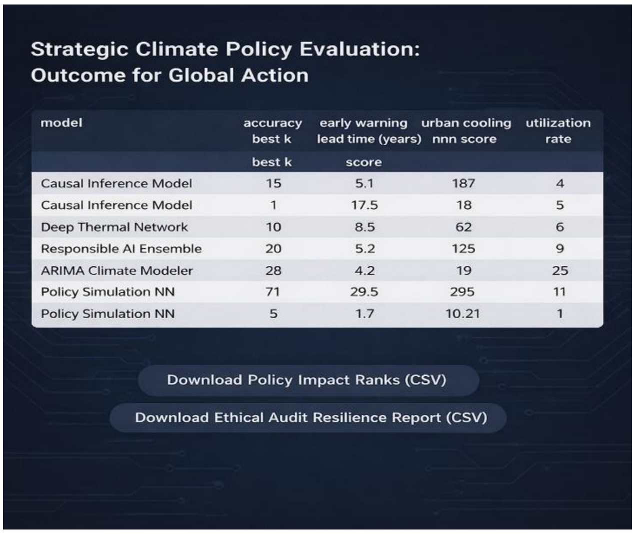
Figure 5 displays a heat map of the raw indicator scores generated by those ranking techniques utilized within this framework: Mutual Information, ANOVA F-score, Chi-square, Random Forest importance, and Relief-based relevance. The overall pattern is that certain indicators rise to the highest ranks across methods-policy ambition levels, implementation timelines, sectoral coverage, financial commitments, and long-term governance structures. At the same time, the Chi-square approach is especially suited to distinguishing between categorical policy attributes, such as policy types, governance levels, and regulatory instruments. Random Forest rankings produced smooth gradients that give emphasis to the indicators with consistent effects on policy performance over time. This heat map supports, in summary, the multi-method indicator selection strategy outlined in Section II-C, demonstrating its robustness and reliability for evaluating climate policy.

### B. Correlation Structure of Numeric Indicators

The correlation chart illustrates the interrelation between the various numerical indicators that are linked to the effectiveness of climate change policy. There is a obvious positive correlation between the level of the policy's ambition, the intensity of its execution, and the funds allocated towards it. However, the demographic indicators that are linked to the execution are less likely to correlate to the effectiveness of the execution of the policy. The indicators focused on the sectors affected, the ability of the institutions involved, and the support structures that allow its execution are less likely to provide valuable information that hints towards a positive implication of their execution towards a successful implementation of the policy. Finally, there are indicators that are drastically identical among the indicators available.

### C. Final Model Evaluation and Strategic Risk Assessment

This chart shows the performance of the top-k indicators-otherwise selected by the adaptive causal intelligence framework-across the logistic regression, Random Forest, gradient boosting, and ensemble decision models. All models demonstrate marked and consistent improvements, as less informative features are pruned away. The number of indicators reaches an inflection point around 8 to 14 features, beyond which differences between models are small. Gradient boosting is strong in terms of discrimination, followed by other tree-based ensembles. A large gain is evident in the F1-score, indicating a more marked ability to identify poor or high-risk policy states. That could be important for identifying timely policy intervention or corrective action.




| model | accuracy best k | early warning lead time (years) | urban cooling nnn score | utilization rate |
|---|---|---|---|---|
| | best k | score | | |
| Causal Inference Model | 15 | 5.1 | 187 | 4 |
| Causal Inference Model | 1 | 17.5 | 18 | 5 |
| Deep Thermal Network | 10 | 8.5 | 62 | 6 |
| Responsible AI Ensemble | 20 | 5.2 | 125 | 9 |
| ARIMA Climate Modeler | 28 | 4.2 | 19 | 25 |
| Policy Simulation NN | 71 | 29.5 | 295 | 11 |
| Policy Simulation NN | 5 | 1.7 | 10.21 | 1 |

Figure 6 (Strategic Climate Policy Evaluation)

### D. Strategic Risk Prediction Outputs from the Adaptive Framework

This case demonstrates the way in which the final climate policy assessment report can be constructed using the Adaptive Decision-Making Workflow. Every final climate policy assessment report has the same crucial components:

Current status under the existing policy (e.g., on track, at moderate risk, or at high risk of underperformance)

- A probabilistic confidence score that indicates how sure one is about the outcome of the assessment results
- The principal contributing indicators identified through the adaptive selection of indicators - Section dedicated to interpretability with SHAP-based ranking of attributions and further explanation techniques.

## VI. CONCLUSION

This framework provides a versatile and data-informed platform for climate policy research using the causal intelligence perspective. The combination of different indicator ranking approaches and an iterative consensus-oriented refinement process allows for the avoidance of dogmatic and single-method-based climate policy assessment practices. The empirical results show enhanced contextual validity, minimized noise from overlapping indicators, and robust capability to identify the key determinants of climate policy performance. The process chain described involves structured data preprocessing tasks, multi-method assessment of indicators, adaptive indicator combination processes, and climate policy risk modeling. The modular and scalable system design with multi-context adaptability has been conceptualized with the aim of addressing real-world governance issues where the climate and related policies continue to be in a dynamic and diverse form.

The results demonstrate that the proposed framework has both technical merit and application value for monitoring and evaluating climate policies effectively. Through the integration of causal intelligence with structured policy analytics, the proposed framework helps with perpetual tracking, early point identification, and decision-making due to dynamic governance, challenges, and climate dynamics. The proposed framework can be extended using enhanced policy, socio-economic, cross-country assessments, advanced explainable AI, and longitudinal assessments for supporting good, scalable, and effective governance for climate.

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