



Reflexive Evidence-Based Multimodal Learning for Clean Energy Transitions

Causal Insights on Cooking Fuel Access, Urbanization, and Carbon Emission

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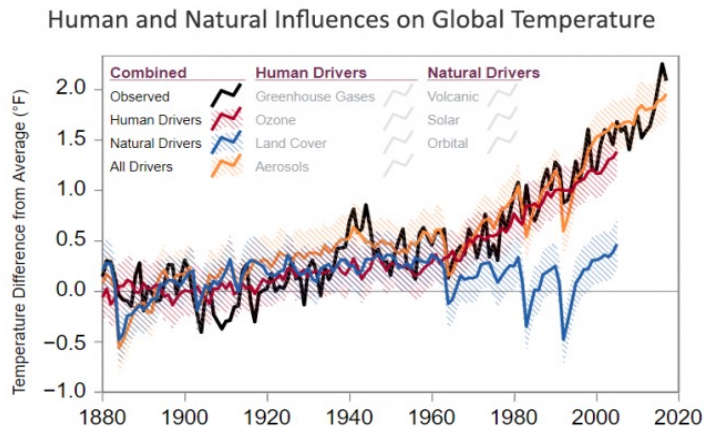
- Rationale: Social Dimensions of Climate Change
- Multimodal Learning with ClimateAgents
- Evidence-Informed Policy Reasoning
- Causal Insights: Cooking Fuel, Urbanization & Emissions
- Conclusion & Future Directions

Disentangling Human Influence on Emissions Patterns

- Long-term global warming is also likely driven by anthropogenic factors.



History (Cornwall, England, 1887)



Science (NOAA,2018)



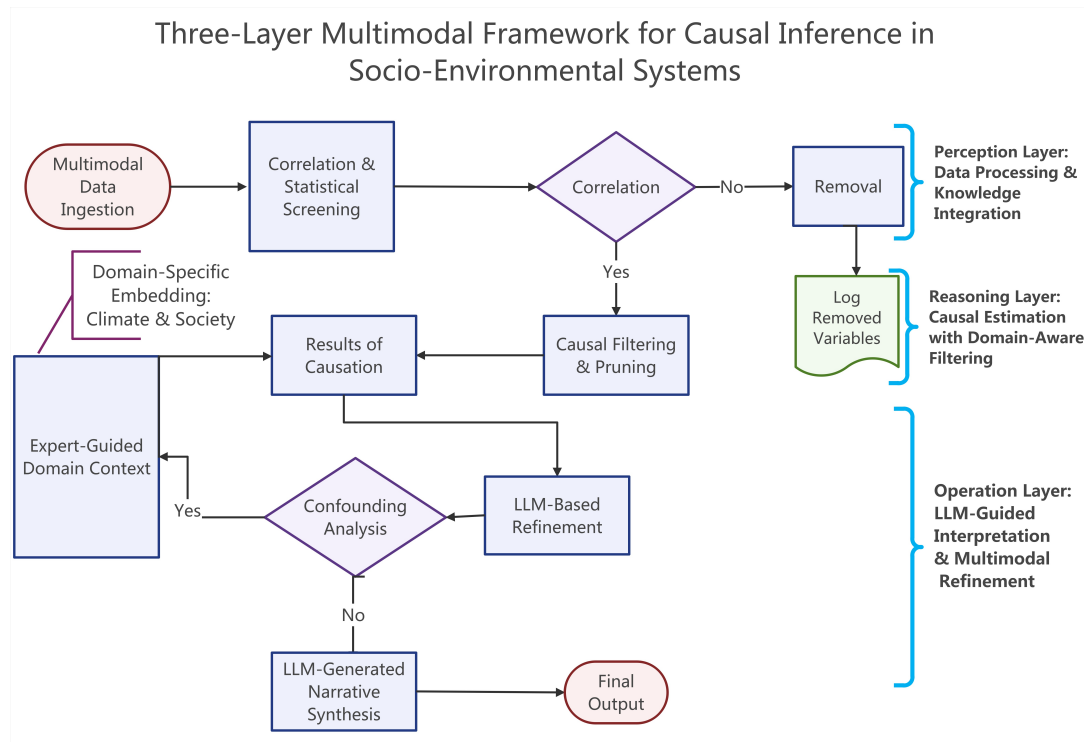
Society (UN,2030)

Advancing Evidence-Based AI Policy for Climate Change

- Need for Actionable Evidence
 - AI policy would benefit from evidence that is **credible** and **actionable**.
- Ensure Credibility
 - Use validated data sources (e.g., World Bank database)
 - Multi-modals
- Align Evidence with Policy Needs
 - Causal
 - Integrate **reflexive machine learning**
 - Use LLMs for Interpretation

Reflexive Multimodal Learning

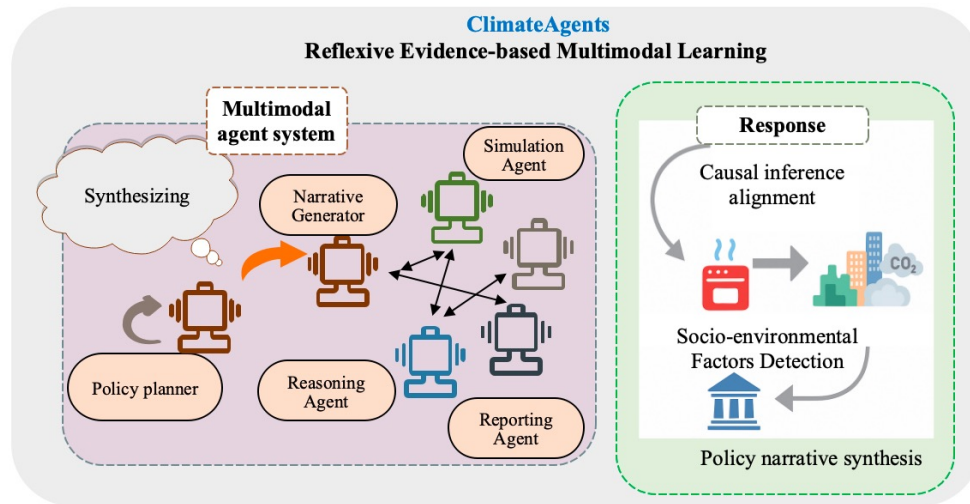
- Multi-agent systems
 - Layer separation (perception, reasoning, operation)
 - Interaction between LLMs (language/text) and structured data (correlation, filtering)
 - Causal reasoning



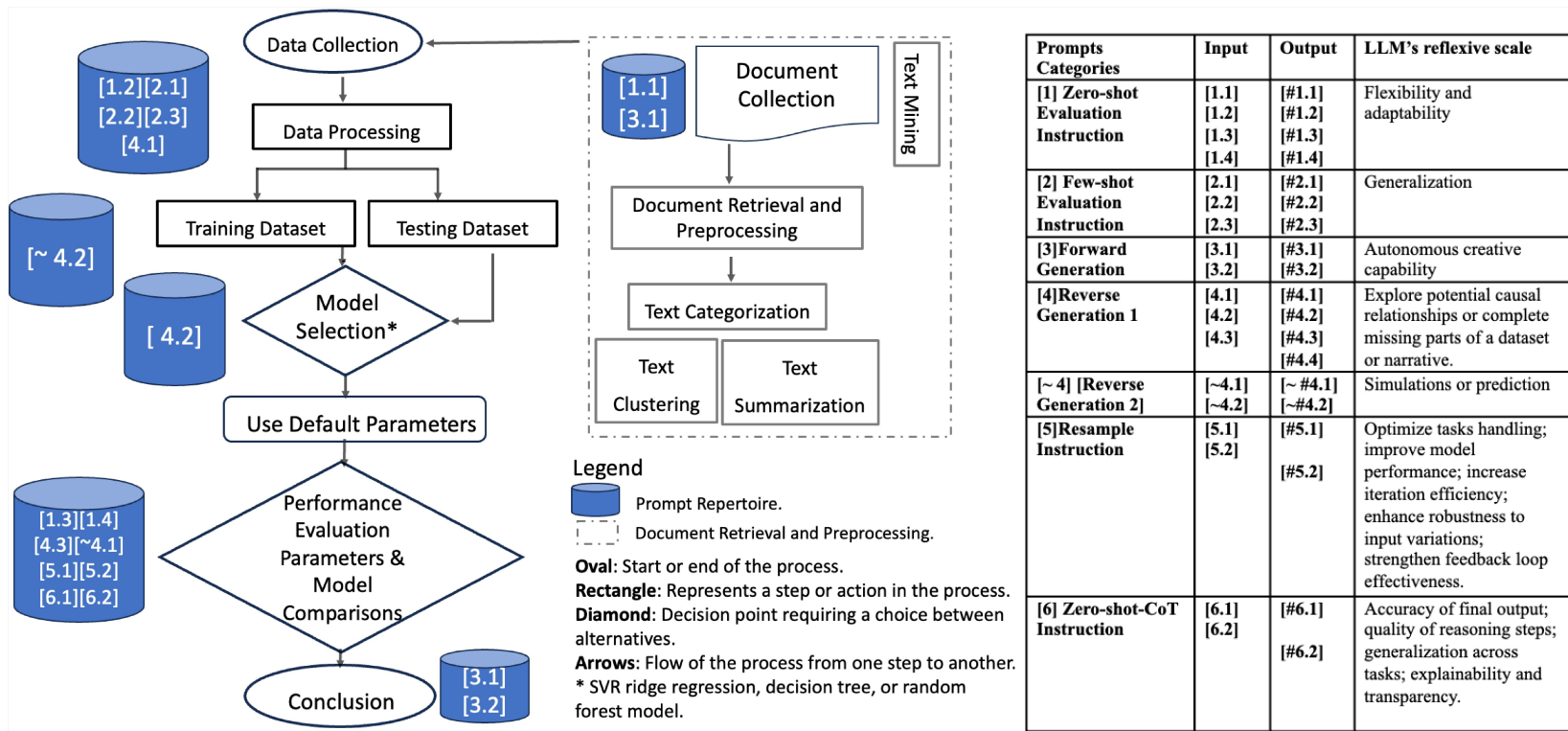
Hybrid AI-Based Framework: ClimateAgents

- AI-driven policy design

-  Policy Planner: Parses prompts, selects features
-  Reasoning Agent: Injects causal logic
-  Simulation Agent: Runs scenarios
-  Narrative Generator: Summarizes outcomes
-  Reporting Agent: Formats and stores outputs



Perception Layer: Retrieval-Augmented Evidence



Reasoning : Societal Factors in Climate Attribution

Key Societal Drivers

 **Clean Fuel Access (Rural):**
Reduces emissions in less urbanized areas

 **Urban Fuel Access:** Key for emissions reduction in dense cities

 **Urbanization:** Drives energy demand; sustainable growth is essential

Reasoning Layer: Causal Effects

1. **Dataset:** Selected variables $\{X_1, \dots, X_{16}\} = \{V^{2000}, Y^{2005}\}$ modeled as:

$$X_i = f_i(\text{pa}_i(X)) + \epsilon_i, \quad p(x) = \prod_i p(x_i \mid \text{pa}_i(x))$$

where $\text{pa}_i(X)$ are parents, and ϵ_i is additive noise.

2. **Score Function:** Defined as $s(x) = \nabla \log p(x)$. A variable X_j is a leaf node if:

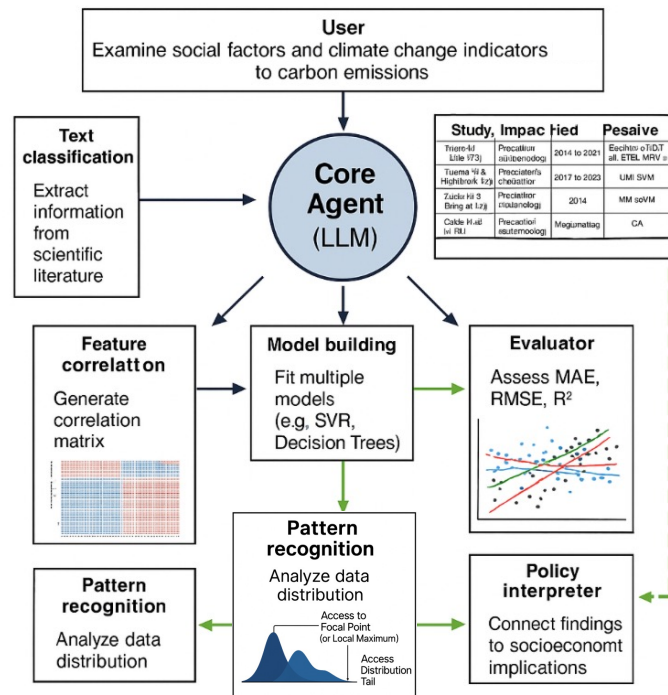
$$\text{Var}_X \left(\frac{\partial s_j}{\partial x_j} \right) = 0, \quad \text{Var}_X \left(\frac{\partial s_j}{\partial x_i} \right) \neq 0 \text{ for parent } X_i$$

Leaf nodes are removed iteratively using Stein gradient estimator with RBF kernel to estimate Jacobian (Rolland et al., 2022).

3. **CAM Pruning:** Refines causal structure by eliminating spurious links:
 - *Structural:* SID, SHD
 - *Predictive:* Precision, Recall, F1 score
 - *Deviation:* L2 distance

Operation Orchestrate : From Representation to Action

- Translate learned representations into actionable insights
- Task-specific modules
- LLM agent orchestrates the pipeline
- Operationalize reasoning
- Bridging statical learning and domain-aware interpretation



Socio-Environmental Narrative Synthesis

- Agent-generated insights emphasize how regional disparities in clean fuel access and urbanization dynamics affect emission outcomes and policy design.

User:

Rural areas (EG.CFT.ACCS.RU.ZS) have lower access to clean fuels than urban ones (EG.CFT.ACCS.UR.ZS), and urbanization (SP.URB.TOTL.IN.ZS) is increasing.

Could variability in clean fuel access affect the effectiveness of environmental policies at reducing emissions?

AI Social-Scientist (GPT-4-turbo):

- **Policy Effectiveness:** Greater variability (standard deviation) in access weakens uniform policy outcomes by reflecting infrastructure inequity.
- **Emission Impact:** Urban-focused policies may yield quick results, but lasting success requires rural inclusion.
- **Urbanization Factor:** Urbanization shifts where and how policies work; less urbanized regions need tailored approaches.
- **Policy Design:** Reducing variability in access could lead to more equitable and impactful environmental strategies.

Implications:

- Targeted investments in rural infrastructure could improve long-term emission reductions.
- Adaptive policy frameworks should consider regional disparities in energy access.
- Integration of socio-environmental data with LLM reasoning may improve decision-making in complex systems.

Conclusion & Future Directions

- **Key Capabilities**

- Models complex socio-environmental dynamics
- Analyzes clean energy, urbanization, and carbon emissions
- Synthesizes heterogeneous data into narratives and visualizations
- Enhances policy relevance with interpretable, evidence-based outputs

- **Current Limitations**

- Causal inference relies on data quality
- Emission models “simplify” reality (not represent)
- Automated simulation is a work-in-progress
- LLMs are not good at causal reasoning (social/linguistic biases)

- **Future Directions**

- Integrate advanced foundation models and generative tools
- Improve scalability, reduce computational costs
- Expand predictive depth and policy simulation capabilities

Reflexive AI for Climate Change Roadmap

- **Reflexive AI for Climate Change Roadmap**: compile development and implementation, empirical validation and societal implications, integration with existing AI technology.
- Project location: <https://github.com/shanshanfy/TowardsReflexiveAI>



Thank You