ARTICLE | OPEN ACCESS

Discovery

Prescriptive AI for Climate Action: A Causal Physics-Informed Optimization Framework for High-Impact Methane Abatement

Bharat Khushalani*

To Cite:
Khushalani B. Prescriptive AI for Climate Action: A Causal Physics-Informed Optimization Framework for High-Impact Methane Abatement. *Discovery* 2026; 62: e18d3283
doi:

Author Affiliation:
Picosoft Research, 5529 163rd CT NE Redmond, WA, 98052 USA

***Corresponding author:**
Bharat Khushalani,
Picosoft Research, 5529 163rd CT NE Redmond, WA, 98052 USA,
Email: bharat.khushalani@picosoftres.org

Peer-Review History
Received: 15 February 2026
Reviewed & Revised: 27/February/2026 to 21/June/2026
Accepted: 30 June 2026
Published: 12 July 2026

Peer-Review Model
External peer-review was done through double-blind method.

Discovery
pISSN 2278–5469; eISSN 2278–5450

ABSTRACT

The pressing need of global warming requires shifting from area-wide forecasting to site-specific, action-oriented reduction approaches, especially for high-impact climate-warming gases like methane CH_4. Present frameworks are inadequate for critical resource distribution. Examples include ranking the sealing of large numbers of abandoned wells, an action priced at about $100,000 per well. A major gap remains in measuring the cause-and-effect what-if impact of a measure compared with a strategy of "inaction". Conventional empirical models are unreliable for this problem as they fail to guarantee the physics validity needed for reliable policy choices. We present the Causal physics-inspired policy optimization (C-PIPO) Framework. This new method systematically combines a Physics-inspired neural network (PINN) at its core. This network imposes the scientific limits of the Transport-diffusion equation. It helps produce physically coherent counterfactuals. These cause-and-effects are passed into a multi-criteria optimization module. The module recommends the best policy ordering by weighing climate gain against budget cost and environmental justice. C-PIPO provides cost-effective, clear, and auditable decision rule guidance. It changes AI's function from forecasting warning to action-guiding decision-making for faster climate response.

Keywords: Methane concerns; Physics-informed neural networks; Optimization; Environment

1. INTRODUCTION

The worldwide climate conditions have become such that urgent actions are now needed. The climate emergency needs critical and focused efforts for diminishing harmful gases. Notably for gases that live only for a short period of time, powerful heat-trapping gases such as methane (CH_4) (Magazzino et al., 2024). Emissions like methane create a separate problem. They have a strong short-term warming effect on the planet (Liu et al., 2025). Their main origins are of local, varied character. This requires fine-resolution tracking and remediation methods. For successful climate mitigation action, resource distribution should be grounded on a site-specific decision process (Perez-Dominguez et al., 2021). The area-wide monitoring is extended. Rather, we must shift towards the best place-based distribution.

DISCOVERY SCIENTIFIC SOCIETY

The control efforts face a central issue. It is the magnitude and excessive expense of control efforts (Gaucher et al., 2025; Stoerk et al., 2025). Orphaned oil and gas boreholes are unplugged, unused boreholes (Brown et al., 2024). These have no accountable owner or operator (Boutot et al., 2022). There is a financial burden associated with such ownerless oil and gas wells. It rests on the public authority or the taxpayer (Raimi et al., 2021). These gas wells present ecological hazards like methane emissions. They are also responsible for the pollution of the water levels as well as dangerous gas discharges (Gianoutsos et al., 2024; Kang et al., 2023). They arise when companies go into bankruptcy, or when they simply abandon such sites, or when operators leave (Meehan et al., 2025). These boreholes create dangers that require costly cleanup. They often require national or condition financing (Kang et al., 2021). If the state intends to emphasize the closing of these boreholes, then it must think of a typical spending of around a hundred thousand dollars per well (Martínez-Santos et al., 2020). This is a considerable investment cost. This demands a reliable, data-based ranking framework. This plan should be founded not merely on an observed emission rate, but also on how much effect the capping of such a well can have.

An attributable effect is the actual effect of a measure or occurrence (a policy action) on a result. It is assessed by contrasting what really occurred with a "what if" case. This second situation is “hypothetical”. It distinguishes real cause-and-impact from simple association. This is critical for assessing marketing programs, decision rule modifications, or new attributes. It does this by simulating a reference case from associated comparison data. For the case of oil boreholes, the difficulty is basically rooted in interventional reasoning (Shokouhi et al., 2009; Salem et al., 2022). One case is Decision rule A, such as capping Well X. The other case is alternative policy B, such as capping Well Y or performing a baseline scenario.

This paper proposes the Physics-constrained causal policy optimization (C-PIPO) Framework. This framework is used to minimize the difference between air-quality forecasting and resource recommendation. C-PIPO is designed to overcome the constraints of strictly data-based models. It does so by combining high-accuracy Physics-Informed AI-based Networks (PINNs). These are used to create physically valid conjectures for models related to transport of airborne particles (Hu et al., 2025; Rawden et al., 2026; Michek et al., 2026; Moreno et al., 2024). These surmises are then fed into to a multi-objective module that improves the decision rules. This module evaluates climate influence, considers funding conditions, and then does fair distribution of the benefits. This integration acts in a systematic manner. It delivers resilient policy recommendation which are physics-guided.

The framework depends upon the understanding that the resource-demanding climate mitigation process is nothing but a critical resource distribution problem. Ownerless well sealing is one such issue (Collins et al., 2022; Li et al., 2023). It aims to create a dependable model for modeling the alternative policy scenario. That is, a model to simulate what would happen if the policy action happened. Due to moral and practical restrictions, randomized controlled trials (RCTs) occur sparingly in atmospheric policy action. The framework that the PINNs incorporate has principles of preservation built into it (Farea et al., 2024). They provide the basis for the erroneous effect systems. High expense control means that the system must improve in order to make efficient use of resources. This needs the integration of sophisticated optimization modules together with the attributable representation.

2. MATERIALS AND METHODS

2.1. Inadequacies of Data-Driven Models in Geophysical Systems

The use of solely data-based Deep Learning (DL) methods to complicated earth-system flow behavior faces methodological weaknesses (Cresswell-Clay et al., 2025). The effectiveness of these methods is directly limited by the learning data. The amount of the available model training set and its caliber influence the accuracy. For doing source-level atmospheric surveillance, available field data is limited (Rosales et al., 2025). It depends substantially on synthetic datasets (Morales-Garcia et al., 2025; Wesseling et al., 2024). These datasets miss the differences in spatial contexts and particular wind velocities. Diverse emission cloud features often characterize the field emission events. These methane cloud properties are also absent in these datasets. The shortage and imbalance in data contributes to weak transferability when the model is in practice implemented in live operational settings. The precision factor of Convolutional Network-based Networks (CNNs) for methane cloud identification is less (around 35%) (Jahan et al., 2024; Melo et al., 2020; Pang et al., 2023).

Statistical learning models experience a basic limitation. It is their failure to enforce mechanistic physical balance rules. It is quite likely that a model that is optimized only on measured data will predict a condition that results in the breaking of fundamental physics-based guidelines. This may incorporate significant underlying standards such as mass balance or momentum. Such breaches will lead to physically unrealistic predictions for airborne transport and dispersion. Such a breakdown on the part of such methods to conform to mechanistic coherence is not only a scientific defect. It is also a considerable policy risk. Decision rule makers cannot rely on results that might conflict with basic scientific knowledge.

Moreover, systematic data distortions are an origin of geographic inequality. Location-based unfairness, or geographic inequality, is the unequal spread of resources. The supports add healthcare, good schools, jobs, facilities and green domains. These are throughout various spatial regions. These lead to gaps in quality-of-life conditions. They shape consequences and opportunities for people based on where they live. It's a fundamental idea in geography and sociology. It shows how position, often connected to social and economic position, race, or ethnicity, determines access to the essential needs. The site also affects the general welfare creating benefits for some places and drawbacks for others. Location-based unfairness causes the methods to perform weakly in under-sampled regions. Same for traditionally underserved areas. Depending on methods used, hazards create unfair consequences as far as evaluations of climate consequences are concerned. There is also a risk in resilience planning. It calls for a combined approach that tackles environmental fairness.

2.2. The Policy Challenge: Correlation versus Causality

AI performs well at estimation and projection. It is strong at some types of optimization processes. It is good at identifying which optimal decision variables can be used under a fixed system architecture. Nevertheless, critical climate decision rule choices, require estimating the interventional effect of a deliberate action. Controlling particular facility emissions or sequencing particular well sealing are instances of such policies. Conventional forecasting models measure correlations in archival records. They are limited for this objective. They cannot estimate what the consequence would have been under an unseen, alternative-scenario state. Understanding the present emission cloud size does not show the advantage of capping the well without a strict what-if analysis. Policy actions are less effective without such an interventional structure. This cause-and-effect framework also has to be strong. Flawed system results in the wrong allocation of financial resources. Such resources are already limited. They fail to achieve essential goals for equitable environmental protection and control efficacy.

There is an intrinsic challenge in carrying out randomized field experiments (RCTs) in ecological contexts. The trials concerning atmospheric interventions require a replacement for alternative-scenario consequence creation. Some boreholes are major emitters. But they cannot be permitted to emit constantly just for the purpose of forming a comparison group for policy evaluation. The scientific field must introduce a method that can simulate these hypothetical states with correctness as well as mechanistic coherence.

2.3. Near-Source Quantification and Numerical Limitations

For the abatement ranking to be efficient, we require to calculate the emissions at the fine scale (0-10 meters). This is the vital for assessing single emitting emitters like orphaned boreholes. Existing remote sensing technologies are restricted to aerial or satellite monitoring. These generally operate with thresholds exceeding 10 to 100 kilograms of CH_4 per hour. This granularity is too rough to maximize efficiency interventions. There are hundreds of thousands of specific low-volume sources of leakage.

To tackle this limitation, hybrid empirical methods have been suggested for near-emitter estimation. Gaussian plume models (GPDMs) are one such. GPDMs use measured CH_4 concentration distributions together with airflow velocity readings. They estimate the emission flow rate of methane through a flow back-calculation procedure. GPDMs are broadly validated and accepted by regulatory agencies like the Climate-related Protection Agency (EPA) for wide-ranging risk assessments. Their deployment at the fine scale (0-10 m) needed for orphaned boreholes remains a new and understudied domain. GPDMs rely on the calibration of the variables. These coefficients are for air-layer stability, terrain roughness, and individual dispersion plume types. This data-derived reliance of the GPDMs limits their ability to transfer. This is real particularly when estimating complicated, chaotic, ground-level flow. The behavior of such a dynamics is due to the changing release cause attributes. This underscores the need for estimating strategy that directly solves the basic earth-system flow equations. The methods are not just highly general probabilistic models, but they are also computationally semi-empirical. Hence, their capacity to manage defined, consequential methane levels is in doubt. Need for physics-based modeling results from about the necessity that the answer should be both data-sparing and physics-informed. The methodology of Physics-Informed Machine-learning Networks is valuable in such situations.

3. RESULTS

The Causal Physics-Informed Policy Optimization (C-PIPO) framework is organized as a combined three-step workflow. The first step is a Physics-constrained neural network (PINN) for physics-valid time-varying modeling. The second step is a Causal design for generating policy-based hypothetical outcomes. The third step is a Multi-goal decision optimization system for obtaining recommendation-based decision rule sequences.

3.1. Foundation: The Physics-Informed Neural Network

The PINN operates as the main physics-based mechanism. It is able to resolve the derivative-based formulas (PDEs) that control atmospheric movement. This design varies from standard DL (Deep Learning) methods. It incorporates physics-based constraints (which are known) straightforwardly into its objective function. It acts as a stabilizing constraint. This is an effective constraint. It reduces the error of the PDE. This entire process puts a limit on possible solutions to scientifically valid states. This guarantees that predictions align to conservation laws. Also, it performs broadly successfully even with a few inputs or when the model inputs are imperfect.

The simple controlling equation is the Advection-diffusion residual used in the PINN physical-equation loss, essentially the squared equation mismatch of

$$\partial c/\,\partial t + u \cdot \nabla c - \nabla \cdot (k \nabla c) - s$$

Figure 1 shows the methane distribution forecast from a reduced two-dimensional advection-dispersion equation. The basis is maintained operating throughout the simulation, representing the reference inaction policy. The dispersion plume is carried in the wind-carried direction by the wind field while spreading distributes the amount sideways.

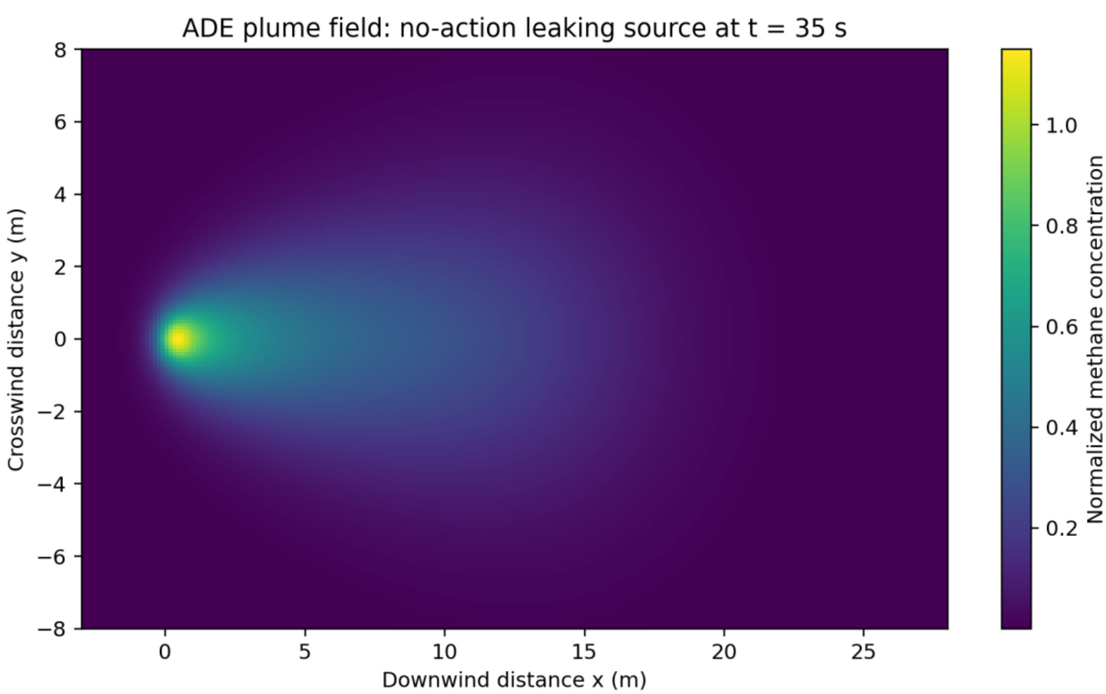

Figure 1. ADE dispersion plume distribution under the baseline scenario.

Figure 2 displays the what-if concentration pattern when the methane basis is turned off after the time of action. Relative to the no-intervention case, the density spatial field is lower because the emission term is eliminated from the controlling equation. This matches the policy action in which capping a leaking well sets the applicable source component to zero.

Figure 3 charts the methane density along the plume axis at several time points. The maximum concentration travels in the windward direction. This is due to advection. It becomes wider due to mixing. This shows the space-time dynamics that the PINN must capture. Transport equation error is minimized.

Figure 4 contrasts the methane density under two outcomes: (i) a do-nothing policy and (ii) basis capping. The no-step line keeps rising because the basis continues emitting. The policy action trend increases more gradually after capping. The separation between the two curves results from the prevented methane load.

Figure 5 graphs the change between the no-step methane load and the policy action methane total amount. It gives a straightforward display of the cause-and-effect impact of the control decision rule. A greater amount shows a greater projected mitigation benefit from the policy action.

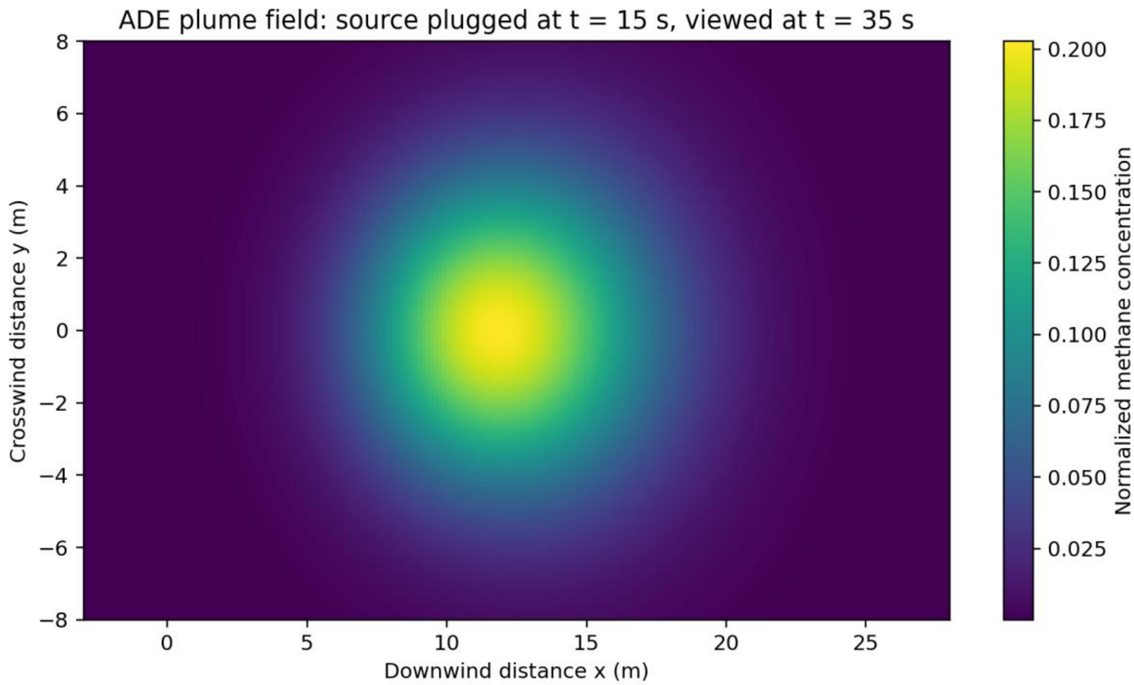

Figure 2. ADE dispersion plume domain after basis capping.

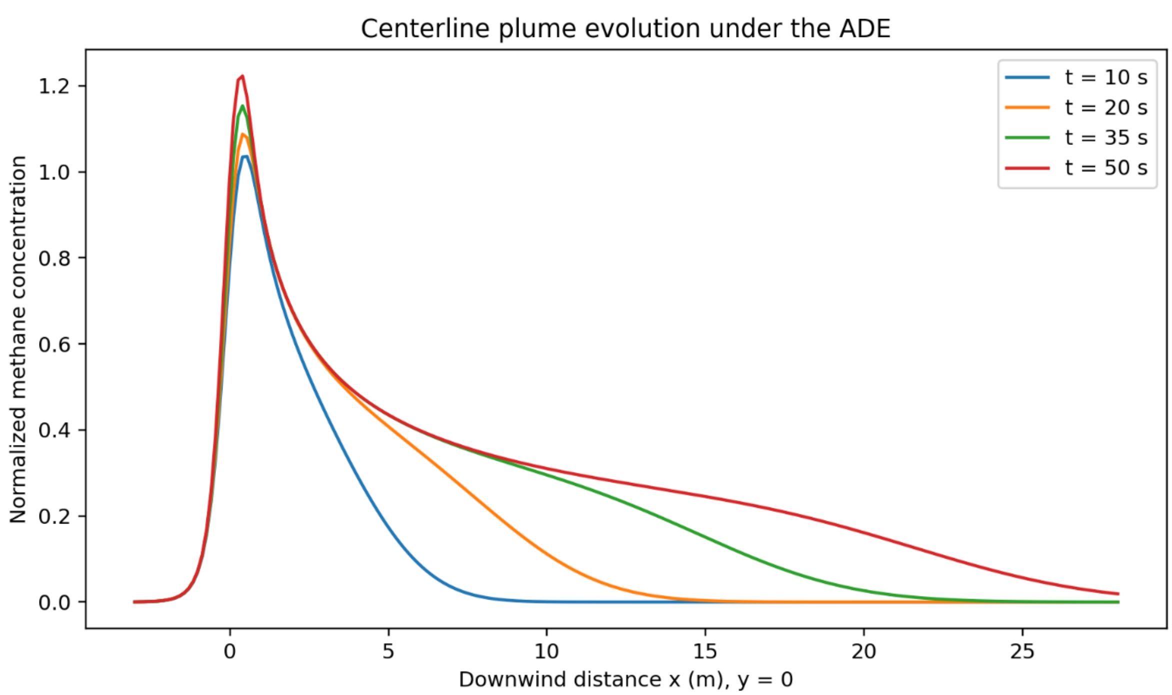

Figure 3. Central plume concentration change over time.

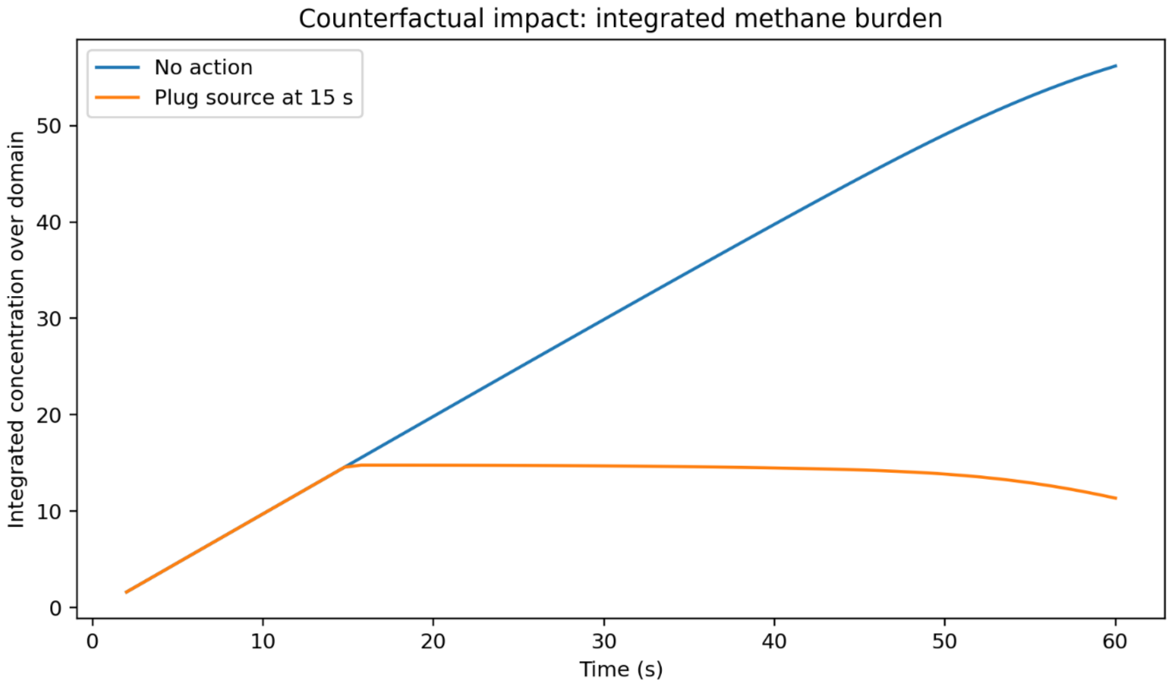

Figure 4. Alternative-scenario total methane load.

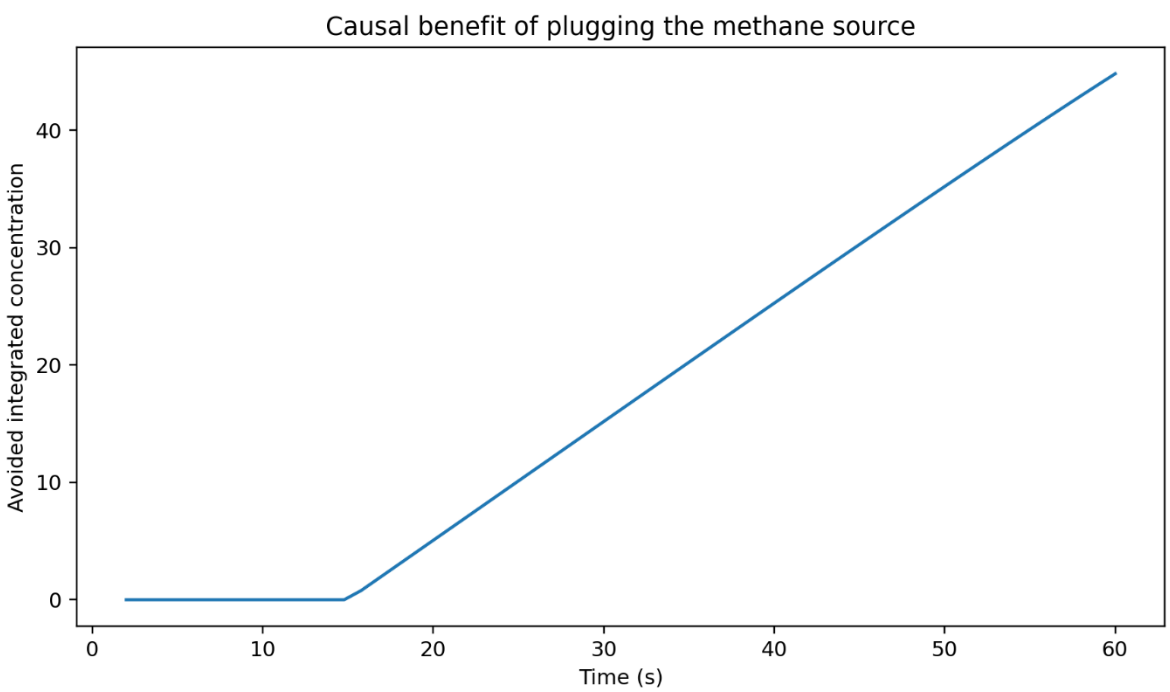

Figure 5. Attributable benefit of capping.

3.1.1. Governing Equations and the Physics Loss Term ($\mathcal{L}$_PE)

For methane dispersion, the underlying governing equation is the Advection-dispersion equation (ADE). This relates to the space-time development of methane density (c) as affected by atmospheric movement (advection) and diffusion (dispersion). The PINN lowers the imbalance objective. It does so within the space-time domain. It supports the network's model output:

$$\mathcal{L}\_\text{PE} = \frac{1}{N_{\text{col}}} \sum_{i=1}^{N_{\text{col}}} \left| \frac{\partial c_{\text{PINN}}}{\partial t} + u \cdot \nabla c_{\text{PINN}} - \nabla \cdot (k \nabla c_{\text{PINN}}) - s_{\text{PINN}} \right|^2$$

When the process conditions are either irregular or complex, the addition of constraints in the model is crucial. The constraints help in providing steadiness and fidelity.

Figure 6 depicts the pointwise error of the advection-dispersion equation. It is used within the penalty system of PINN. Places with a larger remaining imbalance are where the model's prediction does not follow the physics equation very well. A PINN is trained to make this imbalance as small as possible. This helps the model follow the correct physical rules across different locations and times.

Figure 7 shows how the transport-equation error changes when the estimated physics values do not match the predicted density field. The error is smaller when the airflow speed and dispersion values are correct and work well together. The error becomes larger when the airflow speed or dispersion value is incorrect. This shows that the physics-based penalty can help check whether the PINN is learning realistic physical behavior.

Figure 8 separates the transport-equation error into four main parts: (i) Change over time (ii) Movement caused by airflow (iii) Spreading or dispersion (iv) Emissions from the source. The graph shows that different physical processes are more important in different parts of the emission cloud. This breakdown helps explain how the PINN balances movement, spreading, and emissions when making predictions.

Figure 9 evaluates central axis methane density patterns for diverse atmospheric flow velocities. Greater atmospheric flow rates carry methane further with the wind, moving the density profile and altering the region impacted by the dispersion plume. This justifies the demand to represent the flow velocity distribution clearly in the ADE-built PINN model specification.

Figure 10 sets side-by-side lateral density curves for diverse dispersion parameters at a set downstream point. Bigger dispersion settings generate more dispersed and less peaked dispersion plume distributions. At the same time, lower-volume dispersion magnitudes keep the dispersion plume more focused close to the plume axis. This shows the physics-based effect of the diffusion matrix in governing plume dispersion.

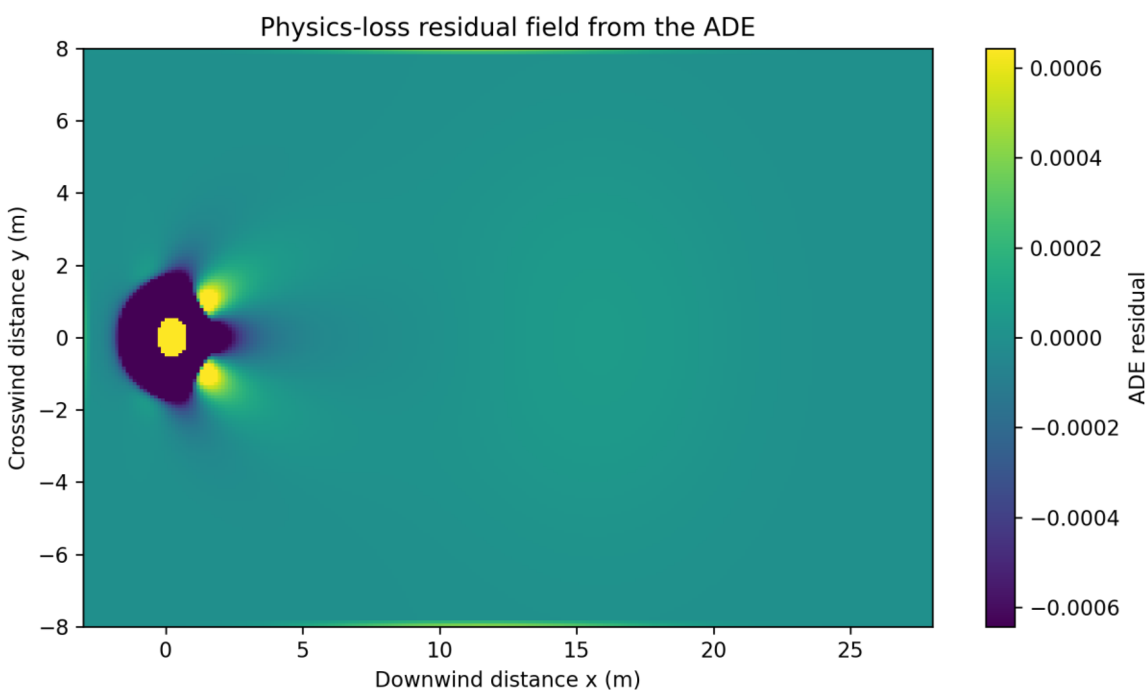

Figure 6. Physics-penalty error field from the ADE.

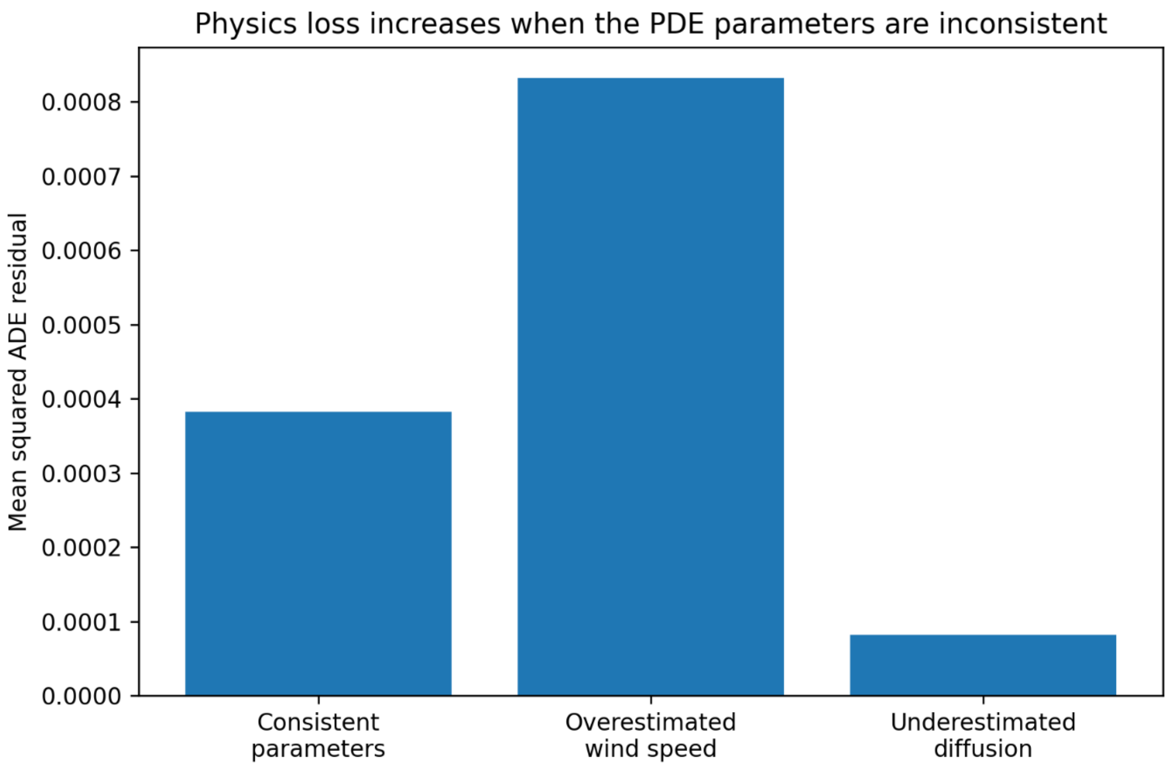

Figure 7. Physics-penalty reaction to parameter inconsistency.

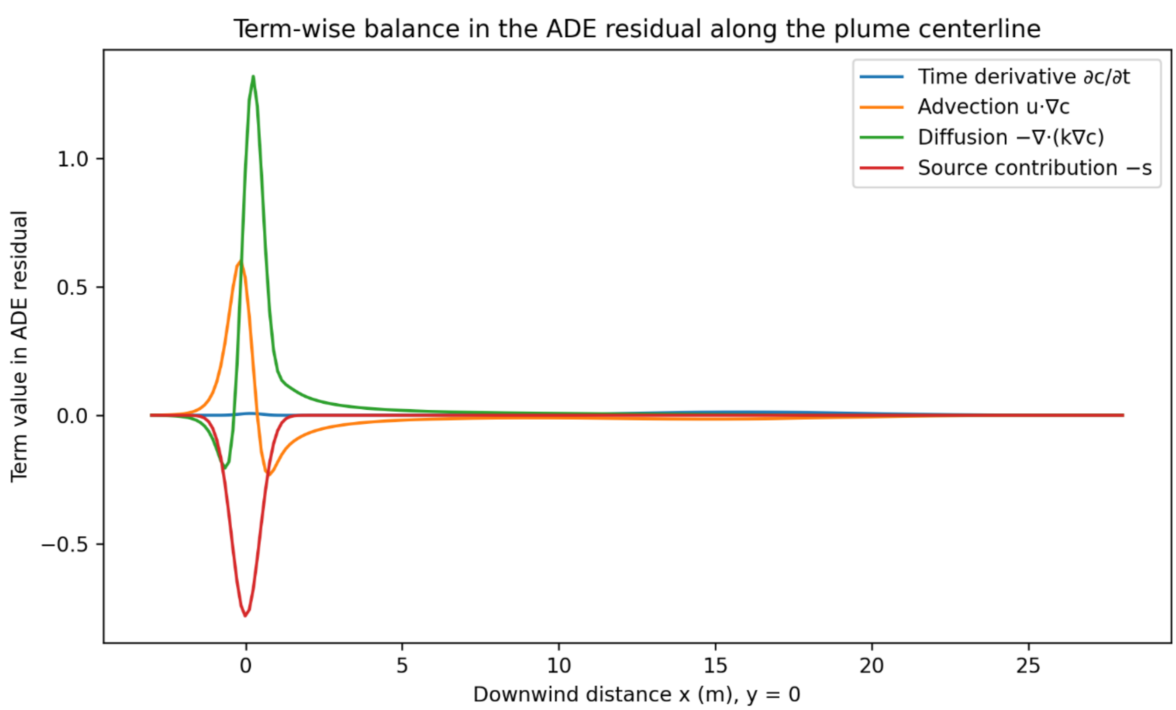

Figure 8. Component-by-component ADE balance along the central plume path.

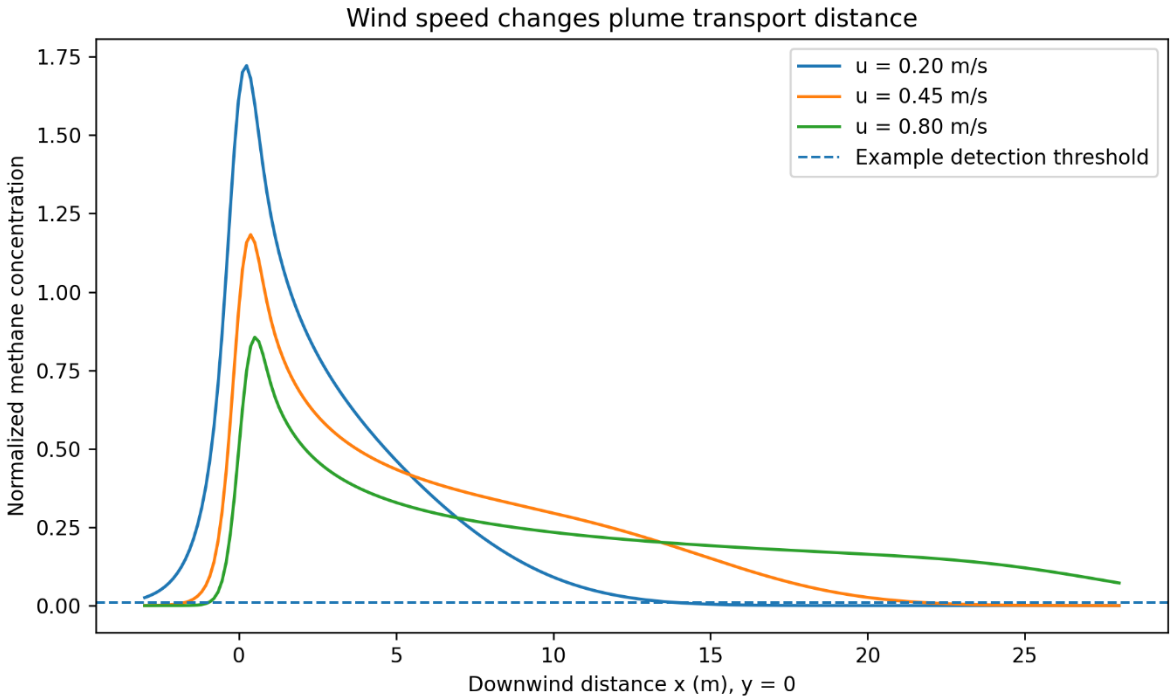

Figure 9. Result of atmospheric flow speed on dispersion plume advection.

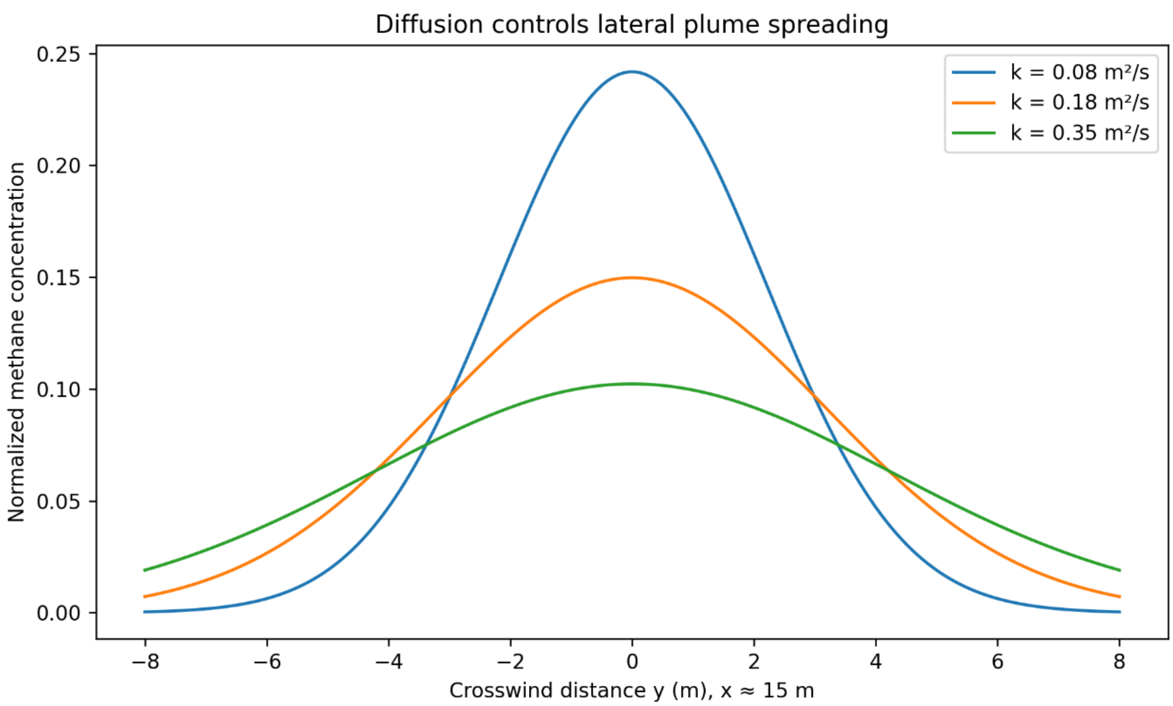

Figure 10. Consequence of dispersion on sidewind dispersion plume dispersion.

3.1.2. Constraints and Data Integration ($\mathcal{L}_{Dt}$)

The total error function must also include an observation-matching term. This term limits the difference between the prediction and field observations. Examples include highly source-level sub-parts per million (sub-ppm) sensor readings gathered near defined unplugged inactive wells. High-detail dispersion plume attributes pre-processed by specialized DL approaches are best-fit for instantaneous identification. Extra error terms are imposed for the starting and edge conditions. These are necessary for correctly specifying the state of the atmospheric system, including ground bounce-back and the near-ground atmospheric layer limits.

3.1.3. Computational Efficiency and Sustainability

By placing physics knowledge, they substantially lower the dependence on large training data collections. They also reduce the linked computing strength necessary by data-hungry deep learning methods or slow established CFD (CFD) solution methods. This implementation effectiveness limits power use and emissions footprint. It matches the framework with rules of resource-conscious ML essential for environmentally responsible AI development. The PINN architecture is capable of providing CFD-level fidelity at significantly lower processing expenses. This makes it an environmentally and financially beneficial option for industry use cases.

3.2. Causal Architecture: Generating Counterfactual Potential Outcomes

The C-PIPO framework uses the physics-guided PINN engine to model the Counterfactual results, for any set mitigation intervention. In standard causal inference, field observations only offer the observed consequence under the actual treatment case. PINNs are used here to simulate the essential unmeasured alternative system conditions.

3.2.1. Defining the Policy Space and Treatment

The set of policy options is delimited as the set of available source-level control actions. In the setting of orphaned well control, one option captures the reference "Do-nothing policy" condition. In this condition, the well continues to leak. Another option captures the decision rule to "Plug Well." The consequence is delimited as the summed atmospheric methane density. It may also be measured as the corresponding climate-warming impact. This measure is taken over a defined practical region and planning period. It assumes the implementation of the decision rule.

3.2.2. PINN as the Counterfactual Generator

To simulate the alternative-scenario consequence, where well is effectively plugged, the PINN is executed with an essential designed change to its physics-based error term. Particularly, the pollutant output source component corresponding to well is set to zero within the PDE-error calculation.

The PINN model result supplies the modeled atmospheric density under the what-if policy. This density spatial field is then aggregated within space and time to calculate the possible consequence. This device modifies the incoming physics, mainly the source component. It then examines the physically compatible system behavior. This is a rigorous framework for identifying a cause-and-effect framework in PDEs. The method honors the space-time cause-and-effect structure built into physics-based frameworks. This helps prevent settling toward incorrect solutions that afflict established PINNs in turbulent or unstable domains.

3.2.3. The Causal Impact Loss ($\mathcal{L}_{\text{Causal}}$)

The main climate goal is to find interventions that increase the cause-and-effect impact. This impact is delimited as the decrease in combined methane density obtained by the policy action. It is measured compared to the control. The optimization system includes an error term. This term relates to policies which optimize the computed mitigation benefit.

3.3. Multi-Objective Policy Optimization (C-PIPO)

The last step of C-PIPO combines the climate benefit with key real-world constraints. Specifically, it combines the financial resource burden and fair distribution of environmental benefit. To obtain the best action-guiding policy. The total target is to minimize the combined objective function, which balances these conflicting goals:

$$\min_{a \in A} \mathcal{L}_{\text{CPP}}(a) = w_C \cdot \mathcal{L}_{\text{Cua}}(a) + w_R \cdot \mathcal{L}_{\text{Rsuc}}(a) + w_E \cdot \mathcal{L}_{\text{Eut}}(a)$$

3.3.1. Resource/Cost Constraint ($\mathcal{L}_{\text{Rsuc}}$)

This term captures the implementation constraints and economic load connected with the control decision rule. This includes the constant expenditure of capping a single well (roughly $100,000) or the total constrained budget assigned for control within a defined budgetary timeframe. This error guarantees that the decision rule calculated is cost-wise practical and economical. This stops the framework from only recommending the simple, unlimited computed field of capping all validated contributors irrespective of economic feasibility.

3.3.2. Environmental Equity Constraint ($\mathcal{L}_{Eut}$)

The framework should comply with the responsible and fair standards essential for ethical AI use. To ensure this, a fairness loss term is added. This limit makes sure that funding assignment is equitable and deliberately reduces current location-based unfairness, natural in data spread and past climate benefit risk analyses. It discourages policies that ignore interventions in zones or groups that show high risk. It also discourages policies for which pollution burden measurements are insufficient. Using estimation techniques, the best-solution search for equitable resource distribution is performed. This ensures that the technology advances equitable environmental protection. Table 1 recaps the practical functions of the main loss terms within the C-PIPO structure.

Table 1. Controlling objective terms within the C-PIPO Framework

Error function Component	Purpose and Mathematical Basis	Aim within C-PIPO	Connected Decision rule Dimension
Physics-based penalty $\mathcal{L}_{PE}$	ensures the remaining imbalance of the Advection-dispersion equation (ADE) and physics-based domain-boundary requirements.	Guarantees mechanistic coherence and the mass conservation principle in dispersion plume estimating.	Fidelity & Trustworthiness
Data Error ($\mathcal{L}_{Dt}$)	Limits the gap between PINN computed value and observation data (e.g., source-level sensor readings).	Anchors the physics-based model to actual readings and system restrictions.	Verification & Tracking
Interventional effect Error ($\mathcal{L}_{Cua}$)	Quantifies the estimated contrast between the "Do-nothing policy" candidate consequence and the "Policy action" consequence.	Prioritizes interventions that make the greatest composite mitigation benefit τ	Impact & Control
Fairness Error ($\mathcal{L}_{Eut}$)	Allocates resources to maintain control efforts and reduce high-risk or disadvantaged neighborhoods.	Secures just allocation of environment-focused reduction and conformity with responsible guidelines.	Fairness & Oversight

4. DISCUSSION

4.1. Comparative Advantage and High-Fidelity Quantification

The C-PIPO framework has important advantages for engineering and policymaking. It improves on traditional measurement methods. It also reduces unfair differences caused by measuring at different scales. This allows accurate measurements to be taken very close to the pollution source. This is essential for the impactful handling of specific source-level physical systems like unplugged inactive wells. By operating as a time-continuous neural dynamic model that solves foundational PDEs, C-PIPO supplies a robust substitute to methods. Broad statistical exposure models (such as kriging or land-use statistical modeling) and surpass the generalization shortcomings of partly empirical GPDMs. These are limited by coefficient calibration at the fine-scale near-ground layer. The PINN's are very reliable when it comes to enforcing physics-based constraints. These constraints fall within the full space-time domain. PINNs are more transferable compared to traditional empirical methods. This often leads to difficulty in representing nonlinear climate dynamics. It also faces challenges as far as predicting new, sudden system changes are concerned.

4.2. Operationalizing Prescription and Explainable Policy

At its core, the C-PIPO method changes the climate policy decision process. Instead of after-the-fact forecasting method, it makes recommendations which are anticipatory. By generating an accurate thought experiment, it preserves the validity of the underlying physics. In this way, if there is any type of intervention, its estimated mitigation benefits can be measured directly. This is an immediate and confirmed connection. It links principles of physics-based estimating with optimization which is guided by actions. It enables strong prioritization of "high-emitting sources." Such a ranking is built on estimated preventable effect. It does not rely on just the measured size.

The capability to deliver an improved, validated action-guiding plan at its core speeds up the schedule from recognition to effective abatement. This is in contrast to forecast warnings that require large manual analysis and consideration to identify the best action path. Also, the PINN groundwork supplies essential interpretability for the policy guidance. Because the recommended step is immediately inferred from minimized residuals of widely accepted physics equations (the ADE), the reasoning underlying the decision rule is naturally explainable and confirmable. This transparency is essential for building public confidence, supporting regulatory acceptance, and securing adherence, notably within multifaceted environmental policy settings.

4.3. Addressing AI's Dual Climate Challenge

Successful deployment of C-PIPO deals with the essential twofold problem related to AI. The first need is to use AI for climate measures. The second need is reducing the substantial environment-focused financial burden related to using large computing models. The processing efficiency of PINNs requires far less data. It also requires fewer computing resources than large-scale deep learning designs. This reduces the system's electricity demand. It also has positive impact on water requirements. This is an engineering solution. It is a field approach. It promotes sustainable and efficiency-aware AI growth. By incorporating the requirement, C-PIPO ensures that the tool is used responsibly. This tool is a budgetary-resource-saving tool. It maintains the rules of environmental protection. Such rules are unbiased. Such rules make judicious use of technical capacity and regulations. Table 2 shows a side-by-side overview, emphasizing the change in function offered by the C-PIPO framework.

Table 2. Comparison of Methane Estimation and Policy Evaluation Methods

Methodology	Dominant Computed value	Decision rule Relevance	Size Limitation	Mechanistic coherence
Satellite/Aircraft Imaging:	Total large-scale pollutant output rates (kgh^{-1}).	Broad inventory, oversight and enforcement.	Weak spatial resolution; high calculation threshold (10+ to 100+ kgh^{-1})	Poor, built on low-resolution inverse estimation methods.
Adjacent to-Basis GPDMs	Calculated release methane pace gh^{-1}	Prioritization of separate boreholes	Highly source-level (0-10 m), struggles with unstable edge layers.	Poor. It rests on hybrid empirical setting adjustment.
Conventional Deep Learning (e.g., ResNet)	Emission plume identification/Classification	Straightforward flagging system	Weak generalization; small to case of model training set.	Absent (entirely empirical); risk of physics-based inconsistencies.
C-PIPO Framework:	Most effective Decision rule, action guidance; Alternative-scenario Benefit (τ)	**Recommendation-based policy choice (Interventional effect) for restricted funding assignment.**	High accuracy, adaptable to micro- or meso-scope motion.	High (specifically ensures Component Rate-of-change Mathematical relations).

5. CONCLUSION

The Physics-Constrained Causal Policy Optimization, or C-PIPO, framework is a new approach for using artificial intelligence to support immediate climate action. It combines reliable physics-based modeling with counterfactual analysis. The physics-based part helps the model follow real-world physical laws. The counterfactual part helps compare possible actions and recommend which policy may produce the best result. These physics-modeling strengths come from Physics-Informed Machine-learning Networks. Together, they help C-PIPO address key shortcomings in traditional empirical and computational methods. These shortcomings appear in site-specific atmospheric policy evaluation. This integration provides decision rule makers with a reliable and explainable tool. The tool can derive physically compatible alternative-scenario scenarios. It also makes optimized, economical, and fair resource distribution possible. This is a requirement for handling expensive and spatially scattered environmental problems such as unclaimed well reduction.

The framework combines efficient computing with fairness requirements. Its computing efficiency comes from the PINN model. Its fairness constraint helps ensure that the results do not unfairly affect certain communities. This gives the framework a special advantage.

It is an advanced technical tool, but it is also designed to operate under strict oversight and follow environmental justice principles. Future work areas for the C-PIPO framework involve improving its engineering main and expanding its range of applications. Technically, avenues remain for incorporating C-PIPO with high-level model structures. Examples include Quantum-classical physics-informed neural networks (QPINN-MAC), to potentially use quantum-based best-solution search methods for faster convergence of the multi-goal objective function in many-variable spaces. Further work must concentrate on including random variables into the PDE remaining imbalance error to enhance uncertainty estimation and reliability when estimating unstable or unstable atmospheric models.

The policy use of C-PIPO's cause-and-effect framework should be broadened further than local methane emissions. The action-guiding method is clearly applicable to other resource distribution challenges involving airflow and fluid behavior. Examples include improving site-specific air pollution reduction plans. Other examples include measuring the interventional effect of ecosystem-based interventions on site-level climate indicators. One such intervention is the improvement of rock mineral weathering. By persisting to rank first both scientific strictness and justice-oriented anticipation, C-PIPO creates an expandable and ethical framework for decision-guiding machine intelligence in worldwide climate policy management.

Acknowledgement

Author is thankful to the Picosoft Research members who collected some data for this study.

Author Contributions

Sole contribution from the single author.

Informed consent

Not applicable.

Conflicts of interests

The author declare that they have no conflicts of interest, competing financial interests or personal relationships that could have influenced the work reported in this paper.

Ethical approval & declaration

Not applicable. This article does not contain any studies with human participants or animals performed by any of the authors.

Funding

This research did not receive any external funding like specific grant from funding agencies in the public, commercial, or nonprofit sectors.

Data and materials availability

All data associated with this study are present in the paper.

REFERENCES

1. Boutot J, Peltz AS, McVay R, Kang M. Documented orphaned oil and gas wells across the United States. Environmental Science & Technology 2022; 56(20):14228–14236. doi:10.1021/acs.est.2c03268
2. Brown CS, Kolo I, Lyden A, Franken L, Kerr N, Marshall-Cross D, Watson S, Falcone G, Friedrich D, Diamond J. Assessing the technical potential for underground thermal energy storage in the UK. Renewable and Sustainable Energy Reviews 2024; 199:114545. doi:10.1016/j.rser.2024.114545
3. Collins W, Orbach R, Bailey M, Biraud S, Coddington I, DiCarlo D, Peischl J, Radhakrishnan A, Schimel D. Monitoring

methane emissions from oil and gas operations. PRX Energy 2022; 1(1). doi:10.1103/prxenergy.1.017001
4. Cresswell-Clay N, Liu B, Durran DR, Liu Z, Espinosa ZI, Moreno RA, Karlbauer M. A Deep Learning Earth System Model for efficient simulation of the observed climate. AGU Advances 2025; 6(4). doi:10.1029/2025av001706
5. Farea A, Yli-Harja O, Emmert-Streib F. Understanding physics-informed neural networks:Techniques, applications, trends, and challenges. AI (Basel, Switzerland) 2024; 5(3):1534–1557. doi:10.3390/ai5030074
6. Gaucher Y, Tanaka K, Johansson DJA, Boucher O, Ciais P. Potential and costs required for methane removal to compete with BECCS as a mitigation option. Environmental Research Letters 2025; 20(2):024034. doi:10.1088/1748-9326/ada813
7. Gianoutsos NJ, Haase KB, Birdwell JE. Geologic sources and well integrity impact methane emissions from orphaned and abandoned oil and gas wells. The Science of the Total Environment 2024; 912:169584. doi:10.1016/j.scitotenv.2023.169584
8. Hu C, Chen B, Jiao K, Wang Q, Zhao C. Modeling natural convection by solving conservative transport equations with physics-informed neural networks. AI Thermal Fluids 2025; 4:100018. doi:10.1016/j.aitf.2025.100018
9. Jahan I, Mehana M, Matheou G, Viswanathan H. Deep Learning-Based quantifications of methane emissions with field applications. International Journal of Applied Earth Observation and Geoinformation: ITC Journal 2024; 132:104018. doi:10.1016/j.jag.2024.104018
10. Kang M, Boutot J, McVay RC, Roberts KA, Jasechko S, Perrone D, We T, Lackey G, Raimi D, Digiulio D, Shonkoff S, Carey J, Elliott E, Vorhees D, Peltz A. Environmental risks and opportunities of orphaned oil and gas wells in the United States. Environmental Research Letters 2023; 18(7):074012. doi:10.1088/1748-9326/acdae7
11. Kang M, Brandt AR, Zheng Z, Boutot J, Yung C, Peltz AS, Jackson RB. Orphaned oil and gas well stimulus - Maximizing economic and environmental benefits. Elementa (Washington, D.C.) 2021; 9(1). doi:10.1525/elementa.2020.20.00161
12. Li S, Wang C, Gao P, Zhao B, Jin C, Zhao L, He B, Xue Y. High-spatial-resolution methane emissions calculation using TROPOMI data by a divergence method. Atmosphere 2023; 14(2):388. doi:10.3390/atmos14020388
13. Liu Y, Wan Y, Dai Y, Fan L, He H. Review of methane emission source tracing methods in oilfield regions. Gas Science and Engineering 2025; 142:205708. doi:10.1016/j.jgsce.2025.205708
14. Magazzino C, Madaleno M, Waqas M, Leogrande A. Exploring the determinants of methane emissions from a worldwide perspective using panel data and machine learning analyses. Environmental Pollution (Barking, Essex:1987) 2024; 348:123807. doi:10.1016/j.envpol.2024.123807
15. Martínez-Santos P, Martín-Loeches M, Díaz-Alcaide S, Danert K. Manual borehole drilling as a cost-effective solution for drinking water access in low-income contexts. Water 2020; 12(7):1981. doi:10.3390/w12071981
16. Meehan DN, Liu M, Kang M, Peltz AS. Environmental issues with orphaned wells. SPE Annual Technical Conference and Exhibition. Presented at the SPE Annual Technical Conference and Exhibition, Houston, Texas, USA 2025 October 13. doi: 10.2118/227933-ms
17. Melo RO, Costa MGF, Filho CFFC. Applying convolutional neural networks to detect natural gas leaks in wellhead images. IEEE Access:Practical Innovations, Open Solutions 2020; 8:191775–191784. doi:10.1109/access.2020.3031683
18. Michek NE, Mehta PM, Huebsch WW. Flight dynamics modeling using physics-informed neural networks. AIAA Journal 2026; 64(1):241–257. doi:10.2514/1.j063991
19. Morales-García J, Ramos-Sorroche E, Balderas-Díaz S, Guerrero-Contreras G, Muñoz A, Santa J, Terroso-Sáenz F. Exploiting synthetic data generation to enhance pollution prediction. Applied Soft Computing 2025; 175:113076. doi: 10.1016/j.asoc.2025.113076
20. Moreno Soto Á, Cervantes A, Soler M. Physics-informed neural networks for high-resolution weather reconstruction from sparse weather stations. Open Research Europe 2024; 4:99. doi:10.12688/openreseurope.17388.1
21. Pang S, Sun L, Tian Y, Ma Y, Wei J. Convolutional Neural Network-driven improvements in global cloud detection for Landsat 8 and transfer learning on Sentinel-2 imagery. Remote Sensing 2023; 15(6):1706. doi:10.3390/rs15061706
22. Pérez-Domínguez I, Del Prado A, Mittenzwei K, Hristov J, Frank S, Tabeau A, Witzke P, Havlik P, van Meijl H, Lynch J, Stehfest E, Pardo G, Barreiro-Hurle J, Koopman J, Sanz-Sánchez MJ. Short- and long-term warming effects of methane may affect the cost-effectiveness of mitigation policies and benefits of low-meat diets. Nature Food 2021; 2(12):970–980. doi:10.1038/s43016-021-00385-8
23. Raimi D, Krupnick AJ, Shah JS, Thompson A. Decommissioning orphaned and abandoned oil and gas wells:New estimates and cost drivers. Environmental Science & Technology 2021; 55(15):10224–10230. doi:10.1021/acs.est.1c02234
24. Rawden JI, Vanderwel C, Symon S. Physics-informed neural networks for passive scalar emission and transport. Physical Review Fluids 2026; 11(2). doi:10.1103/wjlv-sy4j
25. Rosales CM, R Bratburd J, Diez S, Duncan S, Malings C, Pant P. Open air quality data platforms for environmental health

research and action. Current Environmental Health Reports 2025; 12(1):27. doi:10.1007/s40572-025-00487-6

26. Salem AM, Yakoot MS, Mahmoud O. Addressing diverse petroleum industry problems using machine learning techniques: Literary methodology-spotlight on predicting well integrity failures. ACS Omega 2022; 7(3):2504–2519. doi:10.1021/acsomega.1c05658
27. Shokouhi SV, Aamodt A, Skalle P, Sørmo F. Determining root causes of drilling problems by combining cases and general knowledge. In: Lecture Notes in Computer Science. Case-Based Reasoning Research and Development; pp. 509–523. 2009. doi:10.1007/978-3-642-02998-1_36
28. Stoerk T, Rising J, Shindell D, Dietz S. Global methane action pays for itself at least six times over. Science (New York, N.Y.) 2025; 390(6772):eadu7392. doi:10.1126/science.adu7392
29. Wesseling J, Drukker D, Gressent A, Janssen S, Joassin P, Lenartz F, van Ratingen S, Rodrigues V, Sousa J, Thunis P. Using synthetic data to benchmark correction methods for low-cost air quality sensor networks. Air Quality, Atmosphere, & Health 2024; 17(5):979–996. doi:10.1007/s11869-023-01493-z