

## A Blueprint for Integrated Climate Intelligence

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## Abstract

Climate information is advancing faster than the decision systems designed to use it. Emergency response operates on timescales of hours, whereas societal adaptation unfolds over decades. Yet climate science, impact assessment and policy remain poorly integrated, limiting coherent action across timescales. We argue that artificial intelligence should be developed not only as a domain-specific tool, but as an integration layer linking fragmented physical, social and institutional systems. This Perspective outlines a blueprint for Integrated Climate Intelligence built on three pillars: fairness, which prioritizes vulnerability alongside data availability; speed, which reduces the latency between assessment and action; and robustness, which quantifies uncertainty under extrapolation and high-stakes decision-making. We further propose a Climate AI Trust Index as an evaluation framework for assessing whether climate AI systems are sufficiently rigorous, equitable and decision-relevant for operational use.

**Keywords:** artificial intelligence, climate intelligence, climate policy, uncertainty quantification, climate justice, earth system modeling, climate risk

## 1 Introduction

In October 2024, a *DANA* system (*Depresión Aislada en Niveles Altos*, an extreme precipitation event caused by an isolated depression at high levels) delivered a year’s worth of rainfall to areas around Valencia, Spain, in under eight hours. Meteorological services accurately predicted the hazard and issued red alerts early that morning. Yet civil protection warnings and protective action were delayed for several crucial hours (roughly a twelve-hour gap between forecast availability and effective response) by which time flash floods had already trapped thousands in vehicles and homes, killing more than 200 people Martin-Moreno et al. (2025). The tools were present; the integration was missing (Box 1).

This disconnect is not new, but it is becoming more consequential. Forecasting and monitoring capabilities have advanced rapidly Rolnick et al. (2022); Schneider et al. (2023), while the systems that translate climate information into timely action remain fragmented across institutions, data streams, and decision contexts. Recent work on integrated early warning systems Camps-Valls et al. (2025) makes a similar point: hazard prediction has improved substantially, but impact prediction, communication, and decision support remain weak links in the chain Reichstein et al. (2025); Lumbroso et al. (2025). The problem also extends beyond rapid-onset disasters Rafiezadeh Shahi et al. (2026). Climate risk management spans time horizons from hours to decades Schneider et al. (2023), yet scientific information, impact assessment, and policy response are typically developed in parallel rather than as parts of a coherent operational system.

We argue that AI should be developed not only as a domain-specific enhancer but also as an **integration layer** connecting fragmented capacities across physical, social, and institutional domains. AI’s role is not to replace governance or automate politically consequential decisions, but to support integration across the science-to-action chain: linking forecasts to impacts, impacts to vulnerability, and decision support to transparent institutional workflows. Related work has highlighted the potential of foundation-model architectures for cross-disciplinary climate research Eyring et al. (2024b); Ou et al. (2026); Manivannan et al. (2026). We take a distinct perspective: rather than focusing on a specific model class, we frame AI broadly as infrastructure for **Integrated Climate Intelligence** across science, impacts, and societal response.

This Perspective develops that argument around three architectural pillars: **fairness**, prioritizing vulnerability and adaptive capacity over data density; **speed**, reducing the

latency between climate information and usable decisions; and **robustness**, quantifying uncertainty and stress-testing performance under extrapolation. Together, these define a blueprint for Integrated Climate Intelligence and motivate evaluation frameworks that assess decision relevance, equity, and trustworthiness alongside predictive skill.

**Box 1: The Integration Gap in Practice**

The October 2024 DANA in Valencia illustrates the integration gap as a systemic failure. Meteorological agencies accurately predicted the hazard; the absence of an integration layer allowed political failures Galvez-Hernandez et al. (2025) and institutional latency to delay the response until it was too late.

Stage	Status Quo (Valencia, 2024)	Integrated AI Blueprint
<b>Prediction</b>	<i>Metric: Precipitation.</i> Forecasts predicted rainfall accumulation (mm). Translating accumulation into flood depth required separate, offline hydrological modeling that lagged behind the event.	<i>Metric: Decision-relevant impact.</i> Hybrid AI fuses weather forecasts with high-resolution topography to predict local inundation and exposure in real time, focusing on risk to life rather than water volume.
<b>Translation</b>	<i>Manual and Linear.</i> River authorities monitored sensors; data was relayed manually to emergency centers. Delays accumulated at every handover, producing critical gaps.	<i>Integrated and Parallel.</i> Data pipelines update a shared operating picture in real time as thresholds are crossed, reducing delays caused by sequential handovers across agencies.
<b>Decision</b>	<i>Discretionary and Unaccountable.</i> Officials delayed action, but ambiguous risk information allowed political inaction to shelter behind scientific uncertainty.	<i>Pre-defined and Transparent.</i> Uncertainty-aware forecasts provide calibrated confidence intervals and inform pre-defined operational protocols. When officials override, <b>the decision to delay becomes an explicit, attributable political choice.</b>
<b>Outcome</b>	<i>Information without Action.</i> Accurate forecast, catastrophic losses.	<i>Systemic Intelligence.</i> Forecasts are translated into actionable response guidance.

**The Counterfactual:** With a more integrated warning-to-action system, hazard forecasts could have been combined with local flood modeling, exposure and vulnerability information to support earlier evacuation guidance and emergency deployment. AI will not replace public authority, but can help bridge the path between warning and usable action.

## 2 The Three Failures of Fragmentation

The Valencia tragedy is symptomatic, not exceptional. Current climate risk management remains fragmented across data collection, modeling, impact assessment, communication, and decision support. We identify three structural failures, each corresponding to an architectural requirement that integrated systems must satisfy.

### 2.1 The Data Equity Gap

Climate data infrastructure reflects a strongly uneven geography. Weather stations, flux towers, and monitoring networks remain disproportionately concentrated in the Global North Su et al. (2026), while tropical forests, wetlands, and many small island and low-income regions remain comparatively sparsely observed. The issue is not only data coverage, but also control: observations from vulnerable regions often flow to processing centers elsewhere, where models are trained and evaluated according to priorities that may be remote from the communities most exposed to climate risk. Climate AI can reinforce extractive patterns unless questions of benefit, access, and governance are addressed directly noa (2025).

The resulting bias is often structural rather than incidental. Models and benchmarks optimized for aggregate performance tend to reward accuracy where data are dense, labels are reliable, and operational feedback is available Camps-Valls et al. (2025); Eyring et al. (2024a). That can leave data-sparse and high-vulnerability settings underrepresented in both model development and evaluation. A system that performs well on average may therefore still fail precisely where the social value of prediction is highest. Breaking this cycle requires more than expanded sampling. It requires evaluation frameworks stratified by region, hazard context, and vulnerability; model objectives that explicitly account for where errors matter most; and data governance arrangements that restore meaningful control and benefit to affected communities. Improving performance in one region need not come at the expense of another, but performance should be judged against decision relevance and equity, not only global averages. *This gap motivates the fairness pillar.*

### 2.2 The Speed Mismatch

A central bottleneck in climate intelligence is the latency between information and action. Whether for rapid-onset hazards requiring guidance within hours or slower-onset risks where planners need timely updates, the challenge is rarely the absence of scientific information but the delay in translating it into usable decisions Reichstein et al. (2025); Tiggeoven et al. (2025); Najafi et al. (2024).

This latency is not simply bureaucratic inefficiency. It reflects the way climate-risk information is produced across disconnected stages: forecasts are generated in one system, translated into hazard or impact estimates in another, interpreted through separate institutional workflows, and only then communicated into decision processes. Each handoff can introduce delay, uncertainty, or inconsistency. Thus, high-quality information often reaches decision-makers after the most critical intervention windows have narrowed or closed. The bottleneck is not prediction speed but system-level responsiveness across organizational boundaries Oh and Bartos (2025); Wang et al. (2025).

*Closing this gap is the objective of the speed pillar.*

### 2.3 The Validation Crisis

A further limitation is that many AI systems are still evaluated in ways that do not map cleanly onto the needs of climate decision-making. Standard validation often emphasizes predictive skill on held-out historical data through metrics such as RMSE, correlation, or classification accuracy Camps-Valls et al. (2025); Eyring et al. (2024a). These are useful, but they do not by themselves establish whether a model remains reliable under extremes, distribution shift, or in the downstream decision contexts for which it is intended. A model can perform strongly on average and still be poorly calibrated or operationally fragile under extreme events, distribution shifts, and novel hazard combinations that define real-world climate decision-making. Although out-of-distribution testing and extreme-event evaluation are increasingly recognized in parts of the literature Eyring et al. (2024b,a), they remain unevenly adopted and are not yet sufficient to establish deployment readiness across the diverse settings where climate intelligence is expected to operate.

Interpretability Hrast Essenfelder et al. (2025) and uncertainty are central requirements here. When models function as black boxes, domain experts cannot easily assess whether predictions reflect robust physical and social relationships or brittle correlations. And without calibrated uncertainty, decision-makers cannot distinguish confident inference from extrapolative speculation. This often results in a quiet failure mode: technically advanced systems remain underused because institutions do not trust them enough to rely on them in high-consequence settings Machen et al. (2025), thereby biasing decision-making Zarekarizi et al. (2020). Validation must therefore move beyond accuracy alone toward decision utility. Relevant questions include whether a model improves outcomes in deployment, whether uncertainty is appropriately calibrated, and whether performance holds in the extreme or high-vulnerability cases that drive real-world relevance. Until evaluation reflects those criteria more consistently, the gap between technical capability and operational adoption will persist.

*The robustness pillar addresses this failure directly.*

## 3 A Blueprint for Integrated Climate Intelligence

The integration failures described above share a common origin: climate AI research has often been organized around what machine learning can do within individual domains, rather than around what decision-makers need across them Rodriguez-Pardo and Tavoni (2026). To close the gap between climate information and climate action, AI must serve as the connective tissue between Earth system science and societal response. Three architectural pillars, illustrated in Figure 1, define this shift towards integrated climate intelligence.

### 3.1 Fairness: Architectural Equity

Vulnerability inversely correlates with data availability Su et al. (2026); noa (2025). Standard architectures optimizing for aggregate error systematically fail in data-sparse regions where accurate prediction matters most. This is not a bug to be patched; it is a design flaw requiring architectural correction.

**Fair evaluation and objective design** challenge the assumption that aggregate accuracy is an adequate measure of model fitness. When benchmarks reward performance averaged across regions, they implicitly weight data-rich areas more heavily, since those regions contribute more labeled samples and more reliable ground truth. The consequence is that a model can achieve state-of-the-art scores while systematically underperforming where predictions matter most. Addressing this does not require trading off accuracy in one region against another. Rather, it requires evaluation stratified by vulnerability and hazard

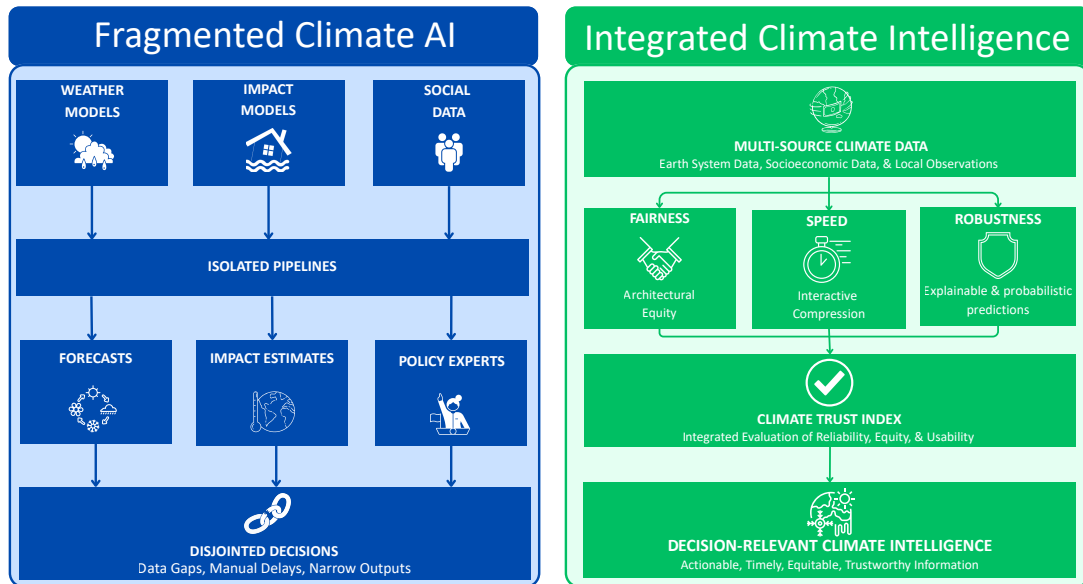


Figure 1: Conceptual framework for Integrated Climate Intelligence. The figure contrasts siloed AI applications (left) with an integrated framework centered on societal needs and organized around three design pillars: fairness, speed, and robustness.

context Rolf et al. (2021); Camps-Valls et al. (2025), and training objectives that reflect the uneven social value of prediction. A small error in flood forecasting for coastal Bangladesh, where adaptive capacity is limited, can carry different operational consequences than the same error for the Netherlands. Making this asymmetry explicit in objective functions and evaluation protocols is not a post-hoc fairness adjustment; it encodes what the system should optimize from the outset.

**Spatially-informed priors** address the epistemic problem: how to make reliable predictions where ground-truth observations are sparse. Bayesian frameworks can encode physical constraints (e.g., conservation of mass, energy balance, hydrological connectivity) as prior beliefs that regularize learning in data-poor regions Karniadakis et al. (2021); Bracco et al. (2025). A model predicting river discharge in an unmonitored West African basin can borrow physical structure from well-observed systems, preventing the spurious correlations that emerge when models overfit to noise in small samples Kratzert et al. (2019); Nearing et al. (2024). Transfer learning Immorlano et al. (2025) extends this logic: representations learned from data-rich domains can bootstrap performance in data-sparse contexts, though thorough validation remains essential to avoid transferring biases.

**Federated learning** Mohr et al. (2025) addresses the political economy of data. Current practice extracts observations from vulnerable regions, processes them in institutions of the Global North, and returns predictions—if at all—on terms set by those institutions. Federated architectures invert this flow: models travel to the data sources rather than the data traveling to the models. Local institutions retain control over raw observations while contributing to global model improvement through gradient updates. This is not merely

a privacy technology; it can also support stronger forms of data sovereignty by allowing local institutions to retain greater control over raw observations and participation in model development.

Together, these mechanisms can help ensure that integration does not replicate the extractive patterns that contributed to current inequalities. Fairness is not a constraint on performance—it is a redefinition of what performance means.

### 3.2 Speed: Interactive Compression

In many forecasting contexts, the speed mismatch is no longer primarily computational: modern AI can produce predictions orders of magnitude faster than traditional numerical methods. The bottleneck is integration: manual handoffs between physical models, impact assessments, and decision platforms that consume months of expert coordination. Solving this requires architectural changes at three levels.

**Neural emulators** compress the computational core. Process-based Earth system models (e.g., CMIP6 ensembles Eyring et al. (2016)) require supercomputer hours for single-scenario runs. Machine learning models trained on their outputs can approximate input-output mappings at a fraction of the cost Van Katwyk et al. (2026). Recent foundation models demonstrate this for weather and ocean forecasting: Aurora produces operational-quality forecasts for weather, air quality, and ocean waves at computational costs orders of magnitude below those of numerical methods Bodnar et al. (2025), while MedFormer achieves similar compression for Mediterranean ocean forecasting Epicoco et al. (2025). An important caveat applies: these emulators excel at interpolating within the distribution of their training data, but long-term climate projection involves fundamentally out-of-distribution conditions, including novel forcing scenarios, slow feedbacks, and nonlinear tipping points that may not be represented in historical simulations. Emulation of existing scenario ensembles is feasible; replacing process-based climate models for genuinely new projections remains an open challenge Eyring et al. (2024b); Ou et al. (2026). The computational barrier to real-time *forecasting* is falling; the barrier to faithful long-term *projection* persists.

But emulator speed is meaningless without **integration infrastructure**. Current pipelines require manual reformatting at every interface: climate model outputs must be post-processed, regridded, bias-corrected, and fed to impact models, each step requiring expert intervention. An integrated architecture can reduce these handoffs through standardized interfaces, interoperable data schemas, and automated data fusion. The goal is a **queryable climate intelligence layer**: decision-makers can pose questions (“How does a 15% monsoon deficit affect rice yields in south India under current insurance structures?”) and receive probabilistic assessments on operationally relevant timescales, rather than after months of bespoke model coupling and expert mediation.

The operational implication is a shift from **static reporting to dynamic decision support**. Traditional climate services produce periodic assessments that are useful for long-term planning but inadequate for crisis response. Interactive systems enable continuous scenario exploration: testing policy sensitivity, stress-testing infrastructure investments, optimizing resource allocation as conditions evolve. For weather-related decisions, this could compress assessment cycles from months to days, transforming the relationship between climate knowledge and climate action.

### 3.3 Robustness: Calibrated Extrapolation

Speed without reliability is dangerous: climate action increasingly requires extrapolation beyond conditions present in the historical record, precisely where standard deep learning is most vulnerable. Two architectural requirements help address this challenge.

**Hybrid physics-AI architectures** provide a safety floor. Pure data-driven models learn statistical regularities from training distributions; when deployed under novel conditions, those regularities may not hold. Embedding physical laws as hard constraint bounds the space of possible outputs Beucler et al. (2021); Karniadakis et al. (2021). A model predicting atmospheric dynamics must respect conservation of mass; a hydrological model should not generate negative streamflow; an ocean model should not produce temperatures below the freezing point of seawater. These constraints are not learned: they are imposed architecturally, ensuring that even under extreme distribution shift, predictions remain physically plausible Ebel et al. (2024).

**Uncertainty-aware inference** distinguishes confident predictions from speculation. Standard neural networks output point estimates without indicating reliability, a fundamental failure mode for high-stakes decisions. Conformal prediction offers one promising path, providing statistically guaranteed coverage without distributional assumptions Angelopoulos and Bates (2023): not a single point estimate, but a prediction interval with calibrated coverage. Crucially, such intervals automatically widen when models extrapolate beyond their training support, providing decision-makers with calibrated uncertainty rather than false confidence.

Their combination converts scientific output into decision-relevant information. When predictions are highly confident relative to the stakes involved, they can support pre-authorized protocols (evacuations, resource allocation, insurance payouts), thereby reducing the burden of deliberation under time pressure. When confidence is low, they flag the need for expert review, guarding against both unchecked automation and decision paralysis. The appropriate confidence threshold is not fixed; it depends on the asymmetry between the costs of a false alarm and inaction, which varies across hazard types and decision contexts. For flash floods, where the cost of inaction is measured in lives, lower confidence may justify action; for infrastructure investment, where false alarms carry high economic costs, higher thresholds are appropriate. As Box 1 illustrates for the Valencia case, the integrated system does not remove political accountability, but it replaces epistemic ambiguity with transparent, calibrated risk information against which decisions can be evaluated.

Robustness connects directly to fairness: calibrated uncertainty identifies where models are unreliable, precisely the data-sparse regions where vulnerable populations concentrate. And both fairness and robustness are operationally meaningless if information arrives too late. The three pillars are interdependent: fairness defines what the system must optimize, speed determines whether the output arrives in time to matter, and robustness establishes whether it deserves to be trusted when it does.

## 4 The Policy Deliverable: The Climate AI Trust Index

Architectural principles require enforcement mechanisms. Without standards, the market for climate AI tools risks optimizing for the wrong objectives: benchmark performance over operational fitness, aggregate accuracy over distributional equity, and computational impressiveness over decision relevance Kaack et al. (2022); Rodriguez-Pardo and Tavoni (2026). This risk is already materializing. Leaderboards privilege average predictive skill, creating incentives to maximize performance where data are dense while neglecting the distributional tails where climate impacts are concentrated Eyring et al. (2024a); Rolf et al. (2021). Procurement and deployment decisions often proceed without systematic

assessment of equity, extrapolation safety, or decision utility Machen et al. (2025). The result is a growing ecosystem of climate AI tools whose failure modes under real-world operational conditions, particularly in data-sparse, high-vulnerability settings, remain insufficiently characterized. As the economic stakes of AI-enabled climate action grow Stern et al. (2025), so does the cost of deploying systems that have never been evaluated against the conditions they will face in practice.

We propose the **Climate AI Trust Index**: a multidimensional evaluation framework for distinguishing research-grade demonstrations from deployment-ready climate intelligence infrastructure. Complementary to Model Cards Mitchell et al. (2019), which document model properties without adjudicating fitness for use, the Trust Index evaluates whether a system is sufficiently rigorous, equitable, useful, and efficient for the decision context in which it is intended to operate. It draws on precedent from AI efficiency benchmarking Luccioni et al. (2025b) and extends the logic of operational verification frameworks already maintained by meteorological agencies Haiden et al. (2012); Rodwell et al. (2010) to include dimensions currently absent from standard evaluation: equity, robustness under distribution shift, and decision relevance. At this stage, the Trust Index is intended as a structured framework for evaluating deployment readiness across use cases, not as a finalized universal standard with fixed thresholds.

**Box 2: The Climate AI Trust Index**

A framework for evaluating whether climate AI systems are ready for operational deployment.

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Axis	Evaluation Criterion	Deployment Threshold
<b>Rigor</b>	Performance under out-of-distribution extremes and robustness to distribution shift, not only historical averages.	Physical consistency under stress; uncertainty intervals widen appropriately under extrapolation; no conservation-law violations under stress testing.
<b>Equity</b>	Spatial parity, subgroup calibration, and performance in vulnerability hotspots.	No systematic exclusion of high-vulnerability populations; positive skill in the large majority of vulnerability hotspots; global performance cannot justify local failure.
<b>Utility</b>	Time-to-information and value relative to the operational decision window and declared use case.	Decision-relevant outputs delivered within the action window; ensemble or scenario capacity sufficient for probabilistic assessment when required.

*Deployment constraints: efficiency, sustainability, transparency, and contestability should be reported alongside model performance. Climate-critical systems should favor efficient architectures over frontier-scale compute where comparable performance is achievable.*

## 4.1 The Logic of Each Axis

**Rigor** inverts current evaluation incentives. Standard benchmarks reward average performance across historical distributions, which can obscure whether a model remains reliable under the rare, high-impact conditions that drive climate risk Camps-Valls et al. (2025); Eyring et al. (2024a). A flood prediction system that performs well on mostly dry days while missing the single catastrophic event may score well by aggregate metrics and still be operationally inadequate. The Trust Index, therefore, requires evaluation under distribution shift, on synthetic or stress-tested extremes, and for physical consistency and uncertainty calibration Beucler et al. (2021); Angelopoulos and Bates (2023). A model that remains confident while producing physically implausible outputs fails this criterion regardless of historical benchmark performance. Where relevant, causal or mechanistic plausibility should also be assessed Runge et al. (2023); Bracco et al. (2025).

**Equity** replaces aggregate metrics with distributional requirements. A precipitation model with high global correlation that systematically underperforms in sub-Saharan Africa may be publishable, but it is not deployment-ready if the performance deficit falls on populations with the least adaptive capacity noa (2025); Su et al. (2026). The equity axis requires reporting of spatial parity, subgroup calibration, and minimum positive skill in vulnerability hotspots Rolf et al. (2021). Climate intelligence infrastructure should not systematically exclude the populations it is designed to protect. A model cannot compensate for failure in the Sahel with exceptional performance in Switzerland.

**Utility** recognizes that the value of climate intelligence is both time-bounded and context-dependent Reichstein et al. (2025); Lumbroso et al. (2025). A perfect flood forecast delivered after the flood has receded is worthless; a rapid but uncertain warning that enables evacuation saves lives. The utility axis evaluates time-to-information, fitness for the declared use case, and the value of information relative to realistic alternatives. A model marketed for emergency response must operate within the emergency decision window Najafi et al. (2024); a model for adaptation planning must demonstrably improve planning decisions rather than simply produce faster outputs.

These axes should be interpreted together. A system that is fast but uncalibrated is dangerous. A system that is accurate on average but systematically fails vulnerable populations is inequitable. A system that is physically coherent but too slow to inform action is operationally irrelevant. The specific thresholds operationalizing each axis (minimum spatial parity gaps, ensemble size requirements, latency ceilings) should be calibrated through stakeholder consultation and iterative deployment, and will evolve as both capabilities and climate risks change.

## 4.2 Operationalizing the Index

Standards matter only if institutions with procurement authority adopt them. Three implementation pathways offer immediate traction, each leveraging existing mandates.

**Public climate services** already maintain rigorous verification frameworks. ECMWF, NOAA, and the Copernicus Climate Change Service assess bias, skill, and reliability for numerical weather prediction Haiden et al. (2012); Rodwell et al. (2010), and initiatives like Copernicus' *OBSERVER* are beginning to extend this to AI-based systems. These frameworks do not yet systematically evaluate subgroup calibration, performance across vulnerability gradients, or robustness under unprecedented extremes. The Trust Index extends this infrastructure rather than replacing it, adding dimensions that matter when systems support societal decisions, not just scientific benchmarking. For agencies already investing in verification, the marginal cost of incorporating equity and robustness dimensions is modest relative to the gain in policy relevance.

**Multilateral climate funding** channels billions annually toward adaptation and resilience Stern et al. (2025). The Green Climate Fund, World Bank adaptation programs, and bilateral development agencies increasingly support AI-enabled early warning systems, crop yield models, and climate risk assessments. These institutions already require fiduciary, environmental, and social safeguards. The Trust Index adds a technical layer: systems deployed in vulnerable settings should demonstrate minimum performance, transparency, and non-exclusion in those settings before receiving public funding. This creates a design incentive: developers seeking climate finance must optimize for fairness and utility, not only for capability.

**Carbon market verification** represents a distinct and urgent application. Voluntary carbon markets increasingly rely on AI-enabled monitoring, reporting, and verification (MRV) Streck (2021). Because incentives in this space can reward speed and low cost over rigor, quality varies enormously. Recent analyses have found that many REDD+ projects generated credits for carbon reductions that never occurred West et al. (2023); Sasaki (2025); Yu et al. (2023). The Trust Index can provide independent certification distinguishing robust MRV from unreliable alternatives. Given the intensity of current scrutiny over offset integrity, demand for credible evaluation frameworks is significant.

Operationalization must also account for compute and energy trade-offs. Many climate applications can benefit from hybrid, modular, and domain-specific architectures that are substantially more efficient than large-scale general-purpose foundation models Kaack et al. (2022); Luccioni et al. (2024, 2025a); Fernandez et al. (2025). Efficiency and sustainability should be treated as design constraints, reported alongside predictive performance Luccioni et al. (2025b); Schwartz et al. (2020). In climate-critical settings, a model that is marginally more accurate but dramatically more energy-intensive may not be the better deployment choice.

### 4.3 Governance and Accountability

The certification authority determines legitimacy. A Trust Index controlled by commercial AI developers invites regulatory capture; one controlled solely by academic scientists risks disconnection from operational realities. Effective governance requires structured multi-stakeholder input, a principle increasingly recognized in AI regulation more broadly Smuha (2025); Casonato and Olivato (2024).

We propose a tripartite structure. **Technical criteria:** robustness under distribution shift, physical consistency, and subgroup calibration should be set by domain experts spanning climate science, machine learning, and statistics, with explicit representation from the Global South to prevent criteria that implicitly advantage data-rich contexts. **Equity criteria:** non-exclusion floors, vulnerability weighting, and acceptable parity gaps should be validated with participation from affected regions, ensuring that populations bearing climate risk have a voice in defining acceptable performance Machen et al. (2025). **Utility criteria:** time-to-information, scenario capacity, use-case fitness, should be informed by operational decision-makers: emergency managers, agricultural planners, infrastructure investors.

This governance structure should be housed within existing international institutions rather than created from scratch. The World Meteorological Organization, the IPCC, and UNFCCC each offer partial foundations Alliance for Hydromet Development (2024). The exact institutional home matters less than the principle: deployment standards for climate AI should be public-interest infrastructure rather than proprietary market instruments. Governance must do more than ensure representation in setting the criteria; it must also adjudicate trade-offs, revise thresholds in light of deployment experience, and provide formal mechanisms for contesting certifications when systems fail in practice. In this sense,

the Trust Index is not only a framework for inclusion but also an institutional process for resolving disagreement, updating standards, and assigning accountability under real-world conditions.

The Index must be **public, versioned, contestable, and inclusive**. Proprietary certification enables gaming; transparent criteria and public evaluation datasets enable independent scrutiny. Version control acknowledges that today’s thresholds may be insufficient as capabilities advance and impacts intensify. Contestability requires formal mechanisms for challenging certifications when systems fail in deployment: designing this appeals process is itself a governance challenge that must be resolved before the Index can claim full credibility. Inclusivity means that no community should be excluded from the benefits of climate AI or from participation in governing the systems that affect them.

The Trust Index is not a static checklist but a living framework for accountable deployment, evolving with science, responsive to failure, and governed by those with the most at stake.

## 5 Challenges and Safeguards

The transition to Integrated Climate Intelligence is not simply a technical upgrade. Even if the architectural blueprint outlined above is increasingly feasible, its implementation faces significant physical, institutional, and energy constraints. These safeguards are not external to the framework proposed here; they define the conditions under which Integrated Climate Intelligence can be considered legitimate and deployable.

### 5.1 The Physical Baseline: AI Cannot Replace Observation

A central risk of the “AI-first” narrative is the false premise that synthetic or reconstructed data can substitute indefinitely for physical observation; they cannot. **Fairness mandates measurement.** While transfer learning, data reconstruction, and physically informed priors can improve performance in data-sparse regions, they still depend on a backbone of observational infrastructure to anchor, validate, and update model behavior Su et al. (2026); Bracco et al. (2025); Karniadakis et al. (2021). If AI adoption were used to justify the decommissioning of weather stations, in situ monitoring systems, or satellite programs, the result would not be greater intelligence but weaker ground truth: the validation crisis would deepen rather than recede, because the empirical basis needed to audit models would progressively disappear. The integration layer should be treated as a multiplier of physical infrastructure, not as a substitute for it.

### 5.2 The Energy Paradox

There is an obvious tension in using energy-intensive machine learning to address a crisis driven by unsustainable energy use. Training large foundation models can require substantial computational resources, and repeated fine-tuning or deployment at scale may carry non-trivial environmental costs Schwartz et al. (2020); Luccioni et al. (2024, 2025a); Fernandez et al. (2025). This does not mean that climate AI is inherently self-defeating, but it does mean that efficiency must be treated as a design constraint rather than a secondary optimization target. Integrated Climate Intelligence does not need to rely on frontier-scale general-purpose models. Many climate applications are better served by hybrid, modular, and domain-specific architectures that achieve strong performance at substantially lower computational cost Kaack et al. (2022); Van Katwyk et al. (2026). The field should adopt Green AI principles not only in retrospective reporting but in model design, procurement, and deployment Schwartz et al. (2020); Stern et al. (2025). A model should not

be considered preferable simply because it is larger. In climate-critical settings, a marginal gain in predictive accuracy may not justify a dramatic increase in energy use, hardware requirements, or barriers to participation by institutions with limited computational resources Luccioni et al. (2024, 2025a).

### 5.3 Institutional Inertia and Epistemic Risk

The silos described in Section 2 persist not only because of technical limitations, but because they are reinforced by academic, bureaucratic, and professional incentives. Funding agencies separate “Physical Sciences” from “Social Sciences”; universities separate “Computer Science” from “Earth Science”; operational agencies often divide forecasting, risk analysis, and policy response across different mandates. Building an integration layer, therefore, requires more than better models. It requires institutional coordination and a workforce that can operate across disciplinary boundaries: researchers fluent in both atmospheric physics and machine learning, and decision-makers equipped to act on probabilistic information rather than waiting for deterministic certainty Machen et al. (2025). Beyond workforce gaps lies a governance question: *who controls* integrated climate intelligence? Systems that shape resource allocation, warning thresholds, or risk assessments should be housed within institutions accountable to affected populations, not governed primarily by commercial incentives or opaque proprietary standards Machen et al. (2025); Smuha (2025); Casonato and Olivato (2024). Public legitimacy is not incidental here; it is part of operational reliability.

Transparency requirements may also conflict with commercial interests. Some AI climate systems rely on proprietary architectures or restricted training data, and developers may resist the public evaluation and open benchmarking that the Trust Index demands. This tension between accountability and intellectual property is not unique to climate AI, but the stakes are distinctive: when a proprietary model informs evacuation decisions or carbon credit issuance, the case for independent, reproducible evaluation outweighs the case for trade secrecy. Governance frameworks must explicitly navigate this tension rather than assume transparency will emerge voluntarily.

A further challenge is epistemic risk. Black-box integration can fail in ways that are difficult to diagnose under crisis conditions. Unlike process-based algorithms, which can often be interrogated component-by-component, neural systems may distribute failure across many parameters and interacting modules Cho and Ackom (2025); Debnath et al. (2023). For that reason, meaningful “human-in-the-loop” capacity should remain an operational requirement for the foreseeable future, especially in high-consequence settings. In many applications, legacy physical models and expert oversight should continue to run in parallel as failsafes; not because AI is unusable, but because high-consequence systems require redundancy, traceability, and institutional trust.

## 6 Conclusion

The Valencia disaster illustrates the core argument of this Perspective. The hazard was forecast, warnings were issued, and relevant information existed across meteorological, hydrological, and societal systems. Yet protective action was delayed until the most critical response window had closed. The failure was not in any single component but in the absence of an architecture connecting prediction, impact assessment, communication, and response into a system that could function coherently under time pressure.

This Blueprint argues that AI can help close that gap: not as a replacement for governance, expertise, or physical science, but as an **integration layer** linking them. The three design requirements are inseparable: **fairness**, so that vulnerable populations are not

systematically excluded; **speed**, so that information arrives within the window in which it can matter; and **robustness**, so that outputs remain trustworthy under extrapolation and stress. The **Climate AI Trust Index** translates these principles into a deployment framework, enabling funders, regulators, and public agencies to evaluate whether systems are equitable, reliable, efficient, and decision-relevant in the settings where they are actually used.

A key task now is to turn this blueprint into a research and institutional agenda: integrated benchmarks for coupled climate–society systems; multimodal models constrained by physical and causal structure; streaming infrastructures for real-time climate intelligence; participatory data governance; and public certification mechanisms for high-consequence climate AI. Progress should be measured not only by predictive accuracy, but by whether it improves society’s capacity to anticipate, deliberate, and respond.

The next preventable failure will not occur because climate science lacked insight. It will occur because insight was not connected to action in time. Fragmentation is the bottleneck. Integration is the breakthrough. The climate crisis will not wait for incremental coordination. The window is measured in years, not decades. The question is no longer whether integrated climate intelligence is possible: it is whether we will build it in time.

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