Computation to Choose a Future: Planetary Stewardship in the Age of AI

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Abstract

The accelerating transformations of the Anthropocene demand governance systems capable of anticipating and steering complex, nonlinear Earth-system dynamics. Existing models optimize for likely trajectories rather than exploring a broader set of futures. This commentary introduces the concept of Computational Foresight (CF)—an integrative framework combining artificial intelligence, simulation, and complex-systems modeling to augment human anticipation and collective reasoning about the future. CF organizes foresight into five interlinked functions forming a continuous, reflexive cycle for anticipatory governance. It draws on advances in machine learning, reinforcement learning, causal inference, and generative modeling to detect emerging signals, map feedbacks, and test "what if" interventions within virtual environments. CF thus shifts computation from prediction to possibility mapping, treating uncertainty as a resource for learning. The paper outlines the key technical and ethical frontiers of this transition: validation under deep uncertainty, reasoning in open-ended domains, alignment with human values, prevention of algorithmic closure, pluralistic model integration, and genuine human–AI collaboration. CF is proposed as a new layer of civic and scientific infrastructure for Earth system stewardship, aiming to enable societies not merely to forecast the future but to co-design it through transparent, participatory, and adaptive intelligence.

1 Introduction

Human activity has become a geological force, reshaping the climate and biosphere [81]. Governance systems built for gradual change struggle to respond to the pace and complexity of today's systemic risks [11]. Current approaches often operate in disciplinary or institutional silos, treating challenges as separate rather than interlinked. Policy responses remain slow, fragmented, and constrained by difficulties in integrating data and knowledge across scales [26]. Governing the Anthropocene therefore demands new modes of coordination and imagination that can match the complexity, speed, and interconnectedness of Earth system change.

Recent advances in Earth system science further underscore the urgency of this shift. Multiple components of the Earth system—including the West Antarctic Ice Sheet, the Atlantic Meridional Overturning Circulation, tropical forests, and monsoon regimes—are now approaching states of heightened instability, where small perturbations can trigger abrupt and potentially irreversible transitions. These elements interact through teleconnections, forming clusters of cascading risks that propagate across food, energy, water, and ecological systems. Stewardship in this context requires anticipatory capacities that can recognize emerging instability, map plausible cascade pathways, and evaluate transformation strategies within safe and just Earth system corridors.

Non-peer reviewed preprint submitted to EarthArXiv. Currently under review at Earth's Future.

Diverse fields have attempted to address this challenge. Transition design and sustainability transitions research have sought to orchestrate systemic shifts toward just and regenerative futures [37, 50]. Foresight and futures studies have developed participatory and anticipatory methods to navigate uncertainty [89]. Meanwhile, Earth system science has advanced integrative frameworks such as planetary boundaries and Earth trajectories, depicting multiple possible pathways for humanity's relationship with the planet [69, 81]. Together, these perspectives converge on a common need: to move from prediction and control toward stewardship and deliberate transformation.

At the same time, computation has been extending the limits of human cognition [23, 13]. From the Limits to Growth simulations of the 1970s [51] to contemporary agent-based models that capture adaptive behavior and emergent social–ecological dynamics [2], and to contemporary Integrated Assessment Models (IAMs) [88] and Earth System Models [25] that underpin IPCC scenarios, computational tools have been central to how societies visualize global trajectories and understand non-linear change. Yet most approaches have traditionally emphasized prediction —quantifying what is likely—rather than designing what is desirable. With Artificial Intelligence (AI) now increasingly shaping policy analysis and decision-making [3], a shift is emerging [7, 60, 22, 16, 55]: from using computational models to forecast the future to using computation to explore, test, and co-develop alternative pathways consistent with societal values and planetary constraints [72].

Building on this trajectory, this commentary advances the concept of *Computational Foresight (CF)* [60]: a framework in which humans and machines work deliberately together in the design and governance of futures, providing e.g. early-warning insights, scenario exploration, and adaptive strategy as an architecture for planetary stewardship. The five stages of CF—Exploration, Sensemaking, Imagination, Strategy, and Adaptation—form a continuous human–machine learning loop (see Figure 1). CF extends the foresight ethos by transforming computation from a predictive tool into an active collaborator in human imagination and strategy. The following sections unpack each stage, examining how emerging capabilities—such as digital twins, adaptive modeling, and hybrid intelligence—can strengthen foresight practice and support anticipatory governance in the Anthropocene.

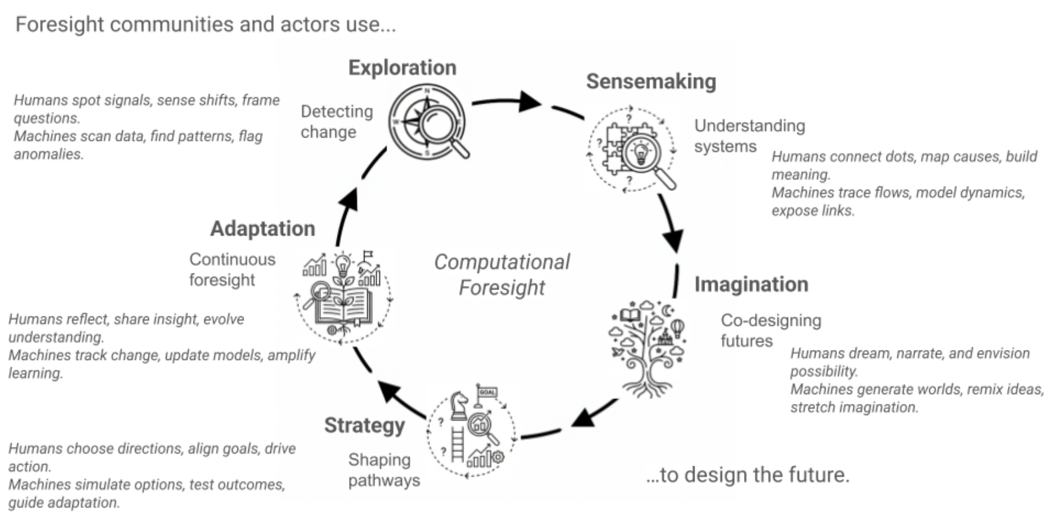

Figure 1: Human and machine intelligence intertwined in the evolving cycle of foresight.

While CF draws inspiration from established approaches such as Robust Decision Making [48], Exploratory Modeling [4], Decision Making under Deep Uncertainty [49], Dynamic Adaptive Policy Pathways [32], and Anticipatory Governance [12], it reconceptualizes foresight as a learning architecture where computational models and publics co-learn. Unlike these traditions, which rely on expert-led modeling and static ensembles of scenarios, CF introduces AI-native mechanisms—generative simulation, reinforcement learning, and hybrid human–machine reasoning—to continuously explore, test, and reinterpret futures as data, values, and feedbacks evolve. CF extends these earlier frameworks from decision support to cognitive human-AI co-design, shifting computation from prediction and optimization to an open-ended, reflexive process of collective sensemaking and planetary stewardship.

2 From Prediction to Foresight in the Anthropocene

Prediction often reduces the future to a single expected trajectory. From a computational standpoint, prediction is the act of conditioning on present data to estimate the most probable future outcome under a fixed set of model assumptions. Foresight, by contrast, maps the structure of possible futures [35]—the ensemble of counterfactual trajectories, decision pathways, and value trade-offs. In essence, prediction narrows futures to what is most probable; foresight maps the full landscape of uncertainty, exploring how choices and feedbacks yield alternative trajectories. Because Earth and social systems are complex adaptive systems [78]—characterized by feedbacks, emergence, nonlinearity, and path dependence—prediction alone offers limited leverage [9, 45]. Computation must therefore operate within complexity: navigating interacting processes that co-evolve across scales and sometimes reorganize abruptly [66, 68, 23]. CF takes this as a design premise, treating the future not as a trajectory to forecast but as a dynamic system to understand and engage. Figure 2 illustrates how CF reframes the role of computation—from optimizing forecasts to mapping and co-designing futures.

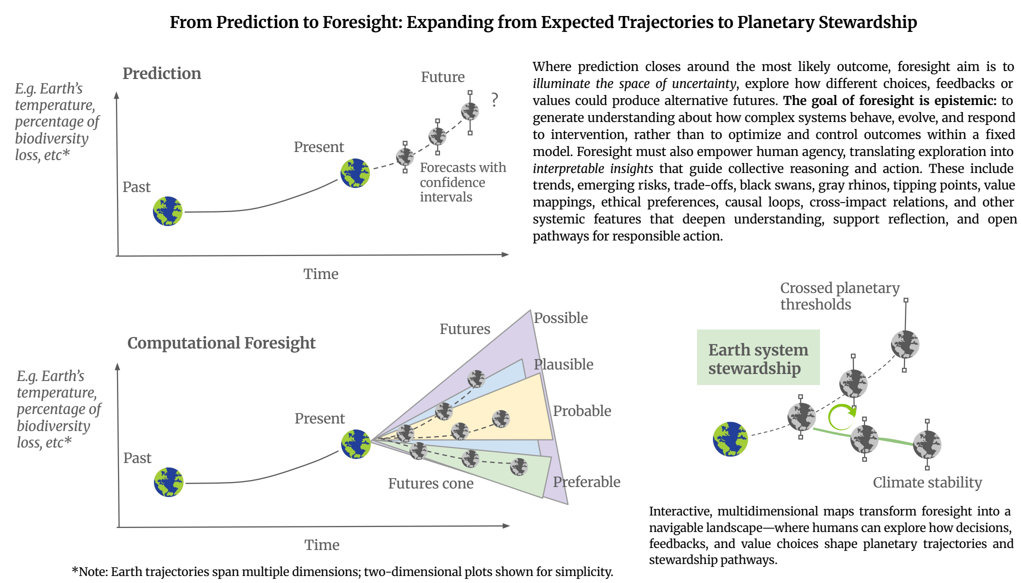

Figure 2: Reframing computation from optimizing forecasts to co-designing futures. The diagram contrasts prediction—focused on a single expected trajectory—with foresight, which maps a multidimensional space of possible futures. Interactive, multidimensional visualizations can support Earth system stewardship by enabling humans to explore risks, trade-offs, and feedbacks—transforming computation into a tool for collective reasoning and future design.

Among existing computational paradigms, reinforcement learning (RL) is perhaps the closest analogue to foresight [84]. Like foresight, RL involves an agent navigating a dynamic environment through iterative cycles of observation, action, and feedback. The agent learns a policy—a mapping from states to actions—that improves performance over time based on experience. This process balances exploration (trying new actions to learn about the environment) and exploitation (using known strategies to maximize outcomes). In this sense, RL embodies a minimal form of anticipatory learning: it builds knowledge of how present actions influence future states. Yet, RL remains bounded by the logic of optimization. The agent's exploration is instrumental—it aims solely to maximize a predefined reward function within a fixed environment. It does not explore to understand the environment itself, to question the reward structure, or to examine unintended consequences of its own behavior.

Foresight-oriented computation extends this paradigm. Its purpose is not only to identify actions that maximize rewards, but also to reveal those that minimize them [71]—actions that may drive systems toward undesirable or irreversible states. Here, exploration becomes epistemic rather than purely instrumental: it seeks to map thresholds, inflection points, and tipping dynamics within complex systems, where small interventions can trigger large transformations. The objective is thus not to discover a single optimal policy, but to understand the structure of the possibility space—the trade-offs, uncertainties, and emergent feedbacks that shape collective outcomes. Reward functions themselves become objects of inquiry: multi-dimensional, contested, and evolving. Computation, in this sense, is not a predictor of one future but a generator of many counterfactual worlds through which societies can learn to act with foresight.

Still, prediction and control remain essential within foresight. Accurate prediction provides the empirical foundation needed for exploration—it anchors models in observed dynamics and tests their assumptions. Likewise, control mechanisms help assess the stability, resilience, and responsiveness of systems once alternative pathways have been envisioned [71]. In this broader frame, prediction and control become instruments of calibration rather than ends in themselves: they serve the epistemic goal of learning how systems behave, where they may fail, and how they might adapt.

3 The Foundations of Computational Foresight

Computational Foresight (CF) reframes computation as an engine of exploration rather than prediction—hybrid human–machine systems that map, test, and navigate the multidimensional landscape of possible futures. CF aims to provide a computational interface between scientific modeling, ethical reflection, and participatory governance. It can support operationalizing key frameworks in sustainability governance by translating their normative principles into dynamic, testable models. For example, enabling exploration of the systemic dynamics defined by the Planetary Boundaries framework [70, 80] and the Safe and Just Operating Space paradigm linking social foundations with ecological ceilings [65]. By connecting these frameworks with simulation and anticipatory modeling, CF will support the aims of Earth System Governance and Global Commons Stewardship [8, 69]. It should also align with initiatives such as UNESCO's Futures Literacy and Future Earth [54], which seek to democratize foresight and collective learning. Through these integrations, CF aims to reframe computation as a civic infrastructure for planetary stewardship. The design of CF is guided by six principles that anchor its technical and ethical orientation:

1. **Sustainability and intergenerational justice:** Balance present needs with long-term resilience; apply the precautionary principle.
2. **Inclusion and transparency:** Ensure diverse participation; make models auditable and contestable.
3. **Systems integration:** Trace feedbacks across coupled human–Earth systems; design policies robust across futures.
4. **Scientific rigor and data integrity:** Use validated models, unbiased data, and transparent uncertainty characterization.
5. **Human–AI hybridization:** Combine human creativity and ethics with AI's analytical power through collaborative intelligence [53].
6. **Iterative design and learning:** Embed foresight in a continuous cycle of monitoring, reflection, and adaptation.

3.1 The Reflexive Human-AI Cycle for Earth System Stewardship

The future design cycle emphasizes anticipation, vision-building, and strategic action in response to emerging change [17, 87]. It provides the organizing structure for CF—an iterative learning system that strengthens collective understanding and adaptive capacity (Figure 1).

CF does not seek to automate decision-making but to amplify human judgment through hybrid intelligence [92, 27]: the integration of human insight and computational reasoning [75, 40]. Humans contribute contextual awareness, ethical reflection, creativity, and the ability to reason across uncertainty and values, while machines provide analytical depth, scalability, and the power to simulate complex systems and uncover hidden feedbacks. Together, they merge creative foresight with computational rigor [7]. The central challenge of hybrid intelligence is to build explainable, adaptive architectures that align machine reasoning with human purpose and foster trust through transparency and shared situational awareness [75, 40]. In this vision, explainable AI and visualization tools become civic instruments for collaborative foresight—where humans and machines co-create understanding, interrogate uncertainty, and render complex interconnections visible, debatable, and governable. For example, AI can identify an emerging 'gray rhino' (a highly probable, high-impact risk), but explainable AI must communicate why that event is emerging by exposing underlying causal loops or patterns discovered in the data. This exposure allows human experts to validate the model's structure against domain knowledge, rather than merely accepting a black-box prediction.

3.1.1 Exploration: Detecting Change and Mapping Possibility

Exploration is the sensing stage of foresight—detecting early signals of change such as emerging trends, precursors to tipping points, and other anomalies that may evolve into systemic shifts [74, 31]. Its goal is not prediction but preparedness: cultivating situational awareness of evolving dynamics and potential disruptions [90, 64, 1].

AI can strengthen this capacity in substantive ways. Today's systems can scan vast, heterogeneous data streams to identify weak or nonlinear signals, latent correlations, and early indicators of systemic stress across environmental, social, and economic domains [29, 36]. They can detect precursors to regime shifts in climate, ecosystems, or finance, revealing vulnerabilities before they become crises [45, 33, 61, 15]. Language models can map emerging narratives in scientific literature, patents, and public discourse, tracing conceptual drift and value realignment across sectors [41, 31]. Generative modeling can also exploit uncertainty to generate plausible but unseen scenarios [39], expanding the "possibility manifold" and supporting creative hypothesis formation about future developments [22]. Techniques such as superforecasting and prediction markets can further aggregate distributed human and machine judgments into probabilistic expectations—helping distinguish transient noise from genuine signals of structural change [86, 96, 47, 76, 30]. It could further act as a cognitive amplifier in horizon scanning and expert consensus [16], synthesizing thousands of signals and ranking them by novelty, uncertainty, or systemic importance.

3.1.2 Sensemaking: Understanding Systems and Interconnections

Sensemaking translates scattered observations into coherent models of how systems behave and interact [17, 35]. Where exploration focuses on detecting change, sensemaking seeks to explain it—mapping causal structures, feedbacks, and dependencies that determine system behavior. Traditional foresight methods such as causal-loop diagrams, cross-impact analysis, and system-dynamics modeling reveal feedback mechanisms and identify potential leverage points within coupled human–environment systems.

AI could extend these analytical capacities in both depth and scale. Machine learning can uncover non-linear and cross-scale dependencies across heterogeneous datasets, while causal discovery algorithms infer directional relationships and reveal feedback structures among variables [62, 73]. Graph-based and deep-learning methods support structural mapping of global networks—trade, migration, energy, and biodiversity—exposing interdependencies, vulnerabilities, and emergent properties of complex systems [66, 5, 42]. AI could facilitate collective sensemaking by delivering interactive trade-off maps (e.g. Pareto fronts) and sensitivity analysis visualisations that translate computational discoveries into a shared navigable landscape. These outputs are essential for creating the required shared situational awareness across diverse stakeholders, enabling them to collectively locate potential leverage points and points of systemic failure.

By integrating multimodal data—text, imagery, and time series—AI can also discover non-obvious linkages across domains [97]. This capacity is essential for tracing complex, non-linear feedbacks, such as those caused by short-lived events such as climate forcers, whose regional and temporal impacts require high-fidelity simulation. Beyond identifying correlations, AI can facilitate collective sensemaking by clustering and visualizing diverse inputs from experts, citizens, and stakeholders [27]. It can help researchers form hypotheses about potential drivers of change by extrapolating from incomplete or uncertain data and reveal cross-scale feedbacks that bridge local signals with global trends [43, 34].

A particularly powerful extension of these capabilities lies in digital twins—high-fidelity, continuously updated simulations that couple empirical data with theoretical models of complex systems [95]. Acting as computational laboratories, digital twins reproduce the evolving dynamics of coupled human–Earth systems, enabling researchers and policymakers to test hypotheses, trace cascading effects, and visualize interdependencies as they unfold across scales and sectors. By embedding sensing, simulation, and feedback in a unified framework, they transform sensemaking into a dynamic process of learning within complexity rather than observation of it.

3.1.3 Imagination: Envisioning and Co-creating Futures

Imagination constitutes the generative phase of foresight—where alternative futures are not only analyzed but actively constructed and made discussable. It translates analytical insight into value-rich worlds through scenarios, artifacts, and narratives that enable collective reflection and choice [14, 21, 17, 64]. Scenario design helps decision-makers move from "what will happen" toward "what could or should happen," revealing ethical tensions, opportunities, and pathways under deep uncertainty [63, 9].

AI could amplify this creative process. Large language and diffusion models can generate scenario ensembles, synthesize data-driven narratives, and visualize counterfactual trajectories constrained by physical and social plausibility [19, 99, 18, 101]. Crucially, one of the human roles is to impose ethical and normative constraints (e.g. non-negotiable climate boundaries or social justice minimums) that guide the generative AI to explore the space of preferable futures. These generative frameworks could expand the horizon of foresight—exploring more diverse futures than human teams could feasibly produce alone while maintaining traceability and coherence. In sustainability and policy design, such systems expose trade-offs, synergies, and emergent risks across pathways [78].

Futures-literacy and co-creation processes should engage communities in articulating desirable futures and testing assumptions about change [28, 54, 101]. AI can mediate and scale these processes by supporting multilingual collaboration, interactive scenario-building, and real-time visualization [100, 59, 24, 94]. It can also model collective preferences [16, 85], generating alternative visions that reflect diverse values and contexts.

Finally, imagination demands reflexivity. Meta-foresight systems could evaluate whether scenario sets are sufficiently plural, detect epistemic or regional biases, and highlight which perspectives or futures remain underrepresented [7]. This reflexive layer of CF should turn imagination into both a creative and critical act—one where computational systems not only help design futures but also help societies reflect on how and for whom those futures are imagined.

3.1.4 Strategy: Designing Pathways and Negotiating Transformation

Strategy is where vision meets action—the phase that links imagined futures to present decisions [64, 90]. Traditional foresight applies methods such as backcasting, roadmapping, and adaptive pathways to translate scenarios into plans that are robust across multiple plausible worlds.

In CF, strategy becomes a domain of generative experimentation—where interventions are tested, adapted, and negotiated within simulated environments. Integrated and participatory models allow societies to visualize how technological, economic, or social actions reshape systemic trajectories and interact with planetary boundaries [72]. Within complex adaptive systems, strategy shifts from optimization to robustness and adaptive capacity, exploring pathways across shifting attractors, emergent feedbacks, and potential regime transitions. Generative and reinforcement learning models support this process by constructing plausible yet unseen scenarios, enabling counterfactual reasoning and virtual testing of "what if" interventions before acting in the real world [22, 71].

Simulation Intelligence advances this capability by coupling simulation, learning, and optimization into a unified framework for strategic discovery [46]. Rather than testing predefined scenarios, simulation intelligence enables agents to learn the dynamics of complex systems and iteratively explore strategies that co-evolve with their environments. Simulation intelligence couples learning and simulation to discover the underlying structure of problems and strategies robust across contexts.

A related development is the rise of mixture-of-experts architectures [23, 45]—ensembles of specialized models reasoning collaboratively across domains. Within CF, mixture-of-experts can operationalize strategic pluralism: linking climate, economic, and social simulators into distributed decision systems that weigh competing objectives and uncertainties in real time [23]. Such architectures extend strategy beyond optimization toward deliberation, where diverse computational perspectives expose trade-offs transparently and support inclusive negotiation of transformation pathways—a step toward computational democracy in practice [57].

3.1.5 Learning and Adaptation: Evolving Foresight

The final stage embeds feedback, reflection, and iteration into foresight itself [35, 17]. Insights from earlier stages are revisited in light of new evidence, ensuring that foresight remains a living, self-correcting process. Traditional approaches rely on monitoring indicators, evaluating outcomes, and adjusting strategies as social and environmental conditions evolve. Adaptive governance frameworks institutionalize this reflexivity, recognizing that foresight is never complete.

AI could substantially amplify this adaptive capacity. Machine learning can continuously integrate environmental, economic, and social data—detecting early-warning signals, deviations from expected trajectories, and shifting baselines [67]. Language models can synthesize emerging evidence, identify conceptual drift across science, media, and policy, and highlight when collective assumptions begin to erode. Beyond static monitoring, AI could even adaptively redirect analytical attention as new signals emerge—a form of AI-assisted curiosity that sustains situational awareness and supports proactive sensemaking. Together, these capabilities enable anticipatory learning: continuously updating understanding as the world itself changes. At a broader scale, meta-learning systems could compare outcomes across foresight initiatives, identifying recurring biases or success factors and building institutional memory for what works—and what fails.

Embedding these learning processes within participatory frameworks is essential to keep adaptation transparent and inclusive. Explainable AI and interactive dashboards could make model evolution visible—showing how and why strategies change—and invite dialogue rather than impose adjustment. In this way, AI becomes part of a distributed learning network that connects local insights to global intelligence, allowing diverse actors to co-adapt their understanding of a changing world.

Ultimately, Learning and Adaptation both close and reopen the future design cycle. As new data reshape understanding, exploration begins anew—scanning, sensing, and re-imagining in light of what has been learned. In this vision, foresight becomes an enduring practice of collective reflection: an evolving partnership between human judgment and computational intelligence.

3.1.6 Illustrative Studies: From IAMs to Destination Earth

Several operational initiatives already reflect the principles of CF, showing how computation, learning, and governance are converging to support anticipatory planetary stewardship. Three examples—the evolution of solvers for IAMs, the AI for Global Climate Cooperation competition, and the European Union's *Destination Earth* (DestinE) programme—demonstrate this progression from analytical modeling to generative simulation ecosystems.

IAMs have long supported climate policy by linking physical, economic, and social dynamics to explore transformation pathways [88]. Yet most still rely on opaque optimization solvers that privilege mathematical efficiency over interpretability, exploration under deep uncertainty, or representation of multi-agent dynamics. Emerging studies already point toward a shift in this direction. For instance, [72] apply interpretable multi-agent RL to IAMs, demonstrating how adaptive agents can learn cooperative strategies if their goals are aligned; [98] shows how RL-based IAM negotiation studies can illustrate cooperative equilibria; [10] integrates IAMs with multi-objective multi-agent RL to explore equitable Pareto-optimal climate policies; [23] couple IAMs, agent-based, and Earth-system models within a mixture-of-experts framework to bridge decision scales and test policy robustness. Within a CF paradigm, such developments could evolve into adaptive and transparent simulation laboratories—tools for understanding and navigating Earth's coupled human–environment systems rather than merely optimizing a solution within an IAM. Embedding simulation intelligence—combining RL, causal inference, and probabilistic reasoning—would enable IAMs to explore alternative strategies across shifting feedbacks, multidimensional goals, and constraints instead of converging on a single optimum. In this way, IAMs become components of a distributed foresight ecosystem: exploratory, interpretable, and resilient across assumptions.

The Destination Earth (DestinE) [56] programme operationalizes many principles of CF at continental scale. Led by the European Commission, DestinE is building digital twins of the Earth system—interactive, high-resolution simulations that couple physical, hydrological, and socio-economic processes to inform climate adaptation and disaster-risk governance. Its architecture integrates physics-based models, impact applications, and AI-driven data assimilation and visualization within a unified workflow running on Europe's exascale computing infrastructure. Designed through co-design with users, DestinE supports scenario testing, policy evaluation, and real-time exploration of extreme events through storyline-based simulations. It thus provides a prototype for evidence-informed, adaptive governance, but also faces characteristic challenges of CF: maintaining transparency and traceability, managing computational intensity, and embedding participatory and ethical oversight alongside technical innovation. As an evolving planetary infrastructure, DestinE exemplifies how digital twins can transform computation from retrospective prediction to interactive foresight—a shared medium for reasoning about planetary futures.

Together, these initiatives mark a shift from analytical to generative foresight—where computation moves beyond projecting outcomes to reasoning about them. The next frontier of planetary modeling lies not in a single predictive engine, but in federated ensembles of hybrid human–machine intelligence designed to co-create, deliberate, and govern sustainable Earth trajectories.

4 Readiness, Governance, and Ethics of Computational Foresight

AI's potential to augment foresight is immense, yet its readiness remains limited. Current systems excel at pattern recognition and prediction but lack several key capacities required for responsible future design. By clarifying what CF requires, we can begin building these foundations deliberately rather than retrofitting them later. Readiness in CF is not solely a matter of technical maturity. It involves epistemic readiness—the capacity to reason under deep uncertainty; institutional readiness—the ability to integrate computational insights into deliberative and adaptive governance; and ethical readiness—the cultivation of reflexivity and value alignment in socio-technical systems.

In the long term, CF could evolve into a system of systems—a self-improving architecture that links environmental, social, and economic knowledge within a continuous learning loop. Such a framework would integrate diverse data sources, fuse insights across models, and adapt dynamically as new evidence and feedback emerge. It would combine strong simulation intelligence, uncertainty quantification, causal reasoning, and interpretability. Human interfaces would remain central, using visualizations and participatory tools to help users understand systemic interactions, risks, and alternative pathways. While these capabilities remain aspirational, they outline a research agenda for building foresight infrastructures that learn across systems and with humans. Table 1 outlines key desiderata for CF—a design philosophy for technically capable, collaborative, and human-centered systems.

4.1 Technical Readiness and Emerging Challenges

Validation remains a central challenge for CF [71, 58]. As AI-driven systems grow more complex, they should no longer aim for a single deterministic prediction but instead generate a spectrum of plausible futures shaped by multiple interacting models and decisions. Traditional validation methods—anchored in accuracy metrics and benchmark labels—are inadequate for such open-ended contexts. Foresight therefore requires broader evaluative criteria: plausibility, resilience, coherence, and normative desirability, recognizing that "validity" depends as much on human judgment and context as on computation.

In this setting, falsification [58] provides a more appropriate epistemic anchor than conventional verification. While prediction seeks to confirm what is most likely, foresight advances by systematically ruling out what is implausible, unstable, or normatively undesirable. In practice, this means stress-testing assumptions, exploring sensitivity to uncertainty, and identifying trajectories that violate physical, social, or ethical constraints. Such disciplined elimination strengthens foresight not by proving what will work, but by clarifying what will not—narrowing the field of viable strategies and reducing the risk of catastrophic surprise. In this sense, falsification becomes a generative process: each discarded scenario refines understanding of system limits and leverage points.

Because complex adaptive systems exhibit feedbacks, thresholds, and emergent behaviors, validation must emphasize plural and comparative reasoning across models. Small perturbations can produce disproportionate outcomes, making agreement among diverse models more informative than precision within any single one. The goal of CF validation, then, is not to resolve uncertainty but to map it—to reveal how different assumptions, architectures, and value choices shape the envelope of possible futures [11]. Through such plural and participatory validation, CF builds decision confidence not by asserting certainty, but by illuminating the boundaries of the knowable.

Importantly, uncertainty quantification must evolve beyond aleatory uncertainty—randomness inherent in data—to encompass epistemic uncertainty, which stems from gaps in knowledge, imperfect models, and limited observations [91]. Epistemic uncertainty is, in principle, reducible: better data, improved models, or new observations can narrow its range. In contrast, deep uncertainty arises when stakeholders do not know, or cannot agree on, the system structure, the probability distributions of key variables, or the values and objectives that define success [48, 49, 93]. In foresight, epistemic and deep uncertainty are not merely an obstacle but the very space where imagination, creativity, and plural futures emerge [83, 54, 93, 55]. While computational techniques such as ensemble modeling, probabilistic programming, and Bayesian calibration can formalize and propagate aspects of epistemic uncertainty within known model structures, they cannot resolve deeper ignorance or unmodeled dynamics. Addressing such uncertainty requires interpretive and participatory approaches—scenario discovery, deliberative modeling, and expert elicitation—that surface assumptions and make uncertainty itself a shared object of inquiry [44].

Beyond validation and uncertainty, several foundational challenges remain for CF's technical readiness. Causal modeling is essential to move from correlation to intervention [62]—enabling models not only to describe but to reason about how actions propagate through coupled socio-environmental systems. Despite advances in causal discovery and structural learning, integrating these methods into dynamic, data-scarce, and value-laden contexts remains a major frontier. Likewise, representation learning—how complex systems, institutions, and human values are encoded for computation—requires designs that preserve interpretability, inclusivity, and contextual nuance. Value alignment adds a further layer: CF systems must learn not only from data but from deliberation, embedding normative reasoning and ethical reflection into adaptive models. Finally, computational efficiency and interoperability remain practical constraints, especially for digital twins and large-scale ensemble simulations that CF depends on.

Most machine-learning architectures optimize for fixed objectives in static environments and struggle in novel or changing environments. Foresight is, by contrast, inherently open-ended [79]: it must learn under uncertainty, revise its framing as new information emerges, and remain responsive to continual change. Developing architectures that enable discovery, reframing, and learning to co-evolve with human understanding remains one of the most difficult—and least understood—frontiers for CF.

These challenges culminate in a broader readiness question: how CF systems can close the loop—linking exploration, simulation, and feedback into continuous learning. Simulation Intelligence [46] forms a central backbone of CF but faces persistent hurdles. The core difficulty lies in designing simulations that not only generate solutions but also test and refine them within the systems they represent. Because all models simplify complex dynamics, internal feedbacks can reinforce their own assumptions. A simulation may thus optimize within its model of the world while diverging from reality—a dynamic akin to reward hacking in machine learning, where systems exploit poorly specified goals. This creates a foresight alignment problem: models that perform well internally may still misalign with ecological or human values. Mitigating this requires plural and reflexive validation frameworks that integrate multiple models, epistemologies, and data regimes [23]. Cross-model comparison can expose inconsistencies and hidden assumptions, shifting validation from confirming single-model accuracy toward understanding where models converge or diverge—and why. Embedding such feedback within participatory and ethical review processes would enable CF systems to learn not only what is possible, but what remains acceptable and just.

Finally, authentic human–AI collaboration—the core of hybrid intelligence [75, 40]—remains an open frontier. Despite progress in explainability and interactive interfaces, genuine co-learning remains rare, risking over-trust in brittle systems [27].

4.2 Governance, Ethics, and Epistemic Justice

Realizing the promise of CF requires embedding it within institutions that are transparent, participatory, and accountable [27, 52, 8]. Governance must move beyond aspirational principles toward mechanisms that evaluate not only technical performance but also diversity of futures explored, adaptability to surprise, and the social and ethical resilience of proposed pathways. Foresight audits—analogous to environmental impact assessments—could evaluate robustness, value alignment,

Table 1: Desiderata for CF tools.

Dimension	Desideratum	Description / Rationale
1. Openness and Transparency	Open data, models, and workflows	Publicly inspectable and reproducible systems enable contestation, accountability, and collective trust.
2. Interpretability and Explainability	Human-understandable reasoning	Models must expose logic, uncertainty, and limitations to avoid opaque decision support.
3. Validation and Uncertainty Management	Explicit treatment of uncertainty	Protocols for testing robustness, exploring failure modes, and communicating limits as resources for deliberation.
4. Ethical and Value Alignment	Integration of ethics, justice, and sustainability goals	Embed normative frameworks (e.g., SDGs, planetary boundaries) to align foresight with shared social and ecological values.
5. Participatory Accessibility	Interfaces for inclusive engagement	Enable diverse publics—communities, policymakers, Indigenous voices, youth—to explore and shape futures interactively.
6. Multiscale Integration	Link local, regional, and global systems	Connect micro-level actions to macro-level feedbacks across scales of decision-making.
7. Reflexivity and Self-Auditability	Capacity for meta-foresight	Systems should monitor biases, scenario diversity, and narrative dominance, adapting through ethical reflection.
8. Adaptive and Continual Learning	Evolving with new data and feedback	Tools should update responsibly with new knowledge and stakeholder input, reflecting a living foresight process.
9. Hybrid Intelligence	Human–machine co-creation	Design for cooperative reasoning where humans guide, critique, and learn with models, maintaining oversight and empowerment.
10. Sustainability and Equity of Access	Low-carbon, inclusive infrastructures	Promote energy-efficient algorithms and equitable access to compute resources.
11. Governance Integration	Connection to policy cycles	Align with institutional foresight processes (e.g., UN or national platforms) to ensure uptake and accountability.

and societal implications, while uncertainty and bias audits ensure that scenarios remain traceable and contestable.

The ability to "compute the future" is concentrated in a few powerful institutions, risking a technocratic foresight imagined by and for the few. Building a Foresight Commons—shared infrastructures, open datasets, and participatory modeling environments—would democratize anticipatory capacity and redistribute epistemic power, turning foresight from a proprietary advantage into a civic right.

At a deeper level, CF must resist algorithmic closure—the tendency of computational systems to collapse plural and contested realities into seemingly objective outcomes [77, 6, 20]. Closure arises when models privilege dominant narratives or easily measurable objectives, thereby excluding alternative worldviews and constraining imagination. Preventing this requires deliberate openness: participatory design, diverse epistemologies, and reflexive validation processes that keep the space of possibility porous and contestable [82, 38].

Institutional and ethical reflexivity must therefore be core design principles. Oversight bodies should review model assumptions and data provenance, while participatory assemblies and AI-assisted deliberation embed foresight within public reasoning. At global scales, initiatives such as an International Panel on Computational Foresight or Global Foresight Data Framework could align national efforts under shared norms of sustainability, equity, and inclusion.

Ultimately, CF governance must balance innovation with stewardship—creating institutions capable not only of managing computational foresight, but of learning from it. By linking technical validation with ethical reflection, CF can evolve as a collective, plural, and revisable practice of planetary sensemaking.

5 Conclusion: Choosing Our Futures Responsibly

Governed wisely, computation can serve as a compass in future design, helping humanity navigate the Anthropocene with foresight: sensing early shifts in Earth systems, deliberating on their implications, and coordinating actions that sustain a just and habitable planet. Yet today's AI supports only fragments of this foresight cycle. Few systems reason causally across scales, engage ethical or cultural diversity, or support adaptive pathways that evolve with feedback. Tools for scenario design and policy learning remain largely experimental, reflecting AI's limited capacity for contextual judgment and reflexive adaptation.

Computational Foresight (CF) therefore remains a vision under construction. Its promise lies not in more prediction, but in transforming how intelligence itself is designed and governed—enabling systems that reason causally, co-create with humans, integrate uncertainty, embed ethics, and translate exploration into actionable and interpretable insights. Only through this integration of technical, ethical, and civic dimensions can computation become a genuine instrument of collective intelligence.

The true test of foresight is whether it expands human understanding and agency. Achieving this requires humility, diversity, and continual ethical vigilance—qualities no algorithm can automate. Cultivating computational stewardship means aligning technological power with planetary care, fostering futures literacy, and embedding long-term thinking within institutions of governance.

The coming decade offers a critical window to realize this vision. Progress will depend on three converging efforts: (i) developing hybrid intelligence systems that learn with and from humans; (ii) institutionalizing transparency, participation, and ethical audit in all foresight processes; and (iii) building a global community of practice that treats computation as a civic infrastructure for planetary stewardship. Through shared modeling architectures, open data, and participatory collaboration, CF can evolve from a conceptual framework into a practical architecture for anticipatory governance—transforming foresight into a core capability for sustainable Earth futures.

Ultimately, CF reframes planetary governance from prediction and control toward stewardship grounded in pluralism, reflexivity, and learning. By weaving together human judgment, computational exploration, and Earth system insight, CF can strengthen democratic capacities for anticipation and align governance with the biophysical realities of a rapidly changing planet.

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