# *Non-linear dynamical approaches for multi-sector climate resilience under irreducible uncertainty*

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## Abstract

Internal climate variability (ICV) remains a major source of uncertainty in climate projections, complicating impact assessments across critical sectors. Given that ICV emerges from the nonlinear interactions of the climate system, we argue that nonlinear dynamical (NLD) approaches can improve its characterization, providing physically interpretable insights that strengthen adaptation strategies and support multisector decision-making. However, despite their suitability for such problems, NLD approaches remain largely underutilized in the analysis of initial condition large ensembles (LEs). We argue that a diverse suite of NLD approaches offers a promising pathway for systematically extracting robust insights from LEs. If effectively applied and systematically integrated, these methods could fully harness the potential of LEs, uncovering underlying patterns and variability across ensemble members to refine fundamental insights from climate projections. This will help bridge the gap between complex climate dynamics and practical resilience strategies, ensuring that decision-makers, resource managers, and infrastructure planners have a more reliable foundation for navigating irreducible uncertainty.

## Introduction

A conservation biologist studying ectothermic species faces a persistent challenge: climate model projections from an initial condition large ensemble (LE) yield markedly different extinction risks and timelines. In some projections, population decline occurs within decades, while in others, species persist despite climate change. How should conservation strategies account for such variability? Similarly, an infrastructure planner designing flood defenses must reconcile conflicting estimates of extreme rainfall. Across different ensemble members within an LE, projections of a once-in-a-century storm event vary significantly, raising critical questions about risk-informed decision-making. Meanwhile, policymakers tasked with managing freshwater resources in the Amazon Basin confront another uncertainty: depending on the choice of initial conditions (ICs) in climate simulations, projections indicate either water scarcity or widespread flooding.

These examples illustrate how internal climate variability (ICV) remains a fundamental challenge in climate science and decision-making, introducing uncertainty across diverse sectors—ecological conservation, infrastructure design and planning, and resource management—each requiring decisions based on future climate conditions. Despite the increasing sophistication of climate models, climate researchers and decision-makers face the challenge of interpreting a wide range of plausible futures, where outcomes diverge not just due to differences in model structure or choice of emissions scenarios, but also due to ICV[1-3]. While various approaches such as model weighting, ensemble averaging[4-7], and concepts of deep uncertainty[8] help address model and scenario uncertainty in a multi-model, multi-scenario framework, ICV encapsulated in Earth System Model (ESM) based LEs[9,10] presents a distinct challenge. Emerging from the chaotic nature of the climate system, ICV generates variability that can be comparable to or even exceed the uncertainty introduced by model differences and emission scenarios[1,11-13] (SI Fig 1-3).

As a result, unlike other sources of uncertainty, ICV remains irreducible and fundamentally unpredictable beyond a few years to a decade[14,15] making it difficult to incorporate into conventional climate research and risk-based frameworks[16-19]. Multi-model, multi-scenario ensembles primarily capture differences in model response or external forcing rather than the spread of plausible futures arising solely from ICV. In contrast, LEs provide a means to systematically capture ICV and the resulting irreducible uncertainty, yet their full potential remains constrained by knowledge gaps in how to extract fundamental and decision-relevant insights from LE-based climate projections. Maximizing the utility of LEs and advancing our understanding of ICV and its implications require methodological innovations that enhance analysis and interpretation.

A range of analytical approaches have been used in climate science to study climate variability and change. Statistical methods, extreme value theory (EVT), and process-based models have long been central to understanding the climate system. More recently, machine learning (ML) techniques, such as physics-guided approaches, have been applied to extract complex patterns from climate data[20,21] including output from LEs generated by ESMs. While nonlinear dynamical (NLD) approaches have been successfully used in climate research[22], they remain largely underutilized in the context of ESM-based LEs, where they offers a novel approach for analyzing ICV. Unlike statistical approaches that often assume stationarity and linearity, or ML models that typically prioritize predictive accuracy over interpretability, NLD provides a physics-based framework for analyzing the nonlinear, high-dimensional climate system and its variability while offering physically interpretable insights into its evolution, predictability, and structural properties. Given their ability to describe complex, high-dimensional systems governed by nonlinear interactions, NLD approaches are particularly well-suited for characterizing the emergent properties of ICV and their implications for climate research and assessments of impact and risk.

These methods can be applied to LEs as they exist or adapted to better address specific challenges in the analysis of ICV. In addition to its standalone advantages, NLD can complement existing statistical and ML methods, enhancing the extraction of meaningful patterns and improving the interpretability of ICV. Ensuring the systematic integration of NLD methodologies with existing modeling approaches will help bridge the gap between theoretical climate research and its practical applications. Furthermore, incorporating NLD into the study of ICV has the potential to drive innovations within NLD itself, much like how the study of weather predictability has led to fundamental advances in nonlinear dynamical systems theory. Similarly, the methodological demands of LEs and ICV analysis may lead to new developments, enhancing the ability to characterize internal variability and nonlinear interactions in the climate system.

Beyond their potential to drive methodological advancements, NLD tools applied to LEs can provide deeper insights into ICV and its role in shaping climate variability. To fully leverage LEs for understanding ICV, several methodological and conceptual gaps must be addressed. In this perspective, we identify five key areas where further investigation is needed, and where NLD methods are particularly well-suited to advancing our understanding:

1. **Characterizing climate variability, connectivity, and causality,** particularly in characterizing ICV.
2. **Predictability and prediction skill,** as the chaotic nature of the climate system places fundamental limits on how far into the future certain phenomena can be anticipated.
3. **Uncertainty characterization and quantification,** where traditional methods are not suited for investigating ICV.
4. **Change detection and tipping points,** since internal variability can mask or amplify emerging climate signal or lead to abrupt transitions.
5. **Climate decision support and communication,** where decision-makers must interpret projections that include irreducible uncertainty, complicating adaptation and mitigation planning.

While NLD methods have been applied in select areas of climate research[22], their potential for systematically studying ICV within LEs remains largely untapped. In this perspective, we propose that integrating NLD approaches with LEs could provide new insights into ICV and its role in shaping climate projections. Unlike conventional methods, this approach offers a pathway to explore the nonlinear properties of the climate system, potentially leading to a deeper understanding of ICV. Specifically, we suggest that NLD tools can help address key challenges in characterizing climate variability, improving predictability, quantifying uncertainty, detecting tipping points, and informing climate decision-making. We further propose that bridging NLD tools with existing statistical, EVT, and process-based models as well as with concepts of deep uncertainty, will allow for a robust framework for extracting physically interpretable insights from climate projections, particularly in the presence of irreducible uncertainty (Fig 1). Through this synthesis, we highlight opportunities for systematically integrating NLD into investigations of  LEs and ICV, extending capabilities beyond existing methodologies to support more robust decision-making in the face of uncertainty.

In this paper, we explore how NLD methods such as Lyapunov exponents, entropy measures, attractor reconstruction, and bifurcation analysis (Table 1) can be expanded and adapted to bridge key knowledge gaps in climate research related to ICV. Through a set of proof-of-concept use cases, we illustrate how ICV influences climate impact assessments and decision-making and discuss how integrating NLD with statistical and machine learning approaches can provide new insights into the complex, nonlinear behavior of the climate system.

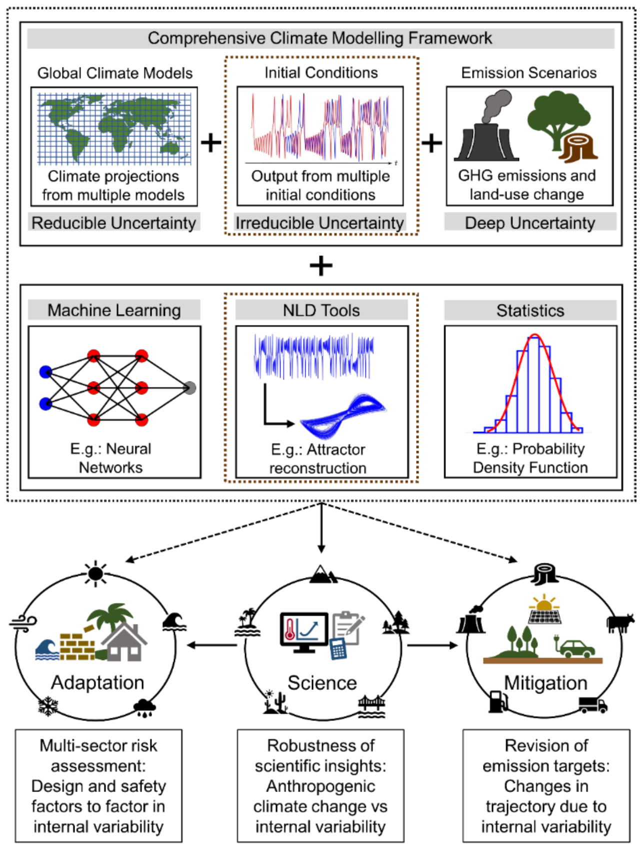


**Figure 1| Climate insights for flexible adaptation measures and decision-making.** Climate insights for flexible adaptation and decision-making. Incorporating multiple initial condition simulations within conventional climate modeling frameworks, combined with nonlinear dynamical approaches, enables robust insights into climate system behavior from Earth system and global climate models. The framework accounts for uncertainty from model spread (reducible), internal variability (irreducible), and emission scenarios (deep uncertainty). Nonlinear dynamical tools complement and, in some cases, enhance predictive insights from conventional statistical and machine learning methodologies. These advancements improve impact assessments and inform flexible adaptation strategies. They also support robust decision-making and policy formulation aimed at enhancing climate resilience under irreducible uncertainty

**Table 1**: Selected nonlinear system approaches that may be suitable for solving earth system tasks related to predictability, change detection, uncertainty, teleconnections, and prediction and predictive skill.

| Analytical Task | Earth System Task | Potential Nonlinear System Approach |
|---|---|---|
| Predictability | Quantifying sensitivity of ESM to ICs | **Lyapunov exponents and Chaos Theory:** Determine sensitivity to ICs by computing Lyapunov exponents, which measures the rate at which trajectories in a dynamical system diverge. |
| | Determining predictability limits of climate | **Bifurcation Analysis:** Identify the conditions under which small changes in parameters can lead to qualitative changes in system behavior, helping to determine predictability. |
| Change detection | Identifying climate change | **Attractor Reconstruction:** Use techniques such as phase space and embedding theorems to reconstruct the attractor of the climate system, identifying changes in the attractor's structure over time. |
| | Identifying tipping points | **Bifurcation Analysis:** Detect tipping points by identifying early warning signals such as increased autocorrelation and variance, indicative of critical slowing down of components of the climate system. |
| Uncertainty | Characterizing irreducible uncertainty due to internal climate variability | **Stochastic Resonance and Noise-Induced Transitions:** Model the impact of internal variability using stochastic differential equations, exploring how noise can induce transitions and contribute to irreducible uncertainty. |
| Teleconnections | Characterizing spatial connectivity structures and teleconnections | **Complex Network Analysis and Synchronization Phenomena:** Utilize complex network theory to analyze teleconnections, identifying community structures, hubs and synchronized regions in the climate network. |
| Prediction and predictive skill | Nonlinear prediction at climate scales | **Machine Learning with Nonlinear Dynamical Systems:** Capture and predict the evolution of large-scale nonlinear climate dynamics using machine learning methods such as reservoir computing or recurrent neural networks |

## Opportunities for applying NLD approaches to climate projections from large ensembles

NLD approaches provide a structured framework for analyzing climate projections from ESM-based LEs, offering new ways to interpret ICV and irreducible uncertainty. While these methodologies have been applied in other areas of climate science, their systematic use in LE-based analyses remains limited.

The integration of NLD into weather forecasting serves as a blueprint for how NLD approaches can be systematically applied to LEs. The recognition that weather is inherently chaotic[23] has driven key developments in nonlinear dynamics, including chaos theory. NLD tools have been pivotal in studying the chaotic nature of weather, revealing inherent and practical limits and spatial patterns of predictability[24,25] and exploring how these limits shift in a warmer world[26]. These insights have in turn informed operational weather forecasting, supporting emergency preparedness and response. Similarly, systematic application of NLD to LEs can unlock robust scientific insights, enhancing climate adaptation and mitigation strategies. Establishing pipelines from analysis to decision-making would improve the usability of LE-based projection and ensure climate research accounts for a range of plausible futures.

Moreover, the broader adoption of NLD methodologies in LE analysis presents an opportunity for user-driven innovation. As demands for tailored climate information grow, user needs could shape NLD development, fostering a reciprocal relationship where scientific progress and practical applications drive methodological refinement as has been seen in weather forecasting and ecology.

Although NLD methodologies—often in combination with statistical tools—have been successfully applied to climate observations and models of varying complexity, their systematic use in ESM-based LEs remains scarce. Here, we explore how selected NLD methods, including snapshot attractors and climate networks, address five key challenges in LE contexts: climate characterization, predictability, change detection, uncertainty quantification, and decision support. We also review existing LE applications, summarizing selected studies in Table 2, detailing models used, methodologies employed, and key insights gained.

### *Challenge 1: Climate characterization, connectivity, and causality*

The climate system exhibits complex connectivity structures, including proximity-based dependencies and teleconnections, with varying levels of detectable correlations and causal relationships. NLD approaches provide a robust framework for analyzing these properties, offering physically interpretable methods to assess the intrinsic characteristics and causal mechanisms within an LE.

In LEs, small perturbations to ICs generate a range of plausible climate trajectories, resulting in differences in the magnitude and spatial patterns of climate variables across ensemble members. These variations suggest that underlying connectivity and causal structures may also differ within the ensemble, requiring systematic methods to quantify and compare these differences. Understanding how internal variability influences large-scale climate modes and their associated teleconnections is critical for both process-based studies and climate risk assessments.

One approach to studying these connectivity structures is climate network (CN) analysis, which emerged from the intersection of climate science and network theory[29]. CNs have been used to explore the internal structure of the climate system under climate change and have been successfully applied to study teleconnections, identify community structures, hubs, and synchronized regions within the climate network, detect climate change, and establish causal relationships. However, applications of CNs in higher-complexity climate models have largely been limited to multi-model ensembles[30] and direct observations[31]. Expanding CN-based approaches to LEs would enable a more systematic investigation of ICV and its influence on climate connectivity across ensemble members[32], providing a broader and more robust understanding of internal variability-driven changes in network structure and causality.

**Table 2**: Selected studies that obtain climate insights related to four of the key challenges identified in the paper by applying nonlinear dynamical approaches to observations, conceptual models and global circulation and Earth system models

| Related Studies | Tool(s) | Data and/or Model | Climate Insights |
|---|---|---|---|
| **Challenge 1: Climate characterization, connectivity, and causality** | | | |
| Chekroun et al., 2011[82] | Pullback attractor | Stochastically forced Lorenz model,<br>Low-dimensional, nonlinear stochastic model of ENSO | Exploring the system's dynamics and statistics |
| Shi et al., 2022[83] | Convergent cross mapping | Observations | Detecting drought propagation |
| Wang et al., 2018[84] | Convergent cross mapping | Observations, Reanalysis | Effect of soil moisture on precipitation |
| **Challenge 2: Predictability and Prediction Skill** | | | |
| Ramesh and Cane, 2019[44] | Attractor reconstruction | General circulation model | Predictability of tropical Pacific decadal variability |
| Krishnamurthy et al., 2019 and references therein[27] | Phase space reconstruction | Observations | Nonlinear climate forecasting of Indian monsoon |
| Sahastrabuddhe and Ghosh, 2021[42] | Nonlinear local Lyapunov exponent | Observations | Limits of predictability of SSTs |
| **Challenge 3: Change Detection and Tipping Points** | | | |
| Drótos et al., 2015[28] | Snapshot attractor | Forced Lorenz-84 model | Change detection of mid-winter westerly windspeeds |
| Charo et al., 2021[49]<br>Charo et al., 2023[50] | Branched manifold analysis through homologies | Stochastically forced Lorenz model | Detection of tipping points |
| Boers et al., 2022 and references therein[48] | Bifurcation | Paleoclimate data | Detection of tipping points |
| **Challenge 4: Uncertainty characterization and quantification** | | | |
| Shukla et al., 2006[55]<br>Seo et al., 2014[54] | Relative entropy | Subset of CMIP3 models,<br>Subset of CMIP5 models | Climate model evaluation |
| Sane et al., 2024[59] | Shannon entropy, mutual information | GFDL-ESM2M (Ocean component) LE | Internal vs forced variability |
| Pierini et al., 2016[85] | Pullback attractor | Low order quasi-geostrophic double-gyre ocean model | Climate change in the presence of natural variability |

Another promising approach for analyzing climate connectivity and causality is convergent cross mapping[33], which offers a means to identify and quantify nonlinear causal relationships between climate variables. This approach can assess lagged and asymmetric interactions resulting from system inertia and feedback mechanisms, providing deeper insights into how ICV shapes climate variability.

The snapshot attractor framework[28,34,35] offers a particularly powerful approach for analyzing climate variability in non-stationary systems and is one of the few NLD tools that have been directly applied to ESM-based LEs. Unlike traditional attractors, which assume stationarity and rely on long time series, snapshot attractors are constructed using values from initial condition ensemble members at a single time instant. This unique property allows them to capture transient dynamics and represent the full range of plausible climate states at each timestep, making them particularly well-suited for studying the behavior of the climate system within LEs. Additionally, the snapshot attractor framework can capture the qualitative behavior of the mean and variability of climate variables at a specified time and separate internal variability from the forced climate change signal[36].

A notable methodological innovation within this framework is the development of instantaneous correlation coefficients (ICC) and snapshot empirical orthogonal function (SEOF) analysis[37], which modifies standard statistical measures and combines them with NLD tools. This represents a unique example of integrating statistical methodologies with NLD approaches to fit an ensemble framework. Unlike conventional analyses that compute correlations and empirical orthogonal functions over time, ICC and SEOF are calculated across ensemble members at each time instant, leveraging the additional information provided by LEs. This ensemble-based snapshot approach enables the tracking of the time evolution of dominant climate modes and reveals potential changes in their relationships with key climate variables. These methodologies have been applied to investigate teleconnections associated with the Arctic Oscillation (AO) and the El Niño–Southern Oscillation (ENSO), providing insights into how ICV influences their spatial and temporal expression under climate change[36-39]. Broader application of these methods to ESM-based LEs could further improve the understanding of how internal variability modulates dominant climate modes, underscoring the potential of snapshot attractors and related innovations to advance insights into ICV.

By applying these NLD methodologies within LEs, it becomes possible to quantify differences in internal variability across ensemble members, improve the interpretability of climate projections, and enhance both process-level understanding and communication of findings.

***Challenge 2: Predictability and prediction skill***

The extreme sensitivity of climate models to ICs fundamentally limits their predictability and predictive skill, and the predictability limits of the climate system remain an open question[40]. Estimating these limits and evaluating the predictive skill of climate models are essential for understanding model strengths and weaknesses, ultimately enabling the optimized use of model outputs.

LEs provide a robust framework for systematically studying how small differences in ICs lead to divergent climate trajectories, enabling the evaluation of spatial and temporal patterns in predictability. Despite this potential, the use of NLD tools, remains largely untapped in the context of  LEs. The Lyapunov exponent has been widely applied to assess predictability limits at weather, seasonal, and decadal scales, and its integration with LEs could unlock new insights by leveraging multiple realizations of plausible futures. For example, the nonlinear finite-time local Lyapunov exponent[41], which measures the local, finite-time growth rate of perturbations in non-stationary systems, offers a quantitative measure of the climate system's predictability limits. Recent applications[42] demonstrate that this approach can reveal predictability limits beyond weather scales, identifying regions and processes that enhance predictability. These insights can help pinpoint areas where better representation of physical processes is needed, supporting targeted model improvements and advancing the predictive skill of climate models.

Unlike in weather forecasting, where predictability limits are typically measured in days, climate models offer the potential to leverage sources of extended-range predictability. Slowly varying climate components, such as sea surface temperature, and periodic nonlinear oscillations, such as the ENSO, serve as key sources of extended-range predictability on climate timescales[27]. These sources could be further leveraged within climate modeling frameworks to enhance predictive skill. NLD approaches, including CN methodologies and phase space reconstruction-based approaches[43], are particularly well-suited for analyzing the behavior of these long-range connections. By capturing nonlinear dependencies and complex interactions, NLD tools offer significant potential for improvement of model performance by revealing how these predictors influence large-scale climate variability.

Given that climate models represent high-dimensional dynamical systems, they can be conceptualized as attractors in phase space. Attractor reconstruction, based on embedding theorems, allows for the reconstruction of the climate system's attractor, providing insights into geometry and dynamics relevant for predictability studies[43,44]. These properties help define the boundaries of predictable behavior, identifying the allowable states of the system and revealing how the system evolves in response to perturbations. Beyond traditional methods, there is an opportunity to advance these insights by combining NLD with ML. In particular, ML techniques can be employed for feature extraction from reconstructed attractors, uncovering novel patterns and structures that influence predictability.

Applying these NLD methodologies to ESM-based LEs would enable the quantification of confidence intervals for predictability limits under climate change and yield metrics of variation in prediction skill across ensemble members. Such insights would not only improve understanding of the sources and limits of predictability but also enhance the communication of model reliability to stakeholders. By providing clearer indications of where and when climate projections are most reliable, these methodologies could support better-informed decisions in sectors dependent on climate information, such as disaster preparedness, infrastructure planning, and resource management.

### *Challenge 3: Change detection and tipping points*

Accurate quantification of climate change is critical for building climate resilience. Detecting tipping points and early warning signals of abrupt transitions in the climate system is essential for understanding, managing, and mitigating the risks of sudden and potentially irreversible changes in the Earth system. NLD tools are particularly well-suited for detecting and quantifying both gradual and abrupt climate changes, enabling the identification of precursors that serve as early warnings for tipping points.

Many conventional methods for change detection assume a stationary climate. In contrast, the snapshot attractor, which focuses on the instantaneous state of the climate system, offers a robust approach for detecting changes in non-stationary climates when applied to LEs, avoiding biases introduced by averaging periods[45]. In simplified models, the evolution of the shape and size of the snapshot attractor has been used to qualitatively detect climate change over time, Measures such as the Wasserstein distance, which determines the distance between a reference attractor and subsequent attractors, have been employed to quantify these changes[46]. Extending these approaches to ESM-based LEs, in combination with the snapshot attractor framework, could enable robust detection and quantification of the magnitude and timing of climate change. Such advancements would provide critical insights for engineering applications and policy decisions, offering more reliable estimates of when and where climate impacts might emerge.

Beyond change detection, identifying abrupt shifts or tipping points in the climate system is critical for timely intervention and response. Minute perturbations to ICs in simplified climate model-based LEs have shown the potential for drastically different climate outcomes, such as transitioning between a snowball Earth and a warm climate[47]. This indicates that ESM-based LEs could provide deeper insights into tipping points in the presence of ICV. Recent studies have employed various NLD-based methodologies for tipping point detection in observations and simplified models. For instance, changes in attractor properties[48], branched manifold analysis through homologies[49,50], and snapshot attractor–tipping probability assessments using bifurcation analysis[51] have been applied to detect tipping points in observations and simplified models. Network-based indicators such as normalized degree, average path length, and betweenness centrality have also been used to detect tipping points at global scales, revealing early warning signals of potential system shifts[52].

Applying these methodologies to ESM-based LEs could yield deeper insights into tipping points in the presence of ICV, revealing how internal variability influences the timing and likelihood of critical transitions. Integrating these approaches with analyses of the underlying dynamics of the climate system (Challenge 1) would enhance our understanding of tipping point dynamics and support the early detection of warning signals. Additionally, there is a significant opportunity to combine NLD with ML for a more robust analysis of tipping points. While NLD tools can identify early warning signals based on attractor properties, ML techniques can facilitate efficient detection and classification of these changes in large datasets. Such integration ensures a comprehensive exploration of plausible futures, including critical worst-case scenarios that might otherwise be overlooked.

Given the potentially catastrophic consequences of crossing tipping points and the possibility that gradual climate change could exceed the adaptive capacity of natural and manmade systems and critical services, these advancements could play a pivotal role in informing climate policy and guiding effective mitigation and adaptation strategies.

***Challenge 4: Uncertainty characterization and quantification***

Identifying and delineating sources of uncertainty, as well as defining the range of their magnitudes in climate projections, is critical for obtaining robust scientific insights from LEs in the presence of irreducible uncertainty. Accurate uncertainty quantification not only increases the interpretation of insights from climate models (including those from Challenges 1–3) but also plays a pivotal role in informing climate risk assessments, guiding infrastructure design, and supporting policy decisions. This is particularly important when the magnitude of internal variability is comparable to that of the forced signal due to increased greenhouse gas emissions. NLD methods, such as entropy measures and complex networks, provide promising opportunities for characterizing and quantifying uncertainty in climate projections, offering a pathway toward more actionable and reliable climate information.

The concept of entropy has numerous applications in evaluating historical simulations of climate models. For example, relative entropy, approximate entropy, and sample entropy have been used to assess uncertainty in multi-model ensemble simulations (including those with multiple ICs) by comparing them against observations[53-55]. Similarly, community structures derived from complex networks (CNs) have been applied to compare general dynamics within models, providing a dynamics-based framework for model comparison rather than relying solely on statistical properties[56]. Both these approaches can be adapted for future climate projections from LEs, with entropy measures capturing statistical differences and CNs capturing dynamical variations across ensemble members. This adaptation would enable a comprehensive quantification of ICV, providing uncertainty bounds for climate projections. Such insights are crucial for robust decision-making, helping to avoid maladaptation by ensuring that climate risks are assessed within the full range of plausible futures

There is also promise in adapting entropy-based measures and CN-derived community structures for model evaluation within a LE-based context. Conventional climate model evaluation methods typically compare a single model realization against observations. However, the chaotic nature of the climate system means that unforced fluctuations may evolve differently in the real world compared to any single model run. This discrepancy can lead to an over- or underestimation of model accuracy, resulting in false confidence in insights that may not fully capture the range of plausible outcomes.

To address these limitations, the concept of observational LEs has been introduced[57], providing a framework to better account for internal variability when evaluating climate models. Additionally, artificial neural networks have been applied to LE evaluation[58], demonstrating potential but still limited their broader adoption. Building on these advances, we suggest that entropy-based measures and community structures derived from CNs could offer a streamlined and interpretable approach for model evaluation using ESM-based LEs. By capturing both statistical properties and dynamical behavior using NLD methods, this framework would enable a more robust assessment of model performance. Such an approach would provide clearer guidance on how to appropriately interpret model outputs, ensuring that users can better understand the strengths and limitations of climate projections. Ultimately, these insights could support more reliable climate risk assessments, informed infrastructure planning, and evidence-based policy decisions, enhancing the practical utility of LE-based climate information.

The identification of time of emergence of climate change signal is important for climate impact and risk assessment. The delineation of the forced signal from internal variability in a LE has already been achieved using Shannon entropy in conjunction with mutual information[58] as well as via a snapshot attractor approach[36]. Kullback-Leibler divergence criteria (KLDC), which provides the distance between two probability distributions and has already been used for model comparisons[53], can also be adapted for this purpose. This could be done by using KLDC to compare the output of individual ensemble members (representing the superposition of internal variability and the forced signal) with that of the multi-model ensemble mean (representing the forced signal when the ensemble is sufficiently large[60]). This approach allows for estimating the ratio between internal variability (noise) and the forced signal, helping to determine when the forced climate signal will emerge from ICV. These insights improve preparedness for future "climate surprises," where ICV may amplify the forced signal, and increase the accuracy of detecting mitigation benefits.

***Challenge 5: Climate decision support and communication***

Despite the availability of LEs and widespread recognition of the importance of ICV in climate projections, research and decision-making communities continue to rely predominantly on multi-model ensembles and emission scenarios, often overlooking ICV. This oversight is exacerbated by the lack of established frameworks for seamlessly integrating ICV-related insights into policy, engineering design, and climate risk assessment tools. As a result, the full range of plausible futures is frequently excluded from adaptation planning, leading to misallocated resources, misplaced efforts, and a false sense of preparedness for future conditions.

Flexible adaptation measures centered on concepts of deep uncertainty[8] are essential for addressing the inherent uncertainties in climate projections. As discussed in the previous challenges, NLD methods applied to LEs, provide insights that support the development of more adaptable solutions. Integrating these insights into a revised risk assessment framework that accounts for ICV enhances their applicability. For example, while uncertainty cannot be eliminated altogether, NLD methods can help identify areas of high/low or reducible/irreducible uncertainty, allowing for optimized resource allocations by focusing on flexibility where needed and applying targeted solutions where possible. Without such approaches, there is a risk of wasted resources, economic disruption, and impacted communities.

To effectively support decision-making, ICV insights must be communicated clearly. Combining scientific approaches with stakeholder engagement ensures that climate research remains relevant, trustworthy, and tailored to user needs. For instance, policymakers often operate under significant uncertainty[61], while engineers designing stormwater systems require precise information and uncertainty quantification. Recognizing these differing needs enables scientists to produce actionable information, increasing its likelihood of use in robust decision-making. This requires open communication and the co-production of knowledge with stakeholders[62]. In turn, this knowledge exchange can drive innovation within the field of NLD, helping scientists identify new tools and methods most needed to explore the Earth system and inform robust climate decisions.

A roadmap thus emerges demonstrating how strengthened climate resilience can be accomplished through the integration of NLD approaches into the analysis of LE outputs, establishing clear pathways to translate novel insights into actionable strategies that acknowledge irreducible uncertainty

## NLD methods offer potential solutions to challenges in ecological conservation, infrastructure design and resource management

The presence of irreducible uncertainty makes the traditional reliance on a single "best guess" future unsuitable, as this may lead to adaptation and mitigation strategies that are either insufficient or unnecessary[18]. In this section, based on 3 use-cases (Fig 2, SI 4&5), we discuss how NLD tools, when combined with other methodologies, can provide actionable insights and robust solutions for three key sectors: ecological conservation, infrastructure design, and freshwater resource management. Here we discuss the challenges posed by ICV in each use case, then propose how NLD methodologies can address these challenges.

### *Ecological conservation: Identifying tipping processes and early warning signals*

Ectothermic species experience increased extinction risk as a consequence of long-term climate change, with short-term fluctuations in temperature further influencing extinction risk of these species to climate change[63,64]. Since the extinction of a species is an irreversible loss, there is minimal room for error in the insights guiding species conservation decisions. As demonstrated in our first case study (Fig. 2d, SI 4a & 5), species extinction in response to climate change arises from the interplay between anthropogenic forcing and ICV, where certain ICs trigger tipping processes that drive extinction. This is a characteristic that may extend to endothermic species that are more sensitive to climatic conditions. In such cases, the irreversible nature of extinction may warrant prioritizing worst-case scenarios rather than considering an envelope of possibilities to safeguard ecological stability. NLD tools can be used to analyze tipping processes and identify early warning signals of tipping points[65], helping to direct conservation and mitigation efforts toward critical factors driving abrupt transitions. This approach can enhance conservation strategies by highlighting extinction risks and determining the urgency of intervention. This approach offers a more effective and efficient pathway to address the critical challenge of species extinction.

### *Infrastructure design: Constraining uncertainty in extreme rainfall projections*

The intensity of a 100-year rainfall event, a key threshold for risk assessment[66] (Bell and Tobin, 2007), varies significantly among IC ensemble members, especially under higher emission scenarios (Fig. 2e and SI 4b), as shown in our second use case. This irreducible spread complicates the selection of threshold-based design and operational parameters for infrastructure. Resource constraints and concerns about maladaptation[67] further amplify this challenge.

To capture the full spectrum of possibilities in climate extremes—from the most optimistic to the most severe—ensembles incorporating multiple ICs, models, and emission scenarios are essential. For deeper insights, approaches from NLD that explore the mechanics of extreme events[68,69] and obtain predictive insights in dynamical systems[70] can be adapted for studying climate extremes. Snapshot attractors[34], attractor reconstruction, recurrence analysis[71], and topological data analysis[72] provide a robust framework for estimating the magnitude of extremes based on attractor properties such as geometry, density, and trajectory in phase space. Embedding ML approaches within this framework enhances analysis by tracking attractor properties.

Concurrently, integrating EVT into this NLD framework refines the uncertainty bounds derived from LEs[73,74]. As IC ensemble members share the same model physics, they can be combined as data from a single distribution, increasing the sample size for extreme value analysis. This integration not only constrains uncertainty estimates but also supports adaptive infrastructure systems resilient to future climate extremes. Moreover, these approaches can be extended to other climate extremes, including heatwaves, cold snaps, and severe wind events.

***Resource management: Unraveling spatial variability and intersectoral interdependencies***

The variability in spatial patterns of freshwater availability, as illustrated in our third use case focused on the Amazon Basin (Fig. 2f and SI 4c), is a critical factor in resource management. Differences in these patterns, driven by ICV, complicate decisions regarding resource allocation and management across sectors such as agriculture, power generation, and manufacturing.

NLD measures, including the correlation integral and spatio-temporal entropy, provide a robust framework for analyzing these spatial patterns. When combined with domain knowledge, these insights help identify critical hotspots where targeted decision-making is required. For instance, in the context of water availability for power generation, domain expertise can highlight regions where warmer or scarcer water may reduce generation capacity or even necessitate plant shutdowns[75]. Identifying such hotspots, alongside associated uncertainty bounds estimated using a multi-model, multi-scenario, and multi-IC ensemble, enhances understanding of resource availability and the exceedance probability of the adaptive capacity of natural and manmade systems.

Furthermore, the sectors represented in our use cases—water resources, ecosystems, and lifeline infrastructure such as dams and reservoirs—are interconnected. Complex network approaches can be employed to explore cascading events and impacts across these sectors, providing a framework to incorporate interdependencies into resilience planning. This integrated approach allows for the assessment of compound risks and the development of robust adaptation strategies, aligning with the growing need for holistic climate resilience planning in interconnected systems.

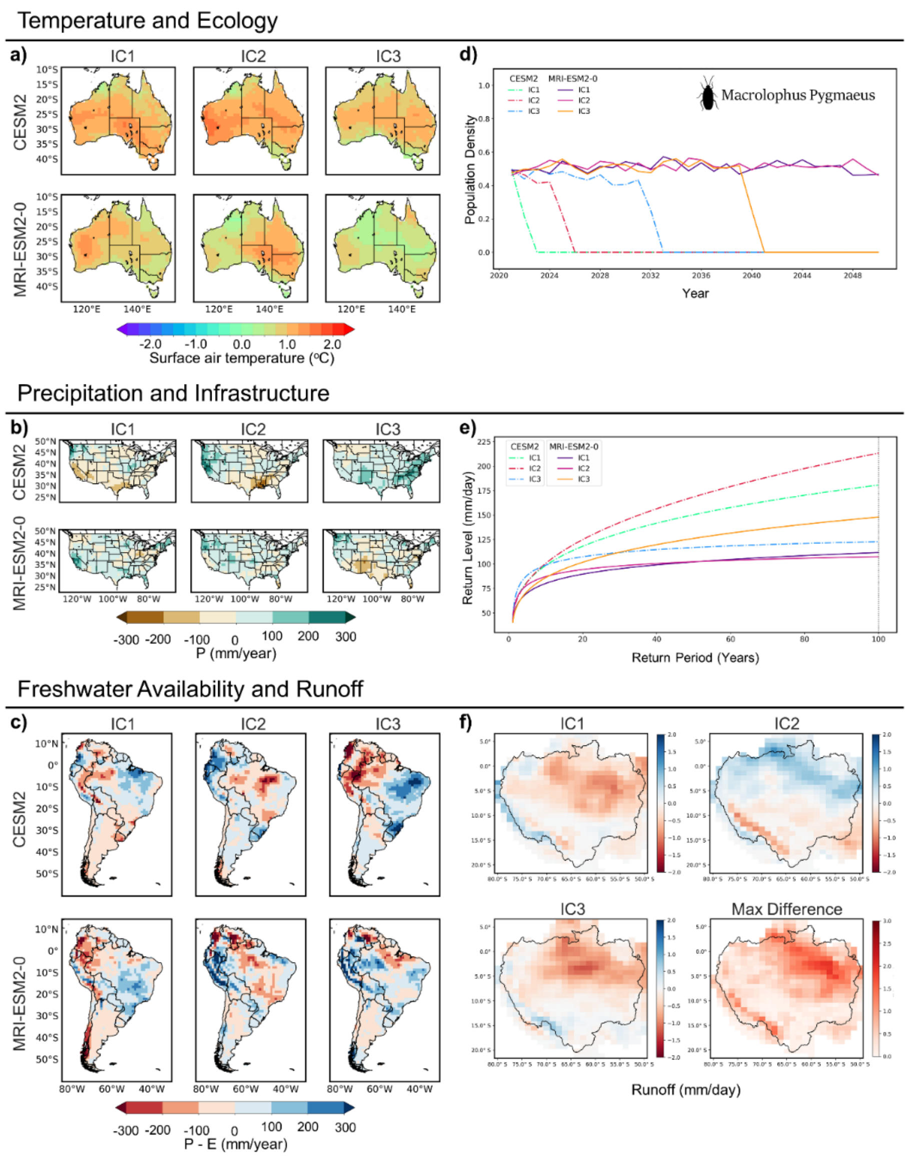


**Figure 2 | Sensitivity of earth system models to initial conditions and implications for multi-sector impact assessment.** The variability in the spatial pattens of average decadal changes in (a) temperature over Australia, (b) precipitation in the United States, and (c) freshwater availability (calculated as the difference between precipitation and evaporation) in South America in the 2040s (2040-2049), relative to the 2020s (2020-2029) from two CMIP6 climate models (CESM 2, MRI-ESM2-0) and 3 initial conditions under SSP585. The role of internal climate variability in impact assessments is shown for (d) projected population density of *Macrolophus pygmaeus* (where a decline to zero indicates local extinction), (e) IDF curves for a 24-hour precipitation event at the Earth system model grid point corresponding to Boston, and (f) decadal changes in mean runoff in the Amazon Basin (analysis for runoff is shown only for CESM2). These results highlight the strong influence of choice of initial conditions on impact assessments and the need to account for internal climate variability in adaptation planning. (See Supplementary Information for details).

## Conclusions

NLD tools hold immense untapped potential for addressing complex challenges in the climate system, particularly in understanding and quantifying ICV. This perspective highlights how NLD approaches, at times integrated with complementary methodologies such as statistical techniques, machine learning, EVT, and domain knowledge can overcome persistent challenges in climate science. These include evaluating climate models[17,76], identifying the forced, emission-driven climate signal in projections[77-80], and detecting climate mitigation benefits[19,81]. Furthermore, NLD's ability to capture nonlinear, high-dimensional interactions offers a pathway towards redefining climate predictability and uncertainty frameworks. Future research should explore the development of universal dynamical metrics for ICV, enabling standardized assessments across models and scenarios and ensuring that NLD remains central to next-generation climate science. These advances could fundamentally reshape how future climate uncertainties are conceptualized and operationalized in resilience planning. By embedding such insights into existing analytical frameworks, we can strengthen dynamic climate decision support, optimize resource management, minimize maladaptation risks, and build resilience across critical sectors, establishing NLD's pivotal role in advancing the future of climate science.

**Supplementary information.** This article has an accompanying supplementary file.

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**Declarations**

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**Ethics approval and consent to participate:** Not applicable

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**Materials availability:** Not applicable

**Code availability:** Code availability is upon reader interest.

**Author contribution:** ARG, RM, AR and UB defined the problem and conceptualized the paper with contributions from other authors. PD, AKP, AR and KD performed the experiments. RM, PD and AR carried out the data analysis. RM wrote the paper with significant contributions from AR and ARG. All authors contributed to revisions with significant contributions from JW and UB.

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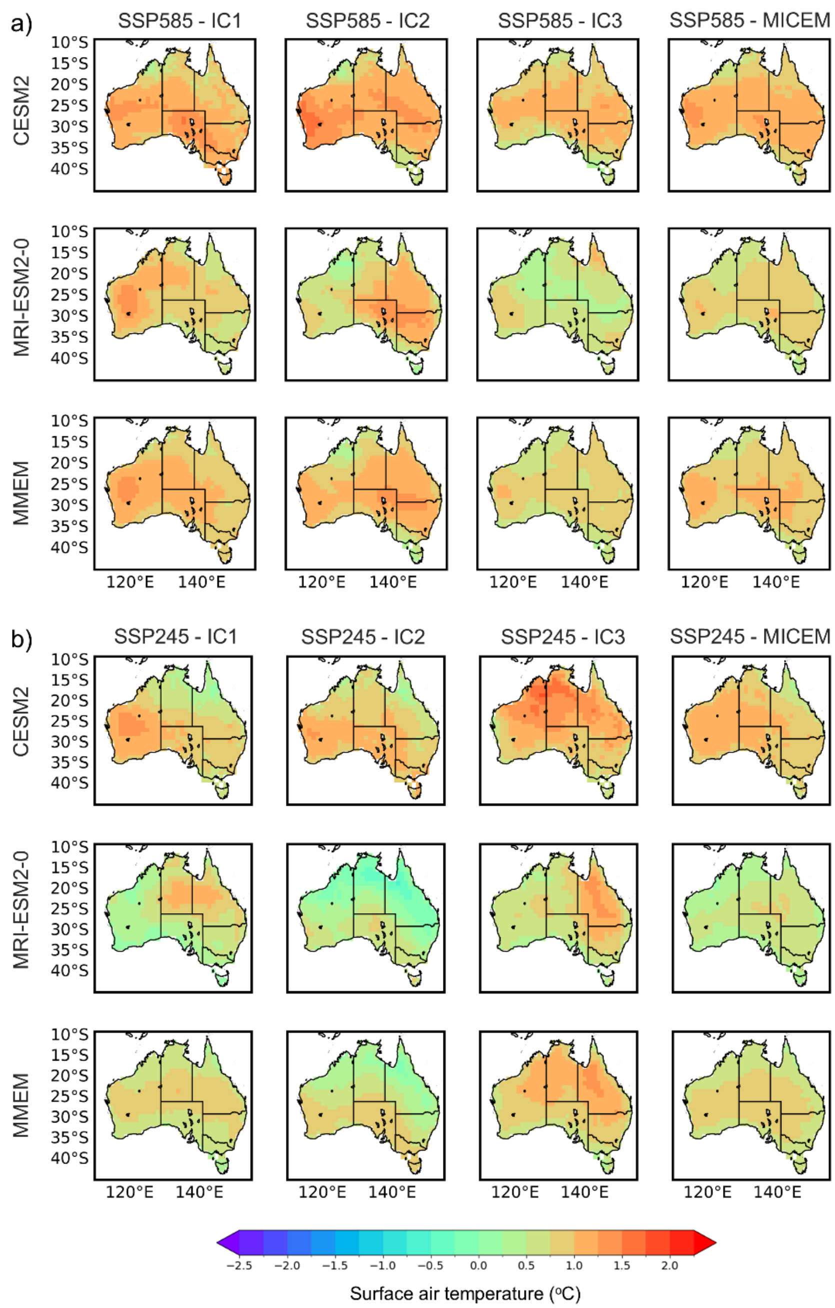
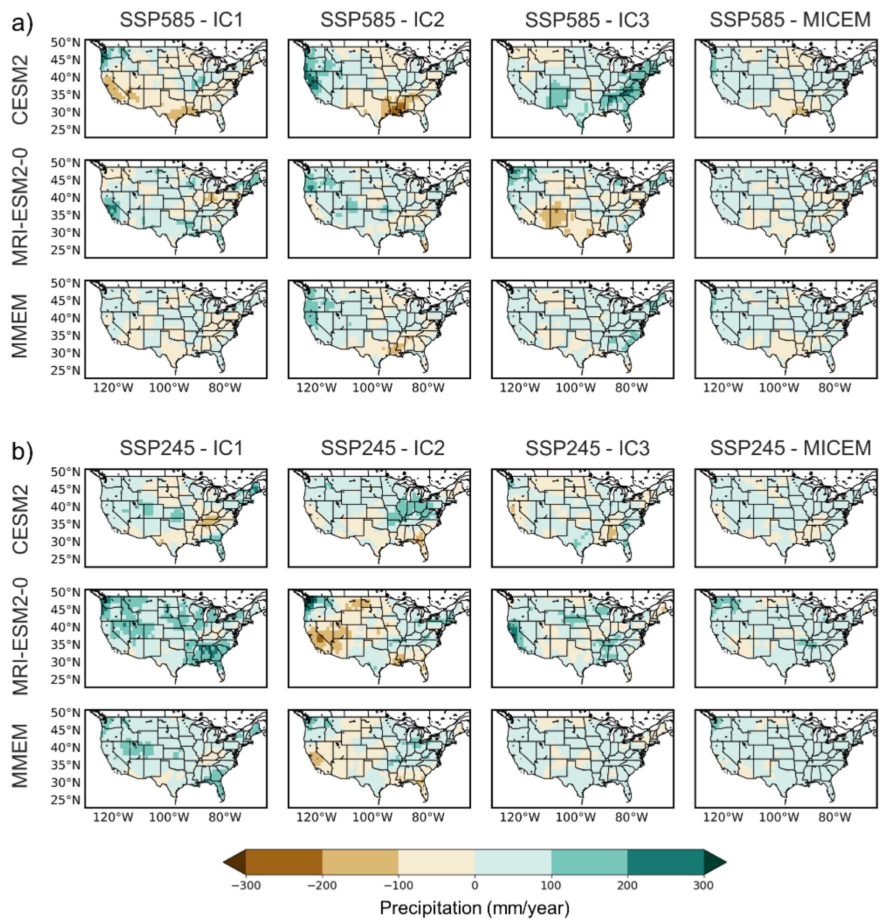
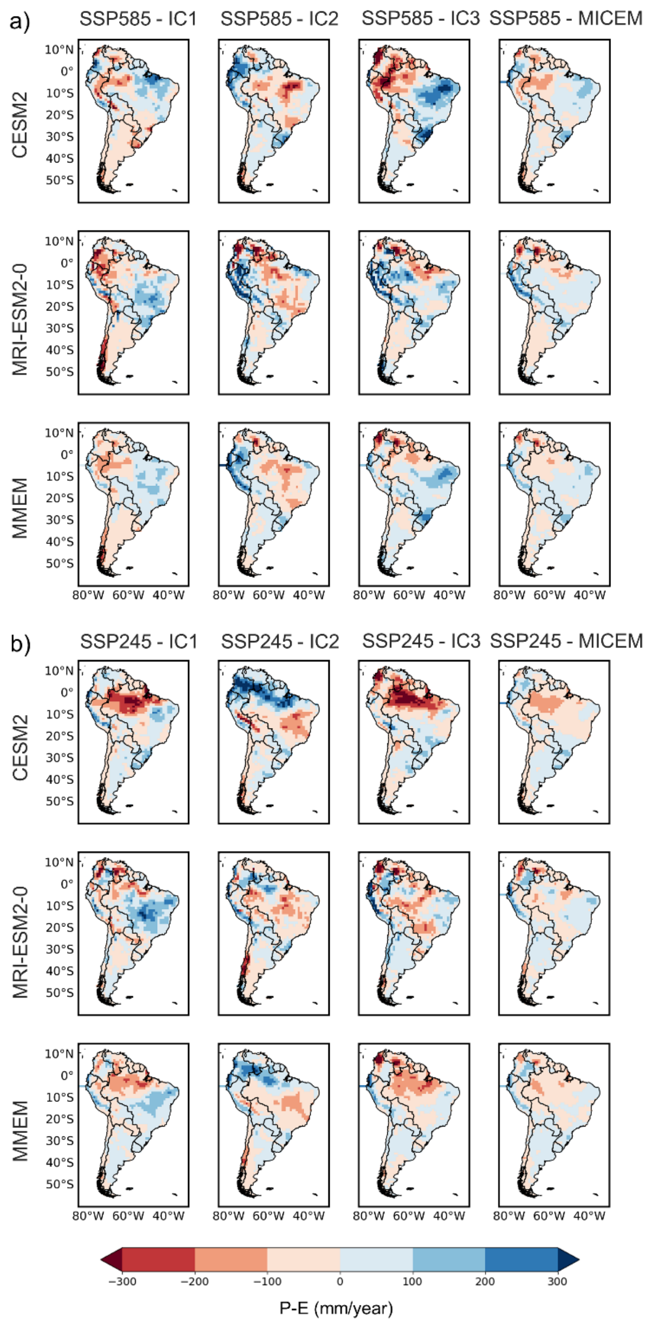
## Supplementary Information: Figures



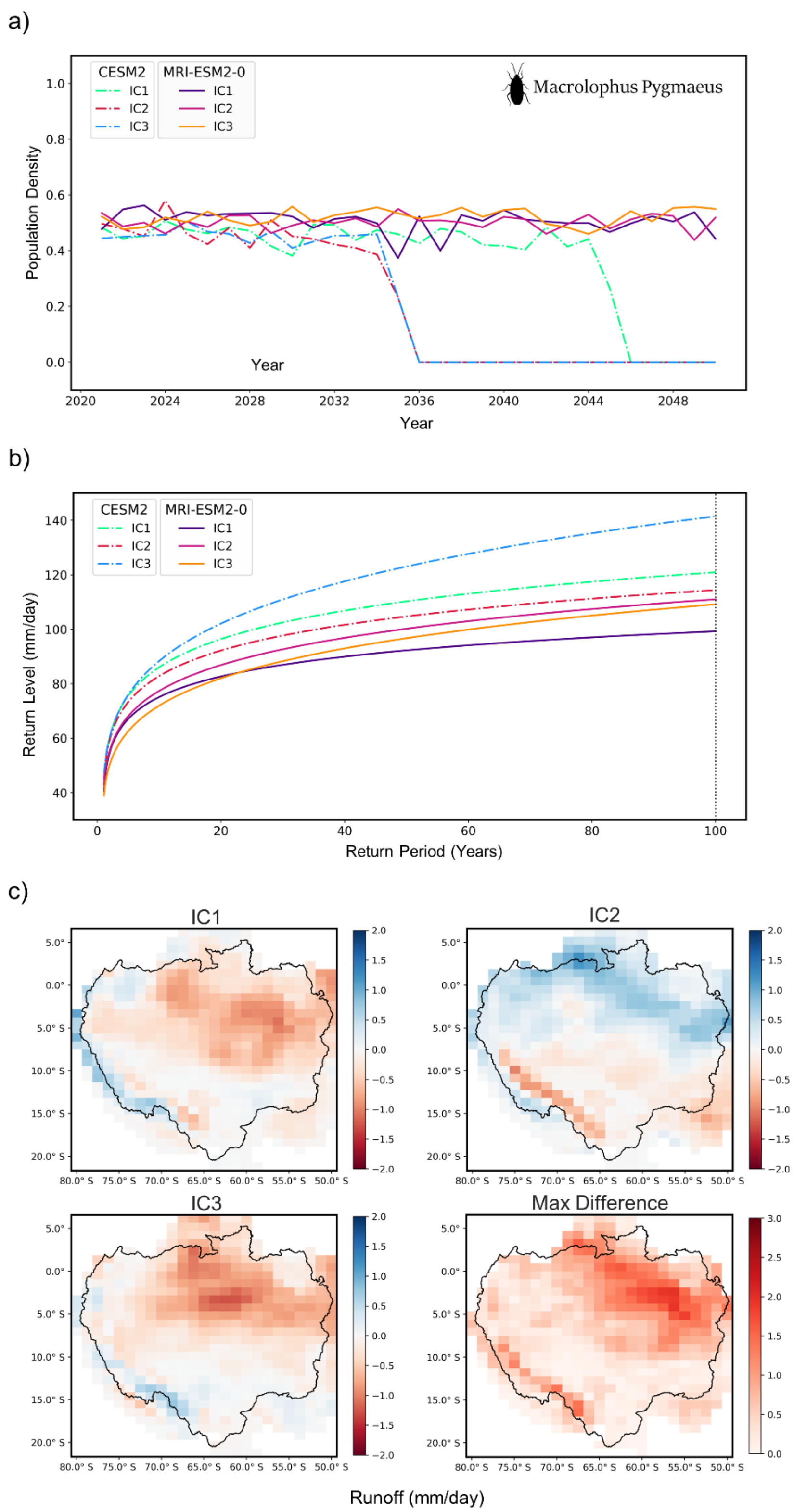

**Supplementary Information Figure 1**| (a) Changes in mean temperature (°C) over Australia in the 2040s (2040-2049), relative to the 2020s (2020-2029) from two CMIP6 climate models (Row 1: CESM 2, Row 2: MRI-ESM2-0) and 3 initial conditions (columns 1-3) under emission scenario SSP585. In panel (a): The top and middle rows of the fourth column show the three-member initial condition ensemble mean (MICEM) for each of the models while columns 1-3 in the last row show the two-model ensemble mean (MMEM) for each of the initial conditions. The bottom-right figure shows the overall mean of initial condition and multi-model ensembles. (b) Same as for panel (a), but for the emission scenario SSP245.



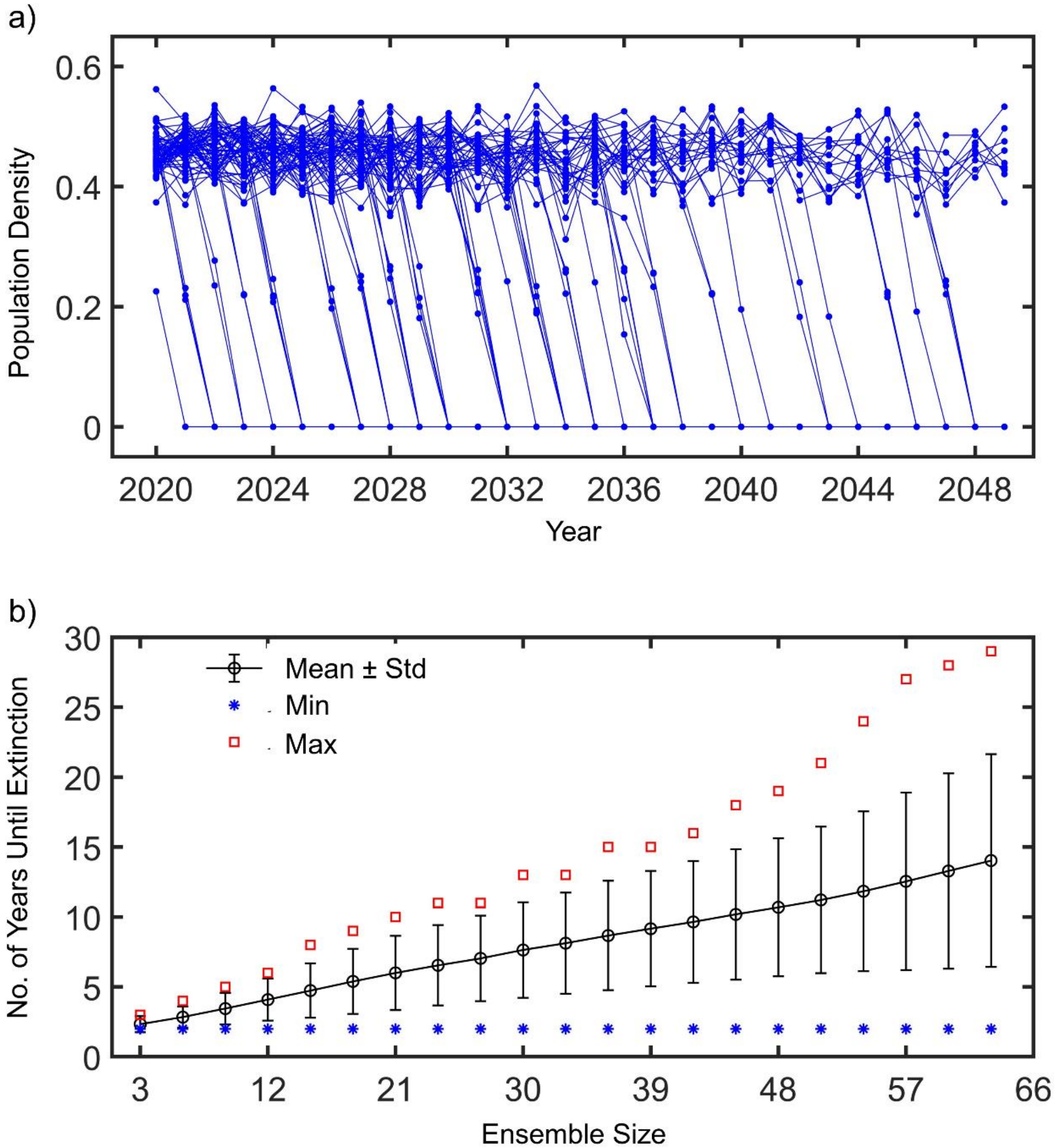

**Supplementary Information Figure 2**| (a) Changes in mean precipitation (mm/year) over The United States in the 2040s (2040-2049), relative to the 2020s (2020-2029) from two CMIP6 climate models (Row 1: CESM 2, Row 2: MRI-ESM2-0) and 3 initial conditions (columns 1-3) under emission scenario SSP585. In panel (a): The top and middle rows of the fourth column show the three-member initial condition ensemble mean (MICEM) for each of the models while columns 1-3 in the last row show the two-model ensemble mean (MMEM) for each of the initial conditions. The bottom-right figure shows the overall mean of initial condition and multi-model ensembles. (b) Same as for panel (a), but for the emission scenario SSP245




**Supplementary Information Figure 3**| (a) Changes in freshwater availability (mm/year) over South America, calculated as the difference between precipitation (P) and evaporation (E) in the 2040s (2040-2049), relative to the 2020s (2020-2029) from two CMIP6 climate models (Row 1: CESM 2, Row 2: MRI-ESM2-0) and 3 initial conditions (columns 1-3) under emission scenario SSP585. In panel (a): The top and middle rows of the fourth column show the three-member initial condition ensemble mean (MICEM) for each of the models while columns 1-3 in the last row show the two-model ensemble mean (MMEM) for each of the initial conditions. The bottom-right figure shows the overall mean of initial condition and multi-model ensembles. (b) Same as for panel (a), but for the emission scenario SSP245




**Supplementary Information Figure 4|** Impact assessment for (a) ecology (same as Fig 2d), (b) infrastructure design (same as Fig 2e) and (c) water resources (same as Fig 2f) under the emission scenario SSP245.




**Supplementary Information Figure 5|** (a) Population density of *Macrolophus Pygmaeus* (with population density falling to zero indicating local extinction) for the 30-year period from 2020-2049 from EC-Earth3 (CMIP6) for 72 initial conditions under SSP245. 63 of the 72 initial conditions show local extinction of the species within the next 30 year period. (b) The uncertainty range in impact assessment as obtained from the 63 ensemble members that show extinction. Here the ensemble members are ordered from the shortest to longest time to local extinction and the different sized ensembles are created by adding members in the ascending order of time till extinction. The mean, standard deviation, minimum and maximum for different ensemble sizes are shown here to depict the minimum possible uncertainty range that can be obtained from the different initial condition runs.

# Supplementary Information: Data and Methodology

## Data:

**Supplementary Information Table 1:** The earth system models, emission scenarios, initial condition simulations and frequency of temperature, precipitation, evaporation, and runoff data obtained from CMIP6 archive for analysis.

| Variable | Emission Scenario | Model | Initial Condition Simulations |
|---|---|---|---|
| Temperature (Daily) | SSP585 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r1i1p1f1, r3i1p1f1, r5i1p1f1 |
| | SSP245 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r1i1p1f1, r2i1p1f1, r3i1p1f1 |
| | | EC-Earth3 | All available initial conditions (72) from CMIP6 archive |
| Precipitation (Daily) | SSP585 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r1i1p1f1, r2i1p1f1, r3i1p1f1 |
| | SSP245 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r3i1p1f1, r4i1p1f1, r5i1p1f1 |
| Evaporation (Monthly) | SSP585 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r1i1p1f1, r2i1p1f1, r3i1p1f1 |
| | SSP245 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | | MRI-ESM2-0 | r3i1p1f1, r4i1p1f1, r5i1p1f1 |
| Runoff (Monthly) | SSP585 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |
| | SSP245 | CESM2 | r4i1p1f1, r10i1p1f1, r11i1p1f1 |

Temperature, precipitation, evaporation and runoff data (table 1) was obtained from the CMIP 6 data archive for CESM2 and MRI-ESM2-0 for the emissions scenarios SSP585 and SSP245. Data for 3 initial condition ensemble members was obtained for each of the models. In addition, temperature data from all available initial conditions (72) under SSP245 was obtained for EC-Earth3 (CMIP6). The models were selected based on data availability at the needed temporal frequencies (daily and monthly) and high spatial resolution (100 km resolution) with at least 3 initial condition ensemble members available for each of the variables of interest for the period 2020-2049. The emissions scenarios were selected to represent moderate and extreme future trajectories. Analysis was focused on the 30-year period from 2020 to 2049 to reflect a near-term time horizon that is of interest to stakeholders and policymakers.

## Methodology and Interpretation:

### Impact of internal climate variability on climate variables:

To analyze the impact of internal climate variability on climate variables, an ensemble of 2 models (CESM2, MRI-ESM2-0), 3 initial conditions and 2 emissions scenarios (SSP585, SSP245) was utilized. This ensemble with 12 members ("super" ensemble) was considered sufficient as the analysis here was carried out only as proof-of-concept case studies. The analysis was carried out over Australia (temperature), United States (precipitation) and South America (freshwater availability) to demonstrate the importance of internal variability at regional scales in different parts of the world.

For the analysis of climate variables, the changes in decadal averages, calculated as the difference between 2040-2049 and 2020-2029, was obtained for temperature (fig 2a, SI 1) and precipitation (fig 2b, SI 2) at a daily temporal resolution and for fresh water availability (fig 2c, SI 3) (calculated as the difference between precipitation and evaporation) at a monthly temporal resolution. This was done for each emission scenario and for each model as well as for each initial condition. The multi-model ensemble mean (MMEM), the multi-initial condition ensemble mean (MICEM) as well as the mean of all available simulations was also calculated for each variable and emission scenario (SI 1-3).

Our results, in agreement with past studies (Deser et al., 2012, Deser et al, 2014, Deser and Phillips 2023, Monier et al., 2015), indicate that, in the near-term, the choice of initial conditions leads to different but plausible futures, where differences between ensemble members are comparable to those arising from choice of model or emissions scenario (Fig 2, SI 1-3). The inclusion of initial conditions with model and emissions scenario thus widens the spread of simulations, often producing differing magnitudes and contrasting geographic patterns of projected change. This holds true for all the variables and geographic locations explored in this study. Typically, depending on the location, time horizon and variable of interest, 10-100 ensemble members are needed to obtain robust scientific insights in the presence of internal variability while also determining the full range of possible outcomes (Milinski et al., 2020). Nonetheless, this simplified experiment highlights the need for a "super" ensemble that includes ensemble members generated by a combination of multiple models, initial conditions, and emission scenarios.

### Use-cases for impact assessment

The "super" ensemble described above is used to illustrate the importance of capturing the internal variability through initial condition simulations for impact assessments and decision making. It is important to note that these assessments are carried out using global scale data and a number of simplifications with the sole purpose of demonstrating the sensitivity of impact assessment studies to the choice of initial conditions.

#### *Use-case 1: Ecological Conservation*

The daily population density of the ectotherm *Macrolophus pygmaeus* (Fig 2d, SI 4a) was calculated based on the daily temperature data from the "super" ensemble for the period 2020-

2049 using location (Europe) and thermal tolerance data published in Deutsch et al., 2008. and the methodology described in Duffy et al., 2022. Here population density falling to zero indicates local extinction (in Europe) of the species. For simplicity, we assume that the insects are unable to migrate to a new habitat and that local extinction of the species is solely determined by local temperature changes.

In addition, the population density of *Macrolophus pygmaeus* was also calculated using temperature data from the 72 initial condition runs from EC-Earth3 (SI 5a). Next, the minimum possible range in irreducible uncertainty in the time horizon of local extinction was calculated for different ensemble sizes (SI 5b). As the first step in this analysis, the ensemble members (63 out of 72 initial condition runs) for which local extinction occurred within the 30-year period from 2020-2049 were identified. Next, the ensemble members were ordered from the shortest to longest time to extinction and the different sized ensembles were created by adding members in the ascending order of time till extinction. For example, the 3-member ensemble is made up of the members that project the three shortest timeframes till extinction. The 4-member ensemble is made up of the 3-member ensemble and the ensemble member with the fourth shortest timeframe till extinction. Thus, a given ensemble represents the minimum possible range in irreducible uncertainty produced from a set of multiple initial condition runs. Any other randomly selected ensemble of a similar size will have a larger range in uncertainty.

Our results show that both the extinction risk and time horizon of extinction exhibit considerable variation across different models, emissions scenarios, and initial conditions. This illustrates how choice of climate projections can influence the possibility and timing of species extinction. While we may be able to narrow this spread by reducing model uncertainty (either by model improvement or better model selection) and selecting a specific emission scenario, the variation generated by differences in initial conditions will remain irreducible. Since ectotherms are sensitive to fluctuations in temperature, the extinction risk of these insects can be influenced by the magnitude of temperature variation due to internal variability and the sequence in which they unfold. This is true even when changes in mean temperature are well within the species' optimal range. However, the irreducible uncertainty introduced by multiple initial condition runs will remain, even in a more comprehensive study, and even if the exact time of extinction might differ from our results.

***Use-case 2: Infrastructure Design***

The IDF curves (Fig 2e, SI 4b), for a fixed duration of 24 hours, were generated using daily precipitation values from the "super" ensemble for the period from 2020-2049 for the nearest grid point corresponding to the City of Boston (latitude 42.3601 and longitude -71.0589). The Generalized Extreme Value distribution was used for the extreme value analysis.

The precipitation return levels vary considerably across the "super" ensemble, with the greater spread between initial condition ensemble members of a given model for higher return periods and for higher emission scenarios. For example, the intensity of a 100-year event (a rainfall event with a 1% chance of occurring in a given year), a threshold that that is often used for risk assessment and communication (Bell and Tobin, 2007), varies significantly among initial condition ensemble members of a particular model. This is especially true for higher emission scenarios. While our case study uses a single grid point from a global scale model, a robust estimation of IDF curves at small spatial scales would require either statistical or dynamical downscaling of the projection data. However, the global-scale models will pass the internally generated atmospheric variability to their regional counterparts (Xie et al., 2015), thus propagating the irreducible uncertainty (albeit with a different magnitude) to regional and local scale assessments.

***Use-case 3: Resource Management***

The changes in runoff for the Amazon river basin (Fig 2f, SI 4c) was calculated as the difference between the decadal means of 2040-2049 and 2020-2029, at a monthly temporal resolution for each emission scenario and each initial condition for CESM2. In order to identify the regions where the largest disagreement among initial conditions occur, the maximum difference in changes in runoff was calculated using equation 1.

Maximum difference among initial conditions = Max $\{R_1, R_2, R_3\}$ – Min $\{R_1, R_2, R_3\}$ ------(1)

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