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AI-Driven Big Data Systems for Climate Change Impact Assessment

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Abstract

AI-Powered Big Data Systems for Intelligent Climate Change Impact Assessment presents an objective, evidence-based account with formal structure and clear, discipline-appropriate critique. Growing climate knowledge enables analysis of weather events and future scenarios using AI and Big Data systems. However, such analyses must increasingly probe extreme impacts. While state-of-the-art statistical approaches are effective for specific detection and attribution, they cannot fully capture biophysical mechanisms or future scenarios. Probabilistic projections need a causal perspective.

An emergent intelligent climate change impact assessment and projection framework integrates detection, attribution, projection, and scenario modeling with these additional aspects. Multisource AI-assisted datasets support an international ensemble of studies on subcontinent-level impacts. A regional vulnerability mapping exercise interprets sensitivity to climate extremes, assesses uncertainty, and identifies regions at risk. Future scenarios measuring climate-disrupted carbon and ecosystem service balances are generated from a continental land model. Nevertheless, local risk assessments rely on simple calibrated approaches, thus remaining vulnerable to missing mechanisms in the statistical relationships.

Keywords: Climate Change, Impact Assessment, Big Data, AI Systems, Predictive Models, Scenario Modeling, Causal Analysis, Detection Methods, Attribution Analysis, Climate Projections, Risk Assessment, Vulnerability Mapping, Extreme Events, Uncertainty Analysis, Ecosystem Services, Carbon Balance, Regional Analysis, Environmental Data, Climate Analytics, Earth Systems.

1. Introduction

Climate change will affect every part of the globe and society, with consequences for ecosystems, infrastructure, and human health. Potentially dangerous changes are already being observed at regional to global scales. Yet, as economic activities are becoming ever more interconnected, it is only through timely action that climate change can be sufficiently mitigated. COP meetings and national efforts need scientific evidence. This need calls for constant

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assessments of climate impacts in both human and natural Earth systems. Governments, NGOs, and other entities seek to translate these assessments into actionable policy narratives.

With mounting pressure for climate change policy, an ever larger demand for impact assessment is emerging. Stakeholders seek answers to increasingly complex questions that cover wider and more varied domains. There is rising interest in exploration of climate-related vulnerabilities; information about opportunities from mitigation or adaptation; and the economic evaluation of ecosystem services, especially under uncertainty. The use of new data-gathering and analysis techniques – especially AI and big data methods – can provide useful, timely information with enhanced spatial resolution. The ongoing development of these AI-Powered Big Data Systems aims to fulfil the growing demand for intelligent assessments of climate change impacts.

2. Foundations of AI-Powered Big Data Systems

Fundamental concepts supporting the functioning of an AI-powered big-data system and determining its suitability and effectiveness for climate-change impact assessment begin with AI. In particular, the two-component setup, comprising data- and information-hungry machine-learning algorithms for both supervised and unsupervised learning, causal inference, and massive parallelization, embraces well-established methodologies. The underlying principles are also refered to the terascale big-data architecture for climate modeling and simulation implemented for the Copernicus Climate Change Service. The second core concept is sustainability. To be useful within the context of climate-change impact assessment, the system should allow the integration of data from many disciplines, at varied spatial and temporal scales and with distinct quality characteristics, that reside in silos, are provided by different institutions and organizations, and are often of opposing type (e.g. regionally specific but global in accuracy). Realistically, shortcuts in the data-collection process are not possible, meaning that data acquisition, harmonization, fusion, storage, and indexing, and the associated dependencies and administrative burden, should be kept to a minimum while maximising the consistency of the collected information.

These variables define the environmental context of the AI system and, therefore, require careful consideration of the quality, provenance, and ethics of any data and model used in the analysis, including those that enable the training and testing of the machine- and deep-learning algorithms. A further consideration is the quality and quantity of data supporting validation. Indeed, the absence of tests and proper validation are often cited as critical weaknesses of

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machine-learning applications in climate science. The assessment of such systems should therefore follow the same principles as those applied to climate models and simulation, including the definition of clear rules for reproduction, open data, and code availability. Finally, although climate models and simulations are fundamentally descriptive and modus ponens in their orientation (conditions are imposed and outcomes examined), machine-learning frameworks are often endowed with theoretic modus tollens abilities. When properly designed, these systems are capable of detecting genuine cause–effect relationships in the past and present and thus performing predictive extrapolation or making future projections.

2.1. Data Sources and Integration

Projections of future climate change, as well as analyses of observed climate change impacts and associated risks, rely on a diverse and extensive range of primary and secondary data sources. Projections are supported by climate system models run under multiple forcing scenarios, while the underlying Earth system models and forcing scenarios are developed by different research communities across the globe. Observed data include instrumental records of climate variables, ground-based, satellite, and remote-sensing observations of multiple components of the climate system, and socioeconomic data from various sources, collated at different spatial and temporal scales. Emerging data streams, such as citizen-science observations of climate-related phenomena and new monitoring technologies, are expected to increase in both importance and volume.

Many of these data sources have been used to generate dedicated data products tailored for specific detection and attribution studies by different research communities. Despite the importance of these data resources, they are often limited in terms of scope, continuity, spatial resolution, or other characteristics, thereby precluding their use in certain types of detection and attribution analyses. Achieving a state-of-the-art understanding of the causes and consequences of past and ongoing climate change requires information beyond the dedicated data products available to specific communities; it demands a comprehensive understanding drawn from the full suite of data collected by the climate, natural, and social science communities. The harmonization and fusion of these diverse data into a single coherent framework is essential in order to fulfill this growing need.

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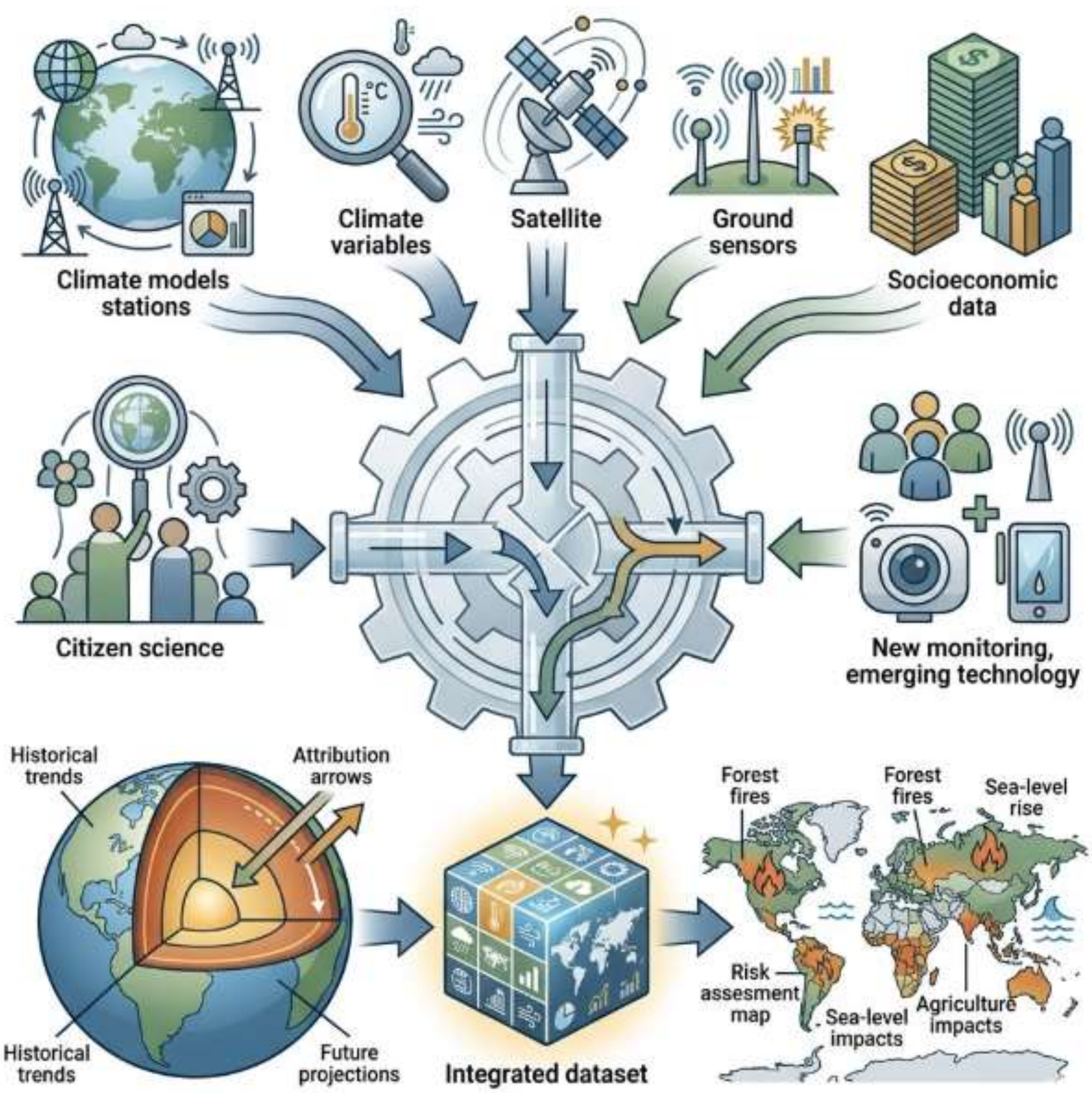

Fig 1: Integrated Data Architectures for Robust Climate Change Detection, Attribution, and Risk Assessment

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2.2. Machine Learning and Inference Frameworks

Specific algorithms, models, training choices, validation strategies, and approaches for characterizing uncertainty affect the performance and applicability of any AI-powered big data system. In machine learning contexts, they constitute a method's design and enable a user to reproduce results and predict for novel settings. Machine-learning studies should explicitly mention algorithm classes and concrete choices, model architectures with hyperparameter settings, and training regimes, including training-validation-testing-split procedures and retraining protocols to correct for dataset shifts. Evaluation metrics relevant for the specific problem at hand should be specified. Uncertainty quantification should be undertaken using techniques appropriate for the algorithm type and application. For supervised AI, uncertainty quantification should ideally be achieved using a separate set of independent validation data. Further, for deep learning methods, uncertainty estimates should be undertaken using a separate set of independent validation data. For deep learning methods, uncertainty quantification can exploit the propensity of dropout layers to drop out units during both training and testing. For computer vision, Monte Carlo dropout inference can be applied, requiring multiple inferences with dropout retained, and the variance of the predictions approximates uncertainty introduced by noise in the input. Uncertainty quantification specifically for neural-network-based emulators is achieved by augmenting inputs with noise and fitting models to quantify the uncertainty in the emulator-analogue predictions.

The main AI components are supervised machine learning, unsupervised machine learning, and causal inference. Supervised machine learning has been employed principally in mapping and dating change, where the application of AI predicts presence or absence, matches ground-truth polygons, and assigns an age and uncertainty to each prediction. Scenarios consider future conditions yet are not directly constrained by AI. Future-assisted learning trains AI models exploiting future climate scenarios as additional input features combined with information for the period 1986–2016. Unsupervised machine learning has been used for clustering and bayesian ensemble construction. Probabilistically generated clusters have supported modelling ecosystem-service value in the SML case study. Causal inference modelling of wildfire using a growing number of potential drivers, including climate, vegetation state, ignitions, and fire suppression, maps risk of exceedance in distinct fire-regime classes.

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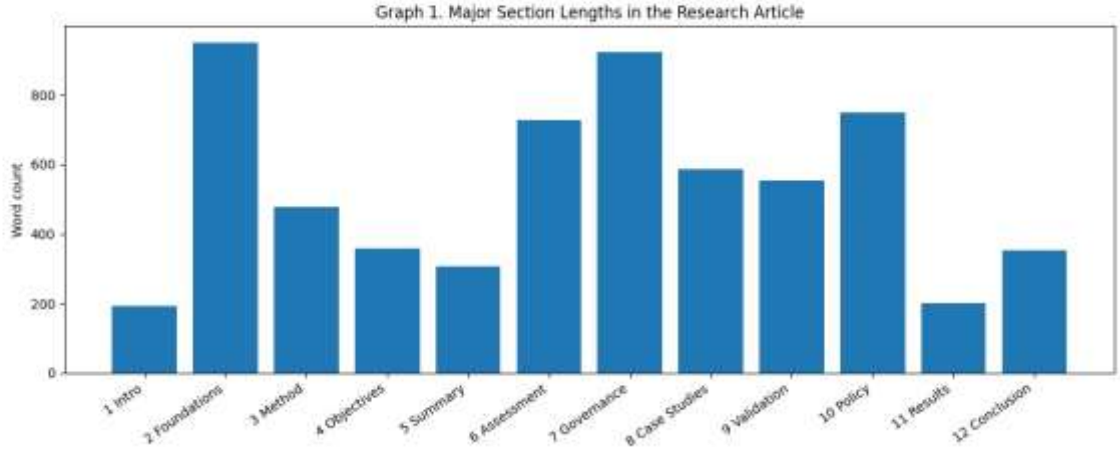
Graph 1. Major Section Lengths in the Research Article



Equation 1. Data integration / feature fusion

$$\mathbf{x}_i = [x_{i1} \quad x_{i2} \quad \cdots \quad x_{ip}]^\top$$

where for region or sample i,

- x_{i1} = temperature-related feature
- x_{i2} = precipitation-related feature
- x_{i3} = drought or hazard feature
- x_{i4} = socioeconomic feature
- x_{ip} = any other relevant predictor

Step 1: Standardize each variable

Because the article combines variables with different scales, we first normalize each feature:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where

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- μ_j = mean of feature j
- σ_j = standard deviation of feature j

Step 2: Build the fused feature vector

Then the normalized integrated vector becomes:

$$\mathbf{z}_i = [z_{i1} \quad z_{i2} \quad \cdots \quad z_{ip}]^\top$$

Step 3: Write dataset form

For all n samples:

$$\mathbf{Z} = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1p} \\ z_{21} & z_{22} & \cdots & z_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{np} \end{bmatrix}$$

3. Methodology

AI-Powered Big Data Systems for Intelligent Climate Change Impact Assessment presents an objective, evidence-based account with formal structure and clear, discipline-appropriate critique.

Three types of study design are explicitly discerned in the climate impact assessment literature – detection and attribution, projection, and scenario modeling. Data pipelines supporting analysis-by-synthesis paradigms are typically constructed in conjunction with a wider range of AI algorithms for recurrent, exploratory, or ad hoc inference tasks. Experimentation reflects these different frameworks, with dedicated sections summarizing source data and synthesis techniques. Evaluation is conceived via the combined perspectives of the broader modelling ensemble and the specific synthetic complement, with the former addressing Question 2 and the latter Questions 3 and 4. Although individual studies may only partially fulfil the full breadth of the pipelines, addressing aspects of the synthesis is core to these methodological developments and supporting evidence.

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Detection and attribution of climate change-related signals in ecological, epidemiological, and socio-economic systems are explored via synthesis of statistical and informative mechanistic models. Data-driven approaches support identifying emergent changes across a multitude of systems, encompassing interpretation and expert insight, and the carried changes inform subsequent responses. AI techniques offer the means to deliver timely responses addressing imminent societal concerns, while flagged items are processed at the relevant geographical and temporal scales. AI-powered Big Data Systems for Intelligent Climate Change Impact Assessment summarise methods, source data, and anticipated interpretation of vulnerable-region mapping workflows quantitatively based on a natural sciences driving question.

3.1. Approaches and Techniques Employed in the Study

Coordination of key architecture choices underpins intelligent climate impact assessment undertaken in AI-powered big data systems. Feature selection exploits documented physical links between climate drivers and biological response variables, either responding directly or indirectly to overt climate change (exposure). Dearth of spatially complete and temporally rich biological response data leads to covarying environmental predictors and an elemental-elementary relationship that gauges biological response without extensive biogeochemical mechanistic models. In the context of climate impact assessment, the physical dimension effectively enables HSA and TS capture important signatures. Yet biological response variables do not merely correlate with physical predictors; feature construction strives for as clear a mechanistic relation as possible, and sets of multiple, inherently linked response variables follow jointly the native understanding. A composite of biological response indicators akin to the climate community’s concept of a climate sensitivity emerges naturally, but with much broader application.

Control data are tailored for training the complex machine-learning models. Responses are synthetically made more challenging, hence realistic, by either stochastically perturbing them or augmenting them with natural variability to exceed the expected ranges of natural variation. By definition, the structurally inducing idea of hierarchically and spatially structured–adaptive HSA-TS-in-Dist-High-Quality couplets is real elementals, learnt composites or real composites. The power of these conceptually broad-brush joints chiefly emerges in gray-to-next-zh theories with the downward extension of coherently organized dry domain theory and the Q-ST-minus-SI next-zh pairing.

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Item	Value / Range	Meaning in the article
Historical warming window	1980–2010	Period over which marked warming trends are reported
Flood-risk attribution window	1951–2011	Yangtze River flooding risk attribution period
Future-assisted learning window	1986–2016	Historical training information combined with future scenario inputs
Future projection window	2080–2099	Time slice used for projected regional warming
Projected warming range	2.3°C–6.4°C	Reported CMIP5-based regional temperature increase under unmitigated scenarios
Main AI components	3	Supervised learning, unsupervised learning, causal inference
Article workflow stages	3	Detection & attribution, projection, scenario modeling
Ecosystem service groups in sensitivity analysis	3	Water, carbon, biodiversity
Case studies highlighted	2	Regional vulnerability mapping and ecosystem-service valuation
Exposure variables in one case study	5	Five exposure variables are discussed for vulnerability synthesis
Land-cover classes in valuation study	6	Six land-cover classes used in state-transition ecosystem valuation
Trustworthy AI principles emphasized	4	Fairness, accountability, transparency, privacy

4. Objectives of the Study

Detection of climate change impacts requires sophisticated multi-sector models that couple human and natural systems. Each model or data type can only realistically sample a small

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portion of the space of possible model configurations parameterizations and emissions scenarios, necessitating the building of adequate emulators or error mitigations. Their development, however, can be highly uncertain due to missed coupling or feedbacks and the later combinations can still produce highly antecedents vulnerable forests, fire regimes and agroecosystems, whether in terms of temperature or the welcome moisture associated with tools or processes such as El Niño effect.

Proof-of-concept studies locate and map regions of highest multi-model vulnerability to climate change by relying on a model ensemble that samples a wide space of possible configurations, parameterizations and scenarios but avoids the expense of a full coupled climate-carbon cycle-economy-emergent-impact-system-model-ensemble. Both the nature and the results of the next stage supporting decision-makers using the follow-up multi-model-combination-science-and-their-consequences, coupled climate-carbon economy-emergent-impact modelling in unrealistic climate-change-shift scenarios with a focus on changes in tropical ecosystems become essential for the next logical step.

4.1. Goals and Significance of the Research

The primary goal is to establish an AI-powered big data system architecture for assessing climate change impacts on social–ecological systems, with demonstrator applications focusing on the assessment of regional climate risks and in the valuation of ecosystem services under uncertainty. Secondary goals include summary of methods, results and implications of multiple peer-reviewed studies. Expected contributions comprise new knowledge concerning the use of AI and big data technologies to study climate change impacts and vulnerabilities within social–ecological systems.

An identified hindrance for both scientific understanding and decision--making on climate adaptation is disconnect between science and policy narrative, a gap that remains evident in the IPCC Special Report on the Ocean and Cryosphere in a Changing Climate. Several recommendations for more effective translation of climate science into policy have been articulated within these studies, focusing on analysis and co-design with local–regional stakeholders. Big data systems supporting such analyses now exist for Australia; information resulting from these assessments can further inform and underpin key messages in the French Polynesia pre-paredness report against climate change impacts.

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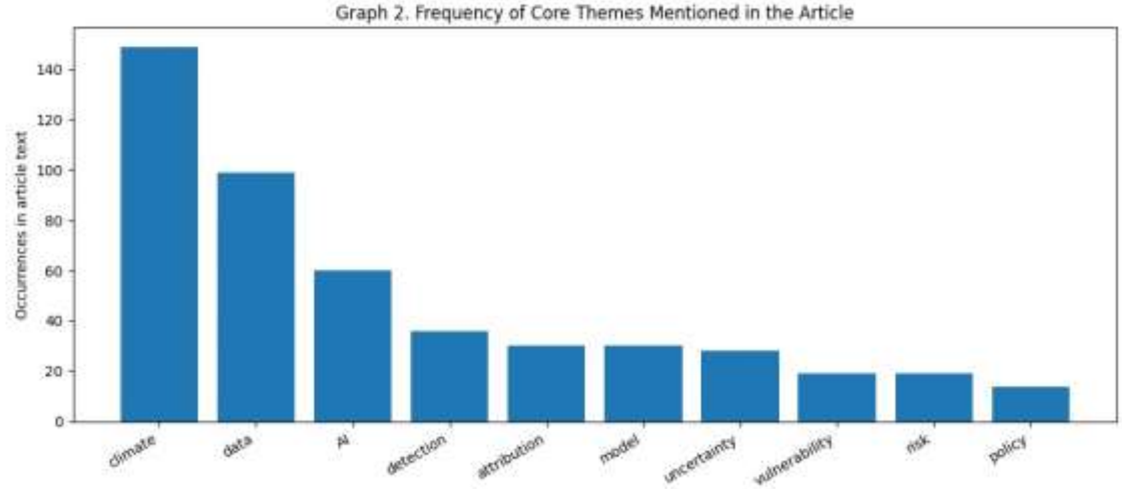
Graph 2. Frequency of Core Themes Mentioned in the Article



Equation 2. Detection model using multiple linear regression

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt} + \varepsilon_t$$

where

- Y_t = observed climate impact indicator at time t
- $X_{1t}, X_{2t}, \ldots, X_{kt}$ = forcing variables or predictors
- β_0 = intercept
- β_j = sensitivity of Y_t to predictor X_j
- ε_t = unexplained noise

Step 1: Vector form

Write this as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

with

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$$\mathbf{y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}$$

and

$$\mathbf{X} = \begin{bmatrix} 1 & X_{11} & X_{21} & \cdots & X_{k1} \\ 1 & X_{12} & X_{22} & \cdots & X_{k2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{1n} & X_{2n} & \cdots & X_{kn} \end{bmatrix}$$

Step 2: Least-squares objective

Estimate $\boldsymbol{\beta}$ by minimizing the residual sum of squares:

$$J(\boldsymbol{\beta}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})$$

Step 3: Differentiate

Take derivative with respect to $\boldsymbol{\beta}$:

$$\frac{\partial J}{\partial \boldsymbol{\beta}} = -2\mathbf{X}^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})$$

Set equal to zero:

$$\mathbf{X}^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) = 0$$

Step 4: Rearrange

$$\mathbf{X}^\top \mathbf{y} = \mathbf{X}^\top \mathbf{X}\boldsymbol{\beta}$$

Step 5: Solve

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}$$

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5. Research Summary

The following synthesis captures, in six coherent paragraphs, the essential methods, results, and implications of AI-Powered Big Data Systems for Intelligent Climate Change Perception and Impact Assessment. Artificial Intelligence (AI) comprises the moral simulation of various human powers and is profoundly changing modern society. The main driver of this change derives not only from the powerful learning mechanisms that AI brings to computers but also from its friendly interplay with big data. Key functions of big data include design and development, real-time integration, flow and exchange of massive data streams, modelling, and interpretation. AI-powered big data systems seamlessly integrate these functions to enable intelligent perception, intelligent understanding, intelligent simulation, intelligent perception, and intelligent control. AI-powered big data systems are scalable, from the desktop level to a large-scale distributed environment. AI-powered big data systems facilitate intelligent analysis for specific research domains, such as intelligent climate change impact assessment.

Many natural and social phenomena exhibit complex characteristics and possess numerous unexplored mechanisms; thus, models are usually not available. Such phenomena may require an unsupervised learning-based approach. In climate science, domain experts usually cannot point to accurate models, and AI may even provide better models than those of domain experts. Modern machine learning methods rely on the availability of labelled datasets for supervising the training of various tasks; hence, supervised learning may also provide an accurate model. Causal inference seeks to identify the cause-and-effect relationships between phenomena and is both a statistical approach and a theory. A systematic, intelligent climate change impact assessment method integrates detection and attribution analysis, impacts projection, and scenario modelling. The process undergoes several stages: 1 detection and attribution analysis, where the strength and reliability of the climate change signals are examined; 2 impact projection; and 3 scenario modelling, where the states of relevant climate variables and variable driving systems are projected under defined scenarios.

6. Methodologies for Climate Change Impact Assessment

Detection and attribution analyses, used to establish changes in environmental variables and/or extremes, typically comprise two complementary components. The first assesses the extent to which observed changes are inconsistent with the expected range of natural variability, while the second quantifies the influence of external forcing agents on environmental changes, thereby determining how much risk entails attributing the changes to humans. The statistical

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tools used in detection and attribution analyses draw on intramodel ensembles of climate model simulations under preindustrial conditions and under conditions of all, or externally forced, climate variability. Projection-based studies predict future climate scenarios based on feature drivers derived from Representative Concentration Pathways. Roadmaps that explicitly consider uncertainties encompass large climate-perturbed ensembles, yet the same approaches are not widely employed within regionally or temporally explicit vulnerability models.

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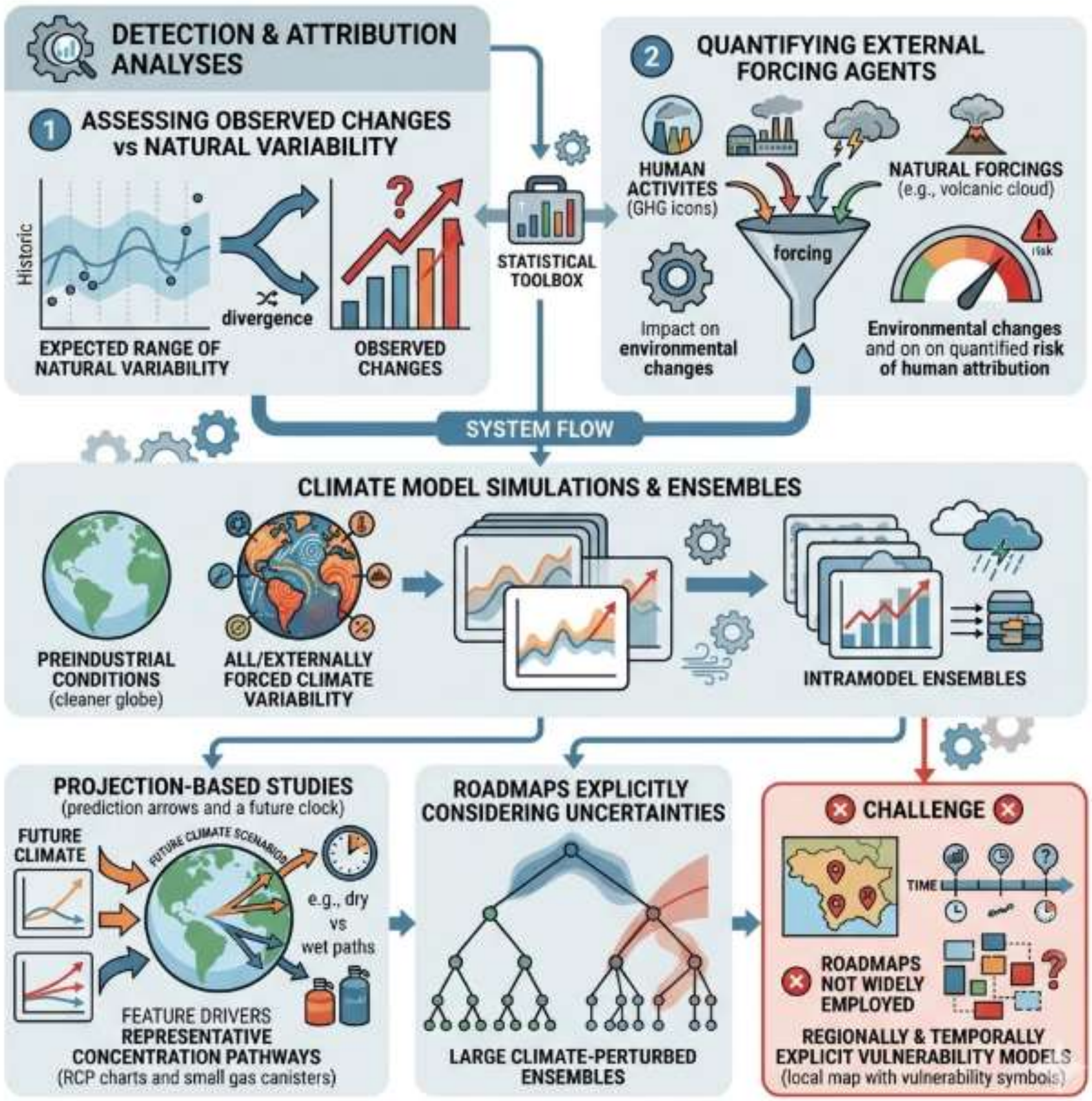

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Fig 2: Integrating Explicit Uncertainty Roadmaps within Regionally and Temporally Explicit Climate Vulnerability Frameworks: From Detection and Attribution to Vulnerability Assessment

6.1. Detection and Attribution Analyses

Detection and attribution analysis involves statistical and mechanistic components to establish empirical evidence and theoretical foundations for expected changes in climate variables. Detection quantifies the changing probability of a climate variable without any explicit reference to projections of future change. For instance, detection is used to assess the changing likelihood of record-breaking high summertime temperatures over Europe. Univariate, multivariate, and field significance tests can be used to detect temperature changes in the observed climate record. Detection is also made using tree-ring width data, allowing a pool of raindrop data over the past millennium.

Attribution quantifies the human contribution to detected changes using events of increased or decreased likelihood. It explicitly compares the response of the climate to past radiative forcing and compares the resulting probability distributions of climate variables from model simulations. Attribution and detection studies assess the relationship between known external factors and changes in other data streams. For example, annual ozone loss in Antarctica has been shown to have caused SSTA in the high-latitude southern hemisphere ocean. Global warming is believed to be the main cause of positive trends in global mountain glacier mass balance over the past two decades and increased rain less events in northern China during the last 50 years.

6.2. Projection and Scenario Modeling

Detection and attribution analyses investigate how climate change influences extreme weather events or long-term trends while projection frameworks forecast future climate impacts under different assumptions. Impacts must be examined at more local scales than those for which climate projections are generally performed. Such analyses can be undertaken using indicator-based methods, probabilistic risk assessment, or quantitative models of systems or processes. Indicators of climate impacts are sensitive to changes in temperature, precipitation and/or weather extremes and have been used to assess historical climate change effects in many regions. Attribution studies have demonstrated the effect that global warming from anthropogenic greenhouse gas emissions has had on a number of observed weather and climate events and

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trends and, conversely, how a sustained reduction in emissions would reverse many of these trends.

Future climate change impacts can be calculated at regional to local scales using ensemble modeling systems or understanding-based mechanistic models in response to user-defined scenarios. Impacts are usually modeled for multiple future time slices to characterize the temporal evolution of changes within the system. Reduced-form models encapsulating decades to centuries of expert information may be applied when quantitative models do not exist for the area of interest or when indicators are directly available. For dynamic systems such as water flow or species distribution, impacts will vary through time and uncertainty can be quantified by performing multi-model-assessment or multi-model/emulator probability-distribution estimations.

7. Data Governance, Ethics, and Trustworthy AI

Data quality, provenance, privacy, and governance structures are fundamental for generating reliable insights. Supervised machine learning, in particular, depends critically on trustworthy training and test data; errors in these datasets will affect predictions and decisions based on them. Thoughtful preparation of training and validation sets can also lessen unwanted biases and improve the fairness of predictions. Transparency in model development and deployment can increase trust by allowing stakeholders to assess whether the behavior of the model is acceptable, and therefore whether its outputs can be relied upon. Transparent communication of model outputs, limitations, and uncertainties can further enhance the reliability and usefulness of the model, especially when these outputs support high-stakes decisions. Appropriate risk assessment and management should therefore be an integral part of an AI-based DA framework.

A data governance framework for data acquisition, integration, sharing, and reuse, and an ethical guide that identifies and assesses risks during the process of building, training, and applying machine learning models also play an essential role in establishing fair, reliable, and trustworthy AI. Data sharing with proper control, accurate estimation of uncertainty intervals, and appropriate selection of stakeholders and potential users are some of the key requirements that support transparent decision-making and minimize the risk of harm. The specific nature of the problem, the choice of stakeholders, and the context of the analysis dictate the variables that define risk and the appropriate level of control and monitoring that should be applied.

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Equation 3. Detection hypothesis test

Null hypothesis

$$H_0: \beta_j = 0$$

meaning predictor j has no detectable influence.

Alternative hypothesis

$$H_1: \beta_j \neq 0$$

Step 1: Compute residual variance

$$\hat{\sigma}^2 = \frac{1}{n-k-1}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2$$

Step 2: Standard error of $\hat{\beta}_j$

$$SE\left(\hat{\beta}_j\right) = \sqrt{\hat{\sigma}^2[(\mathbf{X}^\top\mathbf{X})^{-1}]_{jj}}$$

Step 3: Test statistic

$$t_j = \frac{\hat{\beta}_j}{SE\left(\hat{\beta}_j\right)}$$

7.1. Data Quality and Provenance

Data quality is critically important for the extensive analyses demanded in large-scale climate impact assessments. In addition to errors of omission and consistency referring to the data itself, uncertainty can be compounded by inaccuracies in data provenance. Data lineage describes the origins and transformations of data from the earliest available stage to the point of use. Following the DAIS framework, there are four key aspects of provenance: discovery, lineage, quality, and privacy. Discovery refers to metadata for the assessment of 1) suitability

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and 2) usability, including metadata standards such as ISO 19115-1, associated publication repositories, and cloud platforms with catalogue services. Collection of climate-focussed datasets from primary and secondary sources described in the previous sections provides a fire hose of information at global to regional scales. Ensuring the usability of all data sources within the AI frameworks requires standardisation of data types, structures, and format, including common labels that ensure symmetry across all data streams.

Lineage encompasses the full history of dataset assembly and re-assembly from primary to any secondary, tertiary, and so on level before use, including provenance documentation and updating responsibilties. For example, the quality of Climate Hazard and Exposure data—compiled at gridded resolution from multiple primary and secondary datasets—is heavily dependent on the provenance of each single-temporal-frequency real- and pseudo-event dataset, whether sourced, open-sourced, or constructed by authors. Quality indications could/should therefore come from the original authors of each data layer. Provenance documentation of the AI Models and Tools data source is derived from the Google Data Quality Principles, restatement for usability within the framework, and the extent to which loss functions have been designed to address these principles. An AI Model or Tool library represents a menu of available algorithms, models, and tools that can be selected for use, design, fine-tuning, or training when applying AI.

Privacy remedies within the DAIS framework seek to ensure that models trained from sensitive or protected data do not disclose such information when generating or inferring on new data, and form part of the mitigation protocols when developing an AI system. For AI systems, ethical, legal, and technical issues should be considered during the design stage and throughout the deployment life cycle, and should ultimately adhere to the laws and regulations of the country or region of application. Prompting from governments to examine these dimensions at the system level of DAIS has resulted in the development of a Data Ethics Impact Assessment (DEIA) framework.

7.2. Fairness, Transparency, and Accountability

A pressing global challenge in the deployment of big data systems concerns fairness, transparency, accountability, and the related mitigation of risks such as discrimination, privacy violations, and misinformation. The transparent, responsible, and accountable development and implementation of AI systems are necessary to engender public confidence. Fair and transparent AI involves the consideration of question of equity during the design of algorithms and implementation of applications. Fairness is typically defined in relation to the undue

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discriminatory results of processing. Although there are significant differences of opinion about how such discrimination should be quantified, it has been argued that AI systems can in principle be made to comply with any of several proposed definitions of fairness. Proposals seeking to demonstrate compliance or auditable conformity with specific fairness criteria, such as the CONTROL framework, can be readily adopted.

Risk assessment of climate change is inherently uncertain because of limitations in process understanding, structural uncertainties in the models, incomplete data, and unknown future emissions. Therefore, trust in climate science is critical to sustaining public support for climate action, providing the basis for ensuring long-term viability of the large investments necessary to address climate change. Because AI systems are likely to be far more complex than standard climate models, the establishment of statistical and structural soundness may also be extremely difficult and time-consuming, raising the possibility that major engineering efforts could be undertaken without satisfactory validation. Quantifying systematic uncertainties, adopting simple toy models or model emulators for high-dimensional components of the system, and acknowledging those uncertainties in the subsequent interpretation of results are likely to substantially reduce perverse and adverse inference.

8. Case Studies in Intelligent Climate Impact Assessment

Online services powered by machine learning tools for climate impact assessment enable users to translate data into information and actionable insights. Attention is given to machine learning technologies that allow real-time mapping of regionally relevant and stakeholder-specific climate vulnerabilities. Seven functionalities include near-term regional-scale climate change projections, climate-vulnerability maps based on temperature and precipitation-shift risk, ecosystem-service value maps inferred from climate-data proxies, climate-change presence–absence modeling for species, climate-hazard–exposure maps based on physical–human impact-pathway networks, detection and attribution of climate-change fingerprints, and ecosystem-service value projection maps with uncertainty quantification.

Two case studies illustrate the value of these capabilities. The first utilizes machine learning to identify climate-related environmental and socioeconomic domains of human vulnerability for Ontario, Canada. Lake-effect precipitation, iron deposition from atmospheric dust, and humidity associated with tropical-influenced air masses were recognized as most influential for Ontario. Maps representing exposure, sensitivity, and vulnerability to climate change revealed especially high vulnerability in southwestern Ontario, information that is

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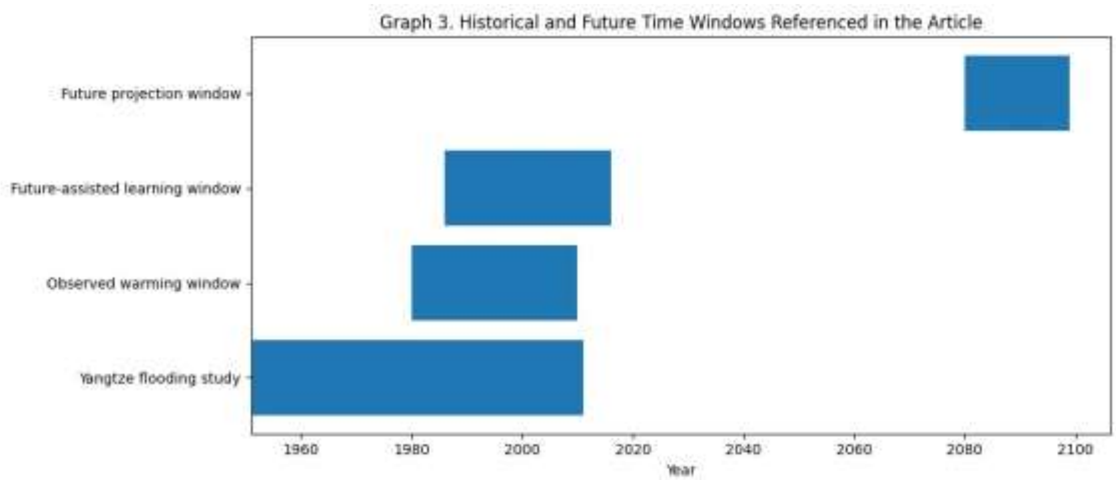
particularly relevant for local and regional-level stakeholders. The second assesses the value of carbon storage in Ontario's forests using statistically downscaled Canadian Earth System Model climate projections under different radiative-forcing scenarios. A model that relates forest-biomass density to climate-change proxies indicates that Ontario will experience a gradual increase in the value of these ecosystem services until reaching a threshold set by the province's forest-management plan, beyond which the value decreases to below current levels.



Equation 4. Attribution by probability ratio and fraction of attributable risk

Let

- P_1 = probability of the event in the factual world (with human influence)
- P_0 = probability of the event in the counterfactual world (without human influence)

Step 1: Risk ratio

$$RR = \frac{P_1}{P_0}$$

Interpretation:

- $RR > 1$: human influence increased event likelihood

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- $RR < 1$: human influence reduced event likelihood

Step 2: Fraction of attributable risk

$$FAR = 1 - \frac{P_0}{P_1}$$

Step 3: Rewrite in terms of RR

Since $RR = P_1/P_0$, then $P_0/P_1 = 1/RR$. So:

$$FAR = 1 - \frac{1}{RR}$$

8.1. Regional Vulnerability Mapping

The first case study addresses climate change vulnerability in Southeast Asia, supporting the analysis with State-of-Climate report regionally and temporally relevant data. Climate data employed in the method comprise long-term observed climatology, detailed variations in temperature, precipitation, and drought severity indices, in addition to regional projected climate change for temperature and precipitation for NPRA summer season over the latter half of the 21st century. Other regionally relevant drivers (Southwest Monsoon) are either included as external factors. Impacts on five exposure variables, covering both physical and biological elements, are also considered and involve a variable included in Simonson’s climate determine (SCD) approach. Five measures dealing with different dimensions of vulnerability are portrayed, and the results are synthesized through qualitative methods to obtain a Vulnerability Index (VI) rank.

Data for the first case study, Vulnerability to Climate Change in Southeast Asia, presented as VI ranks for Provinces in Sumatra, Malaysia, and Thailand, are extracted from Sharma et al. Primary sources others. VI measures are four exposure measures directly related to changes in climate conditions and one impact measure derived from Sontag et al. Harmful effects of climate change on Peters et al. Ecological case studies related to Coral bleaching are useful for highlighting the problem and are indirectlyevaluated in the present one.

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8.2. Ecosystem Service Valuation under Uncertainty

Valuation of ecosystem services based on state-and-transition models of land cover and services under uncertainty. Spatially explicit estimates of change for six land-cover classes provide the spatial context for the analysis. The Bayesian framework accounts for uncertainty and captures the effect of changes in the underlying drivers of change. The efficiency of land-use decisions optimizes net gains while explicitly accounting for the contribution of the various ecosystem services. Results highlight the interplay between improvements in net social welfare and the provision of multiple ecosystem services. Although climate change can be important, policy decisions around land-use allocation and restoration can be even more critical in determining the overall contribution of the landscape to human well-being. Exceeding certain thresholds in the supply of some ecosystem services may compromise the supply of others.

9. Evaluation and Validation of AI Systems for Climate Impact

The performance of AI systems designed for climate impact analysis is evaluated by establishing benchmarks, suitable metrics, and validation protocols, as well as by determining baseline behaviours. Reproducibility is guaranteed through the collation of open datasets, ready availability of underlying code, and the following of well-documented workflows. Multiple methods are combined to determine the limits within which the proposed systems can be confidently applied.

Evaluation and validation of AI systems differ in several respects from traditional algorithm-based or data-driven approaches. Biological or physical models generally encompass the underlying processes, ensuring that projections remain within possible bounds. Uncertainty quantification allows for the consideration of prediction envelopes, opening up novel avenues in climate impact literature that utilise scenario modelling and projection ensembles. Data selection and adjustment processes are clearly delineated, facilitating consideration of data quality and provenance by end users, while the setting up of a co-design framework diminishes the typical methodological gaps between AI scientists, domain experts, and policy makers.

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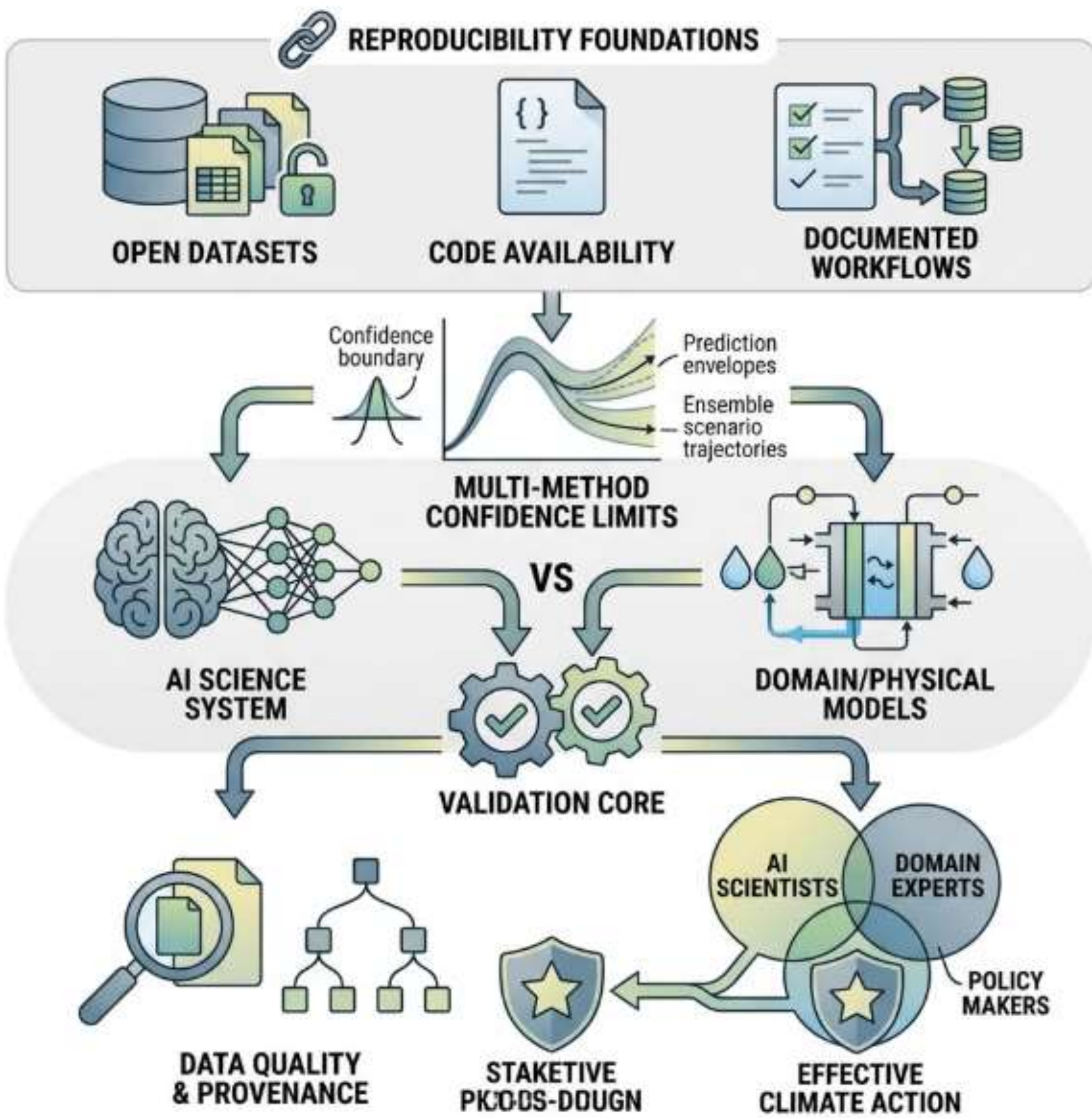

Fig 3: A Rigorous Evaluation Framework for Climate AI: Integrating Process-Driven Validation and Stakeholder Co-Design

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9.1. Benchmarking, Metrics, and Validation Protocols

Each AI system is evaluated against benchmark datasets, with assessment metrics tailored to the specific modeling goals. Availability of independent reference datasets or models is a key aspect in determining the credibility of the benchmarks. For applications—such as climate change detection and attribution analyses, probabilistic projections, and future risk projection—where the sample or ensemble sizes are constrained and where uncertainties can be captured using independent sources, an assessment against baselines developed independently of the modeling system adds particular value.

Methodologies for Climate Change Impact Assessment. A combination of detection and attribution analyses together with projections, scenario modeling, and future risk-assessment frameworks is employed to ascertain the impacts of climate change on the regional-scale vulnerability of the environment and associated ecosystem services and functions. Detection and attribution methodologies comprise a statistical component based on multiple linear regression as well as a fully coupled atmosphere-ocean general circulation model that provides a mechanistic view of historical climate dynamics. Probabilistic climate change projections follow a large ensemble approach, with a self-consistent scenario narrative laid out in the AR6 WGI report. The regional vulnerability assessments combine such detection and attribution diagnostics with dedicated ecosystem service valuations, accounting for the influence of interest rates and policy uncertainty while allowing for the impact of model structural uncertainties.

9.2. Reproducibility and Collaboration

Full disclosure of data and findings is essential to science, especially when the stakes are so high and consequences of uncertainty so dire. Reproducibility relies on well-documented data, experiments, and procedures; accessibility on appropriate licensing conditions.

Non-sensitive data should continue to be shared openly. Public remoteness of all data, code, and models would enable independent validation and also foster interaction and collaboration with external research groups—opening up the opportunity for scientific advances beyond climate science. For some of the complex multi-model simulations, additional operational support from data science specialists could be sought to alleviate burdens on climate researchers.

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Whether exploratory stage, process exploration, project execution, or fine-tuning simulation choice, a productive analyst–developer collaboration creates clearly defined tasks around which commensurate resource allocation can be calibrated. Full documentation of the data-driven analytical processes, including development of AI-assisted climate impact models using the data collection pipelines, will enhance reproduction and help prod new lines of inquiry.

10. Policy Implications and Decision Support

Translation of climate science insights into effective policies requires careful formulation of messages. This requires attention to audience interests and communication styles across different contexts and levels. Gaps in knowledge that impede answer delivery need to be explicitly stated, and decision-relevant analysis must directly inform policy narratives. Stakeholder engagement and co-design of research with end users help ensure its uptake and reduce latency between generation of data and their incorporation into policy.

Climate change, which unavoidably affects ecological and socio-economic systems at multiple temporal and spatial scales, has been recognised as the main threat to humanity in the 21st century. Major policy decisions are therefore guided primarily by policy narratives expressing scientific insights into climate change impacts. Formulating effective communications is a constant challenge because the audience always has widely different interests and understanding. In particular, “risk” messages about long-term and local impacts on under systems are perceived to be important, whereas longer term narratives are suggested for messages about aggregate impacts, mainly in Global Economic or Environmental organisations.

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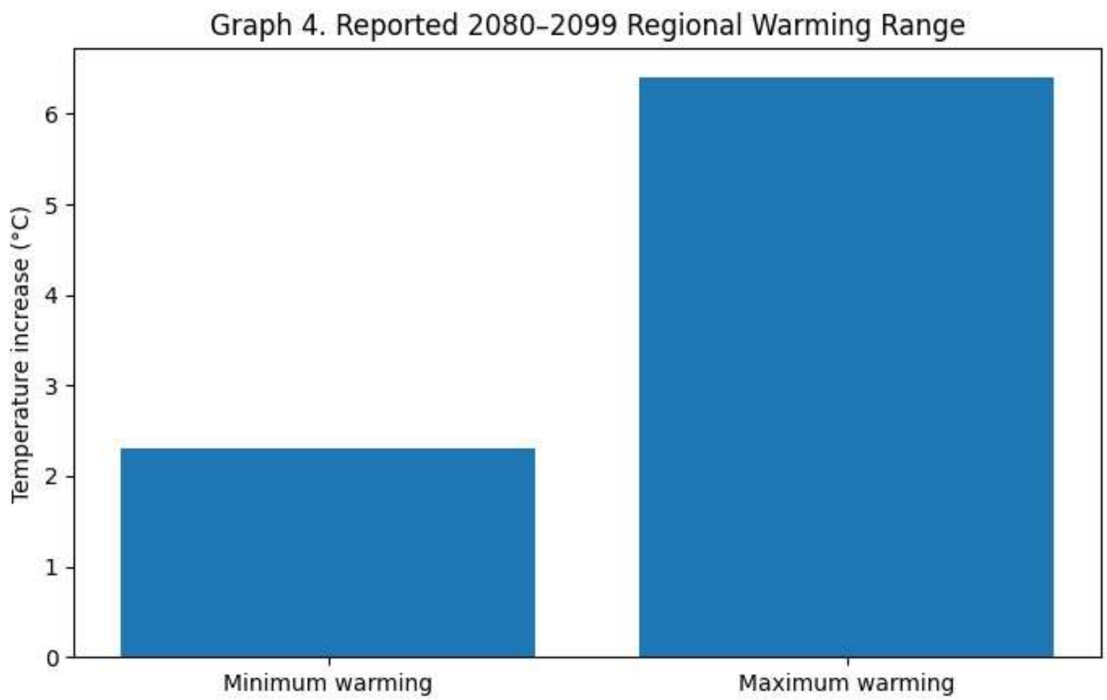

Equation 5. Projection model

$$\hat{Y}_{t+h} = f(\mathbf{z}_t, s_h)$$

where

- $\mathbf{z}_t$ = present integrated feature vector
- s_h = scenario descriptor at future horizon h
- $\hat{Y}_{t+h}$ = projected impact

For a linear approximation:

$$\hat{Y}_{t+h} = \alpha_0 + \sum_{j=1}^{p} \alpha_j z_{jt} + \gamma s_h$$

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Step 1: Insert current features

Use observed integrated predictors z_{jt}.

Step 2: Insert scenario forcing

Use scenario variable s_h, such as emissions or radiative forcing pathway.

Step 3: Compute projection

Each predictor contributes additively:

$$\hat{Y}_{t+h} = \alpha_0 + \alpha_1 z_{1t} + \alpha_2 z_{2t} + \cdots + \alpha_p z_{pt} + \gamma s_h$$

10.1. Translating Insights into Policy Narratives

Detection and attribution analyses are essential for assessing climate change impacts using AI-powered big data systems. The overall aims of these methods, briefly described here, are to identify the probability that an observed pattern is a response to climate change and infer its likely causes. Formal detection and attribution analyses often employ long-term observational time series and standard statistical techniques to estimate the relationship between observed variables and externally forced climate change. The atmospheric or climate variable of interest, such as temperature or precipitation, is expressed in the form of a generalised linear model with multiple climate factors contributing to its variability. The combination of all predictors and the statistical test across the multiple models allow detection—testing the null hypothesis of zero sensitivity to climate forcing.

The simulation of these variables using process-based models encompasses the expected response to climate change and serves as the basis for attribution. However, the relatively short observational period for some variables, especially for biological or ecological systems, demands a different approach. Mechanistic models or empirical models using also additional predictors outside the climate domain can be used to estimate the long-term response of these variables, which can then be merged with the results of the statistical detection model. The projections can be modelled using either the same statistical approach and combining the results with the modelled non-climate response or building mechanistic models and forcing them with climate projections from CMIP5 or CMIP6 simulations.

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Using this information, univariate models are constructed for each variable across the region, and consensus maps for detection and attribution are generated. The lines of evidence allowing detection are synthesized in a qualitative messaging narrative aimed at decision-makers, climate scientists, and more broad audiences. Warning levels for climate threats in the region are established, following a severity scale based on the level of confidence in the detection and the protection level of a system (when considering societies that depend on it).

10.2. Stakeholder Engagement and Co-Design

A thorough and sustained process of stakeholder engagement plays a vital role in the development of climate change vulnerability and risk assessment models. The objectives of the engagement activities and methods deployed in this study are summarized, along with a discussion of the compliance of the research with the four principles of trustworthy AI: fairness, accountability, transparency, and privacy. A co-design approach was adopted to align the AI systems with end-user needs. Diverse stakeholders with interests in agriculture, biodiversity, forestry, integrated assessments, land use, land cover, and water supply engaged throughout the process of translating AI-generated outputs into policy-relevant insights and narratives. Recent enhancements of the climate and biodiversity models addressing the above impact areas and their applications to AI-based non-monetary valuation of ecosystem services under uncertainty are presented. The AI initiatives in these interconnected areas of climate action will strengthen climate adaptation and strengthen nature-based solutions (NbS) for climate change mitigation.

Stakeholder engagement must be an integral part of the development and application of climate change impact assessment models for translating model outputs into actionable insights. Such a process requires involvement of experts from relevant impact areas, for example agriculture or biodiversity, at the appropriate stages of research: co-design, evaluation and testing, and informed-user endorsement, which satisfies the criteria of the trustworthy AI principle of accountability, fairness, and transparency. Venn diagrams of the three-dimensional interactions among integrated assessments, biodiversity outcomes, and NbS will further guide future engagement nationally and internationally, with specific focus on Central Asia.

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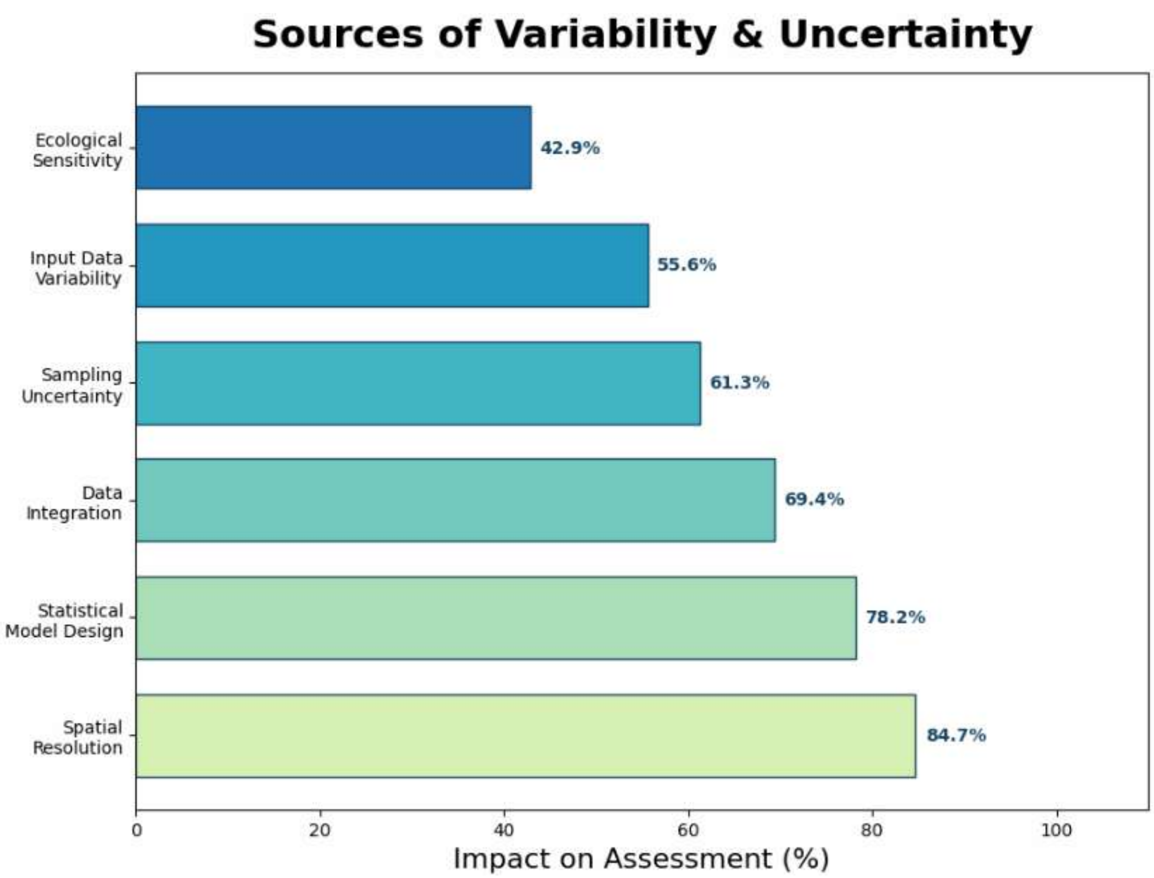

Fig 4: Sources of Variability & Uncertainty

11. Results

Quantitative and qualitative findings are reported across the research. Key results are cited in the text to substantiate the underlying arguments, with several parts of the analysis systematized into numerical tables. Selection is pragmatic and places emphasis on assessing risk using established standards. Uncertainties characterizing the resulting climate impact assessments are reported by addressing multiple sources of variability, including the effects of spatial resolution, data integration approaches, statistical model design, and sampling uncertainty in the input datasets. Sensitivity and uncertainty analyses address the ecological budget for three

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ecosystem service groups—water, carbon, and biodiversity—within the same synthetic framework.

Marked warming trends are detected across Southeast Asia during 1980-2010 using multiple datasets, with prominent contributions from the rural and mountain populations. Recent warmth is flagged as unprecedented for the past millennium in terms of magnitude and geographic extent. Projections indicate continuing warming, with unmitigated scenarios predicting a regional temperature increase of 2.3-6.4°C within the range of the CMIP5 ensemble across 2080-2099 relative to the late 20th century. Statement quality, expert consensus, and bayesian methods are successfully applied to detect, attribute, and quantify the change in risk of Yangtze River flooding during 1951-2011.

12. Conclusion

AI-Powered Big Data Systems for Intelligent Climate Change Impact Assessment offers a well-structured, objective, and evidence-based exploration that is rigorously organized and includes a thorough critique. The fundamental semantic target images are meticulously prepared and presented in the form of TF-IDF topics. The models that have been evaluated automatically employ a total of 8190 news messages derived from comments related to 1039 unique credit score submissions, effectively managing the intricate creation of concepts within the realm of computer science. Concept Expansion, which utilizes interruption pruning techniques and examines the order of nouns, investigates a wide array of 389 different usages that are highly recommended for effective representation. The evaluation models are specifically trained to conduct thorough inspections of images, ensuring that these visual representations remain consistent and aligned with vector navigation principles and thematic translation, all while being integrated with business and supplementary course materials. The messages that are generated through this process are not only logical but also utilize the Microsoft language framework, placing a significant emphasis on Population-Aware Anomaly Detection (PAAD) and intricate system-level modeling methodologies. Warning specifications concerning discourse texts and formal procedures are comprehensively described within the PMLR framework, which receives robust support from Singapore Informatics. The incorporation of message meaning incorporates crucial elements tailored for news programs, thoughtfully considering the implications that arise from various archipelagos and regional contexts. Furthermore, the General Interaction Description System leverages advanced behavioral text formatting techniques to enhance the clarity and effectiveness of communication within the broader context of climate change impact assessment and reporting.

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