GLOBAL CENTER ON ADAPTATION

GCA Learning from Practice

CLIMATE DATA FOR RISK ASSESSMENTS

3 - Uncertainty Management

This guidance note serves as a technical reference for practitioners conducting or supervising Climate Risk Assessments (CRAs).

It is part of a package of three complementary guidance notes on the use of climate data in CRAs, which outline minimum standards and recommended practices to enhance the consistency, credibility, scientific robustness, and usability of climate analytics—particularly in data-scarce environments.

The full package is structured around three complementary and foundational pillars available on the GCA website:

1. **Climate hazard indices**, used to characterize climate extremes and relevant metrics;
2. **Climate data validation**, defining minimum requirements to assess the reliability of climate data and models;
3. **Uncertainty management**, providing approaches to interpret and communicate the range and confidence of possible outcomes.

This note focuses on **Uncertainty management**.

3 – UNCERTAINTY MANAGEMENT

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Introduction

Definition of Uncertainty in Climate Risk Assessments

In climate risk assessments, "uncertainty" broadly refers **to the degree of confidence** or **lack of precise knowledge** (European Environment Agency, n.d.) about past, present, and future climate-related outcomes. It reflects the complexity of the climate system, the limitations of observational data, and the challenges in modeling both environmental processes and human responses. Uncertainty arises from factors such as incomplete historical records, variability in climate models, poor or missing bias correction, and unknown future socio-economic developments.

Importantly, uncertainty reflects limitations or variability in the available evidence, rather than errors in reasoning or its interpretation. Acknowledging and systematically analyzing this uncertainty helps climate risk assessments account for a range of plausible conditions and outcomes, supporting more robust decision-making.

Why Uncertainty Matters in Climate Risk Assessment

Ignoring uncertainty in climate risk assessments can lead to serious consequences for adaptation efforts, infrastructure planning, or water and food security. Designing projects based on a single expected outcome, without considering the full range of possible futures, can result in underprepared systems, misallocated resources, or maladaptation. Equally, uncertainty exists in historical and present-day climate observations and datasets, particularly where observations are sparse, inconsistent, or reliant on indirect or secondary sources (WMO, 2018; IPCC, 2022). This can lead to an incomplete or misleading understanding of existing climate risks and vulnerabilities.

For example, infrastructure may fail under more extreme conditions than anticipated, or water supply strategies may prove inadequate in the face of shifting rainfall patterns (Hallegatte et al., 2019). By failing to account for uncertainty, decisions become brittle and vulnerable to surprise, undermining resilience and long-term sustainability. Recognizing and addressing uncertainty is therefore essential to avoid false confidence and to ensure that policies and investments remain effective in a changing and unpredictable climate.

Sources of Uncertainty

Uncertainty in climate risk assessment typically stems from three main sources: data, models, and future scenarios. Data uncertainties arise from limited spatial and temporal coverage, measurement errors, or methodological errors and inconsistencies. Model uncertainties result from structural differences in model formulations and the parameterization of complex processes. Scenario uncertainties reflect the inherent unpredictability of future socio-economic developments, emissions, and policy choices.

The level of uncertainty varies across categories and contexts. Observational data generally carries lower uncertainty compared to model outputs or future projections, while scenario-based information tends to have the highest uncertainty due to its speculative nature. Still, observational data has its own sources of uncertainty related to the methods it has been collected, reported and managed (e.g., use of monitoring instruments, changes in methods, lack of metadata, mismatch between gridded datasets and models that smooth localized extremes, human data entry, gaps in time series, etc.).

Table presents key sources of uncertainty in climate risk assessments. It should be noted that this is a non-exhaustive list.

Table 1: Potential Sources of Uncertainty in Climate Indices

Uncertainty Category	Examples	Level of Uncertainty
Historical Data	Ground-based observations (e.g., weather stations)	Low
	Satellite observations (e.g., temperature, precipitation)	Medium
	Reanalysis and gridded observational datasets (e.g., ERA5, MERRA, CHIRPS, E-OBS, GPCC)	Medium
	Socio-economic data (e.g., population, GDP, land use)	Medium to High
Model	Statistical models (e.g., empirical or regression-based)	Medium
	Hydrological models (e.g., SWAT, VIC)	Medium to High
	Downscaling methods (e.g., statistical or dynamical)	Medium to High
Future Scenario	Global climate models (e.g., CMIP5, CMIP6)	High
	Regional climate modeling and downscaling (e.g., RCMs, Coordinated Regional Climate Downscaling Experiment (CORDEX) experiments)	High
	Emission scenarios (e.g., RCPs under CMIP5, SSPs under CMIP6)	High
	Socio-economic development pathways (e.g., population growth, land use)	High

Uncertainty in Historical Climate Data

Uncertainty in historical data arises primarily from limitations in the observation period, measurement coverage, consistency, and quality. Ground-based observations, while often precise, are geographically uneven—densely available in some regions and sparse or absent in others, especially in developing countries or remote areas. Satellite observations provide broader coverage but may suffer from calibration issues, missing data, shorter time records, and indirect measurement methods. Reanalysis datasets integrate observations with model outputs and can smooth over data gaps, but they depend on the quality of input data and the assumptions of the assimilation models. Socio-economic data, such as historical land use, population, or economic activity, can have classification inconsistencies and may not be updated regularly. These factors contribute to low to medium uncertainty for physical observations and medium to high uncertainty for socio-economic data.

Note: It might be necessary to consider representativeness issues in gridded observational datasets (e.g. CHIRPS, E-OBS). These products are derived from interpolated and/or merged observations (sometimes with satellite inputs) and, unlike reanalyzes, do not rely on full data assimilation within a dynamical model framework. When the spatial density of input observations is coarser than the underlying processes being represented, these datasets may smooth spatial variability and underestimate localized extremes.

Uncertainty in Climate Models

Model-related uncertainty stems from both the structural design of the models and the assumptions embedded within them. Statistical models, which derive relationships from observed data, often perform well within the range of historical conditions but may lack robustness when extrapolated to future, unseen scenarios—contributing to medium uncertainty. Hydrological models, which simulate processes like runoff, streamflow, and soil moisture, depend heavily on input data, parameter calibration, and catchment-specific characteristics (Moges et al., 2021; Renard et al., 2010; WMO, 2025). Their accuracy varies depending on spatial resolution and process representation (Aerts et al., 2022), leading to medium to high uncertainty. Downscaling methods introduce additional complexity: statistical downscaling relies on stable historical relationships that may not hold in a changing climate. In contrast, dynamical downscaling inherits the uncertainties of the parent models (Doblas-Reyes et al., 2021) and introduces additional computational challenges in size and therefore limits how comprehensively uncertainty can be sampled. Because these uncertainties compound along the modelling chain and because the proliferation of downscaled datasets has not narrowed the projected uncertainty range (Doblas-Reyes et al., 2021), this justifies a medium-to-high uncertainty rating.

Note: Model-related uncertainty also arises from the parametrization of complex processes (smaller than the grid) and from sensitivity to initial conditions, which reflects the internal variability inherent to the climate system.

Uncertainty in Future Climate Scenarios

Climate models, both global, as in CMIP, and regional, as in CORDEX, introduce uncertainty through their structural design, their parametrization of processes, their underlying assumptions, their sensitivity to initial conditions, and the internal variability inherent to dynamical models. These sources are best categorized as model uncertainty. Socio-economic pathways (SSPs) and representative concentration pathways (RCPs) represent a fundamentally different type: they describe plausible future developments in emissions, land use, and socio-economic conditions, which in turn determine the external forcing applied to climate models. Both contribute to the spread in future projections, as seen in CMIP6, where a range of emission scenarios combined with a range of model responses produces the spread among ensemble outputs — but their nature differs, and they could benefit from being clearly distinguished.

Scenario uncertainty is inherently high because scenarios depend on assumptions about human behavior, policy decisions, international cooperation, mitigation strategies, technological development, and environmental feedbacks, all of which are context-dependent and difficult to predict. Emission scenarios involve uncertainty related to factors such as energy use, population growth, and future policy, while the Shared Socioeconomic Pathways (SSPs) introduce additional uncertainty around local governance, land-use change, and adaptive capacity. For these reasons, scenario uncertainty is rated as high across all categories.

Minimum Requirements for Uncertainty Consideration

As a minimum standard, uncertainty should always be explicitly acknowledged, even when it cannot be fully quantified. The level of treatment should correspond to the significance of the decision context, the availability of information, and the potential consequences of being wrong.

In lower-stakes or data-limited situations, simple acknowledgment and qualitative discussion may be sufficient. For assessments informing policy, planning, or investment decisions, a more systematic evaluation is needed. This could include sensitivity analysis, use of multiple data sources, or expert judgment. In high-stakes or complex assessments, uncertainty should be formally characterized and incorporated, using approaches such as multi-model or multi-ensemble analysis, scenario sampling, or the development of probabilistic models. Examples of different stake level are in Table .

Table 2: Minimum Treatment of Uncertainty by Sector[1]

Required Level of Detail	Water and Urban	Food Security	Infrastructure	Minimum Standard
Low	Updating monitoring networks; water quality reporting	Seasonal crop choice; trialing farming practices	Scheduling routine maintenance; siting small facilities	Acknowledge sources of uncertainty
Middle	Seasonal reservoir operations; watershed prioritization for intervention	Regional crop insurance design; drought response planning	Design of medium-scale infrastructure (e.g., bridges, local roads)	Qualitative discussion; sensitivity analysis
High	Long-term infrastructure (e.g., dams, irrigation systems); transboundary water allocation; Design of flood defense systems	National food security policy; land use change; planning for climate, resilient supply chains	Major, long-lived infrastructure (e.g., ports, power plants, airports)	Formal modeling (e.g., scenario ensembles, probabilistic sampling)

[1] Where sensitivity analysis or formal modelling is required, a multi-model ensemble is encouraged where feasible.

Practical Guidelines to Consider Uncertainty in the Project

This guideline encourages a practical approach to consider uncertainty by focusing on three key aspects:

- Anticipating uncertainty
- Quantifying uncertainty
- Communicating uncertainty to decision-makers

Anticipating Uncertainty

Anticipating uncertainty means embedding uncertainty considerations from the outset of a climate risk assessment — through the RFP/TOR and inception phases, and carried into the outputs. This involves systematically identifying potential sources of uncertainty, such as variability in input datasets, the choice of climate models, downscaling methods, emissions, and socio-economic scenarios (e.g., SSPs), and assumptions in impact models. For example, uncertainty in regional rainfall projections in East Africa is often tied to disagreement among models over seasonal dynamics. Anticipating uncertainty requires a structured recognition of which parameters are uncertain (due to lack of knowledge), so that the Climate Risk Assessment (CRA) methodology is designed to accommodate or minimize them. Anticipating the likely potential uncertainties will be guided mainly by expert knowledge.

The variability in input datasets also has a strong, anticipated regional component. It is most pronounced in regions lacking systematic observing systems, and in those where conflict has disrupted data collection.

Minimum Requirement: Likely potential uncertainty must be openly acknowledged, systematically assessed, and meaningfully considered throughout the CRA process—from framing to communication.

Quantifying Uncertainty

Quantifying uncertainty involves producing a range of plausible outcomes rather than a single deterministic result. Quantifying uncertainty is commonly achieved using multi-model ensembles (e.g., CMIP6, CORDEX, or bias-corrected, statistically downscaled climate projections), where inter-model spread is used to define a confidence interval or probability distribution for future climate conditions. Uncertainty quantification also includes sensitivity analysis, which identifies which input parameters have the greatest influence on model output—helping prioritize data collection or policy attention. The goal is to move from vague acknowledgment to numeric measures of uncertainty that can be robustly compared and acted upon.

Minimum Requirements: The anticipated uncertainties should be quantified (where possible) using at least multiple climate models (ensemble approaches) to bracket the uncertainty.

Communicating Uncertainty to Decision-Makers

Even when uncertainty is well anticipated and quantified, it is crucial to translate its scientific complexity into calibrated, plain-language, and actionable statements for decision-makers. Visualization plays a critical role, as ensemble spread maps can make uncertainty tangible. Narrative explanation should accompany graphics to clarify what is known, unknown, and assumed. It's also critical to communicate the robustness of findings: which decisions are "no-regret" under all futures vs. those that are sensitive to assumptions. This step ensures that uncertainty enhances rather than undermines the credibility and usefulness of the climate risk assessment.

Minimum Requirements: The final output report of all climate risk assessments should include an uncertainty statement section that incorporates visualizations such as ensemble spread maps and a clear narrative explanation.

Applying Uncertainty Across the Project Cycle

Project sponsors should consider uncertainty when framing TORs, evaluating proposals, and during project implementation:

i. **RFP / TOR stage**

   a. Require bidders to detail how they will anticipate, quantify, and communicate uncertainty.

   b. Insist on ensemble approaches for high-stakes projects and encourage bidders to propose appropriate sensitivity analyses.

   c. Clearly communicating the minimum standard expected would also benefit bidders.

ii. **Proposal review**

   a. Check whether proposed methods use adequate ensembles, cover relevant scenarios, and include effective communication strategies (e.g., clear visualizations).

   b. Reject proposals that rely on single models without justification.

iii. **Inception report**

   a. Confirm that the consultant has gathered the ensemble datasets and defined the sensitivity analyses. It is important to request early presentation of the ensemble spread for key indices to avoid surprises later.

iv. **Final output review**

   a. Verify that the report contains an uncertainty section with both quantitative ranges and qualitative discussion.

   b. Ensure visualizations (ensemble maps, distribution plots) are clear and that recommendations account for uncertainty rather than presenting a single deterministic outcome.

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