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## Statistical representation of uncertainty in complex systems: Theory, computation, and applications

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### Abstract

Complex systems are inevitably influenced by uncertainty arising from random variation, partial information, nonlinear interactions, and multi-level dependencies. Proper statistical treatment of this uncertainty is essential for producing dependable models, improving predictive performance, and guiding rational decision-making. This paper examines approaches for representing uncertainty by linking theoretical principles with computational practices and applied use cases. Core statistical foundations, such as probabilistic reasoning, stochastic modelling, and Bayesian frameworks, are discussed together with non-probabilistic methods, including fuzzy and interval-based representations, where data or assumptions are limited. Emphasis is placed on techniques for uncertainty propagation, sensitivity evaluation, and model adjustment, which collectively help assess the reliability of system outputs under uncertain conditions. Recent advances in computational strategies, such as simulation-based methods, reduced-complexity models, and machine-learning-assisted analysis, are reviewed for their ability to manage high dimensionality and computational demands. Examples from environmental systems, engineering applications, financial modelling, and biological processes illustrate the practical value of incorporating uncertainty into system analysis. Ongoing challenges related to data integration, computational efficiency, and model scalability are also addressed. The study concludes that explicit representation and systematic analysis of uncertainty are central to advancing the understanding and practical management of complex systems in real-world settings.

**Keywords:** Uncertainty modelling, Complex systems analysis, Statistical methods, computational techniques, Predictive reliability

### Introduction

Complex systems exhibit intricate behaviour arising from nonlinear interactions, feedback processes, and coupling across multiple spatial and temporal scales. These characteristics make exact prediction difficult and often render deterministic modelling approaches inadequate. Uncertainty in such systems originates from diverse sources, including stochastic variability, incomplete observations, simplifications in model structure, and limited understanding of underlying processes. When uncertainty is ignored or inadequately treated, model outputs may appear overly precise and lead to incorrect conclusions. Statistical representation of uncertainty offers a structured approach to formally describe, analyse, and interpret variability and incomplete knowledge within complex systems, thereby improving the credibility of model-based inference (Ghanem *et al.*, 1991) <sup>[4]</sup>.

The mathematical treatment of uncertainty is fundamentally grounded in probability theory and statistical inference. Within this framework, uncertain system parameters and states are represented as random variables or stochastic processes, allowing both inherent randomness and knowledge-related uncertainty to be quantified. Bayesian methods have gained particular prominence because they provide a consistent mechanism for incorporating prior knowledge and observational data into uncertainty assessment. By updating probability distributions in light of new information, Bayesian inference supports parameter estimation, model calibration, and predictive analysis in a transparent and logically coherent manner (O'Hagan *et al.*, 2006) <sup>[7]</sup>. These properties are especially valuable in complex systems where direct experimentation is

limited, or system behaviour cannot be fully observed.

Nevertheless, probabilistic descriptions alone may be insufficient in cases where data availability is limited or where defining precise probability distributions is not feasible. To address such situations, alternative uncertainty representations, including interval methods, fuzzy sets, and evidence-based frameworks, have been proposed. These approaches emphasise bounded uncertainty and partial belief, offering flexibility in modelling epistemic uncertainty when probabilistic assumptions are weak or unjustified (Sudret *et al.*, 2008) <sup>[12]</sup>. In many practical applications, hybrid uncertainty frameworks that integrate probabilistic and non-probabilistic elements are adopted to better reflect the heterogeneous nature of uncertainty present in complex systems.

A key objective of uncertainty analysis is to determine how uncertainties in model inputs influence system outputs. Uncertainty propagation techniques are designed to trace the transmission of input variability through mathematical or computational models, enabling quantification of output uncertainty. Monte Carlo simulation remains a widely used reference approach due to its general applicability and conceptual simplicity. However, its computational cost increases rapidly with model complexity and dimensionality, limiting its practicality for large-scale systems (Smith *et al.*, 2014) <sup>[11]</sup>. As a result, more efficient techniques such as polynomial chaos expansion have been developed to represent stochastic system responses using orthogonal basis functions, significantly reducing computational demands while maintaining accuracy (Xiu *et al.*, 2002) <sup>[13]</sup>.

Sensitivity analysis complements uncertainty propagation by identifying which uncertain inputs have the greatest impact on model outputs. Global sensitivity analysis methods, particularly those based on variance decomposition, quantify the contribution of individual parameters and their interactions across the entire input space. These methods are essential for complex systems, where nonlinear relationships often obscure intuitive understanding of dominant uncertainty sources (Sudret *et al.*, 2008) <sup>[12]</sup>. Insights gained from sensitivity analysis support model simplification, guide experimental design, and help prioritize data collection efforts without compromising predictive reliability.

Advancements in computational resources and data-driven methodologies have further expanded the scope of uncertainty representation in complex systems. Surrogate modelling approaches, such as Gaussian process regression and reduced-order models, enable efficient uncertainty analysis for computationally intensive simulations. At the same time, machine learning techniques are increasingly integrated into uncertainty quantification workflows to exploit large and heterogeneous datasets (Smith *et al.*, 2014) <sup>[11]</sup>. While these approaches enhance predictive capability, they also introduce additional uncertainties related to model structure, training data quality, and generalization beyond observed conditions, reinforcing the need for rigorous statistical treatment.

Across application domains, including climate modelling, engineering systems, finance, and biological networks, explicit representation of uncertainty has become essential for reliable decision-making. In climate studies, uncertainty analysis supports scenario evaluation and risk-based policy development. In engineering, it underpins reliability assessment and safety-oriented design. In all cases, transparent and systematic treatment of uncertainty improves model interpretability, enhances robustness, and strengthens confidence in system-level predictions (Ghanem *et al.*, 1991) <sup>[4]</sup>. Despite remaining

challenges related to scalability and data integration, statistical uncertainty representation is now recognized as a foundational component of complex system analysis.

## 1. Conceptual Foundations of Statistical Uncertainty Representation

The statistical treatment of uncertainty in complex systems relies on well-established theoretical constructs that define how uncertainty is identified, measured, and interpreted within mathematical models. Probability theory forms the central foundation of these constructs, providing a consistent framework in which uncertain system states and parameters can be expressed as random variables governed by probability distributions. This formulation enables uncertainty to be systematically analyzed and propagated through complex, nonlinear models, supporting inference and prediction under uncertain conditions (Jaynes *et al.*, 2003) <sup>[5]</sup>. In systems characterized by strong interactions and emergent behaviour, probabilistic representations offer the flexibility required to capture variability while maintaining logical consistency.

A fundamental theoretical issue in uncertainty modelling is the distinction between aleatory and epistemic uncertainty. Aleatory uncertainty reflects intrinsic randomness in system behaviour and is generally irreducible, such as fluctuations driven by environmental variability. Epistemic uncertainty, by contrast, arises from incomplete knowledge, limited data, or imperfect model structure and may be reduced through improved information or refined modelling. Although both forms can be represented mathematically within probabilistic frameworks, their interpretation and implications for decision-making differ significantly (Der Kiureghian *et al.*, 2009). Clear separation of these uncertainty types is therefore essential for meaningful risk assessment and model evaluation in complex systems.

Bayesian theory provides a particularly powerful approach for representing epistemic uncertainty by interpreting probability as a degree of belief conditioned on available evidence. Within this framework, uncertainty is updated dynamically as new data are incorporated, allowing prior assumptions to be revised in a mathematically coherent manner. Bayesian methods are especially advantageous in complex systems where direct measurement is limited, experimental replication is costly, or system behavior cannot be fully observed. By explicitly accounting for parameter uncertainty, observational noise, and model discrepancy, Bayesian inference enhances the credibility and transparency of predictive analyses (Gelman *et al.*, 2014) <sup>[3]</sup>. Despite their strengths, probabilistic frameworks may not always be suitable, particularly when uncertainty cannot be characterized by well-defined probability distributions. In such cases, non-probabilistic approaches offer alternative theoretical representations. Interval-based methods describe uncertainty using bounded ranges without imposing distributional assumptions, making them appropriate for poorly constrained parameters. Fuzzy set theory extends this idea by allowing partial membership, thereby capturing vagueness and imprecision commonly encountered in expert knowledge and qualitative assessments (Zadeh *et al.*, 1978) <sup>[14]</sup>. These approaches are especially useful during early stages of model development or in decision-support contexts with limited quantitative data.

Evidence theory, often referred to as Dempster–Shafer theory, provides a more general framework for uncertainty representation by distinguishing between belief, plausibility, and ignorance. Unlike classical probability, this approach allows uncertainty to be distributed across sets of possibilities,

facilitating the combination of information from multiple, potentially conflicting sources. Such flexibility is valuable in complex systems where data originate from heterogeneous sources and expert judgment plays a significant role (Der Kiureghian *et al.*, 2009). However, challenges related to computational scalability and interpretability have restricted its application in large-scale models.

In practical applications, complex systems rarely exhibit uncertainty that can be adequately captured by a single theoretical framework. Consequently, integrated or hybrid representations that combine probabilistic and non-probabilistic approaches are increasingly adopted. These hybrid frameworks enable different uncertainty sources to be modelled using representations best aligned with their underlying characteristics, improving realism and analytical robustness. Such theoretical integration underpins contemporary uncertainty quantification methodologies and supports more reliable analysis of complex, uncertain systems (Jaynes *et al.*, 2003) <sup>[5]</sup>.

## 2. Computational Approaches for Uncertainty Quantification in Complex Systems

The practical implementation of uncertainty representation in complex systems relies heavily on computational methods capable of handling nonlinear models, high-dimensional parameter spaces, and expensive simulations. Computational uncertainty quantification (UQ) provides the tools required to evaluate how uncertainty in model inputs, parameters, and structure affects system-level predictions. These approaches translate theoretical uncertainty frameworks into actionable numerical procedures, enabling uncertainty-aware simulation, prediction, and decision support across scientific and engineering domains (Smith *et al.*, 2014) <sup>[11]</sup>.

Sampling-based methods form the foundation of many computational UQ techniques. Monte Carlo simulation remains the most widely used approach due to its conceptual simplicity and broad applicability. By repeatedly sampling from input distributions and evaluating the corresponding model outputs, Monte Carlo methods provide statistically consistent estimates of output uncertainty. However, their convergence rate is slow, and computational demands increase substantially for high-dimensional systems or models with expensive evaluations, limiting their feasibility in large-scale complex systems (Rubinstein *et al.*, 2016) <sup>[8]</sup>.

To address these limitations, variance-reduction and advanced sampling strategies have been developed. Techniques such as importance sampling, Latin hypercube sampling, and quasi-Monte Carlo methods improve computational efficiency by strategically exploring the input space. These methods reduce the number of required simulations while maintaining accuracy, making them suitable for uncertainty analysis in engineering design, risk assessment, and environmental modelling applications (Rubinstein *et al.*, 2016) <sup>[8]</sup>. Despite these improvements, sampling-based approaches may still struggle with strongly nonlinear or multi-scale systems.

Spectral and surrogate-based methods provide an alternative computational paradigm for uncertainty quantification. Polynomial chaos expansion (PCE) represents uncertain model outputs as series expansions of orthogonal polynomials defined over random inputs. This approach enables efficient computation of statistical moments and sensitivity indices with significantly reduced computational cost compared to brute-force sampling (Xiu *et al.*, 2002) <sup>[13]</sup>. PCE has been successfully applied to a wide range of complex systems, particularly when input uncertainties can be reasonably approximated using known

probability distributions.

Surrogate modelling techniques further enhance computational tractability by replacing expensive numerical models with fast-to-evaluate approximations. Methods such as Gaussian process regression, response surface models, and reduced-order models approximate system behaviour while preserving uncertainty information. These surrogates allow extensive uncertainty analysis, sensitivity studies, and optimization to be performed with manageable computational resources (Forrester *et al.*, 2008) <sup>[2]</sup>. However, surrogate accuracy depends strongly on training data quality and coverage of the input space, necessitating careful validation.

Recent developments in data-driven modelling have introduced machine learning as a complementary tool for uncertainty quantification. When integrated with statistical frameworks, machine learning methods can capture complex nonlinear relationships and extract information from large, heterogeneous datasets. Techniques such as Bayesian neural networks and probabilistic graphical models explicitly represent predictive uncertainty, addressing limitations of deterministic learning algorithms (Smith *et al.*, 2014) <sup>[11]</sup>. While promising, these approaches require careful treatment to avoid overconfidence and ensure interpretability.

Overall, computational approaches play a central role in translating uncertainty theory into practical analysis tools for complex systems. No single method is universally optimal; instead, method selection depends on system complexity, data availability, computational cost, and the nature of uncertainty. Integrating sampling-based, spectral, surrogate, and data-driven techniques provides a flexible and robust computational foundation for modern uncertainty quantification (Forrester *et al.*, 2008) <sup>[2]</sup>.

## 3. Uncertainty Propagation and Sensitivity Analysis in Complex Systems

Uncertainty propagation is a central component of uncertainty quantification, concerned with evaluating how uncertainty in model inputs, parameters, and initial conditions influences system outputs. In complex systems, nonlinear interactions and feedback mechanisms often amplify or dampen uncertainty in non-intuitive ways, making direct analytical solutions impractical. Propagation methods provide a systematic means of translating input uncertainty into output variability, allowing predictions to be interpreted probabilistically rather than deterministically (Smith *et al.*, 2014) <sup>[11]</sup>. This capability is essential for assessing model reliability and for supporting risk-informed decision-making in uncertain environments.

Classical uncertainty propagation relies heavily on sampling-based approaches, particularly Monte Carlo simulation. By repeatedly sampling uncertain inputs and evaluating the corresponding model responses, Monte Carlo methods approximate the probability distribution of system outputs. Although asymptotically exact, these methods require a large number of model evaluations to achieve stable estimates, especially in high-dimensional parameter spaces typical of complex systems (Rubinstein *et al.*, 2016) <sup>[8]</sup>. Consequently, computational efficiency becomes a limiting factor, motivating the development of alternative propagation techniques that balance accuracy and cost.

Spectral methods, such as polynomial chaos expansion, offer an efficient framework for uncertainty propagation by representing stochastic system responses as series expansions of orthogonal basis functions. These methods enable direct computation of statistical moments and probability distributions without

extensive sampling, significantly reducing computational effort. Polynomial chaos techniques are particularly effective for systems with smooth responses and moderately sized uncertainty spaces (Xiu *et al.*, 2002) <sup>[13]</sup>. Their integration with numerical solvers has made them a powerful tool for propagating uncertainty in engineering and physical systems.

Sensitivity analysis complements uncertainty propagation by identifying the relative importance of uncertain inputs in driving output variability. Global sensitivity analysis methods quantify the contribution of each input parameter and its interactions over the entire uncertainty space. Variance-based techniques, such as Sobol's indices, are widely used because they provide an intuitive decomposition of output variance and remain valid for nonlinear and non-additive models (Saltelli *et al.*, 2010) <sup>[10]</sup>. In complex systems, sensitivity analysis helps distinguish dominant uncertainty sources from negligible ones, improving model transparency and guiding data acquisition strategies.

The combined use of uncertainty propagation and sensitivity analysis is critical for model refinement and validation. By revealing how uncertainty flows through a system and which parameters exert the greatest influence, these methods support model simplification without significant loss of predictive capability. They also enable targeted uncertainty reduction by prioritizing measurement and calibration efforts where they are most effective (Sudret *et al.*, 2008) <sup>[12]</sup>. Such integrated analysis is essential for managing complexity and improving confidence in model-based predictions.

Uncertainty propagation and sensitivity analysis form a complementary pair of analytical tools that transform abstract uncertainty representations into actionable insights. Their application enables robust interpretation of model outputs, supports risk assessment, and enhances the credibility of predictions derived from complex systems. As computational capabilities continue to advance, these methods will remain foundational to uncertainty-aware modelling and decision support (Smith *et al.*, 2014) <sup>[11]</sup>.

#### 4. Model Calibration and Validation under Uncertainty

Model calibration and validation are critical steps in uncertainty-aware modelling of complex systems, ensuring that mathematical and computational models provide credible representations of real-world behaviour. Calibration involves adjusting uncertain model parameters so that model outputs align with observed data, while validation assesses the model's ability to reproduce system behaviour beyond the calibration dataset. In complex systems, these processes are inherently uncertain due to measurement error, limited observations, and structural imperfections in the model itself. Statistical approaches explicitly account for these uncertainties, allowing calibration and validation to be framed as probabilistic inference problems rather than deterministic fitting exercises (Kennedy *et al.*, 2001) <sup>[6]</sup>.

Bayesian calibration has become a dominant framework for uncertainty-aware parameter estimation in complex systems. This approach treats model parameters as random variables and updates their probability distributions using observational data through Bayes' theorem. A key strength of Bayesian calibration is its ability to incorporate multiple sources of uncertainty simultaneously, including parameter uncertainty, observational noise, and model discrepancy. By explicitly representing discrepancy between the model and reality, Bayesian methods avoid overconfidence in calibrated models and provide more realistic predictive uncertainty estimates (Kennedy *et al.*, 2001) <sup>[6]</sup>. These features are particularly important in systems where

simplified models cannot fully capture underlying physical or biological processes.

Model validation under uncertainty extends beyond traditional goodness-of-fit measures by evaluating whether observed data are statistically consistent with model predictions. Rather than asking whether a model is "correct," uncertainty-aware validation assesses whether discrepancies between predictions and observations can be explained by quantified uncertainties. Posterior predictive checks and probability-based validation metrics are commonly used to evaluate model adequacy in this context (Gelman *et al.*, 2014) <sup>[3]</sup>. Such approaches are well-suited to complex systems, where multiple plausible models may coexist, and absolute validation is unattainable.

The interaction between calibration and validation is especially challenging in high-dimensional and nonlinear systems. Overfitting can occur when models are excessively tuned to limited data, leading to poor predictive performance under new conditions. Statistical regularization techniques and hierarchical modelling structures help mitigate this risk by constraining parameter estimates and sharing information across system components (Gelman *et al.*, 2014) <sup>[3]</sup>. These methods improve generalization and enhance the robustness of calibrated models under uncertainty.

Computational demands pose a significant challenge for calibration and validation in complex systems, particularly when models are expensive to evaluate. Surrogate-based calibration strategies address this issue by replacing high-fidelity models with computationally efficient approximations during inference. Gaussian process emulators are widely used for this purpose, as they provide both predictive estimates and associated uncertainty, which can be propagated through the calibration process (Sacks *et al.*, 1989) <sup>[9]</sup>. Such approaches enable practical uncertainty-aware calibration for systems that would otherwise be computationally intractable. They form a crucial link between theoretical uncertainty representation and practical decision-making, ensuring that model-based conclusions are both scientifically defensible and operationally meaningful (Kennedy *et al.*, 2001) <sup>[6]</sup>.

#### 5. Decision-Making and Risk Assessment under Uncertainty in Complex Systems

Decision-making in complex systems is inherently affected by uncertainty arising from incomplete knowledge, stochastic variability, and model limitations. Traditional deterministic decision frameworks often fail to account for the range of possible system behaviors, leading to decisions that are fragile under changing conditions. Uncertainty-aware decision-making explicitly incorporates probabilistic or bounded uncertainty representations into the evaluation of alternative actions, enabling decisions to be assessed in terms of risk, robustness, and resilience rather than single-point predictions (Ben-Haim *et al.*, 2010) <sup>[16]</sup>. This shift is particularly important in complex systems where small perturbations can trigger disproportionate responses.

Risk assessment provides a formal structure for linking uncertainty representation with decision outcomes. In statistical risk analysis, uncertainty in system inputs and processes is translated into probability distributions of adverse outcomes, allowing risk to be quantified as a function of both likelihood and consequence. Such approaches support rational prioritization of mitigation strategies and resource allocation in complex domains such as infrastructure systems, environmental management, and technological safety (Aven *et al.*, 2014) <sup>[15]</sup>. By integrating uncertainty directly into risk metrics, decision-

makers gain a clearer understanding of potential trade-offs and vulnerabilities.

Robust decision-making frameworks have been developed to address situations characterized by deep uncertainty, where probability distributions are poorly known or contested. These approaches focus on identifying decisions that perform satisfactorily across a wide range of plausible futures rather than optimizing performance for a single expected scenario. Robust optimization and info-gap decision theory are prominent examples that explicitly acknowledge severe uncertainty and prioritize stability and adaptability (Ben-Haim *et al.*, 2010) <sup>[16]</sup>. Such frameworks are particularly relevant for long-term planning in complex systems subject to evolving conditions and incomplete information.

In probabilistic decision analysis, expected utility theory provides a foundational framework for selecting actions under uncertainty by weighting outcomes according to their probabilities and associated utilities. While theoretically rigorous, expected utility approaches may be sensitive to assumptions about probability distributions and stakeholder preferences. As a result, multi-criteria decision analysis methods are often combined with uncertainty quantification to incorporate diverse objectives, conflicting values, and uncertainty in preference structures (Keeney *et al.*, 1993) <sup>[17]</sup>. This integration enhances transparency and supports participatory decision-making in complex socio-technical systems.

The integration of uncertainty quantification with decision-making frameworks requires careful communication of uncertainty to stakeholders and policymakers. Probabilistic forecasts, confidence intervals, and risk metrics must be presented in a manner that supports understanding without oversimplification. Misinterpretation of uncertainty can undermine trust or lead to inappropriate decisions. Therefore, uncertainty-aware decision-making emphasises not only technical rigour but also clarity, transparency, and contextual interpretation of uncertainty information (Aven *et al.*, 2014) <sup>[15]</sup>. Incorporating uncertainty into decision-making and risk assessment transforms uncertainty from a source of ambiguity into a structured basis for informed action. By explicitly acknowledging uncertainty and its implications, decision-makers can evaluate risks more realistically, design robust strategies, and enhance system resilience. In complex systems, such approaches are essential for navigating uncertainty in a systematic and defensible manner (Ben-Haim *et al.*, 2010) <sup>[16]</sup>.

## 6. Applications of Statistical Uncertainty Representation in Complex Systems

Statistical representation of uncertainty has become indispensable in environmental and climate-related complex systems, where uncertainty arises from natural variability, model structure, and future socio-economic pathways. In climate modelling, uncertainty quantification supports ensemble-based projections, enabling probabilistic assessment of temperature trends, precipitation extremes, and associated impacts. Rather than producing single deterministic forecasts, uncertainty-aware models generate ranges of plausible outcomes that inform adaptation and mitigation strategies under uncertain future conditions (IPCC *et al.*, 2021). This probabilistic framing is essential for policy-relevant assessments, where decisions must remain robust across multiple scenarios.

In engineering systems, uncertainty representation underpins

reliability analysis and safety-critical design. Structural and mechanical systems are subject to uncertainty in material properties, loading conditions, and degradation processes over time. Probabilistic reliability methods translate these uncertainties into failure probabilities and risk measures, supporting reliability-based design optimization and lifecycle management (Melchers *et al.*, 2018) <sup>[22]</sup>. By explicitly quantifying uncertainty, engineers can balance safety, performance, and cost while avoiding overly conservative or unsafe design choices in complex infrastructures.

Biological and ecological systems present additional challenges due to high levels of variability, nonlinear dynamics, and limited observability. In ecological modelling, uncertainty quantification enables assessment of population dynamics, species interactions, and ecosystem responses to environmental change. Statistical approaches help distinguish signal from noise in ecological data and support probabilistic predictions of system resilience and tipping points (Clark *et al.*, 2010) <sup>[18]</sup>. Such analyses are crucial for conservation planning and sustainable resource management under uncertain environmental conditions.

In financial and economic systems, uncertainty representation plays a central role in risk modelling and decision support. Market dynamics are influenced by stochastic fluctuations, incomplete information, and adaptive human behaviour, making prediction inherently uncertain. Probabilistic risk models, stress testing, and scenario analysis incorporate uncertainty to evaluate portfolio risk, systemic vulnerability, and potential extreme events (Cont *et al.*, 2013) <sup>[19]</sup>. These approaches enhance financial stability by enabling institutions and regulators to anticipate and manage uncertainty-driven risks.

Across technological and socio-technical systems, uncertainty-aware modelling supports decision-making in the presence of interacting human and technical components. Examples include energy systems planning, transportation networks, and public health systems, where uncertainty arises from demand variability, behavioral responses, and policy interventions. Statistical uncertainty representation enables evaluation of alternative strategies under uncertain conditions, improving system resilience and adaptability (Helton *et al.*, 2012) <sup>[20]</sup>. These applications demonstrate the broad relevance of Applications across diverse domains highlight the transformative role of statistical uncertainty representation in complex systems analysis. By shifting focus from point estimates to distributions and credible ranges, uncertainty-aware approaches improve interpretability, support robust decisions, and enhance trust in model-based insights. As complex systems increasingly inform high-stakes decisions, systematic treatment of uncertainty remains a foundational requirement for responsible modelling practice (Clark *et al.*, 2010) <sup>[18]</sup>.

## 7. Comparative Overview of Uncertainty Representation Methods in Complex Systems

Different statistical approaches to uncertainty representation vary in their theoretical assumptions, computational demands, and suitability for specific types of complex systems. Selecting an appropriate method requires careful consideration of uncertainty sources, data availability, model structure, and decision objectives. Table 1 provides a comparative synthesis of widely used uncertainty representation frameworks, highlighting their core characteristics, advantages, limitations, and typical application domains (Walker *et al.*, 2003; Oberkamp *et al.*, 2010) <sup>[24, 23]</sup>.

**Table 1:** Comparative summary of statistical uncertainty representation approaches in complex systems

| Uncertainty Representation Method    | Primary Uncertainty Type Addressed | Key Strengths                                                                                       | Major Limitations                                                         | Typical Application Domains                                 |
|--------------------------------------|------------------------------------|-----------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------|
| Probabilistic (Classical statistics) | Aleatory and epistemic             | Mathematically rigorous; well-established inference tools; supports uncertainty propagation         | Requires well-defined probability distributions; sensitive to assumptions | Engineering systems, physical sciences, and finance         |
| Bayesian frameworks                  | Primarily epistemic                | Integrates prior knowledge with data; explicit uncertainty updating; accounts for model discrepancy | Computationally intensive; prior specification may be subjective          | Climate modelling, biological systems, calibration problems |
| Interval analysis                    | Epistemic                          | No distributional assumptions; simple interpretation; suitable for sparse data                      | Overly conservative results; limited probabilistic interpretation         | Early-stage modelling, safety analysis                      |
| Fuzzy set theory                     | Epistemic (vagueness)              | Captures linguistic and qualitative uncertainty; flexible representation                            | Lacks probabilistic meaning; limited predictive capability                | Expert systems, decision support                            |
| Evidence (Dempster–Shafer) theory    | Epistemic and ignorance            | Combines multiple information sources; represents ignorance explicitly                              | Computational complexity; difficult interpretation                        | Multi-source decision analysis, risk assessment             |
| Hybrid frameworks                    | Mixed                              | Flexible handling of multiple uncertainty types; improved realism                                   | Increased modeling complexity; integration challenges                     | Large-scale socio-technical systems                         |

Sources: Walker *et al.* (2003) <sup>[24]</sup>; Oberkampf *et al.* (2010) <sup>[23]</sup>.

The comparison highlights that no single uncertainty representation framework is universally optimal. Probabilistic and Bayesian approaches dominate applications where sufficient data and computational resources are available, while non-probabilistic methods remain valuable in data-poor or expert-driven contexts. Hybrid approaches increasingly emerge as practical solutions for complex systems characterized by multiple, interacting sources of uncertainty. Such comparative understanding is essential for designing uncertainty-aware models that are both scientifically defensible and operationally relevant (Walker *et al.*, 2003) <sup>[24]</sup>.

## 8. Integrated Statistical Uncertainty Framework



## 9. Conclusion

Statistical representation of uncertainty is essential for reliable analysis of complex systems characterised by nonlinearity, variability, and incomplete knowledge. By integrating appropriate theoretical frameworks with efficient computational methods, uncertainty-aware modelling improves prediction credibility, model transparency, and decision robustness. Probabilistic, non-probabilistic, and hybrid approaches each play

important roles depending on data availability and system complexity. Explicit treatment of uncertainty enables risk-informed and resilient decision-making while avoiding overconfident conclusions. Overall, embedding uncertainty at every stage of modelling is a fundamental requirement for responsible analysis and effective management of complex systems.

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