The Uncertainty Landscape Beyond Variance

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ENVIRONMENTAL DATA SCIENCE

POSITION PAPER

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Abstract

Modern science has become good at measuring uncertainty. Across statistics, artificial intelligence, economics, Earth observation, environmental modelling and decision science, researchers increasingly invoke uncertainty when interpreting evidence, evaluating predictions and supporting decisions. These disciplines often use the word uncertainty to describe conceptually different scientific situations. Different forms of uncertainty represent different states of knowledge and require different scientific responses. As uncertainty concepts move across disciplinary boundaries, their original meaning may be lost in translation, creating the misleading impression that they describe different amounts of the same uncertainty. Some forms of uncertainty arise from stochastic variability. Others reflect incomplete knowledge that can be reduced through learning. Still others reveal limitations of current models or even existing scientific concepts. Treating these different states of knowledge as merely different amounts of uncertainty can obscure both the nature of scientific evidence and the forms of inference needed for understanding and informed decision-making. We propose an uncertainty landscape whose regions are defined by what is known, what can be characterised probabilistically and what can be learned from additional evidence. Our aim is to reinterpret an existing five-level taxonomy as a cross-disciplinary landscape that links different states of knowledge to the scientific responses they require. Seen this way, uncertainty becomes a guide to where new scientific understanding is needed, rather than merely a limitation to be reduced.

Impact Statement

Scientific disciplines have developed different concepts, terminology, and methods for addressing uncertainty. As research becomes increasingly interdisciplinary and combines statistical inference, artificial intelligence, remote sensing, modelling, and decision science, these traditions meet – but their uncertainty measures do not always carry the same meaning. The uncertainty landscape offers a shared conceptual basis for discussing what different measures represent, what can legitimately be inferred from available evidence, and where the limits of current knowledge lie. We hope this Position Paper will open a broader discussion across environmental data science about whether existing approaches adequately capture the uncertainties confronting contemporary research. Such dialogue can support more coherent uncertainty assessment, more transparent communication of scientific limitations, and more responsible use of evidence in policy and decision-making. It may also help identify situations in which further data or improved methods can reduce uncertainty, as well as those in which new concepts and scientific understanding are required. Ultimately, the paper seeks to make uncertainty a subject of interdisciplinary inquiry instead of being merely a quantity reported alongside results.

1. Introduction

Uncertainty is not a uniform scientific condition that can be treated by a single quantity. Its forms differ in nature, not merely in magnitude. What can be known, quantified, learned from additional evidence, or represented by existing models depends fundamentally on the form of uncertainty involved. Let us use forest monitoring as an introductory example, since it spans a broad spectrum of uncertainty. Over more than three centuries, forest monitoring has evolved from timber inventories into an integrated environmental information system (Schmithüsen, 2013). Early forest inventories relied on compartment-based descriptions of relatively homogeneous stands. During the twentieth century, these were gradually complemented and, in Nordic and many other countries, replaced by probability-based sample surveys following advances in statistical sampling theory (Breidenbach et al., 2020). The development of space-based Earth observation (EO) further transformed forest monitoring. Multispectral satellite imagery extended the spatial coverage of field measurements (Wulder et al., 2012; Hansen et al., 2016), while the introduction of airborne laser scanning and the area-based approach (Næsset, 2002; Nelson, 2013) enabled accurate estimation of forest attributes over large areas. At the same time, advances in EO created growing expectations for timely, spatially explicit information on forest state and change, ultimately supporting near-real-time monitoring of forest resources and the wider environment (Wulder et al., 2012; Hansen et al., 2013; Pettorelli et al., 2014; Hansen et al., 2016). This expectation also accelerated the adoption of artificial intelligence (AI) methods for prediction and analysis (Reichstein et al., 2019) and led to the increasing integration of decision-support models into operational monitoring systems. And thus, originally developed to estimate timber resources for forest planning, modern forest monitoring now integrates probability sampling of field observations, remote sensing, AI, ecological modelling, climate projections, and decision-support systems within the same analytical workflows to provide information for stakeholders ranging from individual forest owners to international organisations such as FAO (Tomppo et al., 2010). Rather than reducing uncertainty altogether, each scientific and technological advance revealed new forms of uncertainty and shifted attention toward different sources of uncertainty requiring new methods of inference. Modern forest monitoring therefore brings together uncertainty concepts from statistics, EO, AI, ecology, economics and decision science that evolved largely independently. Their differences are not merely terminological: they often represent different states of scientific knowledge. Forest monitoring thus serves as an important application area and as a useful laboratory for exploring how different scientific traditions conceptualize uncertainty and how these concepts may be interpreted within a common framework.

Nevertheless, these challenges extend far beyond forest monitoring and are becoming increasingly common across modern science (Reichstein et al., 2019). Transitions have occurred across many areas of sustainability research, where increasingly integrated analytical workflows combine methods from multiple scientific disciplines (Clark & Dickson, 2003; Clark et al., 2016). As these disciplines developed largely independently, they also developed distinct conceptualisations of uncertainty. Economists have long distinguished risk from uncertainty following the seminal work of Knight (1921). Statisticians separate sampling uncertainty from model-related uncertainty (Särndal, 1978; Gregoire, 1998; Fattorini, 2012). In AI, discussions often focus on aleatoric and epistemic uncertainty (Hüllermeier & Waegeman, 2021; Haynes et al., 2023), while decision scientists emphasize deep uncertainty and robustness (Walker et al., 2003). These concepts emerged within different scientific traditions and use different terminology, but their most important distinction is the state of scientific knowledge they represent. Recognising these differences provides the basis for interpreting diverse uncertainty concepts within a common uncertainty landscape.

We argue that many commonly used uncertainty concepts occupy different regions of the same uncertainty landscape. Although several frameworks have been proposed to describe uncertainty (Knight, 1921; Cochran, 1977; Cassel et al., 1977; Särndal, 1978; Gregoire, 1998; Walker et al., 2003; Särndal et al., 1992; Lo & Mueller, 2010; Stirling, 2010; Chambers & Clark, 2012; Kendall & Gal, 2017), they have largely developed within disciplinary boundaries. Across disciplines, these concepts should be interpreted as different states of knowledge rather than different degrees of uncertainty. We therefore adapt Lo and Mueller's (Lo & Mueller, 2010) five-level framework, developed for finance, as a cross-disciplinary landscape. Our contribution is this conceptual reinterpretation: the uncertainty landscape links states of knowledge to the modes of scientific response appropriate for advancing understanding.

2. The Uncertainty Landscape

The uncertainty landscape spans a continuum ranging from complete certainty to radical ignorance. It can be understood through a small number of fundamental questions concerning our state of knowledge. First, *Is the system deterministic and fully known?* Second, *Are the relevant outcomes meaningfully characterised?* Third, *Can meaningful probabilities be assigned?* Fourth, *Can additional data reduce the dominant uncertainty given the current level of knowledge?* (Figures 1) The answers to these questions distinguish different regions of the uncertainty landscape and help explain the progression from complete certainty to radical ignorance.

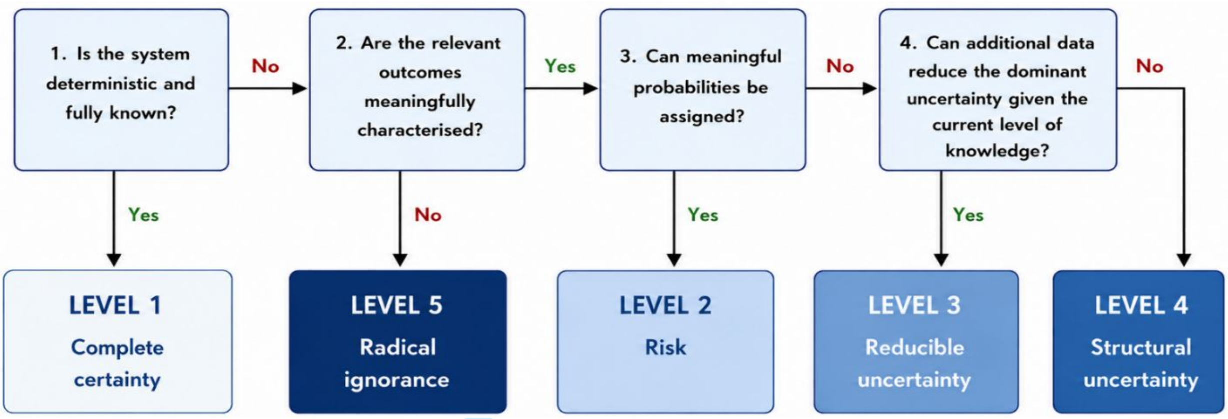

Fig. 1. Decision tree for distinguishing different regions of the uncertainty landscape.

Thus, the landscape is bounded by two reference states. One represents the idealised limit of complete certainty, while the other represents the practical limit of scientific knowledge, where relevant outcomes, mechanisms, or even possibilities remain unknown (radical ignorance). The five levels should therefore be interpreted as conceptual regions within a continuous landscape rather than as discrete categories (Figures 2). Each region is defined by what is uncertain and by the scientific response through which knowledge can most effectively advance. The following sections therefore describe the defining characteristic of uncertainty at each level and the corresponding mode of scientific response.

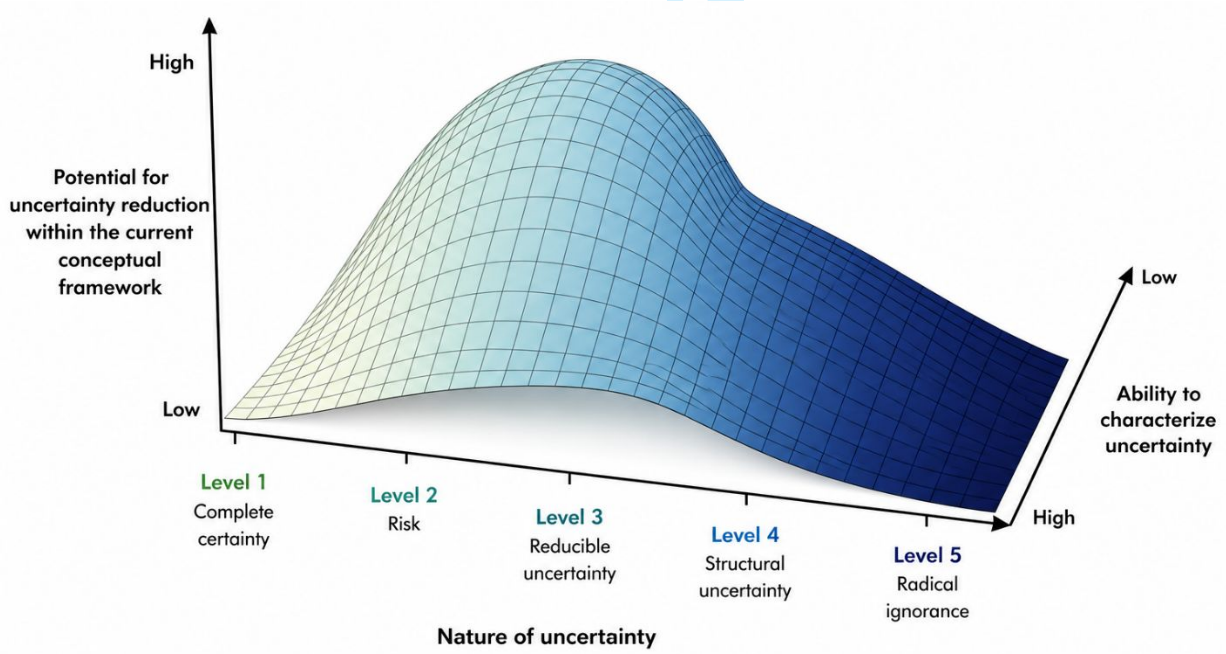

Fig. 2. The uncertainty landscape. Note that the surface is illustrative and schematic: its axes are qualitative and non-metric. The five levels should be interpreted as conceptual regions within a continuous landscape rather than as discrete categories. Level labels have been adapted slightly from Lo and Mueller (2010) to better reflect terminology commonly used across disciplines. (The figure was generated using ChatGPT 5.6 SOL.)

2.1. Level 1: Complete Certainty

At the first level lies complete certainty, an idealized state in which all relevant variables, governing mechanisms, and future outcomes are known exactly. Such complete certainty is best regarded as a conceptual reference point rather than an empirical reality. The closest practical examples are deterministic mathematical and computational operations, where identical inputs processed according to fixed rules always produce identical outputs (Bjerknes, 1904). Yet determinism alone does not imply complete certainty. Bjerknes's (Bjerknes, 1904) early formulation of weather forecasting envisioned atmospheric evolution as a deterministic physical problem, provided that the state of the atmosphere could be known with sufficient accuracy. Lorenz (1963) later demonstrated that deterministic systems may exhibit sensitive dependence on initial conditions, the *butterfly effect*, such that small uncertainties in the initial state can grow rapidly and ultimately limit predictability. Thus, a system may be deterministic while our knowledge of its trajectory remains uncertain.

Conversely, many real-world systems may appear almost deterministic because the combined effects of numerous stochastic processes make alternative outcomes increasingly improbable. Such apparent certainty reflects *statistical inevitability* rather than true determinism: individual outcomes remain uncertain, but aggregate behaviour becomes highly predictable due to the underlying probabilistic regularities. It therefore belongs to the domain of probabilistic reasoning considered in Level 2.

2.2. Level 2: Risk

The second level corresponds to risk, a state in which the outcome of a particular event is unknown, while the possible outcomes and the probabilistic mechanism generating them are known or can be adequately characterised. Unlike complete certainty, the outcome cannot be predicted exactly; however, uncertainty can be characterised using probability distributions. A simple example is a fair coin toss. The possible outcomes are known, but the outcome of a single toss is unknown. Because each outcome has a known probability of one half, repeated tosses can be characterised probabilistically: as the number of tosses increases, the proportion of heads becomes increasingly concentrated around one half, even though the outcome of each individual toss remains uncertain. This level is grounded in probability theory (Kolmogoroff, 1933), which provides the mathematical basis for representing quantifiable uncertainty and underpins statistical inference, such as design-based inference under probability sampling (Neyman, 1934; Cochran, 1977; Cassel et al., 1977). It also underpins the distinction between risk and uncertainty (Knight, 1921), expected utility theory(Von Neumann & Morgenstern, 1944), and the practical management of quantified risk in actuarial science (Freeman, 1931; Bühlmann, 1970). Typical examples include games of chance, repeated random sampling, and insurance portfolios, where uncertainty is present but can be adequately described using probability theory.

Probability sampling is a canonical Level 2 case. It underpins design-based inference applied across many disciplines, including official statistics, public health, sociology, engineering, and forest monitoring (United Nations & National Household Survey Capability Programme, 2005; Levy & Lemeshow, 2008; Tomppo et al., 2010; Montgomery, 2020). Under design-based inference, sampling variance arises from randomisation in the sampling design; larger samples can reduce its magnitude without changing its source (Neyman, 1934; Cochran, 1977). Other uncertainty concepts belong to Level 2 only when their stochastic behaviour can be adequately characterised probabilistically. Random measurement error, such as instrument noise or observer variability, provides one example, whereas systematic effects, calibration uncertainty, or poorly understood biases may instead reflect reducible (Level 3) or structural uncertainty (Level 4) (Hibbert, 2013). Similarly, a statistical model error term belongs to Level 2 when the remaining variation is reasonably represented by a stable probabilistic mechanism(Fisher, 1922; Davidson and MacKinnon, 1993; Greene, 2018); unexplained variation arising from model misspecification instead belongs to Level 4. In AI, the former corresponds broadly to aleatoric uncertainty (Hüllermeier & Waegeman, 2021; Haynes et al., 2023).

Despite their different terminologies, these examples describe the same fundamental state of knowledge: uncertainty arising from stochastic mechanisms whose probabilistic behaviour is known or can be adequately characterised. Such uncertainty cannot be eliminated through additional observations alone; the scientific response is therefore to improve measurement where relevant and account for the remaining variability through probabilistic inference.

2.3. Level 3: Reducible Uncertainty

The third level concerns reducible uncertainty. This is a state in which the possible outcomes and the general structure of the problem are largely understood, but important parameters, relationships, or probability distributions remain unknown and must be inferred or learned from data. Level 3 uncertainty arises because information is incomplete. Additional observations, experiments, or improved estimation can reduce uncertainty and improve understanding of the system. Accordingly, this level encompasses the inferential component of statistical inference, machine learning, and Bayesian analysis, where unknown model parameters and system relationships are learned from data. Level 3 represents the principal domain of scientific learning, where evidence is used to transform incomplete knowledge into progressively more reliable understanding.

Forest monitoring provides a concrete example: biomass relationships and links between field variables and remotely sensed data must be learned from finite observations (Næsset, 2002; Duncanson et al., 2022; Fassnacht et al., 2024). Uncertainty in resulting biomass products therefore depends partly on data coverage, parameter estimation, and the learned relationships. In AI, epistemic uncertainty similarly denotes uncertainty due to limited knowledge; its parameter- and data-limited components map naturally to Level 3, whereas uncertainty about the appropriate model can extend into Level 4 (Hüllermeier & Waegeman, 2021; Abdar et al., 2021; Haynes et al., 2023).

The distinction between Levels 2 and 3 lies in what is uncertain. Regression illustrates it directly: in a biomass model, stochastic variation around a known relationship is Level 2, whereas uncertainty in the estimated relationship or its parameters is Level 3. Additional observations can reduce the latter, not the former.

Levels 2 and 3 often coexist in the same uncertainty measure. Confidence intervals can reflect sampling variation under design-based inference (Level 2) (Cochran, 1977), parameter uncertainty under model-based inference (Level 3) (Cassel et al., 1977), or both, as in hybrid inference (Ståhl et al., 2011; Fattorini, 2012; Fortin et al., 2018; Saarela et al., 2023). Likewise, prediction intervals typically combine irreducible stochastic variability (Level 2) with parameter uncertainty (Level 3) (Cassel et al., 1977; McRoberts et al., 2018; Saarela et al., 2020). In Bayesian inference, posterior credible intervals for model parameters quantify uncertainty associated with those unknown quantities (Level 3), whereas posterior predictive intervals additionally incorporate irreducible stochastic variability (Level 2) (Gelman et al., 2013). The landscape therefore classifies the source of uncertainty, not the statistical summary used to express it. The corresponding scientific response is to reduce incomplete knowledge through additional observations and scientific learning.

2.4. Level 4: Structural Uncertainty

The fourth level corresponds to structural uncertainty. This is a state in which some uncertainty still originates from unknown parameters or limited data, but also from incomplete understanding of the system itself. At this level, the challenge is more about determining whether the underlying model structure or inferential framework, and their associated assumptions provide an adequate representation of reality. Consequently, learning from new observations may reduce some uncertainties, while leaving others largely unresolved because they arise from limitations of the model structure or inference itself.

Structural uncertainty takes different forms across scientific disciplines. While Level 3 mainly concerns unknown parameters within an accepted model, Level 4 concerns the model itself and whether it provides an adequate representation of the system. A related distinction appears in mining Geostatistics, where Matheron (1986) separated the problem of estimation within an adopted model from the broader problem of choosing the model through which the phenomenon is represented. In statistics, economics and environmental modelling, this may involve model misspecification, omitted variables, structural shifts or non-stationarity (Lo & Mueller, 2010; Chambers & Clark, 2012).

This is relevant for forest monitoring because models are necessarily based on observations made under past conditions, while forests and their environment are changing. Climate-driven changes in forest growth, changing disturbance regimes, shifts in species and previously unobserved interactions among ecological processes, together with changes in human intervention, may therefore challenge relationships derived from historical data (Millar et al., 2007; Seidl et al., 2017). Wildfire provides a useful example: models based on observed relationships among climate, vegetation and fire may become less reliable as more frequent extreme heat, prolonged drought and changing fire behaviour alter these relationships. The problem then moves beyond estimating wildfire risk

(Level 2) or model parameters (Level 3) to asking whether the historical relationships represented by the model still hold (Level 4). This resembles a *structural shift* in time-series econometrics (Aue & Horváth, 2013) and *distribution shift* in AI, where models are applied under conditions that differ from those on which they were developed (Quiñonero-Candela et al., 2008).

In practice, structural uncertainty may show up when plausible models, assumptions or data sources give systematically different results. Other warning signs are unexpected prediction failures, poor performance under new conditions, or inconsistencies between independent sources of evidence (Oreskes et al., 1994; Chambers & Clark, 2012). Such problems cannot necessarily be resolved by collecting more data or estimating the parameters more precisely. Standard methods for uncertainty quantification, including confidence and prediction intervals in frequentist inference, bootstrap-based uncertainty assessment, and Bayesian posterior summaries such as credible intervals, may provide useful information, but they do not in themselves quantify uncertainty about the model structure (Lo & Mueller, 2010).

The Level 3-4 boundary is blurred because ensembles, Bayesian model averaging and multi-model projections can vary model structure while estimating parameters (Kennedy & O'Hagan, 2001; Raftery et al., 2005; Lakshminarayanan et al., 2017). These methods can represent uncertainty across candidate models but cannot establish that the candidate set adequately represents the system. The problem is especially clear at the observation–model interface, where apparently equivalent quantities such as aboveground biomass, leaf area index or soil moisture may differ in definition, scale or observation operator (Raoult et al., 2025). Variance, mean squared error and interval estimates can provide a shared statistical language, but their numerical comparability depends on whether the underlying quantities are commensurable.

The distinction between reliability and validity provides another useful perspective on the transition from Level 3 to Level 4 uncertainty. Reliability concerns the consistency and precision of measurements, estimates, or model predictions, and is therefore primarily associated with uncertainty arising from stochastic variability and parameter estimation. Validity, on the other hand, concerns whether the measurements, variables, assumptions, or model structures adequately represent the phenomenon of interest. A statistical model may therefore produce highly reliable estimates with narrow confidence intervals while still providing an inadequate representation of reality(Lucas, 1976). This is so because essential processes have been omitted, assumptions violated, or causal relationships misspecified (Lo & Mueller, 2010; Chambers & Clark, 2012).

Across disciplines level 4 often becomes apparent when confidence in parameter estimates continues to increase while confidence in the underlying conceptual representation does not. Additional data may improve perceived precision, yet persistent disagreement among alternative models, repeated prediction failures, or changing system behaviour indicate that the principal uncertainty lies in the representation of the system itself rather than in the estimation of its parameters. The corresponding scientific response is therefore to challenge existing assumptions, test alternative representations, and revise the models or conceptual frameworks used to understand the system.

2.5. Level 5: Radical Ignorance

The fifth level represents radical ignorance. Uncertainty at this stage implies that important outcomes, processes, or causal mechanisms are unknown. This level is often associated with the concept of unknown unknowns, meaning sources of uncertainty that may not yet be recognized (Wynne, 1992; S. O. Funtowicz & Ravetz, 1993; Stirling, 2010; S. Funtowicz & Ravetz, 2025).

The literature on *Black Swan* events emphasises one important aspect of this idea, namely the possibility of consequential but unforeseen events (Taleb, 2007). Post-normal science similarly highlights decision-making under conditions where uncertainty is high, values are contested, stakes are large, and decisions are urgent (S. O. Funtowicz & Ravetz, 1993; S. Funtowicz & Ravetz, 2025). These perspectives differ in emphasis, but they share the recognition that important future developments may arise outside current models, expectations, and even existing conceptual frameworks. Level 5 should be regarded as a property of the current state of scientific knowledge. Scientific advances may transform previously unimagined outcomes into recognised mechanisms that can subsequently be investigated, modelled, and sometimes even assigned probabilities. From the perspective of the uncertainty landscape, developments that once appeared entirely unforeseen may later become explicable within an expanded body of knowledge. The world need not have changed; what has changed is our understanding of it. The uncertainty has not disappeared but has moved to a different region of the uncertainty landscape.

When important variables, mechanisms, or outcomes have not yet been conceived, additional empirical evidence alone may therefore provide little guidance unless accompanied by new theories, concepts, or ways of interpreting the system. Historical breakthroughs illustrate the point that phenomena become tractable only after new concepts make them conceivable.

The distinction between Levels 4 and 5 is conceptually clear, although the transition between them is often gradual in practice. At Level 4, uncertainty concerns the adequacy of models, assumptions, relationships, or probabilities used to represent a problem, while the relevant outcomes can still be meaningfully contemplated. At Level 5 relevant outcomes or mechanisms may themselves remain outside current scientific understanding.

Although Level 5 uncertainty cannot be quantified using conventional statistical methods, it remains highly relevant for decision-making. Long-term planning, policy design, and resource management frequently require decisions whose consequences extend into futures that cannot be fully anticipated (Marchau et al., 2019). The corresponding scientific response shifts therefore from prediction towards conceptual exploration, probing for unrecognised vulnerabilities, exploring alternative futures, and continuously updating understanding as new evidence emerges; while decision-making, increasingly relies on robustness, adaptability, resilience, and precaution (Lempert, 2019; Marchau et al., 2019).

3. Applying the Uncertainty Landscape

The uncertainty landscape is most useful as a diagnostic: before choosing an inferential or decision method, researchers should ask whether outcomes are known, probabilities are meaningful, and the dominant uncertainty is reducible within the current model. Scientific disagreements can then be distinguished as disputes about estimates, model adequacy or the limits of current concepts.

The controversy surrounding the forest-change estimates reported by Ceccherini et al. (Ceccherini et al., 2020) provides an instructive example. Using the Global Forest Change map developed by Hansen et al. (2013), the study reported substantially larger increases in forest harvesting across Europe than those indicated by national forest inventory statistics, leading to contrasting interpretations of recent forest change (Palahí et al., 2021; Wernick et al., 2021; Ceccherini et al., 2021; Breidenbach et al., 2022). Although the debate was often framed as a disagreement about harvesting estimates, many of the underlying issues concerned the interpretation of remotely sensed observations, the assumptions underlying the analytical framework, and the conclusions that could legitimately be supported by the available evidence. In the terminology proposed in this Position Paper, the discussion therefore extended beyond Level 3 uncertainty associated with estimation within a given framework to Level 4 uncertainty concerning the adequacy of the observational and inferential framework itself. The episode illustrates that major scientific disagreements may arise not only from conflicting estimates, but from different interpretations of what the available evidence actually represents.

A related challenge arises when quantities derived from different observational and inferential frameworks are combined within a new analysis. Kowalski et al. (Kowalski et al., 2026) for example, combined independently derived remotely sensed products within a new inferential framework to reconstruct forest biomass losses across Europe from 1985 to 2023, reporting a cumulative loss of 6.5 ± 0.8 Pg. While the reported uncertainty characterises precision within the adopted framework, the uncertainty landscape raises a broader question: to what extent does such precision also reflect the validity of the assumptions and upstream products on which the framework depends? Distinguishing reliability from validity is therefore particularly important when multiple estimated products and inferential frameworks are combined.

More generally, the uncertainty landscape can help interpret apparent discrepancies among estimates of the same physical quantity derived from different observational and modelling frameworks. Aboveground biomass, for example, may be estimated from EO, process-based ecosystem models, or field inventories (Reichstein et al., 2019; Duncanson et al., 2022). Although these products are intended to represent the same physical quantity, they differ in their measurement principles, assumptions, and inferential approaches. Consequently, apparent disagreement among products may reflect differences both in estimation uncertainty and in the frameworks through which the underlying quantity is observed and represented. The uncertainty landscape helps distinguish uncertainty arising from measurement and estimation within a given inferential framework from uncertainty associated with the assumptions underlying the framework itself.

Finance provides a parallel. Classical portfolio theory represents investment risk probabilistically (Level 2) (Markowitz, 1952; Sharpe, 1964), whereas structural change or previously unrecognised mechanisms can undermine that description and move the problem towards Levels 4–5 (Taleb, 2007; Lo & Mueller, 2010).

The conceptual uncertainty landscape also has implications for decision-making. As uncertainty progresses from quantifiable risk to structural uncertainty and ultimately radical ignorance, appropriate decision strategies increasingly shift from prediction and optimisation towards robustness, adaptability, resilience, and precaution. Similar transitions have been recognised in economic decision theory, where increasing uncertainty may alter the criteria used to evaluate alternative decisions. For example, rather than selecting the option with the highest expected return under a single probabilistic model, decision-makers may instead favour strategies that perform reasonably well across a wide range of plausible futures, even if they are not optimal under any single scenario (Marchau et al., 2019; Kay & King, 2020).

Even where uncertainty can be represented probabilistically, it can change how future outcomes are valued. Uncertainty about the appropriate future discount rate can imply a declining certainty-equivalent discount rate over longer horizons (Weitzman, 1998, 2001). This shows that uncertainty can alter decision criteria, not merely widen intervals around predicted outcomes.

4. Conclusion

By interpreting disciplinary uncertainty concepts as states of knowledge, the landscape links statistical inference, AI, economics, decision science, EO and environmental modelling within one framework (Table 1).

Table 1. Summary of the five levels of the uncertainty landscape.

Level	What does uncertainty primarily reflect?	Scientific response
1	Nothing (idealised certainty)	Deterministic prediction
2	Known or adequately specified probabilistic variation	Probabilistic inference; improve measurement where relevant
3	Incomplete knowledge of model parameters and system relationships	Additional observations and scientific learning
4	Limitations of assumptions and model structure	Model criticism and conceptual revision
5	Limits of current scientific understanding	Conceptual exploration and robust decision-making

The five levels should be understood as progressively different states of knowledge that place fundamentally different constraints on what can be inferred from observations, and models. Each region calls for a different scientific response: risk for probabilistic inference, reducible uncertainty for learning, structural uncertainty for model criticism and revision, and radical ignorance for exploration together with robust decision-making. Scientific progress therefore means more than reducing variance within accepted models; it also requires recognising when models or concepts must change. The key question is not only *How much uncertainty remains?* but *What kind of uncertainty are we facing?*

Abbreviations:

EO	Earth Observation
AI	Artificial Intelligence

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Established the foundational distinction between quantifiable risk and uncertainty, providing an early conceptual basis for distinguishing states of knowledge according to whether probabilities can be meaningfully assigned.

2. Neyman, J., 1934. On the Two Different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection. *Journal of the Royal Statistical Society 97(4)*, 558–625. https://doi.org/10.2307/2342192.

Established the theoretical foundations of probability sampling and design-based inference, exemplifying uncertainty that arises from a known randomisation mechanism and can therefore be quantified probabilistically.

3. Cassel, C.-M., Särndal, C.-E., Wretman, J.H., 1977. *Foundations of inference in survey sampling*. New York, NY (USA) John Wiley.

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4. Lorenz, E.N., 1963. Deterministic Nonperiodic Flow. *Journal of the Atmospheric Sciences 20(2)*, 130–141. https://doi.org/10.1175/1520-0469(1963)020%3C0130:DNF%3E2.0.CO;2.

Demonstrated that deterministic systems can exhibit sensitive dependence on initial conditions, establishing a fundamental limit to predictability even when the governing dynamics themselves are deterministic.

5. Lo, A.W., Mueller, M.T., 2010. Warning: Physics Envy May Be Hazardous to Your Wealth! *Journal of Investment Management 8(2)*, 13–63. https://doi.org/10.48550/ARXIV.1003.2688

Developed the five-level taxonomy of uncertainty that this Position Paper reinterprets as a cross-disciplinary landscape linking different states of scientific knowledge to their appropriate scientific responses.

6. Hüllermeier, E., Waegeman, W., 2021. Aleatoric and epistemic uncertainty in machine learning: an introduction to concepts and methods. *Machine Learning 110*, 457–506. https://doi.org/10.1007/s10994-021-05946-3.

Provides a systematic account of aleatoric and epistemic uncertainty in machine learning, offering an important bridge between AI terminology and the distinction between stochastic and reducible uncertainty developed in this Position Paper.

7. Walker, W.E., Harremoës, P., Rotmans, J., Van Der Sluijs, J.P., Van Asselt, M.B.A., Janssen, P., Krayer Von Krauss, M.P., 2003. Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment 4(1)*, 5–17. https://doi.org/10.1076/iaij.4.1.5.16466.

Developed a conceptual framework for characterising uncertainty in model-based decision support, helping establish the distinction between uncertainty that can be quantified within models and uncertainty concerning models and their underlying assumptions.

8. Stirling, A., 2010. Keep it complex. *Nature 468(7327)*, 1029–1031. https://doi.org/10.1038/4681029a.

Argued for distinguishing risk, uncertainty, ambiguity and ignorance rather than collapsing them into a single quantitative conception of uncertainty, closely anticipating the cross-disciplinary interpretation advanced here.