



The inherent uncertainty in geosciences

György Hetényi¹ · László Balázs^{2,3} · Zoltán Barcza^{4,5} · Eszter Békési⁶ ·
Erzsébet Györi⁷ · Anikó Kern^{2,5} · Norbert Péter Szabó⁸ · Gábor Timár²

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1 Introduction

The Hungarian national holiday on August 20th has been celebrated since decades with a spectacular evening firework show. In 2006 the event was washed away by a storm and took victims, and although the weather has been predicted accurately, no precautions have been taken. Since 2006 the weather forecast for August 20th has gained political importance, with a dedicated government task force (GTF) deciding on holding or postponing the celebrations. In 2022 the fireworks have been advertised as “Europe’s largest”. The synoptic weather situation in central Europe on 20 August, 2022 was particularly complex, shaped by a humid, wavy front system. Meteorological data and numerical simulations available by noon predicted precipitation for the evening with 80% probability. The Hungarian Meteorological Service (HMS) representatives reported these probabilities to the GTF, and the GTF decided to postpone the fireworks. In the evening, there was neither rain nor thunderstorms. On the next working day, the chairwoman and the deputy chairman of HMS were dismissed by the government. The official reason has not mentioned failure to comply with the festive forecast, but the coincidence has sent this message to society.

The authors, including several members of the editorial board of this journal, summarize here the sources, the nature and the interpretation of probability and uncertainty

✉ György Hetényi
gyorgy.hetenyi@unil.ch

¹ Institute of Earth Sciences, University of Lausanne, Lausanne CH-1015, Switzerland

² Department of Geophysics and Space Science, Institute of Geography and Earth Sciences, ELTE Eötvös Loránd University, Budapest H-1117, Hungary

³ Wigner Research Centre for Physics, Budapest H-1121, Hungary

⁴ Department of Meteorology, Institute of Geography and Earth Sciences, ELTE Eötvös Loránd University, Budapest H-1117, Hungary

⁵ Faculty of Forestry and Wood Sciences, Czech University of Life Sciences Prague, Prague CZ-16521, Czech Republic

⁶ Institute of Earth Physics and Space Science, Sopron H-9400, Hungary

⁷ Institute of Earth Physics and Space Science, Kövesligethy Radó Seismological Observatory, Budapest H-1112, Hungary

⁸ Institute of Geophysics and Geoinformation Science, University of Miskolc, Miskolc-Egyetemváros H-3515, Hungary

inherent to Earth sciences, to shed light on the reliability of methodologies especially in Meteorology and Geophysics. We also stress the importance to communicate uncertainty to a broader audience, and the need for education and outreach to optimize the information transfer from science to society, from kindergarten to top-level decision making.

2 The multiple sources of uncertainty

Uncertainty typically stems from multiple sources, which we group into three main categories: limited observations, the non-linear nature of processes on Earth, and the limited ability and capacity of modelling. Uncertainties from these are always combined, for example even the best models of a poorly described process remain poorly interpretable, and even the best data can only be poorly constrained with inappropriate modelling approaches. We here develop on these three categories of uncertainty sources.

2.1 Limited observations

Due to the vast spectra of temporal and spatial scales on Earth compared to those of humans, our observations of the Earth system and its sub-systems are only locally observed. The atmosphere is more easily accessible, but it is impossible to instrument every relevant cell at all times to track its dynamic variations. Changes in the solid Earth are in general slower, but direct observations are even more limited. The subsurface is not penetrable to instruments deeper than (so far) 12 km, while Earth's radius is 6371 km, which is like scratching an apple's skin. We thus must rely on various sorts of remote sensing techniques, let it be meteorological or geophysical, which comes with two inconveniences. First: it remains impossible to image physical properties or status beyond a given resolution. Second: very often the observation system's configuration is uneven in space and in time. This preconditions the outcome of numerical weather predictions (NWP) in the same way as geophysical surveys.

Improvement in 3D or 4D data collection can be achieved by using several types of observations. In meteorology, for example, land-, sea- and atmosphere-based data collection is combined with data provided by satellite-based instruments that is collected and processed e.g., by the European Centre of Medium-Range Weather Forecasts (ECMWF). This, together with data assimilation techniques had a major contribution to improving the medium-range weather forecasts after 1999 (e.g., Bauer et al. 2015), and also allowed highlighting the importance of using parameters such as radiance (e.g., Eyre et al. 2021) as well as to quantify the relative contributions of observation types (e.g., Saunders 2021). Despite the huge amount of data assimilated and used in the NWP models, the state of the atmosphere described is far from perfect during weather forecasting, which highly contributes to the uncertainty of the predictions.

2.2 The non-linear nature of processes

The processes described by meteorology and geophysics are non-linear, which means that little changes in the system can lead to forthcoming changes that are not proportional to the initial change. For example, minor changes in mechanical stress-increase usually do not lead to an earthquake, but at one point they do. In practice, this means that the well-established linear tools of mathematics can only be applied by approximation to describe

these natural processes. If the system description is handled by linearization to achieve fast processing tools, the approximation induces uncertainties.

Another approach is to employ probabilistic methods, which include non-linear inversion, aiming at estimating unknown parameters of the non-linear system. Inverse methods, relying on some implementation of the Bayes theorem, are widely used in meteorology, and in a wider context in other climate-related scientific fields. They do not remove all uncertainties, but may help to reduce and to better constrain them, which aids their assessment.

2.3 Limited ability and capacity of modelling

Natural processes are simulated by numerical models, which require physical equations. For example, NWP models employ equations from fluid dynamics and thermodynamics (together they are referred as the governing equations) to simulate atmospheric flows and the energy balance of the surface and the air. The equations plugged into numerical models are considered the best to our knowledge, but research reveals new couplings and interactions which means the equations don't exactly describe how nature works. Additionally, numerical methods that are used to solve the equations in a computer code are also associated with some numerical error.

Because of the hitherto evoked reasons carrying uncertainty, researchers perform large numbers of model simulations, either to explore the range of plausible scenarios (e.g., weather forecast), or to estimate the likely set of parameters (e.g., of a reservoir, or for seismic hazard assessment). The number of simulations depends on the length of the calculation and the available time. Irrespective of these simulations being part of an ensemble technique (i.e., several model runs with perturbed initial conditions instead of a single run), or of a random or guided sampling of the parameter space (e.g., Monte Carlo method), the outcome is not one result but a considerable amount of results, which need to be interpreted together. It is not enough to discuss the best model, instead the set or sets of models with meaningful outcomes have to be assessed. This most often leads to a statistical description of probabilities, with models that are more plausible and others that are less. By assigning numbers to how plausible these results are, quantitative probabilities and uncertainties (variances, confidence intervals) are given.

3 Disciplinary examples

3.1 Meteorology

It is well recognized that the atmosphere is a chaotic and extremely complex system, thus NWP models inherently contain simplifications and are associated with considerable uncertainty. For modelling purposes, ensemble predictions were introduced in NWP to address the uncertainties to some extent (Buizza 2008); the approach gained popularity due to the recognition that the joint (forward) application of imperfect models is typically more successful than application of a single, well-calibrated model. The ensemble method is inherently probabilistic, nevertheless it has become part of our everyday life (e.g., through smartphones) as the probability of weather events can be quantified. This is not the *true* probability, but a probabilistic estimate based on our current knowledge of how the atmosphere works, based on the available observations, and based on the implemented numerical

methods – in other words: to the best of our knowledge (which is continuously improved and updated).

The ECMWF is the most important NWP centre in Europe, and runs global models twice a day. It issues an ensemble system comprising 50 members, called Ensemble Prediction System (EPS). It is important to note that the spatial resolution of EPS (which is associated with the scale of the resolved atmospheric motions) is always worse than that of the so-called high-resolution forecast (HIRES, frequently called deterministic forecast). This fact adds another level of uncertainty to the evaluation. We need to mention here that even the best NWP can provide false forecasts for a given location for precipitation even if the model is perfect (see Göber et al. 2008 for a great explanation). This is caused by the simple fact that the models work with a given grid geometry and provide data for the average of the grid cell. In current NWP models this grid cell can be as large as a 100 km² (and even larger for EPS) so there is no chance to capture small-scale precipitation events that we see each Summer, that can sometimes provide large amount of rain over small areas that is not even captured by the observation network.

3.2 Geophysical exploration and reservoir modelling

The exploration and exploitation of geo-resources (water, geothermal, hydrocarbon, ores) requires a particularly good understanding of the state and processes of the underground. The physical properties of geological formations are extracted from surface geophysical surveys and borehole logging, while reservoir-related simulations are carried out by modelling. All these carry uncertainties.

In exploration, and in particular in the very valuable and high-resolution well logging, model parameters such as petrophysical and geometrical quantities with their uncertainties are estimated by inverse modelling. In practice, several physical parameters are measured during wireline logging measurements. However, because of the acquisition type measuring once for all parameters at a time while the instrument is moved up the hole, the statistical distribution of the observed physical parameters cannot be established. In this case it is often assumed that the measured data types follow a Gaussian distribution, and are uncorrelated or even independent (e.g., Alberty and Hashmy 1984; Ball et al. 1987; Baker Atlas 1996). This assumption inherently carries uncertainties, which may be reduced by further actions, such as repeated measurements in the depth points, specifying the full covariance matrix in the data space, or the so-called interval inversion method in rock formations with similar properties. For example, with appropriate mathematical formulation, the estimation error of the reservoir parameters could be significantly reduced, by at least 20% depending on the petrophysical parameters (Dobróka et al. 2016; Szabó and Dobróka 2020). The chances of avoiding local minima can be reduced by global optimization methods (e.g., genetic algorithm). The method of most frequent value (Steiner 1991) also provides a robust solution for a wide range of probability distribution types, and has been applied in other field as well, such as geophysical data processing (Nuamah et al. 2021) and astronomical geodesy (Völgyesi and Tóth 2021). These and other mathematical approaches help reducing (but not totally removing) the uncertainty and noise inherent to wireline logging data.

In a later stage of geo-resource characterization, probabilistic models are commonly used to predict reservoir behaviour, with the help of history-matching. Such models are usually very complex and computationally demanding, thus they require robust inversion techniques that are able to account for uncertainties of a large set of parameters and

immerse calibration data. Ensemble-based techniques, that can predict a large number of potential scenarios instead of a single prediction, are becoming increasingly important in reservoir simulation as well. Due to the complexity and non-linearity of reservoir models, methods that are capable of reproducing observations and correctly quantifying uncertainties with feasible computational costs are still rare. For instance, Emerick and Reynolds (2013) compared ensemble methods to evaluate their performance on a non-linear reservoir model. Their findings may help with selecting a suitable prediction technique for a specific reservoir engineering problem.

3.3 Earthquakes

Among natural hazards, earthquakes carry one of the largest destruction potential. Because they can neither be prevented nor precisely predicted, earthquakes have a high potential to cause casualties, injuries and damage in the built and natural environment. In order to reduce risks by appropriately constructing and preparing society, the first step is to determine seismic hazard.

Probabilistic seismic hazard analysis (PSHA) is the standard method used, which is a framework that allows estimating the rate or probability of exceeding a given level of ground-motion or intensity at a site within a specific time interval. Input parameters to PSHA, such as past and current seismicity patterns, seismic wave attenuation, local geology causing site effects, are all subject to significant uncertainty. Two types can be distinguished: the aleatory and the epistemic uncertainty. The existence of the aleatory uncertainty is clear, which is the inherent randomness in earthquake occurrence and ground-motion generation, while the epistemic uncertainty is related to the lack (or gap) of knowledge. For example, until March 11, 2011, the large Tohoku earthquake of magnitude 9.1, residents of Japan's Tohoku coast were proud of their tsunami defence system, they felt protected. The available history had no record of giant earthquakes at the Japan Trench off Tohoku, therefore the largest future earthquakes along different segments of the trench were expected at magnitude 7 to 8. The incompleteness of seismic catalogues is a general problem, especially in low-to moderate seismicity regions where the available history of seismicity is almost always too short to reliably establish the spatiotemporal pattern of large earthquake occurrence.

Epistemic uncertainty is commonly handled through a logic tree framework, which is composed by either-or branches, with each branch representing a credible model at a given percentage of probability. This way, epistemic uncertainty is considered by specifying the credible alternative models for the probability density functions, transfer functions, attenuation relations, and activity rates (Abrahamson 2000). The main effort in hazard estimation is to handle aleatory variability and reduce epistemic uncertainty, nevertheless uncertainties persist; this must be considered by structural engineers and decision-makers.

4 Decision making

All information, probabilities and uncertainties above constitute “only” half of the input to decisions made in relation with geosciences, which we can summarize as hazard. The other half input to decision making is the vulnerability and exposure of a group of people and their natural or built environment. Taken together, these form potential risks, and decision makers have to weigh the different inputs.

The reasons for uncertainties on the hazard side have been detailed above. For decision makers, who are often non-specialists, the probabilities are often condensed into one (or few) decision variables (such as the probability of a thunderstorm, the probable geo-resource reserves, the probability of a given magnitude earthquake). Decision makers need to collect a similar (possibly also simplified) input on vulnerability and exposure for the range of the decision parameters, and, ultimately, compare the resulting risk with what level is tolerable and intolerable.

While these may sound logical, there is one further aspect: the decision makers need to request and assess the uncertainties of the inputs, and take those into account in the final decision. This is far from trivial, as the quantification of uncertainties can only be as good as the inherited uncertainties from observations, non-linearity and model simulations. While it is relatively easy to communicate the most probable value, it is relatively hard to word the level of uncertainty.

In meteorology, NWP is a computer-aided tool, and the human factor should always be present for the interpretation of the results. If there is a relatively small probability for the occurrence of a severe weather event that can threaten human life, additional factors need to be considered and a complex decision must be made. This is sometimes difficult, and sometimes it is not justified by the forthcoming real scenario; nevertheless, decisions are based on our actual state of knowledge which is inherently imperfect.

In geo-energy applications such as hydrocarbon and geothermal production, mining activities, subsurface sequestration and storage, reliable predictions are necessary to assess future production or storage scenarios and associated risks, and to decide on the feasibility of a project. Considering the energy future of our society, geo-resource estimates are subject to non-negligible political exposure.

Seismology also regularly experiences earthquake scenarios that reach beyond the research community and trigger public discussion. A relatively recent example is the trial in L'Aquila, Italy, related to a magnitude 6.3 earthquake in April 2009. This earthquake was preceded by very unfortunate communication from an official, and followed by turmoil involving the media, the public, and scientists (see Cocco et al. 2015 for details). The outcomes of the trial process had great impact on how scientists communicate to decision makers and society.

In summary for decision making: while ensemble models are successfully used in risk management and decision making worldwide, results and uncertainties should always be interpreted by experts, and translated to the target audience.

5 Need for communication and education

The subsequent communication of probabilities and uncertainties is not straightforward, neither to formulate, nor to understand.

On the sender side, geoscientists are aware of the uncertainties, but don't always communicate about it. One of our motivations with this editorial is to encourage authors to discuss uncertainties in their scientific publications, and to dedicate specific studies to it (see also the recent special issue on uncertainty: <https://link.springer.com/journal/40328/volumes-and-issues/56-4>). When it comes to communicating with the public, it is important to find good analogies, and to think of the communication as an educational exercise. A few examples:

- A scenario with a given probability P also means that there is $1-P$ chance that it does not happen. People appreciate this as millions are playing lottery, hoping for an infinitesimally low probability event to occur – and sometimes it does occur, at unpredictable intervals.
- Already in kindergarten children must appreciate probabilities. Who draws the shorter stick to start a game? How often one throws a 6 with a dice?

On the receiver side, uncertainty is continuously communicated to us in everyday life, and not just in the weather forecast: we hear about the *expected* government budget deficit, *expected* arrival times or delays in transportation, *expected* number of pupils starting a given school year, etc. It is all about stating a present opinion of something that will happen or will be seen in the future – and, often, with a different outcome than one thought. This difference to what was expected is what we need to assume as the result of uncertainty.

We stress that education is a key element to provide a good basis for society to understand uncertainties. By education we don't only mean STEM-classes at higher level, but any subject at any level. At the time of writing this editorial, the famous École Normale Supérieure in Paris, France, is organizing a public event to discover, understand and tame uncertainty (https://www.nuit.ens.psl.eu/programme?start_time=0&end_time=1440). The rich program illustrates that uncertainty is present in everyone's daily life, from biology to physics, from law to finances, from literature to music, and from geology to climate.

6 Conclusions

What is uncertainty? It is when the answer to a question is not black-or-white (Fig. 1). Uncertainty is inherent in geosciences because of the observation types, the non-linear nature of processes, and the limited ability and capacity of modelling. Uncertainties from multiple sources add up, and we use mathematical tools to reduce them as much as possible. Nevertheless, uncertainty persists, and has to be properly communicated to each target audience. For the most efficient communication pathway, experts and decision makers must train how to explain uncertainty, and the public should receive appropriate education early on to perceive what uncertainty represents. The best defence against natural hazards remains prevention that should be based on hazard knowledge. This way, we – both as

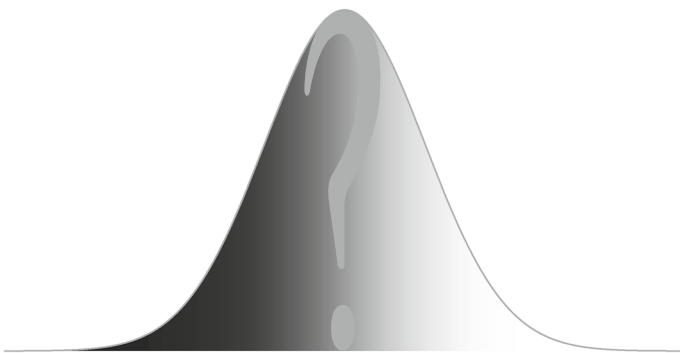


Fig. 1 What is uncertainty? It is when the answer is not black-or-white. The *area* under the Gaussian curve represents a linear distribution of grey shades

individuals and as groups – can learn and train when to organize or cancel events involving crowds, or simply which morning to take an umbrella.

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Declarations

Conflict of interests György Hetényi is Editor-in-Chief, Eszter Békési is Managing Editor, Norbert Péter Szabó and Gábor Timár serve on the Editorial Board of the journal; they have fully withdrawn themselves in advance from the evaluation process of this article. The authors have no financial or proprietary interests in any material discussed in this article.

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