Uncertainty as a driving force for geoscientific development

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ABSTRACT

Geoscientists invest significant effort to cope with uncertainty in Earth system observation and modeling. While general discussions exist about uncertainty and risk communication, judgment and decision making, and science communication with regard to Earth sciences, in this paper, we tackle uncertainty from the perspective of Earth science practitioners. We argue that different scientific methodologies have to be used to recognize all types of uncertainty inherent to a scientific finding. Following a discovery science methodology results in greater potential for the quantification of uncertainty associated to scientific findings than staying inside hypothesis-driven science methodology as is common practice. Enabling improved uncertainty quantification could relax debates about risk communication and decision making since it reduces the room for personality traits when communicating scientific findings.

INTRODUCTION

Mankind lives in a dynamic environment and is exposed to ever-changing environmental conditions. Since ancient times Earth system observation has been triggered by the desire to adapt to dynamic processes, e.g., by foreseeing hazardous events, extracting or dumping materials and/or utilizing Earth system processes. The latter experienced sustainability as a growing side condition to be met since mankind became increasingly aware that their actions interact with Earth system dynamics (e.g., Liverman and Roman Cuesta 2008; Brondízio and Moran 2014). Foresighted adaptation and sustainable utilization require insight into the Earth system and its dynamics in order to understand and foresee functionality and reactive behavior, respectively. While Earth system *observation* can be seen as a fundamental scientific paradigm (Hey et al. 2009), asking for the collection of (potentially useful) data about state variables of the Earth system, process functionality understanding goes beyond and requires the subsequent definition of a current-state or process description *model* with its theoretical foundation accessible to human cognition and in line with available observations.

Since the development of modern science, vast knowledge advancement strongly rooted in experimentation and reasoning as scientific methodology rather than doctrines has led to generalized descriptions of Earth system functionalities. Early modern Earth science generally considered the world around us a nomological reality, and thus strived to develop theories expressed by deterministic models linking observed state variables of the Earth system and their process dynamics, e.g., as described in the Newtonian clockwork cosmos and culminated in Laplace's demon[1] (e.g., Solomon and Higgins 2009).

For more than a century, scientists have been aware that the concept of determinism does not hold for modeling many phenomena, e.g., stream phenomena in the atmosphere or the Earth's outer core. Beginning in the 19th century, theories of chaos, fuzziness, or probability became an integral part of scientific work when striving to model the functionality of the Earth system. It required moving away from the idea of a purely nomological reality leading to model concepts beyond determinism.

Figure 1 summarizes the work flow of today's geoscientific efforts dedicated to gaining insight into Earth system functionality comprising phases of data acquisition, data processing, and decision making. The key steps of this work flow are (i) observing/sampling nature resulting in data imaging (aspects of) reality, (ii) assessing observational quality, e.g., by describing observational precision and accuracy during data acquisition, (iii) data processing for derivation/construction/emphasis of features (hypothetically) considered particularly useful, (iv) developing a model of reality, and (v) making decisions based on interpretation of data processing and modeling results in order to (a) adapt to reality, (b) foresee functionality and reactive behavior of the Earth system, or (c) hypothesize about expected but not yet confirmed/observed effects thus defining promising future research directions.

The final decision-making step is critical, since it governs how we adapt to the Earth system and its dynamics by relying on process understanding as expressed by the modeled Earth system evolution. Rooted in the scope of science, it must match the information content of the database. In the sense of modern science, this should ideally be the only basis for decisions. If there were no informational uncertainty about the Earth system by the database and its processing, deterministic decision making would be possible and justified. However, if the information content of the database and processing methodology left room for adding personality traits of human interpreters or decision makers to the decision making process, e.g., ability to cope with reality complexity, ego, risk shift, anxiety level, etc. (e.g., Bezerra et al. 1996) determinism in the final interpretations cannot exist. The consequences, including, for example, uncertainty and risk communication, judgment and decision making, science communication etc., have been broadly discussed for a long time, often using examples from Earth system science (e.g. Oreskes and Conway 2010, Fischhoff 2011, Parker 2017).

Practical limitations of observational accuracy and precision (e.g., Taylor 1996) and observational effort will prohibit ever reaching a deterministic state for decision making, even if the process of interest underlying the experimental and reasoning efforts were be truly deterministic. Earth scientists are mostly aware of the indeterminate nature of their object of study and the consequences of the limited number and accuracy of available observations. For various reasons, including for example methodological limitations, convenience, and lack of communication tools, they partly produce and/or present their findings in a way that uncertainty information inherently present in the context of discovery is neglected, e.g., tomographic image reconstruction in geophysics (Hoffmann and Dietrich 2004). This does not necessarily mean that these scientists are not aware of the uncertainty associated to their discoveries or models, but they rely on the expectation that contemplators (peer scientists or laymen) will be aware of (and consider) the presence of some, albeit (yet) unspecified, unquantified, and uncommunicated, uncertainty[2].

In this contribution, we review uncertainty occurring in Earth sciences and explain why we see it in Earth system observation and analysis as a key driver for research progress. We compare the potential of model-based Earth system analysis to data-driven analytics for the quantification of uncertainties associated to data processing and geoscientific findings. Acting as practitioners in Earth science and science communication, with this contribution we want to redirect attention to the role of uncertainty in the dynamics surrounding knowledge development in Earth system science. With this discussion we hope to stimulate deeper studies illuminating the tense issue between uncertain science and the societal willingness to accept scientific indetermination.

UNCERTAINTY AND FIELDS OF SCIENTIFIC RESEARCH

Limited observational accuracy and precision as well as a limited number of observations are the fundamental sources for practical indetermination of natural processes when observed (e.g., Friedel 2003). In decision making, they are classically related to aleatory and epistemic uncertainty, and sometimes not properly differentiated (Kiureghian and Ditlevsen 2009). Aleatory uncertainty of measured data can be quantified if observational accuracy and precision are known (e.g., JCGM 2012)[3]. It can be reduced by more precise and accurate observations. Practically, it is not possible to fully overcome aleatory uncertainty in Earth observation. Traditionally, experimental design in measurement equipment engineering is concerned with the development of optimal measurement devices (e.g., Arora 2016). This does not necessarily mean that all possible efforts are made to minimize the aleatory uncertainty of the observational output of a measurement device. Instead, observational quality and observational effort are compromised by striving to optimize accuracy and precision of observations at moderate costs.

Epistemic uncertainty of measured data results from the bandwidth limitation of experiments discretely sampling the Earth system. Bandwidth limitations can be of spatial, temporal, or physical nature, e.g., by facing a minimal and/or maximal resolution limit in space and/or time or technology-specific limitations, such as signal frequency ranges emitted or recorded by a measurement device. Despite usually knowing the bandwidth limitations of an experiment, it is impossible to quantify the amount of information an experiment has missed. It could even be that nothing of relevance could have been observed outside the range and resolution limits of an experiment – but we cannot know without extra experimental effort. Epistemic uncertainty can be reduced by increasing the information return of experiments, e.g., by careful experimental design which is the task of the domain scientist researching on Earth and environment, but it can never be quantified.

Ontological uncertainty (Lane and Maxfield 2005) is related to the general appropriateness of experiments and methods used for sampling the Earth system and subsequent data processing, since design of devices, experiments, and subsequent data processing is impacted by hypotheses about Earth system functionality and their relation to the state variables observed. Ontological uncertainty cannot be quantified and scientists are usually unaware of its presence in their work flows and efforts when learning or doing Earth science within a scientific paradigm, i.e., a canon of insights, theories, and models widely accepted by the members of a scientific community (Kuhn 1970). Earth science strives to search for generally new methods, processing techniques, etc. to retrospectively reveal and potentially overcome ontological uncertainty of current methodology.

In addition, semantic uncertainty (Beven 2016) may occur in communications among scientists, but (mutual) misunderstanding leading to erroneous believes or model concepts in the mind of individual scientists or scientific groups commonly conducting experimental observation, data processing, and/or interpretation can be broken down to individual perception of aleatory, epistemic, or ontological uncertainty accompanying the available information. In this paper we will exclude this rather social uncertainty from our discussions.

These types of uncertainty are well recognized within some Earth science domains, e.g., hydrology (e.g. Beven, 2016). Sometimes, subdivisions with regard to modeling or measurement-related uncertainty are made for epistemic uncertainty. We want to emphasize that no dualism of aleatory and epistemic uncertainty exists, albeit both are often treated as closely linked, since these are the only uncertainties to be evaluated by probabilistic statistics. Note that even the selection of a distribution function for modeling aleatory uncertainty in statistical data analyses comes with ontological uncertainty about the appropriateness of the choice made.

Science classically addresses aleatory, epistemic, and ontological uncertainty individually (Table 1). Alternatively, epistemic uncertainty can also be reduced by data integration in the sense of multi-sensor data fusion (Liggins et al. 2008), i.e., motivated by the idea to replace epistemic uncertainty inherent to an experiment and the resultant data set by co-located information provided by another experiment and data set. Over the last three to four decades growing automation of data acquisition reduced costs for Earth observation leading to the trend to acquire physically disparate multi-sensor databases over the same survey area, thus relaxing the need to select the most suitable sensor or data set during the planning stage of an experiment (Figures 1a and b), which cannot be done without ontological uncertainty.

Data integration immediately raises the question of how to link different data sets. This can most easily be achieved qualitatively by a joint interpretation, which bears an interpreter-dependent level of ontological uncertainty. Alternatively and more reproducibly, data integration can be done by means of models learned independently from the given database and considered as transferable and valid by the scientific community[4]. This means that the linkage model f: X $\rightarrow$ Y defining the integration of the data domains X and Y is *a priori* considered to be known. For example, f can be expressed by a (stochastic) differential equation or a rather empirically found function, e.g., by regression analysis of other data. Following this concept adds ontological uncertainty to data integration and thus complicates interpretation and final decision making. Strictly speaking, the assumption to know the linkage model deterministically would even question the necessity to measure more than one data set. Instead, often the general nature of the linkage model is assumed to be known under uncertainty. Hence, calibration is required to fit f to i observed data readings $x_i \in$ X and $y_i \in$ Y. This can be realized by tuning model coefficients based on the available data sets so that f matches the observation results in X and Y sufficiently well. Since the individual measurements in X and Y suffer aleatory uncertainty, it is impossible to solve the calibration problem in a deterministic sense by finding *the right* tuning parameters. Instead, we must consider it more as probabilistic definition of calibrated model coefficients, e.g., in the sense of coefficient ranges associated a suitable distribution function (e.g., Tronicke and Paasche 2017). However, this gives the integration problem a probabilistic character, but such stochastic uncertainty analyses exclude the ontological uncertainty added to the integration problem by a priori selection and acceptance of a distinct type of *f*. Even a meta-analysis including several human-generated types of *f* does not allow for ontological uncertainty assessment since independency of the chosen models and representativeness for all possible models cannot be granted (Pirtle et al. 2010).

Alternatively, the data linkage function *f* can be learned based on the information provided by available observations in X and Y. Methodologies can range from simple regression analysis to sophisticated data analytics, e.g., deep learning algorithms with low suitability for cognitive understanding of the learned linkage function by humans. Particularly critical is the learning limit, which is controlled by the aleatory uncertainty associated to the data sets sampling X and Y discretely (Figures 2a and b). Away from this, any learned continuous function *f* becomes a predictive model, which goes along with assumptions about validity and inter-/extrapolation of the learned model, adding ontological uncertainty in regions where X and Y have not been sampled (Figure 2c). Reduction of epistemic uncertainty in the data sets by good experimental design can help to narrow the extension of predictive regions of the model (Figure 2d). If aleatory uncertainty is quantitatively recorded and is acquired with the data, learning *f* can be reasonably limited to find f: $x_i+e_{i\mathrm{x}} \rightarrow y_i+e_{i\mathrm{y}}$. e_x and e_y are aleatory uncertainties for the *i*th pair of *x* and *y* and should be considered as samples drawn from potentially different and unknown random distributions. This makes learning *f* an indeterminate task when not overfitting the problem. Accuracy and precision of *f* are directly related to accuracy and precision of the information about X and Y. Such data-driven integration is a promising way of turning epistemic uncertainty into quantifiable aleatory uncertainty. It avoids adding ontological uncertainty by a priori selection of *f*. The final decision making step after data-driven integrated analysis remains uncertain, but uncertainty is more accurately quantifiable since it comes to a large extent as aleatory uncertainty. This will reduce the importance of personality traits in decision making and reduces the amount of ontological uncertainty in decisions about adaptation to the Earth system.

DISCOVERY-SCIENCE VERSUS HYPOTHESIS-DRIVEN SCIENCE AND THEIR DEALING WITH UNCERTAINTY

Traditionally, experimental design in Earth system sciences is hypothesis-driven. For example, experimental setup and observations are designed following a hypothesis postulating expected behavior or states of the Earth system and may even postulate which observational data might be particularly suitable. This is done based on process understanding and accepted conventions ("good practices") forming the theory and model canon of a geoscientific domain (Kuhn 1970). For practical reasons, other data are often not acquired or considered in the experiments and subsequent data processing, but random deviations may occur depending on opportunities, dependencies, and skills (Knorr Cetina 1984). Hypotheses can be falsified by the following experiments and resultant data, but never universally verified (Glass and Hall 2008). Working with hypotheses bears the risk of distorted experimental design or reasoning during data processing thus increasing chances to meet the hypothesis. This is directly related to ontological uncertainty in the hypothesis-driven science approach when developing models, i.e., in the simplest case turning an unfalsified hypothesis into a confirmed hypothesis

(Refsgaard and Henriksen 2004) employed from here on to model states or processes of the Earth system.

Hypothesis-driven approaches are often rooted in the assumption that the Earth system can be described by generalized theories or models, usually described in mathematical-analytical form (Figure 3) found by means of induction from observations made elsewhere in space or time or deduction from existing theory. This scientific method is often taught as the working method of a distinct geoscientific domain and has experienced no change over the last decades (compare for example the textbooks of Berckhemer (1990) and Clauser (2016): both provide introductions to geophysics) Earth system models match reality more or less closely, but critically suffer from ontological and possibly epistemic uncertainty. History shows that proven and once widely accepted models had to be given up or became special cases of a more general process description when new or improved experimental methodology became available or scientific paradigms with their portfolio of theories, under which hypotheses and models were developed, were superseded. Hypothesis-driven scientific approaches are learned when experiencing the training necessary to become member of a scientific community. Scientific methodology means here to learn the existing theory and modeling canon of a specific community and, based on that, how to hypothesize to explore promising research directions intended to prove and expand the paradigm of the community (Kuhn 1970). Flaws in the learned scientific paradigm due to ontological uncertainty when developing the paradigm accepted by the community are hard to recognize from inside the domains paradigm (Kuhn 1970).

Discovery science approaches (e.g., Aebersold et al. 2000; Figure 3) usually ignore process functionality models, and are thus sometimes referred to as hypothesis-free, which is strictly not true. Compared to hypothesis-driven approaches, employed preconceptions are more general, e.g., the assumption that disparate data sets sampling the same reality must be compliant and thus justify a common (integrated) analysis, but the actual definition of "compliant" may remain unclear or specified on a cross-domain meta level, e.g., segmentation or continuity are considered proper hypotheses for integrated data analysis. Learning "rules" or "pattern" from a given database opens the way to learn interrelations between data types for which no integrating mathematical-analytical model concept exists yet[5]. This clearly allows moving beyond some inherent limitations of hypothesis-driven science (which has no reason to hypothesize that data types not included in current models and the underlying theory may be of relevance). This allows for cross-domain data integration learning data linkage models *f* beyond methodological limits of geophysics, hydrology, and all the other domains of Earth sciences and thus broadens the potential capability to replace epistemic by aleatory uncertainty. In turn, any newly considered data set adds its aleatory uncertainty which is unwanted in terms of error propagation, particularly if the added aleatory uncertainty of a data set exceeds the reduction of epistemic uncertainty in the database. This comparison suffers uncertainty in itself since epistemic uncertainty cannot be quantified. The error propagation point of view suggests that a hypothesis-based a priori selection of "the most suitable" data sets may appear promising to prevent inflating aleatory uncertainty by considering data sets not really contributing relevant information, but instead brings in ontological uncertainty (which is not included in classical error calculus and stochastic uncertainty analyses) if the selection rules are rooted in accepted paradigms or models.

To unfold its full potential, discovery science requires a change in measurement system experimental design. Here, the objective should move away from developing more precise and accurate observation methods (a traditional goal that cannot be reached in ultimate perfection), but instead observational uncertainty must be realistically quantified. A reduction of the considered database, and thus an exclusion of the aleatory uncertainty of some data sets with marginal information contribution, is only justified in discovery science approaches recursively run with reduced databases thus allowing posteriorly identifying importance of distinct data sets to find good models. Results of such analyses will not be transferable without ontological uncertainty. Discovery science as a scientific method is often neglected in the training of young Earth and environmental scientists since their training program is defined by the classical theory paradigm of their geoscientific domain. This is also partly reflected by the discussions about uncertainty and uncertainty handling in distinct geoscientific communities, e.g., in hydrological sciences (e.g., Refsgaard et al. 2007; Gupta and Nearing 2014; Beven 2016; Nearing et al. 2016; Carsteanu et al. 2016) since discussions largely stay inside the paradigm of the community. For example, hydrological process simulation and prediction relying on mathematical-analytical process understanding models bear ontological uncertainty that cannot be assessed by the various techniques developed and discussed for uncertainty appraisal by the community (e.g., Refsgaard et al. 2007). Instead, a different scientific methodological approach, e.g., discovery science, is required to benchmark process-description-based modeling results relying on an a priori accepted theory. Limited observation capacities may currently hamper the application of discovery science approaches on continental or global scale Earth simulation and prediction tasks with reasonable local-scale resolution, but hypothesis-based simulations matching output of discovery science approaches at least on the regional scale may help to assess and understand ontological uncertainty potentially present in process-model-based simulations of the Earth system.

Discovery science has already changed some research areas in recent past, like biology, medicine, or economy. We expect it to be of growing importance in Earth sciences, too. However, uncertainty cannot diminish by following discovery science approaches. Ontological uncertainty due to unrecognized misconceptions can be reduced and scientific results come with an increased component of aleatory uncertainty. This makes uncertainties of scientific research results generally more quantifiable which should be the desire of individuals and societies asking for a good informational basis for adaptation to Earth systems. Earth system models can only approach reality, and uncertainty is the measure of dissimilarity between model and reality. To be of maximal value, uncertainty must be small *and* quantifiable, and this is what current developments in discovery science with its potential for cross-domain integrated data analysis strive to improve. However, we are still far from reaching this goal since even at the first step, the data acquisition, state-of-the-art practices have to be changed. For example, instead of building new measurement devices reducing costs and measurement errors, realistic quantification of measurement errors must become an equally considered optimization goal in optimal measurement device design.

Discovery science approaches can lead to an apparent increase of uncertainty compared to results of uncertainty analysis techniques from hypothesis-driven science approaches, such as error propagation, expert elicitation, stochastic uncertainty analysis, etc., all done under the same paradigm and its unrecognized ontological uncertainty. Despite the increase in aleatory uncertainty, model uncertainty can be better quantified which makes uncertainty information a better value on its own that should be considered in processing, interpretation, communication, and decision making when concerned with Earth system observation and modeling. In the desire to adapt to dynamic processes and in combination with the awareness that uncertainty will never diminish, quantification of uncertainty is a fundamental and naturally inherent goal of Earth science progression, independent of external incentives.

CONCLUDING THOUGHTS

Earth system observation and modeling inherently include uncertainty. This arises from truly non-deterministic causality in Earth system functionality as well as epistemic and aleatory uncertainty inherent to Earth observation. The latter prohibits, even in cases of deterministic causality, determined statements about Earth system states and dynamics.

Developments in the recent past, such as multi-sensor sampling of Earth processes and data and information integration techniques, reflect the desire to better cope with uncertainty in Earth system data processing and modeling, forming the basis for adaptation decisions to Earth system dynamics. To be of real value, aleatory uncertainty reduction must accompany quantification during Earth observation.

Uncertainty assessment of scientific findings cannot be achieved when staying within a single scientific methodology, e.g., hypothesis-driven science. A priori acceptance of theories and models, e.g., in stochastic analysis of model parameters, excludes ontological uncertainty and results in overoptimistic uncertainty quantification. In turn, focusing exclusively on discovery science without an accompanying process understanding bears the ontological uncertainty of relying on rather arbitrary pattern matches related to processes not stable beyond the observation period.

Individuals and stake holders should request scientific advice about adaptation to Earth system dynamics together with maximally quantified uncertainty. Incentives putting exploitation interests over understanding interests hamper honest uncertainty quantification and communication. Instead, uncertainty must be considered a valuable outcome inherent to any scientific endeavors addressing complex systems like Earth and environment. Uncertainty can never be overcome but different types of uncertainty can be converted into other types and different scientific methods can be combined. Pushing awareness of uncertainty quantification as a cross-methodological task and development of incentives better rewarding uncertainty quantification of scientific findings would reduce the room for personality traits in the interpretation of scientific findings and thus relax debates about risk communication, judgment, framing, and decision making in Earth sciences.

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NOTES

1: Even nowadays many fields of geosciences maintain deterministic model concepts, e.g., pedo- or petrophysical transfer functions in soil science and geophysics, respectively (e.g., Schön 2004). Irrationally, geoscientific communities sometimes accept the parallel existence of concurrent deterministic models (e.g., see table 5.3 in Wair et al. 2012), and even additions (e.g., Mola-Abasi et al. 2015). We think that such behavior reflects a diffuse traditional desire for causal determinism as well as a lack of alternative non-deterministic concepts accepted throughout or developed within a distinct geoscientific community.

2: External incentives may reinforce this behavior. For example, if utilization and exploitation interests take precedence over understanding and cognitive interests, be it on the level of national innovation strategies or the evaluation of individual scientists, then scientific findings are considered products which have to demonstrate their usefulness soon after finishing the production process (Weingart 2008). Uncertainty quantification and communication may then be considered disturbing by the users of scientific products and financiers of scientific endeavors as well as scientists themselves.

3: Precision and accuracy refer to random and systematic measurement errors, respectively. Random errors could be assessed by repeated measurements made with the same device at the same location under the assumption that no significant change of the observed state variables occurred during repeated observations. Systematic errors are specific for measurement devices. They could be assessed when employing a sufficiently large number of devices at the same location simultaneously. If the random errors for the measurements of each device are known, the systematic error components could be analyzed. Note, laboratory calibration of devices does not guarantee for reliable quantification of systematic errors under field observation conditions. Unfortunately, many data sets in Earth and environmental science come nowadays with no or poor aleatory uncertainty quantification, e.g., by only paying attention to random errors assessed by a very low number of repeated measurements and often simply described under the assumption of a distinct model, e.g., the normal distribution considered in Gaussian error statistics and their simple measures such as standard deviation.

4: Scientific models are rooted in observations and built on one or more hypotheses retrospectively drawn from the analysis of information, e.g., available in the form of measured data and/or other models. Turning retrospectively drawn hypothesis into a priori valid models that can be transferred over space and time bears always ontological uncertainty, since the correctness of this conversion cannot be ultimately proven (e.g. Popper 1989).

5: This scientific method also bears ontological uncertainty, e.g., by facing the risk to recognize and accept patterns as scientific findings which do not hold beyond the periods of observation. A popular example is the apparent linkage of the heliacal rise of the Sirius and the Nile flood cycle identified by the ancient Egyptians. Over the long existence of the Ancient Egyptian culture, the apparent pattern broke.

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FIGURE CAPTIONS

Figure 1: Work flow towards gaining insight into Earth system functionality and decision making for adaptation to system dynamics. (a) Relying on "the best/most suitable" data set. (b) Relying on a multi-sensor database comprising disparate but co-located data sets. Each data set is processed individually and a joint interpretation is done prior to decision making. (c) The same as in (b) but with information exchange between different data sets during the processing to realize a quantitative data fusion. $\mathbf{d}^0$ denotes observed data, j equals the number of data processing steps, n denotes the number of data sets, a and b denote two different data sets, **e** quantifies aleatory uncertainty, E is the final decision, and P_k are the personality traits of the k^{th} member of the interpreting/decision making group of human individuals. Note, from (a) to (c) the information content of the database increases as well as the level of data fusion. When following discovery science principles in (c) this leads to reduced importance of P_k thus approaching towards the ideal status of $E=f(\mathbf{d}_1^{end},\ldots\mathbf{d}_n^{end})$;

Figure 2: Linkage of data domains X and Y. (a) Dots locate samples labeled x_1 to x_4, coming with no aleatory uncertainty. Observations could be modeled by a linear function depicted by the dashed gray line. (b) The same as in (a) but now with aleatory uncertainty in Y indicated by the length of the arrows. For simplicity, aleatory uncertainty in X is ignored. Note that now different linear models fit the data sufficiently well. (c) Epistemic uncertainty resultant from discrete sampling and limited bandwidth when probing X leaves also room for finding other simple models explaining the samples equally well. Between the sampling locations and beyond the sampled range limited by x_1 and x_4 all models are predictive. (d) The same as in (c) but with

reduced epistemic uncertainty by extending the sampled bandwidth in X by x_6 and reduced sampling interval by considering x_5. The added samples eliminate some models, but nevertheless leave room for more than one continuous model. Note, compared to x_3 and x_4, x_5 has been sampled in a region of higher model sensitivity, since the considered models differ significantly at this location.

Figure 3: Based on data, two different scientific methodologies can be followed when striving towards scientific findings. Hypothesis driven science comprises the paradigms of generalized theory and models and numerical simulation. Discovery science focuses on pattern recognition and data science. Examples for each paradigm are provided in parentheses. Note, examples for data science are not taken from Earth sciences, since we do not see substantial achievements of this emerging paradigm in this domain yet (Hey et al. 2009, modified).

TABLE CAPTION

Table 1: Types of uncertainty in Earth observation and data processing and attempts to reduce them.

Figure 1

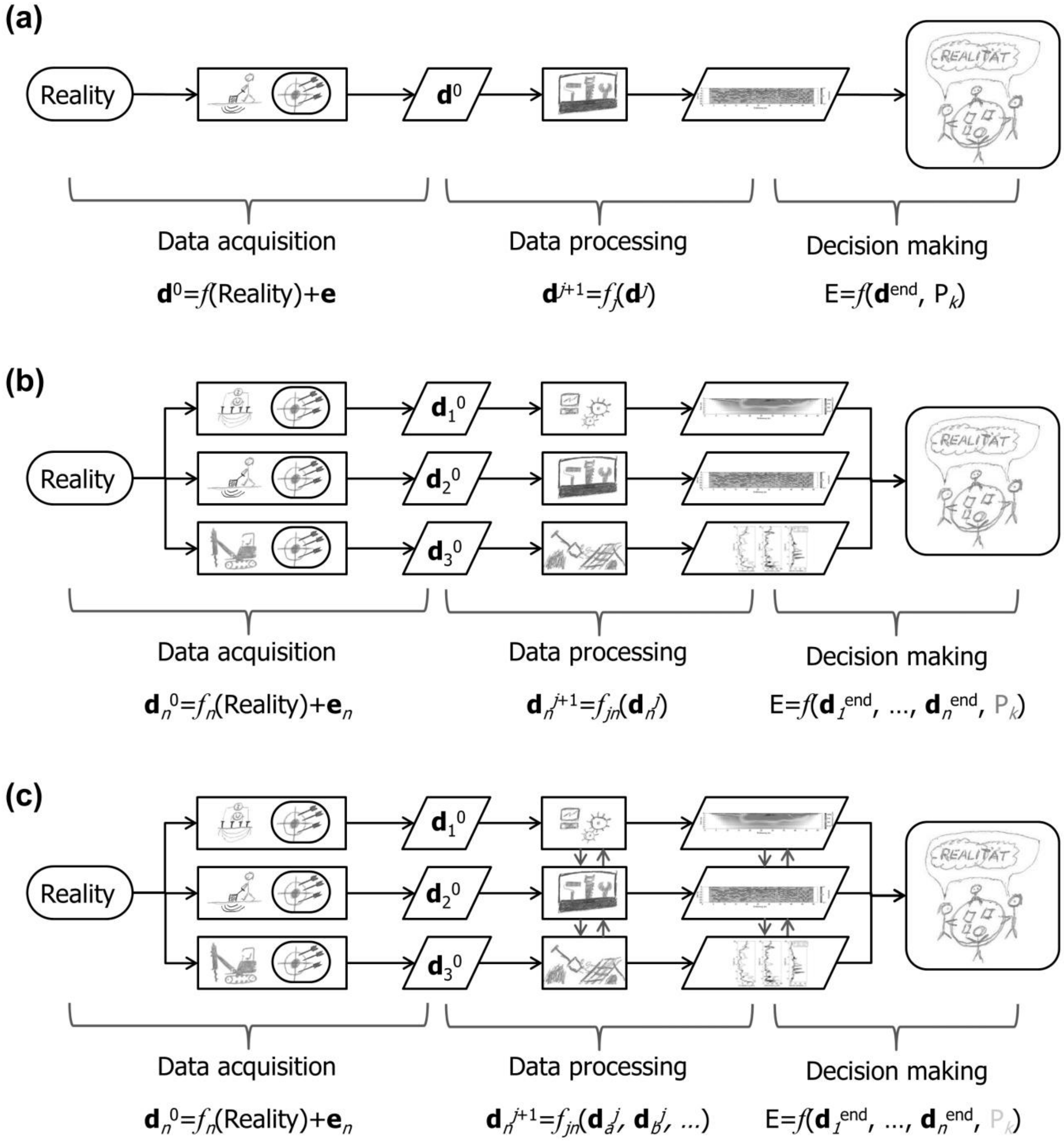
(a)
Reality
d⁰
Data acquisition
d⁰=f(Reality)+e
Data processing
d^{j+1}=f_j(d^j)
Decision making
E=f(d^end, P_k)
(b)
Reality
d_1^0
d_2^0
d_3^0
Data acquisition
d_n^0=f_n(Reality)+e_n
Data processing
d_n^{j+1}=f_jn(d_n^j)
Decision making
E=f(d_1^end, …, d_n^end, P_k)
(c)
Reality
d_1^0
d_2^0
d_3^0
Data acquisition
d_n^0=f_n(Reality)+e_n
Data processing
d_n^{j+1}=f_jn(d_a^j, d_b^j, …)
Decision making
E=f(d_1^end, …, d_n^end, P_k)
REALITÄT

Figure 2

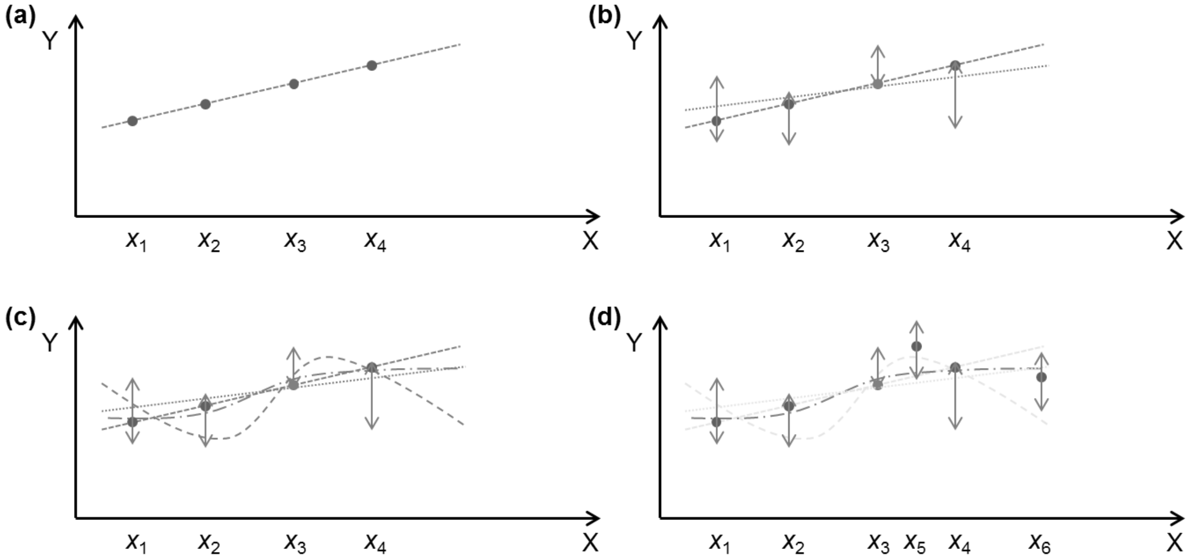

Figure 3

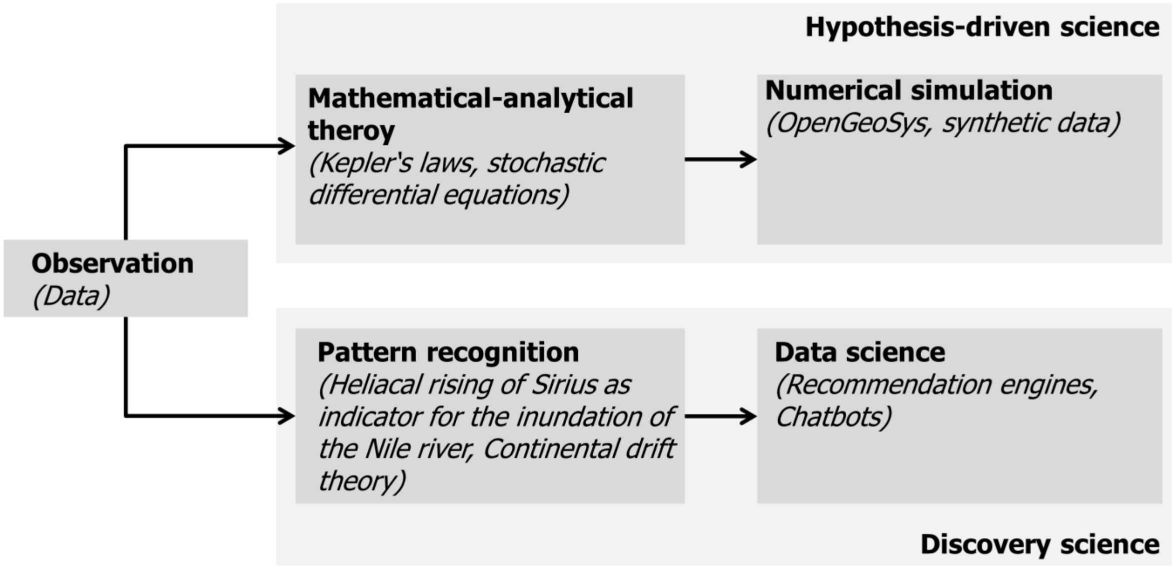
Hypothesis-driven science
Mathematical-analytical theroy
(Kepler's laws, stochastic differential equations)
Numerical simulation
(OpenGeoSys, synthetic data)
Observation
(Data)
Pattern recognition
(Heliacal rising of Sirius as indicator for the inundation of the Nile river, Continental drift theory)
Data science
(Recommendation engines, Chatbots)
Discovery science

Table 1

<table>
<tr><th colspan="2">Uncertainty</th><th>Aleatory</th><th>Epistemic</th><th>Ontological</th></tr>
<tr><td colspan="2">Cause</td><td>Limited observational accuracy and precision</td><td>Band-limited experiments</td><td>Inappropriate methodology</td></tr>
<tr><td colspan="2">Recognizable</td><td>Yes</td><td>Yes</td><td>No</td></tr>
<tr><td colspan="2">Quantifiable</td><td>Yes</td><td>No</td><td>No</td></tr>
<tr><td rowspan="2">Reduction by</td><td>Individual approach</td><td>Increase observational accuracy and precision</td><td>Increase experimental information return</td><td>New methodology</td></tr>
<tr><td>Data integration</td><td colspan="3">Requires linkage model f for linking the information content of data sets $\mathbf{d}_i$ and $\mathbf{d}_j$, $\mathbf{d}_i=f(\mathbf{d}_j)$; Epistemic uncertainty is reduced by replacing it with

aleatory uncertainty:
Data-driven linkage model f learned by the given database, $\mathbf{d}_i\pm\mathbf{e}_i=f(\mathbf{d}_j\pm\mathbf{e}_j)$. Aleatory uncertainties $\mathbf{e}_i$ and $\mathbf{e}_j$ for both data sets are never zero and must be quantitatively known to avoid overfitting of f; Finding f is a non-deterministic problem.

ontological uncertainty:
f is defined by a model, which is transferred to the given database. Appropriateness of the transferred model is hypothesized but cannot be validated.</td></tr>
</table>