How to use the impossible map – Considerations for a rigorous exploration of Digital Twins of the Earth

Robert Reinecke[1,2,*], Francesca Pianosi[3,4], and Thorsten Wagener[1]

[1] Institute of Environmental Science and Geography, University of Potsdam, Potsdam, Germany
[2] Institute of Geography Johannes Gutenberg-University Mainz, Mainz, Germany
[3] School of Civil, Aerospace and Design Engineering, University of Bristol, Bristol, UK
[4] Cabot Institute, University of Bristol, Bristol, UK

Abstract

The term "Digital Twins of the Earth" has rocketed into scientific use and policymaker discourse by promising a virtual replica of our planet. While the potential of a digital representation of reality is captivating for environmental monitoring, decision-making, and scientific inquiry, the term lacks a clear and shared definition and may be misleading. It conceals that all digital representations are models and, as such, will always be detached from reality. Detailed simulation models are excellent digital laboratories that allow us to interrogate our theories about the world in ways otherwise not possible, given the limited scales at which we can run real-world experiments, yet a perfect representation of reality is impossible as it would be exactly as complex. As we embark on the journey of building such detailed models, one question we must ask is, "How can we ensure that they can be explored with scientific rigor?" Here, we discuss possible ways to utilize a model's internal variability to understand its dominant controls to increase our understanding of both the models we build and the world that they represent.

Keywords

Digital Twin; model evaluation; sensitivity analysis

Code availability

The code used to calculate the example in Figure 4 can be found at https://github.com/rreinecke/SONAR and could be used as a baseline for future method development.

1. Digital Twins are here, but do not forget the delta

The term Digital Twin of the Earth is increasingly used in the environmental and Earth sciences (Bauer et al., 2021; Pedersen et al., 2022; Hazeleger et al., 2024). However, it refers to different research tools ranging from a very complex model (Bauer et al., 2021; Hazeleger et al., 2024) to a model that assimilates live satellite data (Li et al., 2023), or to a high-resolution 3-D model of a country (BKG, 2022) or all of these terms at once (Blair, 2021; Ossing et al., 2023) — a clear definition for the environmental science is currently lacking (Barricelli et al., 2019). Here, we assume that Digital Twins of the Earth refer to model representation of the Earth systems that aim to be as complete as possible in their process representation. They are advertised as the new scientific frontier and key to enabling a transition into a green and sustainable future (European Commission, 2019; Voosen, 2020) by allowing interactive "causal inquiries" for decision support (Hazeleger et al., 2024). The

Correspondence:
Contact R. Reinecke at reinecke@uni-mainz.de

Cite this article as:
Reinecke, R., Pianosi, F., & Wagener, T.
How to use the impossible map – Considerations for a rigorous exploration of Digital Twins of the Earth
Socio-Environmental Systems Modelling, vol. 6, 18786, 2024, doi:10.18174/sesmo.18786

Socio-Environmental Systems Modelling
An Open-Access Scholarly Journal
http://www.sesmo.org

perceived potential for advancements in scientific understanding and for operational forecasting is vast and includes both geophysical processes and the effects of human activities (Voosen, 2020; Bauer et al., 2021; Slingo et al., 2022; Hazeleger et al., 2024). Their growing importance is reflected in massive investments. The EU Commission alone puts forward 1 trillion € for the green transition of the EU, which includes the creation of Digital Twins of the Earth (Bauer et al., 2021). Estimates for maintaining related targeted modeling chains are in the order of 250 million US$ per year (Slingo et al., 2022).

Digital Twins originated in manufacturing engineering (Grieves, 2014) and are used in various research communities beyond the Earth sciences (Barricelli et al., 2019; Raj, 2021). The original idea is to create a one-to-one representation of a physical object so that its properties (e.g., structure properties) can be tested in a way that is cheaper than building and testing a physical replica (Grieves, 2014; Raj, 2021). Transferring this terminology to the environmental domain implies that we know as much about the underlying processes of earth systems as we know about the artifacts we have engineered ourselves. This might be misleading: for example, while we can reasonably specify the structural properties of a wind turbine, we cannot describe soil properties over larger scales without considerable uncertainties (Vereecken et al., 2022). Also, the further we "zoom in" (i.e., increase the spatial and/or temporal resolution of the analysis), the more feedback might emerge as relevant (Saltelli et al., 2024). Using the term Digital Twin is thus problematic as it suggests that we can create a digital representation that allows us to stress-test the structural properties of the Earth system with any desired degree of accuracy and precision.

Every model is a simplification of reality, and its creation requires simplifying assumptions that will unavoidably lead to uncertainties (Figure 1). So, no matter what we call a digital representation of the Earth system, it will remain a model, and every step along the model building process will take it further away from reality (Beven, 2012). We refer to this as the distance delta in Figure 1, which depends on how well we know the system. Digital Twins of the Earth are also often coupled models of multiple sub-systems, and this coupling will add additional uncertainty as we make assumptions on how they should be coupled (Puy et al., 2022). A key element in using Digital Twins of the Earth is, therefore, to scrutinize the consistency of the model behavior with our expectations and to remember the distance between the model and reality – the delta – when using the model.

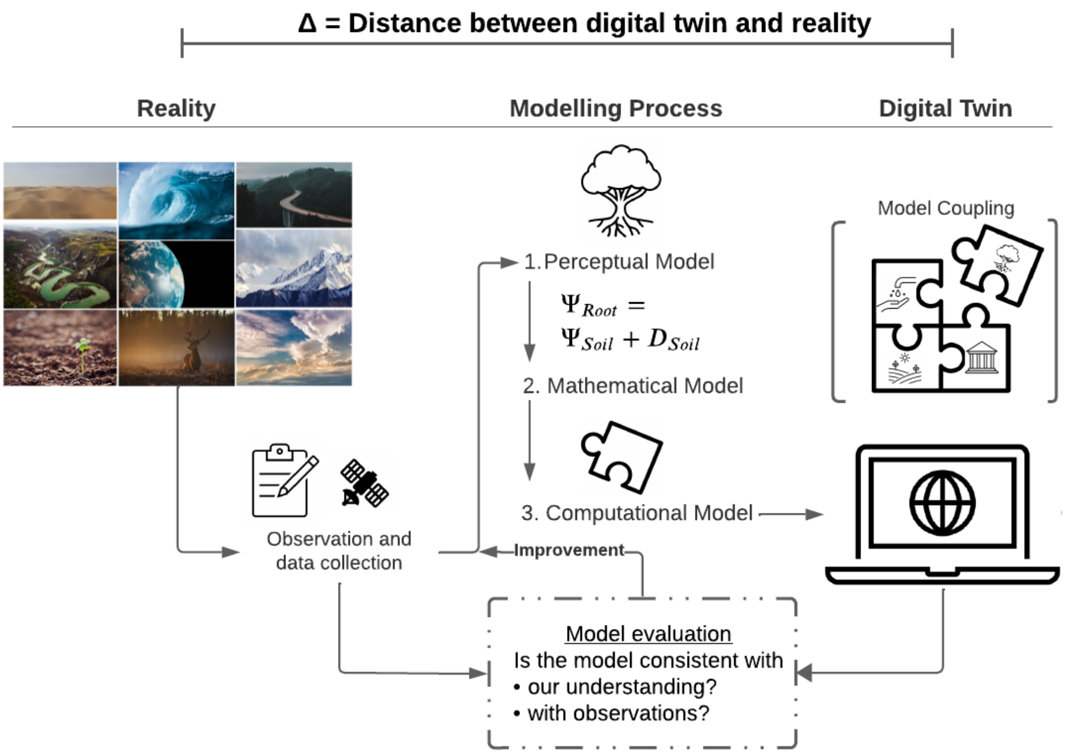

Figure 1: A digital representation of earth systems is always disconnected from reality by a distance delta. Each step in the modeling process– building a perceptual model, building a mathematical model, and building a computational model (Beven, 2012) – moves the "Digital Twin" further away from reality.

2. We can enable a rigorous exploration of complex models of the Earth

So, do we have the strategies to understand how earth systems models function and how well they reflect our understanding of reality as they continue to grow in complexity (Eyring et al., 2016)? How can we rigorously question the model's capabilities and improve our process knowledge (Saltelli et al., 2020), especially when simulating transient systems under climate and other environmental changes (Wagener et al., 2022), which significantly limits the value of comparing models to historical data (Gleeson et al., 2021)?

One way to begin addressing these questions might be through sensitivity analysis, i.e., a systematic analysis of how variations in the model input factors translate into variability in the model outputs (Wagener & Pianosi, 2019; Razavi et al., 2021; Saltelli et al., 2021). This would enable us to understand the controls of simulated processes and attribute output uncertainty to its multiple input sources.

However, a rigorous sensitivity analysis may require thousands to millions of model runs, which would necessitate prohibitively ample computational resources (Puy et al., 2024). Maybe surprisingly, lack of computational resources does not seem to be the main limiting factor to the current application of sensitivity analysis by environmental modelers. As shown in Figure 2, the number of factors varied in published sensitivity analyses and did not increase as much as the available computational resources. Some hypothesize that there is still a lack of knowledge in modeling communities regarding how to apply these methods (Ferretti et al., 2016); if so, this needs to be addressed as we move towards using increasingly complex models. In any case, it is helpful to consider what other strategies for model evaluation are also available.

Figure 2: The complexity of computational experiments for model exploration has not increased in line with available computational power. The left y-axis shows the number of factors (e.g., model parameters) in 160 global sensitivity analysis studies published from 2006 to 2020 in the environmental modeling domain. Grey dots indicate previous reviews from Song et al. (2015) and Vanrolleghem et al. (2015) (both focus on hydrologic modeling only). Blue dots indicate an additional 100 studies collected here (see Supplementary Material A for methodology). The grey line is a linear regression where the grey area shows the 95th confidence interval (excluding three outliers, see Supplementary Material A). The red line shows the availability of computing power (right y-axis) as log scale in giga FLOPS (Floating Point Operations Per Second).

Digital Twins of the Earth produce incredible amounts of data. Each of their grid cells – of which there can be millions – establishes an input-output relationship as a consequence of the chosen model's equations and parameter values. We postulate that we can utilize these data for model evaluation and possibly even for gaining a new understanding of the process. One opportunity is to explore so-called functional relationships, which can be defined as the co-variation of variables across space and/or time that underpins our theoretical knowledge of the Earth's functioning (Gnann et al., 2023). Past studies that have used this approach include, for example, Mu et al. (2021), who examined how groundwater might help to buffer vegetation function during multi-year droughts (here shown as the relationship between groundwater availability as water table depth and the ability of the canopy to cool itself through evapotranspiration expressed as the temperature difference between the canopy and the air temperature; Figure 3a); Reinecke et al. (2024) who showed the global relationship between water table depth and slope in global groundwater models (Figure 3b); MacDonald et al. (2021) who used ground observations to identify the functional relationship between groundwater recharge and precipitation across water limited domains; and Gnann et al. (2023) who investigated to what extent that functional relationship was replicated by global hydrological models (Figure 3d).

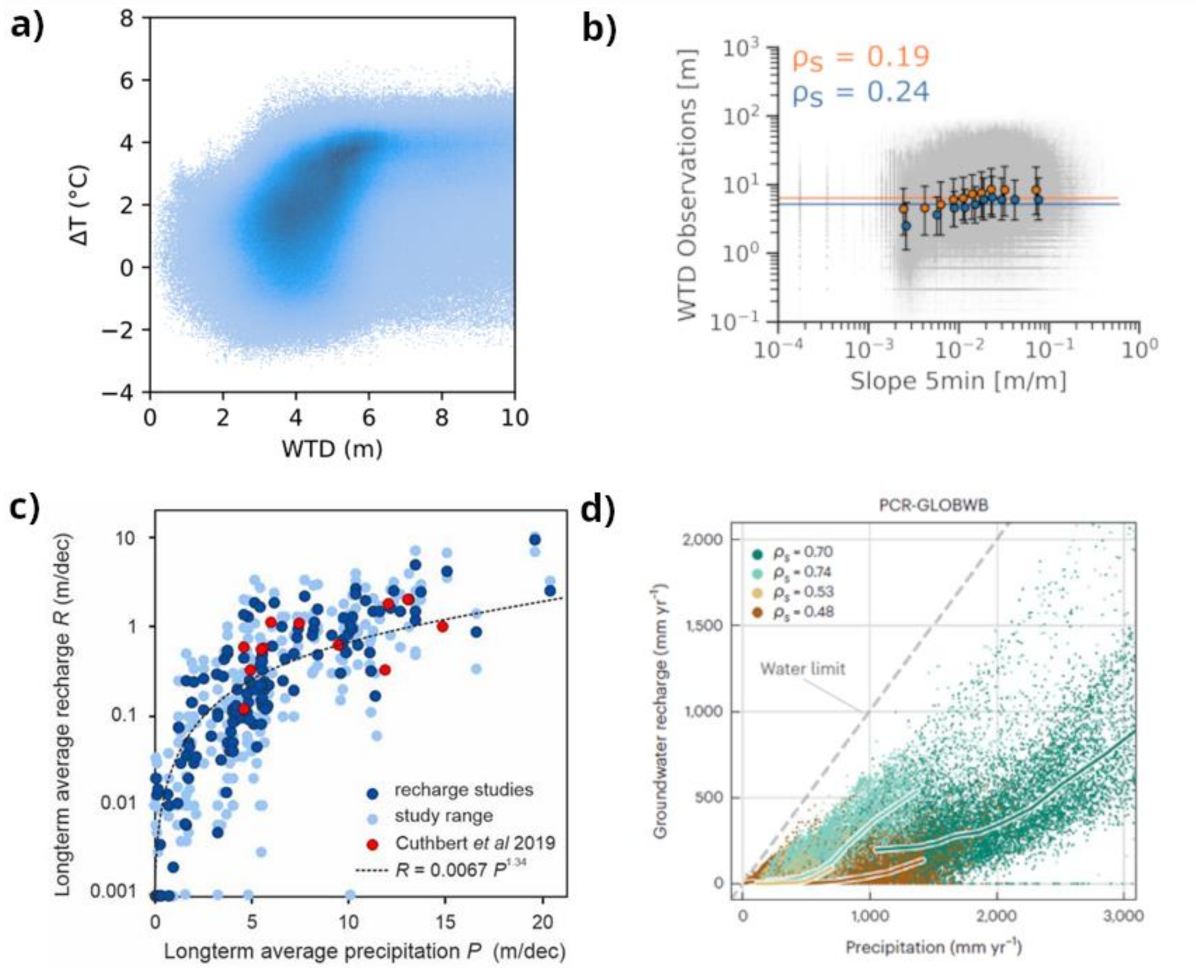

Figure 3: Functional relationships that can be found in data (a-c) and models (d). (a) shows transpiration offset trough air temperature difference (canopy temperature – air temperature) vs. water table depth (WTD) as a density scatter plot during heatwaves in Australia (adapted from Mu et al. (2021)), (b) observed water table depth vs. terrain slope globally (adapted from Reinecke et al. (2024)), (c) groundwater recharge vs precipitation over Africa (adapted from MacDonald et al. (2021)), and (d) groundwater recharge vs. precipitation globally as simulated by the PCR-GLOWB model (adapted from Gnann et al. (2023)).

One area for innovation is that we do not have a good way to automatically find such functional relationships in complex datasets such as the ones shown in Figure 3, where relationships will likely exist for potentially unknown subsets of the total data. In Figure 4, we show how the result of such an algorithm could potentially look like. Such an algorithm would need to organize data in a hierarchical manner automatically. Earth system processes are driven by different factors across space and time scales (Pattee, 1972), vary along gradients (Lesk et al., 2021), and exhibit thresholds (Zehe & Sivapalan, 2009). Thus, an automated method should also be able to identify and represent relationships hierarchically to represent the diversity in subdomains of the data.

Different from conventional tree algorithms, such as CART (Breiman et al., 2017), where the splitting criterion at each level is typically based on increasing classification accuracy in the subsequent nodes, the split would need to quantify an increase in the strength of a functional relationship. For example, Gnann et al. (2023) used the Spearman rank correlation as a first approach - but other metrics to quantify more complex relationships would be possible. An example to sketch out the idea is given in Figure 4. Here, we analyze the simulation outputs (30-year averages on a spatial resolution of 0.5°) of one of the global hydrological models also investigated in Gnann et al. (2023) (for details, see Supplementary Material B). We tested the code on multiple models and chose a tree that illustrates the idea best (the application to other models yields different trees). The code utilized in this example searches for drivers of groundwater recharge. The tree's root shows the highest identified driver for recharge across the global domain (each scatter point is one 0.5° grid cell of the model), which is precipitation. We find a non-linear relationship between recharge and aridity index in warm regions (grid cells where the mean daily temperature is greater than 26°C), which is stronger than the overall relationship between precipitation and recharge. For colder regions, the recharge-aridity relationship is less strong. Whether the found relationships are correct or meaningful is then up to the scientist. Further implementation of such an algorithm would need to show how robust it is in detecting such relationships and how choices in the algorithm impact its outcome.

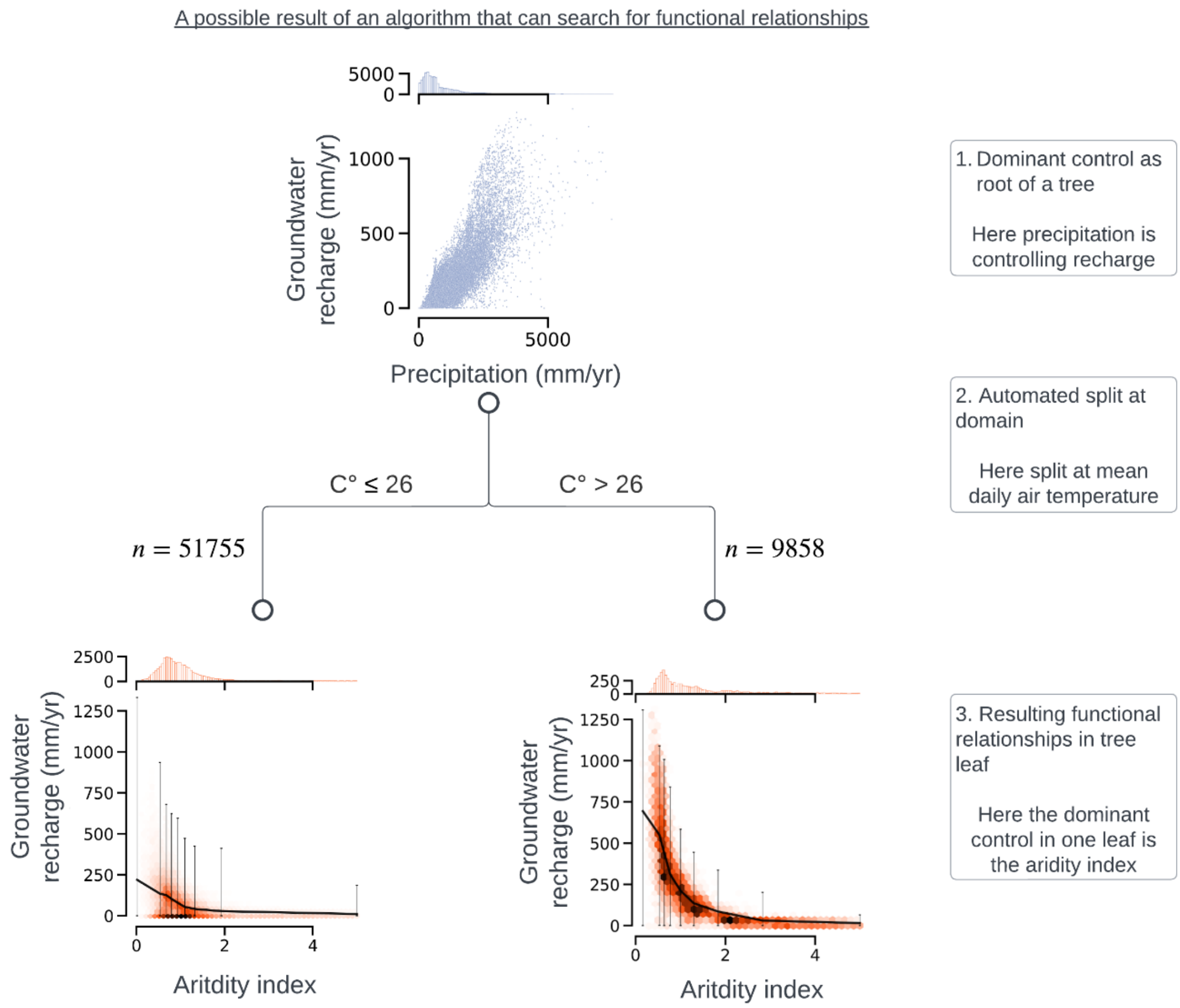

Figure 4: A possible output of a not-yet-existing algorithmic solution to automatically identify functional relationships in large datasets. The relationship is summarized with a black line in the two leaves of the tree. Variable n denotes the number of data points falling into each leaf. Details on the underpinning methodology are in Supplementary Material B. Different choices in how to split the data and how much data is used for a split will likely influence the robustness of the approach.

3. We need to invest in understanding the delta

Digital Twins of the Earth are here to stay. The concept of a digital representation of reality is appealing and already well-established in engineering. Facing increasingly dramatic consequences of global change in the Earth system, it is also necessary to build better modeling systems for early warning of natural disasters, informing data collection and decision-making, and gaining new scientific knowledge. However, the real value of Digital Twins of the Earth depends on how far they are removed from reality and, importantly, on how much we can understand and quantify the difference between the model's behavior and that of the real system. Investing resources to evaluate models will be pivotal in ensuring they serve society best. Finding new ways to explore the incredible amounts of data they produce will be important, e.g., finding and analyzing large-scale functional relationships.

We must also ensure that we use the term Digital Twin carefully and communicate clearly that a model remains a model, and do not convey the wrong message that we do not have to worry about the model's distance from reality. The "reductionist view of nature as a machine" encoded in Digital Twins may erode democratic principles as they may end up being used as political instruments for justification and control (Saltelli et al., 2024). This issue reminds one of the cautionary tale of the map maker in which a ruler in a magical land desires a perfect map (see Figure 5 and Box 1). Such a map is as impossible as a perfect digital representation of reality. Scientists and decision-makers alike should not fall for this fallacy. Decisions and assessments will always be uncertain. With increasing model resolutions and better visualization of outputs, it will get harder and harder not to confuse model outputs with reality. Past studies have already called for clear rules when communicating model outputs for decision-making (Grimm et al., 2020) and uncertainty (Fischhoff & Davis, 2014). Any investment in Digital Twins of the Earth must include investments in methods to ensure their appropriate use – even if the latter is less flashy.

Figure 5: Illustration of the map maker's tale (Carroll, 1893; Borges, 1981; Gaiman, 2006). Our desire for an apparatus that enables us to fully replicate our world reminds us of the mapmaker tale. A perfect map is a perfectly impossible map – or a perfectly impossible model. CC BY-SA 4.0.

Box 1: The map maker's tale is a cautionary story of Digital Twins. Scientists and decision-makers alike should heed this tale as a warning to pursue the Digital Twin of Earth blindly.

The map maker's tale

Retold in various versions (Carroll, 1893; Borges, 1981; Gaiman, 2006), it tells the story of a mighty emperor and his desire to possess a detailed map of his kingdom. So, detailed, it is a 1:1 representation of everything, "revealing the secrets in the deepest seas as well as things beneath the roots of trees" (Gaiman, 2006). Such an immensely powerful and accurate map would be useless, as it would be as complex to understand as the world it represents – a perfect twin.

Digital Twins as impossible maps

Our desire for an apparatus that enables us to replicate our world fully reminds us of the mapmaker tale. A perfect map is a perfectly impossible map – or perfectly impossible model. Like a map, a model's value lies in smartly simplifying our complex reality. Hence, it is always somewhat removed from reality by its pure definition.

Acknowledgements

RR and TW acknowledge support from the Alexander von Humboldt Foundation in the framework of the Alexander von Humboldt Professorship endowed by the German Federal Ministry of Education and Research (BMBF). We further thank the artist Malaika Mack for illustrating the map maker's tale. We licensed the illustration as Creative Commons BY-SA (https://creativecommons.org/licenses/by-sa/4.0) to allow further reuse in the scientific community for talks or lectures.

Supplementary Material

The Supplementary Material can be found online at: https://sesmo.org/article/view/18786/18236.

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