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REVIEW

From Virtual Labs to Real Ecosystems: A Review of Digital Experimental Engineering in Environmental Research

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ABSTRACT

Environmental research is facing increasingly complex, dynamic, and difficult systems to study with only traditional laboratory or field experiments. In this regard, digital experimental engineering has become a promising model for connecting virtual experimentation with real-world ecosystem observation and intervention. This review analyzes how environmental experimentation has evolved to integrate digital systems incorporating sensing networks, simulation platforms, and digital twins, data assimilation, hybrid artificial intelligence, and adaptive control, over the years since traditional virtual laboratories. It integrates the conceptual foundations of the field, its key methodologies and technical architectures, and its applications in climate and atmospheric science, hydrology, soil and agricultural systems, biodiversity and ecosystem ecology, pollution control, and urban environmental management. The review indicates that digital experimental engineering broadens the realm of environmental inquiry by enabling more iterative, scaled, and responsive experimentation, especially in systems where direct manipulation is limited by scale, cost, or risk. Simultaneously, it determines the essential restrictions connected with data asymmetry, model uncertainty, ecological realism, reproducibility, governance, and standardization. The paper presents the argument that the future of digital experimental engineering is not to substitute the traditional experiments, but to restructure the relationship they have with the monitoring, modeling, and decision-making. By contextualising these developments through a single experimental lens, this review explains why the field remains novel, why it is currently maturing, and why it would be important to environmental science and sustainability governance in the future.

Keywords: Digital Experimental Engineering; Digital Twin; Environmental Research; Virtual Laboratories; Ecosystem Management

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1. Introduction

The objects of study are becoming more dynamic, interconnected, and data-rich than ever before, and environmental research is entering a period of such change. Climate change, biodiversity degradation, water insecurity, soil erosion, the transfer of pollution, and coupled human-natural system perturbations can no longer be adequately understood through observations and experiments at individual sites [1,2]. Environmental systems change both spatially and temporally, are influenced by nonlinear interactions, and experience rapidly changing anthropogenic stressors. In such circumstances, traditional experimental paradigms, as basic as they may be, often have severe limitations in controllability, reproducibility, cost, speed, and ecological representativeness. Precision and repeatability can be achieved in laboratory experiments, which often oversimplify real ecosystems. Field experiments are realistic in terms of the environment but are hard to standardise, costly to maintain, and susceptible to uncontrolled variability. Between these two poles of the spectrum, environmental science has long required a more adaptable experimental framework capable of integrating mechanistic knowledge, real-time observation, simulation, and intervention [3–5].

Recent developments in sensing technologies, remote observation platforms, scientific computing, artificial intelligence, cyber-physical systems, and digital twins are beginning to redefine how environmental experiments are conceived and implemented. Researchers can now incorporate models directly into the experimental cycle rather than treating them as an interpretive device after the data have been collected. Virtual laboratories, scenario testing via simulations, real-time data assimilation, autonomous monitoring networks and adaptive decision algorithms are enabling the creation of digitally represented and digitally engineered design experiments. Experimental systems under this new paradigm can be continuously updated over time with new observations and put under various hypothetical stressors, and can be linked to management action in near real time. These features are particularly desirable in environmental research, where predicting system behaviour before instigating expensive or hazardous interventions is of scientific as well as social significance [6–8].

Such a shift can be termed as a move towards virtual laboratories to actual ecosystems. The first virtual environmental science laboratories were mainly intended to simulate processes numerically under controlled assumptions, e.g., watershed hydrology, atmospheric transport, ecosystem productivity or contaminant fate. These virtual worlds enabled sensitivity analysis, scenario comparison, and parameter testing, but tended to be disconnected from the real-time conditions of environmental systems. Modern generation of the digital experimental methods goes beyond the stagnant simulation. Digital systems can more closely replicate, interpret, and even direct real-world ecosystem experiments by combining streams of environmental sensor data, unmanned platforms, geospatial data infrastructure, cloud and edge computing, machine learning, and process-based models. The experimental unit no longer necessarily consists of a bench-scale device or a field plot; it can now be a networked digital-physical system that involves laboratories, observatories, landscapes, and administrative systems [9,10].

The idea of digital experimental engineering is becoming increasingly topical in this context. Digital experimental engineering in this review is the deliberate design, assembly, and use of digital technologies to aid, supplement or partially automate experimental procedures throughout environmental research. It encompasses constructing virtual experimental systems, integrating computational and physical systems, adapting experimentation using real-time feedback, and deploying digital twins and autonomous platforms to study ecosystem behaviour under both observed and simulated conditions. This is a concept that is important to conventional environmental modelling [11]. Modelling is the sole purpose of modelling the behaviour of a system in order to represent or predict it, whereas in digital experimental engineering, the model is embedded in an experimental architecture, with the ability to interact with data, support hypothesis testing, inform measurement strategies, and aid intervention design. It is thus not merely a computational extrapolation from environmental science, but a new methodology for conducting environmental experiments in complex, uncertain, and changing contexts [12].

This shift has been found to be especially relevant in environmental research, as some of the most pressing scientific problems at the moment involve systems that are too large, too heterogeneous, or too sensitive to be directly experimented with using only traditional methods. As an example, river basins cannot be controlled like a laboratory reactor, but with digital twins, in situ sensing, and forecasting models, controlled virtual experiments on nutrient transport or flood risk may be possible. Wetland restoration projects have long timescales and uncertain climatic forcing, yet digital experimental structures have the potential to support the iterative testing of management strategies prior to implementation. Cities and towns, farms and forests, and coastal strips are all becoming more productive sources of dense observational data that can be input into experiment-based digital platforms. This is making environmental experimentation less about isolated measurements and more about dynamic cycles among observation, simulation, prediction, intervention, and validation [13].

Despite related topics having been surveyed in the literature, such as digital twins, smart environmental monitoring, ecological modelling, AI in Earth systems, and cyber-physical infrastructures, most existing reviews are organised by field, technology, or application. Others focus more on virtual simulations, whereas others focus on sensing networks, machine learning tools, or domain-specific case studies such as hydrology, smart agriculture, or atmospheric prediction. What is still largely lacking is a concerted critique that would view these developments as part of a broader shift in experimental paradigms. In particular, there is no synthesis of how environmental research is changing to become digitally assisted analysis, to digitally engineered experimentation, and how this transformation is permitting the creation of closer relationships between virtual testbeds and real ecosystems [14,15].

It is specifically this integrative perspective that makes the current review novel. First, instead of treating virtual labs, digital twins, AI tools, or autonomous sensing systems as distinct technical themes, this article situates them within a single conceptual framework: digital experimental engineering. This framing highlights the logic of experimentation that connects these technologies, how they can be used to generate hypotheses, design an experiment, provide closed-loop control, reduce uncertainty, and intervene in the real ecosystem. Second, the shift from controlled digital to open ecological systems is explicitly discussed in this review. It does not just focus on the advantages of virtual experimentation but also on the scientific and technical needs to translate digital insights into ecosystem-scale knowledge and management. Third, the review will span various environmental areas, such as climate and atmospheric systems, hydrology, soil and agricultural systems, biodiversity and ecosystem ecology, and pollution control. By comparing these domains within the same framework, it becomes feasible to identify common architectures, transferable methods, and cross-cutting issues that may easily be overlooked in expert reviews. Fourth, this paper pays special attention to validation, reproducibility, ecological realism, and standardisation, which are central to developing digital experimental methods but are often underdeveloped in highly technical discourses [16].

Another significant input of this review is that it does not view digital experimental engineering as a technological fad but as a reconfiguration of methods used in environmental science. Experimentation, monitoring, modeling and management have been weakly coupled in a highly sequential fashion in traditional practice. These activities within the emerging paradigm are being incorporated more into ongoing work processes. Models are updated with observations; models are redesigned to sample new evidence; autonomous systems gather evidence; digital platforms assess intervention scenarios; and field outcomes are used to refine the model. This closed-loop form has significant consequences for knowledge production about the environment. It can reduce the time gap between hypothesis and testing, increase the scalability of experiments, and accommodate rapid changes in environmental conditions. Meanwhile, it also raises serious issues of the propagation of uncertainty, blinding in data-driven inference, technological inequality, interoperability, and the danger of misconstruing digital fidelity as ecological truth. The critical review is thus required not only to summarise the progress but also to evaluate the circumstances under which digital experimental engineering may produce robust, actionable and scientifically plausible environmental knowledge [16–18]. The idea is depicted in **Figure 1**, showing how traditional environmental experiments are transformed into digitally integrated, ecosystem-connected experimental engineering.

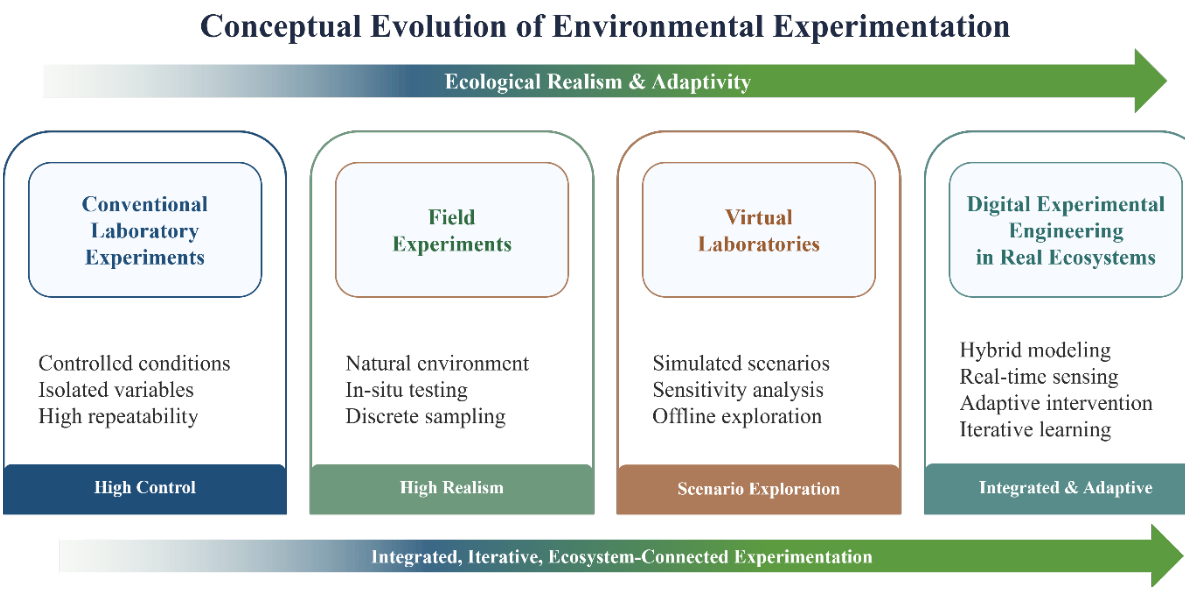

Figure 1. Conceptual evolution of environmental experimentation from conventional laboratory and field approaches to virtual laboratories and ecosystem-connected digital experimental engineering.

In this regard, this paper reviews the conceptual bases, enabling technologies, technical architectures, large-scale applications, and enduring constraints of digital experimental engineering in environmental research. It poses the question: how digital experimental systems are transforming experimentation on scales, what is different about them compared to previous types of virtual modelling, and how they have already demonstrated transformative potential, as well as what obstacles are still limiting their application to real ecosystems. Coupled together through a single framework, the review aims to clarify the current state of the field and to inform a future approach to further methodological development. Finally, the shift from virtual labs to real ecosystems is not simply a matter of more computation in environmental science. It heralds more profound change to smart, adaptive and connected experimental systems that can facilitate the future generation of environmental discovery and stewardship [8,18–20].

2. Conceptual Foundations and Evolution

2.1. From Conventional Experimentation to Digitally Mediated Environmental Research

The two main experimental conditions used in environmental science are the laboratory, where variables can be controlled with high precision, and the field, where this is not possible but ecological realism is maintained. This split has spawned a methodological antagonism over the years. Laboratory experiments are essential to isolating mechanisms, causal relationships, and repeatability, but tend to oversimplify the heterogeneity, stochasticity and cross-scale interactions of environmental systems. Field experiments, in turn, are less realistic but offer a more reliable representation of natural conditions due to their high cost, slow feedback, logistical complexity and replication issues [21]. Often, the systems that most require investigation are watersheds, forests, urban atmospheres, coastal areas or agricultural landscapes, and these cannot be directly manipulated at the scale at which answers to urgent scientific and management problems are needed.

This tension was partially resolved by the development of computational modelling, which created virtual experimental spaces in which environmental processes could be modelled, disturbed, and tested under different conditions. The process-based models, numerical simulators, and subsequent data-driven predictive tools allowed researchers to experiment with circumstances that were either unreachable, unsafe or unaffordable in a real-world setting. These virtual strategies broadened the areas of experimentation and enhanced the ability to conduct a scenario analysis. Nevertheless, the initial forms of digital experimentation were largely not connected to the functioning of real ecosystems. Model calibration was frequently done in retrospect, rarely updated, and used only as an analysis tool rather than as an active element of an experiment. In this regard, digitalisation did not necessarily change the experimental logic of environmental research but rather improved it [22].

The transformation underway is deeper. Digital technologies are not merely post hoc or isolated simulation but a growing part of the very experimental cycle. There is a shift in environmental research toward systems in which sensing, simulation, prediction, control, and validation are coupled in near real time. This transition is the transition of providing experiments with digital assistance to engineering experiments digitally. The difference is significant. A traditional experiment can involve the measurement or analysis of digital tools, but digital experimental engineering reorganizes the research process to involve digital infrastructures in the process of hypothesis formulation, intervention selection, adaptation of measurements and uncertainty treatment. The experimental process is iterative, data-responsive, and increasingly capable of operating in both the virtual and physical worlds.

These convergent factors have led to this evolution. Sensor networks, remote sensing, autonomous platforms and citizen science data streams have provided greater density and continuity in environmental monitoring. Meanwhile, larger and more complex environmental simulations can be updated at higher benefit frequencies as computational resources have become more powerful. Machine learning has also facilitated the fast extraction of features, finding patterns, detecting anomalies, and modeling surrogates, and cloud and edge architectures enable the use of multiple processors in a dynamic environment. All these developments have provided the technical means of experiments, which are no longer preprogrammed but are adjusted as the system of the environment reacts. This flexibility is particularly important in open systems where disturbances, thresholds, and feedback can arise together without prior warning [23–25].

However, this development should not be viewed as merely the digitalisation of traditional experimentation. Instead, it is a continuum of growing methodology. The timeless relevance of field measurements, experimental laboratory studies, and mechanistic reasoning is beyond doubt. The difference is that there is an opportunity to integrate these strategies further within a digitally aligned structure. The conceptual dilemma, then, is not the possibility of digital systems to substitute traditional experimentation, but how to expand it in a manner that does not harm ecological realism, scientific rigour, or interpretability.

2.2. Defining Digital Experimental Engineering in Environmental Research

Digital experimental engineering within environmental research can be seen as the discipline of planning and coordinating digital infrastructures to design, operate, and optimise coupled virtual and real-world experimental processes. It includes virtual lab use, digital twins, cyber-physical systems, adaptive sensing, AI-based decision-making frameworks, and simulation-based intervention plans to support experimental inquiry in complex environmental contexts. It is not the presence of digital technology itself, but the degree to which digital technology can be used as an active constituent of the experimental architecture [26].

This framing differentiates digital experimental engineering from related notions that are often equated. An example of environmental modeling attempts to describe the dynamics of a system and produce predictions, but it is not always an experimental framework unless the outputs of the model are used to design, sequence or adjust measurements and interventions. Smart monitoring systems enhance environmental observations, but monitoring alone is descriptive, except when used to drive a structured hypothesis test or closed-loop experimentation. Digital twins are especially pertinent, as they aim to maintain a dynamic digital analogue of a physical system, although even in this case, the concept has varying definitions. A digital twin can be as basic as a regularly updated model dashboard in other applications; more robust versions enable synchronisation, prediction, optimisation, and operational control. All these notions are overlapped by digital experimental engineering, which focuses on coordinating experimental reasoning among them [27].

Three operational criteria uniquely distinguish digital experimental engineering from related concepts. First, closed-loop experimental agency: the digital system does not merely represent or predict but actively designs, sequences, and adapts experimental treatments based on real-time feedback. Second, hypothesis-testing primacy: predictive accuracy or state awareness serves the goal of causal inference, not as an endpoint. Third, hybrid experimental units: the unit of experimentation becomes a configurable digital-physical assemblage—sensors, models, decision rules, and targeted interventions—rather than a fixed spatial or temporal boundary. Digital twins lacking adaptive intervention logic or hypothesis-driven redesign remain simulation platforms; virtual laboratories without real-time ecosystem coupling remain scenario engines.

This definition is particularly effective in environmental studies since it emphasizes the fact that experimentation does not imply only direct physical manipulation. The corresponding experimental act, typically across a variety of ecological and geophysical settings, can include the design of virtual perturbations, the optimisation of observation schedules, the exploration of alternative management pathways or the adaptation of intervention strategies to evolving system states. An experimental system could be a river basin digital twin that assesses nutrient-reduction scenarios, a wildfire-risk platform that guides adaptive monitoring, an urban climate system that contrasts green-infrastructure interventions across various simulated futures, and so on, when designed for hypothesis testing and evidence generation.

Meanwhile, the concept should be used sparingly. Emerging literature tends to term any digitally enabled environmental workflow as intelligent, autonomous, or experimental. This kind of language may defog weaknesses of methodology. A system that takes in data on the fly is not an experiment; a machine learning model that forecasts ecological variables is not a generator of causal knowledge; and a digital twin that reflects current conditions may not be able to capture the structural uncertainties that are of greatest interest to management. This is why digital experimental engineering does not need to be characterized by technological sophistication but by epistemic role: it needs to play a role in the design, implementation, or interpretation of experiments in a manner that enhances the reliability, flexibility or breadth of environmental investigation.

The notion also calls into question the definition of the experimental unit. In classical designs, the unit can be a sample, reactor, plot or mesocosm. In digital experimental engineering, this unit can be a hybrid configuration of sensors, models, decision rules, control algorithms and partial real-world interventions. This broadened concept enables experimentation at scales that were previously separated. But it also makes validation more complicated, in that success is determined not just by the performance of each component but by the behaviour of the entire system [28–30].

2.3. Evolution from Virtual Laboratories to Ecosystem-Connected Systems

Digital experimentation in environmental science can be considered to follow a developmental path that can be discussed in three general stages. The initial phase was the use of static or semi-static virtual laboratories. These environments offered computational spaces of sensitivity analysis, scenario testing, and theoretical exploration. They were useful for isolating process relationships and minimising the cost of physical experimentation, especially in hydrology, atmospheric science, and biogeochemical modelling. Nevertheless, they were generally loosely tied into the process of environmental change and were common-sense approximations of reality.

The second phase brought the digital models and empirical observation closer together. The use of sensor networks, satellite data, geographic information systems, and automated monitoring platforms enabled more frequent updates of model states and comparisons of simulations to real system behaviour at much finer time resolution. This step was a great advance in calibration and prediction, but most systems were still purely observational. The model feedback was not extensively utilised in the experiments, even though data were incorporated into models. The informed prediction was monitored, but did not always redesign the experiment itself [31].

The third phase, which is now beginning to appear in various fields of the environment, is that which entails feedback-oriented, ecosystem-linked digital systems. In this case, digital infrastructures are not merely reflections of environmental conditions; they are involved in the selection of observation targets, the assessment of intervention alternatives, and adaptive management in the face of uncertainty. Examples of this phase include digitally controlled watershed management systems, ecological restoration systems aided by drone monitoring and predictive algorithms, and urban environmental control systems that employ real-time data to prototype and refine mitigation strategies. It is not real-time data that is important, but the ability to close the loop among observation, simulation, and action.

There are significant scientific implications to this shift of virtual labs to ecosystem-linked systems. It broadens the size and time sensitivity of experimentation, enabling environmental scientists to experiment with hypotheses in changing conditions and not just in fixed designs. It also makes experiments more practical and more directly connected to management decisions. But the nearer these systems approach operational control, the more they must confront the complexity of real ecosystems. In contrast to artificial industrial systems, ecosystems are historically contingent, can only be observed in part, and are generally controlled by processes that are nonlinear, path-dependent and are not well constrained by available data. This implies that the same integration that promises digital experimental systems plunges them into greater depths of uncertainty.

One such crucial aspect, then, is that connectivity to real ecosystems is not necessarily enhancing scientific validity. More coupling can, in other instances, provide an illusion of reality and conceal structural model errors, sensor biases, or unquestioned assumptions in decision algorithms. It is not just a matter of linking digital systems to the environment, but also of ensuring they are scientifically relevant. To ensure successful integration of an ecosystem, scale compatibility, data quality, process representation, and the distinction between prediction accuracy and causal adequacy must be carefully considered. Devoid of this discipline, digital experimentation risks being operationally impressive but epistemologically shallow [32].

3. Major Methodologies and Technical Architectures

3.1. Virtual Experimental Platforms as the First Operational Layer

The most common form of digital experimental engineering in environmental research is virtual experimental platforms, which remain among the most popular methodologies to date. Their essence is to build computational worlds where environmental processes can be simulated with assumptions to enable researchers to test hypotheses, compare scenarios, and conduct sensitivity studies of systems without direct intervention in the physical world. Such platforms have long been used in hydrology, atmospheric science, ecology, and pollution studies to numerically experiment with flow regimes, contaminant transport, vegetation change, species interactions, and land-use change. Their advantage is that they are relatively flexible: they can be tried repeatedly, perturbed, and explored over a wide range of parameters at costs often much lower than those of field campaigns or long-term physical experiments [33].

But the convenience is not the only methodological value of virtual experimental platforms. They offer a formal area where the hypotheses about the environment may be operationalised. Inseparable variables in the field can be varied selectively, rare events can be repeatedly simulated, and management strategies can be evaluated before being implemented. In this regard, virtual platforms are not just analytic tools but structured spaces for experimental reasoning. They are most powerful where there is a scarcity of empirical data, the interventions are risky, and the experimental target is large and slow-moving and thus cannot be manipulated directly. As an illustration, responses of ecosystems to multi-decadal warming, nutrient control strategies at a basin scale, or the propagation of wildfire under alternative weather sequences are more easily studied in a virtual environment than in a purely physical one [34].

However, with these benefits come important limits that must be read. Model structure, parameter assumptions, and data availability are inevitable constraints in virtual experiments. The illusion of rigor of a platform may hide weak foundations of epistemology in cases where the underlying processes are simplified or ill-posed. This becomes especially problematic in environmental systems characterised by threshold effects, emergent interactions, and incompleteness of observability. A virtual medium can be highly internally controllable yet poorly represent ecological reality. Consequently, the usefulness of such platforms is determined less by the level of computational sophistication than by the robustness of the correspondence between simulated processes and the real environmental processes of interest.

Another drawback is that many virtual experimental platforms are not temporally connected to real systems. They can be benchmarked against historical data and have no operational connections or continuous updates to current environmental conditions. The platform is an engine of scenarios in such instances and is not an experimental system. This difference is important because digital experimental engineering increasingly requires non-predictive yet responsive architectures. Thus, although virtual experimental platforms are still considered foundational, their modern-day applicability lies in their integration with real-time observation, adaptive control, and validation workflows. They are not to be their future as isolated digital laboratories, but rather a part of wider experimental ecosystems [35].

3.2. Digital Twins and Synchronized Representations of Environmental Systems

The digital twin is one of the most powerful and controversial concepts of recent methodological advances. A digital twin has a general meaning in environmental research, where a dynamic digital model of a physical environmental system is continually or periodically updated with observed values and used to aid analysis, prediction, and decision-making. A digital twin should have a long-lasting relationship with the physical twin, unlike static models or one-off simulations. It is also thought to be bidirectionally interactive in stronger interpretations, i.e. the digital system not only consumes data about the physical world, but uses it to influence interventions, management actions or adaptive experimental design [36].

The appeal of this architecture is that it formalises the shift of simulation to synchronised experimentation. A digital twin can absorb hydrometeorological data, approximate the system's current state, and predict how the system might respond to changes in reservoir operations or nutrient-reduction policies in watershed studies. Digital twins can be used in urban environmental management, which involves sensor data, atmospheric models, energy use patterns, and land-surface information to assess the interventions on mitigating heat or controlling pollution. The twin concept provides an opportunity to compare alternative pathways for ecosystem restoration under unpredictable climate and land-use conditions and to integrate monitoring feedback.

Digital twins have a scientific potential in three capabilities. The former is state awareness: it enhances knowledge of the existing environmental situation by combining heterogeneous data with mechanistic or hybrid models. The second is anticipatory experimentation: these methods enable virtual testing of interventions under circumstances that remain tied to the existing system states [37]. The third is adaptive learning: with new observations coming in, the digital representation can be recalibrated, uncertainty can be updated, and new experiments can be redesigned. All these characteristics bring environmental experimentation into a more closed-loop format, where hypotheses, predictions, measurements, and interventions are developed iteratively.

This promise is, nevertheless, applied too liberally in the environmental literature, in the sense in which the digital twin is conceptualised. Most systems termed twins are dashboards or forecasting platforms, or loosely decoupled, periodically updated models. Although these systems may still be applicable, they should not be used indiscriminately, as this could lead to overstating methodological maturity. A real-life digital twin must be more than data visualisation or a regular model rerun; it must be a sustained and scientifically significant correspondence between digital and physical conditions, along with model revision and decision-support mechanisms. In its absence, the language of twinning could obscure unresolved issues of data quality, scale incompatibility, process representation, and operational reliability [38].

The other methodological issue arises from the nature of environmental systems. Digital twins were originally introduced in industrial and engineering settings where the boundaries of systems, design parameters and control variables are relatively narrowly defined. Environmental systems are much less cooperative. Boundaries are permeable, system histories are important, disturbances can be exogenous and unpredictable, and much of the dynamics of interest is only partially visible. As a result, environmental digital twins are seldom perfect reflections of reality. They are chosen constructions whose validity is determined by what it has captured, what it has left out and the purpose with which the twin is to be utilized. A twin that is optimized to predict streamflow might not be an appropriate representation of nutrient cycling, another that is optimized to manage urban air quality might not capture social behaviors that determine emissions. The methodological implication is that digital twins are supposed to be designed as experimental infrastructures (purpose-specific) and not ecosystems in general.

The strongest and most emerging twin architectures are hence based on modularity. Rather than making a single, monolithic digital expression, they aggregate interoperable data ingestion, state estimation, process simulation, uncertainty analysis, visualisation, and decision support. This modularity is particularly useful in environmental research, as it enables the architecture to be modified as new data sources, models, or management needs emerge. It also provides clearer opportunities to evaluate critically, as modules can be evaluated individually prior to the integrated system being assessed as an experimental platform [39].

3.3. Data Assimilation, Model Coupling, and Hybrid Intelligence

The methodological essence of digital experimental engineering is not that of a particular model or device, but in the combination of data and models on a scale. The environmental systems produce various sources of information, such as in situ sensor data, lab data, remote sensing data, historical data and citizen data. These sources differ significantly in spatial resolution, temporal frequency, accuracy, and semantic meaning. To convert them into a coherent experimental system, there is a need to have architectures in place with the capabilities for assimilation, harmonisation, and inference [40].

One of the most important means through which this is possible is through data assimilation. Assimilation, in general, can be defined as the process of relating observations to model predictions to estimate the changing state of a system. These methods have long been applied in weather forecasting and hydrological prediction in environmental research, but are now increasingly applied in ecosystems studies, water quality networks, soil systems, and restoration monitoring. They are significant to digital experimental engineering since they transform raw monitoring into operationally significant system updates. Instead of simply archiving new information, the architecture applies it to update its perception of existing conditions and thereby, re-plan future experimental actions.

Intimately connected with assimilation is model coupling. The numerous environmental questions cannot be resolved within one disciplinary model since the processes of interest are in the atmosphere, hydrology, biogeochemistry, vegetation, infrastructure, and human activity. Coupled models are becoming a part of methodological architectures that bridge these domains. To give an example, hydrological, hydraulic, land-surface, and urban infrastructure modules can be needed to perform flood risk experimentation. Precision agriculture platforms can connect soil moisture models, crop growth models, weather forecast and remote sensing observations. Habitat suitability models can be used in conjunction with disturbance dynamics and land-use projections in biodiversity systems. This type of coupling provides more explanatory power, but also more easily introduces error propagation, due to the fact that uncertainty in a single submodel may cause the overall performance to be biased [41,42].

It is due to this that hybrid intelligence has emerged as a significant methodological impetus. By hybrid intelligence here, it is the integration of mechanistic models, statistical inference and machine learning in a single architecture. Purely process based models can be interpretable and causal, but can be computationally costly or inefficient in nonstationary situations. Models based solely on data can be useful in extrapolating more complex relationships but can fail in extrapolation and can be not very informative about the mechanics of the situation. Hybrid systems strive to leverage their advantages. Examples of this strategy include physics-informed neural networks, machine-learned simulations of computationally costly simulations, data-driven emulators that adhere to conservation laws, and using AI to help solve optimization problems.

The most important aspect of hybrid intelligence in the digital experimental engineering is that it enables the experimentation to be responsive and interpretable. Machine learning has the potential to speed up state estimation, anomaly detection, and scenario screening, and the components based on processes can maintain scientific coherence and can reason in a mechanistic way. Integration is not however a success by default. Hybrid architectures may be opaque when machine learning elements take over without any defined boundaries, or brittle when mechanistic assumptions are too strict to adapt to the variability of reality. Systems that optimize the novelty of algorithms are not the most plausible ones, but rather the systems that explicitly specify which tasks are assigned to data-driven elements, which are mechanistically based, and how conflicts between them are addressed.

In terms of methodology, this field requires higher criteria than are typical today. Numerous studies introduce hybrid systems as providing better predictive performance, but provide little discussion of the causal adequacy, transferability, or failure modes. Omissions like these are grave in an experimental context. A well-predicted model in one basin, forest type or urban district may not assist in valid intervention design in another basin. Digital experimental engineering must have architectures to not just accommodate data, but also rationalize the validity of experimental inferences under varying conditions [43].

3.4. Human-in-the-Loop Systems and Autonomous Experimentation

Digital experimental engineering can be described as automation-oriented, but environmental experimentation still relies heavily on human judgment. It is not a transitional problem of technological immaturity, but a structural fact. Environmental systems have conflicting priorities, imprecise observations, changing regulatory environments, and numerous phenomena that cannot be completely represented in formal models. Consequently, methodological architectures are becoming more and more developed not to achieve a complete autonomous working mode, but to the human-in-the-loop system, where expert knowledge and algorithmic adaptation are chosen deliberately [44].

Digital platforms can be used to create candidate experimental designs, detect anomalies, suggest intervention scenarios, or optimise sampling plans, with the plausibility, ethical concerns, and local relevance determined by human researchers or managers in such systems. For example, a restoration site can focus on areas where adaptive monitoring can be implemented through remote sensing and predictive modelling, while field ecologists determine the ecological significance or practicality of proposed locations. A watershed decision system can be used to identify nutrient-reduction strategies with desirable modelled results, but domain experts are needed to determine the social acceptability and hydrological feasibility of these alternatives.

This communication cannot be considered as a flaw of online systems. Instead, the human-in-the-loop design can be considered one of the methodological strengths of environmental digital experimentation, as it helps to avoid the problem of confusing optimization with understanding inherent in the architecture. Human expertise will not only have prior knowledge but also the ability to identify context, novelty, and ambiguity that might not be captured by the system's suppositions. Meanwhile, the digital platform is capable of expanding human reasoning by searching a bigger space of possible scenarios, having a sustained situational awareness, and recording experimental decisions with more uniformity [45].

Another frontier is, nonetheless, the autonomous experimentation. Recent developments in robotics, UAVs, edge AI, and adaptive control enable certain environmental platforms to adapt measurement regimes, deploy sensors on the fly, or activate new observations when a specified condition is detected. Automated laboratory systems are already capable of performing some of the functions of closed-loop experimentation in environmental chemistry and microbial ecology. Event-responsive data collection is increasingly supported in the field by autonomous water samplers, drone-based vegetation surveys, and mobile sensing platforms. They are particularly useful in situations where disturbances are intermittent, temporary, or dangerous, including harmful algal blooms, fires, pollutant spills, or flash floods.

Nonetheless, assertions of independence in the ecological systems should be approached with care. In contrast to industrial automation, environmental autonomy operates in contexts where goals can be unpredictable, and outcomes extend beyond quantifiable performance metrics. A self-directed monitoring system that maximises efficiency can be insensitive to rare, ecologically important states of the ecosystem. A single intervention that prioritises short-term benefits might overlook long-term resilience or equity issues. The methodological question is not whether or not autonomy is possible, but how it is limited, audited, and regulated. Significant environmental independence must then be both discriminatory and responsible; directed toward distinct experimental tasks rather than the extensive replacement of scientific judgment [46].

3.5. Experimental Design in Closed-Loop Digital Environments

One of the biggest shifts in classical approaches to the environment is the design of experiments when digital systems are incorporated into the loop. Conventional designs can pre-determine treatments, controls, sampling schedules and evaluation criteria. Conversely, digital experimental engineering is increasingly aiding adaptive design, where experiments are modified with real-time information. This can involve the dynamic allocation of sampling effort, sequential testing of intervention options, or an iterative refinement of model ensembles as new evidence comes in.

This flexibility comes in handy more so in open systems and uncertain systems. Environmental disturbances are often irregular, system responses may be nonlinear, and the most informative sampling events may not be known in advance. This can be addressed by closed-loop architectures that can update priorities as the system evolves. A river monitoring network could enhance sampling during a period of rapidly increasing flow. A soil management platform can adjust the timing of interventions in response to changes in the weather forecast. With a biodiversity monitoring system, drone surveys can be redistributed to regions with the greatest uncertainty in the model. They are not just technical modulations; they are a radically new experimental logic where information value formulates design on an ongoing basis [47].

The change brings about methodological advantages, as well as emerging threats. Adaptive design can make it more efficient and relevant, but it also makes inference more challenging, since the experiment does not have a predetermined course. Statistical assumptions constructed for static designs are not always applicable to experiments where data collection is based on past model outputs. Premature convergence is also a risk, as the system is too narrow in its consideration of currently popular hypotheses and fails to consider alternative explanations. In this regard, closed-loop experimentation should not be undertaken merely to exploit known information, but also to explore uncertainty.

The most promising strategies, hence, are based on the Bayesian design, reinforcement learning, active learning, and decision-theoretic frameworks but are tailored to the constraints of the environment. These techniques can institutionalise trade-offs among the cost of measurement, the reduction of uncertainty, and the risk of intervention. However, their success depends heavily on the validity of the previous assumptions and objective functions. This is a challenge in the environmental context where values and outcomes tend to be multidimensional. A design of a good experiment cannot be simplified to information gain only, but it should also take into consideration ecological, operational, feasible and societal implications [48].

3.6. Interoperability, Platforms, and Reproducible Infrastructures

There is no digital experimental architecture that can be effectively implemented without having a strong interoperability infrastructure. Environmental research generally entails disaggregated data formats, heterogeneous software ecosystems, field-specific standards, and institutional impediments to sharing. This fragmentation hinders the ability to integrate sensors, models, and decision tools, and, in most cases, experimental systems cannot be scaled beyond pilot demonstrations. Consequently, interoperability has become a methodological issue rather than a technical add-on.

Interoperability has a number of levels. At the data level, systems need to have common semantics, metadata standards and machine-readable provenance to enable observations across the sources to be effectively integrated. Interoperability at the model level requires interfaces that enable components to communicate their states, parameters, and uncertainty representations without extensive manual reengineering. At the platform layer, it needs architectures that can integrate cloud computing, edge devices, visualisation tools, and user control layers. Such requirements are particularly critical for environmental digital twins and closed-loop systems, where latency, synchronisation, and version control directly affect the reliability of an experiment [49].

The close relation is with reproducibility. Digital infrastructures can enable saving workflows, storing a history of decisions, and revealing parameter settings more transparently than most traditional environmental experiments. Containerised workflows, versioned data pipelines, executable notebooks, and open model repositories facilitate this. However, code availability is not the only issue in the reproducibility of digital experimental engineering. Since systems are dynamic and can be based on streaming data, reproducibility also requires retaining the context of decisions, data availability states, and model versions that informed the experiment at each point in time. In this regard, auditability cannot be dissociated from reproducibility.

One of the most important lessons is that the level of infrastructure maturity can be as much a determinant of scientific believability as algorithmic sophistication. Numerous proof-of-concept studies show new ways of integrating, but only a small number of systems are constructed that are maintainable, interpretable, and transferable to other sites. In the absence of interoperable and reproducible infrastructure, digital experimental engineering would be just a set of customised case studies rather than a consistent approach to environmental science [50,51].

4. Applications in Environmental Research

4.1. Climate and Atmospheric Systems

One of the first and most impactful areas in which digital experimental engineering has emerged is climate and atmospheric research. This is partly because atmospheric systems are inherently difficult to control, and their dynamics are highly sensitive to scale, boundary conditions, and coupled feedbacks. Numerical modelling and data assimilation have been long-standing quasi-experimental techniques in weather and climate science. The current shift is the growing accessibility of these tools to adaptive, digitally mediated experimental systems that bridge the testing of virtual scenarios with continuous Earth observation, automated forecasting, and intervention-oriented decision support [52].

Digital experimentation can be particularly useful in climate research, since the systems of interest operate on time scales beyond the capabilities of typical field studies. Physical space cannot be experimentally simulated to replicate planetary climate under alternative greenhouse gas pathways. Still, digital platforms enable scenario comparisons, perturb model structures, and test hypotheses about sensitivity, tipping behaviour, and regional impacts. These abilities were the mainstay of climate science. Still, the recent developments in remote sensing, high-performance computing, and AI-enhanced emulation have enabled climate-oriented experimentation to become more iterative and operational. More and more climate models are no longer just long-range projection devices but also elements of an experimental architecture that can take in observational data, incorporate uncertainty distributions, and produce regionally specific stress tests for use in adaptation planning [53].

A good illustration of the shift in the approach to passive modelling toward digitally engineered experimentation is provided by atmospheric applications. More and more air quality systems are using in situ sensors, satellite retrievals, transport models, and machine learning to assess interventions to control emissions, predict pollution episodes, and experiment with the likely outcomes of regulatory scenarios. The systems could serve as experimental platforms for testing various mitigation measures under varying meteorological conditions and then implementing them in the real world. Digital experimentation has also been at the centre of heat island investigations in urban settings, with models connected to geospatial information and sensor networks being tested to assess alternative greening, shading, and built-environment changes.

However, the effectiveness of such applications must not blind one to their methodological deficiencies. Climate and atmospheric digital experiments have a long history of high computational maturity, and face long-standing issues of scale mismatch and structural uncertainty. Global and regional climate models can credibly model broad trends, but they still cannot reliably capture local ecological or social implications for intervention design. Air quality systems can provide precise short-term predictions but may be less effective at identifying causal sources in rapidly shifting emission regimes. This implies that digital experimental engineering in the climate and atmospheric sciences is highly advanced in predictive power, yet unbalanced in its capacity to support fine-grained causal inference and locally based management decisions. The field shows the strength of digital experimentation at scale and indicates how challenging it is to actionize large-system simulations into ecosystem-specific action [54,55].

4.2. Water, Hydrology, and Aquatic Environments

One particularly promising area of digital experimental engineering has been hydrology and aquatic environmental research, as it is a field with a strong tradition of measurement and one that urgently requires it. Examples of such dynamic environments include river basins, lakes, wetlands, reservoirs, groundwater systems, and coastal waters, where direct experimentation is often challenging, costly, and socially limited. Meanwhile, these systems are becoming increasingly effective at producing dense observational data through gauging networks, remote sensing, autonomous sampling, and water quality monitoring. This combination makes them well-suited to experimental architectures that combine real-time data, predictive models, and adaptive control [56].

Digital experimental systems are currently used in watershed science to study the effects of flood forecasting, sediment transport, reservoir operations, nutrient cycling, and land use on watersheds under various conditions. Online systems enable scientists to explore the effects of changes in precipitation regimes, infrastructure, or management options that are too dangerous or unethical to implement on a large scale without pre-testing. These systems get even closer to the digital twin model when paired with live data streams, as they enable the persistence of state estimation and decision-based scenario testing. The latter types of architectures are particularly useful when hydrological extremes are rising due to climate change, and the cost of management failure is high.

Another valuable advantage of digital experimentation, as demonstrated by water quality research, is the ability to combine mechanistic and adaptive approaches. There are complex interactions among flow conditions, drivers of eutrophication, biogeochemical responses, contaminant transport, land-use drivers, and episodic events. Conventional sampling is not always able to capture this variability, particularly when it occurs in critical, albeit short-lived, disturbances. This can be overcome using digital systems, which involve continuous monitoring, event-driven sampling, predictive alerting, and model-directed observation design. This brings about a more responsive form of experimentation where measurements are focused on where and when most informative [57].

Additional examples of the shift toward experimenting with ecosystems connected to virtual analysis include wetland and coastal systems. The restoration work in these environments is usually characterised by uncertainties of hydrologic controls, vegetation feedbacks, nutrient processes, and long-term resilience to sea-level rise or sediment supply changes. Digital experimental architectures can compare restoration options, measure the sensitivity of ecosystem trajectories, and dynamically update forecasts as field observations are gathered. In this regard, they not only enable analysis but also continuous experimental stewardship.

Nevertheless, some of the most challenging issues in the area are also revealed in water-related applications. Boundary assumptions, missing inputs, and unresolved subsurface or biochemical processes are particularly known to cause hydrological and aquatic systems to be notorious. Digital infrastructures can develop a sense of operational confidence that is not necessarily accompanied by epistemic depth. As an illustration, a watershed management site can have great success with streamflow forecasting yet be poor at reflecting nutrient retention or the quality of ecological habitat. In the same way, online management of reservoirs can be optimised for flood reduction or water provision, but may underestimate downstream ecological impacts. These two demonstrations are part of a larger point: the success of applications often depends on which system functionality is emphasised, and inadvertent digitally engineered experimentation can reduce the questions the environment poses. In water, therefore, the actual problem lies not so much in the incorporation of information and models, but in the sustainability of plural and ecologically significant goals in the experimental design [41,58–60].

4.3. Soil, Agriculture, and Biogeochemical Systems

Soil and agricultural systems occupy a significant intermediate position between the complexity of open ecosystems and the control afforded by experimental procedures. They are more amenable to intervention than regional climate or watershed systems, but are highly diverse and sensitive to local history, management, and environmental variability. This renders them particularly applicable to digital experimental engineering, which has the potential to bridge plot-scale measurements, landscape observations, mechanistic models and management decision-making in adaptive contexts [60].

Precision management has come to the fore of digital experimentation in agricultural research. Fertiliser regimes, irrigation, machine vision, crop growth models, and soil moisture forecasting are all now being united to test their combinatorics. Such systems can be operational experiments in which treatment can be manipulated in response to changing field conditions rather than being predetermined. The potential advantages are significant: it is possible to optimise inputs, increase resource efficiency, and reduce environmental externalities. On a larger scale, sustainable intensification, climate adaptation, and agroecosystem resilience are also experimented with using such architectures.

The area of soil systems is very rich but methodologically challenging. Microbial processes, carbon and nutrient cycling, structure, hydrological exchange, and plant interactions occur across the microscale to the landscape scale in soil. Classical experiments are useful in mechanistic terms but have limited applicability to sites. Digital platforms can provide a solution to this by bringing together heterogeneous data and allowing testing of scenarios over a broader range of spatial scales. In the context of soil carbon studies, such as digital experiments, it can be used to compare land management approaches, investigate model sensitivities, and test the sensitivity of estimates to climatic and biological uncertainties. They can also know when and where interventions are most effective in minimising losses, while maintaining productivity in nutrient management [61].

One of the strongest cases supporting digital experimental engineering is biogeochemical applications, which allow relating processes that are experimentally separable but theoretically inseparable in practice. Carbon, nitrogen, phosphorus, water, and biological activity are closely interconnected, and management activities often create unintended changes in the system elsewhere. Digitally integrated experiments can better reveal such interactions than siloed field trials, particularly those that use mechanistic models with observational updates. They are also able to extrapolate experimental logic over longer periods, which is of great use for legacy effects, recovery curves, and gradual biophysical change.

However, these applications also showcase how easily digital systems can make themselves seem certain. Agricultural platforms tend to be most effective in fairly well-instrumented, highly managed environments, which, again, may not reflect the variety of agroecosystems around the world. Tuned or weakly observed parameters can be used to create detailed soil models. In precision agriculture, there is also a tendency to prioritise the optimisation of yields or input efficiency over broader ecological concerns, such as supporting biodiversity, long-term soil health or socio-environmental equity. Consequently, digital experimental engineering needs to be evaluated critically with respect to performance in the context of soil and agriculture, as well as the values that the systems under optimisation entail. This technology is strong in that its scientific and social value lies in whether it contributes to objectively sustainable experimentation or rather to a more sophisticated manipulation of aspects of production [62].

4.4. Biodiversity, Ecosystem Ecology, and Conservation

Some of the most conceptually ambitious and methodologically challenging uses of digital experimental engineering are applications in biodiversity science and ecosystem ecology. Biodiversity and ecosystem interactions are high-dimensional, partially observable, contingent on history, and highly context-dependent, unlike hydrological or agricultural systems, where many variables are measurable at any point in time and can be associated with relatively well-known process models. The abiotic conditions are not only important for species responses but also for interspecific interactions, behavioural adaptations, dispersal constraints, and disturbance regimes, which are hard to formalise. This is why digital experimentation in this field has been developed more unevenly, but its potential is quite significant [63].

Habitat and landscape modelling used in conservation planning is a significant area of application. The use of digital systems is increasingly focused on remote sensing and spatial ecology, species occurrence data, and climate projections to experiment with the consequences of fragmentation, land-use change, restoration interventions, and protected area design. The platforms enable conservation practitioners to compare potential management approaches before implementation and to focus monitoring efforts on areas of uncertainty or greatest risk to the ecosystem. Digital experimentation in restoration ecology can be used to assess the probability of different planting patterns, hydrological manipulations, or disturbance mitigation strategies that support target species and ecosystem processes under future conditions [64].

The other significant advancement is in automated biodiversity surveillance. Biodiversity monitoring is also being reshaped by camera traps, acoustic sensors, eDNA pipelines, and drone-based ecological surveys, which produce far more data with much higher temporal resolution than is possible with traditional field methods alone. Once these streams of data are connected to predictive models and adaptive observation strategies, they start to enable digitally mediated experimentation. In the case of intensity monitoring, a shift in focus can be made to areas of intense change, new species discoveries or regions where competing ecological hypotheses are at variance. This introduces a more active association between observation and deduction than traditional monitoring programs typically achieve.

The broader ecosystem ecology also benefits from digital experimental systems that connect process knowledge to scale. Architectures involving flux towers, lidar, satellite products, growth models, and disturbance simulations now enable studies of forest systems to understand carbon dynamics, drought stress, fire vulnerability, and regeneration pathways. The same argument can be made concerning grasslands, coastal ecosystems and urban ecological networks. In both instances, digital experimentation broadens the ability to test other futures and to measure ecosystem responses to complex, interacting stressors [65,66].

Nevertheless, biodiversity and ecological applications also uncover certain inmost epistemic issues in digital experimental engineering. Most of the ecological variables of greatest interest, such as resilience, functional diversity, trophic stability, and adaptive capacity, cannot be observed directly or easily converted into simple measures. This leads to the common use of digital systems that rely on proxies, which may not fully represent ecological reality. Distribution patterns, e.g., may be predicted by a habitat suitability surface, without accounting for the processes that maintain viable populations. A restoration model can be optimal with respect to vegetation cover but lacking in community composition or ecosystem functions. The risk remains that digital experimentation in ecology will be most influential in the simplest-to-quantify systems, rather than in those that pose the most important questions [67,68].

This indicates that full automation or high-confidence prediction may not be the actual contribution of digital experimental engineering to biodiversity science, but rather, the organization of how to cope with uncertainty. Most useful systems in this field will probably be those that assist in detecting knowledge gaps, directing adaptive monitoring, and assessing plausible ways to intervene, rather than purporting to have complete control over the complexity of the ecological system. Digital experimentation can significantly reinforce conservation science, yet it must be clear of the boundaries of representation in the living, dynamic ecosystems.

4.5. Pollution Control, Urban Environments, and Socio-Environmental Systems

One of the most conspicuous and practically significant applications of digital experimental engineering is now urban and pollution-related applications. The reason is that cities and industrial-environmental interfaces are highly instrumented, policy-relevant and changing rapidly. They provide a setting where sensing, computation, management, and intervention can be more directly connected than in most natural ecosystems, yet with much greater environmental complexity. This has seen the implementation of digital experimental systems to test the impacts of air pollution reduction, wastewater treatment, solid waste management, urban heat reduction, green infrastructure performance, and contaminant risk pathways.

One area that has already matured as an application is air pollution control. Digital systems combine sensor data, atmospheric dispersion models, emission inventories, and machine learning to predict pollution episodes and experiment with the probable consequences of control policies. These are especially useful when interventions can be modelled as alternative emission scenarios and assessed before implementation. Process monitoring, anomaly detection, and model-based optimisation are also being developed for digitally engineered experimentation in the industrial and wastewater settings. Such systems may assist adaptive control of performance in treatment and aid in detecting the pathways of contaminants that would otherwise be hard to detect through manual experimentation alone [69,70].

This is not based on pollution alone, but rather an extension of this logic to urban environmental systems. City digital twins are becoming more integrated with land-surface, mobility, infrastructure, environmental sensor, and climatic data to experiment with interventions such as street tree placement, cool roofing, stormwater design, and traffic control. These architectures are also touted as means of transitioning to sustainability due to their ability to explore alternative futures under changing climatic and demographic conditions. They can also, in theory, facilitate more participatory environmental governance by making trade-offs visible and enabling comparisons of policy options.

The most important aspect of these applications is that they lie at the crossroads of environmental processes and human decision-making systems. In contrast to a distant ecosystem digital twin, an urban environmental platform is frequently a direct input to regulatory decisions, planning goals, and civic services. This provides digital experimentation with a particularly social-technical aspect. The response of a system is not the sole focus of the experiment, but the possibility, acceptability, and distributional implications of an intervention pathway.

At that, the socio-environmental applications reveal that technical success is insufficient. Urban digital experiments can be streamlined towards the variables that are most readily quantifiable, such as traffic flows, surface temperatures, pollutant concentrations, and factors of vulnerability, justice, informal land use, or behaviour change, while overshooting the factors of vulnerability, justice, informal land use, or behaviour change. Pollution control systems can provide incentives to focus on compliance measures, without measuring cumulative exposure burdens or ecosystem-wide impacts. Digital experimental engineering in such contexts can end up supporting constrained governance logics if the architecture is structured around administrative convenience rather than environmental complexity. The question of whether cities can be digitalised into an experimental space is thus not crucial, but rather whose interests are coded into the models, goals, and rules of control that organise experimentation [71].

5. Challenges, Limitations, and Emerging Trends

5.1. Scientific and Technical Challenges in Digitally Engineered Environmental Experimentation

Although rapidly evolving, the field of digital experimental engineering in environmental research is constrained by a complex of scientific and technical challenges that extend beyond implementation issues. Such difficulties stem from the nature of environmental systems themselves: they are heterogeneous, nonlinear, historically contingent, and only partially visible. In contrast to rigidly regulated industrial systems, ecosystems will not offer steady limits, all measurable state variables, and general operating principles. This means that the digital architectures designed to model and experiment with these systems must initially operate with incomplete knowledge [72].

Among the most intractable problems are those related to data. The digital systems found in the environment are often described as data-rich, but this is an extremely uneven characterisation. Certain variables are measured continuously at a high resolution, whereas others are sparsely measured or not at all. The data streams can vary in size, rate, precision, and semantics, making them challenging to integrate even before commencing interpretation. Remote sensing can offer extensive spatial resolution but may not capture subsurface, biochemical, or ecological processes that are central to experimental inquiries. Temporal continuity can be provided by in situ sensors, which are usually not uniformly distributed and are prone to calibration drift, failure, or maintenance lapses. Consequently, there can be a pretence of plenty of data alongside dire informational blindness. It is not only the absence of data, but also a disproportion in the types of environmental reality that are brought to light in digital form.

Such an asymmetry influences the construction of models. Process-based, statistical, or hybrid models are commonly used in digital experimental systems to convert raw observations into an actionable, represented form. But any such models are selective. They anticipate certain processes, simplify others or omit them, and the omissions are seldom neutral. A hydrological platform that is fine-tuned to forecast streamflow may not be a good reflection of nutrient retention or habitat dynamics. A biodiversity system can be used to monitor species presence without considering interaction networks or evolutionary adaptation. This selectivity cannot be avoided even with very complex digital twins, since the environmental world is far more than can be completely encoded in a practical model. Therefore, it is not so much a scientific problem to make models more realistic as to determine which simplifications are admissible for a given experimental objective. This must be methodological clarity that is yet unbalanced in the literature [29,73].

Another significant limitation is the computational burden. Digital experimentation (real-time or near-real-time) necessitates repeated ingestion of heterogeneous data, repeated state estimate updates, scenario generation, uncertainty propagation, and visualisation or control functions, often controlled or displayed to a human user. When systems are spatially large, process-rich or tightly-coupled across domains, these operations can become extremely demanding. Some of these barriers have been minimised by high-performance computing and cloud infrastructure, though they remain. Many systems in practice alleviate this tension by substituting complex mechanistic representations with reduced-order models or emulators, or machine learning surrogates. Although it is faster to operate, it can simply shift the burden of computational tractability onto interpretability and reliability. The more responsive a system is to digital, the more likely it is that the slickness of the technical work will mask the methodological shortcuts.

Synchronisation is another technical challenge. Digital experimental engineering often aims to preserve a continuous relationship between the state of the environment and its digital model. However, open systems that rely on delayed, incomplete or measured observations at incompatible scales are hard to synchronise. An example of a digital twin of a wetland is one that can update hydrological states quickly, whereas vegetation dynamics or microbial processes change more slowly and are only indirectly measured. Equally, urban ecological systems can combine traffic and weather information in real time, but cannot detect behavioural and institutional changes that alter emission patterns. When this happens, the digital system might seem synchronised, but in fact only a fraction of the relevant dynamics is being refreshed. It poses a danger of spurious contemporaneity, in which the architecture is designed to convince decision-makers that the digital representation is more accurate than the real state of the system [74,75].

These technical and scientific problems illustrate a larger argument: that digital experimental engineering is successful not because of the accumulation of new data, higher speeds, or a more connected world, but because it addresses the mismatch between what is measurable and what must be known. The discipline is thus restricted not so much by the lack of computational tools as by the challenge of constructing scientifically plausible digital models amid deep environmental uncertainty.

5.2. Experimental and Epistemic Limitations

In addition to technical issues, digital experimental engineering faces a set of experimental and epistemic constraints that make it a more challenging source of environmental knowledge. Of the most significant of these is the correlation between prediction and understanding. Numerous digitally mediated systems can impressively perform forecasting, classification, or optimisation for such tasks, particularly when well-endowed with dense observational data and capable of flexible learning. Nonetheless, good predictive accuracy does not imply strong causal knowledge. Environmental research does not rely solely on the ability to anticipate outcomes; it is also about discovering mechanisms, distinguishing drivers from correlations, and assessing whether the results can be extrapolated to settings beyond the study [76].

This is important because digital systems can create an illusion of explanatory power through operational effectiveness. A model can accurately predict the occurrence of a harmful algal bloom or urban heat intensity without sufficiently describing the interacting ecological or social mechanisms that produce these effects. When this model is subsequently applied to the design of interventions, it might aid in making short-term, locally successful decisions, but it is weak in the face of changed circumstances. In this respect, digital experimental engineering may sometimes maximise action before gaining understanding. Such an order is not necessarily inappropriate, especially in the context of urgent management; however, it transforms the epistemic level of the acquired knowledge.

The second constraint concerns ecological realism. Digital experimentation has been defended as a bridge between the controlled analysis of virtual environments and the complexity of real ecosystems. The bridge is not symmetrical, however. Digital systems introduce ecological variability into the experimental process, yet they also reorganise that variability into a form that can be processed by computation. The processes are discretised, the monitored variables have priority over the unobservable ones, and the behaviour of an ecosystem is mapped onto the state variables, thresholds, and response functions. These changes are not only needed but also imply that the digital environment can never be an objective reflection of ecological reality. The more complicated the system, the more consequential this translation is. Some of the most crucial dimensions of system change may be hard to formalise or even manifest in the digital architecture in biodiversity, restoration, and socio-ecological contexts in particular [77,78].

Even experimental control is limited in aspects that cannot be eradicated by digital integration. Experimental rigour is typically linked with repeatability and control of variables in laboratory science. Such conditions are seldom allowed in environmental systems. Even closed-loop digital systems, which are adaptive redesigns of measurements and interventions, remain embedded in contexts where weather anomalies, historical legacies, species movement, or human activities cause uncontrollable perturbations. It implies that digital experimental engineering can broaden the range of experimentation without fully addressing the classical question of causality in open systems. In other instances, adaptive digital design can go so far as to make inference even more complex, since interventions and measurements are adjusted based on the system's past state. The experiment becomes smarter and smarter, as well as more contextually sensitive, yet path-dependent [79].

Reproducibility can, in principle, be enhanced by digital infrastructures through storing code, data pipelines, and decision histories. However, adaptive environmental experiments tend to generate paths that depend on real-time measurements and site factors. Two experiments constructed using the same architecture can be very different since they experience different environmental histories. This implies that the reproducibility of digital environmental experimentation does not necessarily imply precise repeatability. Rather, it might require being perceived as procedural transparency, traceability of adaptation and comparability of reasoning in the face of changing conditions. The issue is that such a reframing has not been entirely standardised within the field of environmental science, and it remains uncertain how digitally adaptive experiments ought to be measured with respect to conventional standards of rigour [80].

The last epistemic constraint is the scale transfer. Numerous digital systems perform well within the environments in which they were designed to operate, but are less resilient when transferred across regions, ecosystems, or governance environments. This is not a technical implementation issue but a structural issue. There are variations in environmental systems in terms of data infrastructure, institutional capacity, process dominance, and regimes of disturbance. An effective digital platform within a single agricultural region, watershed or city might be based on local assumptions that are not apparent until it is transferred to a different area. Digital experimental engineering, thus, may tend to be more demonstrative than generalising. The maturity of the field will also depend in part on the ability to develop architectures and validation strategies that are not an afterthought regarding transferability [81,82].

5.3. Governance, Ethics, and Standardisation

As digital experimental engineering becomes increasingly relevant in real-world environmental management, governance and ethics are inseparable from its issues. This is especially the case in areas where online platforms shape the choices of the populace, resource distribution, restoration policies or regulatory measures. The ecological implications of these systems are never strictly technical. Still, they are determined by the values that have been coded, the risks that are prioritised, and the knowledge that is counted in the experimental process.

One of the governance concerns is ownership and access to the data. The digital systems used to monitor the environment typically rely on data from public agencies, private infrastructure, research institutions, and community monitoring efforts. However, these data are hardly ever regulated within a single framework. Some are open, others proprietary, and even those sensitive because of land rights, ecological protection or commercial interests. The imbalanced access to data can thus generate the imbalanced access to experimentation. Properly endowed areas or facilities may be capable of building more sophisticated digital twins and adaptive experimental ecosystems, whereas others may have only fragmented or low-resolution systems. This poses a risk of making digital experimental engineering a means of reinforcing existing disparities in environmental knowledge production and management capacity [83].

Another significant issue is algorithmic transparency. With the growing role of machine learning and hybrid intelligence in digital experimental architectures, users find it increasingly difficult to understand how outputs are produced, on which assumptions they are based, and in which contexts they are most prone to fail. Opacity is not just a technical inconvenience in the context of environmental decisions. It affects accountability. If a digital system suggests a restoration plan, pollutant control measure, or adaptive sampling regime that is subsequently harmful or ineffective, no blame can be placed on it unless the system's logic is subject to examination. The explainability requirement is thus not explicable in terms of user trust; it is part of the environmental governance ethical infrastructure.

The matter is further complicated by social-environmental systems, in which digital experimentation affects communities in various ways. Urban environmental forums, such as those, can maximise interventions based on the reduction of heat or the efficiency of mobility or the reduction of emissions without considering the distributional effects across neighbourhoods. Conservation digital systems can be landscape or species-focused based on modelled ecological significance, without sufficiently accounting for local livelihoods, cultural values, and land tenure realities. The ethical issue in such instances is not merely bias in its technical sense, but the constriction of environmental thought to variables accessible through digital expression. Governance should go beyond merely ensuring equity in data and algorithms to encompass how inclusiveness is determined in what constitutes a desirable experimental result.

One of the most pressing practical needs is standardisation. Currently, there is a broad set of systems in the field known as virtual labs, digital twins, smart observatories, autonomous platforms, or AI-assisted experimental systems, and there is a lack of clear differentiation of architectures or functions. This theoretical slackness renders comparison challenging, and it can overstate maturity. Environmental studies should have higher standards for terminology, reporting, validation, and interoperability, as well as for uncertainty communication. In the absence of such standards, it is difficult to determine whether a particular system is actually performing digitally engineered experimentation or merely reformulating traditional modelling and monitoring in new terms [84].

Publication quality and cumulative science also need to be standardised. Research based on SCI standards increasingly requires the ability to reproduce results in a repeatable workflow, transparency of the models used, uncertainty estimates, and a strict separation between prediction and causal inference. However, most studies in this field continue to focus on system structure and case-specific performance, but few report on the failure modes, assumptions or constraints of transfer. Mature field needs not only spectacular case studies but also well-drilled reporting cultures that enable the comparison, reuse, and critique of architectures. Governance and standardisation are not marginal issues in this regard; they are the preconditions for the long-term validity of digital experimental engineering.

5.4. Emerging Trends and Future Directions

Besides these issues, indications of a new wave of conceptual and technical growth of digital experimental engineering are emerging. There is an increasing trend of incorporating foundation-scale AI and scientific machine learning into workflows in the environmental domain. Such systems offer more flexible representation learning, enhance multimodal fusion, and better handle sparse, heterogeneous data. Ideally, they would help close the gap in the disjointedness that has traditionally plagued environmental digital systems. For example, models trained at scale on remote sensing, sensor data, textual metadata, and environmental simulations can be used to generate more adaptive hypotheses, identify anomalies, or generate scenarios.

But this is not only a computational importance of this tendency. When designed thoughtfully, AI systems can transform the digital environmental experimentation process for fixed pipelines into more exploratory and responsive forms of scientific support. They may aid in the discovery of informative areas of uncertainty, suggest candidate interventions or create reduced-order models of complex systems for rapid screening in experiments. However, they also escalate the issues of obscurity, overgeneralization, and latent bias. They will be useful only to the extent that they are incorporated into architectures that retain interpretability and domain accountability, and are not used as general-purpose solution engines [85]. The relationship between current limitations and emerging future directions is synthesised in **Figure 2**.

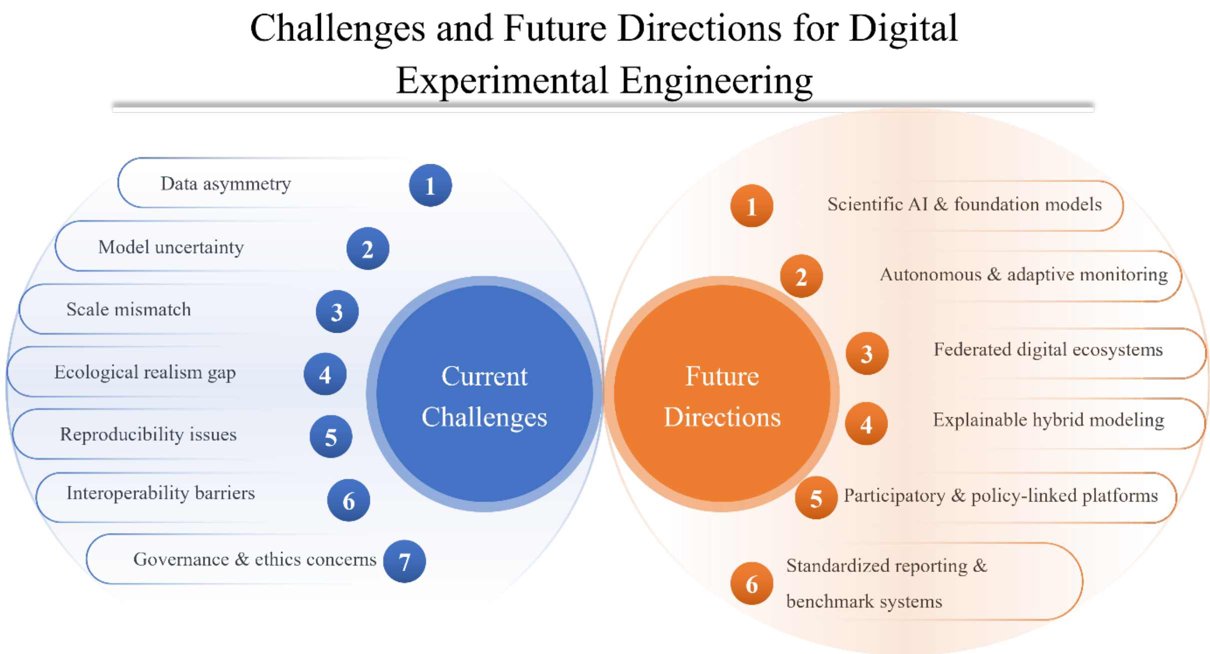

Figure 2. Schematic summary of the challenges and emerging future directions in digital experimental engineering for environmental research.

The second direction in the development is selective autonomy in field experimentation. Incremental innovations in robotics, edge computing, drone systems, and autonomous sensing are gradually enabling environmental platforms that can adjust data-collection strategies without human command. This is particularly crucial for episodic or risky phenomena such as floods, wildfire smoke, or contaminant spills, or fast-changing disturbances in an ecosystem. Adaptive deployment of sensors, event-driven sample collection, or real-time reconfigurating observational networks may eventually be part of autonomous environmental exploration. However, it is not likely that human researchers will be completely replaced in the future; rather, more advanced forms of human-machine interaction will emerge, with routine adaptation automated and strategic interpretation human-directed [86].

The third trend is a shift towards federated and distributed digital ecosystems. Rather than constructing one centralised twin or platform to a particular environmental domain, the future architectures can be composed of more interconnected yet somewhat independent modules that would be active between and among institutions, regions, and scales. This would enable more robust and scalable experimentation, particularly in cases where data cannot be centrally stored because of governance, privacy, or infrastructural limitations. Federated approaches are of particular interest in environmental research, as they reflect the distributed nature of ecosystems and offer an opportunity to retain local specificity. These systems can facilitate cross-site experimentation between sites without necessarily imposing complete homogeneity of data and models.

Another growing interest is to combine digital experimentation with process-facing and participatory processes. The previous stages of environmental digitalization tended to concentrate on the tools that are applicable by the experts behind the scenes. New systems are more apt to interface with the planners, managers, communities, and regulators. This has the potential to expand the applicability of digital experimental engineering by further streamlining the applicability of scenario testing, uncertainty exploration, and intervention trade-offs to a wider range of stakeholders. Simultaneously, it makes communication more stakes. To be deliberative, environmental digital systems will have to represent their uncertainty, assumptions and limitations in ways that can be deliberated over, not just in ways that present technical outputs [87].

Lastly, there seems to be a shift in the field towards more clearly acknowledging that effective digital experimental engineering needs to be purpose-oriented, as opposed to technology-oriented. Initial excitement tended to focus on the newness of digital twins, AI, or autonomous monitoring as objectives. The subsequent step will probably be more rigorous with an emphasis on what combination of tools should be implemented in different environmental questions, scales, and governance situations. This maturation is significant as indiscriminate digitization is not rewarded by environmental systems. They reward architectures that are capable of being both adaptive, without becoming opaque, integrated, without becoming brittle, and operationally useful, without losing scientific credibility.

The issues and further directions mentioned in this part indicate that the field of digital experimental engineering can be viewed as an area that is in the process of shifting towards possibility to discipline. The fact that it promises is a fact. It increases the size, sensitivity, and integrative capacity of environmental experimentation in ways not possible with traditional methods. It enables closer interaction between virtual and real systems, enables adaptive intervention design and creates new avenues in dealing with environmental complexity that are becoming more rapidly changing.

Meanwhile, the drawbacks of the field are also crucial to consider. The data are not evenly distributed, the models are not comprehensive, causal inferences are difficult, and ecological realism is not fully represented in digital versions. Governance and ethics are not selections but systemic factors that determine what these systems are justified in doing. The standardization is not finished yet, and much of the existing literature is not as critical in its approach as technical construction [88].

6. Conclusion

Digital experimental engineering is becoming an important methodological shift in environmental research. As demonstrated in this review, the field is part of a broader movement towards more integrated, ecosystem-connected experimental networks that include sensing, modelling, simulation, prediction, and adaptive intervention. This change does not rest solely on the introduction of more sophisticated computational tools into current workflows. Instead, it is a reorganisation of how environmental experiments are conceived, carried out and assessed in the context of complex, open and highly dynamic systems.

Among the key lessons of this review is that the notion of digital experimental engineering cannot be perceived as a technology but rather as an experimental architecture. There are virtual experimental platforms, data assimilation frameworks, autonomous observation networks, human-in-the-loop decision environments, and hybrid AI model systems that contribute to this architecture in various ways. They are united by the fact that they enable more iterative and responsive relations among observation and inference, testing scenarios and environmental reality, and scientific knowledge and environmental action. These methods extend the limits of experimentation in climate science, hydrology, soil and agricultural systems, biodiversity research, pollution control, and urban environmental management beyond what can be done solely with traditional laboratory and field techniques.

Meanwhile, this review has highlighted that the emergence of digital experimental engineering is not even and conceptually immature. The claims of synchronisation, scalability, and adaptability are part of its appeal, but these aspects also pose serious limitations for the field. Environmental systems can only be viewed in part; model structures will be selective, and ecological processes can be too large to be represented on digital platforms. Operational usefulness does not necessarily confer scientific strength, and predictive success does not necessarily confer causal understanding. The closer digital systems get to real-world management, the more urgent the questions of uncertainty, validation, transparency, and transferability become.

Another significant point of the review is that the most significant challenges are not technical. Standardisation, ethics, and governance will be at the forefront in ensuring that digital experimental engineering grows into a valid and generalised scientific model. The field is at risk of being split into loosely related case studies and overstretched claims without a clearer definition, stronger interoperability standards, reproducible workflows, and more transparent reporting of assumptions and uncertainties. Similarly, when digitally mediated experimentation favours only the easiest-to-measure or optimise variables, it could make environmental knowledge shallower rather than more profound. To keep the field on course, the future of the field is a critical balance: prediction and explanation, responsiveness and interpretability, automation and expert judgment, and technological ambition and ecological realism.

Another finding of this review is that digital experimental engineering will probably be of the most use not where it tries to substitute conventional experimentation, but where it builds upon it and reconfigures it. Lab experiments, field observations over time, manipulations or controlled manipulations, and knowledge of the domain still cannot be done away with in anchoring environmental knowledge. The true power of digital systems lies in their ability to bridge these types of evidence at scale, accelerate adaptive learning, and enable experimentation in settings where direct manipulation is not possible or is prohibitively expensive and hazardous. This way, digital experimental engineering can be regarded as a complement, rather than a substitute for, existing scientific practice.

In the future, the discipline will become an increasingly significant contribution to the sustainability science and environmental governance. As climate risk increases, ecosystems will become more unstable, and management decisions will become more uncertain, faster, more integrative, and more operationally relevant. Experimental systems that are faster, more integrative, and more operationally relevant will be in high demand. This will likely be hastened by scientific AI, distributed sensing, the development of autonomous monitoring, and federated digital infrastructures. Nonetheless, the extent of their success will be determined by whether they or embedded in scientifically disciplined and socially responsible frameworks.

To sum up, the shift to the real world enabled by virtual labs represents a significant change in the experimental horizon of environmental studies. Digital experimental engineering provides an avenue to a more adaptive, scalable, and interconnected way of inquiry, with the potential to connect environmental observation, simulation, intervention and decision-making in ways never seen before. Whether it will be of long-term importance will hinge not just on technical advancement, but also on whether the field can establish its epistemological underpinnings, address its constraints candidly, and establish criteria that enable digital experimentation to be scientifically sound and environmentally worthy.

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References

[1] Smith, P., Calvin, K., Nkem, J., et al., 2020. Which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertification? Global Change Biology. 26(3), 1532–1575.

[2] Fu, B., Wu, X., Wang, Z., et al., 2022. Coupling human and natural systems for sustainability: Experiences from China's Loess Plateau. Earth System Dynamics. 13(2), 795–808.

[3] Shakibamanesh, A., Ghorbanian, M., Dehkordi, A.R., et al., 2024. A Review of the Emerging Urban Laboratory Ecosystem: Emphasizing the Role

of Virtual Reality Laboratories in Smart Development. Journal of Architecture and Urban Planning. 17(45).

[4] Potkonjak, V., Gardner, M., Callaghan, V., et al., 2016. Virtual laboratories for education in science, technology, and engineering: A review. Computers & Education. 95, 309–327.

[5] Perera, D., Abunada, Z., AlQabany, A., 2024. Coupled human and natural systems: A novel framework for complexity management. Sustainability. 16(22), 9661.

[6] Breitling, D., 2024. Virtual Laboratories: Mesocosms and Gameworlds. Theory of Science/Teorie Vedy. 46(2).

[7] Vidyalakshmi, G., Gopikrishnan, S., Boulila, W., et al., 2025. Digital twins and cyber-physical systems: A new frontier in computer modeling. Computer Modeling in Engineering & Sciences. 143(1), 51–113.

[8] Mihai, S., Yaqoob, M., Hung, D.V., et al., 2022. Digital twins: A survey on enabling technologies, challenges, trends and future prospects. IEEE Communications Surveys & Tutorials. 24(4), 2255–2291.

[9] Tsihouridis, C., Vavougios, D., Batsila, M., et al., 2019. The optimum equilibrium when using experiments in teaching–Where virtual and real labs stand in science and engineering teaching practice. International Journal of Emerging Technologies in Learning (iJET). 14(23), 67–84.

[10] Ramasundaram, V., Grunwald, S., Mangeot, A., et al., 2005. Development of an environmental virtual field laboratory. Computers & Education. 45(1), 21–34.

[11] Antony, J., 2023. Design of Experiments for Engineers and Scientists. Elsevier: Amsterdam, The Netherlands.

[12] Prabhu, G.R.D., Urban, P.L., 2020. Elevating chemistry research with a modern electronics toolkit. Chemical Reviews. 120(17), 9482–9553.

[13] Yang, Y., Xie, C., Fan, Z., et al., 2024. Digital twinning of river basins towards full-scale, sustainable and equitable water management and disaster mitigation. npj Natural Hazards. 1(1), 43.

[14] Barker, M., Olabarriaga, S.D., Wilkins-Diehr, N., et al., 2019. The global impact of science gateways, virtual research environments and virtual laboratories. Future Generation Computer Systems. 95, 240–248.

[15] Dede, C., Grotzer, T.A., Kamarainen, A., et al., 2017. EcoXPT: Designing for deeper learning through experimentation in an immersive virtual ecosystem. Journal of Educational Technology & Society. 20(4), 166–178.

[16] Adibi, S., Rajabifard, A., Shojaei, D., et al., 2024. Enhancing healthcare through sensor-enabled digital twins in smart environments: A comprehensive analysis. Sensors. 24(9), 2793.

[17] Mohanraj, R., Balaji, S.N., 2025. Digital Twin Technology: A Comprehensive Review of Modeling, Applications, Challenges and Future Directions in Complex System Integration. Archives of Computational Methods in Engineering. 33(3), 3291–3316.

[18] Sajadieh, S.M.M., Noh, S.D., 2025. From simulation to autonomy: Reviews of the integration of artificial intelligence and digital twins. International Journal of Precision Engineering and Manufacturing-Green Technology. 12(5), 1597–1628.

[19] Mazzetto, S., 2024. Integrating emerging technologies with digital twins for heritage building conservation: an interdisciplinary approach with expert insights and bibliometric analysis. Heritage. 7(11), 6432–6479.

[20] Omrany, H., Al-Obaidi, K.M., Husain, A., et al., 2023. Digital twins in the construction industry: a comprehensive review of current implementations, enabling technologies, and future directions. Sustainability. 15(14), 10908.

[21] Fraser, L.H., Henry, H.A.L., Carlyle, C.N., et al., 2013. Coordinated distributed experiments: an emerging tool for testing global hypotheses in ecology and environmental science. Frontiers in Ecology and the Environment. 11(3), 147–155.

[22] Clark, J.S., Gelfand, A.E., 2006. A future for models and data in environmental science. Trends in Ecology & Evolution. 21(7), 375–380.

[23] Eberhardt, L., Thomas, J., 1991. Designing environmental field studies. Ecological Monographs. 61(1), 53–73.

[24] Teutenberg, T., 2025. Laboratory of the Future: Building the Digital Transformation. John Wiley & Sons: Hoboken, NJ, USA.

[25] Makhmudova, D.M., Tadjibaeva, R., 2025. From data to discovery: The growing influence of digitization in technical sciences. In AIP Conference Proceedings. AIP Publishing LLC: Melville, NY, USA.

[26] Newton, P., Frantzeskaki, N., 2021. Creating a national urban research and development platform for advancing urban experimentation. Sustainability. 13(2), 530.

[27] Piras, G., Agostinelli, S., Muzi, F., 2024. Digital twin framework for built environment: a review of key enablers. Energies. 17(2), 436.

[28] Rocca, R., Rosa, P., Sassanelli, C., et al., 2020. Integrating virtual reality and digital twin in circular economy practices: A laboratory application case. Sustainability. 12(6), 2286.

[29] Negahban, A., 2024. Simulation in engineering education: The transition from physical experimentation to digital immersive simulated environments. Simulation. 100(7), 695–708.

[30] Berlato, M., Binni, L., Durmus, D., et al., 2025. Digital platforms for the built environment: A systematic review across sectors and scales. Buildings. 15(14), 2432.

[31] Roda-Sanchez, L., Cirillo, F., Solmaz, G., et al., 2023. Building a smart campus digital twin: System, analytics, and lessons learned from a real-world project. IEEE Internet of Things Journal. 11(3), 4614–4627.

[32] Janeliukstis, R., Chen, X., 2021. Review of digital image correlation application to large-scale composite structure testing. Composite Structures. 271, 114143.

[33] Petersen, A.C., 2012. Simulating Nature: A Philosophical Study of Computer-Simulation Uncertainties and Their Role in Climate Science and Policy Advice. CRC Press: Boca Raton, FL, USA.

[34] Winsberg, E., 2003. Simulated experiments: Methodology for a virtual world. Philosophy of Science. 70(1), 105–125.

[35] Dooley, K., 2017. Simulation research methods. The Blackwell Companion to Organizations. 2017, 829–848.

[36] Li, X., Feng, M., Ran, Y., et al., 2023. Big Data in Earth system science and progress towards a digital twin. Nature Reviews Earth & Environment. 4(5), 319–332.

[37] Botín-Sanabria, D.M., Mihaita, A.-S., Peimbert-García, R.E., et al., 2022. Digital twin technology challenges and applications: A comprehensive review. Remote Sensing. 14(6), 1335.

[38] Rothe, D., 2024. When the world is an object: on the governmental promise of a digital twin earth. International Political Sociology. 18(3), olae022.

[39] de Wilde de Ligny, S., van Geldere, S., Schäfer, M.T., et al., 2025. There is no such thing as a digital twin: Deconstructing sociotechnical imaginaries of digital twin technologies in Dutch urban governance. New Media & Society. 27(8), 4420–4442.

[40] Gouveia, C., Fonseca, A., Câmara, A., et al., 2004. Promoting the use of environmental data collected by concerned citizens through information and communication technologies. Journal of Environmental Management. 71(2), 135–154.

[41] Chen, J., Chen, S., Fu, R., et al., 2022. Remote sensing big data for water environment monitoring: Current status, challenges, and future prospects. Earth's Future. 10(2), e2021EF002289.

[42] Karagiannopoulou, A., Tsertou, A., Tsimiklis, G., et al., 2022. Data fusion in earth observation and the role of citizen as a sensor: A scoping review of applications, methods and future trends. Remote Sensing. 14(5), 1263.

[43] Havlik, D., Schade, S., Sabeur, Z.A., et al., 2011. From sensor to observation web with environmental enablers in the future internet. Sensors. 11(4), 3874–3907.

[44] Bianchini, M., Maffei, S., 2020. Facing the Fourth Industrial Revolution: empowering (human) design agency and capabilities through experimental learning. Strategic Design Research Journal. 13(1), 72–91.

[45] Arnold, S.M., Ricks, T.M., 2026. Integrated Computational Materials Engineering (ICME) Capability Maturity Levels for Ecosystems Enabling Digital Transformation. National Aeronautics and Space Administration: Washington, DC, USA.

[46] Schoitsch, E., 2021. Trustworthy smart autonomous systems-of-systems–resilient technology, economy and society. In Proceedings of the 29th Interdisciplinary Information Management Talks (IDMIT), Kutná Hora, Czech Republic, 1–3 September 2021.

[47] Cetiner, S.M., Muhlheim, M.D., Flanagan, G.F., et al., 2014. Development of an Automated Decision-Making Tool for Supervisory Control System. Oak Ridge National Laboratory (ORNL): Oak Ridge, TN, USA.

[48] Veiga, T., Renoux, J., 2023. From reactive to active sensing: A survey on information gathering in decision-theoretic planning. ACM Computing Surveys. 55(13s), 1–22.

[49] Akbari, S., 2025. The Role of Digital Tools in Enhancing Transparency and Accountability in Urban Governance: A Conceptual Overview and Early Findings. SSRN Electronic Journal. DOI: https://doi.org/10.2139/ssrn.5374009

[50] Rashid, M., Gani, G., 2025. Reimagining the future of sustainable agriculture in South Asia: Integrating ecological resilience, technological innovation, and inclusive policy reform for transformative agri-systems. In Precision Agriculture and Climate-Re-

silient Farming: Artificial Intelligence, IoT, and Blockchain for Sustainable Agriculture. Deep Science Publishing: Fresno, CA, USA. pp. 118–135.
[51] Ogunkunbi, G.A., 2023. Criteria for Effective Urban Vehicle Access Regulations: An Environmental Perspective. Budapest University of Technology and Economics: Budapest, Hungary.
[52] Muller, C.L., Chapman, L., Johnston, S., et al., 2015. Crowdsourcing for climate and atmospheric sciences: current status and future potential. International Journal of Climatology. 35(11), 3185–3203.
[53] Belter, C.W., Seidel, D.J., 2013. A bibliometric analysis of climate engineering research. Wiley Interdisciplinary Reviews: Climate Change. 4(5), 417–427.
[54] Yadav, A., 2023. A Review: Technological Innovations in Climate Science. Climatology. 174.
[55] National Academies of Sciences, Engineering, and Medicine, 2023. Opportunities and Challenges for Digital Twins in Atmospheric and Climate Sciences. The National Academies Press: Washington, DC, USA.
[56] Tauro, F., Selker, J., van de Giesen, N., et al., 2018. Measurements and observations in the XXI century (MOXXI): Innovation and multi-disciplinarity to sense the hydrological cycle. Hydrological Sciences Journal. 63(2), 169–196.
[57] Vogel, R.M., Lall, U., Cai, X., et al., 2015. Hydrology: The interdisciplinary science of water. Water Resources Research. 51(6), 4409–4430.
[58] Sun, A.Y., Scanlon, B.R., 2019. How can Big Data and machine learning benefit environment and water management: A survey of methods, applications, and future directions. Environmental Research Letters. 14(7), 073001.
[59] Acharya, B.S., Bhandari, M., Bandini, F., et al., 2021. Unmanned aerial vehicles in hydrology and water management: Applications, challenges, and perspectives. Water Resources Research. 57(11), e2021WR029925.
[60] Haag, D., Matschonat, G., 2001. Limitations of controlled experimental systems as models for natural systems: A conceptual assessment of experimental practices in biogeochemistry and soil science. Science of the Total Environment. 277(1–3), 199–216.
[61] Turner, B.L., 2021. Soil as an archetype of complexity: A systems approach to improve insights, learning, and management of coupled biogeochemical processes and environmental externalities. Soil Systems. 5(3), 39.
[62] Smith, P., Cotrufo, M.F., Rumpel, C., et al., 2015. Biogeochemical cycles and biodiversity as key drivers of ecosystem services provided by soils. Soil. 1(2), 665–685.
[63] Westerlaken, M., 2024. Digital twins and the digital logics of biodiversity. Social Studies of Science. 54(4), 575–597.
[64] Caldararu, S., Rolo, V., Stocker, B.D., et al., 2023. Ideas and perspectives: Beyond model evaluation–combining experiments and models to advance terrestrial ecosystem science. Biogeosciences. 20(17), 3637–3649.
[65] Pringle, S., Davies, Z.G., Goddard, M.A., et al., 2023. Robotics and Automated Systems for Environmental Sustainability: Monitoring Terrestrial Biodiversity. UK-RAS Network: London, UK.
[66] Adebayo, A.S., 2025. AI driven species recognition and digital systematics: Applying artificial intelligence for automated organism classification in ecological and environmental monitoring. International Journal of Research Publication and Reviews. 6(2), 31–49.
[67] Ramani, D.R., Kalaiarasan, K., Tangade, S., 2025. Remote Monitoring Advancements: A New Approach to Biodiversity Conservation. Environmental Monitoring Using Artificial Intelligence. 2025, 61–69.
[68] Savage, D., 2022. Ecological and Economic Frameworks for Biodiversity Monitoring. Purdue University: West Lafayette, IN, USA.
[69] Musters, C., De Graaf, H., Ter Keurs, W., 1998. Defining socio-environmental systems for sustainable development. Ecological Economics. 26(3), 243–258.
[70] Rossinskaya, M.V., Tsvetcova, S.N., Rokotyanskaya, V.V., et al., 2018. Management of the socio-ecological and economic systems functioning in a single information space. Revista Espacios. 39(27).
[71] Farias, A., Mendonça, F., 2022. The Urban Environmental System perspective on socio-environmental risks of urban flooding. Sociedade & Natureza. 34, e63717.
[72] Lea-Smith, D.J., Hassard, F., Coulon, F., et al., 2025. Engineering biology applications for environmental solutions: potential and challenges. Nature Communications. 16(1), 3538.
[73] Voulvoulis, N., Burgman, M.A., 2019. The contrasting roles of science and technology in environmental challenges. Critical Reviews in Environmental Science and Technology. 49(12),

1079–1106.
[74] National Academies of Sciences, 2019. Environmental Engineering for the 21st Century: Addressing Grand Challenges. National Academies Press: Washington, DC, USA.
[75] May, D., Terkowsky, C., Varney, V., et al., 2023. Online laboratories in higher engineering education–solutions, challenges, and future directions from a pedagogical perspective. Taylor & Francis. 2023, 779–782.
[76] Willard, J., Jia, X., Xu, S., et al., 2022. Integrating scientific knowledge with machine learning for engineering and environmental systems. ACM Computing Surveys. 55(4), 1–37.
[77] Huvila, I., 2006. The Ecology of Information Work: A Case Study of Bridging Archaeological Work and Virtual Reality Based Knowledge Organisation. Åbo Akademis Förlag–Åbo Akademi University Press: Turku, Finland.
[78] Rive, P.B., 2012. Design in a Virtual Innovation Ecology: A Cybernetic Systems Approach to Knowledge Creation and Design Collaboration in Second Life. Open Access Te Herenga Waka–Victoria University of Wellington: Wellington, New Zealand.
[79] Sahle, M., Melaku, A., 2025. Digital and emerging technologies to evaluate and restore socio-ecological production landscapes and seascapes: A systematic review. GeoJournal. 90(6), 291.
[80] Hitz, G., Galceran, E., Garneau, M.-È., et al., 2017. Adaptive continuous-space informative path planning for online environmental monitoring. Journal of Field Robotics. 34(8), 1427–1449.
[81] Richter, B.D., Warner, A.T., Meyer, J.L., et al., 2006. A collaborative and adaptive process for developing environmental flow recommendations. River Research and Applications. 22(3), 297–318.
[82] Wang, Y., Yang, X., Liang, H., et al., 2018. A review of the self-adaptive traffic signal control system based on future traffic environment. Journal of Advanced Transportation. 2018(1), 1096123.
[83] Mollen, J., 2024. Towards a research ethics of real-world experimentation with emerging technology. Journal of Responsible Technology. 20, 100098.
[84] Seager, T., Selinger, E., Wiek, A., 2012. Sustainable engineering science for resolving wicked problems. Journal of Agricultural and Environmental Ethics. 25(4), 467–484.
[85] Wang, S., Xie, X., Li, Y., et al., 2024. Research on the spatial data intelligent foundation model. arXiv preprint. arXiv:2405.19730.
[86] Iranshahi, K., Brun, J., Arnold, T., et al., 2025. Digital twins: Recent advances and future directions in engineering fields. Intelligent Systems with Applications. 26, 200516.
[87] Huang, H., Lu, J., Jin, L., et al., 2024. The future of environmental engineering technology: a disruptive innovation perspective. Engineering. 41, 153–160.
[88] Tan, W., Wu, S., Li, Y., et al., 2025. Digital twins' application for geotechnical engineering: A review of current status and future directions in China. Applied Sciences. 15(15), 8229.