Do digital twins need people? Integration of the human dimension into digital twins of the natural environment

Sandeep Dhakal[1], Hazel Parry[1*], Yayong Li[2], Barton Loechel[3], and Peyman Moghadam[2,4]

[1] CSIRO Agriculture and Food, Ecosciences Precinct, Brisbane, Queensland, Australia
[2] CSIRO Data61, Queensland Centre for Advanced Technologies, Brisbane, Queensland, Australia
[3] CSIRO Environment, Ecosciences Precinct, Brisbane, Queensland, Australia
[4] Queensland University of Technology, School of Engineering & Robotics, Brisbane, Queensland, Australia

Abstract

Digital Twins (DTs) are dynamic digital representations of physical objects and systems, including their associated processes and environments. Using real-time data analytics, modelling, simulation and 'what-if' scenarios, they can enable valuable understanding and decision-support for managing a system. One potential application of DTs is the management of natural landscapes. However, despite the critical impact of humans on the natural environment, none of the DTs of the natural environment found in the literature include the human systems in that environment. We propose a modular framework for integrating human systems within a DT of the natural environment, to facilitate simulation and modelling of a range of management contexts, objectives and stakeholders across time and space. We then propose four principles as the theoretical basis for modelling the socio-ecological governance systems that underpin DTs of human systems for managing the natural environment. We also provide a use case related to area-wide integrated pest management as an example of the potential application of the proposed framework for collectively managing the natural landscape. The composition and characteristics of this use case as a DT and examples of user engagement at multiple spatial and temporal scales are also described. Finally, we identify some methods such as agent-based modelling, reinforcement learning, and graph neural networks that could be used to incorporate human systems in a DT, along with some examples of their use for similar tasks from the literature. Integrating human systems in DTs of the natural environment will facilitate the development of novel digital decision-support tools that provide stakeholders with different perspectives of the shared natural environment and enable them to understand the impact of various management methods and actions.

Keywords

Digital Twins; modelling human systems; natural landscape management; sustainability; socio-ecological systems

1. Introduction

Digital Twins (DTs) are dynamic virtual representations of actual physical objects or systems (natural, or synthetic) across multiple stages of their lifecycle (Jones et al., 2020). The DT paradigm, in addition to the DT itself, interweaves solutions and technologies for complex system analysis, decision support, and technology integration.

The general principle of the DT paradigm is that there should be a tight coupling between the physical and the virtual counterparts, with varying degrees of two-way communication between them. Kritzinger et al. (2018)

Correspondence:
Contact H. Parry at Hazel.Parry@csiro.au

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differentiated a 'digital twin' from a 'digital model' and a 'digital shadow'. While all are digital representations of a physical object, a 'digital model' lacks any automated data exchange between the physical and digital objects; a 'digital shadow' features only a one-way data flow from the physical to the digital object; and a 'digital twin' has fully integrated data flow between them. With the wider adoption of DTs outside of the original domains, DTs with different levels of coupling of the real and virtual entities have been proposed in both academia and industry. Verdouw et al. (2021) defined a typology of six, potentially overlapping, categories of DTs based on their usage, namely imaginary, monitoring, predictive, prescriptive, autonomous, and recollection DTs.

1.1 Digital twins for managing the natural environment

The popularity and success of DTs in the industrial production and manufacturing domains for optimising the operation of complex processes and human-made objects has led to an increased interest in the development of DTs of the natural environment (Blair, 2021; Verdouw et al., 2021). The utility of the DT paradigm in existing domains indicates that it holds the potential to aid informed decision-making and management of the natural environment. In addition to improving the understanding of the associated processes and interactions in the natural environment, DTs can also help us simulate and understand different management actions, interventions, and their impact on the environment.

The design and development of DTs of the natural environment presents several challenges. While mechanistic modelling is required for reflecting the dynamics of both natural systems and human-made objects, the limited availability of comprehensive data for all components of the natural environment necessitates a much higher degree of reliance on mechanistic modelling. However, capturing and modelling the dynamic nature of the living physical systems, including their uncertainties and idiosyncrasies, is a difficult task. It is also challenging to capture the bidirectional flow of information and feedback among the various components in natural systems that generally exhibit slower responses to events and actions compared to human-made physical systems. Another major challenge is the integration of the complex inter-relationship of the natural environment with the human systems that are an integral part of many natural environments (social, cultural, economic, etc.) as part of the DT.

In the context of managing the natural environment, DTs are most likely to be used for monitoring the environment, predicting the future states of the environment, suggesting management actions and interventions (a prescriptive DT, following the typology of Verdouw et al. (2021)), as well as limited automation (see Figure 1). At the same time, based on Kritzinger et al. (2018), such DTs could be categorised somewhere between a 'digital shadow' and a 'digital twin'.

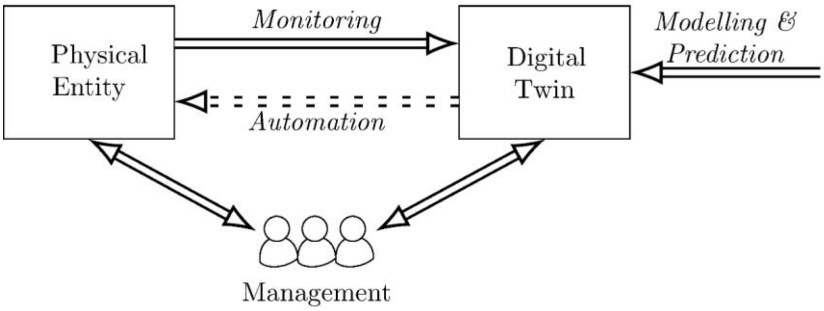

Figure 1: Digital twin usages for the management of the natural environment.

DTs have been proposed for different aspects of the natural environment, such as earth systems (Bauer et al., 2021; Knibbe et al., 2022; Koning et al., 2023), oceans (Lilja Bye et al., 2022), forests (Buonocore et al., 2022; Nita, 2021), water systems (Chen et al., 2023; J. Park & Yang, 2020; Qiu et al., 2022), and agriculture (Alves et al., 2023; Moshrefzadeh et al., 2020), among others. As is evident from these examples, the scale of these DTs ranges from local farms to regional and supraregional environments. It should also be noted that the vast majority of these DTs are in the early maturity stages (based on the DT maturity stages presented in Uhlenkamp et al. (2022)), with most ranging from architecture or framework proposal to early prototypes (see Supplementary Material).

1.2 Inclusion of the human dimension

The increasing dominance of humans over several aspects of the natural environment means that humans are both driving, and adapting to, changes in the natural environment (Calvin & Bond-Lamberty, 2018; Motesharrei et al., 2016; Palmer & Smith, 2014). Hence, when modelling any natural environment that exhibits strong, intricate inter-relationships with the human systems, particularly in relation to its management, it is imperative to model the feedback between these systems. Consequently, any DT of the natural environment that does not include the human systems that are crucial to its management is essentially incomplete. Given the dynamic, evolving, and often uncertain nature of the human-environment relationship, it is also insufficient to merely include the human dimension in the form of exogenous input to the DTs. Instead, the human systems must be modelled as fundamental components of the DTs of the natural environment, to enable modelling of the impact of human actions on the natural environment and *vice versa*.

However, to our knowledge, none of the existing DTs of the natural environment (regardless of their maturity), model the human systems within that landscape. Humans, in various capacities, are only proposed as interfacing with the DTs for managing the natural environment. This is also true for DTs of the built environment (e.g. cities) with only a few exceptions such as Castelli et al. (2019), Fan et al. (2021) and Xu et al. (2022). Among the proposed DTs of the natural environment, Bauer et al. (2021) have discussed the inclusion of the human systems in the form of greenhouse gas emissions, pollution, land-cover change or water management. Nevertheless, discussions or frameworks for how to include the human systems as part of the DTs of the natural environment are still lacking from the literature.

This position paper attempts to fill this gap in the literature and discusses how we can take the first steps towards integrating human systems within DTs of the natural environment. Towards this end, we first propose a general framework that addresses where and how models of human systems fit within a DT of the natural environment. Then, we propose four key principles that can be applied to model the human systems in the form of socio-ecological governance systems for managing the natural environment. Finally, we propose agent-based modelling and simulation (ABMS) as one of the most suitable methods for implementing the proposed framework, along with identifying some machine learning (ML) methods that could be used to complement ABMS in this task.

2. The proposed framework

2.1 A modular approach

In most cases, the natural environment can be considered as being composed of three broad components: the geophysical environment, the biosphere within that environment, and the human systems. The DT of a natural environment can, thus, be composed of the corresponding sub-DTs: the geophysical, biophysical, and human systems (social, cultural, economic, etc.) as shown in Figure 2. These sub-DTs will essentially be a highly integrated and dynamic collection of models (either mechanistic or data-driven) corresponding to different aspects of that component. The number of such models and their complexity, as well as the complexity of the overall DT architecture, will depend on the natural environment that is being digitally mirrored and the objectives of the DT. Often, data-driven and mechanistic models will complement each other with higher reliance on mechanistic models when observation data are limited and higher reliance on data-driven models as more real-time data becomes available.

The geophysical DT will predominantly be created or updated from observations and measurements of the inanimate systems of the Earth. The biosphere is likely to be represented through a combination of various data sources for the measurable and quantifiable components, and through mechanistic models for the more dynamic and complex living systems. These two layers will form the foundation upon which the human systems of the natural environment will be represented. The human systems will most likely be represented through a combination of mechanistic and data-driven models; however, many aspects will increasingly be measurable in real-time, such as footfall data, economic transactions, social media, etc. (Birks et al., 2020; Ravid & Aharon-Gutman, 2023). The DT will also integrate human expertise in the form of domain knowledge, management options, and contextual scenarios.

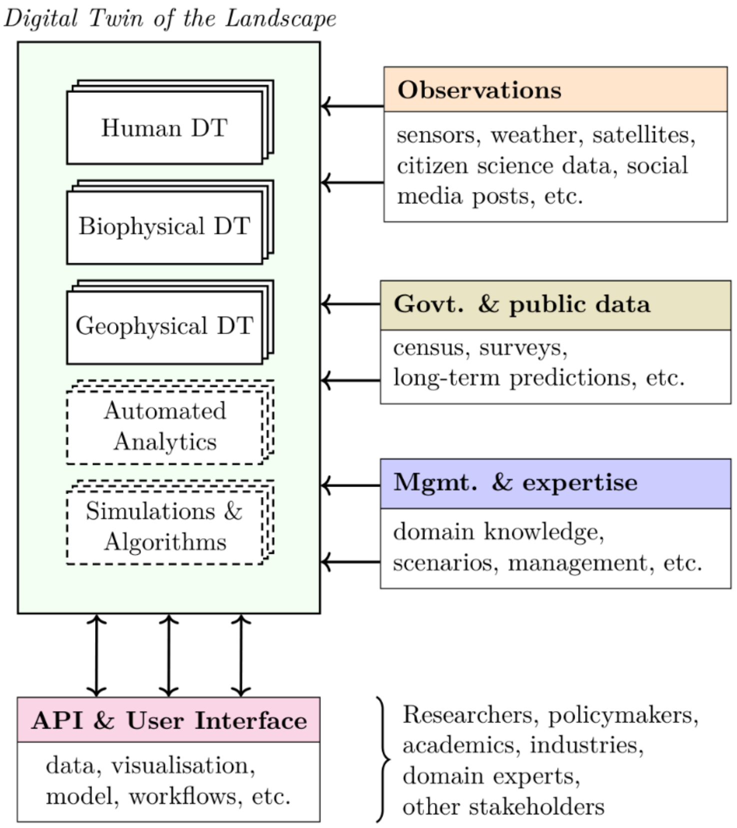

Figure 2: Diagrammatic representation of how the digital twin will integrate various models, simulations, algorithms, data sources, automated analytics, etc. The digital twin, or its components, will receive contextual input from a range of sources; and it will be accessed by diverse stakeholders through a range of user interface options and Application Programming Interfaces (APIs).

The DT (or the models contained within) will receive input in the form of observations (from weather stations, radars, sensors, manual recordings, etc.) and data collected and managed by government and non-government entities (such as census, surveys, socio-economic predictions, etc.) as well as citizen science data, and social media posts, among others. Each component of the natural environment is comprised of multiple entities. For example, a geophysical DT may be comprised of land parcels, weather systems, soil, groundwater, and relevant processes within realm; a biophysical DT may be comprised of plants, animals, and ecosystem interactions; and a human DT could be comprised of farmers, land management practices, and rules and regulations. Associated with these entities are specific parameters or metrics that define observable characteristics important to understanding the system and which relate to potential management actions, e.g. the crop type, animal population size, or type of farmer/farm enterprise. From a landscape management perspective, there can be several management interventions that directly act on the parameters of entities that comprise the three components. These management interventions will eventually impact all three layers, given the complex inter-relationship between the geophysical, biophysical, and human components of the natural environment. Please see Section 3.2 for examples of these entities, parameters, observations, and management actions for the area-wide integrated pest management (AW-IPM) use case.

Furthermore, as shown in Figure 2, the DT platform will allow its users to interface with it through several user interfaces and APIs. These stakeholders could include policymakers, industry bodies, researchers, consultants, those living in and managing the concerned natural environment, among others. The user interface will support actions such as querying the DT for data and visualisations, running simulations for different scenarios, interactive exploration of the current and predicted future states of the natural environment, predicting the impact of management actions, integration with existing workflows, etc. It is expected that these abilities will support more knowledgeable decision making in terms of managing the environment, including better preparations for potential future scenarios.

2.2 Applications across spatial and temporal scales

Any DT of the natural environment that aims to facilitate system understanding and improved decision-making should include support for simulations using multivariate scenarios. The separation of layers and components in the proposed framework allows us to create varying sets of scenarios as contextual inputs that apply to either the entirety or a subset of the DT framework, both spatially and temporally. These scenarios could include, for example, political or economic systems, regulations, regional or global events, markets, cultural changes, weather patterns, and pest intensity. The benefit of separating the scenarios as contextual inputs to the model is that such a method will allow us to test various real, probable, and hypothetical scenarios (or a combination) and simulate management actions accordingly. The scenarios themselves can be dynamic and continually impact the model(s) throughout the simulation.

The DT should not only provide the current state of the natural environment, but also allow the prediction and exploration of its future states at different time points. This includes updating the predicted states based on real-world observations as well as accounting for the impact of different management actions (see Figure 3). For example, the DT should allow its users to simulate and understand the impacts of a set of management actions on the natural environment – by producing future states of the environment with and without those management actions.

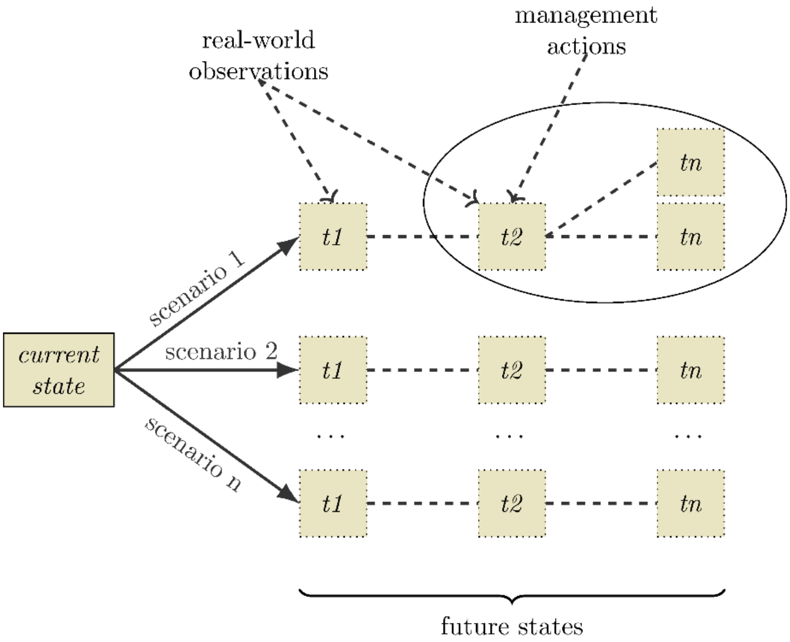

Figure 3: The digital twin of the natural environment should allow us to simulate future states of the environment under a range of scenarios and management actions. It should also support simulating the impacts of available management options.

Most environmental management scenarios are characterised by the presence of a diverse set of stakeholders with competing interests. Therefore, the DT should support defining multiple stakeholders and actors whose actions either impact the geophysical and the biophysical components of the landscape, or who are impacted by changes in those layers. The proposed framework also envisions use cases, applications, and corresponding user interfaces for different actors. These applications and user interfaces should provide these stakeholders their respective views of the natural environment (both current and future states) and allow them to query, run simulations and analyse scenarios based on their perspectives, roles, and requirements.

3. Socio-ecological governance within a Digital Twin

A key aspect of modelling human systems in relation to managing the natural landscape is the selection of principles to guide how the socio-ecological governance system is modelled in the DT. There exist diverse modes of socio-ecological governance and related principles in the literature (Bourceret et al., 2021), but it is beyond the scope of this paper to discuss them in detail. In this section, we present four key principles that guide the way in which we believe DTs should be structured to reflect socio-ecological governance systems, that will allow their use in decision-making for managing the natural environment. We also provide a potential use case of AW-IPM to discuss how these principles of socio-ecological governance within a DT apply to a real-world context.

3.1 Principles of socio-ecological governance systems

That the DT accommodates the multiple ways of governing socio-ecological systems.

In general, we propose that use cases for a DT for managing the natural environment aim to support the various ways that socio-ecological systems are governed, and that they can support multiple forms of governance in combination.

Governance of socio-ecological systems is generally considered to take one of three fundamental forms: hierarchy, market, or community (Bell & Park, 2006). Each form is seen as comprising a unique set of mechanisms that motivate action: hierarchical (top-down, via direction and regulation, based on legitimated authority and the threat of penalty for non-compliance), market-based (individualistic; via incentives, price, exchange, and contract; based on private interests), and communitarian (voluntary action; achieved via education and moral suasion, norms and peer pressure, social honouring and sanctioning; and typically based on trust, reciprocity and commitment to a common cause).

While these three modes of social organisation differ fundamentally in their operating principles, they are often seen operating in combination as each has particular strengths and weaknesses. The art and science of differentially applying the different modes of governance, either singularly but usually in combination, to manage an issue, is known as ‘metagovernance’ (Bell & Park, 2006; Cheshire et al., 2014; Gjaltema et al., 2019; Meuleman, 2009).

A DT should be able to support each mode of governance, identifying the conditions under which a particular mode is most appropriate and specifying the requisite mechanisms to address the issue – regulations, incentives/price, suasion, commitment to a common cause, etc. – whether applied singularly or in combination.

That the DT accommodates both single-agent and multi-agent issues.

These modes of social organisation can be used to motivate and order both individual and collective action in socio-ecological landscapes (Aggarwal & Anderies, 2023; Halik et al., 2018; Ruzol et al., 2017).

Some environmental management problems can be solved by individual or private action, such as where a problem exists on a landholder’s own property, and they can deal with the issue themselves. In such cases, the landholder may be motivated either by the necessity to comply with government regulation (hierarchy), their own private interests (markets e.g., the profit motive, or achieving personal values such as beautification or wellbeing of the environment), or a sense of moral obligation to the greater good of the community and/or ‘suasive’ mechanisms (communitarian values and mechanisms). There may also be a combination of these three drivers. Simple ‘suasive’ (moral suasion) mechanisms to convince agents to act voluntarily typically involve education campaigns, combined with explanations of benefits, and an appeal to act altruistically, for the good of the whole (community, industry, landscape, etc.).

However, most environmental management problems are multi-agent in nature, in that action from several different parties is required to achieve a solution. A multi-agent landscape management problem is one where an individual agent, or collection of individual agents, cannot achieve a desired or required environmental outcome without assistance from one another or external others.

That the DT accommodates the different ways of governing multi-agent issues.

The different modes of governance, or ways of managing issues, provide mechanisms by which interdependence between agents for multi-agent issues can be resolved. Establishing a top-down, hierarchical approach based on legitimated authority is the classical model of ‘government’ as Government (i.e. in the formal sense). Typically, a public entity, such as a government department, issues policy, regulations and directions that coordinate the actions of the various relevant parties, in order to achieve the intended outcome (e.g., rehabilitation of a degraded landscape; biosecurity of the Queensland Fruit Fly in South Australia). Alternatively, market-based mechanisms could be used to resolve multi-agent landscape management problems. These rely on individual (private) agents having incentives to cooperate with others to achieve their own interests, through the mechanisms of price, exchange/trade, and contracts. Thus, interdependencies between private agents acting autonomously are resolved through market mechanisms. However, in practice, many so-called market-based schemes are set up by government and utilise grants, taxes, and subsidies to create incentives for autonomous agents to act in desired ways (e.g., water and carbon trading schemes). This demonstrates how, in practice, different modes of governance are combined to achieve the desired outcome. Lastly, where neither government regulation nor market incentivisation of private agents are expected to be effective, or otherwise suitable, mechanisms to engender voluntary action may be appropriate.

That Collective Action theory provides a sound theoretical basis for the DT in the management of the natural environment.

Voluntary collective solutions can take many forms, from quite casual and loosely organised community groups (e.g. local Bushcare groups) to highly organised and sophisticated group and multi-group (network) structures and processes, led either locally or externally (Graham et al., 2019). There are likewise many theories on collective processes for decision-making on natural resource management and co-governance of socio-ecological landscapes (Everingham, 2009; Meinzen-Dick et al., 2004). However, here, we assert that Collective Action theory, which arises from the field of institutional economics (Ostrom, 1990), provides the most readily identifiable principles for effective co-management. Also known as ‘institutional design’ or ‘common pool resource management’ theory, collective action theory has been extensively applied to natural resource and sustainable socio-ecological management.

3.2 Use case example

We discuss the use case of area-wide integrated pest management, which is representative of a collective action management scenario for a public good with low excludability. In such a case, a multi-actor framework is required, as opposed to single actor decision-making which is generally found at a finer spatial scale where ‘excludability’ is high, such as for a single land parcel like a national park or farm. The entities in our DT must reflect these multiple actors, and management interventions need to consider the multiple objectives the actors may have and the potential interactions between them. We also present the primary purpose and data requirements to develop a DT for managing the natural environment within our proposed framework.

3.2.1 Area-wide integrated pest management

As agricultural industries in many parts of the world face an increasingly ‘chemically-limited’ future due to multiple pressures, existing approaches to pest management need to be redesigned (Pretty, 2018). These pressures include pest resistance, human health concerns, environmental protection regulation, social license, barriers to export markets, and lags in new product development. Integrated Pest Management (IPM) is an approach that has long been advocated as a means through which to navigate such a chemically limited future (Cowan & Gunby, 1996). IPM incorporates beneficials (e.g. predatory insects) into pest management strategies, coordinates the timing of operations to maximise efficacy and increases the diversity of management strategies and enterprises on farm to increase resilience (Kogan, 1998). The need to move beyond the farm-scale as a unit of management to a more cooperative, agroecological, area-wide approach has been coined ‘areawide IPM’ or ‘AW-IPM’ (Deguine et al., 2021; Kogan, 1998).

In order to facilitate AW-IPM, we need decision-making tools that can handle complex systems, support integration of observation data with forecasting of pest population dynamics in real-time and take a scenario-based approach to simulate and understand the impact of multiple existing and novel control methods. Given the importance of collective action for AW-IPM, these tools also need to support coordinated management actions among diverse stakeholders. A DT of AW-IPM, developed using the framework proposed in Section 2 and the principles discussed Section 3.1 can meet these requirements to facilitate decision-support for complex AW-IPM across large agricultural landscapes.

The primary entities that we anticipate would comprise the geophysical, biophysical and human DTs for AW-IPM are given in Table 1, noting that these entities encompass land units and managers not only of farmland but also of other key land units such as home gardens and council land. Examples of parameters and observations associated with these entities are also given in Table 1, along with suggested management actions that could be assessed with the DT. These management actions may relate to geophysical (e.g. crop rotations that suppress green bridges for pests to remain in the landscape) and biophysical, through direct action on the pest populations (e.g. estimating effective dynamic thresholds for pesticide or biocontrol). We would also be able to consider the human dimension of management actions with the DT, such as the different drivers of cooperation among stakeholders, their willingness to bear the expenses to implement AW-IPM and predict the stakeholder involvement thresholds in group action for successful pest management.

Table 1: Composition and characteristics of a digital twin of the natural environment for area-wide integrated pest management.

System	Entities	Parameters	Observations	Management Actions
Geophysical	crop-fields, non-crop habitat, other land uses, climate	temperature, rainfall, etc.; NDVI or landscape metrics; crop type, stage, health	satellite data, government data (e.g. land use), weather data, farm management system records	rotations/land use change, planting (e.g. floral resources)
Biophysical	pests and beneficial populations	population growth rate, damage to crops	trap networks, regional pest reports, pesticide usage surveys, field-based on farm data	pesticide spray, biocontrol
Human	growers, backyard gardeners, institutions (council, pest management groups)	willingness to pay, thresholds for action, drivers for cooperation	social surveys, census data, targeted studies	formation of AW-IPM groups, extension efforts, top-down policy interventions

An important aspect of a DT is how it enables information access and intervention. A DT needs to be dynamic, allowing information extraction and intervention by users (not constrained to ‘experts’), and for users to be able to influence the system trajectory across time and space even if just as simulated scenario outputs (Bauer et al., 2021). In the case of the DT for AW-IPM, users would be able to answer a range of questions across spatial (farm to the entire landscape) and temporal (short-term action to long-term planning) scales. Applications and user interfaces could be designed to allow users to interact with the DT from an appropriate perspective (see Section 2.2). Figure 4 shows the kind of queries the DT could support for diverse stakeholders across both spatial and temporal scales. Ideally, the DT would also be capable of capturing the outcomes of such interventions and updating data accordingly in the DT, to ensure inevitable feedback loops across scales are accounted for.

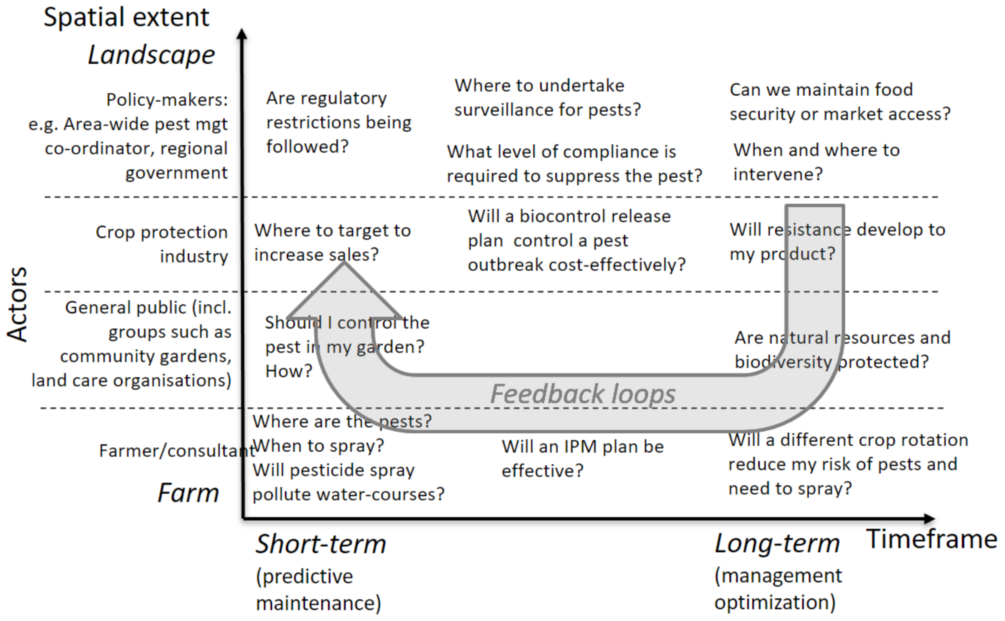

Figure 4: User engagement and some representative queries supported by a DT of AW-IPM across spatial and temporal scales for a range of stakeholders.

4. Modelling methods

Modelling the complex and dynamic system of the natural environment and the human systems within that environment will necessitate the use of diverse methods appropriate to what is being modelled and simulated. Below, we propose that ABMS be used as the primary framework for modelling the human system; and we also identify several methods from ML and computer science in general that could be used in conjunction with ABMS.

Regarding the integration of the geophysical and biophysical systems and processes within the DT of the natural environment, several studies in the literature have previously addressed this issue (Annoni et al., 2023; Koning et al., 2023; Nativi et al., 2021), as well as specific aspects of these systems such as biodiversity modelling (Trantas et al., 2023), climate forecasting (Voosen, 2020), watershed management (D. Park & You, 2023), among others. Similarly, more technical software engineering issues such as implementation (Eramo et al., 2022), software architecture (Ferko et al., 2022; Mostafa et al., 2021), enabling technologies (Fuller et al., 2020), use of Big Data and IOT (Li et al., 2023; Radanliev et al., 2022), have also been discussed in the literature and are beyond the scope of this paper.

4.1 Agent-based modelling and simulation

ABMS is a powerful simulation technique to describe complex, dynamic systems that are comprised of multiple autonomous and interacting agents and characterised by continual change and evolution through time and space (Bonabeau, 2002; Epstein, 2006; Macal, 2016). The structure of agent-based models is based on the interaction of heterogeneous, autonomous agents with each other and their environment. The flexibility of ABMS means that anything from individuals and households to entire societies, or geographical and political entities can be represented using agents.

ABMS has become the leading method for modelling people, organisations, and societies because it provides an explicit framework for modelling human behaviour, causal processes, emergent phenomena, and social mechanisms across most disciplines, including biology, social sciences, business, and archaeology (Macal, 2016). In the case of the DT of a natural environment, ABMS can play a key role in modelling human systems, other biophysical systems whose population and behaviour need to be modelled in the system, as well as to capture the feedback effects (Naqvi & Rehm, 2014).

ABMS only provides the overall framework for modelling and simulating humans, their social structures and networks, and their interactions. Implementing an agent-based model requires considering a wide range of tasks both during the simulation (online tasks), and before or after the simulation (offline tasks). Online tasks include modelling the connections among agents and the flow of information within the network structure, obtaining and perceiving the contextual information from and about the environment, decision-making, evaluating decisions and outcomes, strategy formation, prediction, optimisation and planning, and learning. Offline tasks include parameterising the model, calibrating the agents, validating the model, and processing the simulation outputs. Researchers have used diverse methods from Artificial Intelligence (AI), ML and data-science to implement these tasks in the literature (Platas-López et al., 2023; Zhang et al., 2023). In the following subsection, we provide examples of several methods and technologies that could be used to implement the above.

4.2 Machine Learning and Artificial Intelligence methods

ML methods excel at learning patterns, making predictions, and extracting insights from data, and thus have great potential for implementing and enhancing the capabilities of ABMS during both the offline and online tasks.

4.2.1 Offline tasks

ML is now widely used for agent specification in ABMS in the literature (Ale Ebrahim Dehkordi et al., 2023). Chopra et al. (2023) used neural networks to calibrate agent-based models as part of their epidemiological GradABM, which was used to develop vaccine strategy and policy during the COVID-19 pandemic. Mustafa et al. (2017) developed a hybrid urban expansion model using ABMS where they used logistic regression models to parameterise the decision-making process of agents (developers, farmers and planning permission authorities). Similarly, Sánchez-Maroño et al. (2017) discussed the use of decision trees learned from questionnaire data to develop behavioural rules for agents in an agent-based model. Abdulkareem et al. (2019) used Bayesian Networks to extract and model the behavioural patterns in a spatial disease agent-based model.

In relation to a DT, where the agent-based model can access various data streams integrated with the DT, ML methods can also help integrate these data streams to parameterise the agent-based models or drive agents' behaviour (e.g., perceiving their environment, decision-making or self-learning). For example, Dyer et al. (2022) used graph neural networks (GNNs) to calibrate ABMS parameters in case of 'fully-observed ABM' (when the full trace of the agents' states and interactions are observed). An et al. (2023) leveraged reinforcement learning and convolutional neural networks to equip agents with the ability to self-learn their rules of behaviour directly from the data.

Similarly, AI and ML can also assist with post-simulation tasks such as output data analysis or creating surrogate ML models trained using ABMS data. Surrogate modelling, which involves constructing a statistical model of the ABM to perform detailed model analysis, has been suggested as a solution to the computationally demanding nature of ABM output analysis. Angione et al. (2022) compared multiple ML methods for ABM surrogate modelling and determined that Artificial Neural Networks (ANNs) produced the most accurate model replications. The strengths of ML in detecting patterns have previously been used to detect the patterns of emergence within ABMS that cannot be easily detected by human experts and specialists (Janssen et al., 2019; Peters et al., 2016).

4.2.2 Perceiving the environment and making decisions

Most online tasks within ABMS can be grouped under two broad categories: perceiving their environment, and making decisions to meet their objectives while considering their environment. Agents can be empowered to learn the underlying rules, map relationships between the observed states and outcomes, and make their own predictions under emergent situations using various ML methods. For example, Jäger (2019) re-implemented the famous Sugarscape agent-based model and used ANNs to drive the decision-making of agents instead of theory-driven or empirically determined rules.

Furthermore, since the decision-making process of agents can also be formulated as prediction or classification problems in predefined spaces, supervised ML methods and reinforcement learning (Kaelbling et al., 1996) can be implemented to help the agents deduce efficient and satisfactory behaviours under varying circumstances. For example, Sert et al. (2020) designed an ABMS that simultaneously promoted two conflicting behaviours (segregation and interaction) using a set of rewards based on the agents’ actions. They used reinforcement learning (Deep Q-networks) to help agents efficiently explore the strategies that satisfy the conditions imposed by the rules of interaction within the simulation. This approach can be applicable to many scenarios of collective management of the natural environment where agents need to assess a range of potential and existing behaviours associated with the rules of interactions and rewards.

4.2.3 Capturing interactions among agents

Interactions among agents play a vital role in human systems and increasingly large amounts of data are collected and available from these interactions, including social media data, traffic footfall data, etc. Graph Neural Networks (GNNs) provide one potential method to capture the interaction patterns among agents. GNNs, by using pairwise message passing, help us understand the complex relationships among all the nodes or agents in a network (Scarselli et al., 2009), and they have achieved great success on networked data in various domains, such as social networks, biomolecular networks, and transportation networks (Zhou et al., 2020). When integrated with ABMS, GNNs can provide a mechanism for the agents to improve their awareness of the context in which they operate, in addition to modelling the crucial aspects of human decision-making such as information and innovation diffusion. Chopra et al. (2021) represented the interaction of agents as message passing operations in GNNs to bring scale and efficiency to agent-based simulations and thus overcome some of the scaling issues faced by ABMS when representing the behaviour of large populations in real-world contexts.

5. Discussion

DTs of the natural environment have the potential to become valuable decision-support tools for more informed and effective management of the natural landscape. A critical task while developing a DT of the natural environment is modelling and integrating the human systems in that environment within the overall DT, particularly because of the close inter-relationships between human and other systems and the increasing dominance of human systems. Modelling the dynamic nature of human systems, their uncertainties, and idiosyncrasies as well as the complex inter-relationship between humans and natural systems is, however, not trivial. The DTs of the natural environment in the literature (whether developed or proposed) do not include the human systems as part of the DT.

In this paper, we have proposed a general framework for integrating the human systems within the DT of the natural environment, as well as four key principles to guide how such DTs should be structured to reflect the socio-ecological governance systems. The proposed framework and the principles should be applicable for a wide range of natural environment management scenarios, and we have also provided the use case of AW-IPM as an example. We have also proposed ABMS as the methodological framework for implementing the human systems and identified several ML methods that could complement ABMS in this task.

The integration of machine learning (ML) and artificial intelligence (AI) within DTs of human systems introduces several technical considerations, particularly for critical tasks such as offline agent calibration and online behavioural decision-making. Beyond general limitations (including a heavy dependence on high-quality data, vulnerability to distribution shifts and scalability challenges), these models are inherently susceptible to overfitting, where they may fail to generalise beyond the specific datasets used for training (Purcell & Neubauer, 2023; van der Burg et al., 2021). Furthermore, data bias within training sets can perpetuate existing societal inequalities if the underlying behavioural data is unrepresentative of the diverse stakeholder groups within the landscape. Given the often ‘black-box’ nature of many ML models, these systems can become less interpretable and explainable, creating significant barriers to transparency regarding the DT’s underlying processes and making it difficult for stakeholders to validate emergent behaviours (Kobayashi & Alam, 2024).

These technical constraints necessitate a broader discussion on the socio-ethical implications of integrating sensitive human dimensions into digital frameworks. Given the high reliance on modelling and theoretical assumptions, it is imperative to clarify the risks and implications associated with inherent uncertainty to maintain stakeholder trust, especially in high-stakes landscape management contexts. As larger volumes of behavioural and potentially sensitive personal information are collected and linked within the DT, concerns regarding data quality, privacy and security become increasingly acute (van der Burg et al., 2021). Consequently, addressing these limitations requires the implementation of strong governance, clear consent mechanisms and robust safeguards against misuse to ensure the DT remains a reliable tool for facilitating collective action and informed decision-support.

A DT of the natural environment that integrates human systems, following the framework and principles discussed in this paper, will enable diverse stakeholders, including policymakers, to foresee and analyse the impacts of various management decisions, strategies, and policy instruments under a range of potential scenarios. Doing so will also enable the development of novel digital decision-support tools that help identify when and where to intervene to solve problems, facilitate collective decision making, optimise management, and improve preparedness.

Supplementary Material

The Supplementary Material for this article can be found online at https://sesmo.org/article/view/18760/18444.

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