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What grows, adapts and lives in the digital sphere? Systematic literature review on the dynamic modelling of flora and fauna in digital twins

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ABSTRACT

The modelling of flora and fauna is vital for understanding and digitally representing our environment, yet their dynamic modelling in digital twins lags behind human-made inventions like manufacturing and the built environment. The interdisciplinary nature of this research complicates tracking advancements, and no comprehensive overview exists. This Systematic Literature Review (SLR), using the PRISMA method, addresses this gap by analysing studies on dynamic modelling of flora and fauna in digital twins and 3D city models. It covers descriptive metrics and qualitative aspects, identifying key research fields, directions, users, and developers. Additionally, this SLR details on digital twin data, modelling techniques, actuators, user experience with human-computer interaction, and ethical considerations. The findings highlight that the digital twin concept is being increasingly applied to the dynamical modelling of flora and fauna. Moreover, the broad relevance of this research is demonstrated across various fields including ecology, forestry, urban studies, and agriculture, where diverse methods and technologies are used, though progress remains uneven. Currently, precision agriculture is leading the way in automated, bidirectional synchronisation between digital twins and their physical counterparts. Complementing traditional modelling techniques with AI and machine learning where appropriate, expands modelling capabilities. Meanwhile, multimodal interfaces enhance the immersive user experience. Despite these advances, challenges persist in data availability, foundational knowledge, complex interaction modelling, standardisation and transferability, underscoring the need for continued research. Digital twins for the biotic environment show promise in supporting United Nations Sustainable Development Goals 2, 11, 13, 14, and 15. This overview supports researchers and practitioners in developing digital twin applications which include flora and fauna.

1. Introduction

Simultaneously with technological development, the biotic environment is undergoing drastic transformations today (Mottl et al., 2021; Nolan et al., 2018). The increase of the human population is a catalyst for the expansion of human settlements, accelerated urbanisation (McKinney, 2008; Seress and Liker, 2015; Theodorou, 2022) and rising agricultural demand (Kehoe et al., 2017). Further, pollution, overexploitation of biological resources (Shivanna, 2020), monocultural forestry (Liu et al., 2018a), and other human-made influences (Foley et al., 2005; Tscharntke et al., 2012) facilitate habitat loss, causing biotic homogenisation, loss of biodiversity (McKinney, 2008; Seress and Liker, 2015; Theodorou, 2022), and disrupting ecosystem functioning (Theodorou, 2022). The urgency to efficiently address the human-induced negative changes impacting flora and fauna is acknowledged globally, as in the UN Sustainable Development Goals (United Nations, 2015) and in the European Green Deal (European Commission. Directorate General for Communication., 2021). To address these challenges, the conjunction of natural systems and technologies is gaining momentum, driven by unprecedented advancements in science and technology. This can be observed in agriculture (Purcell and Neubauer, 2023), urban green environments (Brkljačić et al., 2020; Galle et al., 2019) and nature overall in variegated manners (Arts et al., 2015; Mohammed, 2016; Nugent, 2018). Nonetheless, the maturity and

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inclusion of biotic elements in the digital sphere, for example (urban) vegetation, still lag behind those of human-made inventions, such as the manufacturing industry or the built environment (Shirowzhan et al., 2020; Xu et al., 2021) and the previously outlined challenges to overcome stay yet unresolved.

However, with the ongoing increase of data availability, computational power and development of digital tools, especially one concept, promising to tackle complex challenges and wicked problems, stands at the forefront of this technological break-through: the “Digital Twin”. Digital twins are innovative tools integrating multiple established and emerging technologies, bridging the gap between physical assets and their digital counterparts. They enable (real-time) monitoring, diagnostics and prognostics, realistic behaviour in simulations and a continuous bi-directional alignment between the digital and the physical counterparts (Grieves and Vickers, 2017; Kritzinger et al., 2018; Wright and Davidson, 2020). While some scholars use "digital model", and "digital twin" interchangeably, there are key distinctions between digital models, digital shadows, and digital twins. One of the primary differences lies in the data flow and synchronisation between the physical and digital counterparts, which can be either manual or automatic (Kritzinger et al., 2018) (Fig. 1). For a more detailed definition of a digital twin and its differentiation from a digital model or a digital shadow, see Supplement S1.

Originating in the context of industrial design and manufacturing (Grieves and Vickers, 2017), digital twin applications have transcended industrial confines. Digital twins are now a focus of significant research (Botín-Sanabria et al., 2022) and increasingly applied in fields involving flora and fauna, such as cities (Lehtola et al., 2022), forestry (Hejtmánek et al., 2022), agriculture (Pylianidis et al., 2021), livestock-farming (Jo et al., 2018; Neethirajan and Kemp, 2021), ecology (Trantas et al., 2023) and biodiversity (Sharef et al., 2022). The scales in which digital twins are applied in this context range from local (Taubert et al., 2024) through European-wide (Khan et al., 2024b) to global, aiming at supporting e.g. the Earth’s green transition (Bauer et al., 2021). Digital twins are said to hold potential for nothing less than to disrupt the status quo of ecology as a part of its digital transformation (De Koning et al., 2023).

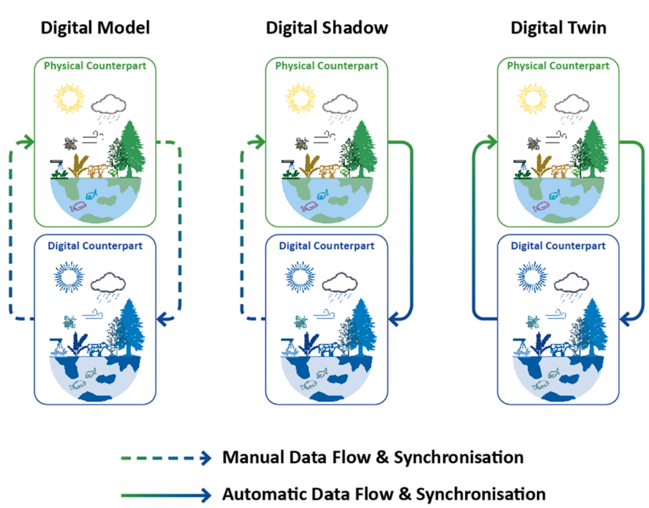

Fig. 1. Conceptual comparison of Digital Model, Digital Shadow, and Digital Twin frameworks as described by Kritzinger et al. (2018) and Botín-Sanabria et al. (2022). Digital models provide static representations of systems with manual data flow and synchronisation (left image, dashed arrows). Digital shadows include unidirectional automatic data flow (middle image, dashed and solid arrows) from the physical counterpart to the digital counterpart. Digital twins incorporate bidirectional automatic data flow (right image, solid arrows), enabling dynamic interactions and feedback between the physical and digital counterparts. This conceptual comparison highlights the progression of modelling paradigms.

1.1. Aim of this systematic literature review

While numerous (systematic literature) reviews and overviews exist on related topics e.g. (urban) digital twins (Deng et al., 2021; Ivanov et al., 2020; Ketzler et al., 2020; Lei et al., 2023; Qian et al., 2022; Shahat et al., 2021) and digital twins in agriculture (Purcell and Neubauer, 2023), no comprehensive overview addresses how flora and fauna are modelled in digital twins. This overview is particularly important, as the dynamic modelling of flora and fauna intersects various fields and therefore provides a centralised resource that consolidates the state of the art and facilitates a deeper understanding of the topic across different domains. Consequently, this Systematic Literature Review (SLR) aims to fill that gap and support researchers and practitioners in developing digital twin applications that include flora and fauna.

In contrast to field-specific reviews on digital twins, such as those focusing on e.g. intensive aquaculture (Føre et al., 2024) or livestock farming (Neethirajan and Kemp, 2021), or a framework for data-driven digital twins in ecology (Khan et al., 2024a), this review adopts a broader perspective. It takes a horizontal, cross-sectoral perspective on flora and fauna modelling in digital twins, avoiding segregation e.g. by species, practice, or domain. This approach allows to highlight the diverse fields where flora and fauna models are employed in digital twins and how needs and approaches differ across applications. Such cross-sectoral awareness is particularly valuable for transdisciplinary knowledge pollination and the design of reusable and transferable flora and fauna models. Moreover, it allows to address e.g. standardisation and technical challenges more holistically.

The field of digital twins is heterogeneous encompassing multiple theoretical and conceptual frameworks as well as manifold research approaches. As the meaning of the term digital twin varies greatly across research fields, for this SLR a digital twin was defined as a digital representation (digital counterpart) of a physical counterpart, encompassing variable modelling methods, e.g. 3D and mathematical models and simulations, as well as information updates that can influence both counterparts directly or indirectly. Notably, real-time data is not always indispensable for dynamic modelling of flora and fauna in digital twins, allowing flexible updating frequencies.

The initial aim of this review was to compile and analyse existing knowledge on dynamic modelling (see Supplement S1) of flora and fauna in urban digital twins (UDT). As a result of the three-dimensional nature of urban planning, UDTs are often accessed and interacted with through 3D city model interfaces. Therefore, and due to the novelty of the term “digital twin” in the urban context (Ferré-Bigorra et al., 2022; Shahat et al., 2021), we anticipated that urban digital twins could be, besides the term “digital twin”, also be discovered with the search phrase “3D City Model”. However, preliminary examinations revealed scant research specifically addressing this nexus. As the implications of urban areas on flora and fauna go beyond city borders (Caldarelli et al., 2023), and as there is potential for knowledge transfer from other domains, the review’s scope was expanded to keep matching articles on dynamic modelling of flora and fauna regardless of discipline. Consequently, the focus shifted from city-wide digital twins to dynamic modelling in all disciplines, prompting a complete revision of the research process.

Given the advances in digital twins, and the lack of a concise overview, this review explores, analyses, and synthesises current research, highlighting achievements, identifying gaps, and proposing future directions. It especially covers descriptive metrics and qualitative aspects, identifying key research fields, directions, users, developers, digital twin data, dynamic models, actuators, user experience, and ethical considerations.

While this review aims to provide a broad overview, it is worth noting that the chosen search terms did not specifically target agricultural practices, such as precision farming or livestock modelling. Consequently, agricultural digital twins are not comprehensively addressed in this review.

2. Materials and methods

In this SLR, the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021) has been applied. The detailed review protocol for this study is available upon request.

2.1. Research questions

This SLR was conducted with the aim to answer the following research questions (RQ):

Research question	Question	Addressed in chapter
RQ 1	When, where, for which purposes, in which fields, by whom and for whom are flora and fauna dynamically modelled in digital twins and 3D city models?	3.1 Context and 3.2 Categorisation of Research Topics
RQ 2	What data collection methods are employed, which digital twin data are generated and used and how is the data managed?	3.3 Data
RQ 3	Which modelling techniques and methods are used for which purposes?	3.4 Models
RQ 4	How are flora and fauna represented, and what methods facilitate user-computer interaction?	3.6 User Experience
RQ 5	Which ethical reflections are considered?	3.7 Ethical Considerations
RQ 6	Which fields show research leadership and what are open challenges and future directions in the dynamic modelling of flora and fauna in digital twins?	All Chapters, especially 4. Discussion

2.2. Definition of keywords and search strings

The keyword strings used for the literature search consisted of two parts (Fig. 2). For the first part, the terms "digital twin" or "3D city model" were employed. The term “3D city model” appeared to be the most widely applied for the urban context, and commonly used for reviews by other scholars, such as (Biljecki et al., 2015). Reflecting the initial focus of this SLR, the search term “3D city model” was retained in the search strings because it effectively captured articles consistent with the definition of digital twins, even when the term “digital twin” itself was not used. The term “digital twin” recently emerged across multiple disciplines. Due to its novelty and manageable number of publications across various disciplines, the search term “digital twin” was chosen.

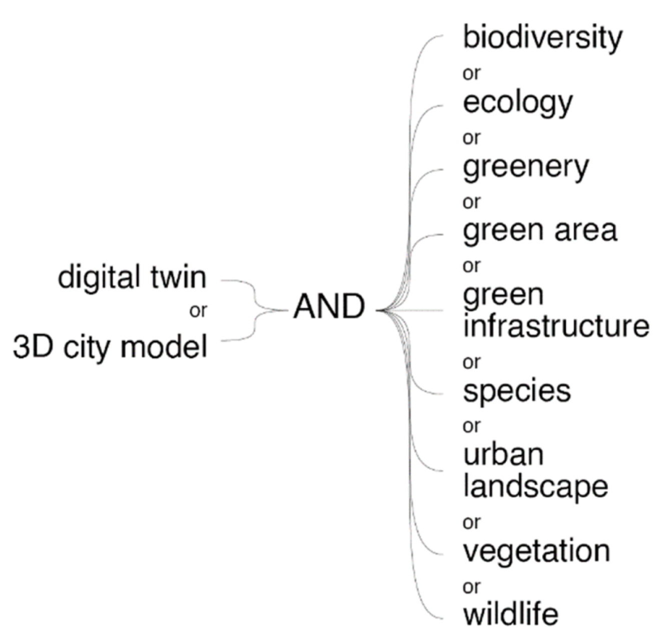

Fig. 2. Combinations of used search terms for the publication collection for the systematic literature review.

To cover the modelling of flora and fauna, the following search terms were selected after preparatory searches to figure out the most auspicious results: “biodiversity”, “ecology”, “greenery”, “green area”, “green infrastructure”, “species”, “urban landscape”, “vegetation”, “wildlife”. The search terms “flora” and “fauna” were excluded as no applicable new articles were found during the preceding searches. The search for “green” was initially excluded, as the term is too vast.

2.3. Publication collection

The initial inclusion period for publications was set from 01.01.2015 until May 18th, 2022. To further include topical records published by February 28th, 2023, the literature search was repeated on this date. The literature search for the publication collection was conducted on 18.05.2022 and 28.02.2023 in three pertinent databases (Fig. 3):

1. Web of Science (WoS, www.webofscience.com), the “Core Search” was used.
2. ScienceDirect/Scopus (www.scopus.com). The scope “Article title, Abstract, Keywords” was used for the searches.
3. Google Scholar. Search results were downloaded with the software “Publish and Perish”, as described in (Harzing, 2010). All Google Scholar search results which exceeded 250 publications were ranked by relevance and only the first 250 were included.

2.4. Publication selection

After identifying the relevant literature from three databases, duplicates were culled. Subsequently, the publications were reviewed independently by two reviewers for eligibility in three phases: by title, by abstract, and by full text (Fig. 3). The following inclusion and eligibility criteria were used:

1. Language: Studies where title, abstract and full text are in English were included.
2. Document types: Videos and webpages were excluded; all other document types were included.
3. Topic: Publications were included if they discuss the dynamic modelling of flora and/or fauna within or for future integration into digital twins or 3D city models. For studies identified with either term “digital twin” and/or “3D city model” inclusion was contingent on the study aligning with the definition of a digital twin outlined in Section 1.1: A digital model of a physical counterpart that is capable of incorporating updates (at flexible frequencies) in the virtual counterparts and influencing the physical counterpart either directly or indirectly.
4. Scope: Publications from all disciplines were eligible for inclusion.

2.5. Data analysis

For the analysis of the included articles atlas.ti web software (https://atlasti.com) and Excel sheets were used. Three types of analyses were carried out to address the research questions:

1. Articles were assigned to mutually exclusive categories based on their content e.g. 3.1.1 Time of publication and 3.2 Categorisation of Research Fields.
2. Content lists of topics relevant to the research question were compiled and systematically categorised based on all included

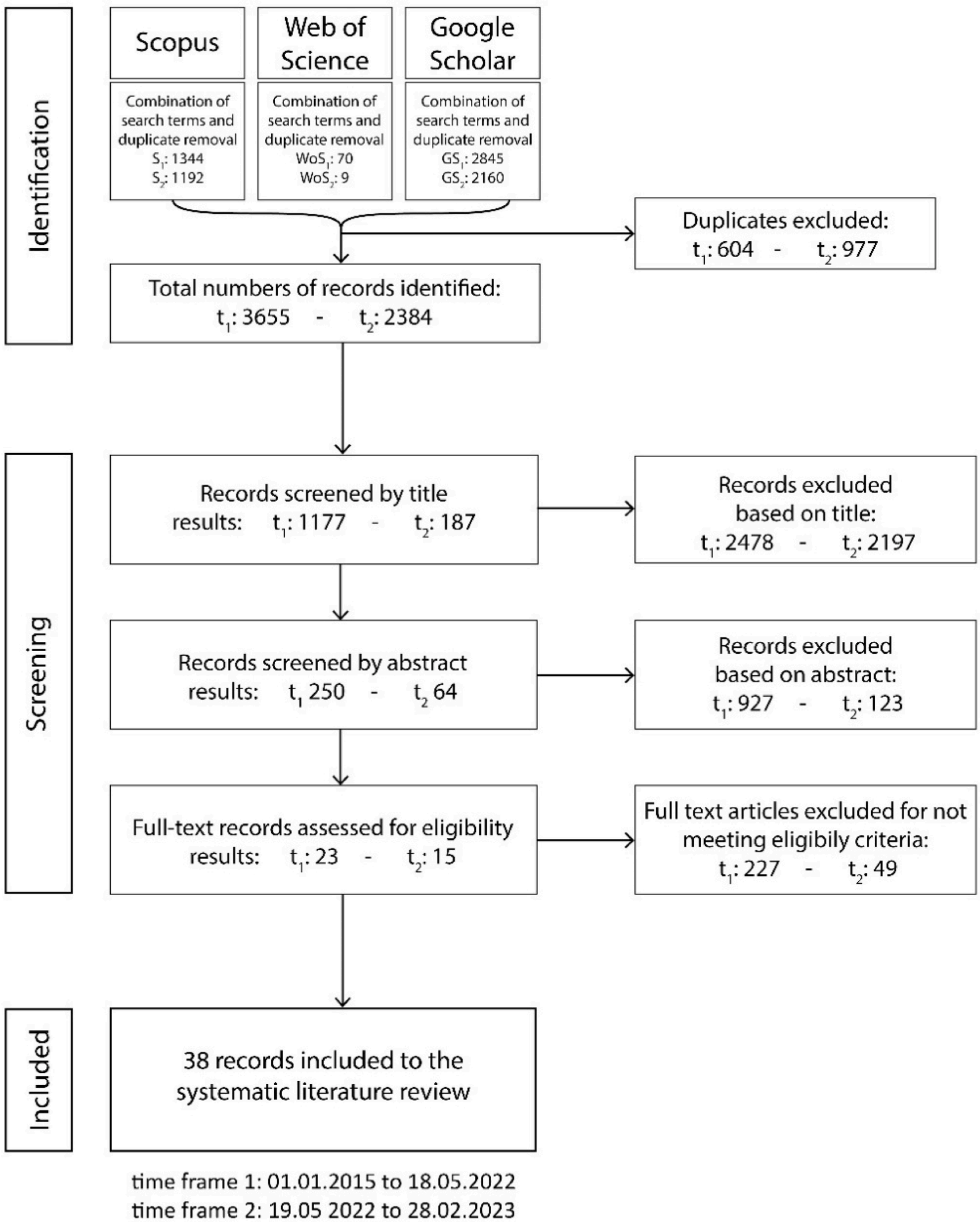

Fig. 3. PRISMA flow diagram (adapted from Page et al. 2021) illustrating the phases of the systematic literature review. It includes the numbers of publications retrieved from the Scopus (S), Web of Science (WoS) and Google Scholar (GS) databases during two data collection time frames (t1 and t2), and subsequently screened and either excluded (right) or included (bottom) in the literature review. Dates of the data collection time frames shown at the bottom of the graph.

articles. Each article could belong to multiple categories, such as "Data" see 3.3.1 and "Models", see 3.4, allowing for comprehensive coverage.

3. Qualitative themes emerging from articles were identified e.g. 3.3.4 Challenges in Data Quality and Availability were added to the content lists of relevant topics. The systematic compilation and categorisation were therefore reiterated.

This review is descriptive in nature and does not include statistical methods, such as meta-analysis. This is due to the heterogeneity of the included studies in terms of their scope, methodologies, and reported outcomes and the lack of quantitative data presented.

3. Results

Out of the total number of 6 039 publications found through the key word search, only 38 publications were eligible for the final inclusion. The included literature was published as journal publications, conference proceedings, congress publications, books, book chapters, master thesis or academic dissertation.

3.1. Context

3.1.1. Time of publication

The number of publications matching the research topic started increasing from 2019 onwards, with a drastic increase of articles containing the search term digital twin (Fig. 4). "Digital twin" ($n = 32$) is considerably more commonly used in the researched context than "3D city model" ($n = 6$). The publications retrieved using the term "3D city model" for this SLR conform to the definition of digital twins. Therefore, subsequent references will solely employ the term "digital twin" for improved readability, except when the context necessitates the differentiation between digital twin and 3D city model.

3.1.2. Spatial distribution of studies by first author affiliation

The largest shares among countries of first author affiliation location were China and Russia ($n = 5$, 13,1 %; Fig. 5).

3.1.3. Developers and users from diverse fields and sectors

The development of digital twins and dynamic 3D-models of flora and fauna is researched by experts from various fields (Shu et al., 2022). The main domains in the selected publications are biology (Shu et al., 2022), agriculture (Majore, 2022; Mishra and Sharma, 2023), agronomy (Skobelev et al., 2020a, 2022a), landscape architecture (Luka and Guo, 2021), urban planning and design (Shu et al., 2022), engineering (Fernández-Alvarado et al., 2021), geoinformatics, computer science, computer graphics (gaming and animation) (Shu et al., 2022), arboriculture, forestry (key forest stakeholders) (Buonocore et al., 2022; Shu et al., 2022), citizen science and education (Harrington et al., 2021).

The selected publications targeted three stakeholder categories:

1. *Academic research*, including research groups from the domains listed in Section 3.1.3, advancing the development and application of digital twins.
2. *Collaboration with other professionals*, e.g. researchers, (small scale) farmers (Johannsen et al., 2021; Klippel et al., 2021; Skobelev et al., 2020a; Zake and Majore, 2022), (political) decision makers (Cirulis et al., 2022; Fernández-Alvarado et al., 2021) and legislators (Mishra and Sharma, 2023) e.g. city authorities (García-Granja et al., 2020; Johannsen et al., 2021), (landscape) architects, engineers and urban planners (Fernández-Alvarado et al., 2021), with the intention of creating e.g. decision support tools or affecting (personal) behaviour (Johannsen et al., 2021).
3. *Engagement with a broader audience*, i.e. stakeholders not directly involved or contributing to the development of the digital tools, such as the general public (Klippel et al., 2021), citizens and consumers (Johannsen et al., 2021), users and learners (Harrington et al., 2021), participants (Cirulis et al., 2022) and non-experts (Harrington et al., 2021).

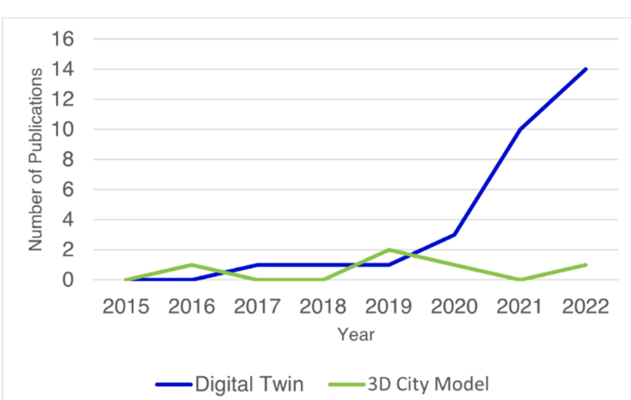

Fig. 4. The number of publications included in the literature review (y-axis) is shown by the year of publication (x-axis) and categorised by the first search term that matched each publication (line color). The year 2023 is excluded from the diagram as it was not fully covered within the literature collection time frame.

3.2. Categorisation of research topics

The dynamic modelling of flora is covered comparably extensively in 34 publications, whereas the publications retrieved through the search process related to fauna modelling appears underrepresented with only four publications. Notably, fauna integration is absent in publications found with the search term 3D city model. A systematic categorisation of the reviewed literature delineates specific domains where dynamic modelling of flora and fauna is employed within digital twins and 3D city models (Fig. 6).

Six publications were found under the search string "3D city model" (Fernández-Alvarado et al., 2021; García-Granja et al., 2020; Kastuari et al., 2020; Tanhuanpää, 2016; Vo et al., 2019; W. Zhang et al., 2022) and the remaining 32 with "digital twin". None of those mentioned both search terms within the same publication.

3.2.1. Flora

The publications treating the dynamic modelling of flora have been structured into six categories aligning with their purposes:

Tree and Forest Modelling: Individual trees, tree groups and trees in forests are the most occurring plants that have been dynamically modelled. The purposes and aims cover the reconstruction of tree skeletons for forest scenario renderings (Wang et al., 2022), the automatic generation and representation of dynamic trees based on physical and biological traits of the respective species (Gobeawan et al., 2021, 2019, 2018) and the immersive representation and projections of forest landscapes for the communication of climate change effects (Klippel et al., 2021). Additionally, dynamic models are used for single tree characteristic and/or forest monitoring, management, maintenance and ecosystem service estimation (Buonocore et al., 2022; Guo et al., 2022; Mongus et al., 2021; Pusztai, 2021; Tanhuanpää, 2016; Wang et al., 2022) as well as the risk assessment including threat assessment through tree growth (Mongus et al., 2021), simulation of forest fire to estimate burning times (Sanchez-Guzman et al., 2022) and for the implementation of early warning mechanisms (Buonocore et al., 2022). Luka and Guo (2021) discuss the roots of trees, whereas most articles focus on above-ground modelling.

Natural Environment and Ecosystems for Preservation Research, Virtual Interaction and Education: Dynamic models of flora have been developed for wetland ecosystems (Lu et al., 2023), bog ecosystems and peatlands (Cirulis et al., 2022), vegetation coverage (Zhao et al., 2022) and a virtual arboretum (Harrington et al., 2021). The purposes of these dynamic models are the monitoring of urban expansion and vegetation coverage (Zhao et al., 2022), the interconnection and mapping of the real and the virtual world (Lu et al., 2023), to foster knowledge dissemination, discussion and for education activities (Harrington et al., 2021). The game-engine based representation of wetland ecosystems (Lu et al., 2023), bogs ecosystems and peatlands (Cirulis et al., 2022) as well as a virtual arboretum (Harrington et al., 2021) had a high emphasis on a (photo-) realistic representation of the environment and e.g. the seasonal dynamic change (Lu et al., 2023). Furthermore they are designed for the user to interact with the 3D virtual environment in immersive ways in real time (Cirulis et al., 2022; Harrington et al., 2021; Lu et al., 2023).

Vegetation-related Micro-Climate and Aerobiological Expose Risk: Dynamic models in this category monitor seasonal variations in tree foliage to evaluate canopy transmissivity for microclimate modelling, focusing on solar radiation distribution (Hofierka et al., 2017), and on aerobiological exposure risks (allergenic potential) emitted by green infrastructure (Fernández-Alvarado et al., 2021).

Open-Field Agronomy: This category refers to agronomical practices in open fields where factors such as climate or soil are not controlled,

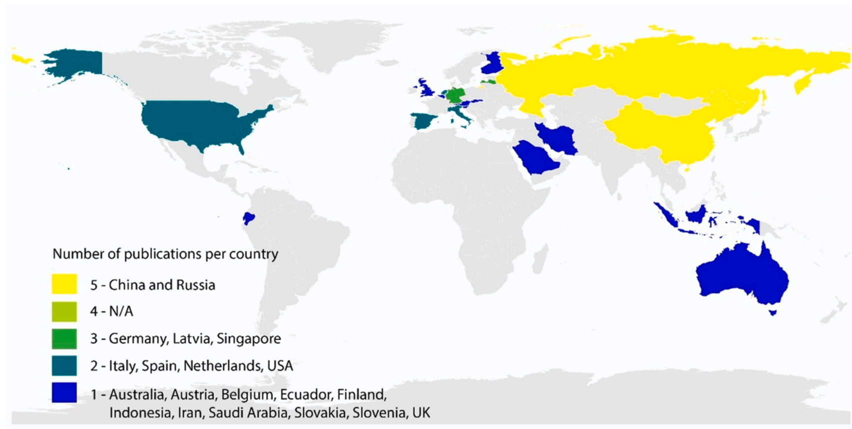

Fig. 5. The number of publications included in the literature review is displayed by country, based on first author affiliation, indicated by country colors on the world map. Countries shown in grey were not indicated as first author affiliation in any of the included publications.

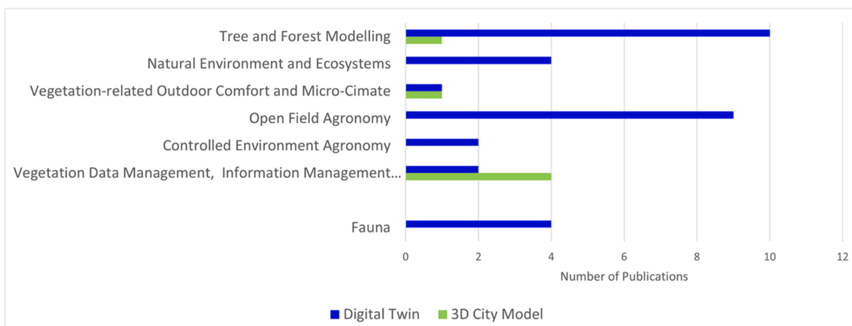

Fig. 6. Number of publications included in the literature review categorised by research focus area (y-axis) and the primary search term used ("Digital Twin" or "3D City Model," indicated by bar color). The x-axis shows the number of publications for each category.

and crops are exposed to natural conditions. Modelled plants encompass grasslands (Purcell et al., 2022), a vineyard (Edemetti et al., 2022), organic potatoes (Majore, 2022), crops (Skobelev et al., 2022b), wheat (Skobelev et al., 2020a), winter-wheat (Skobelev et al., 2022a) and rice (Skobelev et al., 2021). The dynamic plant models and the simulations of their interactions with the environment, such as with soil or atmosphere, aim to improve the economic value, environmental sustainability, and build a basis for plant management and improved decision-making (Edemetti et al., 2022; Purcell et al., 2022; Skobelev et al., 2022b; 2021; Van Evert et al., 2023). These models support plant monitoring, crop management, predictive maintenance, yield forecasting, land use optimisation, and efficient use of resource such as water, fertilizers and pesticides.

The development and use of digital twins in the field of agronomy are more common (Purcell and Neubauer, 2023; Sreedevi and Santosh Kumar, 2020) than reflected in this study. However, Skobelev et al. (2022a) note that the dominant share of these publications primarily focuses on digital twins of the infrastructure facilities, rather than the digital twins of plants, which is the focus of this review.

Controlled-Environment Agronomy: This category is referring to agronomical practices conducted in controlled environments such as greenhouses where e.g. climate, light and humidity are controlled to optimise growth conditions. Publications in this category discuss microclimate control systems and greenhouse crop simulation models (Moin-E-Ddin Rezvani et al., 2021), precision farming and virtual tomato crop use-cases (Knibbe et al., 2022). Both have the purpose to monitor, simulate, predict and regulate the greenhouse itself and the crops.

Vegetation Data Management, Information Management and Modelling: Publications in this category discuss 3D vegetation modelling methods and software, 3D-modelling standards and attribute indicators that are relevant for classifying vegetation (Zhang et al., 2022). More precisely, they discuss dynamic spatial data of trees derived from forest simulations and stored though the Dynamizer in CityGML (Kastuari et al., 2020) and the usage of semantic city models using the CityGML standard for the modelling, monitoring and validating of green façade and roof solutions (Vo et al., 2019). Moreover, parametric trees in Building Information Models (BIM) (Luka and Guo, 2021) as well as the geographic positioning of trees and the integration of an interactive database into a building information model (García-Granja et al., 2020) are considered. Additionally, a Tree Information Model (TIM) as a data exchange platform (Shu et al., 2022) is proposed.

3.2.2. Fauna

Dynamic models of fauna range from the social interactions and behavioural patterns of an abiomimetic robot fish with biological fish (Joordens et al., 2019), to continuous monitoring and assessment of environmental health with smart bat monitors (ultrasonic microphones) (Hudson-Smith et al., 2021), to social-ecological system of urban beekeeping to monitor e.g. the health of bee colonies and anomalies (Johannsen et al., 2021), and to how IoT and digital twins in Precision Livestock Farming (PLF) can improve the health and well-being of farm animals (Mishra and Sharma, 2023).

3.3. Data

Data are one of the key components of digital twins (Zhang et al., 2022a), and therefore an equally indisputable exigency for the dynamic modelling of flora and fauna in digital twins.

3.3.1. *Data categories*

Following Zhang et al. (2022)'s notion of "Digital Twin Data", data described in the publications are organised here into the six categories based on relevance and frequency in the literature: Physical entity-related data, domain knowledge, virtual model-related data, service-related data, fusion data and connection data (Fig. 7, definition in Supplement S2). Each category is integral to the framework of digital twins, providing a structured approach to assembling optimised digital representation and analysis. Given the extent of the physical entity-related data, a separate list can be found in the Supplement S2.

3.3.2. *The rhythm of nature stipulates possible timings and frequencies of data collection*

Digital twins of plants necessitate substantial data (Skobelev et al., 2022a). However, since flora and fauna depend on the rhythms of nature, collecting all types of data year-round in uncontrolled environments — such as open-field agriculture or natural ecosystems — is often hindered by natural fluctuations (Johannsen et al., 2021; Majore, 2022). Greenhouse agronomy or livestock farming depend on the lifecycle of the subject of interest in a controlled environment. In contrast, "outdoor" flora and fauna are depending on e.g. the climatic zone, governed by annual cycles, with the life-cycle phases being influenced by both intrinsic biological factors as well as external conditions like weather (Skobelev et al., 2022a). These dependencies can slow data acquisition and knowledge gain compared to digital twins of human-made infrastructures. Moreover, real-time measurement of some system parameters, like plant sugar levels, is not practically feasible (Knibbe et al. 2022).

Frequencies of data collection alike depend on the object of interest, the data collection method, available resources, as well as the modelling approach. In the selected publications, the frequencies of the data collection range from (near) real-time or continuous data collection via e.g. IoT devices, Global Positioning System (GPS), Radio-Frequency Identification (RFID), etc. (Mishra and Sharma, 2023) to regular updates, where data is collected e.g. once a year (Tanhuanpää, 2016), to irregular input data collection (Mongus et al., 2021).

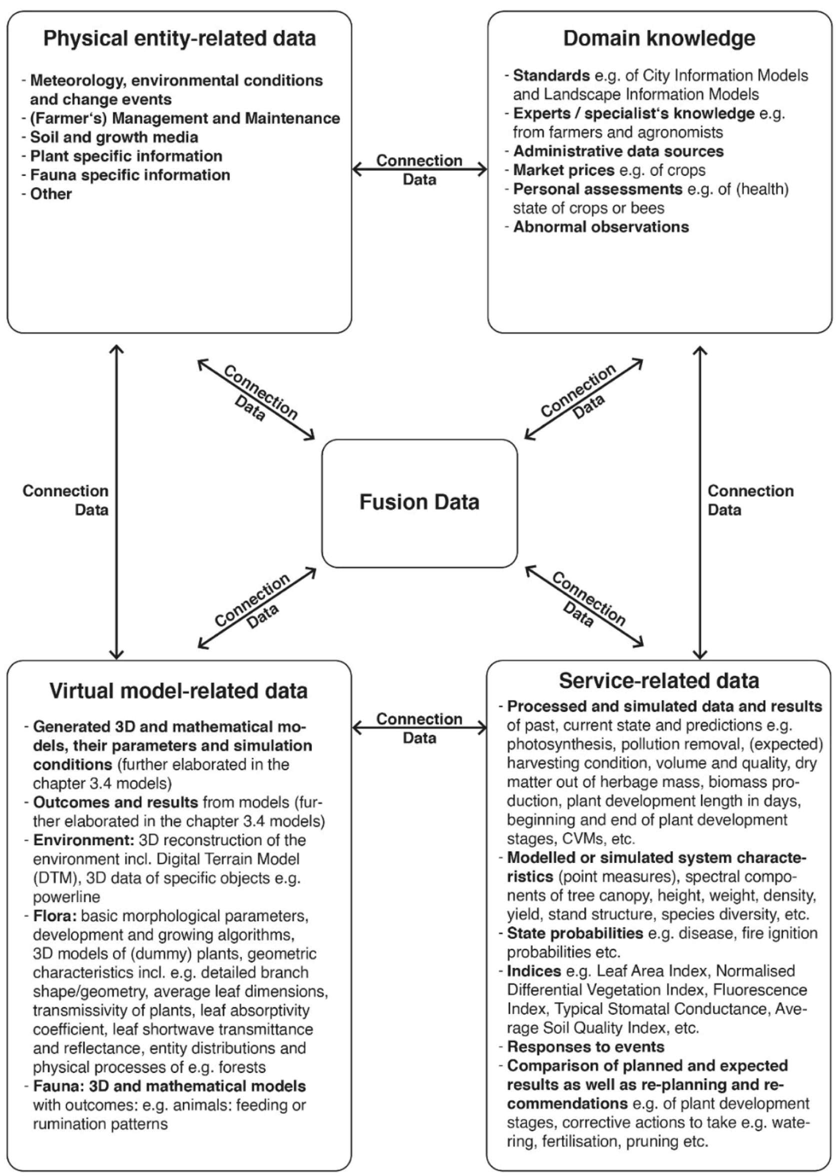

Fig. 7. Data types of flora and fauna models that appeared in the included publications, classified into the six categories of interrelated "digital twin data" types proposed by Zhang et al. (2022). A comprehensive list of the data types in this study that were classified as physical entity-related data, along with a description of the data type classification by Zhang et al. (2022), is provided in the supplement (S2).

3.3.3. Data sources and data collection methods

Data sources commonly include existing databases belonging to the categories "domain knowledge" and "physical entity-related data", covering e.g. historical data (Zhao et al., 2022). Additionally, data is sourced mainly through the following methods:

Spaceborne and Aerial Observation (SAAO) Methods: Spaceborne and aerial observations methods (SAAO) employed in the selected publications include GPS, Airborne Laser Scanning (ALS) (Gobeawan et al., 2019), multispectral data (Zhao et al., 2022), Light Detection And Ranging (LiDAR) scans from Unmanned Aerial Vehicles (UAV) (Edemetti et al., 2022; Lu et al., 2023), air-borne and satellite imagery (Gobeawan et al., 2018; Zhao et al., 2022) and photogrammetry (Kastuari et al., 2020).

Ground-based Methods: Ground-based data collection methods require physical presence or instruments placed directly at the location or object of interest. These methods are more manifold than the SAAO methods. Terrestrial Laser Scanning (TLS) (Guo et al., 2022; Hofierka et al., 2017; Shu et al., 2022), Mobile Laser Scanning (MLS), LiDAR and other Laser Scanning methods (Gobeawan et al., 2018; Wang et al., 2022) are comparable technologies to the SAAO that are typically used for ground-based vegetation data collection.

Ground-based data collection is in many cases still also carried out manually through inspections, field surveys and measurements (Gobeawan et al., 2018; Hofierka et al., 2017; Kastuari et al., 2020; Lu et al., 2023; Luka and Guo, 2021; Skobelev et al., 2022a). Manual methods are said to be subjective, laborious, time-consuming, less data rich than other methods, and hence, expensive (Kastuari et al., 2020; Li and Wang, 2009; Yuan et al., 2018). Moreover, these methods pose challenges in fields like livestock farming (Mishra and Sharma, 2023), and manual data entry into information systems hinders the timeliness and accuracy of information (Knibbe et al., 2022). Due to e.g. the listed shortcomings, coupled with calls for reduced data harvesting costs, Guo et al. (2022) assert that manual data collection is losing attractivity. As an alternative, GPS systems, diverse sensors and IoT technologies and other mobile technologies now enable continuous data collection and improve accessibility (Hudson-Smith et al., 2021; Mishra and Sharma, 2023; Vo et al., 2019). For the automatic updating and integration of collected (raw) data into digital twin systems, cloud computing (Mishra and Sharma, 2023) or (multi access) edge computing (Edemetti et al., 2022) are employed.

From Raw Data to Insights: Data Mining and Synthetic Data Collection: Data mining methods are applied to extract useful information, e.g. derive the tree canopy from a point cloud (Gobeawan et al., 2018). Moreover, (synthetic) data is created through modelling techniques, which are further described in chapter 3.4 Models.

3.3.4. Challenges in data quality and availability

For meaningful knowledge extraction, high-quality data is paramount, and shortcomings on data affect updating frequencies, the Level of Detail (LoD), e.g. complexity of 3D representations, and accuracy of the digital twins, impeding further progress (Xhafa and Krause, 2021). Researchers cite several reasons for insufficient data coverage for dynamic modelling flora and fauna, including restrictions in availability (Van Evert et al., 2023) and affordability of technologies and infrastructure (Wang et al., 2022), inaccuracies and inadequacies in sensing equipment (Knibbe et al., 2022; Wang et al., 2022), and external factors like obstructions in satellite data collection (Kasampalis et al., 2018; cited by Zake and Majore, 2022). Even when data are available, not all data is equal in terms of quality and relevance. The consequences are particularly evident in machine learning applications within digital twins, which require substantial data to effectively learn and refine conditional probabilities e.g. related to plant states and transitions (Johannsen et al., 2021). Moreover, a key challenge lies in the heterogeneity and diversity of data, requiring standardizing data-sharing protocols across digital twin implementations, including data sources and entity attributes. The proliferation of protocols creates technical debt, interoperability issues, and governance barriers, diminishing the value of digital twins at all scales (Buonocore et al., 2022).

3.3.5. Standards and data management systems

Creating digital twins of flora and fauna requires data aggregation and management. One of the main challenges hereby is to ensure interoperability between different databases, systems and standards (Ketzler et al., 2020; Lei et al., 2023). In the selected publications, data management is in most cases not mentioned nor very precisely described.

Urban Environment: For the urban environment, Building Information Modelling (BIM) (García-Granja et al., 2020) and City Information Modelling (CIM) facilitate information sharing and exchange, enhancing the efficiency and sustainability of planning, design, construction, and management. Additionally, Landscape Information Modelling (LIM) addresses the specific needs of landscape architectural projects, enhancing their planning and execution (Shu et al., 2022). City-wide tree registers, which map trees and model tree-level parameters — such as diameter at breast height, volume, location, species group — are employed for tree information management and storage (Tanhuanpää, 2016).

CityGML is a widely used international open standard for urban environments encompassing aspects such as urban geometry, topology, and semantics while supporting various levels of detail (García-Granja et al., 2020; Kastuari et al., 2020; Vo et al., 2019; Zhang et al., 2022). To prevent obsolescence, CityGML has incorporated a mechanism known as Application Development Extension (ADE) to enable the modelling of additional information, not initially anticipated (Kastuari et al., 2020; Vo et al., 2019). Since CityGML 3.0, the Dynamizer module enables the representation and management of dynamic data — such as time-varying tree heights and simulation results — within the 3D city model (Kastuari et al., 2020).

Agricultural Sector: In the agricultural sector, data pertaining to management activities are traditionally stored within Farm Management Information Systems (FMIS). These systems are available in various commercial versions, many of which lack interoperability. Data entry into FMIS is typically performed manually, leading to challenges in obtaining accurate and up-to-date information. Despite the development of standards for data processing, none have achieved widespread adoption. (Knibbe et al., 2022)

Cross-domain: Geographic Information Systems (GIS) are commonly employed for analysing, simulating, visualising and managing geographic data, e.g. in the creation of a virtual bog ecosystem (BogSim-VR) (Cirulis et al., 2022).

Tree Information Modelling (TIM) facilitates cross-disciplinary knowledge sharing about trees, using a Tree Description System (TDS), which standardises tree descriptions with basic information tags and geometric representations. The high Level of Detail (LoD) of TDS makes it adaptable for various applications, integrating forestry science, Functional Structural Plant Modelling (FSPM) and building environments into a unified platform (Shu et al., 2022).

Application Programming Interfaces (API) allow seamless data interaction and are discussed in various contexts, such as for the graphics in the BogSim-VR (Cirulis et al., 2022), integrating third-party data like weather forecasts (Edemetti et al., 2022; Vo et al., 2019), collecting data from bee hive sensors (Johannsen et al., 2021) and connecting Tree Information Modelling (TIM) to Building Information Modelling (BIM) and GIS (Luka and Guo, 2021; Shu et al., 2022).

3.4. Models

3.4.1. System models

The basis of a digital twin can consist of models with varying complexity and integration levels. These range from single models to multi-scale multi-domain models connecting multiple high-level system models that connect sub-models of various aspects of the physical counterparts into one functional and interactive entity. System models presented in the examined literature vary in their structural complexity, from hierarchical or modular system models with one or more sub-models (Buonocore et al., 2022) to model chains or networks, where outputs of sub-models are used as the inputs of subsequent models (Pusztai, 2021; Skobelev et al., 2020a), to simple input-output models of a key phenomenon of the system (Fernández-Alvarado et al., 2021). Additionally, publications contain digital twins that are collections of unconnected models, bound together mainly by a shared physical system or a common user interface (García-Granja et al., 2020).

3.4.2. (Sub-)model aims and temporalities

System models may include (sub-)models developed for one or more model aims, and hence also for one or more temporalities (Fig. 8). For the categorisation of temporalities and the model categorisation, the three types of analytics techniques — descriptive, predictive and prescriptive models — described by (Roy et al., 2022) are adopted. The granularity and spatial scale of sub-models depend on model aims. For example, plant models vary from large-scale parameters, e.g. tree canopy cover or leaf area index (Cirulis et al., 2022), to tree skeleton models for accurate estimations (Chattoraj et al., 2022). Models of animals can range from e.g. modelling the behavioural state of a (bee) colony (Johannsen et al., 2021) to a model of a cattle's individual heart rate as estimated from the changes of blood flow (Mishra and Sharma, 2023). Sub-model structures also reflect the available data collection tools and frequencies, e.g. whether the available weather data is based on continuous monitoring (Buonocore et al., 2022; Skobelev et al., 2022b) or annual statistics (Mongus et al., 2021).

Descriptive Models: Descriptive models (Fig. 8) in many cases form the foundational layer of digital twins. In most presented publications they summarise (Buonocore et al., 2022) and/or visualise (Gobeawan et al., 2018) current system states based on the collected data. In forestry, agronomy and fauna modelling, descriptive models typically aim for (real-time) system monitoring, change detection and information retrieval, (Johannsen et al., 2021; Mishra and Sharma, 2023; Zhao et al., 2022) with their outputs providing the baseline information required for these purposes. Moreover, those models assist with data exploration, decision-making and manual analysis of intervention needs (Mongus et al., 2021). These models output estimates of e.g. system processes or function, such as greenhouse gas exchange (Edemetti et al., 2022; García-Granja et al., 2020; Guo et al., 2022), current product states, such as tree or forest volumes (Buonocore et al., 2022) or honey in the beehive (Johannsen et al., 2021), developmental stages of crops (Skobelev et al., 2022b), or system performance, such as energy efficiency (Purcell et al., 2022). They may also be designed to output specific variables to support decision-making, e.g. tree health (Pusztai, 2021), forest canopy distance from powerlines (Mongus et al., 2021) or social behaviour of a fish (Joordens et al., 2019).

Detection Models: In digital twins, detection models facilitate (real-time) updates by identifying key system states. This supports in ensuring that the virtual counterpart – based on the provided data and depending on updating frequencies – remains dynamically aligned with the physical counterpart. Image analysis-based detection models are, among others, sub-models of descriptive models, detecting either the presence

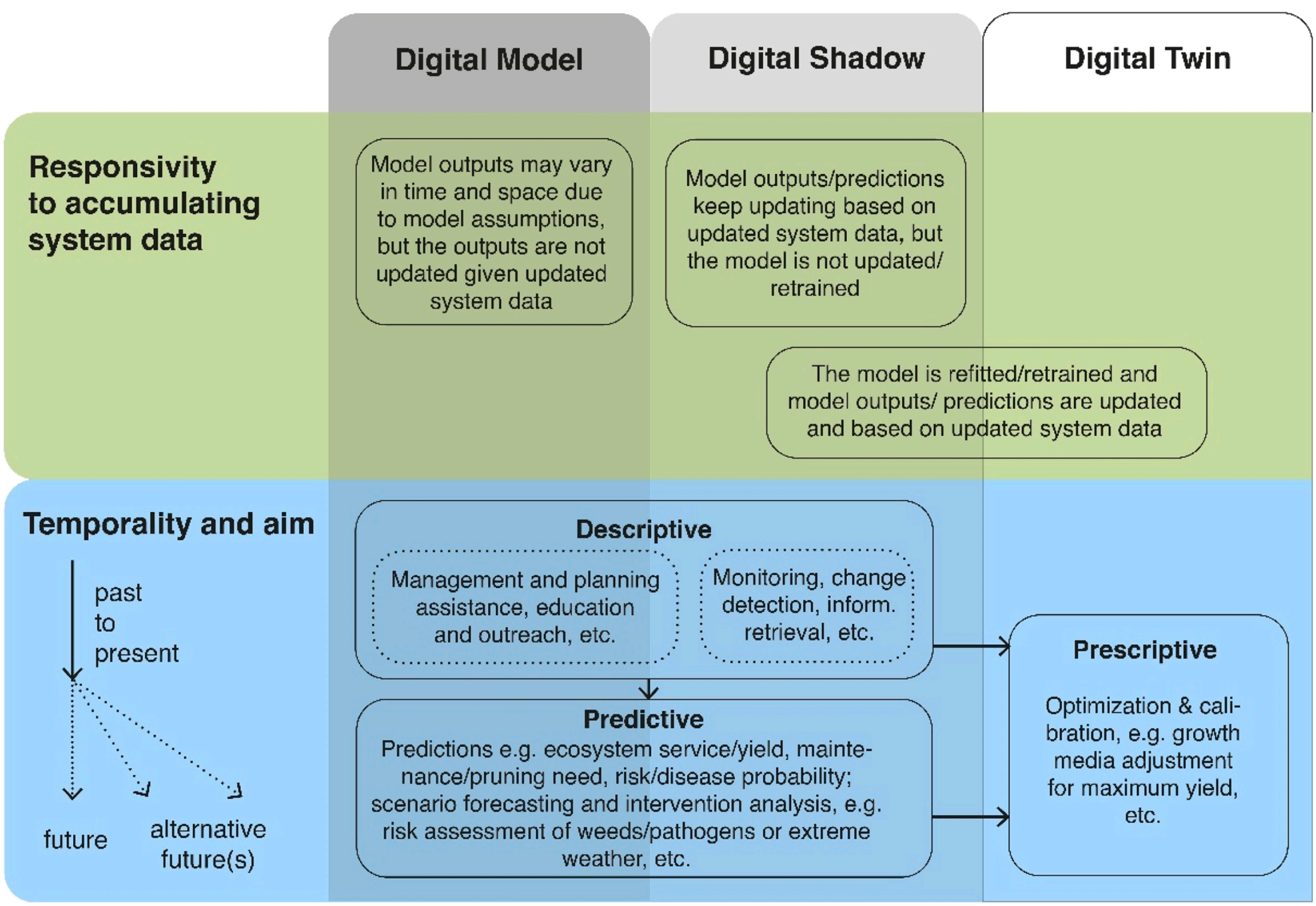

Fig. 8. Aspects of (sub-)models in the included publications, classified according to the type of data flow and synchronisation between the virtual and the physical (columns; for details of the classification, see Fig. 1), responsivity to accumulating system data (green topmost panel), model temporality (light blue bottom panel), and model aim (boxes within the light blue bottom panel). The diagram highlights three primary aims of these systems—descriptive, predictive, and prescriptive—spanning from past to (alternative) futures.

or location of species, phenomena of interest, such as individuals of production animals (Mishra and Sharma, 2023), animal or livestock herds (Majore, 2022), the presence of certain plant species (Chattoraj et al., 2022; Gobeawan et al., 2021) weeds, pathogens (Johannsen et al., 2021), or e.g. indications of fire (Sanchez-Guzman et al., 2022). Sound analysis-based detection models are used to identify the presence of many animal species especially in the context of wildlife monitoring (Hudson-Smith et al., 2021).

Outputs of detection models are used to e.g. analyse animal behavioural stages, stress levels (Mishra and Sharma, 2023), the onset of disease epidemics (Mishra and Sharma, 2023), vegetation coverage (Zhao et al., 2022) or species occurrence and distribution (Lu et al., 2023; Purcell et al., 2022). Furthermore, those models estimate e.g. the expected production performance (Skobelev et al., 2022b), or susceptibility to different environmental hazards (Majore, 2022; Sanchez-Guzman et al., 2022).

Models aiming for system monitoring and change detection also include blockchain technologies to track supply chains and to ensure e.g. the traceability of timber sources (Buonocore et al., 2022) or cattle illness (Mishra and Sharma, 2023). Moreover, descriptive models have been developed for management and planning assistance (Gobeawan et al., 2021; Shu et al., 2022) as well as for public education and outreach (Harrington et al., 2021). These models typically focus on the visualisation of system patterns and processes of interest (Harrington et al., 2021). Along with the progress of time, descriptive models produce a timeline of system states into the past (Harrington et al., 2021).

Predictive Models: Predictive models enhance digital twins by simulating future states of the system. Predictive models (Fig. 8) are used to predict either system characteristics or outcomes at certain time points in the future. Examples include product yield at harvest (Edemetti et al., 2022), the probability of e.g. a pathogen outbreak within a certain time interval (Johannsen et al., 2021), the timing of certain outcomes, such as agricultural product completion, or maintenance/pruning need (Edemetti et al., 2022; García-Granja et al., 2020), or the swarming interval of bee colonies (Johannsen et al., 2021). Plant growth can be modelled using species-specific growth guidelines (Moin-E-Ddin Rezvani et al., 2021; Van Evert et al., 2023), and the structural growth of a plant can be simulated in space using procedural modelling methods (Gobeawan et al. 2018) such as pre-formulated l-system growth rules (Gobeawan et al., 2019). Corresponding data can be collected for predictive modelling of a dairy cow's life cycle phases and structural development (Mishra and Sharma, 2023).

In the case of sparse or sporadic data collection frequencies, predictive models are being used to model the present system state based on data of past system states. Moreover, predictive temporal models are implemented to assess analytical scenarios, such as yield forecasting (Skobelev et al., 2020b) or animal activities (Mishra and Sharma, 2023), and intervention analysis (Fig. 8). These models achieve this by altering the input conditions from real ones, e.g. the harvesting cycle (Majore, 2022; Moin-E-Ddin Rezvani et al., 2021) or the presence of other species (Joordens et al., 2019). These alternative futures can reflect the effects of human interventions or weather events (Skobelev et al., 2022a), for the purpose of analysing e.g. system resilience to extreme weather conditions (Sanchez-Guzman et al., 2022) or the outcomes of changed management (Majore, 2022).

Prescriptive Models: In digital twins, prescriptive models enable real-world interventions by generating actionable insights, which can be implemented through automated feedback loops to actuators or manual decision-making processes, ensuring the physical system adapts dynamically to changing conditions. Precision agriculture, Precision Livestock Farming (PLF) and other production-focused digital twins entail prescriptive (optimisation-calibration) models, where continuously updating system data of the present system state are deployed to evaluate deviations from optimal conditions, e.g. of greenhouse climate or growth media (Moin-E-Ddin Rezvani et al., 2021), beehive humidity (Johannsen et al., 2021) or nutrient intake of animals (Mishra and Sharma, 2023). In some examples robots can then be engaged to automatically modify the conditions of the agricultural system back to the desired optimal state, providing a two-way automated feedback loop between the physical and virtual systems (Skobelev et al., 2022b).

In precision agriculture, predictive and prescriptive models often incorporate elaborate species-specific growth models to simulate crop or timber growth (Buonocore et al., 2022; Skobelev et al., 2022b) or the upcoming animal behaviour (Mishra and Sharma, 2023). Growth models range from simple temporal models that lack interactions with any (spatially varying) environmental predictors, limiting their use to approximate future growth predictions (Luka and Guo, 2021), to highly sophisticated models incorporating e.g. genotype or phenotype effects (Skobelev et al., 2022b) or processes occurring at the level of plant structures (Moin-E-Ddin Rezvani et al., 2021; Shu et al., 2022; Skobelev et al., 2020b) or animal tissue (Mishra and Sharma, 2023).

3.4.3. *(Multi) agent-based models*

(Multi-) Agent-based models are employed in descriptive models to simulate the spatiotemporal patterns and interactions of individuals of reactive species, such as pollinator insects (Johannsen et al., 2021), (biomimetic robot) fish (Joordens et al., 2019), or as a sub-system for plant growth and development (Skobelev et al., 2022b). When agent-based models are used to visualise the presences and densities of species that are too abundant to be tracked on an individual level, the hypothetical movements and behaviours are simulated based on their tracked presences or densities (Mishra and Sharma, 2023). Additionally, agent-based models are employed in predictive models and scenario forecasting, e.g. to test the effects of alternative rules and regulations (Johannsen et al., 2021).

3.4.4. *Visualisation models*

Visualisation models are not always embedded in the digital twin, e.g. in applications where monitoring and interventions rely primarily on indicators (Mishra and Sharma, 2023). However, most digital twins include 2D or 3D visualisation models of the physical system, which serve as the basis for their representation in the digital twin's user interface (Chattoraj et al., 2022; Edemetti et al., 2022; Pusztai, 2021; W. Zhang et al., 2022).

In some cases, visualisations are of avail to estimate other parameters of interest from point cloud data, such as tree species (Chattoraj et al., 2022), basal area (Wang et al., 2022) or tree growth (Mongus et al., 2021). Additionally, 3D visualisation models can act as key parts of 3D spatial analyses, e.g. in the case of estimation of green volume (W. Zhang et al., 2022), shadow casting (García-Granja et al., 2020), analysis of object interaction with buildings (Hofierka et al., 2017) or other objects (Mongus et al., 2021).

The current state-of-the-art for generating 3D tree models and species identification from remote sensing data involves reconstructing trees from point clouds and photogrammetry using deep learning (Chattoraj et al., 2022; Guo et al., 2022; Lu et al., 2023; Pusztai, 2021; Shu et al., 2022). Manual 3D modelling by experts is also used, especially for game engine-based digital twins (Harrington et al., 2021; Lu et al., 2023). Additionally, 3D tree models in digital twins evolve over time based on data-driven growth models (Gobeawan et al., 2021, 2019, 2018; Skobelev et al., 2020b).

3.4.5. *Model fitting and validation*

Mechanistic and Data-Driven Models: Mechanistic and data-driven models are commonly used in the reviewed literature for digital twin systems. Mechanistic models, such as those used for well-studied aspects of the modelled systems, e.g. crop growth, photosynthesis (Moin-E-Ddin Rezvani et al., 2021) or fish tail movement (Joordens et al., 2019), are frequently constructed with mathematical functions known to describe these phenomena. Digital twins also incorporate data-driven statistical models, fitted to data gathered either from the modelled physical or a similar well-studied system (Gobeawan et al., 2021, 2019, 2018). These data-driven models include both state-based and process-based models (Buonocore et al., 2022). Despite advancements, existing mathematical models, including those based on differential equations, statistical data analysis from previous periods, and machine learning approaches, are currently unable to deliver highly accurate plans, e.g. agro-technical, for the entire vegetation period or reliable yield predictions. This challenge arises from the necessity for frequent model retraining, as a range of dynamic factors — such as global climate change, fertilizer application, plant protection products (PPP), and field management techniques — must be continuously accounted for (Skobelev et al., 2021).

Machine Learning (ML) and Artificial Intelligence (AI) Models: ML and AI models represent a specialised subset of data-driven models as they differ from traditional statistical models in their fitting methods and capabilities. For instance, supervised ML methods, such as artificial neural networks, require extensive labelled datasets but can generalise well to similar scenarios. Unsupervised and reinforcement learning techniques, on the other hand, can uncover hidden patterns or optimise decisions in less structured contexts. However, these methods also pose risks, such as overfitting to training data or producing results that lack interpretability, especially when domain knowledge is insufficiently integrated (Rebala et al., 2019). A diverse array of supervised and unsupervised ML methods is used to accurately model phenomena, e.g. those that are non-linear or where understanding the causal relations of phenomena is not essential (Edemetti et al., 2022; Mishra and Sharma, 2023; Skobelev et al., 2020a; Van Evert et al., 2023). Knowledge-driven ML is considered for phenomena where domain knowledge, e.g. procedural rules and constraints could complement the ML approach (Chattoraj et al., 2022). ML methods include e.g. artificial and neural networks (Chattoraj et al., 2022; Mongus et al., 2021). Additionally, ML and AI models are increasingly used in predictive and prescriptive models.

3.4.6. Model responsivity

The responsivity of models to spatial aspects and temporal changes in physical systems varies across publications. Models in digital twins are commonly spatiotemporally explicit, providing different outcomes across space due to i.e. interactions with predefined environmental variables, such as local (micro-) climate (Knibbe et al., 2022; Skobelev et al., 2022a) soil characteristics (Knibbe et al., 2022; Mongus et al., 2021; Skobelev et al., 2022b) or human interventions like pruning (Gobeawan et al., 2021).

However, the presented models are located differently on Kitzinger et al.'s (2018) classification of digital twins, i.e. whether their predictions are automatically updating based on changes in the physical system (Digital Model vs. Digital Shadows vs. Digital Twins). Automatic data collection and processing allows the building of "Smart Cyber-Physical Systems" (Skobelev et al., 2022a), "Smart Digital Twin of a Plant" (SDTP) (Skobelev et al., 2022b) or "Eco-Cyber-Physical Systems" (ECPS) (Majore, 2022), where also the models themselves are automatically calibrated (statistical models) or retrained ((Deep) Neural Networks) along with the accumulation of system data (Edemetti et al., 2022; Johannsen et al., 2021). These models are not yet common in digital twins, as the development of those models is tightly tied to the advances of automatic data collection and processing. Furthermore, the development of AI and ML will support the development of self-learning models (Edemetti et al., 2022; Johannsen et al., 2021).

3.4.7. Model validation and calibration

Regular data collection from the physical counterpart enables ongoing model validation and calibration. This process enhances the accuracy and precision of models beyond their initial construction, which may be based on historical data (Knibbe et al., 2022). For instance, in the case of tree models, field observations are employed e.g. to validate the accuracy of detected risks (Mongus et al., 2021) and to calibrate growth predictions (Guo et al., 2022). Similarly, simulated fish behavioural patterns are validated against the behaviour of real-life fish in corresponding situations (Joordens et al., 2019). The availability of remote sensing data and IoT technologies holds potential for automated model adjustment, further enhancing model fidelity. However, the quality of data is hereby playing a crucial role, as models will only get as accurate as their weakest component. Deficits in input data appearing e.g. due to human error or technical shortcomings, impair the validation and calibration of the respective models and thereby the integrity of their outputs.

3.5. Actuators

Actuators, which automatically transfer outcomes from the digital to the physical world, are key components distinguishing digital twins from digital shadows (Kritzinger et al., 2018). However, only seven out of the 32 reviewed publications found with the search term "digital twin" and none of the articles found with "3D city model" address this aspect. All seven articles discussing actuators are from the field of agriculture. These publications are categorised into "Fauna" for livestock farming (Mishra and Sharma, 2023), "Controlled Environment Agronomy" (Knibbe et al., 2022), and "Open-Air Agronomy" (Edemetti et al., 2022; Majore, 2022; Skobelev et al., 2020a, 2020b; Van Evert et al., 2023).

Besides the benefits attributed to digital twins in general, in agriculture actuators hold potential for addressing challenges in geographically dispersed areas, increasing harvests, and improving animal welfare. Additionally, automated processes could reduce manual labour, freeing up time for other activities (Mishra and Sharma, 2023; Van Evert et al., 2023).

Actuation in digital and precision agriculture is exemplified by autonomous and unmanned machinery like precision planters, spreaders, sprayers, and fully autonomous tractors. However, limitations lie in precision equipment accessibility (Van Evert et al., 2023).

In the case of the digital twins for harvest plants, e.g. tomato plants, high-level guidance on optimal setpoints, such as indoor temperature and pruning rates, is currently provided primarily through consultancy (Knibbe et al., 2022). However, there is potential for automatically relaying the provided decision advice to an actuator (Knibbe et al., 2022; Van Evert et al., 2023). To achieve fully automated control, decision support systems would require control algorithms to automatically calculate and onset the optimal management of inputs and actions (Knibbe et al., 2022).

Future research directions which are not detailed in the analysed literature include developing Eco-Cyber-Physical Systems (ECPS) (Majore, 2022), executive devices for intelligent cyber-physical systems that automate processes like plant growth management (Skobelev et al., 2020a, 2020b), agricultural actuators in vineyards that receive instructions from the digital twin (Edemetti et al., 2022) and robots managing tasks without human intervention for livestock management and precision agriculture (Mishra and Sharma, 2023).

3.6. User experience

3.6.1. Representation

Although it is already possible today to fully automate the connection between the physical and virtual worlds via digital twins, human-computer interaction remains a critical aspect in the development and use of these digital replicas of flora and fauna. The representation and especially the visualisation of the underlying data and models is crucial for helping humans understand vast amounts of digital data, supporting analysis, informs decision-making and behaviours, and fosters data literacy (Gatto, 2015; Rist and Masoodian, 2022; Venkatraman and Venkatraman, 2019).

Representations of flora and fauna in digital twins serve various purposes, primarily aimed at "informing" in the broadest sense. This covers monitoring (Gobeawan et al., 2021; Hudson-Smith et al., 2021; Tanhuanpää, 2016), interpretating simulation outcomes (Purcell et al., 2022; Skobelev et al., 2020a), and providing information, recommendations and data for the decision support (Fernández-Alvarado et al., 2021; Klippel et al., 2021; Skobelev et al., 2020a). The most common form of representation is found to be in 2D maps or 3D, emphasising scientific modelling over photorealistic visualisation. For this purpose, e.g. dummy plants are associated with the plant specific information (Edemetti et al., 2022). However, photorealism is emphasised in specific applications like the virtual arboretum (Harrington et al., 2021) and the virtual scene construction of wetlands (Lu et al., 2023).

Besides the visual representation, Harrington et al. (2021) detail an additional modality in acoustic form, wherein an enhanced multimodal sensory experience, encompassing both visual and acoustic elements, is achieved. Their framework of high information fidelity enables the accurate acoustic replication of the environment, e.g. specific insect and avian populations of each location and season. This approach enhances the accessibility of digital nature experiences for e.g. vision-impaired individuals. (Harrington et al., 2021)

3.6.2. Human-computer interaction

User interfaces form the point of human-computer interaction, representation and communication for digital replicas. Hereby, poor usability can compromise the value of a digital twin by reducing accessibility and practicality (Purcell et al., 2022). Most of the analysed literature does not detail user interfaces, often referring to them generally as platforms or interfaces (Edemetti et al., 2022). Skobelev et al. (2020a, 2022b) describe the development of a specialised user interface, encompassing an ontology editor, a digital twin editor and a multi-agent planning module for their developed SDTP (Smart Digital Twin of Plant). Purcell et al. (2022) propose an interface-driven design focusing on one standardised interface, which can be reused and extended with additional components. This approach simplifies the creation of new interface expansions or services for additional data sources or functionalities. Commonly used interfaces are Graphical User Interfaces (GUIs), 3D, and Spatial User Interfaces, e.g. for virtual city platforms (Gobeawan et al., 2019).

Common mediums for human-computer interaction include Extended Reality (XR), encompassing Augmented Reality (AR) and Virtual Reality (VR) accessed via Head Mounted Displays and controllers (Cirulis et al., 2022; Harrington et al., 2021; Joordens et al., 2019; Klippel et al., 2021; Lu et al., 2023). Additionally, Harrington et al. (2021) connect the VR headset to a treadmill to create a more realistic and immersive physical-virtual environment. Also Cave Automatic Virtual Environment (CAVE) systems, equipped with motion tracking, offer immersive interaction (Lu et al., 2023). Other interaction mediums include PCs (Harrington et al., 2021) with e.g. web browsers (Lu et al., 2023), web applications (Johannsen et al., 2021) and mobile devices such as phones (Skobelev et al., 2020a) or tablets (Cirulis et al., 2022).

The human-computer interaction primarily consists of three main parts:

1. Data input: Users manually input data through tools like online documentation in web applications (Johannsen et al., 2021).
2. Virtual Interaction: Users interact with dynamic models and simulations, involving movement in virtual environments (Edemetti et al., 2022; Harrington et al., 2021; Lu et al., 2023) or altering input variables like pasture and weather to e.g. test or forecast future states of the objects or systems (Purcell et al., 2022; Skobelev et al., 2020b) with real-time updates in the virtual counterparts (Cirulis et al., 2022).
3. Action in Physical Counterpart: Users take action in the physical counterpart based on digital twin information, such as watering crops or feeding colonies. These changes can be manually or automatically (re-) introduced into the digital twin (Johannsen et al., 2021).

3.7. Ethical considerations

Ethical considerations are found in the field of digital twins of agriculture, addressing potential privacy breaches, technology reliability, and the possibility of their misuse (Mishra and Sharma, 2023; Van Evert et al., 2023). Further, Mishra and Sharma (2023) discuss concerns about technologies not aligning with animals' best interests, potential harm to animals, and animals being used solely as data sources. Data-based decision tools in farming raise ethical concerns, particularly regarding shifts in power dynamics between farmers and commercial actors. Often, the data generated are benefiting companies more than the farmers who provide it. Simultaneously, individual farmers may struggle to make the necessary investments to fully benefit from these tools (Van Evert et al., 2023). Knibbe et al. (2022) refer to ethical aspects being discussed in Korenhof et al. (2021) and Van Der Burg et al. (2021).

An emphasis on sustainability and improvements of various aspects, as one of their digital twin development purposes was found in many of the selected publications. In agronomy, aspects such as resource consumption e.g. water (Edemetti et al., 2022) are widely discussed. In this regard it is furthermore prompted that the environmental impacts, including the energy consumption of IT infrastructures and their carbon footprints, need further investigation (Stoll et al., 2019 as cited in Buonocore et al., 2022). The extent to which these concerns are driven by ethical, economic, or other considerations is unclear from the literature.

4. Discussion, future research directions and conclusion

The study of flora and fauna has evolved over centuries, leading to extensive knowledge on the topic. Simple models and simulations are being replaced by complex and highly sophisticated virtual representations which are offering rich, multifaceted insights into the interactions between the biotic and further layers of the digital replicas. As technological advancements continue to accelerate, research in this area is evolving rapidly leading to increasingly heterogenous approaches across different disciplines and applications.

The horizontal, cross-sectoral view on flora and fauna modelling for digital twins allowed this review to highlight the diversity of approaches which are tailored to various developers, disciplines, user groups, and specific purposes, incorporating diverse data, developed and employed models, user experience methods, actuators and ethical considerations. Based on these findings, this review should be regarded as a comprehensive resource showcasing current methodologies and serving as a foundation for future advancements in the diverse fields of flora and fauna modelling in digital twins, rather than as an uniform framework to follow.

4.1. Limitations of this study

Only the scientific publications listed in the three databases Scopus, Web of Science and Google Scholar found with the search strings detailed in the Section 2.2 Definition of Keywords and Search Strings, are covered in this review. It is to be assumed that a more comprehensive perspective on the development of the dynamic modelling of flora and fauna in digital twins could have been gleaned from grey-literature inquiries and with the use of additional search terms. Specifically, for the dynamic modelling of fauna, search terms from domains such as agriculture, precision farming, livestock modelling, and aquaculture could provide further insights. Moreover, only studies with titles, abstracts, and full texts available in English were included in this review. While English is widely used in academic publications in this field, this criterion may introduce a language bias by potentially excluding key studies published in other languages.

4.2. Particular focus areas of fauna models for digital twins

As the systematic literature review approach used in this study resulted in an imbalance of articles for fauna and flora, this chapter discusses particular focus areas of fauna models in digital twins. To provide context and address gaps not fully covered in the reviewed literature, select examples from external sources are provided here.

4.2.1. Mobility

While many challenges of flora and fauna modelling for digital twins are similar, some key differences emerge between these two domains of modelling for digital twins. One critical distinction lies in the mobility of most animal species. Data collection for flora models often relies on remote sensing techniques such as LiDAR or multispectral imaging to capture data on plant structures and growth. In contrast, fauna models often incorporate the movement of either individuals or populations. This requir specific spatial data collection methods, such as the use of GPS collars for wildlife monitoring (De Koning, 2025) or fixed monitoring stations equipped with e.g. camera traps (Sharef et al., 2022) or RFID readers (Mishra and Sharma, 2023).

If digital twins rely on updating data to estimate population sizes or species compositions within defined areas, modelling challenges can arise due to the movement of new organisms into the area after the model has been defined. This issue is particularly pronounced in fauna models, where animal mobility introduces variability in shorter time scales respective to flora. For instance, Convolutional Neural Networks (CNNs) have been applied to classify species in camera trap images (Sharef et al., 2022), while machine learning models have been employed to analyse bird species from sound recordings, addressing the complexities of tracking highly mobile organisms (Ovaskainen et al., 2024).

4.2.2. Responsiveness

Another key challenge of fauna modelling is related to the multiple types of animal responsiveness, which operate often on shorter time scales than vegetation dynamics. Fauna models may need to simulate dynamic physiological processes, sensory responses, cognition, and even emotions to replicate animal behaviour (Føre et al., 2024). Due to these multi-dimensional complexities, AI-driven frameworks are employed to model e.g. livestock behaviour (Neethirajan and Kemp, 2021; Tagarakis et al., 2024), fish feeding (Ubina et al., 2023), and the perception and feeding dynamics of dairy cows (Zhang et al., 2024).

4.2.3. 3D modelling

For digital twins that encompass 3D model representations of living organisms, 3D modelling approaches may diverge between flora and fauna digital twins. Whereas flora models focus particularly on the accurate modelling of individual or species-specific structures and growth, fauna models may need to account also for the dynamic nature of animal responsivity and movement. This is exemplified by the models of tail movement to simulate the swimming dynamics of fish (Joordens et al., 2019). The future opportunities of responsive fauna models are exemplified by the neuromechanical model of a fruit fly *Drosophila melanogaster* (Lobato-Rios et al., 2022).

4.3. Research gaps and outlook

Despite the ongoing progress and due to the novelty of the field and its interdisciplinary nature, many research gaps remain unresolved and are only beginning to be explored. Our review identified several trends and challenges in the dynamic modelling of flora and fauna within digital twins, which are summarised into the following categories.

4.3.1. Insufficient understanding of fundamental details and potential knowledge generation

Despite extensive research, a key challenge remains in the limited understanding of interactions between flora, fauna, and their biotic and abiotic environments, such as plant growth (Skobelev et al., 2022a, 2020b) and animal behaviour (Joordens et al., 2019). Improving the understanding of these biological and ecological processes, and integrating them into dynamic models, will enhance accuracy and predictive capabilities. At the same time, digital twins offer potential by enhancing knowledge generation. However, their utility in ecological applications will remain limited without a strong foundational understanding of the underlying biological and ecological processes, which is essential for improving models of biotic interactions in the environment.

4.3.2. Bottleneck: data

Diverse "Digital Twin Data" (Zhang et al., 2022a) is produced and used for dynamic modelling of flora and fauna as elaborated in chapter 3.3 Data. Despite ongoing debates about the necessity of both – ground-based (Hudson-Smith et al., 2021) and SAAO data collection in form of UAVs (Edemetti et al., 2022), researchers still face challenges highlighted in chapter 3.3.4.

Data challenges are widely recognised as a critical bottleneck in the development of digital twins. Beyond the lack of accurate and available data, bias, interoperability, low operating frequencies of data collection and the inability to fully capture dynamic interactions, additional barriers include data heterogeneity and diversity. Variability in spatial and temporal resolution, measurement methods, and data completeness on e.g. species occurrence and functional trait data, can hinder model integration and reliability. Addressing these issues requires besides standardised protocols, data harmonisation, also efforts to fill gaps in underrepresented regions and taxa.

Furthermore, data fusion, forming another data-related challenge itself, plays a pivotal role in overcoming data heterogeneity, which is being researched e.g. for digital twins in ecology (De Koning et al., 2023). This process involves combining data, referred to as fusion data, see Supplement S2, from sensors (also referred to as sensor fusion), databases, and other sources to create a coherent and unified representation. Robust data assimilation techniques are essential to address the inherent uncertainties in both the data and the mathematical models. Developing standardised and scalable approaches for data fusion and assimilation is crucial to enhance the reliability and accuracy of digital twins, particularly for achieving predictive and prescriptive functionalities. (Liu et al., 2018; Macías et al., 2024) Overcoming these challenges will pave the way for comprehensive monitoring of flora, fauna and their environments. This would allow for realistic digital replicas, continuous recalibration, precise prescriptive models and digital twins' responsiveness to changes.

To get closer to this aim, on the one hand inaccuracies in data collection need to be addressed and the reliable methods and techniques for this made accessible to a broad audience. Guo et al. (2022) assert that manual data collection is losing attractivity. A shift in data collection methods – transitioning from manual to automated methods – is likewise presented in the literature beyond this SLR, such as in Tuia et al. (2022) or Rozenstein et al. (2024). This shift in the data collection has the potential to support overcoming mentioned shortcomings (Rozenstein et al., 2024; Tuia et al., 2022). Additionally, the listed shortcomings could be approached through the application of AI technologies, such as computer vision and other methods, enabling the automatic quantification of properties from e.g. video footage and other comprehensive data sources. These advancements hold promise to facilitate the mining of previously uncollected data, higher accuracy, more frequent updates, scalability, cost efficiency, non-invasive monitoring, the discovery of hidden patterns, adaptability to new data, customisation and precision, automation of tedious tasks, and the integration of data from multiple sources.

Data availability could be leveraged by incentivised cross-domain data sharing and the application of FAIR (Findable, Accessible, Interoperable, Reusable) (Wilkinson et al., 2016) data principles. Van Evert et al. (2023) examines the EU Code of Conduct on agricultural data sharing, suggesting that similar Codes of Conduct could help prevent only commercial actors from benefiting from data sharing. On the other hand, for the interoperability of data from various sources, data harmonisation and adherence to standards is substantial.

4.3.3. Models becoming dynamic in nature

There is already a plethora of approaches to modelling flora and fauna across various domains. Traditional ecological modelling techniques, such as agent-based and descriptive models, are prevalent and increasingly being coupled with ML and AI methods. Existing and established models could further evolve by integrating continuous data updates, becoming dynamic in nature, and connecting them to the digital twin concept. To drive actions in the physical counterpart, these models must also incorporate mechanisms for decision-making and actuation, enabling their outputs to influence real-world processes. Such developments enhance the accuracy and efficiency of the dynamic models, enabling them to shift from descriptive to prescriptive.

However, while the field of machine engineering is advancing rapidly, particularly in the digital twin sphere, it is essential to recognise the multifaceted intricacies of natural systems. Flora and fauna possess inherent complexities that distinguish them from machines. Oversimplified models, especially in areas such as environmental sustainability, food production, or those involving living organisms, can lead to unforeseen consequences if not carefully considered. Additionally, applying “Good Modeling Practices” (GMP) as outlined by Jakeman et al. (2024) helps to ensure that models are robust, transparent, adaptable, and reliable, enhances their accuracy, usability, and impact across diverse applications. This is particularly relevant, as the developed models may be influenced by human factors including e.g. biases and uncertainties (Jakeman et al., 2024).

Validation for digital twins is imperative but also uniquely challenging due to (real-time) data integration and the – where applicable – autonomous synchronisation with the real world. Key techniques include (dynamic) data validation, model validation, machine learning-based validations, feedback-loop validation, and scenario-based validation. (Hua et al., 2022; Mertens and Denil, 2024)

Additionally, model acceptance by practitioners is often hindered by a lack of trust and the complexity of models. Strengthening collaboration between researchers, extension workers, and advisors and the application of GMPs is essential to maximise the benefits of data and modelling (Van Evert et al., 2023).

4.3.4. Enhancing interoperability, integration, standardisation and transferability

Interoperability between different databases, software, and digital twin instances is not yet fully established, necessitating the development of and adherence to standards and protocols. Implementing Minimal Interoperability Mechanisms (MIMs) (Ketzler et al., 2020) can help address this challenge. Additionally, Application Development Extensions (ADE), such as those in CityGML (Vo et al., 2019), offer a promising approach for integrating flora (Petrova-Antonova et al., 2024) and fauna into existing standards, enabling the modelling of additional information. A modular approach to developing digital twins of flora and fauna would further enhance the transferability and adaptability of research. In some cases, the source-code is being made publicly available. Doing this in a systematic and formalised way also allows for traceability, validation, model auditing (Jakeman et al., 2024) and e.g. the adaptation and further development (Johannsen et al., 2021).

It is important to emphasise that interoperability or the sharing of the models between systems does not guarantee transferability to other contexts. Specifically, models being designed for particular contexts, e.g. geographic locations and environmental conditions, inherit limiting factors which cannot be transferred offhand.

To date, research on digital twins incorporating flora and fauna has, as stated for the agricultural sector by Purcell et al. (2022), largely focused on experimental feasibility, neglecting key design aspects like scalability, reusability, and simulation. As a result, many advanced digital twin examples lack clear, systematic design principles and essential functionality to ensure long-term value (Purcell et al., 2022). Additionally, there are no universally applied methods, standards, or guidelines for developing the software, software architecture and workflows of such (De Koning et al., 2023) which cause inconsistencies and hinder progress (Trantas et al., 2023).

Addressing these gaps and applying GMPs will further leverage the development of digital twins. However, future research should aim to prioritise the development of standardised methods and design frameworks to address the burgeoning fragmentation of developments. Hereby the emphasis should lie on scalability, reusability, and simulation, ensuring both the long-term value and broader adoption of digital twins of flora and fauna.

4.3.5. Accessibility and user experience

Digital twins were initially focused on accurate, data-driven and mechanistic models, but as their use expanded, the need for accessible, user-centred design has become paramount. Digital twins often encompass complex factual situations, data, and domain-specific models which are not directly accessible and interpretable for users with varying expertise levels. As a result, user experience (UX) plays a crucial role in helping users understand content and enabling evidence-based decision making across fields including agriculture, education and policy-making (Trantas et al., 2023). Developers must therefore elicit and capture stakeholder needs (Jakeman et al., 2024) and consider how output are visualised and interpreted by end-users (De Koning et al., 2023). Digital twins involving sensitive information are typically restricted to expert groups. However, for broader outreach such as educational or participatory purposes, digital twins are increasingly being developed without access restrictions (Johannsen et al., 2021). Whether access is restricted or open, to make digital twins accessible and to foster active application of its users, a range of interfaces and devices are employed, as elaborated in Section 3.5.

While digital twins often are based on 2D and 3D visualisations (Chattoraj et al., 2022; Edemetti et al., 2022; Pusztai, 2021; Zhang et al., 2022), current UX emphasises intuitive, multimodal interfaces, frequently incorporating VR/AR to simplify complex data (Deckert et al., 2020; Harrington et al., 2021). Moving forward, UX will prioritise inclusivity, with adaptive interfaces tailored to user roles and expertise. Enhanced multimodal interactions, e.g. voice and gesture control and biometric feedback along with collaborative, multi-user environments will create immersive experiences (Kern et al., 2022), benefiting applications like collaborative work, virtual testing and education. By lowering technical barriers and supporting personalisation, digital twins aim to engage broader audiences, making these tools valuable for both experts and the public across various fields.

To evaluate how well digital twin systems meet user needs, the User Experience–Digital Twin Maturity Model (UX-DTMM) has been developed. This framework is built on the five pillars of experience: visual understandability, usability, convenience, dependability, and delight factors. It can guide improvements by assigning maturity scores to these aspects, helping to optimise digital twin interfaces for better engagement and functionality (Manickam et al., 2023).

4.3.6. Interdisciplinary synergy for advancing digital twins of flora and fauna

The future of this research relies on progress across various fields and close interdisciplinary collaboration. Integrating advancements from pioneering fields like ML and AI to applications will improve the precision of dynamic models for flora and fauna. Additionally, applying expertise from computer science, ecology, biology in domains like e.g. urban planning and agronomy is crucial to transcends isolated disciplines which is accelerating progress toward comprehensive solutions and can be seen as essential to address complex ecological and environmental challenges arising in different domains.

Moreover, leveraging diverse expertise, as e.g. from the examples showcased in this review, enables researchers to address knowledge gaps through cross-disciplinary collaboration, fostering a dynamic environment for the exchange and integration of ideas, methods and models.

4.3.7. Ethical considerations

Ethical considerations in digital twins, particularly in healthcare (Bruynseels et al., 2018; Popa et al., 2021), medicine (Braun, 2021), and the built environment (Ying et al., 2020), are well-established. However, this literature review reveals that ethical aspects of digital twins of flora and fauna have received less attention compared to other fields or technical aspects. Although ethical considerations are gradually gaining relevance in fields like agri-food (Van Der Burg et al., 2021), they are not commonly discussed within digital twins of flora and are sporadic in fauna. Especially within the living environment, addressing issues such as data privacy and potential misuse is essential to ensure ethical and future-proof applications. Tools like the Mepham's Ethical Matrix for food and agriculture (Mepham et al., 2006; cited by Van Evert et al., 2023) can support decision-makers assess the ethical acceptability and regulations of technologies. Given the nascent stage of digital twins of flora and fauna, everyone involved in the development of those technologies should proactively integrate societal values and ethical considerations already early in the research and development phase.

Additionally, with the increasing application of digital twin technologies, these as a whole system as well as its discrete parts, become more prone to cyber threats with widespread consequences (Bissadu et al., 2024; Praharaj et al., 2024). Therefore, the need to efficiently develop and comprehensively employ cyber security measures should be seen as mandatory (Holmes et al., 2021).

4.3.8. Gradualism: from digital models to closed-loop digital twins

In most cases, digital twins are being developed incrementally, building upon existing models (Rolph et al., 2024). This development process typically follows a progression from digital models to digital shadows, and ultimately to autonomous digital twins. Such an approach allows for gradual integration of advanced capabilities, such as continuous data updates and bidirectional interactions, enabling a systematic evolution towards complete mutual influence between the physical and digital counterparts.

To date, digital twins are still abstractions of the physical counterparts, and the full realisation of this concept, along with its inherent logical challenges, continues to be debated, e.g. for urban environments (Batty, 2018). The term "digital twin" is often applied broadly in the literature, encompassing systems with varying levels of capability - from integrating data at variable frequencies with models to fully autonomous, feedback-controlled cyber-physical systems. Systems that do not adhere to the strict definition of digital twins, particularly those lacking automated feedback between the digital and physical counterparts, are on one handmore accurately described as "digital shadows" (Botín-Sanabria et al., 2022; Kritzinger et al., 2018), "prototype digital twins"(Groeneveld et al., 2024; Khan et al., 2024; Lopez et al., 2020) or similar terms, as proposed by researchers. These distinctions help clarify the difference between systems with limited interaction and fully synchronous digital twins that autonomously influence both – the physical and virtual counterparts, a hallmark of closed-loop digital twins. On the other hand, researchers such as Tagarakis et al. (2024) suggest sector-specific definitions for digital twins. While this approach provides contextual relevance, it also contributes to the fragmentation of research around the term "digital twin".

Despite the potential for automated bi-directional information exchange, this capability level remains underexplored in current research. Notably, the agricultural sector being the only one discussing actuators in the reviewed literature, with e.g. precision agriculture (Van Evert et al., 2023) and ECPS (Majore, 2022), leads in fulfilling the closed-loop digital twin criteria. These forerunners provide inspiration for future development in e.g. urban and ecological applications, though not as a universal blueprint.

Regardless of the potential realisation of the digital twin concept, the necessity and appropriateness in every field is to be questioned. A nuanced, context-specific approach is essential, with digital shadows in some cases being more suitable given the current technological state. These tailored approaches ensure digital (twin) technologies are both practical and ethically sound across diverse fields.

4.3.9. Yet underexplored but big potential

This review has demonstrated that the digital twin concept is being developed and applied across diverse fields, including among others ecology, forestry, agronomy, livestock farming and urban sciences. These applications highlight the versatility and potential impact of integrating natural elements and environments into digital twins. Yet, compared to the rampant development, level of detail and application of the digital twin concept in human-made areas such as manufacturing (Semeraro et al., 2021; Tao et al., 2019), cities (Lei et al., 2023; Shahat et al., 2021), engineering (Jiang et al., 2021) and aerospace (Botín-Sanabria et al., 2022; Liu et al., 2021; Phanden et al., 2021), the digital twins of flora and fauna still remain significantly underexplored. However, the development of digital twins for flora and fauna is accelerating and is continuing to do so. Especially in ecology, publications such as from De Koning et al. (2023) and Trantas et al. (2023) give guidance and outlook to the future of digital twins in this field. Further, a multitude of theoretical frameworks, such as digital twins of forests (Buonocore et al., 2022) are currently being developed but are not yet fully implemented. Prototype digital twins, such as those developed within the BioDT project (BioDT, 2024) for e.g. invasive alien species (Khan et al., 2024) and the Digital Twin of the Earth (Bauer et al., 2021; Nativi et al., 2021) are currently being elaborated and tested. These theoretical frameworks and development suggestions are expected to be put into practice and tested soon and together with the already existing protype digital twins going to be refined based on real-world application, feedback and new scientific insights.

Applying theoretical frameworks, refining prototypes, addressing the previously listed challenges and taking proactive steps toward overcoming them offer significant potential for advancing the inclusion of flora and fauna in digital twins. By doing so, this field is expected to make up leeway with the development of digital twins in the pioneering domains.

Ultimately, dynamic modelling of flora and fauna through digital twins offers a transformative approach to addressing complex challenges outlined in the introduction and advancing the United Nations Sustainable Development Goals (SDGs). Future digital twins could enhance biodiversity monitoring and conservation (SDGs 14 and 15), enable precise predictions of climate change impacts (SDG 13), and optimise sustainable agricultural practices (SDG 2). Additionally, they could inform urban planning (SDG 11) by integrating natural habitats into city designs, promoting sustainable living environments and fostering more-than-human approaches to cities.

Declaration of generative AI in scientific writing

Statement: During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Laura Mrosla: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Henna Fabritius:** Writing – review & editing, Writing –

original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization, Supervision. **Kristiina Kupper:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Fabian Dembski:** Writing – review & editing, Supervision. **Pia Fricker:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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Data availability

Data will be made available on request.

References

Arts, K., Van Der Wal, R., Adams, W.M., 2015. Digital technology and the conservation of nature. Ambio 44, 661–673. https://doi.org/10.1007/s13280-015-0705-1.

Batty, M., 2018. Digital twins. Environment and Planning B: urban analytics and City science 45, 817–820. https://doi.org/10.1177/2399808318796416.

Bauer, P., Stevens, B., Hazeleger, W., 2021. A digital twin of Earth for the green transition. Nat. Clim. Chang. 11, 80–83. https://doi.org/10.1038/s41558-021-00986-y.

Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., Çöltekin, A., 2015. Applications of 3D City models: state of the Art Review. IJGI 4, 2842–2889. https://doi.org/10.3390/ijgi4042842.

BioDT, 2024. BIODT | digital twinning to predict how biodiversity responds to global change [WWW Document]. BioDT. URL. https://biodt.eu/ (accessed 7.15.24).

Bissadu, K., Hossain, G., Vajpayee, P., 2024. Agriculture 5.0 cybersecurity: monitoring agricultural cyber threats with digital Twin technology. In: 2024 IEEE World AI IoT Congress (AIIoT). Presented at the 2024 IEEE World AI IoT Congress (AIIoT). IEEE, Seattle, WA, USA, pp. 0252–0258. https://doi.org/10.1109/AIIoT61789.2024.10579017.

Botín-Sanabria, D.M., Mihaita, A.-S., Peimbert-García, R.E., Ramírez-Moreno, M.A., Ramírez-Mendoza, R.A., Lozoya-Santos, J.D.J., 2022. Digital Twin technology challenges and applications: a comprehensive review. Remote Sens. (Basel) 14, 1335. https://doi.org/10.3390/rs14061335.

Braun, M., 2021. Represent me: please! towards an ethics of digital twins in medicine. J. Med. Ethics 47, 394–400. https://doi.org/10.1136/medethics-2020-106134.

Brkljačić, T., Majetić, F., Tarabić, B.N., 2020. Smart environment: cyber parks (connecting nature and technology. Management Association, I.R. (Ed.). Megacities and Rapid Urbanization. IGI Global, pp. 205–227. https://doi.org/10.4018/978-1-5225-9276-1.ch010.

Bruynseels, K., Santoni De Sio, F., Van Den Hoven, J., 2018. Digital twins in health care: ethical implications of an emerging engineering paradigm. Front. Genet. 9, 31. https://doi.org/10.3389/fgene.2018.00031.

Buonocore, L., Yates, J., Valentini, R., 2022. A proposal for a forest digital twin framework and its perspectives. Forests. 13, 498. https://doi.org/10.3390/f13040498.

Caldarelli, G., Arcaute, E., Barthelemy, M., Batty, M., Gershenson, C., Helbing, D., Mancuso, S., Moreno, Y., Ramasco, J.J., Rozenblat, C., Sánchez, A., Fernández-Villacañas, J.L., 2023. The role of complexity for digital twins of cities. Nat. Comput. Sci. 3, 374–381. https://doi.org/10.1038/s43588-023-00431-4.

Chattoraj, J., Yang, F., Lim, C.W., Gobeawan, L., Liu, X., Raghavan, V.S.G., 2022. Knowledge-driven transfer learning for tree species recognition. In: 2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV). Presented at the 2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV). IEEE, Singapore, Singapore, pp. 149–154. https://doi.org/10.1109/ICARCV57592.2022.10004314.

Cirulis, A., Taube, L., Erics, Z., 2022. Automated generation of digital twin in virtual reality for interaction with specific nature ecosystem. In: Antona, M., Stephanidis, C. (Eds.), Universal Access in Human-Computer Interaction. User and Context Diversity. Springer International Publishing, Cham, pp. 187–202. https://doi.org/10.1007/978-3-031-05039-8_13. Lecture Notes in Computer Science.

De Koning, K., 2025. The crane radar: development and deployment of an operational eco-digital twin. Ecol. Inform. 85, 102938. https://doi.org/10.1016/j.ecoinf.2024.102938.

De Koning, K., Broekhuijsen, J., Kühn, I., Ovaskainen, O., Taubert, F., Endresen, D., Schigel, D., Grimm, V., 2023. Digital twins: dynamic model-data fusion for ecology. Trends Ecol. Evol. (Amst.). https://doi.org/10.1016/j.tree.2023.04.010. S0169534723000903.

Deckert, A., Dembski, F., Ulmer, F., Ruddat, M., Wössner, U., 2020. Digital tools in stakeholder participation for the German Energy Transition. Can digital tools improve participation and its outcome? The Role of Public Participation in Energy Transitions. Elsevier, pp. 161–177. https://doi.org/10.1016/B978-0-12-819515-4.00009-X.

Deng, T., Zhang, K., Shen, Z.-J., 2021. A systematic review of a digital twin city: a new pattern of urban governance toward smart cities. J. Manage. Sci. Eng. 6, 125–134. https://doi.org/10.1016/j.jmse.2021.03.003.

Edemetti, F., Maiale, A., Carlini, C., D'Auria, O., Llorca, J., Maria Tulino, A., 2022. Vineyard Digital Twin: construction and characterization via UAV images – DIWINE proof of concept. In: 2022 IEEE 23rd International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM). Presented at the 2022 IEEE 23rd International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM). IEEE, Belfast, United Kingdom, pp. 601–606. https://doi.org/10.1109/WoWMoM54355.2022.00094.

European Commission. Directorate General for Communication., 2021. European Green Deal :Delivering On Our Targets. Publications Office, LU.

Fernández-Alvarado, J.F., Coloma-Miró, J.F., Cortés-Pérez, J.P., García-García, M., Fernández-Rodríguez, S., 2021. Proposing a sustainable urban 3D model to minimize the potential risk associated with green infrastructure by applying engineering tools. Sci. Total. Environ. 812, 152312. https://doi.org/10.1016/j.scitotenv.2021.152312.

Ferré-Bigorra, J., Casals, M., Gangolells, M., 2022. The adoption of urban digital twins. Cities. 131, 103905. https://doi.org/10.1016/j.cities.2022.103905.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science (1979) 309, 570–574. https://doi.org/10.1126/science.1111772.

Føre, M., Alver, M.O., Alfredsen, J.A., Rasheed, A., Hukkelås, T., Bjelland, H.V., Su, B., Ohrem, S.J., Kelasidi, E., Norton, T., Papandroulakis, N., 2024. Digital Twins in intensive aquaculture —challenges, opportunities and future prospects. Comput. Electron. Agric. 218, 108676. https://doi.org/10.1016/j.compag.2024.108676.

Galle, N.J., Nitoslawski, S.A., Pilla, F., 2019. The Internet of Nature: how taking nature online can shape urban ecosystems. Anthropocene Rev. 6, 279–287. https://doi.org/10.1177/2053019619877103.

García-Granja, M.J., de-Cózar-Macías, Ó.D., Blázquez-Parra, E.B., Gutiérrez-Sánchez, A. B., 2020. Optimization of the management and maintenance of urban elements through geolocation and linking of interactive database to the construction information model. In: Cavas-Martínez, F., Sanz-Adan, F., Morer Camo, P., Lostado Lorza, R., Santamaría Peña, J. (Eds.), Advances in Design Engineering. Springer International Publishing, Cham, pp. 597–604. https://doi.org/10.1007/978-3-030-41200-5_65. Lecture Notes in Mechanical Engineering.

Gatto, M., 2015. Making research useful : current challenges and good practices in data visualisation. https://ora.ox.ac.uk/objects/uuid:526114c2-8266-4dee-b663-351119249fd5.

Gobeawan, L., Lin, E.S., Tandon, A., Yee, A.T.K., Khoo, V.H.S., Teo, S.N., Yi, S., Lim, C. W., Wong, S.T., Wise, D.J., Cheng, P., Liew, S.C., Huang, X., Li, Q.H., Teo, L.S., Fekete, G.S., Poto, M.T., 2018. Modeling trees for virtual Singapore: from data acquisition to Citygml models. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-4/W10, 55–62. https://doi.org/10.5194/isprs-archives-XLII-4-W10-55-2018.

Gobeawan, L., Wise, D.J., Wong, S.T., Yee, A.T.K., Lim, C.W., Su, Y., 2021. Tree species modelling for digital Twin cities. In: Gavrilova, M.L., Tan, C.J.K. (Eds.), Transactions On Computational Science XXXVIII. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 17–35. https://doi.org/10.1007/978-3-662-63170-6_2. Lecture Notes in Computer Science.

Gobeawan, L., Wise, D.J., Yee, A.T.K., Wong, S.T., Lim, C.W., Lin, E.S., Su, Y., 2019. Convenient tree species modeling for virtual cities. In: Gavrilova, M., Chang, J., Thalmann, N.M., Hitzer, E., Ishikawa, H. (Eds.), Advances in Computer Graphics. Springer International Publishing, Cham, pp. 304–315. https://doi.org/10.1007/978-3-030-22514-8_25. Lecture Notes in Computer Science.

Grieves, M., Vickers, J., 2017. Digital Twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Kahlen, F.-J., Flumerfelt, S., Alves, A. (Eds.), Transdisciplinary Perspectives on Complex Systems. Springer International Publishing, Cham, pp. 85–113. https://doi.org/10.1007/978-3-319-38756-7_4.

Groeneveld, J., Martinovic, T., Rossi, T., Salamon, O., Sara-aho, K., Grimm, V., 2024. Prototype biodiversity digital twin: honey bees in agricultural landscapes. RIO 10, e125167. https://doi.org/10.3897/rio.10.e125167.

Guo, Y., Luka, A., Wei, Y., 2022. Modeling urban tree growth for digital twins: transformation of point clouds into parametric crown models. Wichmann Verlag, DE. 10.14627/537724021.

Harrington, M.C.R., Bledsoe, Z., Jones, C., Miller, J., Pring, T., 2021. Designing a virtual arboretum as an immersive, multimodal, interactive, Data visualization virtual field trip. MTI 5, 18. https://doi.org/10.3390/mti5040018.
Harzing, A.-W., 2010. The Publish Or Perish book: Your Guide to Effective and Responsible Citation Analysis, 1. Tarma Software Research Pty Ltd, Melbourne.
Hejtmánek, L., Hůla, M., Herrová, A., Surový, P., 2022. Forest digital twin as a relaxation environment: a pilot study. Front. Virtual. Real. 3, 1033708. https://doi.org/10.3389/frvir.2022.1033708.
Hofierka, J., Gallay, M., Kaňuk, J., Šupinský, J., Šašak, J., 2017. High-resolution urban greenery mapping for Micro-climatemodelling based on 3d City models. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-4/W7, 7–12. https://doi.org/10.5194/isprs-archives-XLII-4-W7-7-2017.
Holmes, D., Papathanasaki, M., Maglaras, L., Ferrag, M.A., Nepal, S., Janicke, H., 2021. Digital Twins and Cyber Security – solution or challenge?, in: 2021 6th South-East Europe Design automation. In: Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM). Presented at the 2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM). IEEE, Preveza, Greece, pp. 1–8. https://doi.org/10.1109/SEEDA-CECNSM53056.2021.9566277.
Hua, E.Y., Lazarova-Molnar, S., Francis, D.P., 2022. Validation of digital twins: challenges and opportunities. In: 2022 Winter Simulation Conference (WSC). Presented at the 2022 Winter Simulation Conference (WSC). IEEE, Singapore, pp. 2900–2911. https://doi.org/10.1109/WSC57314.2022.10015420.
Hudson-Smith, A., Wilson, D., Gray, S., Dawkins, O., 2021. Urban IoT: advances, challenges, and opportunities for mass data collection, analysis, and visualization. In: Shi, W., Goodchild, M.F., Batty, M., Kwan, M.-P., Zhang, A. (Eds.), Urban Informatics. Springer Singapore, Singapore, pp. 701–719. https://doi.org/10.1007/978-981-15-8983-6_38. The Urban Book Series.
Ivanov, S., Nikolskaya, K., Radchenko, G., Sokolinsky, L., Zymbler, M., 2020. Digital twin of city: concept overview. In: 2020 Global Smart Industry Conference (GloSIC). Presented at the 2020 Global Smart Industry Conference (GloSIC). IEEE, Chelyabinsk, Russia, pp. 178–186. https://doi.org/10.1109/GloSIC50886.2020.9267879.
Jakeman, A.J., Elsawah, S., Wang, H.-H., Hamilton, S.H., Melsen, L., Grimm, V., 2024. Towards normalizing good practice across the whole modeling cycle: its instrumentation and future research topics. SESMO 6, 18755. https://doi.org/10.18174/sesmo.18755.
Jiang, F., Ma, L., Broyd, T., Chen, K., 2021. Digital twin and its implementations in the civil engineering sector. Autom. Constr. 130, 103838. https://doi.org/10.1016/j.autcon.2021.103838.
Jo, S.-K., Park, D.-H., Park, H., Kim, S.-H., 2018. Smart livestock farms using digital twin: feasibility study. In: 2018 International Conference on Information and Communication Technology Convergence (ICTC). Presented at the 2018 International Conference on Information and Communication Technology Convergence (ICTC). IEEE, Jeju, pp. 1461–1463. https://doi.org/10.1109/ICTC.2018.8539516.
Johannsen, C., Senger, D., Kluss, T., 2021. A digital twin of the social-ecological system urban beekeeping. In: Kamilaris, A., Wohlgemuth, V., Karatzas, K., Athanasiadis, I.N. (Eds.), Advances and New Trends in Environmental Informatics, Progress in IS. Springer International Publishing, Cham, pp. 193–207. https://doi.org/10.1007/978-3-030-61969-5_14.
Joordens, M., Roopaei, M., Jamshidi, M., Choo, R., Rad, P., 2019. Modeling behavioral dynamics of multi-agent learning using artificial intelligence and digital twins.
Kasampalis, D., Alexandridis, T., Deva, C., Challinor, A., Moshou, D., Zalidis, G., 2018. Contribution of remote sensing on crop models: a review. J. Imaging 4, 52. https://doi.org/10.3390/jimaging4040052.
Kastuari, A., Suwardhi, D., Hanan, H., Wikantika, K., Harto, A.B., Virtriana, R., Trisyanti, S.W., 2020. Implementation of SExI–FS (Spatially Explicit Individual-based Forest Simulator) model using UAV aerial photo data case study: jatinangor ITB Campus. Hayati J. Biosci. 27, 314. https://doi.org/10.4308/hjb.27.4.314.
Kehoe, L., Romero-Muñoz, A., Polaina, E., Estes, L., Kreft, H., Kuemmerle, T., 2017. Biodiversity at risk under future cropland expansion and intensification. Nat. Ecol. Evol. 1, 1129–1135. https://doi.org/10.1038/s41559-017-0234-3.
Kern, L., Dembski, F., Obst, T., Bisinger, L., Falk, B., Wössner, U., 2022. Virtual reality simulators for inclusion and participation: broadening perspectives on accessible cities and public space. In: REAL CORP 2022: Mobility, Knowledge and Innovation Hubs in Urban and Regional Development: Proceedings of 27th International Conference on Urban Planning, Regional Development and Information Society = Beiträge Zur 27. Internationalen Konferenz Zu Stadtplanung, Regionalentwicklung Und Informationsgesellschaft. Presented at the REAL CORP. CORP - Competence Center of Urban and Regional Planning, Vienna.
Ketzler, B., Naserentin, V., Latino, F., Zangelidis, C., Thuvander, L., Logg, A., 2020. Digital twins for cities: a state of the art review. Built. Environ. 46, 547–573. https://doi.org/10.2148/benv.46.4.547.
Khan, T., De Koning, K., Endresen, D., Chala, D., Kusch, E., 2024a. TwinEco: a unified framework for dynamic data-driven digital twins in ecology. https://doi.org/10.1101/2024.07.23.604592.
Khan, T., El-Gabbas, A., Golivets, M., Souza, A., Gordillo, J., Kierans, D., Kühn, I., 2024b. Prototype biodiversity digital twin: invasive alien species. RIO 10, e124579. https://doi.org/10.3897/rio.10.e124579.
Klippel, A., Sajjadi, P., Zhao, J., Wallgrün, J.O., Huang, J., Bagher, M.M., 2021. Embodies digital twins for environmental applications. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. V-4–2021, 193–200. https://doi.org/10.5194/isprs-annals-V-4-2021-193-2021.
Knibbe, W.J., Afman, L., Boersma, S., Bogaardt, M.-J., Evers, J., Van Evert, F., Van Der Heide, J., Hoving, I., Van Mourik, S., De Ridder, D., De Wit, A., 2022. Digital twins in the green life sciences. NJAS: Impact Agric. Life Sci. 94, 249–279. https://doi.org/10.1080/27685241.2022.2150571.
Korenhof, P., Blok, V., Kloppenburg, S., 2021. Steering representations—towards a critical understanding of digital twins. Philos. Technol. 34, 1751–1773. https://doi.org/10.1007/s13347-021-00484-1.
Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018. Digital Twin in manufacturing: a categorical literature review and classification. IFAC-PapersOnLine 51, 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474.
Lehtola, V.V., Koeva, M., Elberink, S.O., Raposo, P., Virtanen, J.-P., Vahdatikhaki, F., Borsci, S., 2022. Digital twin of a city: review of technology serving city needs. Int. J. Appl. Earth Observ. Geoinform. 114, 102915. https://doi.org/10.1016/j.jag.2022.102915.
Lei, B., Janssen, P., Stoter, J., Biljecki, F., 2023. Challenges of urban digital twins: a systematic review and a Delphi expert survey. Autom. Constr. 147, 104716. https://doi.org/10.1016/j.autcon.2022.104716.
Li, Y., Wang, Z., 2009. A VB-based forest field data collection system. In: 2009 S International Workshop on Computer Science and Engineering. Presented at the 2009 S International Workshop on Computer Science and Engineering. IEEE, Qingdao, China, pp. 551–554. https://doi.org/10.1109/WCSE.2009.873.
Liu, C.L.C., Kuchma, O., Krutovsky, K.V., 2018a. Mixed-species versus monocultures in plantation forestry: development, benefits, ecosystem services and perspectives for the future. Glob. Ecol. Conserv. 15, e00419. https://doi.org/10.1016/j.gecco.2018.e00419.
Liu, M., Fang, S., Dong, H., Xu, C., 2021. Review of digital twin about concepts, technologies, and industrial applications. J. Manuf. Syst. 58, 346–361. https://doi.org/10.1016/j.jmsy.2020.06.017.
Liu, Z., Meyendorf, N., Mrad, N., 2018b. The role of data fusion in predictive maintenance using digital twin. In: Presented at the 44th annual review of progress in quantitative nondestructive evaluation, VOLUME 37, Provo, Utah, USA, 020023. https://doi.org/10.1063/1.5031520.
Lobato-Rios, V., Ramalingasetty, S.T., Özdil, P.G., Arreguit, J., Ijspeert, A.J., Ramdya, P., 2022. NeuroMechFly, a neuromechanical model of adult Drosophila melanogaster. Nat. Methods 19, 620–627. https://doi.org/10.1038/s41592-022-01466-7.
Lopez, B., Minor, E., Crooks, A., 2020. Insights into human-wildlife interactions in cities from bird sightings recorded online. Landsc. Urban. Plan. 196, 103742. https://doi.org/10.1016/j.landurbplan.2019.103742.
Lu, S., Fang, C., Xiao, X., 2023. Virtual scene construction of wetlands: a case study of Poyang Lake. China. IJGI 12, 49. https://doi.org/10.3390/ijgi12020049.
Luka, A., Guo, Y., 2021. PlantingSMART: The Parametric Approach for Trees in BIM With Full Lifecycle Application. Wichmann Verlag, DE.10.14627/537705033.
Macías, A., Muñoz, D., Navarro, E., González, P., 2024. Data fabric and digital twins: an integrated approach for data fusion design and evaluation of pervasive systems. Inf. Fusion 103, 102139. https://doi.org/10.1016/j.inffus.2023.102139.
Majore, G., Majors,I. : PoEM Forum 22: Practice of Enterprise Modelling, November 22, 2022, London, UKLink: https://ceur-ws.org/Vol-3327/paper09.pdf.
Manickam, R., Vollmar, J., Prabhakar, G.M., 2023. User experience–digital twin maturity model (UX-DTMM). In: Chakrabarti, A., Singh, V. (Eds.), Design in the Era of Industry 4.0, Design in the Era of Industry 4.0, 2. Springer Nature Singapore, Singapore, pp. 877–889. https://doi.org/10.1007/978-981-99-0264-4_72. Smart Innovation, Systems and Technologies.
McKinney, M.L., 2008. Effects of urbanization on species richness: a review of plants and animals. Urban. Ecosyst. 11, 161–176. https://doi.org/10.1007/s11252-007-0045-4.
Mepham, B., Kaiser, M., Thorstensen, E., Tomkins, S., Millar, K., 2006. Ethical matrix manual.
Mertens, J., Denil, J., 2024. Reusing model validation methods for the continuous validation of digital twins of cyber-physical systems. Softw. Syst. Model. https://doi.org/10.1007/s10270-024-01225-6.
Mishra, S., Sharma, S.K., 2023. Advanced contribution of IoT in agricultural production for the development of smart livestock environments. Internet Things 22, 100724. https://doi.org/10.1016/j.iot.2023.100724.
Mohammed, J.S., 2016. Applications of 3D printing technologies in oceanography. Methods Oceanogr. 17, 97–117. https://doi.org/10.1016/j.mio.2016.08.001.
Moin-E-Ddin Rezvani, S., Shamshiri, R.R., Hameed, I.A., Zare Abyane, H., Godarzi, M., Momeni, D., Balasundram, S.K., 2021. Greenhouse crop simulation models and microclimate control systems, a review. In: Shamshiri, R.R. (Ed.), Next-Generation Greenhouses for Food Security. IntechOpen. https://doi.org/10.5772/intechopen.97361.
Mongus, D., Brumen, M., Žlaus, D., Kohek, Š., Tomažič, R., Kerin, U., Kolmanič, S., 2021. A complete environmental intelligence system for LiDAR-based vegetation management in power-line corridors. Remote Sens. (Basel) 13, 5159. https://doi.org/10.3390/rs13245159.
Mottl, O., Flantua, S.G.A., Bhatta, K.P., Felde, V.A., Giesecke, T., Goring, S., Grimm, E.C., Haberle, S., Hooghiemstra, H., Ivory, S., Kuneš, P., Wolters, S., Seddon, A.W.R., Williams, J.W., 2021. Global acceleration in rates of vegetation change over the past 18,000 years. Science (1979) 372, 860–864. https://doi.org/10.1126/science.abg1685.
Nativi, S., Mazzetti, P., Craglia, M., 2021. Digital ecosystems for developing digital twins of the earth: the destination earth case. Remote Sens. (Basel) 13, 2119. https://doi.org/10.3390/rs13112119.
Neethirajan, S., Kemp, B., 2021. Digital twins in livestock farming. Animals 11, 1008. https://doi.org/10.3390/ani11041008.
Nolan, C., Overpeck, J.T., Allen, J.R.M., Anderson, P.M., Betancourt, J.L., Binney, H.A., Brewer, S., Bush, M.B., Chase, B.M., Cheddadi, R., Djamali, M., Dodson, J., Edwards, M.E., Gosling, W.D., Haberle, S., Hotchkiss, S.C., Huntley, B., Ivory, S.J., Kershaw, A.P., Kim, S.-H., Latorre, C., Leydet, M., Lézine, A.-M., Liu, K.-B., Liu, Y.,

Lozhkin, A.V., McGlone, M.S., Marchant, R.A., Momohara, A., Moreno, P.I., Müller, S., Otto-Bliesner, B.L., Shen, C., Stevenson, J., Takahara, H., Tarasov, P.E., Tipton, J., Vincens, A., Weng, C., Xu, Q., Zheng, Z., Jackson, S.T., 2018. Past and future global transformation of terrestrial ecosystems under climate change. Science (1979) 361, 920–923. https://doi.org/10.1126/science.aan5360.

Nugent, J., 2018. iNaturalist: citizen science for 21st-century naturalists. Sci. Scope 41, 12–15.

Ovaskainen, O., Lauha, P., Lopez Gordillo, J., Nokelainen, O., Rahman, A., Souza, A., Talaskivi, J., Tikhonov, G., Vancraeyenest, A., Lehtiö, A., 2024. Prototype Biodiversity digital Twin: real-time bird monitoring with citizen-science data. RIO 10, e125523. https://doi.org/10.3897/rio.10.e125523.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Syst. Rev. 10, 89. https://doi.org/10.1186/s13643-021-01626-4.

Petrova-Antonova, D., Malinov, S., Mrosla, L., Petrov, A., 2024. Towards a conceptual model of CityGML 3.0 vegetation ADE. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLVIII-4/W10-2024, 155–161. https://doi.org/10.5194/isprs-archives-XLVIII-4-W10-2024-155-2024.

Phanden, R.K., Sharma, P., Dubey, A., 2021. A review on simulation in digital twin for aerospace, manufacturing and robotics. Mater. Today Proc. 38, 174–178. https://doi.org/10.1016/j.matpr.2020.06.446.

Popa, E.O., Van Hilten, M., Oosterkamp, E., Bogaardt, M.-J., 2021. The use of digital twins in healthcare: socio-ethical benefits and socio-ethical risks. Life Sci. Soc. Policy. 17, 6. https://doi.org/10.1186/s40504-021-00113-x.

Praharaj, L., Gupta, D., Gupta, M., 2024. A lightweight edge-CNN-Transformer model for detecting coordinated cyber and digital twin attacks in cooperative smart farming. https://doi.org/10.48550/ARXIV.2411.14729.

Purcell, W., Klipic, A., Neubauer, T., 2022. A digital twin for grassland management. In: 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET). Presented at the 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET). IEEE, Prague, Czech Republic, pp. 1–6. https://doi.org/10.1109/ICECET55527.2022.9873446.

Purcell, W., Neubauer, T., 2023. Digital twins in agriculture: a state-of-the-art review. Smart Agric. Technol. 3, 100094. https://doi.org/10.1016/j.atech.2022.100094.

Pusztai, P., 2021. The advantage of point cloud derived tree modelling on urban greenery maintenance: shortlisting dangerous trees, assessing ecosystem services. A Master Thesis submitted for the Erasmus Mundus Joint Master Degree on Smart Cities and Communities (SMACCs) - University of Mons, Heriot Watt University, International Hellenic University, University of the Basque Country.

Pylianidis, C., Osinga, S., Athanasiadis, I.N., 2021. Introducing digital twins to agriculture. Comput. Electron. Agric. 184, 105942. https://doi.org/10.1016/j.compag.2020.105942.

Qian, C., Liu, X., Ripley, C., Qian, M., Liang, F., Yu, W., 2022. Digital twin—cyber replica of physical things: architecture, applications and future research directions. Future Internet. 14, 64. https://doi.org/10.3390/fi14020064.

Rebala, G., Ravi, A., Churiwala, S., 2019. An Introduction to Machine Learning. Springer, Cham.

Rist, T., Masoodian, M., et al., 2022. Interactive map visualizations for supporting environmental sustainable development goals. In: Ardito, C., Lanzilotti, R., Malizia, A., Larusdottir, M., Spano, L.D., Campos, J., et al. (Eds.), Sense, Feel, Design. Springer International Publishing, Cham, pp. 36–46. https://doi.org/10.1007/978-3-030-98388-8_4. Lecture Notes in Computer Science.

Rolph, S., Andrews, C., Carbone, D., Lopez Gordillo, J., Martinovič, T., Oostervink, N., Pleiter, D., Sara-aho, K., Watkins, J., Wohner, C., Bolton, W., Dick, J., 2024. Prototype Digital Twin: recreation and biodiversity cultural ecosystem services. RIO 10, e125450. https://doi.org/10.3897/rio.10.e125450.

Roy, D., Srivastava, R., Jat, M., Karaca, M.S., 2022. A complete overview of analytics techniques: descriptive, predictive, and prescriptive. In: Jeyanthi, P.M., Choudhury, T., Hack-Polay, D., Singh, T.P., Abujar, S. (Eds.), Decision Intelligence Analytics and the Implementation of Strategic Business Management, EAI/Springer Innovations in Communication and Computing. Springer International Publishing, Cham, pp. 15–30. https://doi.org/10.1007/978-3-030-82763-2_2.

Rozenstein, O., Cohen, Y., Alchanatis, V., Behrendt, K., Bonfil, D.J., Eshel, G., Harari, A., Harris, W.E., Klapp, I., Laor, Y., Linker, R., Paz-Kagan, T., Peets, S., Rutter, S.M., Salzer, Y., Lowenberg-DeBoer, J., 2024. Data-driven agriculture and sustainable farming: friends or foes? Precision Agric. 25, 520–531. https://doi.org/10.1007/s11119-023-10061-5.

Sanchez-Guzman, G., Velasquez, W., Alvarez-Alvarado, M.S., 2022. Modeling a simulated forest to get burning times of tree species using a digital twin. In: 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC). Presented at the 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, Las Vegas, NV, USA, pp. 0639–0643. https://doi.org/10.1109/CCWC54503.2022.9720768.

Semeraro, C., Lezoche, M., Panetto, H., Dassisti, M., 2021. Digital twin paradigm: a systematic literature review. Comput. Ind. 130, 103469. https://doi.org/10.1016/j.compind.2021.103469.

Seress, G., Liker, A., 2015. Habitat urbanization and its effects on birds. Acta Zool. Acad. Sci. H 61, 373–408. https://doi.org/10.17109/AZH.61.4.373.2015.

Shahat, E., Hyun, C.T., Yeom, C., 2021. City digital twin potentials: a review and research agenda. Sustainability 13, 3386. https://doi.org/10.3390/su13063386.

Sharef, N.M., Nasharuddin, N.A., Mohamed, R., Zamani, N.W., Osman, M.H., Yaakob, R., 2022. Applications of data analytics and machine learning for digital twin-based precision biodiversity: a review. In: 2022 International Conference on Advanced Creative Networks and Intelligent Systems (ICACNIS). Presented at the 2022 International Conference on Advanced Creative Networks and Intelligent Systems (ICACNIS). IEEE, Bandung, Indonesia, pp. 1–7. https://doi.org/10.1109/ICACNIS57039.2022.10055149.

Shirowzhan, S., Trinder, J., Osmond, P., 2020. New metrics for spatial and temporal 3D urban form sustainability assessment using time series lidar point clouds and advanced GIS techniques. In: Almusaed, A., Almssad, A., Truong - Hong, L. (Eds.), Sustainability in Urban Planning and Design. IntechOpen. https://doi.org/10.5772/intechopen.89617.

Shivanna, K.R., 2020. The sixth mass extinction crisis and its impact on biodiversity and Human welfare. Reson 25, 93–109. https://doi.org/10.1007/s12045-019-0924-z.

Shu, Q., Rötzer, T., Detter, A., Ludwig, F., 2022. Tree information modeling: a data exchange platform for Tree design and management. Forests. 13, 1955. https://doi.org/10.3390/f13111955.

Skobelev, P., Laryukhin, V., Simonova, E., Goryanin, O., Yalovenko, V., Yalovenko, O., 2020a. Multi-agent approach for developing a digital twin of wheat. In: 2020 IEEE International Conference on Smart Computing (SMARTCOMP). Presented at the 2020 IEEE International Conference on Smart Computing (SMARTCOMP). IEEE, Bologna, Italy, pp. 268–273. https://doi.org/10.1109/SMARTCOMP50058.2020.00062.

Skobelev, P., Mayorov, I.V., Simonova, E.V., Goryanin, O.I., Zhilyaev, A.A., Tabachinskiy, A.S., Yalovenko, V.V., 2020b. Development of models and methods for creating a digital twin of plant within the cyber-physical system for precision farming management. J. Phys. Conf. Ser. 1703, 012022. https://doi.org/10.1088/1742-6596/1703/1/012022.

Skobelev, P., Tabachinskiy, A., Simonova, E., Ermakov, V., Goryanin, O., Strizhakov, A., 2022a. Further advances in models and methods for digital twins of plants. In: 2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA). Presented at the 2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA). IEEE, Biarritz, France, pp. 1–6. https://doi.org/10.1109/INISTA55318.2022.9894246.

Skobelev, P., Tabachinskiy, A., Simonova, E., Goryanin, O., 2022b. Development of crop-simulation multiagent system for smart digital twin of plant. In: 2022 VIII International Conference on Information Technology and Nanotechnology (ITNT). Presented at the 2022 VIII International Conference on Information Technology and Nanotechnology (ITNT). IEEE, Samara, Russian Federation, pp. 1–8. https://doi.org/10.1109/ITNT55410.2022.9848748.

Skobelev, P., Tabachinskiy, A., Simonova, E., Lee, T.-R., Zhilyaev, A., Laryukhin, V., 2021. Digital twin of rice as a decision-making service for precise farming, based on environmental datasets from the fields. In: 2021 International Conference on Information Technology and Nanotechnology (ITNT). Presented at the 2021 International Conference on Information Technology and Nanotechnology (ITNT). IEEE, Samara, Russian Federation, pp. 1–8. https://doi.org/10.1109/ITNT52450.2021.9649038.

Sreedevi, T.R., Santosh Kumar, M.B., 2020. Digital Twin in Smart Farming: a categorical literature review and exploring possibilities in hydroponics. 2020 Advanced Computing and Communication Technologies For High Performance Applications (ACCTHPA). Presented at the 2020 Advanced Computing and Communication Technologies For High Performance Applications (ACCTHPA). IEEE, Cochin, India, pp. 120–124. https://doi.org/10.1109/ACCTHPA49271.2020.9213235.

Stoll, C., Klaaßen, L., Gallersdörfer, U., 2019. The carbon footprint of bitcoin. Joule 3, 1647–1661. https://doi.org/10.1016/j.joule.2019.05.012.

Tagarakis, A.C., Benos, L., Kyriakarakos, G., Pearson, S., Sørensen, C.G., Bochtis, D., 2024. Digital twins in agriculture and forestry: a review. Sensors 24, 3117. https://doi.org/10.3390/s24103117.

Tanhuanpää, T., 2016. Developing laser scanning applications for mapping and monitoring single tree characteristics for the needs of urban forestry. Diss. For. 2016. https://doi.org/10.14214/df.230.

Tao, F., Zhang, H., Liu, A., Nee, A.Y.C., 2019. Digital twin in industry: state-of-the-art. IEEE Trans. Ind. Inf. 15, 2405–2415. https://doi.org/10.1109/TII.2018.2873186.

Taubert, F., Rossi, T., Wohner, C., Venier, S., Martinovič, T., Khan, T., Gordillo, J., Banitz, T., 2024. Prototype biodiversity digital twin: grassland biodiversity dynamics. RIO 10, e124168. https://doi.org/10.3897/rio.10.e124168.

Theodorou, P., 2022. The effects of urbanisation on ecological interactions. Curr. Opin. Insect Sci. 52, 100922. https://doi.org/10.1016/j.cois.2022.100922.

Trantas, A., Plug, R., Pileggi, P., Lazovik, E., 2023. Digital twin challenges in biodiversity modelling. Ecol. Inform. 78, 102357. https://doi.org/10.1016/j.ecoinf.2023.102357.

Tscharntke, T., Clough, Y., Wanger, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., Whitbread, A., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. Biol. Conserv. 151, 53–59. https://doi.org/10.1016/j.biocon.2012.01.068.

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B.R., Zuffi, S., Risse, B., Mathis, A., Mathis, M.W., Van Langevelde, F., Burghardt, T., Kays, R., Klinck, H., Wikelski, M., Couzin, I.D., Van Horn, G., Crofoot, M.C., Stewart, C.V., Berger-Wolf, T., 2022. Perspectives in machine learning for wildlife conservation. Nat. Commun. 13, 792. https://doi.org/10.1038/s41467-022-27980-y.

Ubina, N.A., Lan, H.-Y., Cheng, S.-C., Chang, C.-C., Lin, S.-S., Zhang, K.-X., Lu, H.-Y., Cheng, C.-Y., Hsieh, Y.-Z., 2023. Digital twin-based intelligent fish farming with Artificial Intelligence internet of things (AIoT). Smart Agric. Technol. 5, 100285. https://doi.org/10.1016/j.atech.2023.100285.

Nations, United, 2015. THE 17 GOALS | Sustainable development [WWW Document], 17 Sustainable Development Goals. URL. https://sdgs.un.org/goals (accessed 3.10.22).

Van Der Burg, S., Kloppenburg, S., Kok, E.J., Van Der Voort, M., 2021. Digital twins in agri-food : societal and ethical themes and questions for further research. NJAS:

Impact Agric. Life Sci. 93, 98–125. https://doi.org/10.1080/27685241.2021.1989269.
Van Evert, F.K., Cammarano, D., Kempenaar, C., 2023. Precision agriculture : modelling - introduction. In: Cammarano, D., Van Evert, F.K., Kempenaar, C. (Eds.), Precision Agriculture: Modelling, Progress in Precision Agriculture. Springer International Publishing, Cham, pp. 3–24. https://doi.org/10.1007/978-3-031-15258-0_1.
Venkatraman, R., Venkatraman, S., 2019. Big data infrastructure, data visualisation and challenges. In: Proceedings of the 3rd International Conference on Big Data and Internet of Things. Presented at the BDIOT 2019: The 3rd International Conference on Big Data and Internet of Things, ACM, Melbourn VIC Australia, pp. 13–17. https://doi.org/10.1145/3361758.3361768.
Vo, Nichersu, Wendel, 2019. Modeling, monitoring, and validating green roof and green facade solutions with semantic City models using low cost sensors and open software infrastructures. Urban Sci. 3, 39. https://doi.org/10.3390/urbansci3020039.
Wang, Zhichao, Lu, X., An, F., Zhou, L., Wang, X., Wang, Zhihao, Zhang, H., Yun, T., 2022. Integrating real tree skeleton reconstruction based on partial computational virtual measurement (CVM) with actual forest scenario rendering: a solid step forward for the realization of the digital twins of trees and forests. Remote Sens. (Basel) 14, 6041. https://doi.org/10.3390/rs14236041.
Wilkinson, M.D., Dumontier, M., Aalbersberg, Ij.J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., Da Silva Santos, L.B., Bourne, P.E., Bouwman, J., Brookes, A.J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C.T., Finkers, R., Gonzalez-Beltran, A., Gray, A.J.G., Groth, P., Goble, C., Grethe, J.S., Heringa, J., `T Hoen, P.A.C., Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S.J., Martone, M.E., Mons, A., Packer, A.L., Persson, B., Rocca-Serra, P., Roos, M., Van Schaik, R., Sansone, S.-A., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M. A., Thompson, M., Van Der Lei, J., Van Mulligen, E., Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J., Mons, B., 2016. The FAIR Guiding Principles for scientific data management and stewardship. Sci. Data 3, 160018. https://doi.org/10.1038/sdata.2016.18.
Wright, L., Davidson, S., 2020. How to tell the difference between a model and a digital twin. Adv. Model. Simul. Eng. Sci. 7, 13. https://doi.org/10.1186/s40323-020-00147-4.
Xhafa, F., Krause, P., 2021. IoT-based computational modeling for next generation agro-ecosystems: research issues, emerging trends and challenges. In: Krause, P., Xhafa, F. (Eds.), IoT-Based Intelligent Modelling For Environmental and Ecological Engineering. Springer International Publishing, Cham, pp. 1–21. https://doi.org/10.1007/978-3-030-71172-6_1. Lecture Notes on Data Engineering and Communications Technologies.
Xu, H., Wang, C.C., Shen, X., Zlatanova, S., 2021. 3D Tree reconstruction in support of Urban Microclimate simulation: a comprehensive literature review. Buildings 11, 417. https://doi.org/10.3390/buildings11090417.
Ying, Y., Koeva, M.N., Kuffer, M., Zevenbergen, J.A., 2020. Urban 3d modelling methods: a State-of-the-art review. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLIII-B4-2020, 699–706. https://doi.org/10.5194/isprs-archives-XLIII-B4-2020-699-2020.
Yuan, H., Wang, N., Bennett, R., Burditt, D., Cannon, A., Chamberlin, K., 2018. Development of a ground-based peanut canopy phenotyping system. IFAC-PapersOnLine 51, 162–165. https://doi.org/10.1016/j.ifacol.2018.08.081.
Zake, M., Majore, G., 2022. Application of multi-perspective modelling approach for building digital twin in smart agriculture. In: 2022 63rd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS). Presented at the 2022 63rd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS). IEEE, Riga, Latvia, pp. 1–7. https://doi.org/10.1109/ITMS56974.2022.9937142.
Zhang, M., Tao, F., Huang, B., Liu, A., Wang, L., Anwer, N., Nee, A.Y.C., 2022a. Digital twin data: methods and key technologies. digitaltwin 1, 2. https://doi.org/10.12688/digitaltwin.17467.2.
Zhang, W., Li, X., He, Z., 2022b. Semantic Urban Vegetation Modelling Based On an Extended CityGML Description. Wichmann Verlag, DE. https://doi.org/10.14627/537724020.
Zhang, Yi, Zhang, Yu, Jiang, H., Du, H., Xue, A., Shen, W., 2024. New method for modeling digital twin behavior perception of cows: cow daily behavior recognition based on multimodal data. Comput. Electron. Agric. 226, 109426. https://doi.org/10.1016/j.compag.2024.109426.
Zhao, D., Li, X., Wang, X., Shen, X., Gao, W., 2022. Applying digital twins to research the relationship between urban expansion and vegetation coverage: a case study of natural preserve. Front. Plant Sci. 13, 840471. https://doi.org/10.3389/fpls.2022.840471.