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Digital Twins: Fundamentals and Applications in Wildfire Management

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Contents

1 Introduction

Wildfire digital twins offer a way to study fire and landscape together, in motion. They make it possible to ask not only what is burning now, but what may happen next under different choices. This capability is especially helpful in an era when wildfire is becoming harder to manage as the climate shifts. Seasons are longer, fire behaviour is more extreme, and risk is rising both in wildland and urban landscapes. At the same time, the technical conditions for digital twins are now more plausible than they were a decade ago. Sensing systems, communication networks, and computation increasingly allow near-real-time coupling between data and models. Yet this progress has also made digital twin an elastic term. It is often used for systems that are little more than static models, dashboards, or digital shadows.

Despite differences across domains, recent work on digital twins points to a shared core: a physical system, a virtual counterpart and data flows that keep the two aligned within a layered architecture for data capture, storage, analytics and human interaction. Even so, many systems described in the literature still fall short of this ideal, with weak feedback, limited uncertainty handling and little attention to lifecycle management and governance.

Wildfire applications inherit these ambiguities, but under harsher conditions. Fire spreads quickly, depends on only partially observed fuel, weather, and terrain, and can shift behaviour sharply under extreme conditions. Heterogeneous inputs from satellites, aircraft, UAVs, in-situ sensors, and evolving fuel and asset maps must be fused despite latency, gaps, and uneven coverage. Wildfire twins must also represent exposure, vulnerability, suppression actions, and human behaviour, while remaining compatible with legal and institutional settings that keep humans in the loop.

The main problem addressed in this paper is therefore not whether wildfire digital twins are desirable in principle, but what a realistic and useful wildfire twin should look like, and how far current practice is from that target. The central question is which architectural and methodological elements from industrial, urban, environmental, and disaster-management twins can transfer to wildfire use cases, and which must be adapted or developed anew. Related questions concern where existing wildfire-labelled systems sit on the spectrum from model to twin, which missing practices are feasible, and how such systems can support risk assessment, behaviour modelling, and decision support for firefighters and emergency managers.

The paper addresses these questions in three steps. First, it reviews the history, terminology, and core architecture of digital twins, to clarify how they differ from digital models, shadows, and related concepts. Second, it presents a quantitative meta-analysis of digital-twin publications across domains, to place wildfire work in the broader landscape and identify practices from more mature fields. Third, it examines existing wildfire digital twins in detail, focusing on models, data sources, outputs, and risk representations, and on recurring gaps in uncertainty handling, suppression modelling, validation, and lifecycle management. The synthesis leads to research priorities for the PhD, centred on architecture, data pipelines, behaviour integration, and practical benchmarks for future wildfire twins.

2 Digital Twins

2.1 History

Ideas now grouped under the term "digital twin" (DT) reach back to National Aeronautics and Space Administration's (NASA) aerospace mirror systems, where engineers ran ground copies of manned spacecraft and updated them with in-flight telemetry [1, 2]. Historical accounts read the Apollo 13 "living models" as tightly coupled cyber–physical predecessors of digital twins rather than as isolated simulations [1, 3].

Grieves' early-2000s product-lifecycle work formalises a physical space, a virtual space and their connecting links, later framed as a triad of physical entity, virtual entity and connecting data that can be applied across lifecycle stages [4, 2]. NASA's 2010 Technology Roadmap then introduces "digital twin" as a named construct, describing a virtual spacecraft that runs in parallel with the real vehicle over the full mission profile and is driven by on-board telemetry [5, 1].

Subsequent engineering literature characterizes digital twins as operational models that remain synchronized with their corresponding assets and support monitoring, prognosis and risk-sensitive decision-making throughout system life [6, 7]. Figure 1 condenses this trajectory, from NASA's mirror systems, through Grieves' product lifecycle management (PLM) triad, to the 2010 roadmap and the later diffusion of digital-twin concepts across domains, highlighting the most important events for the field [1, 2, 4, 5, 3].

Recent reviews document this diffusion from manufacturing into urban systems, healthcare, agriculture and environmental applications, where the same triad is used as a general organizing frame for models, data and services over a system's lifecycle [3, 8, 9].

2.2 Terminology and Definitions

"Digital twin" sits among several neighbouring concepts and is applied unevenly across the literature. Many systems labelled as digital twins are closer to static models or dashboards, and several definitions omit features that recent reviews treat as essential, such as continuous data exchange and a clear operational role [11, 6, 8].

A digital model is a virtual representation of a physical system that is updated at specific points in time, for example on initialization [12]. It can be detailed and useful for visualisation or offline analysis, but it is not kept automatically aligned with the real system [12, 13].

A digital shadow builds on a digital model and adds a one-way data feed

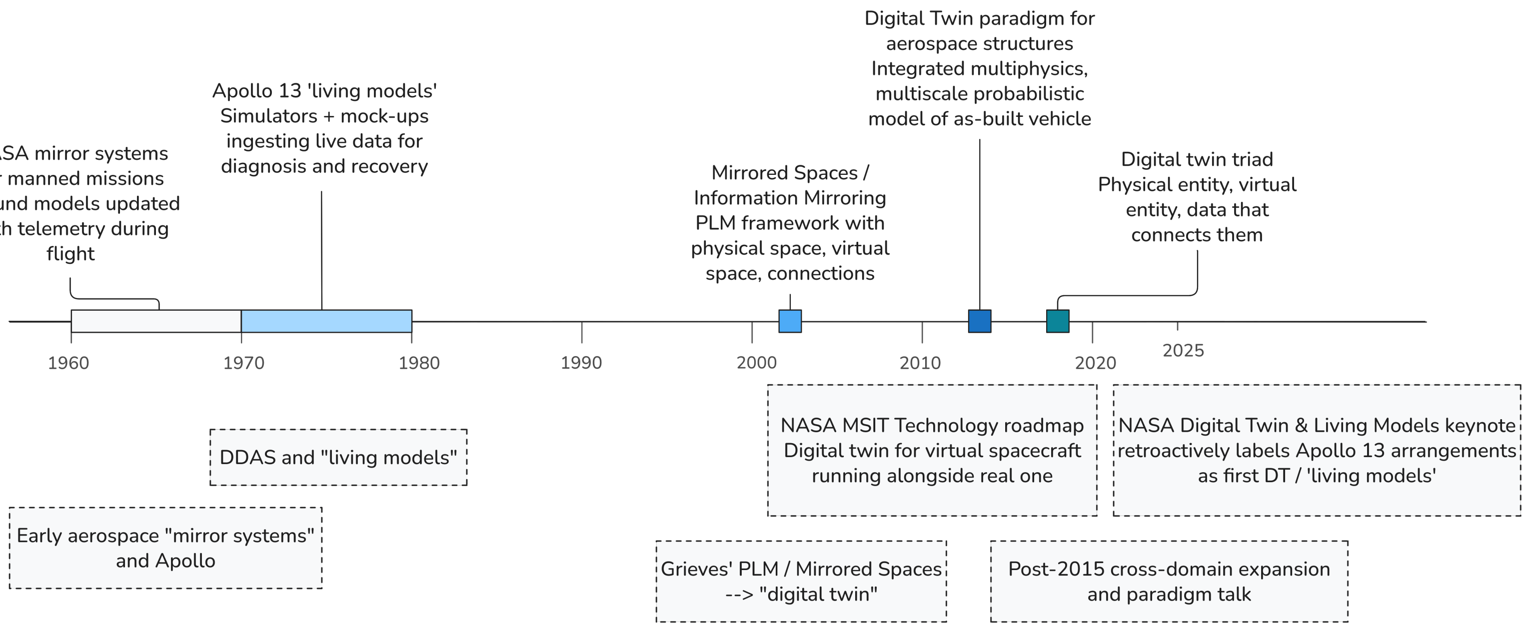

Figure 1: Stylised timeline of digital-twin development, from NASA mirror systems and Apollo 13 living models through Grieves' PLM triad to NASA's 2010 roadmap and the spread into manufacturing, urban, healthcare and environmental applications [1, 2, 5, 6, 10, 8, 9].

from the physical system into the virtual one [12, 14]. Measurements are streamed into the model so its state changes as new observations arrive, but information still flows in one direction and modifying the model does not directly alter how the physical system behaves [12].

A digital twin is defined as a virtual system that is kept aligned with a corresponding physical system and can, in principle, exert influence on that system [12, 4]. Across many definitions, three elements appear consistently: a physical system, a virtual representation of that system and a data link that maintains agreement between the two to a practically useful degree [12, 4]. Recent reviews emphasize sustained synchronization, two-way interaction and explicit operational services as key differentiators from shadows [6, 8, 13].

Cyber-physical systems (CPS) emphasize sensing, computation and actuation for real-time control of physical processes [6]. Digital twins sit at the overlap between such control-oriented systems and service-oriented product–service and data infrastructures, maintaining an explicit virtual representation, consuming live data and supporting operational services that can influence the physical system [8, 7]. Figures 2 and 3 summarize these distinctions visually [12, 9].

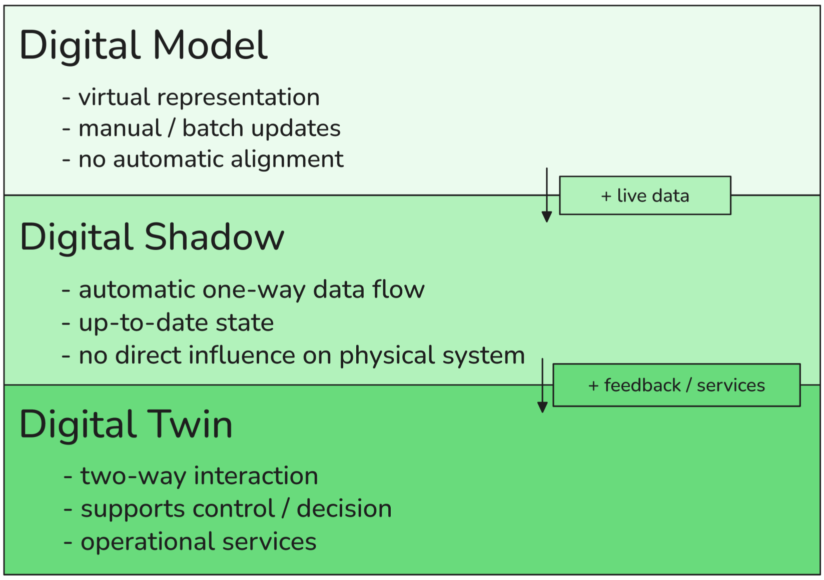

Figure 2: Conceptual classification of digital models, digital shadows and digital twins [12, 6, 13].

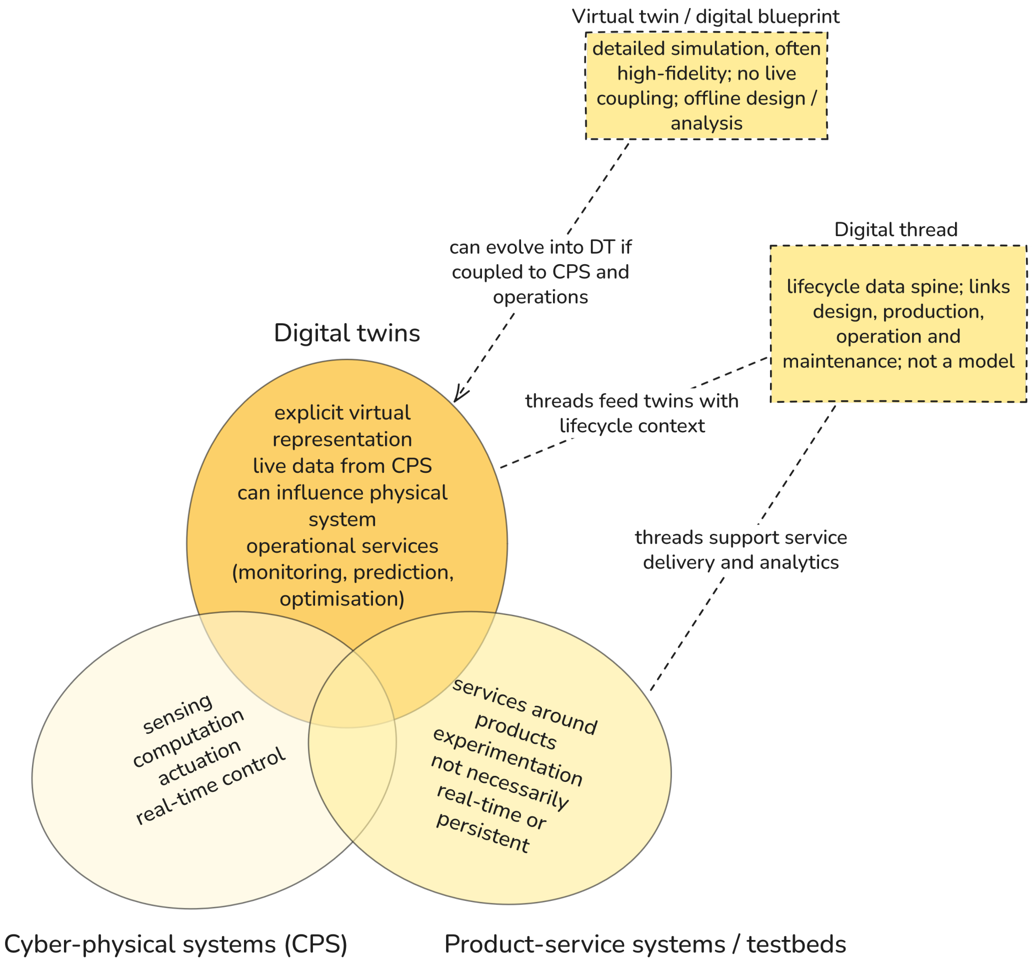

Figure 3: Schematic overlap between cyber-physical systems, product–service systems, digital twins, virtual twins and digital threads [7, 9, 2, 10].

2.3 Core Digital Twin Architecture

Digital-twin architectures are typically specified in terms of a small set of core components and their interconnections, often arranged in multi-layer frameworks for data acquisition, modelling, analytics and interaction. At the core sits a triad of physical entities, virtual representations and the data that link them, with many reference models adding explicit service and interaction layers on top of this structure [12, 4].

Table 1: Typical layers in a digital-twin architecture.

Layer	Main elements	Typical functions
Physical assets	Machines, infrastructure, sensors, actuators	Provide measurements and receive commands from the twin
Data capture	IoT / IIoT devices, edge gateways, field networks	Collect data from assets, perform initial filtering, stream to the platform
Storage and preprocessing	Databases, data lakes, stream processors, ETL tools	Store time-series data, clean and transform inputs, aggregate and index for analysis
Modelling and analytics	Simulation engines, physics models, ML and optimisation services	Run forecasts and "what-if" scenarios, estimate state, detect anomalies, optimise operation
Applications and interfaces	Dashboards, APIs, control-room HMIs, external systems	Present status and predictions, support decision-making, integrate with MES/SCADA and other tools

2.3.1 Core Components

Digital twins are typically described as composite arrangements with a physical part, a virtual part and data connections between them, rather than as single undivided systems [12]. In this view, physical entities and their virtual counterparts are linked by data flows that keep cyber and physical spaces approximately synchronized across the lifecycle [12, 7].

In operational terms, these links pass through interfaces such as dashboards, service application programming interfaces (API) and, where relevant, feedback channels to actuators or control logic [15, 16]. The twin is therefore not only a model, but a mediated relationship between model, data and action [17, 18].

Around this core, reference models usually add service or application layers for monitoring, prediction and optimization and infrastructure layers for communication, storage and security [17, 11]. In platform-oriented descriptions, these layers correspond to concrete services ranging from device connectivity through data pipelines to domain applications [17, 18].

2.3.2 Multi-layer architectures

Architectural descriptions commonly depict a digital twin as a stack of layers rather than as a single block, as summarised in Table 1 [19, 10]. A basic separation distinguishes the physical side, the virtual side and the data path that connects them, while more detailed accounts add layers for capture, storage and preprocessing, modelling and analytics, and application interfaces [19, 17, 20].

Across domains, the same pattern recurs: physical assets and sensing at the bottom, then data capture and preprocessing, then modelling and analytics, and finally applications and interfaces that expose results to users and external systems [17, 16, 21]. This layered view matters later for wildfire, because sensing constraints, data assimilation, analytics and decision-support interfaces each place distinct requirements on the twin.

2.3.3 Synchronization and Data Flow

A central architectural question is how data move between the physical system and its digital counterpart, not only which building blocks are present [12]. One useful characterization distinguishes links from physical to virtual and from virtual to physical and introduces a twinning rate that describes how often the two sides are brought back into alignment, from periodic synchronization to near-real-time updates [12, 22].

Architectures with one-way flow from the physical system into the virtual one are treated as digital shadows: they support monitoring and analysis, but they do not send control information back to the asset [16]. When the virtual side can also send recommendations or control signals, the link becomes two-way and closes the loop, which is the defining feature of a digital twin in many reviews [22, 18].

Across domains, synchronization patterns range from event-driven updates through fixed-interval sampling to near-continuous streams, with corresponding trade-offs in latency, bandwidth and storage [17, 23]. These choices also affect trust, because the degree of alignment between physical and digital states shapes how far users can rely on the twin for prediction and control [24, 25].

2.3.4 Analytics

The analytics layer converts data flowing through the twin into guidance for monitoring, prediction and control, rather than leaving them as raw measurements [19, 17]. Architectural accounts commonly treat physics-based and data-driven models as complementary: physics-based models support interpretation and extrapolation, while data-driven components track patterns and drift that are hard to encode from first principles [12, 22].

Hybrid analytics arrangements therefore recur across the literature, using combinations of simulation, filtering and machine learning to keep the virtual side aligned with the asset over its life [7, 13]. This matters for wildfire applications, where reduced-order models and fast data assimilation must balance physical realism with the speed needed for operational use [26, 27, 28].

2.3.5 Human Interaction

Digital-twin architectures generally reserve explicit space for human interaction, treating socio-technical design as part of the core problem rather than as an add-on [11, 9]. In industrial and infrastructure domains, interaction layers are typically configured for decision support rather than full automation: the twin produces recommendations or candidate actions and operators validate them before execution [14, 21].

Urban and environmental twins show similar patterns, using maps, 3D scenes and dashboard-style tools to communicate system state, scenarios and alerts to planners and operators [29, 30, 31]. These human-facing layers are therefore integral components of multi-layer twin architectures and provide a basis for comparing implementations across domains, including wildfire decision support [32, 33, 8].

2.4 Standards and reference frameworks

Digital twin standardization is young, but converging. The International Organization for Standardization (ISO) 23247 (2021) established an early four-layer manufacturing framework, distinguishing observable manufacturing elements, communication, digital twin core, and user layers [34]. Observable elements include personnel, equipment, materials, processes, facilities, environment, and products; the standard treats these as sources of structured observations rather than as abstract “things” [34]. The communication layer abstracts heterogeneous industrial networks into time-stamped, quality-assessed information services that feed the twin core, instead of fixing specific fieldbuses or protocols [34]. The digital twin layer then groups data management, analytics, and simulation functions, while the user layer collects visualization, decision support, and control applications, making closed-loop actuation through the twin an explicit option rather than an afterthought [34]. Subsequent parts add functional views for ingestion, runtime, and lifecycle management, which align naturally with later maturity schemes that separate concept, development, and operation phases for industrial twins [34].

ISO/IEC 30173 (2023) generalizes this to a cross-domain vocabulary. It defines a digital twin as a digital representation of a target entity whose physical and digital states are kept aligned at an appropriate synchronization rate, and explicitly separates the physical entity, its digital counterpart, and the interaction functions between them [35]. The standard also introduces life-cycle phases for the twin itself, from planning and development through operation to decommissioning, and associates typical roles and responsibilities with each phase [35]. Alongside this, it describes conceptual dimensions such as representation scope (component, system, system-of-systems), functional capability (from status monitoring to prediction and control), and alignment mechanisms (one-way observation versus bidirectional interaction) [35]. These dimensions are qualitative rather than a fixed numeric scale, but they underpin later digital twin maturity models and offer a neutral backbone for mapping sector-specific frameworks [35, 36, 37].

On the industrial side, the International Electrotechnical Commission (IEC) 63278-1 (2023) standardizes the Asset Administration Shell (AAS) as a canonical digital representation for individual assets and asset types, structured into submodels for identification, technical data, documentation, operation, and condition monitoring [38]. In practice, the AAS acts as a component-level digital twin: shells provide harmonized, machine-readable submodels, and plant-level twins compose many shells into system-level representations [38]. Read through ISO/IEC 30173, AAS submodels occupy the representation dimension for component twins, while the ISO 23247 stack describes how many such components are connected, orchestrated, and presented at system level [34, 35, 38]. The Institute of Electrical and Electronics Engineers (IEEE) P3501 (2024) carries the compositional idea into Earth-system twins, treating them as assemblages of domain twins and naming wildfire as a priority domain that must support multi-scale simulation, real-time data assimilation, and coupling to decision workflows [39].

Consortia and domain programmes try to fill the gaps where the formal standards stop. The Digital Twin Consortium emphasizes cross-domain interoperability as an architectural concern, arguing that robust twins separate capabilities such as data ingestion, state management, analytics, and actuation from specific technologies, and that interoperability rests on semantics, identity, and lifecycle traceability at least as much as on message formats [40]. From this perspective, maturity is explicitly multi-dimensional: a twin can be predictive in its physics yet immature in governance, provenance, or integration with the wider digital thread [40]. The Open Geospatial Consortium (OGC) API stack supplies service interfaces for gridded, vector, and sensor data, and the NASA ESDT Standards Framework (2023) shows how existing space and geospatial standards can be combined into a federated Earth-twin stack built on those interfaces [41]. In that stack, distributed providers expose OGC-compliant services, modelling and assimilation components consume these via standard APIs, and user-facing applications sit at the top, so that Earth-system twins are layered but not centralized [41].

Even so, convergence remains limited. Manufacturing, Earth-system, and urban twins have evolved in separate communities; their reference models overlap in shape but not in terminology, granularity, or governance assumptions [34, 35, 38, 40, 41, 39]. Taken together, however, they expose several orthogonal axes along which wildfire digital twins can be positioned: architectural layering from data acquisition to user interaction, capability levels from status to predictive and prescriptive, lifecycle phases from concept to operation, and scope from component to system-of-systems [34, 35, 40, 41]. In practice, a wildfire twin is likely to use ISO/IEC 30173 for high-level concepts, borrow layered and component-assembly patterns from ISO 23247 and IEC 63278-1, and align its data and services with OGC, NASA ESDT, and emerging IEEE P3501 guidance, rather than implementing any single framework end-to-end [34, 35, 38, 40, 41, 39].

2.5 Maturity and Open Issues

Empirical surveys indicate that many systems marketed as digital twins remain closer to digital models or shadows, particularly in buildings and smart-city contexts where "twins" are often BIM models or 3D dashboards with periodic data updates [11, 8]. Maturity frameworks for environmental and life-science twins place most implementations between descriptive status boards and predictive simulators, with limited optimisation and almost no autonomous operation [33, 7]. Disaster-management reviews note that doctrine and legal constraints usually preclude fully automated control, so twins are implemented as decision-support tools rather than autonomous agents [42, 43].

Across domains, recurring open issues include validation under changing conditions, long-term maintenance of data pipelines, interoperability across platforms and vendors, and explicit treatment of uncertainty and risk in outputs [7, 8, 44]. Ontology-driven and knowledge-graph approaches add semantic alignment and governance, especially where twins span multiple organisations or hazards [45, 46].

Standardization has caught up only partially. Most deployed twins predate the ISO/IEC vocabulary, and reference models from ISO 23247, IEEE P3501, IEC 63278, and the Digital Twin Consortium overlap without forming a coherent stack [34, 35, 37, 38, 39, 40]. Manufacturing holds the oldest standards and the highest conformance. Earth-system, urban, and disaster twins rely on newer, partly drafted instruments and typically mix elements pragmatically. Khan et al. argue that measurable correspondence, interoperability, and fidelity should anchor twin evaluation [24], Klar et al. point to the absence of shared maturity assessment [47], and Abdelrahman et al. trace ongoing terminology drift directly to this fragmented landscape [8].

In disaster and outdoor applications, maturity is further constrained by data scarcity, limited instrumentation and institutional caution around automation [42, 33]. Environmental reviews therefore treat descriptive-plus-predictive capability, aligned with existing decision-making procedures and clear uncertainty communication, as a realistic near-term target [16, 33]. For wildfire applications, later sections return to these themes and examine which maturity levels are attainable and which issues are most constraining in practice.

3 Meta-analysis of Digital Twin Applications

3.1 Aims and research questions

Work on digital twins spans factories, aircraft, hospitals, cities, energy systems, environmental monitoring and disaster management, but the application landscape is fragmented and unevenly documented [12, 6]. Conceptual and historical reviews describe core ideas and enabling technologies, yet they leave open where twin implementations actually concentrate, how domains differ in maturity and how much of the literature consists of reviews rather than concrete case studies [48, 7].

This section presents a quantitative, cross-domain mapping of digital-twin applications from 2013 to 2025 using publication records from the Web of Science Core Collection. Searches covered 2013–2025, starting from the first year in which Web of Science records a digital-twin topic hit after NASA's 2010 Technology Roadmap [5]. The analysis addresses three questions:

- RQ1: How are digital-twin publications distributed across major application domains over 2013–2025?
- RQ2: How does the balance between review-oriented and case-oriented records vary across domains, and what does this suggest about relative conceptual versus implementation maturity?
- RQ3: How have publication volumes in key domains evolved over time, and in which venues does domain-specific digital-twin work concentrate?

The goal is to provide an empirical overview of where digital-twin work is concentrated, how it has grown, and how strongly different domains lean towards synthesis versus implementation, without attempting an exhaustive census.

3.2 Methods

3.2.1 Information source and time window

The primary data source was the Web of Science Core Collection. Searches covered 2013–2025 to capture the main phase of digital-twin diffusion beyond manufacturing and the consolidation of Industry 4.0 narratives. Only records classified as "Article" or "Proceedings Paper" were included to focus on peer-reviewed research outputs.

3.2.2 Core search term and domain blocks

All queries used "digital twin" as the core term. A topic search in Web of Science was performed with the condition

$$\text{TS} = (\text{"digital twin*"})$$

applied to titles, abstracts and author keywords.

To distinguish application areas, the core term was combined with domain-specific keyword blocks. Domains were defined at a meso-level that keeps the number of categories manageable while reflecting the spread of digital-twin work in the literature: industrial and manufacturing systems, aerospace and aviation, energy and utilities, urban/transport/infrastructure systems, healthcare and life sciences, agriculture and forestry, environmental and climate systems, disaster and emergency management, and a wildfire-focused subset nested within environmental and disaster domains.

Each domain was associated with a set of topic keywords that capture common labels, assets and contexts in that area, derived iteratively from domain reviews and representative case studies with the aid of an AI-assisted keyword search; Table 2 lists the keyword sets used in the TS field for 2013–2025.

Domain-specific queries therefore took the general form

$$\text{TS}(\text{"digital twin*"}) \text{ AND TS(domain keywords) AND PY}{=}(2013\text{–}2025),$$

with the time window implemented through the publication-year filter.

3.2.3 Approximating review-type and case-type records

To approximate how much work in each domain is devoted to synthesis versus implementation, separate topic queries were run targeting “review-like” and “case-like” records. For each domain, a review-oriented query added terms such as “review”, “systematic review”, “survey”, “literature review” or “bibliometric” to the core and domain blocks, while a case-oriented query added terms such as “case study”, “use case” or “implementation”. For each domain and query type, the number of records returned was extracted directly from Web of Science and used as an indicative count of review-like and case-like publications.

These counts are based purely on keyword matches in titles, abstracts and author keywords and do not result from manual classification, so they serve as approximate signals rather than definitive measures of study type.

Table 2: Topic keyword sets used in review-oriented and case-study-oriented queries by application domain (TS field, 2013–2025).

Domain	**Topic keywords (TS)**
Industrial and manufacturing	factory, *manufactur**, production, "industry 4.0"
Aerospace and aviation	aircraft, airline, aviation, "air traffic", "space mission", spacecraft, satellite
Urban, transport and infrastructure	automotive, bridge, bus, car, "built environment", "city infrastructure", "city management", "city twin", dam, ITS, logistics, metro, municipality, rail, railway, "rail infrastructure", road, "road network", "sewer network", "smart cities", "smart city", "structural health", "supply chain", "traffic control", "traffic management", "transport system", truck, tunnel, "urban infrastructure", urban, "urban mobility", "urban planning", "urban transport", vehicle, "wastewater", "water network", "public transport"
Healthcare and life sciences	biomedical, clinical, hospital, ICU, "health care", healthcare, "life science", patient, "precision medicine", "medical device", "operating room", "personalised medicine", "personalized medicine", surgical
Agriculture and forestry	agriculture, agricultural, crop, farming, forestry, irrigation
Environmental and climate systems	"air quality", *environment**, ecosystem, "atmospheric model", climate, "climate change", catchment, hydrology, meteorolog*, ocean*, "water quality", watershed
Disaster and emergency management	cyclone, "disaster management", disaster, earthquake, emergency, evacuation, flood, flooding, hazard, hurricane, landslide, "risk management", resilience, "storm surge", tsunami, wildfire, "forest fire", bushfire, "wild land fire", "early warning"
Wildfire focused	bushfire, fire, "forest fire", "wild land fire", wildfire
Energy and utilities	"district heating", "energy system", "gas network", photovoltaic, PV, "power grid", "power plant", "power system", "renewable energy", "smart grid", "solar farm", "water distribution", "wind farm", windfarm

3.2.4 Publication-year timelines

To characterize temporal trends, publication-year distributions were derived for the overall digital-twin corpus and for selected domains using the Web of Science "Analyze Results → Publication Years" function. A global topic query with the core term and 2013–2025 filter yielded total digital-twin publications per year, and the same procedure applied to each domain-specific query produced per-year counts by domain. These distributions underlie the timelines in Section 3.4.

It is worth noting that the timelines and domain-level counts are based on database-level aggregates, not on screened and hand-coded study samples. They are interpreted as indicators of broad patterns in attention and growth rather than as exhaustive enumerations of every digital-twin implementation.

3.2.5 Limitations

The use of topic keywords to define domains and to separate review-like from case-like records introduces several limitations. Individual papers can belong to multiple domains, and generic terms such as "logistics" or "built environment" can draw in off-topic records. Some reviews are labeled as articles, and some case studies lack the expected phrases, so the study-type counts are best read as lower-bound estimates.

Because the total number of records exceeds what can be screened manually in a qualification-paper setting, the analysis relies on database-level aggregates restricted to English-language Articles and Proceedings Papers, rather than on a fully hand-coded, multilingual corpus. Later subsections complement these quantitative patterns with selected examples from influential reviews and case studies to give a more concrete picture of how twins are realised in different application areas.

3.3 Publication type representation by domain

Table 4 summarizes the split between review-oriented and case-oriented hits by domain over 2013–2025 by keywords. Manufacturing and urban/transport/infrastructure twins dominate by volume, environmental and climate systems form a substantial stream, and aerospace, agriculture, disaster management and energy appear smaller but still non-trivial. Explicitly wildfire-tagged work is rare, with 8 review-like and 32 case-like hits.

Across domains, case-oriented queries consistently return more hits than review-oriented ones, suggesting that much of the literature presents applications or implementations at least at abstract level. The case–review gap

Table 4: Query-level counts of review-like and case-like digital-twin records by application domain (Web of Science, 2013–2025).

Domain	**Extended category / keyword focus**	**Reviews**	**Case studies**
Manufacturing	Manufacturing, Industry 4.0, factory, production	859	2403
Aerospace	Aerospace, aircraft, spacecraft, satellite	92	214
Urban	Urban, transport, infrastructure	1219	3018
Healthcare	Healthcare, medicine	212	285
Agriculture	Agriculture, crop, farming, irrigation, forestry	89	161
Environmental	Environmental and climate systems	807	2045
Disaster	Disaster, emergency management, hazard	211	472
Wildfire	Wildfire, forest fire, bushfire, wildland fire	8	32
Energy	Energy systems and utilities	118	349

is largest in manufacturing and urban/transport/infrastructure twins and smaller in agriculture, disaster management and energy, which aligns with cross-domain reviews that report dense case material in industrial and urban settings and thinner but growing bodies of work in environmental and hazard-related applications [17, 10, 48, 7, 18].

Later analysis uses simple ratios of review-like to total hits per domain as cautious indicators of how "theorized" versus "implemented" each area appears at query level, recognizing that these measures rest on keyword filters rather than hand-coded study types.

3.4 Publication trends over time

Figure 4 shows the global rise in digital-twin publications between the 2010s and 2025 for the topic query `TS=("digital twin*")`. Counts stay in single digits until the mid-2010s, then climb rapidly from 258 records in 2018 to 651 in 2019 and more than 1000 per year from 2020 onwards, reaching 7787 in 2025. This pattern matches historical and conceptual accounts that place the consolidation and broad uptake of digital twins in the last decade [12, 49, 3, 48].

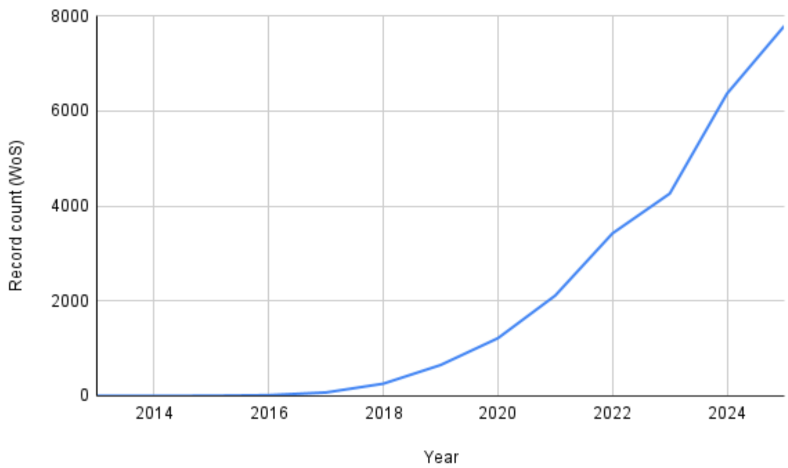

Figure 4: Digital-twin publications per year in Web of Science for the topic query `TS=("digital twin" OR "digital twins")`, 2010–2025.

Domain-specific timelines show how different streams contribute to this aggregate rise. Figure 5 plots per-year publication counts for manufacturing, urban/transport/infrastructure, environmental and climate systems, healthcare and disaster/emergency queries over 2013–2025.[1]

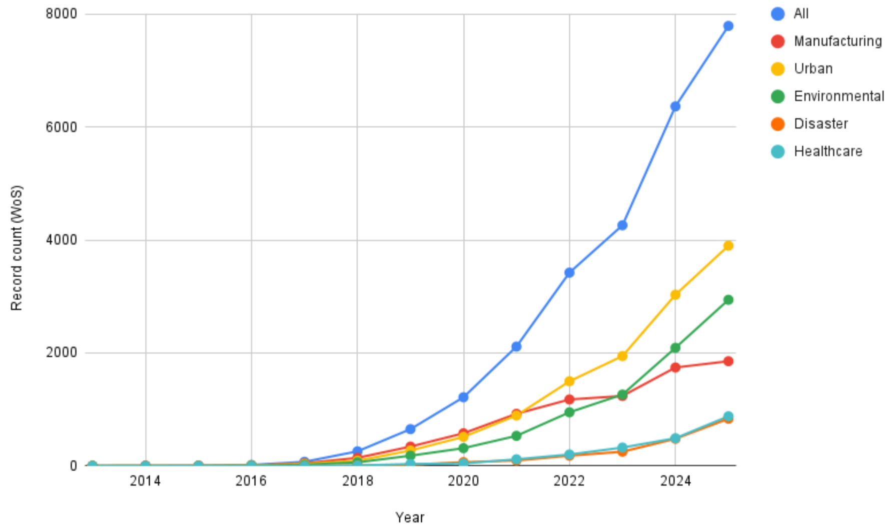

Figure 5: Digital-twin publications per year in selected domains (Web of Science topic queries), 2013–2025.

Manufacturing twins appear earliest and grow steeply after 2016, reflecting sustained interest in digital twins as part of Industry 4.0 and smart-manufacturing programmes [19, 50, 20, 7]. Urban and infrastructure-related twins follow a comparable rise a few years later, as digital-twin ideas are taken up in smart-city and built-environment work and used as platforms for monitoring, planning and decision support [17, 51, 47].

Environmental and climate-focused twins show a similar but slightly delayed pattern, with low activity before 2017 and a marked increase in the early 2020s, aligned with the emergence of maturity frameworks and application-centred reviews in life and environmental sciences [33, 48]. Healthcare twins also increase over this period from a lower baseline, reflecting growing interest in patient-specific and operational twins in precision medicine and hospital management [3, 21, 48]. Disaster and emergency-management twins remain the smallest of the five curves but still show clear growth from the late 2010s onward, consistent with disaster- and resilience-oriented discussions in broader digital-twin reviews [17, 10, 48].

Figure 6 links these aggregate trends to specific conceptual and domain-level

[1]Domain timelines use the same topic keyword blocks as in Table 4, without the review/case filters, and include all article and proceedings records in Web of Science for 2013–2025.

developments by placing widely cited reviews and frameworks on a shared time axis across manufacturing, urban, environmental, healthcare, disaster and wildfire twins [17, 6, 30, 7, 33, 52, 53, 43, 54, 55, 56, 57, 31, 58, 21, 59].

These timelines indicate that digital-twin activity has expanded rapidly across multiple domains in the last decade, with manufacturing and urban systems leading in volume and environmental, healthcare and disaster applications forming smaller but intensifying streams.

3.5 Study-type balance across domains

Table **??** reports review-type versus case-type hits per domain over 2013–2025, and Figure 7 shows the corresponding review shares. The patterns are uneven.

Manufacturing and urban/transport twins show low review shares, with case-type hits outnumbering reviews roughly three to one, consistent with their dense operational literature [17, 3, 7]. Healthcare and disaster queries return smaller volumes but higher review shares, reflecting more conceptual and framework work relative to implementations [21, 18, 48]. Environmental and climate twins sit between these extremes [33, 48]. Wildfire-specific queries return very small counts and are reported for completeness only. Across domains, the split between review and case material gives a rough proxy for how much synthesis has accumulated versus how much work remains at the level of individual reported twins.

To situate this further, the corpus was also used to identify dominant publication venues per domain and to distinguish article from proceedings outlets. Figures 8 and 9 map domains against venues, with cell colour indicating relative frequency, offering a coarse view of where work is concentrated and whether it flows primarily into archival journals or conference channels.

Publication patterns vary by domain but follow a recognizable logic. In manufacturing, work concentrates in journals such as *Applied Sciences Basel*, the *International Journal of Advanced Manufacturing Technology* and the *Journal of Manufacturing Systems*, together with proceedings outlets such as *Procedia CIRP* and *IFAC PapersOnLine*. Urban and environmental twins lean on broad engineering and sensing journals, notably *IEEE Access*, *Applied Sciences Basel*, *Sensors*, *Sustainability* and *Energies*, alongside IFAC, LNCS/LNCE and remote-sensing series such as the ISPRS *Archives* and *Annals*. Disaster-management twins surface both in these mixed-domain venues and in more specialised outlets such as the *International Journal of Disaster Risk Reduction*, *Environmental Modelling Software* and *Process Safety and Environmental Protection*, while healthcare twins are concentrated in medical and digital-health journals including *npj Digital Medicine*, *Frontiers in*

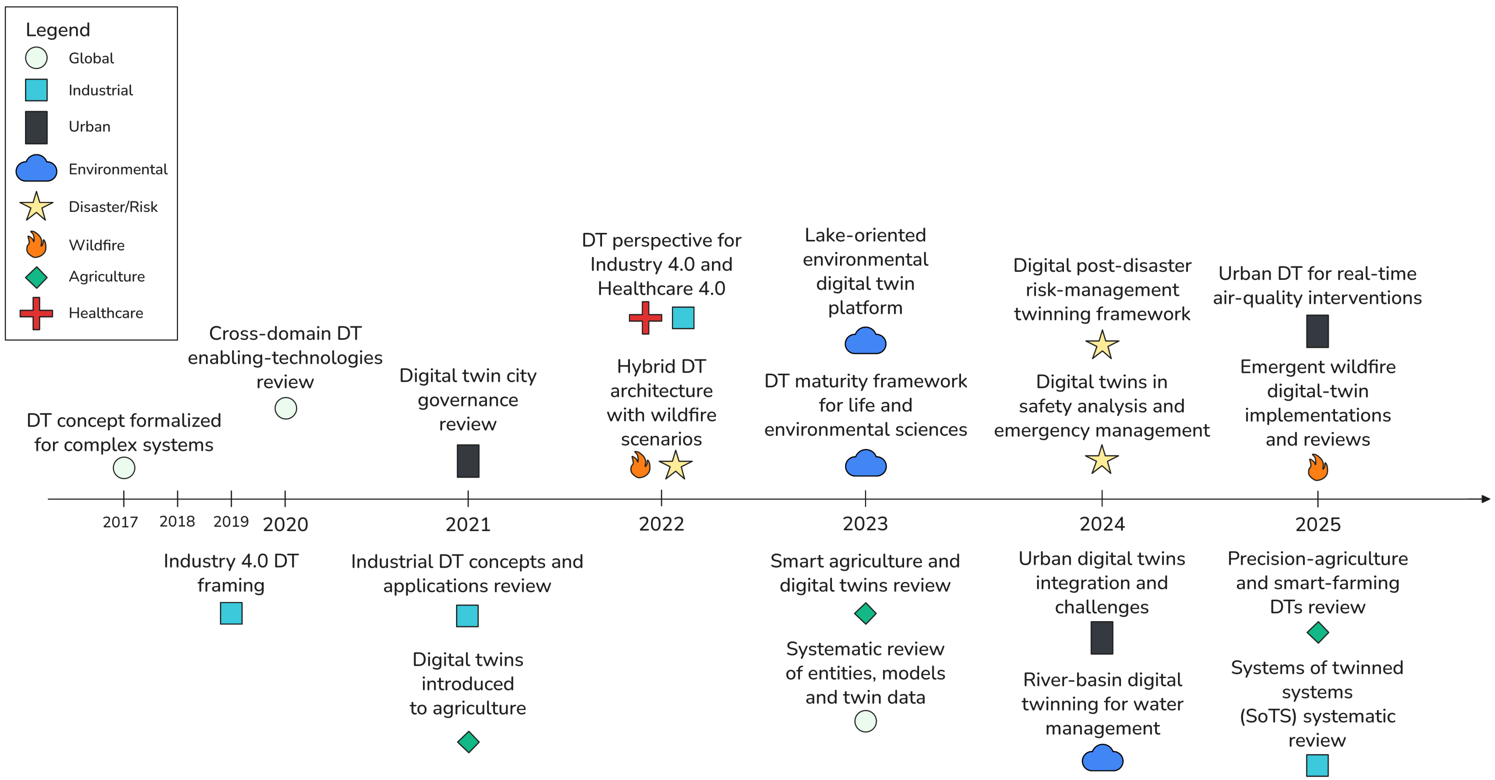

Figure 6: Cross-domain milestone timeline showing selected high-impact digital-twin reviews and frameworks by year and application domain.

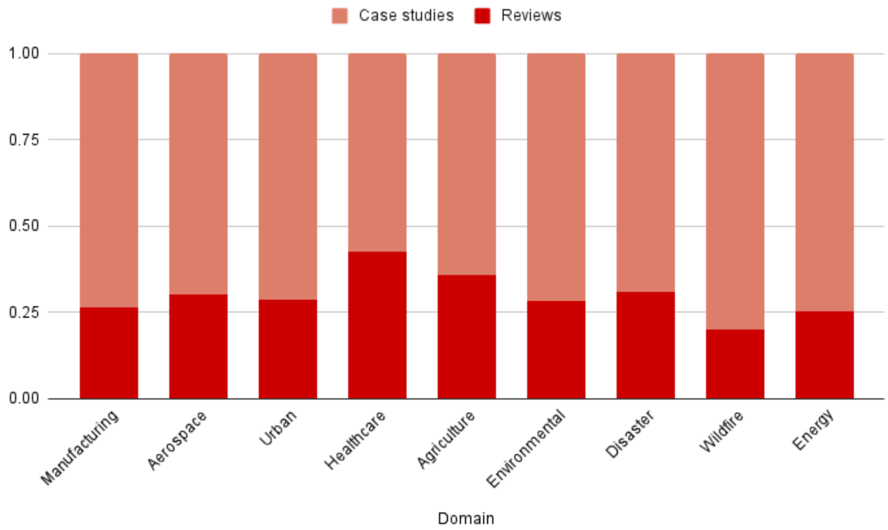

Figure 7: Share of case studies and reviews in digital-twin papers per domain (Web of Science topic queries), 2013–2025.

Digital Health and the *Journal of Medical Internet Research*.

Across all domains, journal articles outnumber conference proceedings. Figure 10 shows the contrast is sharpest in urban work and more balanced in industrial and environmental domains, though still article-leaning. Even in disaster management and healthcare, where absolute counts are smaller, archival journals dominate, suggesting that twin research in safety-critical domains has already settled into more formal publication channels.

3.6 Domain-level applications

Before turning to wildfire twins, it is worth surveying how digital twins are used in adjacent domains. The aim is not coverage but orientation: to expose the architectural patterns, data strategies, and limitations that any wildfire twin will inherit or have to rework. Domains are ordered from the most technically mature to those closest to the wildfire setting. Papers were selected by citation count and filtered for domain relevance.

3.6.1 Industrial and manufacturing twins

Manufacturing accounts for the largest body of digital-twin literature, with 859 review-type and 2403 case-type hits over 2013–2025 (Table 4). Growth is steep after 2016, driven by Industry 4.0 narratives and early work on cyber-

Journal	Manufacturing	Urban	Environmental	Disaster	Health	Total
IEEE ACCESS	151	260	167	41	58	677
APPLIED SCIENCES BASEL	191	234	149	42	16	632
SENSORS	114	151	136	30	22	453
SUSTAINABILITY	69	129	106	40	7	351
INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	162	91	53	7	0	313
JOURNAL OF MANUFACTURING SYSTEMS	158	84	45	11	0	298
IEEE INTERNET OF THINGS JOURNAL	29	124	75	0	21	249
ADVANCED ENGINEERING INFORMATICS	65	83	45	17	0	210
ROBOTICS AND COMPUTER INTEGRATED MANUFACTURING	96	62	40	6	0	204
SCIENTIFIC REPORTS	43	72	43	12	30	200
ENERGIES	37	76	61	12	0	186
AUTOMATION IN CONSTRUCTION	0	113	43	25	0	181
INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	78	57	26	19	0	180
MACHINES	79	52	36	6	0	173
BUILDINGS	0	89	65	15	0	169
INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING	93	38	33	0	0	164
ELECTRONICS	0	72	47	8	11	138
COMPUTERS INDUSTRIAL ENGINEERING	55	41	27	8	0	131
COMPUTERS IN INDUSTRY	55	44	26	0	0	125
IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS	0	73	32	7	0	112
JOURNAL OF INDUSTRIAL INFORMATION INTEGRATION	48	39	24	0	0	111
OCEAN ENGINEERING	0	38	44	9	0	91
REMOTE SENSING	0	43	29	7	0	79
ENERGY AND BUILDINGS	0	36	37	0	0	73
SUSTAINABLE CITIES AND SOCIETY	0	32	29	10	0	71
ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	0	34	25	5	5	69
IEEE COMMUNICATIONS MAGAZINE	0	35	27	6	0	68
IEEE NETWORK	0	39	25	0	0	64
FUTURE GENERATION COMPUTER SYSTEMS (INTL JOURNAL OF ESCIENCE)	0	33	27	0	0	60
IEEE TRANSACTIONS ON CONSUMER ELECTRONICS	0	0	27	0	11	38
NPJ DIGITAL MEDICINE	0	0	0	0	33	33
APPLIED ENERGY	0	0	22	0	0	22
WATER	0	0	0	13	0	13
INTERNATIONAL JOURNAL OF DISASTER RISK REDUCTION	0	0	0	9	0	9
JOURNAL OF MEDICAL INTERNET RESEARCH	0	0	0	0	9	9
ENVIRONMENTAL MODELLING & SOFTWARE	0	0	0	7	0	7

Figure 8: Top journal venue publications per application domain, shown as a heatmap of relative frequency.

Conference / proceedings / book-series venue	Manufacturing	Urban	Environmental	Disaster	Health	Total
IFAC PAPERSONLINE	217	157	109	25	21	529
PROCEDIA CIRP	288	110	84	13	0	495
LECTURE NOTES IN COMPUTER SCIENCE	51	107	92	11	37	298
IFIP ADVANCES IN INFORMATION AND COMMUNICATION TECHNOLOGY	110	79	64	10	0	263
LECTURE NOTES IN NETWORKS AND SYSTEMS	85	76	60	8	8	237
IEEE INTERNATIONAL CONFERENCE ON EMERGING TECHNOLOGIES AND FACTORY AUTOMATION (ETFA)	102	50	41	0	0	193
COMMUNICATIONS IN COMPUTER AND INFORMATION SCIENCE	49	62	58	8	7	184
LECTURE NOTES IN CIVIL ENGINEERING	0	103	55	14	0	172
PROCEEDINGS OF SPIE	40	62	48	8	8	166
WINTER SIMULATION CONFERENCE PROCEEDINGS / WSC	56	50	33	14	7	160
LECTURE NOTES IN MECHANICAL ENGINEERING	73	40	32	0	0	145
IEEE INTERNATIONAL CONFERENCE ON AUTOMATION SCIENCE AND ENGINEERING (CASE / ICASE)	50	27	27	8	0	112
INTERNATIONAL ARCHIVES OF THE PHOTOGRAMMETRY, REMOTE SENSING AND SPATIAL INFORMATION SCIENCES	0	54	35	6	0	95
IEEE INTERNATIONAL SYMPOSIUM ON GEOSCIENCE AND REMOTE SENSING (IGARSS, incl. IGARSS 2024)	0	26	26	19	0	71
54TH / 55TH / 56TH CIRP CONFERENCE ON MANUFACTURING SYSTEMS (CMS volumes, incl. LEADING MANUFACTURING SYSTEMS)	31	0	0	0	0	67
2022 / 2024 IEEE ETFA editions (ETFA 2022, ETFA 2024)	33	26	0	0	0	59
ISPRS ANNALS OF THE PHOTOGRAMMETRY, REMOTE SENSING AND SPATIAL INFORMATION SCIENCES	0	34	23	0	0	57
STUDIES IN COMPUTATIONAL INTELLIGENCE (Springer series)	36	0	0	0	7	43
JOURNAL OF PHYSICS: CONFERENCE SERIES	0	36	0	0	0	36
OCEANS 2025 BREST	0	0	24	0	0	24
IEEE ENGINEERING IN MEDICINE AND BIOLOGY SOCIETY CONFERENCES (EMBC, EMBS proc.)	0	0	0	0	21	21
STUDIES IN HEALTH TECHNOLOGY AND INFORMATICS	0	0	0	0	8	8
LECTURE NOTES IN BUSINESS INFORMATION PROCESSING	0	0	0	0	6	6
2024 IEEE INTERNATIONAL CONFERENCE ON ENGINEERING TECHNOLOGY AND INNOVATION (ICE / ITMC)	0	0	0	5	0	5
IEEE ANNUAL CONFERENCE ON PERVASIVE COMPUTING AND COMMUNICATIONS WORKSHOPS	0	0	0	0	5	5

Figure 9: Top conference and proceedings venue publications per application domain, shown as a heatmap of relative frequency.

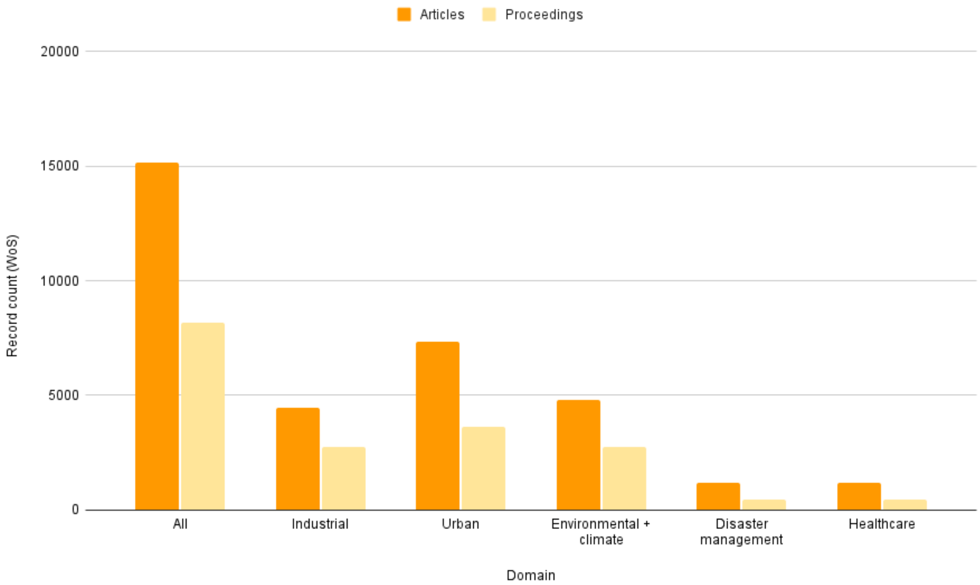

Figure 10: Article versus proceedings records per application domain (Web of Science topic queries), 2013–2025.

physical production systems. The more telling evidence, however, comes from implementation studies. Table 5 covers a purposive selection spanning shop-floor geometry assurance, predictive maintenance, additive manufacturing qualification, reinforcement-learning control, and supply-chain twins. Reported gains in fault-diagnosis accuracy, remaining-life estimation, and reconfiguration time recur throughout. Fully autonomous twins remain rare in safety-critical settings, where twins mostly support rather than replace human decision-makers.

Table 5: Industrial digital-twin implementations: highly cited case studies ordered by citations per year, spanning geometry assurance, reconfigurable manufacturing, predictive maintenance, additive manufacturing, reinforcement-learning control, service architectures and supply-chain twins.

Reference	**Context**	**Key methods and models**	**Validation and metrics**	**Main takeaway for DT practice**
Ivanov & Dolgui 2021 [60]	Supply-chain twin for disruption risk and resilience	Network-state twin combining model-based disruption modelling with data-driven risk analytics across a global supply chain	Scenario analysis of COVID-19 shocks and recoveries; end-to-end visibility and continuity metrics	Extends twin thinking beyond the shop floor to network-level resilience, where visibility and historical disruption data matter more than high-fidelity physics
Xia M. et al. 2021 [61]	DT-assisted deep transfer learning for machine fault diagnosis	High-fidelity simulation twin generating synthetic condition data, paired with a novel sparse de-noising auto-encoder pre-trained on the twin and fine-tuned on one real sample	Triplex-pump fault-diagnosis case; outperforms state-of-the-art data-driven baselines under limited measured data	Shows that a twin can substitute for missing fault data, enabling accurate diagnosis where measured failure examples are scarce
Xia K. et al. 2021 [62]	DT as training environment for DRL control agents	System-level twin of a manufacturing cell interfaced with CAx, PLM and automation platforms; Deep Q-learning trained in simulation and deployed to the physical cell	Case study on learned scheduling and control; robustness and near-synchronous control demonstrated on the physical plant	Establishes the twin as a safe training ground where DRL policies are verified before ever touching the physical line
Luo et al. 2020 [63]	Hybrid DT-driven predictive maintenance of CNC machine tools	Combined DT model-based and DT data-driven algorithm for tool-life prediction over the CNC lifecycle	Cutting-tool life case study; higher accuracy than purely model- or data-based baselines	Demonstrates concretely that hybrid twins beat single-approach predictors on canonical machining--maintenance tasks
Aheleroff et al. 2021 [64]	Digital-Twin-as--a-Service reference architecture and industrial deployment	DTaaS reference model stitching Internet of Things (IoT), cloud, AR and AI, applied to a wetlands maintenance case with remote control and predictive functions	Industrial deployment reporting smart scheduled maintenance, real-time monitoring and remote control	Grounds the DTaaS paradigm in a working deployment and links twin capabilities to mass-individualization service models

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
Leng et al. 2020 [65]	DT-driven rapid reconfiguration of an automated manufacturing system	Semi-physical simulation coupled with bi-level optimisation on an open-architecture machine-tool platform, with feedback loop between cyber and physical cells	Physical implementation; measured reductions in reconfiguration overhead and improvements in system performance	Shows that twins can actively drive physical reconfiguration of hardware, not merely monitor or simulate it
Söderberg et al. 2017 [66]	DT for real-time geometry assurance in individualised production	Real-time simulation twin optimising tolerances, locator positions, clamping and welding sequences during assembly	CIRP-reported assembly use case; discussion of functionality and data models needed for closed-loop quality control	Early demonstration that twins can move simulation from the engineering phase into real-time quality control on the line
Mukherjee & DebRoy 2019 [67]	DT for rapid qualification of 3D-printed metallic components	Comprehensive twin integrating mechanistic, control and statistical models of the printer with machine learning and process big data	Analysis of how the twin reduces trial-and-error tests, defects and time between design and production	Makes a concrete case that twins can shorten certification cycles in additive manufacturing, a historically trial-heavy process
Zheng et al. 2019 [68]	Production-line twin with welding case study	Lifecycle DT framework covering sensing, storage, data mapping and virtual modelling, instantiated on a welding line	Implementation on a welding production line; qualitative reporting of process benefits	Provides a reusable implementation pattern for connecting shop-floor sensing to a virtual production model

3.6.2 Urban, transport and infrastructure twins

The urban, transport and infrastructure domain yields 1219 review-oriented and 3018 case-oriented hits over 2013–2025, making it the second-largest slice of the corpus after manufacturing (Table 4). Surveys and position papers frame urban and infrastructure twins as extensions of smart-city and smart-mobility work, where spatial data, sensor networks and operational systems are stitched into shared platforms for planning and day-to-day operation [17, 8]. Table 6 summarizes a selection of highly cited studies that, together, span the main strands of the domain: IoT and deep-learning analytics pipelines, metaverse-scale visions, participatory city twins, built-environment investigations, citizen-feedback platforms, energy management, campus-scale pilots and administrative city twins.

Table 6: Urban, transport and built-environment digital-twin studies: focus, methods, validation, and implication for DT practice

Reference	**Focus / context**	**Key methods / models**	**Validation and metrics**	**Main takeaway for DT practice**
Li et al. 2022 [69]	IoT big-data analytics pipeline for a city-scale twin	Distributed-parallel CNN over multi-source IoT streams, embedded in a multi-hop transmission twin	Benchmarked accuracy (∼97.8%), energy efficiency and millisecond-level transmission delay against prior DL baselines	Shows how DL on smart-city IoT can be engineered as the analytic backbone of a city twin rather than an auxiliary module
Allam et al. 2022 [70]	Metaverse as a virtual extension of smart-city twins	Upper-level literature review mapping metaverse products and services onto urban sustainability goals	Qualitative synthesis of opportunities and risks; no empirical pilot	Positions twins within a broader platformization debate and flags ethical, social and governance tensions for urban DT agendas
Dembski et al. 2020 [71]	Participatory urban twin of Herrenberg, Germany	3D built-environment model combined with space-syntax networks, mobility and wind simulations and VGI, delivered through a VR platform	Public workshops and survey-based evaluation of the twin as a collaboration and decision-support tool	Early demonstration that urban twins can serve democratic planning, not only technical optimization, when wired to participatory processes
Shahzad et al. 2022 [72]	Digital twins in built-environment asset delivery	Literature review plus ten semi-structured expert interviews; thematic analysis of definitions, enablers and challenges	Five-theme coding of expert views; no quantitative performance metrics	Clarifies how twins relate to BIM, IoT, VR/AR, AI and cloud, and surfaces implementation barriers that recur across infrastructure twins
White et al. 2021 [73]	Citizen-feedback twin of Dublin Docklands	Public 3D web twin combining BIM and IoT with interactive feedback and tagging, plus a flood-evacuation use case	Demonstrator with walkthrough scenarios for planning and flood response; no large-scale empirical deployment data	Frames the twin as a two-way communication channel between administration and citizens, not only an internal planning artefact
Francisco et al. 2020 [74]	City-scale building energy management twin	Smart-meter analytics with temporally segmented benchmarks (occupancy, season, peak demand) feeding a twin-enabled energy platform	Empirical comparison of segmented versus annual benchmarks across a university building portfolio	Shows concretely how real-time meter streams can transform portfolio energy management inside an urban twin

Reference	Focus / context	Key methods / models	Validation and metrics	Main takeaway for DT practice
Lu et al. 2020 [75]	Building- and campus-level twin, West Cambridge	Integrated DT architecture for operation and maintenance, combining BIM, IoT and asset-management data across scales	Case-study deployment on a research campus with system-architecture and workflow evaluation	Offers an influential reference architecture for moving from building twins to campus- and city-level twins while keeping O&M workflows intact
Schrotter and Hürzeler 2020 [76]	Administrative city twin, Zurich	3D spatial-data backbone with open government data, visualization and urban-climate simulations embedded in planning workflows	Operational deployment within Zurich city administration; qualitative reporting on planning and decision-making use	Illustrates the governance side of urban twins: lifecycle management of 3D data, openness and integration with statutory planning

3.6.3 Environmental and climate-system twins

Environmental and climate queries return 807 review-type and 2045 case-type records over 2013–2025, a substantial but more diffuse body than manufacturing or urban work (Table 4). Reviews group this literature into hydrology and flood risk, atmospheric and air-quality modelling, catchment and ecosystem management, and broader observation platforms, often recasting earlier dynamic data-driven application-system ideas under the digital-twin label [1, 17]. Table 7 covers a range of resilience and climate twins. The technical emphasis falls on model-data fusion, ensemble prediction, and multi-scale dynamics: calibrated basin- or national-scale models coupled to real-time portals, fixed and mobile sensors paired with particle-tracking or biogeochemical models, and machine-learning emulators used to reduce computational cost. Outputs reach civil-protection and water-management workflows through APIs, dashboards, and 3D visualisation rather than automated control. Recurring gaps involve data coverage, non-stationary validation, and pipeline maintenance over time. The final rows of the table record five large programmes supplying shared infrastructure and operational cadence for the domain: DestinE, DITTO, Iliad, EDITO, and the NASA AIST ESDT thrust.

Table 7: Hydrological, marine, Earth-system and infrastructure digital twins for climate and resilience: individual studies and large multi-year programmes, with focus, methods, validation and implications for DT practice.

Reference	**Context**	**Key methods and models**	**Validation and metrics**	**Main takeaway for DT practice**
Blair 2021 [77]	Conceptual natural--environment twins	Conceptual synthesis of process-based environmental models with data-driven components and AI/ML, framed as digital twins of the natural environment	No quantitative metrics; reflects on requirements and design patterns using case vignettes	Establishes DTs of the natural environment as an extension of existing modelling traditions, emphasising coupled process–data learning rather than technology branding
Argyroudis et al. 2022 [78]	Climate-resilient infrastructure (perspective)	Perspective on IoT, DTs, BIM and AI as tools for climate-resilient critical infrastructure and SDG-aligned roadmaps	Conceptual analysis aligned with SDGs; synthesizes existing roadmaps and examples rather than introducing new metrics	Argues that DTs and related digital technologies can reduce uncertainty across all phases of resilience evaluation, but require standards, legislation and coordinated alliances to reach scale
Tzachor et al. 2023 [79]	Ocean--sustainability perspective on DTOs	Normative and governance-oriented analysis of DTOs for overfishing, pollution and marine spatial planning, with European DTO as core example	Conceptual review of thematic areas and barriers (data availability, standards, cost); no quantitative validation	Frames DTOs as tools for ocean sustainability while warning that data gaps, interoperability and political economy may limit their impact without targeted governance interventions
Barbie et al. 2022 [80]	Underwater DT prototypes for ocean observation	Collaborative underwater network at Boknis Eck with stage-IV DT prototypes coordinating seabed systems	Field trial during AL547 cruise; scenarios demonstrating DT feasibility in an extreme underwater environment	Demonstrates that DTs can operate as coordination mechanisms for mobile ad hoc ocean-observation networks
Skákala et al. 2023 [81]	ML emulators for marine biogeochemical DTs	ML models emulating a complex physical–biogeochemical model to predict shelf-sea oxygen, aimed at future DT support	Comparative performance across ML models; analysis of drivers and data constraints for skilled oxygen prediction	Shows that ML emulators can support future DTs by accelerating oxygen prediction and informing observation-array design

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
Hazeleger et al. 2024 [82]	Earth-system DTs with and for humans	High-level architecture for Digital Twins of the Earth as coupled physical and social systems; links Earth-system models, impacts modules and interactive user interfaces	No single case study; synthesizes lessons from existing Earth-system DT demonstrators and policy use-cases [82]	Argues that Earth-system DTs must include human impacts and governance both inside and outside the twin, positioning DTs as decision-support systems rather than purely technological artefacts
Destination Earth (DestinE), 2022– [83, 84]	EU operational flagship Earth twin	Two operational DTs (climate adaptation, weather-induced extremes) built by ECMWF, ESA and EUMETSAT; km-scale global models (ICON, IFS-NEMO, IFS-FESOM) on EuroHPC pre/exa-scale systems with DevOps orchestration and a core data lake	Operational launch 10 June 2024; multi-decadal 5–10 km simulations with hourly outputs; continuous real-time quality-control and co-designed sector applications	Shows that large-scale environmental DTs can move from demonstrator to production system when backed by dedicated HPC, a shared data lake and explicit user co-design
DITTO (UN Ocean Decade), 2021–2030 [85]	Global coordination programme for DTOs	Five working groups on ocean observation networks, integrative DT models, interoperability architecture, community engagement and capacity development	No single technical artefact; tracked through white papers, workshops, standards outputs and endorsed Decade Actions	Frames DTO development as a coordination and standards problem first, reminding DT research that governance and community practice are part of twin design
Iliad DTO, 2022–2025 [86]	Federated 56-partner European DTO	System-of-systems architecture with 18+ thematic pilots (oil spill, aquaculture, jellyfish swarms, plastic pollution, ballast water, harbour safety, offshore wind and tidal energy) delivered through an Iliad Marketplace	Pilot-level evaluations across partner sites; showcased at OCEANS 2025 and aligned with Green Deal and SDG indicators	Demonstrates federation as the practical route to DTOs at continental scale, where interoperability and marketplaces matter more than any single twin

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
EDITO, 2022– [87]	EU public infrastructure platform for the European DTO	Cloud-native platform merging Copernicus Marine and EMODnet into a unified Core Catalogue, with explore, create and contribute service tiers	Phase 1 (EDITO-Infra) 2022–2025 delivered the reference infrastructure; Phase 2 (EDITO 2) 2025–2028 scales cloud infrastructure and third-party contribution validation	Shows that persistent public infrastructure, not project-by-project deployment, is needed to sustain federated environmental twins at continental scale
NASA AIST ESDT, 2022– [88]	First US federal DT solicitation for Earth science	ESDT thrust of the AIST programme funding What-Now, What-Next, What-If ESDTs across wildfire, coastal floods, agriculture, ocean carbon, boundary-layer and air-quality domains; AIST-23 targets two to three end-to-end prototypes	AIST-21: 28 awards totalling US$31M over two years, of which roughly ten were ESDT-scoped; AIST-23 selections scheduled toward 2024–2027 prototypes	Establishes ESDTs as a distinct federal research thrust, explicitly federating thematic twins (air quality, wildfire, hydrology) as a path to coupled Earth twins

3.6.4 Disaster-management twins

The disaster, emergency and hazard queries return 211 review-oriented and 472 case-oriented records for 2013–2025, fewer than the urban and environmental sets but still sizeable given the younger age of the field. Reviews cover floods, earthquakes, tsunamis, hurricanes and multi-hazard platforms and frame many systems as digital-risk or post-disaster risk-management twins, emphasizing risk assessment, exposure mapping and scenario analysis over continuous control. Table 8 summarizes these hazard-specific and cross-hazard efforts, from flood and evacuation twins to cryospheric platforms, post-disaster risk-management twins and maturity assessments.

Table 8: Digital-twin work across different disasters: scope, methods, validation and implications for DT practice

Reference	**Context**	**Key methods and models**	**Validation and metrics**	**Main takeaway for DT practice**
Leiva-Araos et al. 2025 [89]	Smart-building fire, electrical and life-safety DTs	Hybrid human–LLM systematic literature review, thematic clustering and gap analysis	Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-style screening with LLM-assisted coding; inter-coder agreement reported rather than hazard metrics	Recurring gaps in interoperability, cybersecurity and dynamic evacuation models limit building-scale DTs, independent of the hazard
Cui et al. 2024 [90]	Glacial-lake outburst flood (GLOF) platform for high-mountain cryosphere	Perspective on a DT spanning seismo-acoustic, hydro-meteorological and remote-sensing data, linked to flood-routing and data assimilation	No empirical benchmark; instead defines four open challenges (sensor interconnection, algorithm libraries, rapid numerical simulation, integrated workflow)	Cryospheric DTs remain aspirational for high-mountain Asia, the Andes and the Caucasus, and hinge on affordable sensor networks in sparsely observed terrain
Zio 2024 [43]	Safety and risk twins across critical infrastructure	Risk and reliability models, scenario-based analysis, fragility-curve coupling	Illustrative case examples, qualitative evaluation, no unified skill score	Digital-risk twins force structured uncertainty quantification and make safety margins explicit inside the DT loop
Lagap & Ghaffarian 2024 [53]	Post-disaster risk-management twins	Systematic review of 42 works; conceptual framework for updating exposure and vulnerability after events	Comparison of pre- and post-event risk maps drawn from the surveyed cases; no new empirical validation	Post-disaster DTs can support recovery planning, but depend on fragile data pipelines and largely ad hoc updating schemes
Metcalfe et al. 2023 [33]	DT maturity in hazard and life-science contexts	Five-level maturity framework (ML1 status, ML2 informative, ML3 predictive, ML4 optimisation, ML5 autonomous) mapped to a DIKW-style pyramid	Qualitative scoring of representative cases against the five levels; no empirical error metrics	Most hazard DTs sit at ML2–ML3, rarely reach optimisation or autonomous stages, and lack explicit feedback loops

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
Tzouvaras 2023 [91]	Seismic and landslide early warning in Cyprus	Sentinel-1 SAR interferometric coherence time series, pixel-level change detection	Cyprus landslide, 15 February 2019; ANOVA and two-tailed t-tests on pre- vs. post-event coherence; detects sudden coherence drop before slope failure	Satellite-only DT prototypes can flag precursors to ground motion with statistically testable metrics, but only on targets with prior SAR baselines
Fan et al. 2021 [92]	Urban evacuation "Disaster City"	Mesoscopic/microscopic traffic simulation coupled to a social-sensing layer over a city DT	Hurricane Harvey (Houston, 2017) case; evacuation times and bottlenecks compared across scenarios; qualitative match with observed network stress	A city-scale DT can expose hidden network bottlenecks, but the system relies on scenario contrast rather than formal skill scores
Cheng et al. 2023 [42]	Multi-hazard DTs	Review of DT architectures and hazard-specific models across flood, seismic and wildfire studies	Narrative synthesis across 60+ studies; no unified metric, reported maturity compared through descriptive criteria	Most hazard DTs stall at risk-assessment level, with weak lifecycle and governance support
Turner et al. 2023 [93]	Flood DTs and urban resilience	CityGML 3D city model, Cesium-ion streaming, IoT water-level sensors feeding hydrodynamic outputs	Maribyrnong (Melbourne) 2022 flood context; qualitative and semi-quantitative resilience criteria across four DT projects	Flood DTs remain patchy on validation, resilience indicators and long-term upkeep

3.6.5 Healthcare twins

Healthcare and medicine queries yield 212 review-oriented and 285 case-oriented hits over 2013–2025, indicating a smaller but rapidly growing literature compared with industrial and urban domains (Table 4). Reviews position digital twins within broader Healthcare 4.0 and personalized-medicine programmes, where digital representations of organs, devices, buildings and patients combine multimodal data and predictive models to support diagnosis, treatment planning and monitoring. They also emphasize that, although enabling stacks resemble those in industrial DTs, safety, regulation and ethics sharply constrain autonomy in medical settings. Table 9 highlights concrete cardiac, IoT and hospital-building twins that span this space, from biophysically detailed whole-heart and ECG-based electrophysiology twins through smart-home monitoring to hospital and indoor air-quality twins with reported operational gains.

Table 9: Selected concrete and position healthcare digital twins: focus, methods, validation and implications for DT practice

Reference	**Context**	**Key methods and models**	**Validation and metrics**	**Main takeaway for DT practice**
Chen et al. 2023 [94]	Smart-home DT for wireless healthcare	DT of dwelling and equipment; WiFi-based fall detection and ECG-based atrial-fibrillation screening with two intelligent algorithms	Experimental study comparing detection algorithms against baselines for fall and AF tasks	Validates that DT-empowered smart-home monitoring can improve detection performance, but within a controlled experimental set-up
Hernandez-Boussard et al. 2021 [95]	Cancer-patient digital twins (CPDTs) for predictive oncology	In-silico patient representations fusing molecular, physiological and lifestyle data with mechanistic cancer models	*Nature Medicine* correspondence; argues from existing CPDT prototypes in breast, lung and blood cancers; no unified empirical metric	Positions oncology as a flagship healthcare-DT domain and calls for shared validation and governance standards across CPDT programmes
Gerach et al. 2021 [96]	Whole-heart electro-mechanical DT	Fully coupled multi-physics heart model (electrophysiology, mechanics, closed-loop circulation) personalised from MRI	Simulations on a healthy volunteer geometry; physiological-plausibility checks and response to an ablation-scar scenario; no patient cohort	Demonstrates feasibility of biophysically detailed personalised cardiac twins, but evaluation is limited to single geometries and no clinical outcomes
Gillette et al. 2021 [97]	Cardiac electro-physiology twins from 12-lead ECG	Anatomical segmentation, fast forward-ECG model and Saltelli-sampling parameter inference	12 MRI-derived geometries twinned in under 4 h; fast forward-ECG compared against a gold-standard bidomain model; functional fit on one subject	Provides a clinically timed pipeline for cardiac-EP twins, strong on technical validation but thin on downstream clinical benefit
Elayan et al. 2021 [98]	Context-aware IoT healthcare DT (ECG)	DT framework for smart healthcare, ML and neural-network ECG rhythm classifiers for heart-condition detection	Five models benchmarked on a public Kaggle ECG dataset; accuracy, precision, recall and F1 reported; neural nets beat classical ML	Shows DT-enabled monitoring can embed ML classifiers cleanly, but validation is offline and dataset-based rather than deployed
Corral-Acero et al. 2020 [99]	Precision cardiology position paper	Mechanistic plus statistical cardiac models combining imaging, ECG and EHR data into patient-level twins	Illustrative review of FDA-cleared tools (HeartFlow FFR-CT, CardioInsight) and cardiac-resynchronisation examples; no unified benchmark	Defines a shared European vision for cardiac DTs and anchors them in regulated "software as a medical device" practice

Reference	**Context**	**Key methods and models**	**Validation and metrics**	**Main takeaway for DT practice**
Peng et al. 2020 [100]	Digital-twin hospital building	Continuous lifecycle integration of static and dynamic data from 20+ management systems; DT control centre with AI diagnosis	One-year deployment in a large Chinese hospital; reported reductions in energy consumption, facility faults and repair requests, with improved maintenance quality	Shows an operational hospital DT with real-world facility gains, focused on building management rather than direct clinical care
Björnsson et al. 2019 [101]	Precision-medicine twins for drug selection	Network models of molecular, phenotypic and environmental factors per patient, computationally treated with thousands of drugs (SDTC strategy)	Conceptual proposal in *Genome Medicine*; no empirical metrics, backed by examples from multi-omics drug-response studies	Frames the healthcare DT as an in-silico drug-screening engine rather than a monitoring tool, and sets the precision-medicine agenda for the field

3.6.6 Agriculture and forestry twins

Agriculture has developed its own digital-twin discourse under smart-farming and precision-agriculture labels, even when it is not treated as a separate category in cross-domain reviews [55, 102, 103]. Case studies cover irrigation, variable-rate nutrient management, controlled-environment agriculture and urban aquaponics, with forestry entering the literature more recently through conceptual frameworks and remote-sensing-driven implementations [104, 105]. Table 10 brings together irrigation-management twins, greenhouse and aquaponics architectures, farm-information-system reviews, and early forest digital twins. The agricultural entries show how implemented twins combine IoT sensing with process-based or data-driven models in real-time farm-information systems, test management strategies and infer resource-efficiency gains over multi-month trials. Most agricultural DTs remain informative or predictive decision-support systems with limited feedback and weak standardization, while forestry twins are newer and narrower.

Table 10: Agriculture and forestry digital twins: focus, methods, validation and implications for DT practice

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
Qiu et al. 2023 [105]	Forest digital twin for stand management	Spatio-temporal remote-sensing and forest-inventory data fused in Cesium Digital Earth Engine with parametric 3D tree models and Bayesian multi-grade growth model	Thinning experiments on real stands; 91.3% match between real forest structure and digital scene, >90.4% diameter at breast height (DBH) and height prediction accuracy, F-index gain of 22.82% when managers interact with the forest digital twin (FDT) in closed loop with the real standn	First forestry DT with two-way interaction and decision feedback; shows that spatial-structure indices can be optimised through coupled human–twin loops rather than one-way visualisation
Alves et al. 2023 [106]	Irrigation--management DT for water saving	FIWARE IoT platform (open-source IoT platform) and discrete-event simulation in Plant Simulation with real-time OPC UA coupling	Application scenario; side-by-side evaluation of alternative irrigation strategies against current practice	Bidirectionally coupled irrigation DT for strategy testing; suggests water savings, but field-scale gains inferred rather than measured at plot level
Purcell & Neubauer 2023 [102]	Systematic review of DTs in agriculture	PRISMA-style systematic literature review (SLR) across smart-farming, livestock and environmental--sustainability applications	Qualitative coding of trends, gaps and open questions; no unified performance metric	Frames agricultural DTs as sustainability tools while flagging technical fragility, data-cost constraints and social–ecological risks that limit transfer to forestry and other biotic systems
Buonocore et al. 2022 [104]	Conceptual framework for a forest digital twin	Nested tree-to-forest twinning with real–virtual digital sockets, flux-tower and remote-sensing integration, and a blockchain-ledger layer for ecosystem-service accounting	Conceptual proposal; no deployment, validation limited to worked design of state variables and data flows	Establishes the canonical FDT reference model and argues that forestry twins must handle biotic state variables and ecosystem-service transactions that agricultural DTs largely ignore

Reference	Context	Key methods and models	Validation and metrics	Main takeaway for DT practice
Nie et al. 2022 [103]	AI and DTs for sustainable agriculture and forestry	Narrative survey of AI-enabled DT applications, enabling technologies and open challenges	Descriptive synthesis across agriculture and forestry; no common metric or coded protocol	Points to strong potential for AI-driven DTs in biotic systems but flags data-cost, connectivity and infrastructure barriers as binding constraints in rural deployments
Chaux et al. 2021 [107]	DT architecture for controlled--environment agriculture	Layered DT architecture using simulation to optimize microclimate control and treatments in greenhouses	Controlled--environment case study; productivity evaluated as yield per unit resource	Shows DT architectures can raise productivity in high-control greenhouses, but at higher energy cost and with domain-specific crop models that do not generalize to open-field settings
Ghandar et al. 2021 [108]	Urban aquaponics DT decision-support system	Cyber-physical aquaponics system combining sensor data, DT state representation and ML-based decision analytics	Three-month trial on a working aquaponics installation; empirical evaluation of production-planning and decision-analytics performance	Demonstrates DT-enabled decision support in a resource-constrained, small-scale setting and shows that coupled fish–plant dynamics can be managed through learning-based analytics
Pylianidis et al. 2021 [55]	Agricultural DTs across 28 use cases	Mixed-methods review mapping DT applications against service categories and technology-readiness levels	Qualitative comparison of benefits and TRL scores; no unified quantitative metric	Finds most agricultural DTs sit at the informative or predictive end with limited closed-loop feedback, and flags weak standardization as the main barrier to cross-farm transfer

3.6.7 Cross-domain afterthoughts

Read across the six domains, the twin literature is less a single paradigm than a set of dialects sharing a vocabulary. Manufacturing delivers production-grade reference architectures and hybrid predictors wired into real machines and supply networks [66, 63, 60]. Urban twins deliver spatial platforms fusing BIM, IoT, and participatory interfaces at building and administrative scales [71, 75, 76]. Environmental twins supply coupled process-data systems and, more recently, continental-scale public infrastructure through DestinE, DITTO, Iliad, EDITO, and the NASA AIST ESDT thrust [83, 85, 86, 87, 88]. Healthcare contributes patient-specific models for cardiology and oncology alongside roadmaps for clinical translation [99, 101, 95]. Disaster twins supply hazard-specific scenario engines that remain decision-support rather than control systems [92, 33]. Agriculture and forestry contribute irrigation and greenhouse decision-support, with forestry only now producing its first two-way implementation [108, 105].

Certain methods recur. Physics-based simulators coupled to IoT feeds dominate manufacturing and environmental work. Data-driven and hybrid learners handle regimes where mechanistic models are too slow or incomplete [61, 81]. Geospatial backbones built on BIM, CityGML, or Cesium anchor urban and forestry twins. Reinforcement learning appears where control is the goal, mostly in manufacturing [62, 65].

Validation is where the domains part ways. Manufacturing twins report quantitative gains against measured baselines. Urban twins mix accuracy metrics with qualitative workshop evaluation. Environmental twins use skill scores, ensemble spread, and operational quality control. Healthcare twins validate against clinical outcomes and imaging endpoints, with cardiology and oncology approaching trial-grade evidence. Disaster twins rely on historical event replays and fragility curves. Agriculture and forestry are the thinnest: multi-month yield trials, strategy comparisons without plot-scale measurement, and a single 91.3% structural match in Qiu et al. as the lone quantitative anchor in the analyzed forestry literature [105].

Several patterns hold across every domain. Fully autonomous twins remain rare outside bounded industrial cells. Federation and shared public infrastructure are the practical route to scale [86, 87]. Validation effort tracks the perceived cost of being wrong: trial-grade in healthcare, measurement-grade in manufacturing, ensemble-based in Earth science, thinner elsewhere. A wildfire twin sits at the hardest intersection of this inheritance. It is a biotic and atmospheric system under disaster-grade time pressure, requires the spatial backbone of urban twins, and needs a validation standard closer to healthcare and manufacturing than the forestry and agricultural literature currently offers.

4 Wildfire Digital Twins

4.1 Overview

Wildfires are becoming more frequent and intense in many regions, with longer seasons and expanding areas at risk [109]. These trends sharpen the need for tools that can forecast fire spread, assess exposure and support decisions under time pressure [43]. Digital twins have been proposed as one way to meet these demands by combining models, data and interaction into tightly coupled cyber–physical systems [7, 17, 110]. A twin in this setting maintains an evolving representation of fuels, topography, weather, fire state and exposed assets, links this representation to spread and impact models, and exposes the results before, during and after events [111, 112]. In principle, a single arrangement of this kind could support pre-season risk assessment, day-to-day preparedness, incident response and post-fire recovery [111, 43]. Figure 11 sketches the main model families and how they relate to typical inputs and roles.

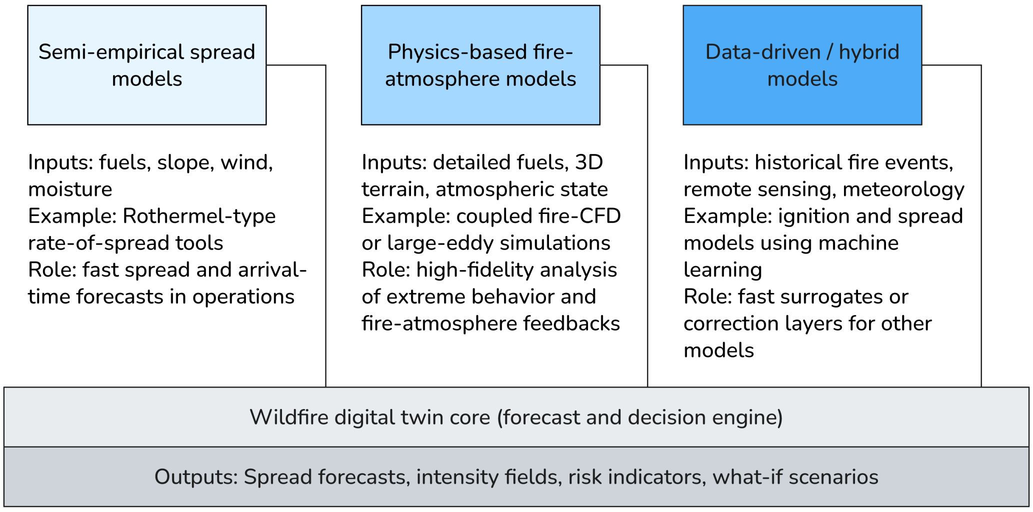

Figure 11: Fire behavior model families in wildfire digital twins

In practice, the phrase "wildfire digital twin" is used inconsistently [112]. Cross-domain evidence shows that many systems labelled as digital twins are closer to digital models or shadows because they lack continuous data exchange, clearly defined operational services or feedback from virtual to physical systems [7, 14, 6]. Definition surveys and maturity frameworks therefore highlight sustained synchronisation, explicit decision-support roles and, at higher levels, some degree of closed-loop behaviour as distinguishing features of full twins [13, 22, 33, 113].

Existing wildfire systems only partially satisfy these criteria. Case studies and reviews describe arrangements for mapping burned area, monitoring active fires, forecasting spread, assessing risk and supporting resource deployment, and increasingly frame them under the digital-twin label [114, 27, 115, 112]. Survey work, however, places most implementations at informative or predictive levels, with limited feedback into operations, incomplete representation of suppression and human behavior and emerging approaches to uncertainty under a changing climate [111, 112, 109].

In this paper, the term "wildfire digital twin" is therefore used in a pragmatic sense to cover systems that at least attempt to maintain an evolving representation of a wildfire-prone landscape or active event and link that representation to models and decision support [7]. Within this broad class, the following subsections distinguish between pre-event, risk-oriented twins and event-time, behavior-oriented twins and assess how far each comes towards the more demanding expectations set out in cross-domain digital-twin work [7, 59, 17]. The remainder of the section reviews the models, data sources and outputs current wildfire twins employ, then examines their use in risk assessment and behavior modeling and draws out gaps and lessons from more mature digital-twin domains [111, 112, 43].

4.2 Models, Data and Outputs

4.2.1 Models

Wildfire digital twins are built around models describing how fires start, spread, and interact with weather, fuels, and terrain [109]. In a twin setting, these models must run fast enough to feed forecasts back into operations while still capturing the processes that drive behavior under extreme conditions [111, 112]. Three broad families dominate: semi-empirical spread models, physics-based fire-atmosphere models, and data-driven or hybrid approaches (Figure 11) [109].

Semi-empirical models use simplified formulas derived from experiments and field data to estimate rate of spread, direction, and intensity as functions of fuel, slope, and wind [109]. The Rothermel surface-fire-spread model and its derivatives are widely used in incident-management systems because they are computationally light and couple easily with Geographic Information System (GIS) data and weather forecasts [116, 111]. In twin prototypes they typically serve as the core engine for perimeter forecasts and arrival-time maps, with inputs updated from live weather feeds and satellite detections [111, 112]. Their main limitation is that they represent fire behaviour in an average sense and struggle with spotting, crown fires, and compound extremes [109].

Physics-based models couple a fire module to a three-dimensional atmospheric solver, resolving heat transfer, combustion, and flow in greater detail [109]. Large-eddy and Computational Fluid Dynamics (CFD) approaches can simulate plume dynamics, turbulence, and fire-induced winds over complex terrain, capturing feedbacks that simpler models miss [109]. The cost is high: high-resolution simulations may take hours to days on large clusters, making direct embedding in near-real-time twin loops difficult without reduction or surrogates [111, 112].

Data-driven and machine-learning models learn statistical relationships from past events rather than encoding fire physics explicitly [117]. Within a twin they act as fast surrogates for complex simulators or as components that correct physics-based forecasts using recent observations [111]. Speed and flexibility are their strengths, but performance depends on historical data coverage and generalisation degrades under novel conditions, including emerging climate extremes [117, 109].

Several wildfire twins adopt hybrid architectures combining these families. One pattern uses a semi-empirical backbone augmented with learned corrections, preserving interpretability while adjusting outputs in light of recent data [111, 27]. Another couples a reduced-order physics-based representation to a data-assimilation scheme, generating a compact basis offline and updating it online as observations arrive [26]. Both introduce additional questions about validation, stability, and uncertainty communication under time-critical conditions [109, 112].

Beyond the fire-behaviour core, wildfire twins embed auxiliary models. Exposure and impact modules translate flames, embers, and smoke into damage estimates using vulnerability curves from broader disaster-risk work [43, 118]. Resource-allocation models describe how crews and aerial assets move under alternative fire scenarios, sometimes using discrete-event simulation or optimization [119]. Energy-water-wildfire twins couple stochastic fire-spread with distributionally robust optimization of microgrid and water-network operations, using incidents such as the Palisades Fire to show how reconfiguration can shorten critical-load outages during evacuation surges [120]. Urban fire-and-smoke twins such as FireCom link plume forecasts to population exposure tools at street resolution [121], and a recent Austin deployment tracks reported incidents in near real time, simulating smoke dispersion using 3D building data to support public-health decisions [122]. Wildfire twins therefore resemble model chains rather than single models, and their behavior depends as much on how components are coupled and updated as on the components themselves [111, 59].

4.2.2 Data

Wildfire digital twins sit on top of heterogeneous data stacks in which multiple classes of measurement and mapping must be combined and kept up to date [111, 112]. Broadly, these sources fall into five groups: satellite and airborne remote sensing, in-situ sensing, static or slowly changing geospatial datasets, human observation streams from citizens and responders, and derived products that fuse several inputs [112, 109, 123, 124]. Table 11 summarizes key data sources, the studies that have applied them in wildfire digital-twin or closely related contexts, and the integration tensions each source introduces.

Table 11: Key data sources for wildfire digital twins, representative sensors, applications and integration tensions in a heterogeneous DT data stack.

Data source	**Sensor / platform**	**Application**	**Spatial / temporal resolution**	**Limitations**
Optical satellites	Sentinel-2	Burned-area, burn-severity and vegetation-recovery mapping for post-fire assessment [114].	10–20 m; revisit days; latency hours–days.	Revisit too coarse for live perimeter tracking; cloud and smoke gaps must be filled from other streams [111, 112].
	Landsat, Sentinel-2, commercial	Burned-area mapping, fuel characterisation and post-event assessment across missions [111, 125].	Tens of metres to a few metres; revisit days–weeks.	Cross-mission products must be harmonised to common grids and band sets before joint use with near-real-time thermal detections [111].
	Multi-sensor optical stack	Urban fire-risk estimation in a city-scale twin [126].	City to region extent; mixed revisit from multiple archives.	Fusion with spread-oriented stacks must reconcile projections, sampling and quality flags [112].
Thermal satellites	MODIS	Active-fire detection and near-real-time monitoring [127].	∼1 km; multiple passes per day; minutes–hours latency.	Coarse pixels miss small or patchy fires and cannot resolve detailed perimeter geometry [127].
	VIIRS	Higher-resolution active-fire detection [127].	∼375–750 m; frequent passes; minutes–hours latency.	Resolution remains coarser than sub-100 m spread grids, so downscaling or probabilistic mapping to model cells is needed.
	MODIS / VIIRS combo	Perimeter updating and inputs to DT-enabled fire-risk classifiers [111, 27, 128].	Km to sub-km pixels; near-global coverage.	Fusion with optical imagery and spread grids must handle differing projections, resampling and detection-confidence schemes [112].

Data source	Sensor / platform	Application	Spatial / temporal resolution	Limitations
Airborne / Unmanned Aerial Vehicle (UAV) platforms	Synthetic UAV (thermal, RGB)	Fire–atmosphere simulations with synthetic UAV streams in a prospective twin [28].	Metre to sub-metre; campaign-based; near-real-time when connected.	High geometric detail is available only during flights; synthetic-to-real transitions need calibrated observation operators and latency handling.
	Operational UAV (thermal, RGB)	Near-real-time perimeter mapping with augmented-reality visualisation [129].	Sub-metre; repeated sorties; connectivity-dependent latency.	Airspace rules, endurance and link capacity yield intermittent streams that must be buffered and fused with continuous satellite products.
	Airborne Light Detection and Ranging (LiDAR), thermal scanners	Canopy structure and fuel-load characterisation [111].	Sub-metre to few metres; infrequent campaigns.	Resolution mismatches with coarser fuel and terrain grids require aggregation rules, adding uncertainty to spread inputs [112][109].
In-situ sensors	Long Range Wide Area Network (LoRaWAN) fuel and weather nodes; cameras	Fuel-moisture, weather monitoring and camera-based smoke detection [115].	Point data; sub-hourly; near-continuous with outages.	Sparse, urban-biased networks leave large regions unobserved [115][112].
	Mixed IoT sensor suite	Inputs to a DT-enabled deep-learning fire-risk classifier [27].	Point and small-area sensors; heterogeneous sampling.	Asynchronous streams and unequal sampling rates complicate alignment for training and live inference.
	Weather stations	Inputs and validation for fire-danger indices and spread models [111].	Stations tens of km apart; hourly to sub-hourly.	Interpolation to model grids introduces structured wind and humidity errors that are rarely propagated to DT output uncertainty [111].
	Air-quality monitors; fuel-moisture probes	Inputs to smoke-dispersion, health-impact and fuel-drying modules [43][130].	Urban to regional networks and plot-scale series.	Different sensor classes have distinct error structures, and upscaling stand-level drying into landscape twins remains ad hooc [109].
Static / slowly changing GIS	Fuel maps, Digital Elevation Models (DEMs)	Baseline burn-property and terrain layers for spread and risk models [111].	Wall-to-wall in mapped regions; updated on multi-year cycles.	Out-of-date fuel maps miss recent disturbances and seasonal shifts, propagating systematic biases into forecasts [111][112].

Data source	Sensor / platform	Application	Spatial / temporal resolution	Limitations
	Building footprints, networks, asset layers	Exposure and vulnerability estimation via overlay with hazard footprints [43][53].	Metre to tens-of-metres positional accuracy; planning-cycle updates.	Lagged asset updates misstate exposure and evacuation options when construction or decommissioning is not captured.
	Geospatial layers in knowledge graphs	Semantic integration of heterogeneous geospatial inputs via GeoSPARQL [131].	Feature-level linkage; update follows source datasets.	Semantic twins reduce syntactic heterogeneity but introduce ontology-alignment and query-performance issues at DT scale [109].
Citizen and crowd observation	Smartphone apps; geosocial media (Twitter/X, Flickr)	Volunteer photo and video reports from the field; geosocial media analysis feeding a decision-support twin [123].	Point reports; event-driven; near-real-time when connectivity holds.	Reports are biased towards populated areas and daylight hours; credibility, deduplication and location inference demand extra filtering [124].
	Dedicated citizen-science apps (e.g. spotFIRE)	Structured fuel-load sampling and fire-event reporting by trained volunteers [132].	Plot to patch scale; campaign and opportunistic sampling.	Coverage depends on volunteer motivation and training; schema drift between apps complicates reuse [132].
	Volunteered Geographic Information (VGI) from social networks	Early detection, perimeter cues and health-impact signals from tweets, posts and geotagged media [124, 133].	Sparse and bursty; minutes to hours; strong language and platform bias.	Noise, rumour and platform API changes make sustained ingestion fragile; false positives can mislead automated alerts [124].
Responder telemetry	Global Positioning System (GPS trackers), Personal Alert Safety System (PASS) beacons, body-worn radios	Crew location, accountability and man-down alerting inside the twin's common operating picture [134].	Sub-metre to tens of metres; near-continuous when link is up.	RF and cellular gaps in rugged terrain cause dropouts; privacy and duty-of-care concerns constrain data retention.
	Wearable biometric and environmental sensors	Heart rate, core temperature, exertion, carbon monoxide (CO) and volatile organic compound (VOC) exposure streamed to incident command [135, 136].	Per-firefighter; seconds to minutes; continuous during sorties.	Heterogeneous vendor APIs, limited standards and high alert-fatigue risk impede fusion with spread models [135].

Remote sensing gives a wildfire twin the coverage it needs to see large, fast-moving events at all [111, 112]. Landsat, Sentinel-2 and commercial constellations map burn scars, fuels and recovery. MODIS and VIIRS detect active fires at kilometre scales [111, 127]. Revisit intervals are hours in most regions, so satellites alone cap the twinning rate [127, 109]. Airborne platforms and UAVs narrow the gap with metre-scale views of fire lines and fuels, and some link directly to augmented reality (AR) and virtual reality (VR) interfaces or to synthetic-to-real workflows such as FIRETWIN [112, 28, 129]. A separate line of work uses the twin to design and supervise swarms of uncrewed aircraft for wildfire surveillance, testing search patterns and task allocation in the virtual environment before and during deployment [137]. These streams arrive through mixed ingestion pipelines. Hot-spot detections and UAV telemetry are pushed in through message queues within seconds to minutes of acquisition [115, 28, 128]. Gridded satellite products and weather forecasts are pulled on fixed schedules from APIs and data lakes [112]. The cadence of ingested changes, not the raw model time step, sets how quickly new observations can alter the virtual state.

In-situ sensing adds local detail and ground truth. Weather stations drive and validate fire-danger indices and spread models. IoT networks measure fuel moisture and micrometeorology. Air-quality sensors and camera networks feed smoke, health-impact and visual-confirmation modules [111, 112, 115, 27, 43, 122]. Deployments are sparse and biased towards populated or high-value areas. Large parts of many fire-prone landscapes remain under-observed even where a nominal twin exists [115, 112].

Static and slowly changing geospatial datasets provide the structural context. Fuel maps and DEMs supply baseline burn properties and terrain. Infrastructure and asset layers support exposure and impact estimation for buildings, corridors and critical services [111, 112, 43, 118]. Treating any of this as static is increasingly risky. Fuels and networks evolve through logging, storms, pests, previous fires and construction [111, 109]. Dynamic updating is the open gap. Out-of-date fuel maps and lagged infrastructure layers bias spread, exposure and evacuation analyses, and proposals for living fuels and dynamic asset registries remain rare in operation [112, 43, 130]. Semantic approaches tackle a different layer of the same problem. Dao et al. build a forest-fire semantic twin that binds sensor observations, geospatial layers and operational records into a multi-ontology knowledge graph exposed through the W3C Semantic Sensor Network (SSN) and Sensor, Observation, Sample, and Actuator (SOSA) ontologies (SSN/SOSA), the GeoSPARQL geospatial extension to SPARQL (GeoSPARQL) and fire ontologies, supporting SPARQL queries and rule-based reasoning for early alerts and resource allocation [131, 43].

Beyond machines and maps, people are themselves a data source. Volunteered geographic information reached wildfire management over a decade ago, when De Longueville and colleagues clustered wildfire tweets and Flickr photos in eight languages to complement the European Forest Fire Information System [124]. Current twins engage citizens in two modes. The first treats social networks as a passive sensor. TEMA, a Horizon Europe project piloted on the 2021 Montiferru fire in Sardinia, runs geosocial-media analysis with sentiment and entity extraction over short texts to reinforce drone and satellite observations, while volunteers and forestry staff send geotagged photos and videos through a dedicated app into the regional operations centre [123]. The George Mason and NASA wildfire twin for Southern California plans the same pattern, placing citizen reports next to satellites, UAVs and ground observations in its AI-driven forecast loop [138, 139]. The second mode is active. The spotFIRE citizen-science app, built by BOKU and SPOTTERON, asks trained volunteers to record vegetation cover, fuel structure and fire events in mountainous regions, producing structured observations that feed fuel and risk layers rather than alerts [132].

Responder telemetry is the other human stream. Commercial systems bundle GPS location, National Fire Protection Association (NFPA)-compliant PASS alarms and man-down alerting into wearables that push crew positions to incident command in near real time. European Union (EU)-level trials such as COTAK and interagency EGP feeds show how these traces can shape resource allocation and evacuation decisions [134]. Newer devices add biometric and environmental channels. Heart rate, core temperature, exertion, atmospheric pressure and gas exposure stream from bands and chest straps to commander dashboards [135, 136]. Few published wildfire twins ingest these streams directly, though the literature on digital twins for safety and emergency management argues that they should, since responder state and position are core to the cyber-physical loop that twin definitions require [43, 118].

European infrastructure projects are beginning to treat these heterogeneous human and machine streams as a shared engineering problem. The interTwin project is building an open, domain-agnostic Digital Twin Engine for environmental extremes, including a wildfire-danger twin that projects fire probability and burned area under climate change and exposes outputs through Network Common Data Form (NetCDF) files, dashboards and Jupyter notebooks [140, 141, 142]. TEMA pushes in a complementary direction, wiring satellite, drone, geosocial and volunteer feeds into a single decision-support platform validated on Mediterranean wildfires and Central European floods [123, 143]. Neither project yet delivers a fully closed-loop wildfire twin. Both treat the integration of citizen and responder data as a first-class concern rather than an afterthought.

Several challenges cut across the whole stack. Latency ranges from minutes to hours for satellite hot spots, varies with airspace and connectivity for UAVs and cameras, and follows fixed update cycles for numerical weather prediction [127, 115]. Spatial footprints span sub-metre UAV imagery, kilometre-scale satellite pixels and sparse station networks, so aggregation, downscaling and resampling to common grids introduce artefacts and complicate assimilation [111, 112]. Uncertainty runs through every part of the data stack. Few systems quantify, propagate and explain these uncertainties in their outputs, even though this is what trustworthy high-stakes decisions require [109, 43, 118, 112].

4.2.3 Outputs

Wildfire digital twins turn models and data into outputs that support prediction, risk assessment and decision-making [111, 112]. These outputs are not only raw numbers or grids but must be packaged in ways that fit incident-management practice, planning workflows and public-communication needs [43, 118]. Table 12 summarizes the main output types found in recent wildfire-twin work, together with their typical time horizons, primary users and delivery channels.

Predictive outputs sit at the core. Spread forecasts show how the fire perimeter and intensity fields are likely to evolve over the next hours to days and provide estimated arrival times at specific locations such as settlements, transport corridors and critical infrastructure [111, 26]. Some twins generate probabilistic variants by running ensembles of simulations with perturbed weather or fuel conditions and reporting confidence bands or exceedance probabilities for key thresholds [112]. These products are usually generated on regular grids or perimeters and then aggregated to decision-relevant units such as administrative areas, evacuation zones or buffers around assets [111].

Risk-oriented outputs emphasize likelihood and consequences rather than just immediate fire geometry. Pre-season or long-term risk twins combine ignition probabilities, fuel conditions, climate indices and historical fire occurrence into relative-risk maps at seasonal to multi-year scales [111, 109]. During events, impact-focused twins overlay forecast perimeters with exposure layers to estimate potential damage to buildings, infrastructure and ecosystems and to identify hotspots of vulnerability [43, 118]. These estimates may be expressed as expected losses, affected-population counts, numbers of assets at risk or qualitative risk classes, following common disaster-risk practice [43].

Decision-support outputs translate predictions and risk information into concrete options. Some wildfire twins propose candidate resource-allocation plans, such as suggested positions for crews, vehicles and aircraft, derived

Table 12: Typical outputs of wildfire digital twins, their time horizons, main users and delivery channels

Output type	**Time horizon**	**Main users**	**Typical delivery / interface**
Spread and arrival-time forecasts	Hours to days	Incident commanders; operations and planning staff	Map-centred dashboards and 3D viewers showing current perimeter, forecast spread and arrival-time contours [111] [26, 112]
Risk and impact maps	Seasons to years (pre-event); hours to days (during events)	Strategic planners; civil-protection agencies; infrastructure operators	Static and interactive risk layers, exposure maps and summary indicators in planning tools and control-room displays [111, 109, 43, 118]
Resource-allocation suggestions and what-if scenarios	Hours to days	Firefighting agencies; logistics coordinators	Scenario tools that display candidate deployment plans, constraints and outcomes, usually embedded in decision-support dashboards [119, 112, 111]
Situation-awareness views (multi-source fused displays)	Minutes to hours	Incident commanders; field officers; coordination centres	Live maps and 3D scenes combining sensors, remote sensing, model outputs and annotations; sometimes augmented-reality mobile apps or terrain-calibrated views with pixel-level fire-origin localisation [28, 129, 115, 144]
Machine-readable feeds (APIs)	Minutes to hours	External platforms; early-warning and public-information systems; infrastructure-operator tools	Web APIs providing forecasts, risk metrics and event metadata for integration into other dashboards or automated workflows [112] [59]

from simulated fire evolution and constraints on access and safety [119]. Others provide what-if tools that let users explore how suppression tactics, trigger points or alternative weather scenarios change outcomes without automating the final choice [111, 112]. In line with broader safety-critical twin practice, these systems are designed as decision-support rather than fully autonomous controllers, with human operators approving and executing actions [43, 118]. Building-scale work points to similar patterns at smaller spatial scales. Kim et al. demonstrate that an informative building fire twin, which matches evolving observations against a library of precomputed scenarios, can deliver near-instantaneous risk assessments and egress guidance and measurably improve evacuation performance without removing humans from the loop [145].

Rich user interfaces are the primary way these outputs reach practitioners. Most wildfire twins expose results through map-centred dashboards or 3D scenes that display current fire extents, forecast perimeters, risk layers and resource status on top of terrain and infrastructure [28, 112]. Some systems use mixed-reality or augmented-reality interfaces, for example mobile applications that project UAV-derived perimeters and risk zones into the field of view of firefighters or planners [129]. Interfaces typically allow users to toggle layers, step through time, query values and annotate scenarios, echoing human-twin interaction patterns reported in other domains [7, 17]. Reviews of digital-twin use in safety and emergency management emphasize that interface design directly shapes which outputs are used, how uncertainty is perceived and how well the twin integrates into existing command-and-control structures [43, 118].

A smaller group of wildfire-oriented twins also provide machine-readable outputs through application-programming interfaces (APIs). These APIs allow other systems, such as early-warning platforms, public-information services or infrastructure-operator tools, to pull forecasts, risk metrics and scenario results and embed them in their own dashboards and workflows [112, 59]. Such programmatic interfaces are a prerequisite for "systems of twinned systems", in which a wildfire twin interacts with other hazard, infrastructure or urban twins rather than operating in isolation [59].

4.3 Risk Assessment

Risk assessment can vary from simple ignition probability to fire outcome probability which asks what can burn, where and with what likelihood, connecting modelled fire behaviour to exposed people, assets and ecosystems and to their sensitivity to damage and disruption [53, 42].

Hazard characterisation quantifies how a fire might behave under specified weather, fuel and terrain conditions. Wildfire-twin and fire-risk systems estimate rate of spread, flame length, fireline intensity, spotting distance and burn probability, typically as gridded hazard layers over operational windows of hours to days [54, 27]. Real-time fire-risk platforms generate ignition- and spread-risk indices on daily or sub-daily time steps to track changing meteorology and fuel moisture [27, 125]. More advanced designs produce ensembles of such layers, so each grid cell carries a distribution of possible outcomes rather than a single deterministic value; Yun et al. demonstrate this for wildfire spread in a hybrid twin, and similar patterns appear in basin-scale and flood-twin work [54, 146, 53].

Handling uncertainty is essential for credible risk estimates. Weather forecasts lose skill with lead time, especially for wind; fuel moisture and fine-scale fuel structure are only partly observed; and spread models rely on parameters calibrated from limited experiments or case studies that may not cover future extremes [146, 109]. Ensemble approaches address this by sampling across plausible inputs and parameter sets and generating families of spread and intensity scenarios whose distributions can be summarised into probabilities or quantiles for each location [54, 27]. Probabilistic machine-learning models and Bayesian frameworks extend this logic, supplying explicit uncertainty estimates for ignition probability or spread rate that can be propagated into exposure and decision models [42, 53]. Disaster-twin reviews argue that such probabilistic treatment should be standard for high-consequence risks, not optional [43, 53].

Exposure and vulnerability describe what lies in the evolving hazard field and how badly it could be affected. Digital post-disaster risk-twinning frameworks define exposure by intersecting hazard layers with building footprints, transport and utility networks, population grids and ecological assets, thereby identifying what is at stake in each cell or zone [53, 119]. Vulnerability captures how prone those elements are to damage and how quickly they can cope or recover. For built infrastructure this includes structure type, fire resistance and defensible-space conditions; for communities, social factors such as age distribution, income, car ownership, language and disability status influence warning uptake and evacuation capacity [53, 42]. Forest-fire studies add ecological vulnerability by combining burn severity with habitat value or post-fire recovery rates to flag areas where even moderate burns have disproportionate ecological consequences [114, 125].

Risk metrics fold these components into quantities that can guide priorities and resource allocation. Expected-loss metrics integrate burn probability, asset values and damage functions to estimate likely physical or monetary losses, sometimes separately for buildings, networks and environmental assets [53]. Composite indices, including "fire risk" scores, weight and combine ignition likelihood, spread potential, exposure and vulnerability into single measures that can be mapped and compared across space and time [53, 125]. Digital-risk-twin frameworks show how such indices can inform response, recovery and reconstruction priorities, and forest-fire studies use similar integrated metrics to identify zones of extreme firefighting danger, evacuation difficulty and ecosystem vulnerability [53, 119]. Reviews argue that making these metrics and their assumptions explicit is a precondition for comparing twins and for judging whether a given system is adequate for specific risk-related tasks [42, 43].

Risk is also time-dependent. Daily to sub-daily fire-risk fields updated with weather and fuel-moisture changes better capture short-term fluctuations in ignition and spread potential than static indices [27]. Combining dynamic hazard estimates with time-varying human and topographic factors yields more realistic assessments of forest-fire danger than static maps and aligns naturally with digital-twin-style monitoring and updating [125]. Urban fire-risk twins extend this idea by coupling daily risk estimates from satellite and environmental data with models of opinion dynamics and group decision-making, as in recent multi-city work that embeds a fire-safety twin into a social decision process [126]. Over longer horizons, exposure and vulnerability evolve as commuting patterns, tourism and land-use and climate trends reshape who and what is present in high-risk areas [53]. Digital-twin and digital-risk-twin perspectives therefore advocate wildfire risk assessments that connect short-term operational horizons, seasonal cycles and long-term adaptation decisions within a single evolving framework rather than treating them as separate exercises [42, 53].

4.4 Behavior Modeling

Fire behaviour describes how the front advances, interacts with terrain and weather, and generates new ignitions over time [54, 109]. Spread depends on wind direction and speed, fuel moisture and loading, fuel structure (surface, ladder, crown) and slope. Small changes in any of these can flip rate of spread or direction, especially under unstable conditions. Spotting, where embers are lofted in convective plumes and transported downwind, can carry fire across control lines and natural barriers. Its likelihood depends on canopy height, fuel type, wind shear and turbulence. It is a major source of unpredictability in crown fires and wildland–urban interface events [109]. Terrain further channels winds through valleys and saddles, accelerates upslope runs and interacts with diurnal wind regimes. As a result, the hazard field evolves on time-scales from gust-level variability to synoptic weather shifts [54, 112]. Most wildfire-twin and fire-risk systems treat the main flaming phase and do not explicitly model the transition from smouldering back to flaming, even though re-ignition is common in large incidents. Recent work on a forest-fire re-ignition twin instead builds a virtual stand-scale environment in which logistic-regression models are coupled to wind and slope fields to estimate smouldering-to-flaming transitions and visualize how UAV-based suppressant drops alter re-ignition probabilities in three dimensions [147].

Different modelling approaches capture these dynamics in complementary ways. Agent-based and cellular-automaton models represent the landscape as a grid or set of agents, with each cell updating according to local ignition and spread rules based on fuel type, slope and wind. Neighbouring interactions generate emergent fire shapes that can approximate observed perimeter evolution, and their locality makes them amenable to GPU or cluster parallelization for near-real-time use [112, 119]. UAV-centred wildfire twins such as Fire Twin adopt a similar philosophy, embedding a simplified elliptical fire-spread model in a centralized monitoring framework and using reinforcement-learning-based trajectory planning with software-defined networking to steer aerial assets towards the most informative parts of the fire front [148]. Zhang and colleagues, for example, construct a digital-twin-style forest-fire rescue system in which a grid-based fire-spread model drives evacuation and resource-allocation decisions on a road network, illustrating how local rules can be embedded in broader decision-support logic [119]. Semi-physical spread models used in many operational tools sit between simple grids and full physics. They apply energy-balance or Rothermel-type formulations with empirical corrections for crown fire and spotting, and are fast enough for repeated runs and ensemble analysis, but less expressive under compound extremes and deep convection [109].

Coupled fire-atmosphere models such as CAWFE, WRF-Fire and NUWRF-SFire embed combustion and heat-release schemes in atmospheric solvers so that heat, moisture and momentum fluxes from the fire modify turbulent flow, and the flow in turn reshapes the fire front [109, 112]. These models can reproduce dynamic plume behaviour, pyrocumulus development and wind reversals near intense fires, and workshop reports highlight their value for detailed case studies and for understanding fire-atmosphere feedbacks in complex terrain [109]. FIRETWIN shows how such simulations can sit at the heart of a twin: CAWFE-generated runs for the King Fire drive an interactive Unreal Engine globe where plume rise, fire-line advance and local wind structures can be explored in three dimensions [28]. The trade-off is computational cost. High-resolution coupled simulations are still reserved for selected incidents, training and analysis, not continuous national-scale operations [109, 112].

Hybrid behaviour models combine these pieces. Yun's hybrid wildfire twin uses a physics-based spread core and overlays a data-driven error-correction model trained on past events to adjust perimeter evolution; similarity search selects historical disasters whose patterns resemble the current event, and the hybrid model reduces wildfire prediction errors by about 50% compared with the physics-only baseline [54]. Zhong and co-authors take a different route, building a reduced-order twin of global wildfire activity from the JULES-INFERNO model: autoencoders compress model states into a latent space, a neural network advances latent states in time, and data assimilation in latent space keeps the surrogate aligned with observations [26, 149]. Their work shows that it is possible to capture large-scale wildfire dynamics at far lower computational cost, though fine-scale behaviour and suppression effects remain outside scope. A complementary line of work integrates meshless discrete-element fire-spread components with machine-learning–based parameter adaptation into a rapid "digital-twin-style" simulator for complex terrains, enabling near-real-time propagation of ember-driven fires on modest hardware [150]. Reviews of wildfire modelling and AI describe similar architectures in which neural networks emulate parts of the fire-environment system or correct systematic bias in predicted rate of spread or flame length, while conservation laws and basic thermodynamics remain in the loop [109, 117].

Emerging work on generative and foundation-style models adds another layer rather than replacing existing approaches. Xu and colleagues argue that generative models such as generative adversarial networks (GANs), variational autoencoders and transformers can learn to generate plausible two- and three-dimensional spread scenarios conditioned on multimodal geospatial inputs, and suggest embedding such generators in digital twins for interactive scenario exploration and training, rather than single best-guess forecasts [151]. Disaster-management reviews of generative AI and large language models also point to their potential for fusing heterogeneous data and generating structured scenario narratives, but warn about validation and responsible use in high-stakes contexts [152]. In a wildfire twin, this would translate into behaviour models that not only propagate one forecast forward but also generate families of plausible evolutions that can be interrogated and stress-tested.

Together, these behaviour models form the dynamical core of most wildfire twins. They set practical limits on what the twin can say about future fire evolution and about the effects of potential interventions, and they shape what kinds of uncertainty information can be offered to decision-makers [54, 26, 28]. The surrounding data and risk components can compensate for some weaknesses, but where behaviour models fail, under extreme spotting, complex terrain flows or novel fuel-climate regimes, the twin itself will be blind, regardless of how polished its interfaces are [146, 109]. Conceptual work on operational wildfire twins echoes this. A recent Croatian study proposes a digital twin for coastal wildland fires that explicitly centres time and future states, couples a human decision-maker with an AI agent and uses UAV reconnaissance as a primary data source for evolving the twin during active response [153]. Taken together, these designs underline that a wildfire twin must represent not only spread dynamics, but also information flows, human movement, aerial platforms and incident-command behaviour if it is to support real operations rather than offline analysis alone.

4.5 Current Gaps and Lessons from Other Digital Twins

Across the literature, most systems labelled as wildfire digital twins sit closer to digital models or digital shadows than to fully bidirectional twins [12, 13, 7]. Terminology reviews note that many claimed twins lack continuous data exchange or clearly defined operational services and therefore do not meet stricter definitional criteria [12, 13]. Existing wildfire examples follow the same pattern. Zamari's Susa Valley framework automates burned-area, burn-severity and vegetation-recovery mapping from Sentinel-2 imagery for post-event analysis, but functions as a one-way shadow without real-time control-room integration [114]. FIRETWIN and NASA's NUWRF-based wildfire-twin concept move closer to a full twin by coupling physics-based fire-atmosphere models with high-fidelity visualisation, multi-modal sensing and ensemble forecasting, yet both remain experimental and are not routine operational services [28, 112]. Recent reviews of wildfire modelling and AI therefore describe most current systems as advanced modelling platforms or partial twins rather than mature, closed-loop digital twins embedded in incident-management workflows [109, 59].

Lessons from other safety-critical domains reinforce this picture. Fully autonomous digital twins remain rare in aerospace, industrial plants and medical devices; twins there overwhelmingly act as decision-support systems, with humans approving or executing actions rather than allowing the twin to control the asset directly [154, 7]. Building-safety twins report similar patterns: Khajavi et al. describe fire and anomaly-detection deployments where the twin provides long-term situational awareness, but operators still mediate alarms and responses over the building lifecycle [154]. At the same time, there are early experiments that couple wildfire-related twins with large language models. Gao et al. combine a "Digital Twin Building", cloud GIS and a multi-agent Instructor–Worker large language model (LLM) system to analyze air-quality data from the January 2025 Los Angeles wildfires and generate health recommendations and numerical policy summaries, illustrating how narrative outputs can sit on top of twin infrastructures without changing their core maturity level [155].

Several structural gaps recur. First, data constraints. Wildfire twins must operate on heterogeneous data streams with strong latency, coverage and resolution limitations, from satellite hot spots with multi-hour effective revisit times through sparse in-situ networks and uneven camera or UAV coverage [156, 157, 27]. These inputs carry substantial uncertainty that is rarely propagated or communicated explicitly, even though digital-twin and digital-risk-twin work argue that high-stakes decision support requires probabilistic outputs and clear confidence information [54, 42, 53]. General DT surveys likewise note that “twin data” is often the least formalised component, with weak data models and limited correspondence measures between physical and virtual states, and call for more systematic treatment of data quality and uncertainty [7, 158, 24]. Notably, the InterAcademy Partnership workshop on wildfire modelling and artificial intelligence reaches similar conclusions, highlighting data standardization, interoperability across modelling platforms and transparent uncertainty communication as priority issues [109].

Second, modelling limitations. Most wildfire-oriented twins embed spread and risk models but treat suppression and human behaviour only superficially, if at all [111, 112]. Physics-based and semi-physical fire-behaviour models remain limited by uncertain initial conditions, incomplete representation of processes such as spotting and wildland–urban fire spread, and high computational cost, while statistical and machine-learning approaches degrade outside their training regimes [54, 125, 109]. Suppression dynamics are largely absent at landscape scale, despite examples such as Fire-X that show how combustion and extinguishment can be co-modelled in other fire contexts [159]. Wildfire-oriented suppression twins are beginning to appear at smaller scales: for example, a digital-twin framework for aerial retardant drops couples a meshless particle model of released material with machine-learning optimization of aircraft dynamics to maximize ground-level effect and pilot safety [160]. Behavioural and operational models borrowed from evacuation and disaster-city twins have only begun to be linked to advancing wildfire fronts and smoke. The available case studies do not yet provide systematic validation against real incident data [92, 119, 59]. As a result, current wildfire digital twins can explore scenarios but cannot reliably estimate how management actions will change outcomes.

Third, evaluation and lifecycle issues. In contrast to flood or earthquake twins, which report standard skill metrics against gauges, inundation maps or damage surveys, wildfire twins lack shared benchmarks, validation protocols and agreed performance measures for perimeter or impact prediction [42, 53]. Yun’s similarity-based hybrid architecture and related work demonstrate sizeable error reductions on specific datasets, but these gains are not yet tied into a broader culture of operational hindcasting and model comparison [54, 112]. Post-fire assessment, recovery and long-term adaptation are also handled largely outside current twin frameworks, even though post-disaster risk-twinning work underlines that recovery phases, changing vulnerability and interdependent infrastructures are central to understanding risk trajectories over time [53, 114]. By contrast, industrial and safety-oriented DT reviews now expect systematic benchmarking, lifecycle-aware correspondence measures and formal maturity models as part of serious twin deployments [19, 7, 43]. These points suggest that wildfire digital twins presently function as informative or, at best, predictive shadows with limited feedback, incomplete representation of suppression and human behaviour, and weak validation, rather than as fully fledged, lifecycle-spanning twins.

These limitations do not mean that the digital-twin concept is ill-suited to wildfire management, but they do imply that expectations must be calibrated and design patterns chosen carefully. Other domains have faced similar constraints around sparse data, uncertain extremes and human-in-the-loop operation, and have converged on particular architectural choices, maturity expectations and governance arrangements. The next section draws on these experiences to sketch what a realistically attainable wildfire digital twin should look like and which elements from industrial, urban and disaster-management twins can be transferred without overstating what such systems can deliver.

5 Synthesis: Wildfire Digital Twins open Questions

The ISO/IEC reference architecture for digital twins (ISO/IEC 30188, currently at FDIS - Final Draft International Standard stage) provides a domain-neutral roadmap of what a complete digital twin system necessarily comprises [25, 17, 12]. At its core, the reference model identifies five interconnected elements.

- *target entity* — the physical or non-physical subject being represented; for wildfires, this is the fire-landscape system spanning fuels, terrain, atmosphere, infrastructure, and human activity.
- *digital entity* composed of data elements (sensor readings, fuel maps, perimeter records, historical logs) and procedural elements (simulation models, analytics engines, optimization algorithms).
- *data connection* that enables ongoing synchronization between target and digital entity, with a clearly specified direction (monitoring, control, or bidirectional) and an appropriate rate of update.
- *services* built on top of the digital entity: analysis, simulation, visualization, and optimization.
- *infrastructure and system aspects* — sensing networks, computing platforms, and the governance, security, and stewardship frameworks that keep the system trustworthy over time.

Beyond components, a digital twin has a *lifecycle*: from conceptualization and design through deployment and active use to decommissioning, archiving, or transformation. Lifecycle integration means that the twin evolves alongside its target entity, reflecting changes in state, structure, and context across all phases. Three *twinning modes* describe the relationship between physical and digital sides: (a) the digital entity updates as the physical changes, an observational, shadow-type coupling; (b) the digital entity can issue commands that alter the physical entity, closing the loop; or (c) both sides converge iteratively in bidirectional equilibration. Which mode is appropriate is a design and governance decision, not a measure of technical ambition.

Surveys and reviews across all application domains consistently find that the majority of systems described as digital twins do not simultaneously satisfy all of the requirements above [146, 7, 42, 13]. The most common deficit is in the *data connection*: many systems update their digital entity manually, periodically, or only at deployment, breaking the continuous synchronization that distinguishes a twin from a model. A second gap is in *services*: systems often reach visualization but omit simulation-backed uncertainty quantification or actionable optimization. A third recurring gap is *lifecycle integration*: implementations cover a single phase,typically incident operations or risk assessment,without connecting to pre-event planning, suppression support, or post-fire recovery [53, 12].

Maturity frameworks from manufacturing, disaster management, and general DT research document the same pattern [33, 161, 47]. Even in the most developed domains (industrial and urban), closed-loop lifecycle-spanning twins remain exceptional. The label "digital twin" is routinely applied across the full spectrum from static model through one-way shadow to bidirectional operational twin, inflating expectations and obscuring meaningful comparisons.

For wildfire, the gap is wider still. The meta-analysis in Section 3 underscores this empirically: with only eight review-type and 32 case-type publications in the Web of Science corpus (2013–2025), wildfire is among the smallest DT application domains. Most existing systems are informative or early-predictive, and the systems labelled as twins are more accurately described as advanced digital shadows or living models — systems with richer data pipelines than a static GIS, but without bidirectional coupling or full lifecycle span [114, 128]. The deficit is not primarily a lack of ambition; it reflects domain-specific constraints that the standard roadmap does not resolve on its own.

Wildfire digital twins inherit all of the generic implementation gaps and encounter a further set of constraints that are specific to the domain.

The most pervasive constraint is data scarcity and unreliability. Satellite imagery (Landsat, Sentinel, MODIS, VIIRS) provides wide spatial coverage but revisit cycles of hours to days are often too slow to track fast-moving perimeters; active-fire products carry geolocation uncertainty and detection limits for small or low-intensity fires [125, 111]. UAV platforms offer higher temporal resolution and flexible deployment but limited spatial coverage and endurance. In-situ weather stations and fuel-moisture sensors provide accurate local readings but are sparsely deployed and systematically biased toward populated or accessible areas, leaving the wildland interior poorly characterized [109].

The static GIS layers that underpin most operational wildfire models — land cover, topographic derivatives, fuel-type maps — present a further problem. Fuels change seasonally and inter-annually through growth, drought, and disturbance; treating a fuel layer as fixed when it is actually stale propagates systematic error through every forecast. Dynamic updating requires repeated remote sensing, lidar surveys, and field sampling campaigns that are rarely sustained across incident and non-incident periods [7, 13].

Perhaps most consequentially, uncertainty is rarely quantified or propagated end-to-end. Individual data sources carry positioning error, temporal mismatch, and classification uncertainty; simulation models add parametric and structural uncertainty; yet outputs like spread forecasts, risk maps and evacuation recommendations are frequently presented as deterministic [146, 42]. Unquantified uncertainty is itself a form of unreliability in high-stakes operational contexts, because it prevents operators from calibrating their reliance on system outputs.

A second challenge is fundamental to operational fire management: models accurate enough to capture the physics of extreme fire behavior are rarely fast enough to be operationally useful, and models fast enough for real-time incident guidance are rarely reliable under the conditions that produce the most dangerous fires.

Physics-based coupled fire–atmosphere models resolve fire–wind feedbacks, crown fire dynamics, and spotting mechanisms that simpler models miss, but they are computationally expensive; runs that require hours cannot guide decisions measured in minutes [111, 117]. Semi-empirical models (Rothermel-based) are operationally embedded in tools such as FARSITE and Phoenix RapidFire precisely because they are fast, but they systematically underperform in the wind-topography interactions, crowning, and ember transport scenarios that characterize extreme events [54, 125]. Machine-learning surrogates offer speed comparable to semi-empirical approaches but degrade outside their training distribution, which is exactly where the most dangerous fire behavior lies.

Hybrid architectures represent the most promising path through this trade-off: physics-based cores corrected online by learned residuals, or reduced-order models that preserve the most relevant physical structure at substantially lower cost [54, 26]. These do not dissolve the tension but allow it to be managed deliberately. Different model tiers deployed for different decisions, with fast approximations supporting immediate tactical guidance and slower, higher-fidelity runs informing strategic planning windows. This tiered design requires explicit architectural commitment, not just the accumulation of more models in a pipeline.

A third challenge distinguishes wildfire from most other DT domains: the operational environment is hostile to the infrastructure that digital twins depend on. Communications infrastructure degrades under smoke, heat, and structural damage. Sensors fail or are destroyed at the fire front. Remote terrain lacks reliable cellular or satellite connectivity. Incident operations span multiple agencies with heterogeneous equipment, data formats, and authentication frameworks.

Industrial and smart-city twins typically assume stable cloud connectivity and dense, calibrated sensor networks. Neither assumption holds on a fire ground. A wildfire twin architecture must therefore be designed from the start for intermittent operation: edge computation that can function offline, opportunistic synchronization when connectivity is restored, graceful degradation of services when data streams are interrupted, and clear protocols specifying what operators can rely on when the system is running in a degraded state [128, 16, 15, 129]. These are not edge cases to be addressed late in system design — they are baseline operating conditions that must shape every architectural decision.

The ISO/IEC 30188 reference architecture includes *optimization* as a service and *actuation* (the control direction of the data connection) as a twinning mode. In many industrial and smart-city applications, closed-loop control is the primary value proposition: the twin monitors the physical system and issues commands to keep it within target bounds [19, 20].

For wildfire management, optimization and actuation are relevant but occupy a different position. Resource allocation, aircraft routing, staged evacuations, and pre-positioning of equipment are legitimate optimization problems, and decision-support tools for these tasks are valuable. However, they are not the central architectural objective of a wildfire twin, and closed-loop actuation is not the goal. Wildfire operations involve life-safety decisions made under time pressure, with incomplete information and clear lines of moral and legal accountability that cannot and should not be delegated to automated systems [43, 53]. Doctrine, liability, and the inherent unpredictability of fire behavior all position the appropriate role of a wildfire twin as decision support, not autonomous control. This framing is consistent with other safety-critical domains: healthcare twins stop at clinical decision support; disaster-management twins generate scenarios and recommendations but reserve decisions for human commanders.

What remains an open and tractable problem is the lack of a *unified optimization layer* within the decision-support role that wildfire twins do play. Resource allocation models, evacuation routing algorithms, and risk-ranked scenario generators exist in separate research silos, each with different data requirements, service interfaces, and output formats [59, 109]. Real incidents require simultaneous reasoning across fire spread, resource availability, infrastructure status, and population exposure; a twin that handles these through non-interoperable analytical fragments provides significantly less value than one that integrates them around a common operational picture. Defining shared service interfaces, data models, and output conventions for this optimization-support layer is a tractable near-term standardization target.

Given the constraints above – unreliable data, the accuracy–usability trade off, intermittent links, and the need to cap autonomous actuation – wildfire digital twins should lean toward rich, interactive decision support environments rather than full closed loop control. These environments are built to support structured what if analysis under uncertainty, not to automate the whole response.

The value of what-if exploration is well documented in adjacent domains. Urban air-quality and smart-city twins demonstrate that presenting complex spatio-temporal information through layered maps, scenario comparisons, and interactive dashboards significantly improves the quality of human decisions under uncertainty [162, 157, 31]. Disaster-management twins for floods and earthquakes show that rapid scenario generators — tools that produce a range of plausible futures under different input assumptions — give operators a structured vocabulary for reasoning about risk, rather than a single deterministic forecast to accept or reject [163, 93, 53]. Agricultural twins confirm the pattern in a domain with strong operational parallels to wildfire: advisory scenario-analysis tools are adopted and trusted more readily than prescriptive systems [102, 164].

For wildfire, a what-if capable twin would allow an incident commander to explore questions such as: *How does the perimeter evolve if wind shifts to the northwest at 18:00? What changes if the planned burnout is delayed by two hours? Which assets are exposed if spotting reaches the eastern ridge?* These questions cannot be answered by a static model or a single deterministic forecast; they require a system that can rapidly re-parameterize, re-run plausible scenarios, and present the resulting distributions — of spread extent, of exposure counts, of arrival times — in forms that support fast, accountable decisions.

Achieving this requires integrating three components that are currently developed separately. First, a fast, tiered modelling stack capable of rapid re-runs across a range of input assumptions. Second, a probabilistic output framework that expresses uncertainty as scenario envelopes or exceedance probabilities rather than point estimates. Third, an interface layer with standardized visual grammars for fire perimeters, spread envelopes, exposure overlays, and uncertainty bands [157, 31, 146]. Standardization of the interface layer is particularly important for operational contexts where crews and commanders move between different systems: common visual conventions reduce relearning time, support training in simulator environments, and make it easier to audit and compare system behavior across incidents.

Augmented reality and mobile interfaces extend what-if capabilities toward the field, where decisions are made closest to the fire. Prototype systems show that field personnel can work effectively with spatially anchored spread overlays and real-time sensor feeds delivered through AR-equipped devices [129]. The gap between proof-of-concept and operationally robust, connectivity-tolerant field tools remains large; the architectural direction is nonetheless clear.

Taken together, the challenges and opportunities identified above suggest a staged roadmap organized across four layers.

The *data foundations* layer must address reliability first: multi-sensor fusion pipelines with explicit uncertainty budgets; task-specific data specifications that link quality requirements to particular decisions (perimeter tracking, pre-season risk mapping, evacuation analysis); and provenance tracking for fuel layers, model runs, and benchmark events. Medium-term priorities include dynamic updating of fuel and exposure layers sustained across incident and non-incident periods. Longer-term priorities are shared standards for data quality and interoperability [58, 93, 109].

The *modelling* layer must resolve the accuracy–usability trade-off through hybrid architectures. Near-term work should focus on hybrid spread cores with online learned correctors, basic suppression-aware scenario generation, and validation against real wildfire events. Medium-term work should address suppression–logistics coupling and rigorous cross-event benchmarking. Longer-term work should pursue knowledge-graph-driven architectures that support adaptive model selection as conditions evolve [45, 46, 159].

The *architecture* layer must be designed for adversarial field conditions from the outset: edge-aware ingestion with graceful degradation, human-in-the-loop what-if dashboards, and unified service interfaces for the optimization-support layer. Medium-term priorities include federated services across agencies. Longer-term targets are regional systems-of-twinned-systems integration [59, 29].

The *governance and evaluation* layer must develop domain-specific maturity metrics, shared benchmark suites spanning different fuel types and management contexts, and lifecycle governance frameworks that link pre-season planning, incident operations, and post-fire recovery into a continuous information flow [33, 161, 47, 43]. Without shared benchmarks and clear capability criteria, each new wildfire twin prototype is evaluated in isolation and contributes little to systematic, cumulative progress.

Table 14 summarizes these priorities across lifecycle layers.

The overarching aim is not to replicate industrial DT sophistication in a domain for which its assumptions do not hold. It is to build wildfire twins that are *fit for purpose*: transparent about their uncertainty, robust under adverse field conditions, grounded in reliable and well-documented data, and genuinely useful to the humans who make consequential decisions about

Table 14: Wildfire digital-twin research priorities by lifecycle layer.

Layer	**Near-term focus**	**Medium-term focus**	**Longer-term focus**
Data foundations	Task-specific uncertainty budgets; multi-sensor fusion with provenance	Dynamic fuel and exposure updating across full incident cycle	Shared quality standards; correspondence measures
Modelling	Hybrid spread cores; suppression-aware pilots; real-event validation	Suppression–logistics coupling; cross-event benchmarking	Knowledge-graph-driven adaptive model selection
Architecture	Edge-aware ingestion; what-if dashboards; unified optimization interfaces	Federated multi-agency services	Regional systems-of-twinned-systems
Governance & evaluation	Domain-specific maturity metrics; ad-hoc benchmark events	Formal capability levels; shared test suites	Lifecycle governance spanning planning, response, and recovery

fire. That target is achievable within the constraints the domain imposes — but only if the data, modelling, architecture, and governance challenges are treated as an integrated design problem rather than as separate technical tasks to be solved independently.

6 Conclusion and future work

A digital twin is only useful when abstract models and data streams condense into information that can solve real problems. This paper has treated wildfire digital twins in that light, as coupled physical-virtual systems that must turn heterogeneous measurements, simulations, and analytics into guidance for people facing fast, destructive fires. It has shown how the idea of a twin grew from aerospace mirror systems and product-lifecycle management, and how multi-layer architectures now organise sensing, modelling, analytics, and interaction across domains.

The meta-analysis of publications from 2013 to 2025 confirms that there is no single canonical digital twin. Different domains work at different resolutions and under different constraints. Manufacturing and urban twins dominate in volume and maturity, with stronger case material and more standardised architectures. Environmental, healthcare, and disaster twins are smaller, but they are growing. They focus more on frameworks, uncertainty, and governance. Wildfire work sits near this edge of the landscape. It is active, but still fragmented, and often closer to advanced models or dashboards than to tightly coupled, lifecycle-spanning twins.

For wildfire, the review points to three layers that must come together. The first is modelling. Semi-empirical, physics-based, and data-driven approaches each capture something important, but none is sufficient on its own under extreme and shifting conditions. The second is data. Satellites, UAVs, in-situ sensors, and evolving fuel and asset maps provide complementary views, but they arrive with latency, gaps, and uncertainty that are rarely carried through to the final output. The third is interaction. Incident commanders, field crews, planners, and communities all need different windows into the twin, and high-consequence decisions depend on clear, uncertainty-aware displays rather than opaque automation.

Experience from other domains suggests a way forward. Industrial and urban twins show how to stabilise the underlying infrastructure through layered architectures, standard interfaces, and measures of correspondence between the physical and virtual sides. Environmental and disaster twins show how to work with sparse data and human-in-the-loop decision-making, using ensembles, risk metrics, and post-event learning instead of aiming for full autonomy. A realistic near-term vision for wildfire digital twins is therefore not an all-seeing system, but a family of architectures that ingest heterogeneous data, couple models that can be stress-tested under extremes, expose probabilistic outputs to operators, and improve through systematic hindcasting and maturity assessment.

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List of Acronyms and Abbreviations

5G - *Fifth Generation (mobile network)*
AAS - *Asset Administration Shell*
AI - *Artificial Intelligence*
API - *Application Programming Interface*
AR - *Augmented Reality*
BIM - *Building Information Modeling*
CAD - *Computer-Aided Design*
CAWFE - *Coupled Atmosphere-Wildland Fire Environment*
CCTV - *Closed-Circuit Television*
CFD - *Computational Fluid Dynamics*
CNC - *Computer Numerical Control*
CPS - *Cyber-Physical System*
CT - *Computed Tomography*
DBH - *Diameter at Breast Height*
DDDAS - *Dynamic Data-Driven Application Systems*
DEM - *Digital Elevation Model*
DT - *Digital Twin*
DTaaS - *Digital Twin as a Service*
DTO - *Digital Twin of the Ocean*
ECG - *Electrocardiogram*
EP - *Electrophysiology*
ERP - *Enterprise Resource Planning*
ESDT - *Earth System Digital Twins*
ETL - *Extract, Transform and Load*
FDT - *Forest Digital Twin*
GAN - *Generative Adversarial Network*
GeoSPARQL - *Geospatial extension to SPARQL*
GHG - *Greenhouse Gas*
GIS - *Geographic Information System*
GNSS - *Global Navigation Satellite System*
GPU - *Graphics Processing Unit*
HMI - *Human Machine Interface*
HTTP - *Hypertext Transfer Protocol*
IAQ - *Indoor Air Quality*
ICU - *Intensive Care Unit*
IEC - *International Electrotechnical Commission*

IEEE - *Institute of Electrical and Electronics Engineers*
IIoT - *Industrial Internet of Things*
IoT - *Internet of Things*
ISO - *International Organization for Standardization*
IT - *Information Technology*
ITS - *Intelligent Transportation Systems*
JULES-INFERNO - *Joint UK Land Environment Simulator - INteractive Fire and Emission algoRithm for Natural envirOnments*
KG - *Knowledge Graph*
LiDAR - *Light Detection and Ranging*
LLM - *Large Language Model*
LSTM - *Long Short-Term Memory*
LoRaWAN - *Long Range Wide Area Network*
MES - *Manufacturing Execution System*
ML - *Machine Learning*
MODIS - *Moderate Resolution Imaging Spectroradiometer*
MRI - *Magnetic Resonance Imaging*
MQTT - *Message Queuing Telemetry Transport*
NASA - *National Aeronautics and Space Administration*
NDVI - *Normalized Difference Vegetation Index*
NetCDF - *Network Common Data Form*
NFPA - *National Fire Protection Association*
NU-WRF - *NASA Unified Weather Research and Forecasting model*
NWP - *Numerical Weather Prediction*
OGC - *Open Geospatial Consortium*
OPC-UA - *Open Platform Communications Unified Architecture*
PACS - *Picture Archiving and Communication System*
PASS - *Personal Alert Safety System*
PLM - *Product Lifecycle Management*
PRISMA - *Preferred Reporting Items for Systematic Reviews and Meta-Analyses*
PV - *Photovoltaic*
RGB - *Red, Green, Blue*
SCADA - *Supervisory Control and Data Acquisition*
SLR - *Systematic Literature Review*
SME - *Small and Medium-sized Enterprise*
SOSA - *Sensor, Observation, Sample, and Actuator (ontology)*
SoTS - *System of Twinned Systems*
SSN - *Semantic Sensor Network (ontology)*
UAV - *Unmanned Aerial Vehicle*
VGI - *Volunteered Geographic Information*

VIIRS - *Visible Infrared Imaging Radiometer Suite*
VR - *Virtual Reality*
WAN - *Wide Area Network*
WRF-Fire - *Weather Research and Forecasting - Fire*

Abstract

Digital twins are increasingly invoked as a transformative concept for environmental hazards, yet their meaning, maturity and practical value in wildfire management remain poorly specified. This paper synthesizes cross-domain foundations of digital twinning, maps recent application trends, and assesses how far current wildfire systems meet stricter digital twin criteria. First, it reviews conceptual and standardization work across manufacturing, urban infrastructure, healthcare, environmental and disaster domains, highlighting common architectural patterns, lifecycle models and maturity frameworks, as well as persistent gaps in interoperability, governance and uncertainty treatment. A quantitative meta-analysis of Web of Science records from 2013–2025 then characterizes the distribution of digital twin publications by domain, the balance between review-oriented and case-oriented work, and dominant publication venues, with manufacturing and urban infrastructure leading in volume, and environmental, healthcare and disaster applications forming smaller but rapidly growing streams.

Building on this cross-domain view, the paper examines wildfire-focused implementations in terms of four core components: data acquisition and assimilation, risk assessment, fire behaviour modelling and user-facing interaction. Existing wildfire "twins" are found to cluster around advanced modelling platforms and digital shadows, often lacking continuous two-way data exchange, explicit uncertainty quantification, or tight integration with incident-management workflows. The analysis identifies promising directions, including hybrid physics–ML behaviour models, ensemble and probabilistic risk outputs, UAV-supported data collection, and programmatic interfaces that connect wildfire twins to wider systems-of-twins. The paper concludes by outlining a research and governance agenda for operational wildfire digital twins that function as human-centred, probabilistic decision-support systems rather than fully autonomous controllers.

Prošireni sažetak

Ovaj rad donosi sveobuhvatan pregled tehnologije digitalnih blizanaca, a posebno izučava primjenu u upravljanju požarima otvorenog prostora. U radu su obuhvaćeni konceptualni okvir i osnovna načela arhitekture digitalnih blizanaca, opisane su ključne komponente sustava, te su analizirane karakteristike tehnologije.Posebna pažnja posvećena je prijenosu koncepata iz drugih domena. Proizvodnja i urbane infrastrukture poslužile su kao referentni primjeri. Time je stvoren teorijski temelj za procjenu operativne vrijednosti digitalnih blizanaca u kriznim situacijama.

Koncept digitalnog blizanca privlačan je zbog mogućnosti upravljanja događajima u stvarnom vremenu. Povezuje fizičke procese s naprednim virtualnim replikama i olakšava operativno donošenje odluka na terenu. Međutim, primjena ove tehnologije na požare otvorenog prostora suočava se s nekoliko tehničkih izazova. Najveći problem je nejasna definicija samog koncepta. Često se obični napredni simulacijski modeli pogrešno deklariraju kao pravi blizanci. Drugi problem odnosi se na izostanak kontinuirane dvosmjerne razmjene podataka; postojeći sustavi nemaju mogućnost izravnog i automatskog djelovanja u fizičkom svijetu. Treći izazov leži u otežanom modeliranju nesigurnosti, gdje npr. ulazni podaci sa senzora i satelita često kasne ili su nepotpuni.

U ovom radu zrelost tehnologije analizirana je kroz opsežnu kvantitativnu meta-analizu znanstvenih publikacija iz baze Web of Science za razdoblje od 2013. do 2025. godine. Usporedbom broja preglednih radova i konkretnih studija slučaja definiran je smjer razvoja tehnologije kroz različite domene, čime je dobiven jasan uvid u stanje implementacije sustava koji bi se mogli koristiti u upravljanju požarima. Pregled literature je potvrdio postojanje obećavajućih rješenja koji veću zrelost postižu u domenama industrijskih digitalnih blizanaca, digitalnih blizanaca urbanih područja i infrastrukture te medicine.

Pregled dosadašnjih istraživanja u području digitalnih blizanaca požara otvorenog prostora ukazuje na manji broj radova s manje povezanim komponentama. Nadalje, analizirane su tehnolgije koje mogu poslužiti kao komponente povezanih digitalnih blizanaca požara , među kojima se posebno ističu hibridni modeli ponašanja požara. Zbog kombiniranja spregnutih modela atmosfere i vatre s algoritmima strojnog učenja, takav pristup ima potencijal riješiti ključni problem računalne zahtjevnosti u stvarnom vremenu.

Osim analize zrelosti, u radu je obrađena problematika asimilacije heterogenih podataka. Ograničavanje pogrešaka u modelima ovisi o kvaliteti ulaznih senzorskih informacija. Besposadne letjelice nude kvalitetno rješenje za lokalno praćenje vatrene fronte, dok aplikacijska sučelja omogućuju pravilnu distribuciju izračunatih parametara. Završni dio rada usmjeren je na ulogu blizanaca u operativnim uvjetima, naglašavajući da se ovi sustavi prvenstveno moraju razvijati kao probabilistički alati za potporu odlučivanju. Umjesto težnje prema potpunoj automatizaciji, pravilno projektirano sučelje i jasan informacijski tok omogućuju zapovjednicima na terenu brže i sigurnije donošenje odluka unutar postojećih incidentnih procedura.