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Digital Twins for Land Use Change

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Abstract Rapid environmental, socio-economic, and geopolitical changes are accelerating transformations in land use patterns worldwide. To effectively monitor and predict these dynamics, DTs offer a promising approach by integrating real-time Earth observation data, climate models, AI-driven analytics, and socio-economic indicators. This paper identifies a critical gap in the application of Digital Twins (DT) frameworks for land use change monitoring, which remains underexplored. We propose a novel two-timescale DT architecture designed to track both rapid event-driven land cover changes (such as floods, wildfires, war-induced damage) and gradual long-term transformations, such as climate-induced agricultural shifts and urban expansion. By bridging the gap between advanced Earth observation technologies and decision-making processes, the proposed framework contributes to the development of AI-enhanced DT systems that facilitate climate adaptation, disaster response, and long-term sustainability in dynamic land systems.

Keywords Digital Twins · Land use change · Earth observation

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1 Introduction: Relevance and Importance of Digital Twins for Land Use Change

Rapid environmental and socio-economic changes necessitate advanced monitoring and predictive modeling of land use dynamics. Climate change is intensifying extreme weather events and driving long-term transformations, such as shifting agricultural zones, deforestation, and urban expansion. Simultaneously, war-induced disruptions—including destruction, displacement, and reconstruction—add further complexity to land use patterns. Effectively managing these challenges requires near-real-time, data-driven tools for informed decision-making.

Digital Twins (DTs) provide a powerful tool for monitoring and predicting land use changes by integrating real-time satellite data, climate models, and socio-economic indicators. Unlike traditional GIS systems, which rely on static maps, DTs continuously process and analyze evolving environmental conditions, enabling dynamic, scenario-based forecasting. In recent years, major organizations such as NASA and the European Union have launched large-scale Earth System Digital Twin initiatives, demonstrating the growing recognition of this technology's potential for environmental monitoring and decision-making.

NASA defines an Earth System Digital Twin (ESDT) as "an interactive, integrated, multidomain, and multiscale digital replica of Earth's state and temporal evolution" [1]. The goal of this DT is to provide a continuously updated and harmonized representation of Earth's systems, allowing for more accurate simulations, scenario analysis, and predictive modeling. It is expected to integrate Earth system models, observational data, historical records, and AI-driven analytics to improve understanding of natural processes and human-induced changes.

Rothe [2] analyzes the Digital Twin Earth (DTE) initiative by the European Space Agency (ESA) and the EU, defining it as a computational model that integrates satellite Earth observation, AI, and simulations to create a high-resolution, interactive replica of Earth's systems. Focusing on governance and political implications, the paper describes DTE as a "visual object"—a real-time simulation tool designed for analyzing environmental changes and supporting policy and decision-making. Reference [3] discuss the role of Digital Ecosystems in developing DTE, with a focus on the Destination Earth (DestinE) initiative. The paper highlights how Big Data, AI, and Earth observation (EO) technologies enable the creation of high-resolution digital replicas of Earth's systems to support climate adaptation, disaster mitigation, and sustainable development. The authors emphasize the need for interoperable digital infrastructures to connect heterogeneous data sources. However, the study does not focus on user feedback mechanisms or the modelling of different scenarios, which are crucial for DT and adaptive decision-making.

Adade and de Vries [4] explore the application of DTs for participatory land-use planning, emphasizing their role in providing dynamic simulations that enhance stakeholder engagement in sustainable land-use strategies. Their study highlights how DTs can improve transparency and decision-making by integrating social, economic, and environmental considerations. However, the paper remains conceptual and generic, lacking details on the technical architecture or data sources required for implementing such DT systems.

While DTs have been widely studied across various fields, their application to land use change remains largely unexamined. As of this writing, a Scopus search returns approximately 30,000 studies (29,767) on DTs, yet only five papers specifically focus on land use change. Most existing research is concentrated on climate modeling, smart cities, and industrial applications, leaving a significant gap in the development of DT frameworks for monitoring and predicting land use dynamics. In particular, [5] propose a Cognitive Soil Digital Twin, a small-scale DT that integrates sensor networks, remote sensing, and AI to monitor and analyze the physical and biological dynamics of soil, focusing on land use changes and ecosystem health at a localized level. This approach aids in assessing soil degradation, agricultural productivity, and climate adaptation strategies at local scale.

Fissore, Vanina et al. [6] propose a DT prototype for Alpine glaciers, integrating Earth observation data and in situ measurements to model glacier dynamics and assess the impacts of climate change.

This paper aims to address the critical gap in DT applications for land use change monitoring by proposing a two-timescale DT framework. While existing DT initiatives primarily focus on climate monitoring and weather prediction, they lack the ability to track both rapid and gradual land use transformations. Given the increasing impact of climate change, extreme weather, and war-induced disruptions, there is an urgent need for real-time and predictive land use modeling that integrates satellite data, AI-driven analytics, and socio-economic indicators.

The objectives of this paper are threefold. First, we review the state-of-the-art enabling technologies for DTs in land use change and environmental monitoring, identifying key gaps in existing frameworks. Second, we present a novel two-timescale DT approach that accounts for both short-term, event-driven land cover changes (e.g., floods, wildfires, war damage) and long-term, gradual transformations (e.g., climate-induced agricultural shifts, urban expansion, post-war land recovery). Finally, we demonstrate the relevance of this approach within the "DT4LC—Developing Scalable Digital Twin Models for Land Cover Change Detection Using Machine Learning" project, a Ukrainian-Swiss Joint Research Programme (USJRP) supported by the Swiss National Science Foundation (SNSF), showcasing its potential for adaptive land management, policy planning, and sustainable recovery.

By bridging the gap between advanced Earth observation technologies and decision-making, this paper contributes to the development of AI-enhanced DT models that can support climate adaptation, disaster response, and long-term sustainability in dynamic land systems.

2 Case Studies: Existing Digital Twin Initiatives in Land and Environmental Monitoring

2.1 Destination Earth (DestinE)—EU Funded High-Resolution Earth System Modeling for Climate Adaptation

Destination Earth (DestinE) is a large-scale initiative launched by the European Union in 2022 with the goal of developing an advanced digital model of the Earth. This initiative is designed to enhance environmental monitoring, climate change adaptation, and disaster management by integrating high-performance computing, artificial intelligence, and Earth observation data [7]. DestinE aligns with the European Green Deal and the Digital Strategy, aiming to provide critical insights for decision-making processes related to climate policy, urban planning, and risk mitigation [8].

The initiative consists of three main components. The DT Engine serves as the computational infrastructure that integrates various Earth system models, allowing for high-resolution simulations and real-time data analysis [8]. The Data Lake is a centralized repository that aggregates and harmonizes data from satellite observations, in-situ measurements, and model outputs, enabling large-scale data processing [9]. The Core Service Platform acts as the interface that provides access to the DTs, offering tools and services for users, including policymakers, scientists, and industry stakeholders [10].

DestinE is implemented through collaboration between three key organizations. The European Space Agency (ESA) is responsible for the Core Service Platform, ensuring accessibility to DestinE's outputs [10]. Meanwhile, the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) manages the Data Lake and oversees data infrastructure [9]. The European Centre for Medium-Range Weather Forecasts (ECMWF) leads the development of the DT Engine and the first two DTs: the Weather-Induced Extremes Digital Twin and the Climate Change Adaptation Digital Twin [8] (Fig. 1).

The two DTs serve distinct but complementary purposes, operating on different time scales. The Weather-Induced Extremes Digital Twin is designed to support short-term forecasting and response to meteorological, hydrological, and air quality extremes. It provides near real-time simulations to improve risk assessments and emergency response strategies, with a focus on short-term time scales ranging from hours to days [8]. In contrast, the Climate Change Adaptation Digital Twin models the long-term impacts of climate change, projecting environmental and socio-economic consequences over multiple decades. This DT enables policymakers to explore future climate scenarios and develop sustainable adaptation strategies [10].

The data foundation of DestinE relies on multiple sources, including satellite pop-observations from ESA's Earth Explorer missions and the Copernicus Sentinel program, in-situ measurements from ground, air, and ocean monitoring networks, and scientific modeling studies from ECMWF and other EU-funded research projects [7].

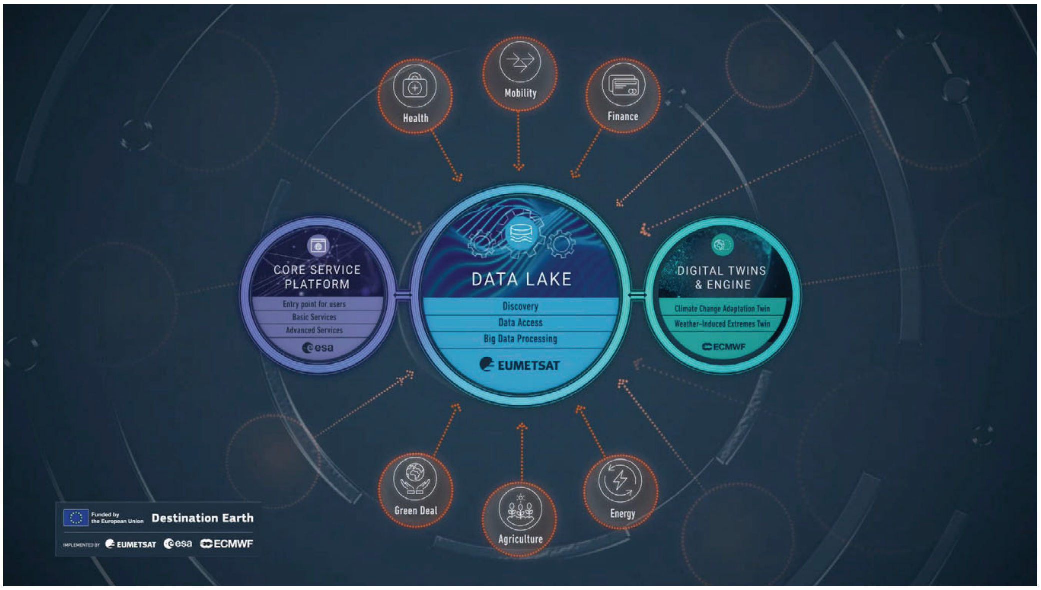

Fig. 1 Access to DestinE data and other cloud-based processing data services that will be available in the Data Lake [9]

DestinE enhances the use of DTs for Earth system monitoring by integrating computational models with real-time observational data, particularly through the Open Data Cube infrastructure for data harmonization. This approach enables detailed analysis of both short-term weather-related hazards and long-term climate trends. DestinE is expected to be fully developed by 2030, providing a foundation for evidence-based policy decisions and enhancing resilience to climate-related risks across Europe and beyond.

2.2 NASA Earth System Digital Twin

Since 2022, NASA has been running the Advanced Information Systems Technology (AIST) program with the goal of developing an ESDT. This initiative aims to create a dynamic, interactive model that replicates the state and evolution of Earth's systems. The ESDT is envisioned as an advanced computational framework that integrates real-time data, artificial intelligence, and predictive models to improve Earth system monitoring and decision-making [1] (Fig. 2).

According to [1], the ESDT should incorporate various Earth system models to simulate atmospheric, oceanic, land, and cryospheric processes. It should also integrate observational data from multiple sources, including satellite imagery, ground-based sensors, aerial and underwater instruments, and socioeconomic datasets. Additionally, historical records will be used to validate models and provide context for current and future predictions. The use of advanced AI and data analytics will enhance

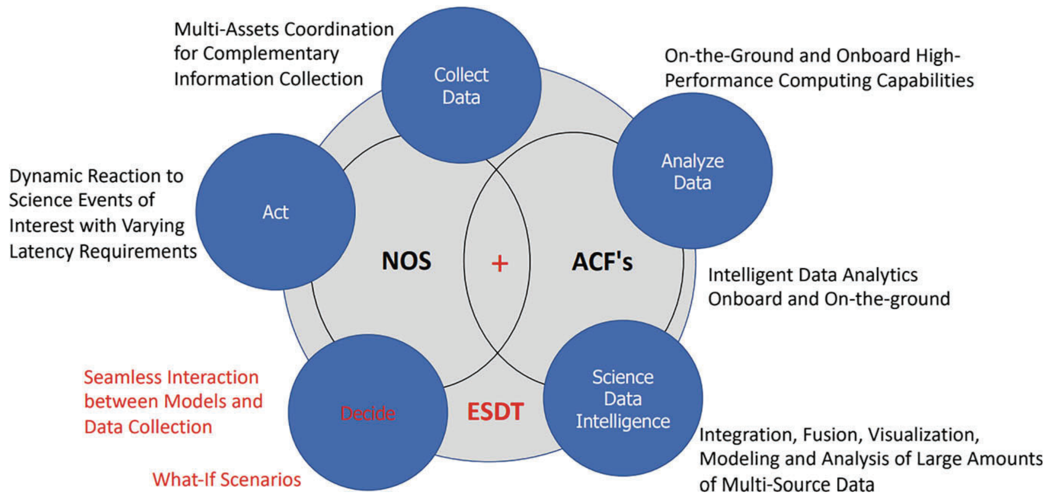

Fig. 2 Earth System Digital Twins (ESDT): New AIST-21 Thrust. Continuous Integration of New Observing Strategies (NOS) and Analytic Collaborative Frameworks (ACF) Techs [1]

the system's ability to identify patterns, improve forecasting, and support decision-making in areas such as climate change adaptation, disaster response, and resource management.

The AIST program plays a critical role in developing information system frameworks for the ESDT, ensuring that these DT components operate cohesively. The program's objective is to create a computational environment that mirrors real-world Earth system dynamics, enabling "what-if" scenario analysis and predictive simulations. This approach is expected to enhance the ability to assess risks, model environmental changes, and develop proactive mitigation strategies. Although the AIST program has been operational since 2022, there are currently no published results of the project in Scopus, indicating that research and implementation are still in progress. At present, the only available documentation on the initiative is a conceptual paper, which outlines the framework and objectives of the ESDT without presenting empirical findings [1].

2.3 Biodiversity Digital Twin

Lecarpentier, Damien et al. [11] explore the development of prototype DTs for biodiversity conservation Biodiversity Digital Twin (BioDT), combining satellite data, ecological models, and artificial intelligence to improve ecosystem monitoring and biodiversity predictions. The BioDT project is funded by the European Union Horizon Europe Programme. The study highlights several key achievements in the field.

First, the authors describe advancements in biodiversity modeling, where they integrate statistical species distribution models with ecological process-based simulations. This approach allows for more accurate predictions of species habitat changes and provides insights into how biodiversity might respond to environmental shifts, such as climate change or habitat destruction. Second, they focus on improved data fusion methodologies, combining satellite imagery, climate data, and field observations. The goal is to create a comprehensive and detailed representation of ecosystems, ensuring that different data sources are harmonized and can be used together effectively. However, the study does not clarify whether real-time data assimilation—the continuous updating of models with new incoming data—has been fully implemented, which remains a challenge in DT development. Third, the research explores scalable computational frameworks, using high-performance computing and cloud-based infrastructures to handle large biodiversity datasets.

While these technologies allow for efficient data storage and processing, it is unclear to what extent real-time data processing and analysis have been fully implemented. The authors emphasize the importance of making DTs dynamic and responsive to new information, but achieving real-time functionality remains an ongoing challenge. Additionally, the study acknowledges several challenges, including data standardization across different sources, the computational demands of large-scale simulations, and the need for interdisciplinary collaboration.

2.4 A New Digital Twin for Climate Change Adaptation, Water Management, and Disaster Risk Reduction

The development and potential of Denmark's national Hydrological Information and Prediction (HIP) system is presented by [12], with a focus on the DK-model HIP and its associated web portal, as a "digital twin" (DT) to improve climate change adaptation, water management, and disaster risk reduction (Fig. 3). The authors present a case study of how real-time dynamic updates of the DK-model HIP simulations, coupled with plug-in submodels, can form a national, real-time risk knowledge base for extreme hydrological events.

The research is framed within the context of EU climate change adaptation strategies and the IPCC AR6 report, emphasizing the role of digital transformation and DTs in enhancing risk assessment based on historical, current, and projected climate impacts. The authors also acknowledge the value of nature-based solutions.

The foundation of this DT is the DK-model HIP system, a detailed hydrological model for all of Denmark. Turning this system into a DT involves several key steps. First, the system continuously pulls in real-time data from a network of sensors across the country. These sensors track groundwater levels, soil moisture, and streamflow. This constant flow of data keeps the DT up-to-date with current conditions. To ensure the model is accurate, it is carefully calibrated using groundwater measurements

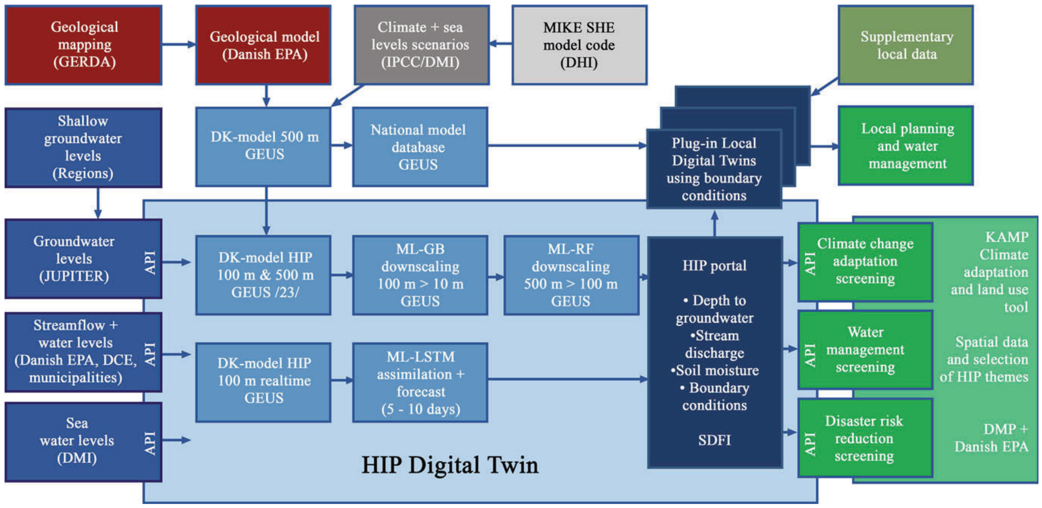

Fig. 3 HIP DT architecture [12]

from a national program. This allows for ongoing checks of the model's performance against real-world data, both now and in the future, under different climate scenarios. The system also uses hybrid machine learning (ML) techniques, combining traditional models with data-driven ML models like Random Forest, Gradient Boosting, and LSTM networks. These ML tools help to refine data, fill in missing information, and speed up simulations.

A key feature is the development of "plug-in digital twins" for local river basins. These smaller, more detailed models can connect with the national HIP DT. By receiving real-time information from the national model, these local twins can provide more precise assessments of water-related risks. Information from these local models can also potentially improve the national-level simulations. All model results, from both the 500 and 100 m resolution models (totaling 5 TB of data), are freely available through the HIP portal. This supports informed decisions about climate change adaptation, water management, and disaster risk reduction. The HIP portal, created by the Danish Agency for Data Supply and Infrastructure (SDFI), is the main interface for the DT. It offers access to model data, simulations, and risk assessments for water managers, emergency responders, and the public. The system works by the DK-model HIP delivering real-time model simulations, updated daily. The goal is to provide a 5–10 day forecast nationwide by 2025, enhancing its use for disaster preparedness. The HIP model can simulate past conditions (1990–2019) and project future climate change impacts for the near (2041–2070) and distant future (2071–2100) under different emission scenarios. As a physical model, it also offers insights into various water processes.

2.5 Digital Twins as an Implementation of the Digital Earth Concept

2.5.1 The "Digital Earth" Concept

The concept of "Digital Earth" was introduced by U.S. Vice President Al Gore in 1998, emphasizing the importance of developing a system that would "integrate all that is known about the planet" [13]. The overarching goal is to create a comprehensive, fully integrated three-dimensional representation of Earth, enabling users to "navigate through space and time, accessing historical data as well as future predictions (based, for example, on environmental models), and facilitating its use by scientists, policymakers, and the general public" [13].

The realization of this vision was proposed through research focused on ten key areas, including but not limited to: (1) information integration; (2) spatio-temporal analysis and modeling; (3) efficient data tiling and management schemes for Earth's curved surface; (4) intelligent data descriptions and filtering; (5) visualization of abstract spatial concepts; (6) computational infrastructure; (7) trust and quality models for information and services; (8) governance and collaborative frameworks; (9) data sharing and open-access policies; and (10) social and economic impacts of Digital Earth [14]. The vision of Digital Earth is supported by the International Society for Digital Earth (ISDE), which has advanced the concept through the integration of evolving digital technologies. Since its inception in 1998, the vision has undergone multiple revisions, with the latest occurring in 2022. The most recent assessment concludes that while many of the initially envisioned technologies are now available, the full potential of Digital Earth remains underutilized [15].

2.5.2 Relation to Digital Twins

Significant advancement proposed at the ISDE 2020 conference [16, 17], was the integration of the DT concept within DE vision. A DT serves as a dynamic link between the physical and virtual representations of the Earth, integrating "thermodynamic properties of our planet with associated environmental, economic, and social phenomena" [15].

In 2021, the definition of a DT was refined as "a digital replica of an Earth system component, structure, process, or phenomenon, obtained by merging digital modeling (particularly learning-based models) and real-world observational data streams. A DT continuously learns and updates itself, functioning as a living digital simulation that evolves alongside its physical counterpart" [3]. In conclusion, the integration of DT technology within the Digital Earth framework holds significant promise for enhancing our understanding and management of complex global systems. As the Digital Earth concept continues to evolve, embracing DT technology could bridge the gap between physical and virtual realities, thereby maximizing the utility and impact of digital earth applications. This integration represents a forward-thinking step toward achieving more sustainable and resilient management of the Earth's resources and environments.

2.5.3 Local Open Data Cubes as a Realization of the Digital Earth Concept

In the research [18], authors analyzed the use of local Open Data Cubes (ODCs) within the Digital Earth framework, emphasizing that "freely accessible Earth Observation (EO) data cube software has become one of the most widely used EO data management tools." The authors advocate for a "think global, cube local" approach, promoting interconnected local EO data cubes to enhance geographic specificity, community engagement, and decision-making efficiency.

Open-source EO data cubes provide a scalable and flexible analytical platform for managing large EO datasets. They support applications ranging from local research projects to global-scale analysis and enable a diverse set of users, from small research teams to large organizations [19]. The adoption of FAIR (Findable, Accessible, Interoperable, Reusable) data principles is critical for ensuring interoperability in EO data cube development [20].

Moreover, the integration of ODCs contributes to the realization of the Sustainable Development Goals (SDGs). EO data has been instrumental in addressing SDG targets related to clean water and sanitation (Goal 6), sustainable cities (Goal 11), marine and terrestrial ecosystems (Goals 14 and 15), and other domains by providing critical geospatial insights [21]. While EO data does not directly deliver SDG indicators, it provides essential spatio-temporal data that can be aligned with SDG targets. For instance, changes in land cover serve as indicators of land degradation or improvement under SDG target 15.3 [18, 22].

2.5.4 Living Earth for Land Cover Change Classification Based on EO Data

In terms of evidence-based decision-making is vital to use standardized descriptions of land cover change processes. References [23, 24] addresses the necessity of reliable and scalable land cover mapping to support Sustainable Development Goal (SDG) reporting. Research highlights EO data has become an essential resource for tracking and reporting SDG indicators, with the capacity to support approximately 40 targets and 30 indicators across various SDGs. However, despite advancements in analytical capabilities, such as ODC and machine learning, many nations lack access to standardized, operational land cover products tailored to their specific reporting needs. Existing land cover datasets are often inconsistent between countries and produced at spatial scales unsuitable for SDG reporting, limiting their practical applicability.

To address these challenges, a global framework was introduced based on the Food and Agriculture Organisation's Land Cover Classification System (FAO LCCS). The FAO LCCS provides a comprehensive taxonomy for land cover classification, offering a hierarchical and modular approach well suited for EO data. The authors introduce Living Earth, an open-source software package optimized for EO data, which enables standardized and globally applicable land cover classification. The system builds on previous efforts such as the Earth Observation Data for Ecosystem Monitoring (EODESM) system and ensures interoperability with existing national EO infrastructures. By maintaining the fundamental principles of the LCCS-2 framework, including its dichotomous and modular-hierarchical phases, Living Earth allows for the classification of landscapes even when complete input data is unavailable. The paper emphasizes that the implementation of Living Earth enhances the ability of nations to track and report land cover changes in a consistent and comparable manner. By identifying key environmental descriptors and prioritizing data collection efforts, the framework provides a practical approach to generating the most relevant input data for SDG target setting. The integration of Living Earth with high-performance computing resources enables the efficient processing of dense satellite time-series data, further improving land cover monitoring capabilities. Additionally, case studies like Digital Earth Australia (DEA) [25] and Swiss Data Cube (SDC) [26] demonstrate the benefits of a pixel-based approach to land cover analysis, enabling direct temporal comparisons at high spatial resolutions.

2.6 Lessons Learned from Existing DT Models

This section explores the ESDTs currently being developed to support environmental monitoring, climate adaptation, and disaster management. These systems integrate multi-source satellite data, AI-driven analytics, and predictive modeling to generate real-time simulations of Earth's processes. Notable initiatives, such as DestinE and NASA's ESDT, mark significant progress in environmental modeling and predictive analytics. One of the key strengths of existing DTs is their ability to assimilate real-time data, incorporating continuous updates from remote sensing and in-situ measurements, ensuring that simulations remain up to date. Additionally, AI-driven predictive analytics improve forecasting accuracy, enabling better anticipation of extreme weather events and more effective mitigation of climate change impacts.

However, despite these advantages, current Earth System DTs are not yet equipped to monitor land use changes effectively. Their primary focus is on climate and environmental variables, with limited support for detailed land use classification and change detection. Most DTs do not account for human-driven land use transitions, such as urbanization, agricultural expansion, or post-war land restoration. Another major challenge is the harmonization of diverse data sources—integrating multi-source satellite imagery, socioeconomic datasets, and in-situ observations requires standardized data pipelines. For instance, [27] emphasize the complexity of harmonizing models from various stakeholders, showing that successful integration requires technical interoperability and an understanding of the nuanced perspectives and interpretive frameworks of diverse data producers. This challenge is especially acute in areas like Land Use Change, where data, despite being from the same sector, must be synthesized into coherent, actionable representations.

High-resolution, near-real-time land use change monitoring also demands vast amounts of satellite data, presenting computational and storage challenges that hinder large-scale applications. Additionally, many existing DTs lack user feedback mechanisms, making it difficult to simulate different scenarios. These issues align with [28], who emphasize that DTs of Earth require sophisticated digital infrastructures to manage vast amounts of data and highlight that current implementations often lack mechanisms for users to effectively interrogate systems and explore response scenarios, which limits their practical application in decision-making processes. Such a gap prevents decision-makers from effectively adapting DT outputs for land use planning and incorporating them into governance policy-making.

To overcome these limitations, existing DT frameworks should be enhanced by integrating advanced land use classification models, multi-source data fusion, scalable computing infrastructure, and user-driven interfaces. The following section explores the data sources and models available to support the development of LUC-DT.

3 Conceptual Framework: A Digital Twin for Land Use Change's Estimation

3.1 Need for a Two-Timescale Approach

Land use change occurs at different temporal scales, requiring a structured approach to effectively capture both short-term disturbances and long-term transformations. Existing DT initiatives, such as DestinE, primarily focus on either high-frequency extreme events or long-term climate trends. However, when applied to land use monitoring, these approaches are often not fully integrated, despite the fact that both rapid disruptions and gradual transitions shape landscape dynamics. To address this gap, we propose a two-timescale framework that accounts for both immediate land cover disturbances and long-term transformations.

Sudden land use changes occur due to extreme weather events, natural disasters, and human-induced disturbances. These changes can significantly alter landscapes within days or even hours, requiring near real-time monitoring. DT models, such as the Weather-Induced Extremes Digital Twin within DestinE, focus on short-term climate hazards but do not fully integrate land cover changes resulting from these events. Floods, droughts, and storms can alter vegetation health and soil properties, while wildfires rapidly deforest large areas and disrupt ecosystems. Conflict-induced destruction, such as war-related infrastructure damage, can lead to sudden changes in urban and agricultural land cover, while environmental accidents, including dam failures and industrial spills, cause abrupt land degradation. To account for such rapid changes, a short-term monitoring component is needed, similar to how the Weather-Induced Extremes DT operates for meteorological events. This component would integrate high-frequency satellite observations, real-time remote sensing indices, and physics-informed AI models to detect and analyze land use changes, providing timely insights for response and mitigation.

In contrast, many land use changes unfold gradually over years or decades, influenced by climatic trends, demographic shifts, and socio-economic factors. The Climate Change Adaptation Digital Twin within DestinE focuses on long-term climate projections, but it does not specifically model land use transitions such as urbanization, agricultural shifts, or reforestation. For instance, rising temperatures and changing precipitation patterns are progressively shifting agricultural zones, affecting crop suitability and farming practices. Glacier melting and permafrost degradation influence hydrological systems and landscapes, while deforestation and afforestation reshape ecosystems and carbon storage over extended periods. Urban expansion and land abandonment, particularly in post-war or economically shifting regions, lead to gradual but significant transformations in land use patterns. These changes require a long-term modeling component, similar to how the Climate Change Adaptation DT models future climate scenarios. By integrating multi-year satellite data, climate models, socio-economic datasets, and machine learning-based land use forecasting, this component would provide a comprehensive analysis of land use trends and their future implications.

Therefore, monitoring of land use change requires a two-scale approach to capture both immediate disruptions and long-term trends. Short-term monitoring enables rapid response to extreme events, while long-term modeling provides insights for policy and sustainability planning. Integrating both perspectives, the proposed DT framework enhances existing initiatives like DestinE by incorporating land use-specific modeling across timescales, ensuring both reactive responses and proactive strategies for effective land management.

3.2 Structure of the Proposed Digital Twin Model

Within Ukrainian-Swiss Joint Research "DT4LC—Developing Scalable Digital Twin Models for Land Cover Change Detection Using Machine Learning" there have been proposed the development of an advanced DT model for monitoring the land cover of Ukraine and Switzerland based on satellite data (Fig. 4). This model should enable effective tracking of both rapid changes related to vegetation indices and gradual transformations in land use classes. Thus, our proposed model includes two branches:

1. **A rapid change branch** for near real-time monitoring and forecasting of vegetation index changes under the influence of climate, including extreme weather conditions, or other factors;

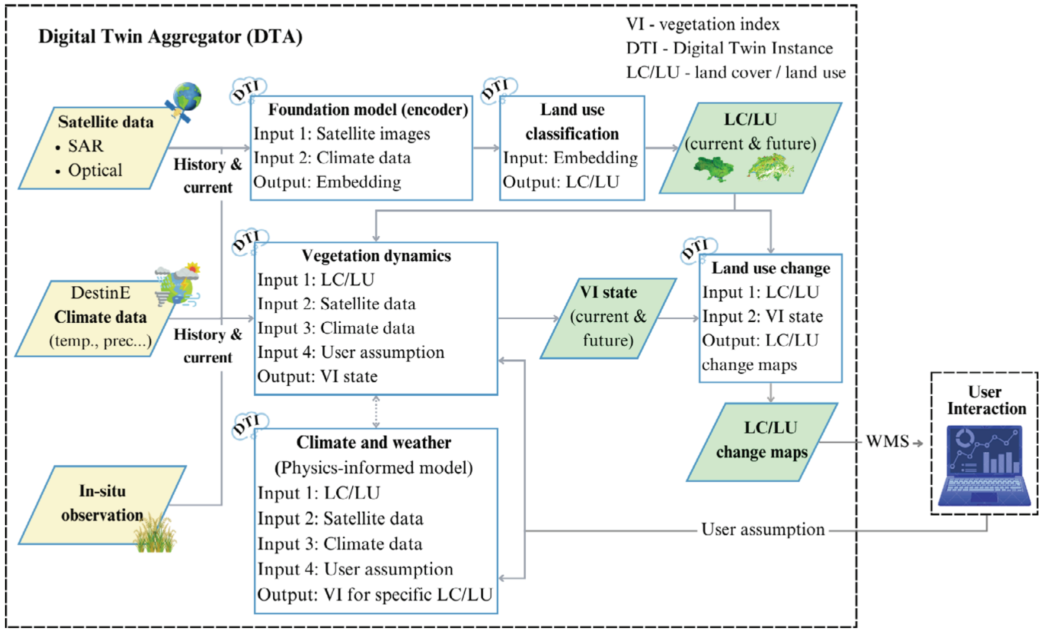

Fig. 4 Architecture of the proposed DT for monitoring land cover changes in Ukraine and Switzerland

2. **A gradual change branch** (slow LULC transformations) focused on analyzing land use class changes twice a year.

One of the key features of our DT is the ability for users to input their own scenarios of future climate changes through the user interface. This interactive capability ensures that the DT is not only a real-time monitoring tool but also a predictive system for landscape development under climate impact.

The proposed DT follows a two-tier vertical architecture. At the lower level, DT Instances (DTI) represent individual models linked to specific physical objects, continuously collecting data about these objects throughout their lifecycle [29]. In the rapid LULC changes branch, these objects are vegetation indices, and the DTI includes a VI Prediction Model and a Physics-Informed Model. In the slow LULC changes branch, the objects are LULC classes, and the DTI consists of a foundational segmentation model (encoder) and a decoder. Additionally, both branches are integrated by a DTI specifically designed for tracking land cover changes.

The DT Aggregator (DTA), in turn, integrates all DTIs, climate data, ground observations, and user assumptions, creating a unified system for land cover monitoring and forecasting.

Rapid change monitoring, particularly vegetation index variations, is performed using the VI Prediction Model. This model incorporates data on land use, satellite imagery, climate indicators, and user-generated climate change assumptions. The VI Prediction Model can be implemented as a spatial recurrent neural network or a transformer model; however, we do not impose strict architectural constraints at this stage. Our goal is to develop a system that, based on historical data, current conditions, and future climate and land use projections, can predict vegetation development for different land cover classes. This will enable users to track the potential development of vegetation after extreme events, such as severe weather conditions or anthropogenic impacts like flooding caused by dam failures. Additionally, they will receive recommendations on optimal future land use strategies, including selecting the most suitable areas for crop cultivation to maximize yields.

To enhance the accuracy of vegetation change forecasting, PINNs are employed for weather predictions [30]. These models incorporate physical principles and real-world constraints to improve the accuracy of climate and weather simulations, which in turn enhances vegetation forecasting. By integrating regional physical characteristics and enforcing physical constraints, PINNs contribute to more reliable assessments of vegetation index conditions for specific land use classes. Thanks to this approach, the DT can provide real-time insights into vegetation health while also improving the precision of long-term environmental predictions. Our DT is designed for simultaneous monitoring of multiple vegetation indices, including NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), GCI (Green Chlorophyll Index), and others. This allows for a comprehensive assessment of vegetation health, drought forecasting, and other ecological risks.

Due to the significant computational costs of constructing LULC segmentation maps and the relatively low frequency of LULC change, the generation of such maps has been assigned to a separate branch—the gradual change branch. This process is intended to be performed twice a year, aligning with the country's agricultural cycles. Specifically, the first map aims to detect the presence of winter crops, while the second focuses on summer crops.

At the core of this branch is a two-component LULC segmentation model. The first component is an encoder derived from existing foundation models, which utilizes satellite imagery and climate data to generate embedded representations. The second component is a decoder that processes these embeddings to achieve precise image segmentation and land use classification. While the encoder remains fixed, the decoder is trained to accurately determine the correct land use class. The outputs of this branch serve as the foundation for the rapid change branch and, when integrated with data from other models, contribute to a comprehensive understanding of land cover transformations.

The final component of our DT is the LULC change model, which integrates predictions of vegetation index and land use class changes to generate land cover change maps. These data are accessible for analysis through a specialized Web Map Service (WMS) accessible in user interface, allowing interaction with the system and input of future climate change assumptions.

4 Discussion: Challenges, Open Questions, and Future Research Directions

The development of a DT for land use change presents several challenges and opportunities. While integrating a two-timescale approach enhances the ability to monitor both rapid and gradual transformations, its implementation requires addressing key computational challenges, ensuring interoperability across diverse datasets, and effectively bridging the gap between technological advancements and decision-making processes. At the same time, the potential applications of such a framework extend beyond environmental monitoring, offering valuable insights for adaptive land management, climate resilience, and policy development.

One of the primary challenges in implementing a DT for land use change is the computational demand required for real-time processing of high-resolution satellite data and predictive modeling of long-term transformations. The short-term monitoring component relies on frequent updates from satellite imagery, climate observations, and machine learning models, requiring scalable cloud-based infrastructure and efficient data processing pipelines. The long-term modeling component, which integrates historical data with predictive simulations, demands robust computational frameworks capable of handling multi-source data fusion and scenario analysis. Optimizing the balance between computational efficiency and accuracy remains a key consideration in ensuring the system remains both responsive and scalable for large-scale applications.

Another critical issue is interoperability, as DT frameworks must integrate data from multiple sources, including satellite imagery, climate projections, in situ observations, and socio-economic datasets. Existing DTs, such as those developed under DestinE, face challenges in harmonizing heterogeneous data streams, particularly when combining optical and radar-based remote sensing with model-driven climate predictions. Standardized data formats, open-access platforms, and advances in AI-driven data fusion techniques are essential for ensuring seamless integration of multi-source datasets. Additionally, improved interoperability would enable better collaboration across different institutional and regional initiatives, fostering a more unified approach to land use change monitoring.

The potential applications of a DT framework for land use change are extensive. In climate resilience, it can support adaptation strategies by predicting shifts in agricultural zones, monitoring deforestation, and assessing the long-term impacts of climate change on land use patterns. In disaster response, real-time monitoring of extreme events such as floods, wildfires, and hurricanes can provide early warnings and guide mitigation efforts. Post-war reconstruction planning can also benefit from DT models, helping to assess damage, prioritize rebuilding efforts, and ensure sustainable land restoration. Furthermore, by integrating socioeconomic data, the framework can support urban planning, resource allocation, and land use policy development, ensuring that decisions are informed by comprehensive, data-driven insights. By addressing computational efficiency, ensuring data interoperability, and improving accessibility for decision-makers, a two-timescale DT for land use change can become a powerful tool for monitoring and managing dynamic land systems. Its ability to integrate high-frequency observations with long-term modeling provides a holistic approach that not only enhances scientific understanding, but also supports practical applications in climate resilience, disaster response, and sustainable land management.

5 Conclusion

Given analysis of major DT initiatives for Earth System, including DestinE, NASA's ESDT, and specialized implementations like the BioDT, reveals that while these systems excel at climate modeling and environmental monitoring, they face significant limitations in land use change applications. Most existing DTs focus primarily on atmospheric and climate variables, with limited support for detailed land use classification and change detection. They often don't give the ability to account for human-driven land use transitions such as urbanization, agricultural expansion, or post-war land restoration. Current models struggle with the harmonization of diverse data sources—integrating multi-source satellite imagery, socioeconomic datasets, and in-situ observations. Land use change monitoring demands substantial computational resources, creating scalability challenges for large-scale applications. Many existing DTs don't support effective user feedback mechanisms, limiting their utility for scenario-based planning and decision support in land management.

To address these challenges, within the Ukrainian-Swiss Joint Research "DT4LC—Developing Scalable Digital Twin Models for Land Cover Change Detection Using Machine Learning," we have developed a novel two-timescale DT architecture designed specifically for land use change monitoring. This framework consists of a rapid change branch and a gradual change branch, integrated through a Digital Twin Aggregator (DTA) system that enables comprehensive analysis across different temporal scales. The rapid change monitoring component focuses on near real-time monitoring of vegetation indices and fast land cover changes caused by extreme weather events, natural disasters, and human activities. It incorporates a VI Prediction Model for tracking multiple vegetation indices, Physics-Informed Neural Networks for enhanced weather forecasting, and real-time satellite imagery processing to detect sudden landscape alterations. This branch enables timely identification of floods, wildfires, drought impacts, and conflict-related landscape destruction, providing critical information for emergency response and short-term adaptation strategies. Complementing this, the gradual change component monitors long-term land use transformations that unfold over years or decades, influenced by climate trends, demographic shifts, and socio-economic factors. Through a foundation model-based land use segmentation approach, it generates comprehensive land cover maps on a bi-annual basis, tracking agricultural transitions, urban expansion, deforestation, and other gradual landscape changes. This component provides essential insights for long-term planning, climate adaptation, and sustainable development policies.

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