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# AI-Powered Digital Twin Framework for Land Use Change in Disaster Affected Regions

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***Abstract*—The increasing frequency and severity of natural and anthropogenic disasters, including those induced by war and climate change, demand innovative tools for monitoring, forecasting, and managing land use change. This paper presents a novel AI-powered Digital Twin (DT) framework tailored for disaster-affected regions, integrating multimodal satellite data, climate reanalysis, and in situ observations. The architecture comprises modular Digital Twin Instances (DTIs), each addressing specific thematic domains, such as vegetation dynamics, land surface temperature, and forest cover dynamics, coordinated through a central Digital Twin Aggregator (DTA). The system supports both rapid and gradual monitoring cycles, enabling timely and scalable assessments. We incorporate recent advances in geospatial foundation models, physics-informed neural networks, and semantic harmonization to address data heterogeneity and scarcity. The framework is demonstrated through pilot applications in Ukraine and Switzerland. In Ukraine, DTIs capture conflict-related cropland losses and forest degradation near the front line, as well as post-flood recovery following the Kakhovka Dam destruction; in Switzerland, annual-scale forest dynamics are assessed, highlighting gradual structural shifts in response to climate and socio-economic drivers. A cognitive user interface further enhances usability by integrating large language models for natural language interaction, improving accessibility for non-technical users. The proposed framework offers a scalable and adaptive approach to land use monitoring, with significant implications for disaster management, environmental recovery, and sustainable development.**

***Index Terms*—AI-Powered Digital Twin, Disaster Management, Land Use Change, Remote Sensing, Geospatial Foundation Models, Physics-Informed Neural Networks, Vegetation Dynamics, Spatio-Temporal Analysis, Multimodal Data Fusion, Cognitive AI Interface, Machine Learning for Earth Observation, Post-Disaster Recovery.**

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## I. INTRODUCTION

The growing complexity of disaster scenarios — driven by the confluence of climate change, extreme weather events, and armed conflicts — demands innovative tools for monitoring, forecasting, and decision-making. Climate-related hazards, such as floods, droughts, wildfires, and heatwaves, are increasing in frequency and intensity, while conflict-induced disruptions — including the destruction of infrastructure, displacement, and unregulated land use — create rapid and often unpredictable changes in land systems. These challenges underscore the need for intelligent systems that operate across spatial and temporal scales to support both immediate response and long-term recovery.

Digital Twins (DTs) — dynamic digital replicas of physical environments — are emerging as transformative tools for Earth observation and disaster management. By integrating real-time satellite data, AI-driven analytics, and simulation models, DTs offer the potential to monitor, analyze, and predict environmental conditions in a continuously updated and interactive framework. As defined by [1], an Earth System Digital Twin (ESDT) is "an interactive, integrated, multidomain, and multiscale digital replica of Earth's state and temporal evolution". Similarly, ESA's Digital Twin Earth (DTE) initiative also integrates satellite Earth observation, AI, and simulations to create a high-resolution, scenario-driven model for supporting environmental governance and resilience [2].

Despite significant advancements in environmental DTs, their application to land use change (LUC) — especially in disaster-prone or conflict-affected regions — remains underexplored. A review of the scientific literature reveals a disproportionate focus on climate modeling, urban infrastructure, and smart cities, with only a small subset of research addressing LUC-specific DTs. For example, in [3], the authors introduced a Cognitive Soil Digital Twin focused on localized soil health and ecosystem monitoring, while in [4], a glacier-focused DT was proposed for climate impact assessment in Alpine regions. These cases demonstrate technical feasibility but lack integration across broader land use systems and disaster scenarios.

Despite substantial investments in global Earth observation initiatives, existing systems fail to address three fundamental requirements for disaster-affected land monitoring: (1) **dual-timescale integration** of rapid event response with long-term recovery tracking, (2) **conflict-specific disruptions** that conventional environmental models cannot anticipate, and (3) **decision-ready outputs** for non-technical stakeholders man-

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aging post-disaster land governance.

Recent disasters exemplify these limitations. The June 2023 destruction of Ukraine's Kakhovka Dam created immediate flooding across 600 km² while triggering long-term agricultural abandonment affecting over 10,000 hectares. Existing monitoring systems could detect the flood extent but failed to provide integrated assessment of immediate crop damage, soil salinization patterns, and multi-year recovery trajectories needed for targeted rehabilitation planning. Similarly, wildfire-flood sequences in climate-vulnerable regions create cascading land use impacts that exceed the scope of single-hazard monitoring frameworks.

Emerging frameworks highlight the potential of DTs for participatory and adaptive land planning. In [5], authors argue for stakeholder-driven DT systems in sustainable land use strategies, though their work remains conceptual and lacks empirical grounding.

While several major initiatives have advanced environmental digital twin capabilities, each exhibits critical gaps for disaster-affected land monitoring.

Destination Earth (DestinE) provides powerful climate modeling through its Digital Twin Engine but focuses primarily on atmospheric and oceanic processes [6], [7], [8], [9]. While technically advanced, its climate models (IFS-NEMO, ICON) run at 5–10 km resolution. It is too coarse for field-level assessments required after events such as the Kakhovka Dam flooding. Land is parameterized as a boundary condition rather than a dynamic variable, preventing detection of rapid land use transitions. Moreover, access requires specialized expertise, and the system lacks monitoring at intermediate scales (weeks to seasons) that are crucial for recovery planning.

NASA's Earth System Digital Twin (ESDT) targets large-scale Earth system processes including the water cycle and wildfire behavior [1]. However, its emphasis on global phenomena means it cannot capture the fine-grained, human-driven land transitions critical for post-conflict recovery assessment. The system lacks integration of socio-economic factors that drive land use decisions in disaster-affected regions.

The Biodiversity Digital Twin (BioDT) advances ecosystem monitoring through AI-enhanced satellite analysis [10]. Yet its own assessments acknowledge limitations in real-time data assimilation and scope restrictions due to data uncertainty. Crucially, it does not address the socio-economic dimensions of land use change, such as agricultural recovery patterns or conflict-induced land abandonment.

Denmark's HIP Digital Twin demonstrates sophisticated hydrological modeling with real-time sensor integration [11]. However, its thematic focus on water management limits applicability to broader land use transitions. The system also struggles to translate national-scale forecasts into locally actionable insights during emergencies.

These limitations reveal a critical research gap: t**he absence of integrated digital twin frameworks that can simultaneously monitor rapid disaster impacts and gradual recovery processes in land use systems, while providing decision-ready outputs for diverse stakeholders**. This gap is especially serious in regions hit by overlapping disasters, such as natural hazards combined with human conflicts, where land use changes occur through both predictable environmental processes and unpredictable human disruptions. This paper addresses these limitations through five key innovations:

1) **Dual-Timescale Architecture**: We introduce a novel framework integrating Rapid Change Monitoring (RCM) and Gradual Change Monitoring (GCM) branches that operate across complementary temporal scales—daily to weekly for disaster response, seasonal to annual for recovery assessment.
2) **Conflict-Informed Modeling**: Unlike existing environmental DTs, our framework explicitly incorporates human conflict as a land use change driver, demonstrated through Ukraine case studies including war-related agricultural abandonment and infrastructure destruction impacts.
3) **Modular Digital Twin Instances (DTIs)**: We develop specialized, interoperable DTI modules for vegetation dynamics, land use classification, climate forecasting, and user interaction, enabling flexible deployment across diverse disaster scenarios.
4) **Physics-Informed Integration**: The framework combines foundation models for land classification with physics-informed neural networks (PINNs) for climate and hydrological modeling, ensuring both data-driven adaptability and physical consistency.
5) **Cognitive User Interface**: We implement the first cognitive AI interface for digital twin land monitoring, enabling natural language interaction and scenario exploration for non-technical stakeholders.

This work is validated through complementary case studies in Ukraine (post-conflict agricultural recovery following the destruction of the Kakhovka Dam) and Switzerland (alpine land use transitions under climate change). These implementations demonstrate the framework's adaptability across different disaster types, geographic contexts, and data availability conditions. Upon completion of the development cycle, the framework and associated code will be released as open-source software to maximize research impact and reproducibility. By addressing the critical research gap in digital twin system, this release will enable researchers to adapt, extend and integrate these methods into their case studies across diverse contexts.

The remainder of this paper is organized as follows. Section II reviews related work on Digital Twin initiatives and enabling technologies for environmental and disaster monitoring. Section III presents the complete digital twin architecture with detailed DTI specifications. Section IV describes use cases demonstrating the application of the DT in disaster-affected and dynamic regions. Section V discusses the main challenges, standardization issues, and open research questions. Finally, Section VI provides conclusions and outlines directions for future work.

## II. Core Data Sources and Modeling Frameworks for Digital Twin Implementation

Designing an effective Digital Twin (DT) for land use monitoring in disaster-prone and dynamic environments requires a robust, interoperable data infrastructure and advanced analytical capabilities. DTs tailored for disaster management must integrate multi-source satellite observations, real-time remote sensing, climate projections, socio-economic indicators, and AI-driven analytics to track both rapid and gradual changes in land systems.

This section explores the core data sources and computational models necessary to support such a DT framework. We examine climate and meteorological datasets, spatio-temporal remote sensing platforms, geospatial intelligence, artificial intelligence (AI) and machine learning methods for predictive modeling, IoT-enabled ground sensor networks, and the emerging role of foundation models in unifying heterogeneous data streams. Together, these components enable Digital Twins to function as responsive, real-time systems that support disaster detection, early warning, damage assessment, and long-term recovery planning, thereby enhancing resilience and adaptive land use management in the face of both climate and conflict-driven disasters.

### A. Climate Data

Climate and meteorological data serve as crucial inputs for DTs in land use change, as they capture key environmental drivers such as temperature shifts, precipitation patterns, and extreme weather events. These factors influence both short-term land cover changes (e.g., floods, droughts) and long-term transformations (e.g., shifting agricultural zones, desertification). The European Union's DestinE initiative exemplifies how advanced climate data integration can support comprehensive environmental monitoring by integrating high-resolution climate reanalysis, real-time weather data, and future climate projections to model environmental changes at multiple scales.

The core of DestinE consists of a cloud-based infrastructure that integrates historical climate reanalysis, real-time weather data, and predictive models. The DestinE Data Lake acts as a centralized repository, storing extensive climate datasets derived from ECMWF's reanalysis products, future climate projections from ScenarioMIP, and high-resolution satellite observations from ESA and EUMETSAT. The Core Services of DestinE allow users to perform on-demand climate simulations, facilitating climate-sensitive decision-making across multiple sectors.

The datasets in the form of Data Cubes (Fig. 1) available through DestinE integrate multiple sources, including ERA5 [12] and ERA5-Land [13], which provide historical reanalysis data covering atmospheric and land surface conditions with high spatial (0.25° for ERA5 vs 0.1° for ERA5-Land) and temporal resolution (up to hourly data from the 1940s to the current date).

For future climate projections, DestinE incorporates the ScenarioMIP experiments, which are part of CMIP6 (Coupled Model Intercomparison Project Phase 6). These include the SSP3-7.0 scenario, representing a high-emissions future with weak global cooperation on climate policies, significant warming, and an increased likelihood of extreme climatic events. The numerical climate models used in DestinE include IFS-NEMO [14], a coupled ocean-atmosphere model optimized for medium-range to long-term forecasting, and ICON [15], an advanced global model employing a dynamical grid size

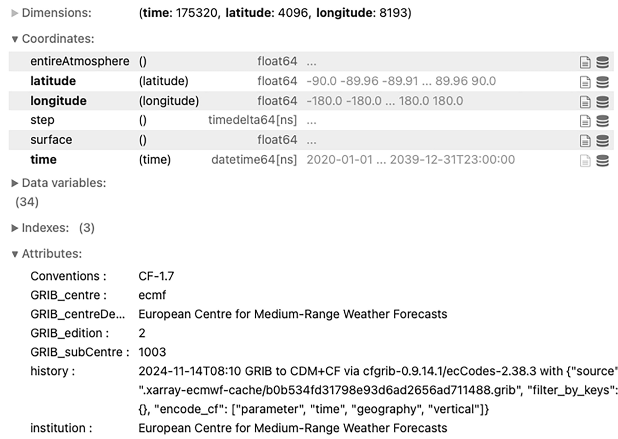


Fig. 1. Data Cube of climate data from IFS-NEMO over DestinE infrastructure

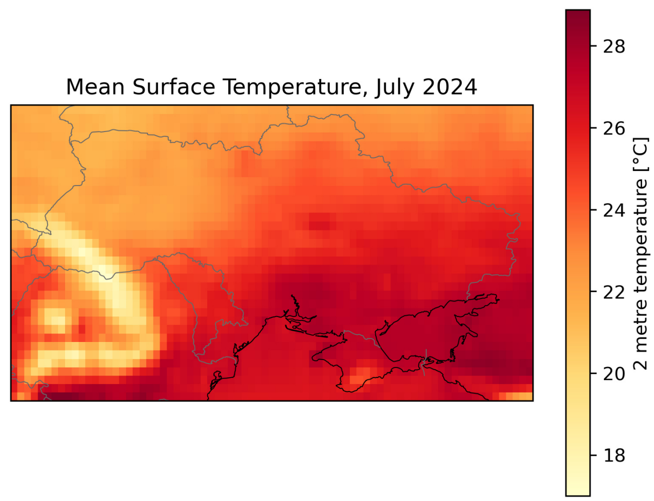


Fig. 2. Mean Surface Temperature for July 2024 over the territory of Ukraine derived from the ERA5 dataset

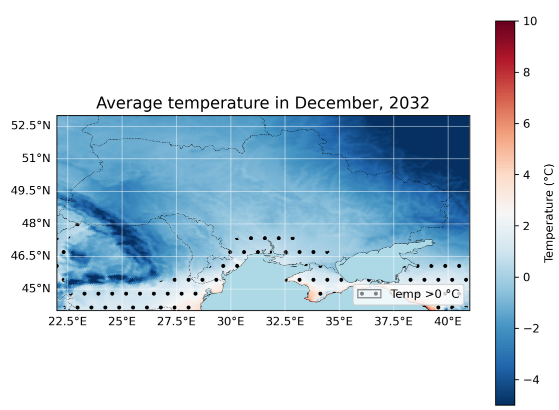


Fig. 3. Mean Surface Temperature for December 2032 over the territory of Ukraine derived from the IFS-NEMO dataset

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(with resolutions of 5 to 10km) for improved representation of atmospheric and climate processes. These models provide critical insights into temperature variability, precipitation patterns, ocean circulation, and extreme weather occurrences with temporal resolution up to 1 hour and a significant time frame (extending to 2031-01-01 for both IFS-NEMO and ICON).

Fig. 2 and Fig. 3 demonstrate practical applications of DestinE climate data for regional analysis in Ukraine. In Fig. 2, a sample workbook was modified to calculate the Mean Surface Temperature for July 2024 over Ukraine's territory, derived from the ERA5 dataset. In Fig. 3, adaptation for the territory of Ukraine was performed for the Mean Surface Temperature calculation for December 2032 over the territory of Ukraine derived from the IFS-NEMO dataset.

### B. Remote Sensing and ODC

Remote sensing technologies, particularly Sentinel and Landsat satellites, provide the spatial and temporal resolution needed for detailed land use monitoring. Their multispectral, thermal, and radar data enable precise detection of land cover changes and vegetation dynamics. Sentinel offers frequent optical and radar observations, while Landsat contributes a long-term historical record, together supporting trend analysis. Integrated with cloud-based platforms, these datasets enable scalable, near real-time analytics for land monitoring and disaster response.

To support the efficient management and analysis of large-scale geospatial datasets, specialized frameworks such as the Open Data Cube (ODC) and Living Earth [16], [17] have been implemented in Ukraine. The ODC is an open-source framework for managing and analyzing large-scale Earth observation datasets in a scalable and distributed way across on-premise HPC environments, cloud platforms such as AWS, Google Cloud, Microsoft Azure, Creodias, etc. ODC provides a structured framework for multidimensional spatiotemporal data indexing, enabling rapid access to multi-sensor, multi-temporal satellite data [18]. The core architecture (Fig. 4) is built on a PostgreSQL database with an optimized geospatial indexing system, facilitating seamless retrieval and processing of raster datasets. The ODC framework is primarily implemented in Python, leveraging xarray, GDAL, rasterio, etc. for high-performance geospatial analysis and parallel computing.

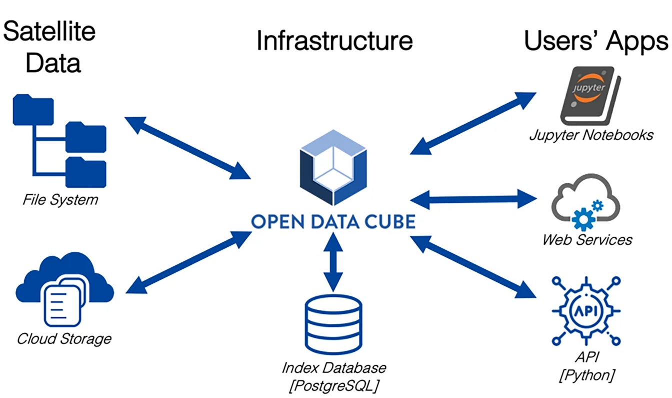
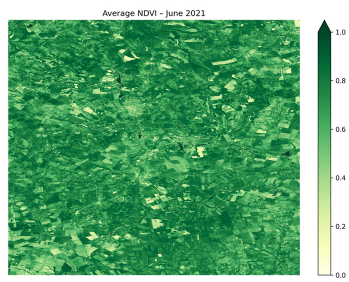



Fig. 4. High-level architecture of ODC [19]

| measurement | name | dtype | units | nodata | aliases | flags_definition |
|---|---|---|---|---|---|---|
| **coastal** | coastal | uint16 | 1 | 0 | [band_01, B01, coastal_aerosol] | NaN |
| **blue** | blue | uint16 | 1 | 0 | [band_02, B02] | NaN |
| **green** | green | uint16 | 1 | 0 | [band_03, B03, green] | NaN |
| **red** | red | uint16 | 1 | 0 | [band_04, B04, red] | NaN |
| **rededge1** | rededge1 | uint16 | 1 | 0 | [band_05, B05, red_edge_1] | NaN |
| **rededge2** | rededge2 | uint16 | 1 | 0 | [band_06, B06, red_edge_2] | NaN |
| **rededge3** | rededge3 | uint16 | 1 | 0 | [band_07, B07, red_edge_3] | NaN |
| **nir** | nir | uint16 | 1 | 0 | [band_08, B08, nir, nir_1] | NaN |
| **nir08** | nir08 | uint16 | 1 | 0 | [band_8a, B8A, nir_narrow, nir_2] | NaN |
| **nir09** | nir09 | uint16 | 1 | 0 | [band_09, B09, water_vapour] | NaN |
| **swir16** | swir16 | uint16 | 1 | 0 | [band_11, B11, swir_1, swir_16] | NaN |
| **swir22** | swir22 | uint16 | 1 | 0 | [band_12, B12, swir_2, swir_22] | NaN |
| **scl** | scl | uint8 | 1 | 0 | [mask, SCL, qa] | {'qa': {'bits': [0, 1, 2, 3, 4, 5, 6, 7], 'val... |
| **aot** | aot | uint16 | 1 | 0 | [aerosol_optical_thickness, AOT] | NaN |
| **wvp** | wvp | uint16 | 1 | 0 | [scene_average_water_vapour, WVP] | NaN |

Fig. 5. s2_l2a collection metadata of Sentinel-2 data indexed in Ukrainian ODC




```python
import numpy as np
import matplotlib.pyplot as plt
from datacube import Datacube

# --- ODC connect ---
dc = Datacube(app='ndvi_june2021')
# --- ROI and timeframe ---
lat, lon = 49, 31
buffer = 0.25
query = {
    'time': ('2021-06-01', '2021-06-30'),
    'x': (lon - buffer, lon + buffer),
    'y': (lat + buffer, lat - buffer),
    'output_crs': 'EPSG:6933',
    'resolution': (-20, 20),
}
# --- Load Sentinel-2 ---
ds = dc.load(product='s2_l2a', measurements=['red', 'nir', 'scl'], dask_chunks={}, **query)
# --- NDVI calc ---
cloud_mask = ds.scl.isin([4, 5, 6, 7])  # non clouded pixels
ndvi = (ds.nir - ds.red) / (ds.nir + ds.red)
ndvi = ndvi.where(cloud_mask)
# --- Averaging NDVI ---
ndvi_mean = ndvi.mean(dim='time', skipna=True)
# --- Visualisation ---
plt.figure(figsize=(8, 6))
ndvi_mean.plot(
    cmap='YlGn',
    vmin=0, vmax=1,
    cbar_kwargs={'label': 'NDVI'}
)
plt.title("Average NDVI - June 2021")
plt.axis('off')
plt.tight_layout()
plt.savefig("ndvi_mean_june2021.png", dpi=300, bbox_inches='tight')
plt.show()
```

Fig. 6. Sample Ukrainian ODC usage: average monthly NDVI over selected ROI for June 2021 (left), sample of code based on ODC Python API (right)

A critical component of ODC's architecture is its ability to leverage cloud-based storage systems, particularly Amazon S3 and other object storage solutions, for handling large Earth Observation datasets. The framework natively supports Cloud Optimized GeoTIFF (COG), an efficient, cloud-native raster format that enables direct access to specific portions of large geospatial files without requiring full dataset downloads and allowing efficient lazy loading, avoiding unnecessary data duplication, and optimizing I/O operations.

The current implementation of ODC for the territory of Ukraine is based on a computation infrastructure hosted over OCRE (Creodias) and an AWS S3 public bucket with Sentinel-2 imagery available in COG format (s3://sentinel-cogs/sentinel-s2-l2a-cogs/). The dataset for the territory of Ukraine (Fig. 5) has been indexed in the ODC PostgreSQL database since 2017 to the current date, utilizing an automated update procedure that requires minimal effort to keep the Ukrainian ODC up-to-date.

Fig. 6 demonstrates a sample of average monthly NDVI calculated with the ODC Python API from Sentinel-2 imagery over the selected ROI.

In terms of data interoperability, ODC supports multiple Earth Observation data sources, including Landsat, Sentinel-1 and Sentinel-2, MODIS, Copernicus datasets, and climate reanalysis products such as ERA5 and CMIP6 scenarios, but for most of them, either local premises or S3 buckets with a "requester-pays" model should be used.

A key advantage of ODC is its open-source ecosystem, which fosters collaborative development and integration of

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domain-specific tools. Global implementations include Digital Earth Australia (DEA), Digital Earth Africa (DE Africa), and the Swiss Data Cube, which provide national and regional-scale geospatial analytics.

### C. Artificial Intelligence and Predictive Models

The combination of comprehensive climate data and analysis-ready satellite imagery creates opportunities for advanced AI-driven analysis and prediction. This subsection explores how machine learning and physics-informed models can leverage these rich datasets to provide both classification capabilities and predictive insights essential for Digital Twin applications.

*1) Machine Learning for Land Cover/Land Use Classification and Change Detection:* Accurate land cover and land use classification is essential for DT systems in land use change applications. Machine learning (ML) and deep learning (DL) techniques enable automated, large-scale mapping by integrating multi-source remote sensing data, including optical and radar imagery, to classify land cover types and monitor changes over time [20].

Several global land cover datasets have been developed using ML and DL techniques, providing essential data for monitoring land use changes. ESA WorldCover, for example, utilizes random forest and deep learning classifiers applied to Sentinel-1 and Sentinel-2 imagery to generate a 10m resolution land cover map [21]. The Copernicus Global Land Cover (CGLS) dataset, derived from Sentinel-2 and PROBA-V data, employs ensemble ML models, including gradient boosting and random forests, to classify land cover at 100m resolution [22]. Similarly, the MODIS Land Cover dataset (MCD12Q1) uses decision tree classifiers on MODIS imagery, providing annual land cover maps at 500m resolution with multiple classification schemes [23]. However, these datasets primarily focus on land cover rather than land use, limiting their application in urban planning and agricultural land use change analysis.

Emerging AI-driven land cover products, such as Google's Dynamic World, utilize deep learning-based segmentation models for near real-time classification at 10m spatial resolution [24]. This dataset integrates Sentinel-2 optical data with neural network-based classification models to provide updates every 2-5 days.

However, it lacks explicit land use classifications that distinguish agricultural land use types, which are critical for land use change Digital Twins. Despite the availability of global land cover products, they do not explicitly address land use and often lack the classification accuracy required at regional scales.

To overcome the limitations of global datasets, national frameworks have been developed to provide more detailed and context-specific land-use information. In Ukraine, annual crop classification maps are produced through support from the World Bank and EU-funded initiatives such as "Supporting Transparent Land Governance in Ukraine" and "Support to Agriculture and Food Policy Implementation (SAFPI)" [25]. These maps are integrated into the State Agrarian Registry and support agricultural monitoring, policy implementation, and harmonization with EU land governance standards.

Switzerland, on the other hand, utilizes the Swiss Land Use Statistics (Arealstatistik Schweiz), which combines remote sensing data with field surveys to produce detailed land use classifications for environmental planning and sustainable land management. In [16], the authors present a downscaling approach for Switzerland's land use/land cover (LULC) data, combining a nearest neighbors algorithm with an expert system to improve the spatial resolution of national LULC datasets. Their method enhances the accuracy of land use classification, making it more suitable for environmental modeling and decision-making at finer spatial scales.

These national frameworks underscore the importance of high-resolution, region-specific land use classification systems. However, to effectively support land use change Digital Twins, these frameworks must be further enhanced by integrating multimodal satellite observations and climatic data, ensuring more precise and dynamic monitoring capabilities.

Beyond classification, a critical challenge in developing land use change Digital Twins involves change detection, which requires identifying land cover modifications over time caused by natural processes or human activities. Despite advancements in ML-based classification, accurately distinguishing complex land use types remains difficult, particularly at the field level. Field delineation—the precise mapping of agricultural boundaries—remains an urgent yet unresolved issue. Existing land cover datasets struggle to define field boundaries with high accuracy, especially in heterogeneous landscapes with mixed cropping systems [26]. To fully integrate ML-based land use classification into DT frameworks, future research should prioritize the fusion of multi-source remote sensing data and interactive user feedback mechanisms. A promising approach for improving land use-specific classification models is the application of foundation models, which leverage large-scale, pre-trained AI architectures to harmonize diverse data sources and enhance classification accuracy across different regions and land use types.

*2) Physics-Informed Neural Networks and Advanced Modeling Approaches:* Recent progress in machine learning has significantly improved environmental modeling, especially for weather and land dynamics. However, standard data-driven approaches often lack physical realism and generalizability in data-scarce or disaster-prone environments. To address these challenges, physics-informed neural networks (PINNs) and other hybrid models have emerged, integrating known physical laws directly into AI architectures. This enhances forecast accuracy, improves model robustness, and supports simulation of complex environmental processes.

In weather and climate prediction, numerical weather prediction (NWP) systems—such as the ECMWF Integrated Forecast System—have traditionally provided high-quality forecasts by solving partial differential equations for atmospheric motion [27]. These methods are powerful but require massive computing resources and are sensitive to initialization errors [28], [29]. Meanwhile, new deep learning models trained on reanalysis datasets, such as ERA5, now demonstrate comparable or even superior performance. Examples include Pangu

[30], GraphCast [31], and AIFS [32], which deliver accurate forecasts at a global scale in a fraction of the time required by NWP. Other models, such as Gencast [33], incorporate uncertainty through generative methods, while foundation models like Prithvi WxC [34] and Aurora [35] support transfer learning across applications. Despite these advances, many of these models still struggle with extreme events and can produce physically inconsistent outputs [29].

PINNs help address these limitations by embedding physical constraints into neural architectures. For example, in storm surge forecasting, PINNs trained on ADCIRC simulations achieved higher accuracy with runtimes 1,000 times faster than referenced DNN methods [36]. Authors mention that the use of PINN, aside from better accuracy and speed, allowed them to work with a smaller dataset. All attributed to the ability to encode certain physical laws inside the base DNN.

In flood modeling, approaches like FloodCast and SC-PINN [37], [38] simulate dynamic flood behavior using adaptive physics-informed methods, outperforming hydrodynamic baselines.

For the FloodCast, the ability to combine satellite data and classical hydrodynamics allowed for the aforementioned enhancement, providing a more comprehensive, mulri-sourced grasp on the flood dynamics.

At the same time, the SC-PINN gave their authors enough flexibility to combine a classic idea of coefficient splitting for wave spatial characterization with a NN to get a more accurate understanding of spatiotemporal flood propagation pattern, achieving higher accuracy on the benchmarks.

Similar benefits have been shown in related areas. In [39], the authors applied a hybrid approach combining convolutional neural networks and physical equations to simulate Arctic sea ice concentration. The paper clearly outlines how PDE discovery can be combined with CNN, showing a promising example of systemic combination our paper suggests for Digital Twins.

In [40], researchers estimated evapotranspiration in Morocco by integrating semi-physical models into PINNs, improving accuracy under varying data availability due to a more robust, physics-motivated, backbone of the model. In [41], authors embedded shallow water equations directly into PINN frameworks to simulate dam-break scenarios, achieving orders-of-magnitude speedups over conventional solvers. Such type of performance is common for certain PINN scenarios, as they allow to “cache” a great deal of computation by embedding it into the physical loss.

More advanced hybrid frameworks are also being developed. NeuroSEM [42] couples PINNs with high-fidelity spectral solvers to simulate complex fluid dynamics, while Dyna-PINN [43] combines reinforcement learning with physics-informed policy learning, increasing sample efficiency and ensuring interpretability. These systems expand the potential use of PINNs in operational settings.

Despite these promising developments, challenges remain. Physics-informed models are sensitive to data quality and show lower adaptability to similar problems, as the physical backbone tends to be tied deeply to the problem’s definition [38]. They also demand more structured input data, as inconsistencies between data and embedded physics can degrade performance. Nevertheless, their ability to enforce physical plausibility and operate in low-data contexts makes them a valuable component of Digital Twin Instances (DTIs), particularly for disaster monitoring, climate forecasting, and land use change assessment.

In our Swiss–Ukrainian Digital Twin framework, PINNs are being considered to improve the accuracy and physical consistency of vegetation dynamics forecasting. In Ukraine, PINN-based modelling could be used to simulate the hydrological impacts of extreme events, such as the destruction of the Kakhovka Dam in June 2023. This large-scale infrastructure failure resulted in rapid flooding along the lower Dnipro River, displacing communities and transforming land use across thousands of hectares. By integrating remote sensing data with physics-informed hydrodynamic models, we aim to assess flood propagation and land cover changes in near real time, offering a replicable approach for disaster monitoring in other conflict-affected or climate-vulnerable regions. This framework is also applicable to alpine environments in Switzerland, where modular PINN architectures enable scalable modeling across varied topographies and climatic conditions.

Integration of physics-guided models is one of the framework goals. At the same time, land cover change data is known to be asymmetric in quantity and quality for different regions. This poses certain obstacles for models which rely on continuous data or assume continuity of the features. As a result, we believe that a development of PINNs compatible with *difference*, not *differential* models is due and is a part of our future research.

In particular, we source inspiration from integro-difference approaches common in certain areas of ecology and weather modelling [44], [45]. These models allow a more robust and transparent approach to data handling, lowering the embedded error levels due to less strict approximation requirements.

### D. Meteorological Data from IoT and Sensor Networks

While satellite observations, climate models and PINNs provide broad-scale coverage, ground-based sensors offer essential validation data and high-temporal-resolution measurements that are crucial for Digital Twin accuracy and reliability.

Meteorological stations play a critical role in real-time climate monitoring, providing high-resolution, ground-based (ground truth) observations for weather forecasting, climate analysis, and validation of remote sensing data. These stations continuously measure key atmospheric variables, including temperature, precipitation, wind speed, humidity, and atmospheric pressure, ensuring accurate assessments of weather patterns and long-term climate trends. The density and distribution of meteorological stations significantly impact the quality of climate models and observational datasets.

In our Swiss-Ukrainian project, we utilize meteorological observations from Swiss and Ukrainian stations. Switzerland operates a high-density meteorological network managed by MeteoSwiss [46], which includes approximately 160 automated stations (Fig. 7) across diverse geographic regions, from lowlands to high-altitude Alpine zones. This extensive coverage provides high-resolution climate data, enabling precise

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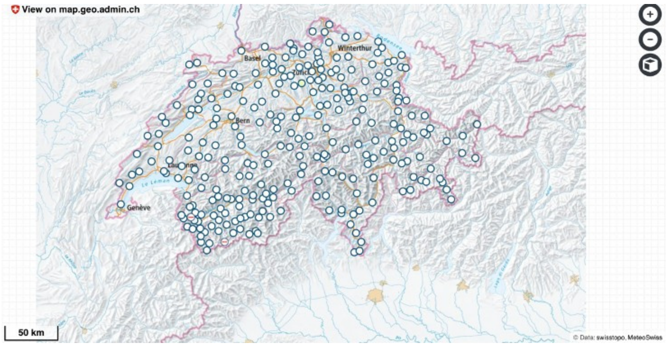


Fig. 7. Automated meteorological stations operated by MeteoSwiss

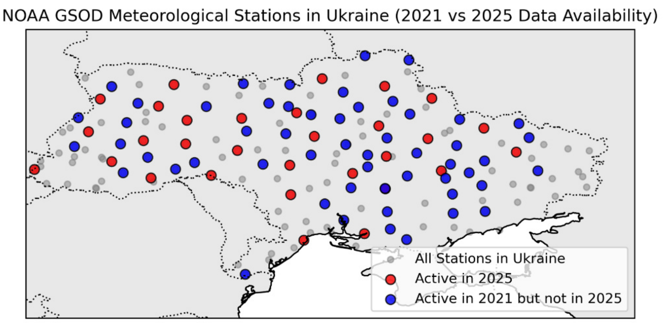


Fig. 8. Meteorological stations in Ukraine available within the NOAA GSOD dataset

monitoring of temperature fluctuations, precipitation distribution, and extreme weather events. The integration of real-time observations with advanced numerical models enhances climate risk assessments, hydrological modeling, and early warning systems for natural hazards such as avalanches and floods.

In contrast, Ukraine's meteorological network, previously comprising around 160 stations before the war, has been severely impacted by the ongoing conflict. As of now, only about 40 operational stations remain publicly available, significantly limiting the country's capacity for high-resolution climate monitoring and forecasting (Fig. 8). Despite its lower station density, the network provides essential climatological data for weather forecasting, agriculture, and disaster risk management.

### *E. Geospatial Foundation Models for Land Use and Vegetation Dynamics*

The rapid development of foundation models (FMs) is transforming how diverse data sources—such as climate reanalysis, satellite imagery, and in situ observations—can be harmonized and analyzed within Digital Twins (DTs). Foundation models are large-scale deep learning architectures trained on broad datasets, typically through self-supervised learning, and are adaptable to a wide range of downstream tasks [47], [48]. Initially developed for natural language understanding, with examples such as BERT [49] and GPT [50], these architectures have expanded into the visual domain through models like ViT and Swin Transformers [51], [52], and further into multimodal systems such as CLIP [53], ConvNet [54], and hybrid models combining both convolutional and transformer elements.

Since 2021, the number of vision foundation models for Earth observation has grown rapidly, with over 58 released as of early 2025 [55]. This ecosystem continues to expand with models of increasing scale and sophistication. Among them, Presto [56] is a transformer pre-trained on pixel-timeseries data from Sentinel-1, Sentinel-2, ERA5, and DEM sources. Prithvi, developed by NASA and IBM [57], is trained on Harmonized Landsat and Sentinel-2 (HLS) imagery and has been applied to multi-temporal crop segmentation and flood mapping. Its enhanced version, Prithvi-EO-2.0 [58], incorporates temporal and geolocation embeddings, improving generalization by up to 8% over its predecessor. EarthPT [59], trained autoregressively on Sentinel-1 data transformed via the CleanSky algorithm, targets spectral and vegetation index forecasting. CROMA [60] introduces separate encoders for Sentinel-1 and Sentinel-2 data and combines them through contrastive learning using a large, unlabeled dataset. DOFA [61] employs neural plasticity and dynamic weight generation to handle input from various sensors and modalities, including multispectral, radar, and hyperspectral imagery. Most recently, the European Space Agency released TerraMind [62], a multi-modal geospatial foundation model developed in collaboration with IBM Research Europe and FAST-EO partners.

These models vary significantly in their architecture, training data, and intended applications, from vegetation dynamics forecasting to burned area mapping. While they show strong promise, especially in early evaluations for disaster-related applications, their operational performance remains inconsistent and in many cases unvalidated. For some tasks, including crop classification under conflict-affected conditions in Ukraine, simpler models, such as Random Forests, still outperform current foundation model baselines, highlighting unresolved issues in scalability, transferability, and harmonization.

In our project, we are actively exploring which foundation models are best suited for integration into the DT framework. This process involves benchmarking their performance across different tasks and geographies. Given the pace of innovation, we anticipate that new models and techniques will continue to emerge throughout the project. Although the transformative potential of FMs for land use change monitoring and disaster management is considerable, their effective deployment will depend on solving critical challenges in data harmonization, generalization, and system interoperability, which we address in the following section.

### *F. Challenges in Heterogeneous Data Integration, Processing, and Scalability*

The development of Digital Twins for land use change monitoring in disaster-prone environments involves several technical challenges beyond data standardization. These include integrating heterogeneous datasets with varying spatial and temporal resolutions, ensuring sufficient computational resources for timely processing, and implementing consistent quality control procedures. Addressing these issues is necessary for building systems that can operate reliably in dynamic and data-constrained environments.

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A fundamental challenge lies in processing and analyzing multi-source data with disparate temporal and spatial characteristics. In the context of Ukraine's agricultural monitoring, integrating Sentinel-2's 10m optical imagery with daily meteorological data from the country's limited weather station network creates complex reconciliation requirements. As highlighted in [63], combining high-frequency meteorological data with lower-frequency satellite imagery involves significant challenges, including aligning differing temporal resolutions, managing spatial resolution discrepancies, and preserving temporal dynamics crucial for accurate crop mapping.

Similarly, Switzerland's high-resolution topographic data must be harmonized with coarser climate projections when modeling, for instance, Alpine land use transitions. This heterogeneity necessitates sophisticated processing chains that handle varying data structures and characteristics. As authors of [64] demonstrate in their work on the Swiss Data Cube, significant challenges arise in harmonizing metadata standards, resolving interoperability issues across diverse spatial and temporal resolutions, and effectively managing analytical workflows for multi-source Earth observation datasets. In Ukraine, where war has disrupted data collection infrastructure, processing pipelines must additionally account for temporal gaps and incomplete spatial coverage in recent observations.

The computational demands for processing Earth observation data at national scales are substantial. Processing a single year of Sentinel-2 data for a country the size of Ukraine requires extensive storage and significant computing resources. This computational intensity multiplies when implementing real-time change detection algorithms essential for the rapid change branch of the DT.

Current approaches leverage distributed computing frameworks to manage these requirements. In [65], authors highlighted the significance of cloud-based platforms, specifically Google Earth Engine, for efficiently managing complex processing workflows associated with large-scale land use monitoring in Ukraine. The authors discussed the necessity of robust computational infrastructures capable of seamlessly processing heterogeneous multi-temporal satellite imagery, emphasizing challenges such as handling non-uniform data coverage, temporal gaps, and spatial inconsistencies. Similarly, the Swiss Data Cube utilizes a hybrid infrastructure combining local high-performance computing with cloud-based processing to handle peak computational demands. As noted in [66], it is important to balance processing efficiency with accessibility, especially when supporting diverse stakeholders. Effective yet adaptable computational approaches capable of operating under intermittent connectivity are especially crucial for Ukraine, where war has impacted the digital infrastructure.

Quality assurance becomes increasingly complex when integrating multiple data streams with different error profiles. Satellite observations covering agricultural regions in Ukraine and mountainous landscapes in Switzerland are subject to various uncertainties, including atmospheric interference, sensor calibration inaccuracies, and terrain-induced distortions. Systematically addressing these factors during data processing is crucial for maintaining data integrity and ensuring the reliability of analytical outcomes.

Inadequate quality control measures can introduce significant errors in land-use classification and change assessments. Analysts must prioritize rigorous quality assurance to detect subtle yet meaningful transformations within DT representations of land use change, as even minor data noise can mask critical developments. Establishing robust validation protocols that effectively differentiate genuine land-use changes from processing artifacts remains an ongoing challenge, particularly in regions where ground-truth data are limited or difficult to obtain.

Data management efficiency demands strategic approaches to storage architecture, computation location, and transmission protocols. As datasets become larger, the principle of processing data close to its source has become increasingly valuable. In [67], this approach is demonstrated through their satellite mobile edge computing (SMEC) framework, which performs initial processing aboard satellites rather than transmitting all raw data to ground stations. Their implementation achieved remarkable improvements, handling up to 12 times more imagery than traditional downloading methods while substantially decreasing energy requirements. Such distributed processing capabilities may become crucial components of DT systems, particularly for rapid change monitoring, where near real-time analysis of satellite acquisitions is essential.

Optimizing data flows for Ukraine's and Switzerland's DT implementations requires addressing each country's infrastructure constraints. Switzerland's robust digital infrastructure naturally supports centralized data processing approaches. In contrast, Ukraine's digital environment — affected by disruptions due to ongoing conflict — necessitates distributed architectures that prioritize resilience, redundancy, and adaptability to changing operational conditions.

These technical challenges underscore the necessity for innovative approaches that balance scientific rigor with practical considerations. Solutions must not only meet analytical accuracy requirements but also remain feasible within operational constraints. Addressing these demands requires scalable, flexible, and resilient processing architectures that reliably support timely and accurate decision-making.

## III. Digital Twin Framework for Land Use Change and Disaster Impact Monitoring

The architecture of our Digital Twin for Land Use Change (LUC-DT) is specifically designed to address disaster-driven and climate-related transformations in land systems, integrating spatio-temporal remote sensing and dynamic modeling to support all phases of disaster management — from early warning to damage assessment and long-term recovery. The system operates across two distinct temporal layers — Rapid Change Monitoring (RCM) and Gradual Change Monitoring (GCM) — and combines real-time satellite Earth Observation (EO) data, high-resolution climate reanalysis, and AI models, including foundation models and physics-informed neural networks (PINNs). Unlike global frameworks such as DestinE or NASA's ESDT, which prioritise global climate extremes, our design introduces a solution-focused approach to disaster- and conflict-affected land use systems. The framework tends to coordinate Digital Twin Aggregator (DTA) and a harmonisation

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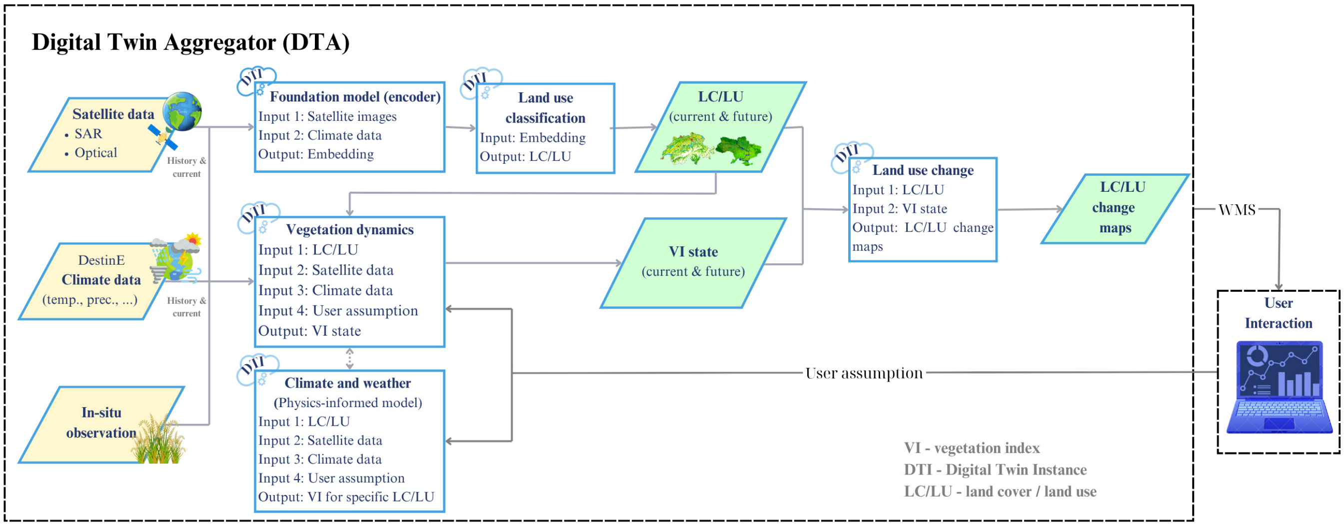


Fig. 9. The core architecture of the LUC-DT

layer to orchestrate multiple thematic Digital Twin Instances (DTIs), enabling modular yet interoperable monitoring across heterogeneous sources.

### *A. Integrated Monitoring of Rapid and Gradual Land Use Change*

RCM operates on daily to weekly time steps and is optimized for detecting disturbances such as fires, floods, or illegal logging. This layer integrates EO data streams—primarily Sentinel-2 optical and Sentinel-1 radar observations—with meteorological forecasts and in situ measurements. Machine learning methods, including temporal sequence models and pre-trained vegetation index classifiers, are applied to analyze time-series vegetation indices (e.g., NDVI, EVI) and detect anomalies. For weather-related extremes, the framework incorporates short-term forecasts derived from physics-informed neural networks that simulate localized atmospheric conditions influencing vegetation state. These predictions are complemented by near-real-time vegetation condition monitoring using optical and radar satellite composites processed via the Open Data Cube (ODC) infrastructure. The use of cloud-optimized GeoTIFFs and distributed ingestion pipelines ensures the efficient handling of high-volume, high-frequency data, providing continuous, spatially detailed monitoring suitable for emergency planning and response. This branch has been validated in Ukrainian and Swiss use cases for detecting crop damage during flooding and identifying illegal deforestation in protected areas.

GCM focuses on long-term structural land transformations and operates at seasonal or annual timescales. This branch supports biannual land use classification aligned with key agricultural seasons (e.g., spring planting, autumn harvest) and performs interannual comparisons to detect trends such as agricultural expansion, urbanization, or land abandonment. It employs encoder-based foundation models fine-tuned on regional datasets to classify land use with improved accuracy and reduced reliance on extensive ground-truth labels. Classification outputs are harmonized across years using standardized class definitions, enabling robust change detection and quantification of land transitions. These long-term outputs are integrated into national-scale land governance systems, supporting EU-aligned applications such as the development of Land Parcel Identification Systems (LPIS) and agricultural subsidy frameworks. In Ukraine, this branch supports annual crop-type mapping and post-war land recovery monitoring, incorporating Copernicus Sentinel data and local (country-level) datasets provided by the Ministry of Agrarian Policy.

This dual-scale structure enables the system to function as both a predictive tool for disaster risk assessment and a decision support mechanism for recovery planning, contributing directly to the goals of resilient and adaptive land governance under increasing environmental and geopolitical pressures.

### *B. Hierarchical Design and Modular Architecture of the LUC-DT*

The core of the architecture (Fig. 9) consists of a multi-instance design comprising a set of Digital Twin Instances (DTIs) and a coordinating Digital Twin Aggregator (DTA). Each DTI is responsible for a specific monitoring function, enabling a high degree of specialization and modularity. These instances operate either in near real-time or at lower temporal resolutions, depending on the nature of the disaster or land use change process being monitored.

This modular approach addresses the heterogeneous data integration challenges by allowing specialized processing pipelines for different data types and temporal requirements.

The proposed framework is intentionally model-agnostic, avoiding specification of particular algorithms for each DTI, in favor of defining the models' key functional roles. This design enables flexible integration and substitution of methods according to task, data availability, and performance requirements, while ensuring adaptability to heterogeneous inputs and long-term system reliability.

The Vegetation Dynamics DTI (Fig. 9) is the core component responsible for rapid change detection within the Rapid Change Monitoring (RCM) framework. This DTI focuses on short-term monitoring of vegetation condition by integrating high-frequency satellite observations and weather data through the Open Data Cube (ODC) architecture. It captures vegetation anomalies by combining Sentinel-2 optical data (NDVI/EVI) to track photosynthetic health with Sentinel-1 radar data to detect changes in physical structure and surface moisture, a synergy critical for assessing complex events like the Kakhovka Dam flood.

The monitoring process is multi-staged. First, to model the expected vegetation response, a baseline regression model is trained using long-term historical meteorological records, integrating ERA5 reanalysis data with the high-resolution E-OBS observational dataset. This model learns the normal relationship between a defined suite of meteorological drivers - primarily 2m temperature, total precipitation, and surface solar radiation - and the corresponding vegetation index for each land cover type and phenological stage. The output is a predicted, weather-driven baseline of what the vegetation condition should be. Second, anomaly detection is performed by quantifying the standardized deviation (z-score) between the real-time observed vegetation index and this predicted baseline. Finally, for stress prediction, these z-score anomalies are ingested by a Vegetation Stress Early-Warning Model (a Random Forest classifier), which assesses their magnitude and persistence to generate a probabilistic stress alert.

Beyond detecting current stress, the DTI forecasts its future evolution using advanced predictive models (Table I). For short-horizon (T+1) predictions, the VI Forecasting Model is used, for more complex scenarios, physics-informed neural networks (PINNs) could be used to simulate short-term, physically consistent stress responses to events like heatwaves or floods, while Spatio-temporal VI Forecasting Model (ConvLSTM [68]) is used to forecast the spread and evolution of these impacts over multiple weeks. By combining EO data with high-resolution weather inputs provided by the Climate and Weather DTI, the Vegetation Dynamics DTI supports proactive disaster response and short-term land condition assessments, providing, for instance, a near real-time view of vegetation loss in the Kakhovka floodplain.

Land Use Classification DTI (Fig. 9) generates land use maps by applying encoder-decoder deep learning models, including fine-tuned Vision Transformers, to harmonized multispectral and radar satellite imagery (Table II). Input data are processed through the Open Data Cube (ODC) framework to ensure standardized spatiotemporal referencing and analysis-ready formatting. The DTI produces land use classifications at a 10-meter spatial resolution, with biannual updates, aligned with key agricultural seasons.

The core classification pipeline incorporates foundation models such as Prithvi-EO-2.0, which uses 3D patch embeddings and temporal-geolocation encoding to capture land use dynamics from time-series satellite data. These models are adapted to regional contexts through supervised fine-tuning using national reference datasets. In Ukraine, training data include annual land use and crop classification maps from

TABLE I
VEGETATION DYNAMICS DTI MODELS DESCRIPTION.

| Model | Inputs | Outputs | Purpose |
|---|---|---|---|
| VI Forecasting Model (Random Forest Regressor) | NDVI/EVI time series (past n periods); land cover/crop type; ERA5/E-OBS meteorological drivers and short-range forecasts. | Predicted NDVI/EVI for T+1 period; prediction intervals (quantiles) for uncertainty; 10 m raster with optional field-level aggregation. | Provides rapid, short-horizon (T+1) VI forecasts by integrating recent VI trends with meteorological drivers. |
| Spatio-temporal VI Forecasting Model (ConvLSTM [68]) | Stacks of NDVI/EVI images (past m periods); DEM/ topography; land cover/crop type; soil/static masks; ERA5/E-OBS meteorology and short-range forecasts. | Multi-step NDVI/EVI forecasts (T+1 to T+4 period); spatially explicit lead-time estimates. | Exploits spatio-temporal context and correlation for robust, medium-horizon forecasting. |
| Vegetation Stress Early-Warning Model (Random Forest Classifier) | Observed and forecast VI anomalies (z-scores); VI trend/slope features; Sentinel-1 temporal variance; forecast meteorology; land cover/crop type. | Pixel-level probability of drought/stress for T+1 period; uncertainty score; 10 m raster map with field-level summaries. | Converts quantitative forecast departures from climatology into actionable, probabilistic stress alerts. |

TABLE II
LAND USE CLASSIFICATION AND CHANGE DETECTION MODELS

| Model | Inputs | Outputs | Purpose |
|---|---|---|---|
| Change detection model (Dynamic Vs [69]) | Pre- and post-event high-resolution RGB/SAR images | Binary change mask highlighting areas of significant change. | Visual foundation model fine-tuned for local disaster context; detects land cover changes by comparing imagery and highlights changed regions. |
| Land Cover/Use classification model (Random Forest classifier) | Sentinel-1/ Sentinel-2 pixel-wise time series; DEM | Land Cover/Use (LC/LU) classification map. | Provides a robust and computationally efficient baseline for generating biannual LC/LU maps, effective for handling multi-source data. |
| Geospatial features encoder (Prithvi-EO-2.0) | Multi-temporal satellite imagery; optional temporal, spatial metadata. | High-dimensional feature embeddings for each image patch. | A geospatial foundation model used as a powerful feature extractor (encoder). Its embeddings can be fed into a simpler decoder for state-of-the-art semantic segmentation. |

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2015 to 2024, developed under World Bank and EU-funded projects (e.g., SAFPI) and integrated into the State Agrarian Registry [70], [71], [72]. In Switzerland, the system leverages the Swiss Land Use Statistics and downscaled LULC products derived from expert-driven hybrid methods [16].

To address data integration challenges, such as differing spatial resolutions, inconsistent class labels, and partial temporal coverage, the DTI includes a harmonization layer that aligns spatial resolution, standardizes class definitions (e.g., FAO LCCS), and filters low-quality observations. Crucially, for monitoring extreme events, this DTI can be triggered into an event-driven mode to create rapid pre- and post-event land cover classification maps for immediate impact assessment. In this mode, following a major disruption like the Kakhovka Dam failure, pre-trained models are quickly fine-tuned with event-specific labels generated via rapid manual annotation to ensure classification accuracy against novel land cover signatures not present in the original training data. Outputs are used for national land governance tasks, including support for the EU-aligned Land Parcel Identification System (LPIS). They also serve as input to the Land Cover Change DTI for temporal analysis. In post-conflict regions, such as eastern and southern Ukraine, the resulting maps are used to assess recultivation and track land recovery.

Land Use Change DTI bridges the RCM and GCM frameworks by analyzing temporal transitions and detecting both rapid and gradual land use changes. This DTI is responsible for detecting and characterizing spatio-temporal transitions in land use by integrating classification outputs from other DTIs over multi-annual periods. The DTI leverages a stack of historical land use maps, delivered by Land Use Classification DTI as its primary input for temporal trend analysis. These maps, generated using supervised machine learning techniques on Sentinel-1 and Sentinel-2 data through cloud platforms including Google Earth Engine (GEE) and CDSE, form the basis for identifying patterns such as cropland abandonment, urban expansion, or forest degradation.

Change detection is performed through temporal comparison of harmonized land use classification layers using spatial differencing and class transition matrices. To ensure temporal consistency, classification outputs are first aligned by standardizing class definitions and spatial resolution. This is particularly important given the heterogeneity of input data and the presence of artifacts arising from sensor differences, seasonal variation, and cloud coverage.

This model enables the DTI to identify both gradual land use trends and abrupt transformations, such as floodplain inundation, fire scars, or the abandonment of agricultural lands due to conflict.

The Climate and Weather DTI (based on physics-informed model, Fig. 9) supplies key meteorological and climate inputs for simulating vegetation dynamics and supporting the broader Digital Twin framework (Table III). It integrates short- and long-term weather data to inform both rapid and gradual land use monitoring.

While the framework is model-agnostic, the following models were implemented for our use cases based on their specific strengths and accessibility. For short- to medium-term

TABLE III
DESCRIPTION OF CLIMATE AND WEATHER DTI MODELS

| Model | Inputs | Outputs | Purpose |
|---|---|---|---|
| ECMWF IFS [73] | Accessed via official ECMWF services (data assimilation handled upstream) | 15-day forecasts (12-hour cadence) for temperature, precipitation, wind, humidity. | Operational weather consumed by vegetation and other DTIs |
| GraphCast [31] | Recent atmospheric analyses/initial states (e.g., ERA5/IFS) | Short-range forecasts used to derive extreme heat/cold indices and regional risk masks. | Early warning for temperature extremes; focus regions needing additional attention. |
| CORDEX Simulations (ICON and IFS-NEMO) [74] | CMIP GCM simulations under multiple SSP scenarios. | Downscaled climate projections (temperature/ precipitation and derived extremes) for multi-decadal horizons. | Scenario-based long-term drivers for vegetation trend evaluation and climate risk assessment. |

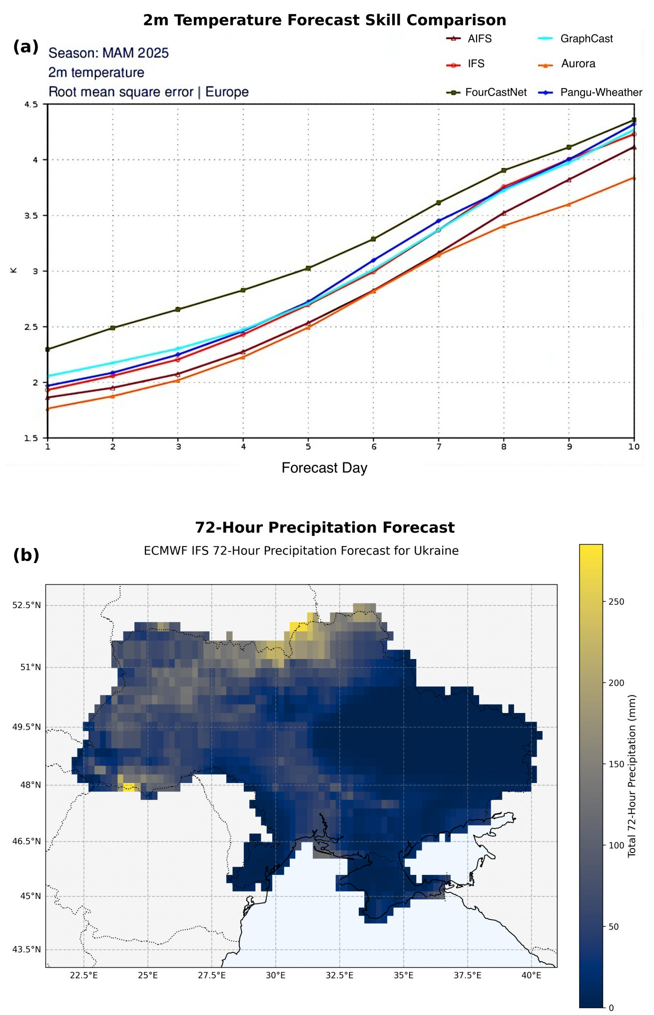


Fig. 10. a) Temperature prediction performance comparison of short-term models. b) Precipitation prediction of ECMWF IFS on Ukraine [73]

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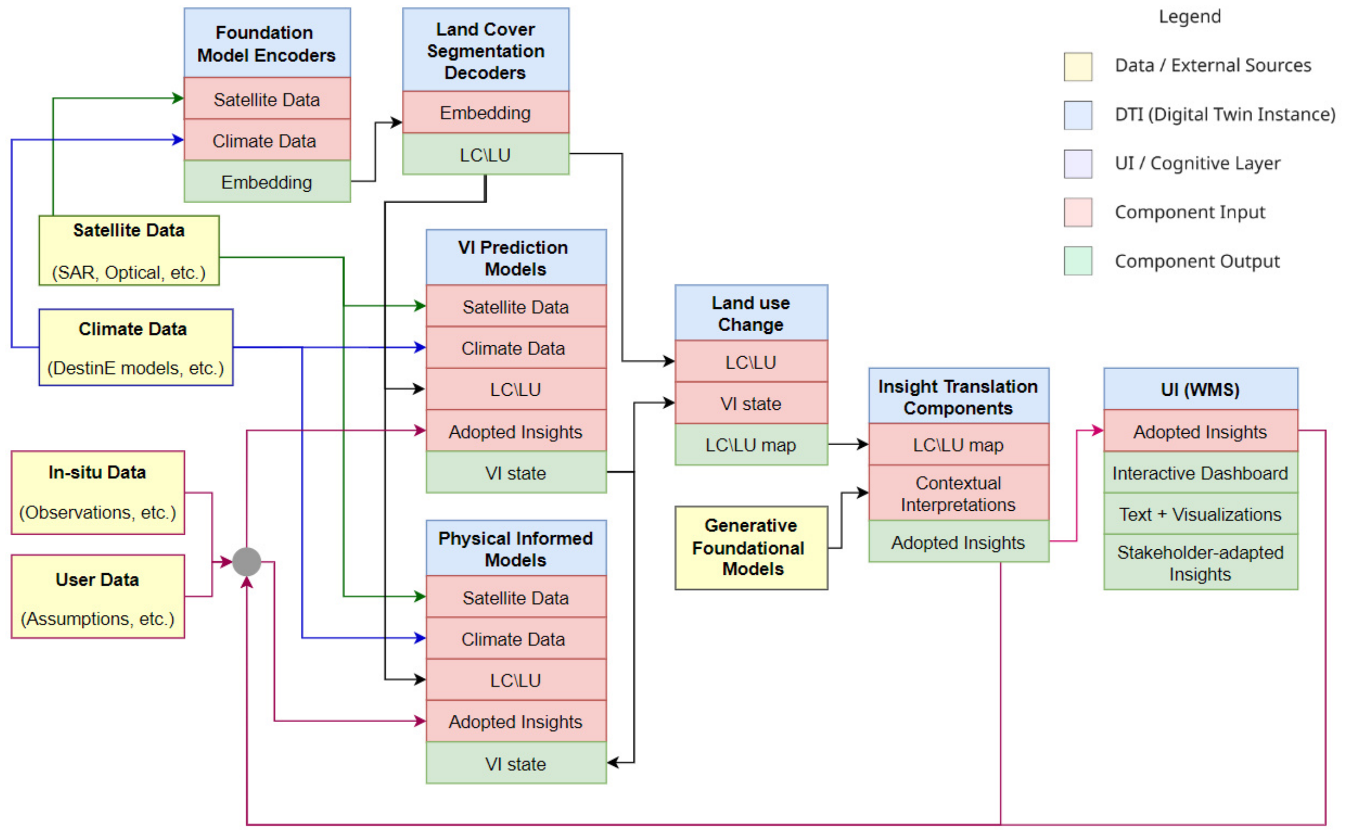


Fig. 11. Schematic representation of the data flow in the developing Digital Twin for Land Use Change

operational forecasting (up to 15 days), the DTI relies on ECMWF IFS forecasts [73]. This model was selected for its proven operational reliability and straightforward accessibility via cloud platforms like Google Earth Engine, which facilitates seamless integration with other satellite data-driven DTIs.

To specifically enhance early warning for high-impact events, GraphCast is used in parallel. As illustrated in Fig. 10, which compares the forecast skill of several leading models, GraphCast shows highly promising and competitive results, particularly for predicting extreme weather events. This specialized capability allows the DTI to flag regions requiring additional attention beyond the standard IFS forecast.

Longer-term assessments rely on an ensemble of projections from CORDEX simulations [74] driven by CMIP ensembles under multiple SSP pathways. To ensure the stability of these projections and align them with historical observations, they are bias-corrected using quantile mapping against the ERA5 reanalysis dataset.

To improve prediction accuracy in data-scarce or high-risk regions, the DTI can incorporate physics-informed neural networks (PINNs). These models embed physical constraints into the learning process and are applied to localized simulations of phenomena such as storm surges and flood propagation. Examples like FloodCast and SC-PINN demonstrate improved performance and efficiency compared to conventional hydrodynamic models. By combining real-time weather forecasts, climate projections, and physics-informed models, the Climate and Weather DTI supports key analytical tasks across the system, including vegetation monitoring, land use change detection, and scenario-based planning.

The Digital Twin Aggregator coordinates the outputs of individual Digital Twin Instances (DTIs), ensuring spatial and temporal alignment and enabling scenario modeling. It also supports cross-validation, integrates auxiliary datasets such as socio-economic indicators, and connects to the User Interaction DTI for system-level access (see Fig. 11).

Within the pipeline, foundation models are being evaluated for generating image embeddings to support land cover classification. Models such as Prithvi and Presto are under consideration; however, at the current state of the art, embeddings do not consistently improve classification performance. As a result, a Random Forest-based classifier is currently used as the baseline for the Land Use Classification DTI.

After feature harmonization and land use classification, outputs from this DTI are passed to the Vegetation Dynamics DTI, which supports rapid-change monitoring. This module integrates satellite observations with current and projected climate variables and can incorporate user-defined scenarios. To enhance consistency with biophysical processes, future versions will incorporate physics-informed neural networks (PINNs).

The DTIs feed into the User Interaction DTI, which allows users to explore outputs, upload new data, and simulate scenarios. Generative foundation models, including large language models (LLMs), are integrated to support interpretation

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and generate land-use recommendations based on observed changes. A cognitive interface with further agent orchestration enables non-technical users to manipulate their own data, receive natural language explanations and explore different on-demand scenarios interactively. Existing DT frameworks, such as DestinE, BioDT or HIP DT, do not provide such coverage for translating technical output into contextual insights, which is crucial for decision-makers in disaster and recovery contexts. The first version of this cognitive interface has already been implemented with conditionally open-source LLM models (LLAMA, Gemini, GPT) and is presented in the following subsection.

## IV. Demonstration of Regional Case Studies

This section presents pilot demonstrations of the proposed modular Digital Twin framework, designed to illustrate feasibility rather than provide comprehensive validation. Two contrasting regional contexts are considered. The Ukraine case demonstrates the integration of multi-source satellite data for monitoring conflict-induced land use change, while the Switzerland case illustrates transferability to gradual, climate-driven land use dynamics through annual-scale forest monitoring [72]. Although preliminary, these examples highlight key strengths of the framework, including scalable spatio-temporal analysis, cloud-based data integration, and the flexibility to incorporate diverse geospatial models as system modules across different geographic settings.

### *A. Application of Vegetation Dynamics DTI for Rapid Monitoring*

As part of our implementation of a DT in the branch of rapid land use/land cover change, we aim not only to monitor the current state of vegetation indices but also to forecast their values over a short period (forecasting horizon), based on assumptions about future weather conditions and land cover class. This allows us to estimate how vegetation will evolve following extreme events, which may result from either natural causes (such as extreme weather) or anthropogenic impacts (for example, the war in Ukraine, including the destruction of the Kakhovka Dam and the subsequent flooding of surrounding areas).

To achieve this, we are developing a regression model that forecasts vegetation index values at the pixel level n days ahead (the forecasting horizon). At this stage, we have implemented a Random Forest Regression model within the Google Earth Engine (GEE) environment. The model consists of 150 decision trees, each limited to a maximum of 500 leaf nodes to prevent overfitting and reduce the complexity of individual trees. Bagging was applied with a sample fraction of 0.6 (bagFraction = 0.6). These hyperparameters were optimized experimentally through multiple model runs and evaluation of $R^2$ and RMSE. The final parameter set was chosen to maximize $R^2$ and minimize RMSE.

The training methodology incorporates both satellite observations and climate data, reflecting the integrated approach outlined in Section 3. To train the model, we randomly selected 250 points (Fig. 12) within the area of interest near

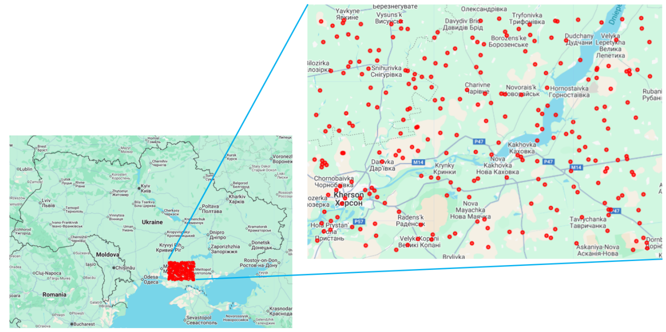

Fig. 12. Distribution of randomly selected training points for VI forecasting model

the Kakhovka Dam and collected time series data for them over the period from January 1, 2022, to January 1, 2024. The training points were implemented as a FeatureCollection dynamically generated on the GEE server and were not stored locally. The points were randomly distributed across the study area using internal randomization procedures in GEE to ensure spatial coverage and minimize clustering. The intended total sample size was 250 locations × 3 ten-day composites × 24 time steps = 18,000 records; however, due to missing satellite data on some dates caused by cloud cover, the actual number of training records was 11,699.

Each training sample included the following input features:

- 10-day mean composites of vegetation indices (from Sentinel-2) over the past 30 days.
- Daily mean temperatures from ERA5-Land for the past 30 days.
- Forecasted daily temperatures for the next n days (forecasting horizon).
- Land cover class values for the past 30 days, based on outputs from our Digital Twin's gradual land use/land cover change branch.

The satellite data used for training were pre-processed to remove clouds using the s2cloudless algorithm. Input features were selected experimentally by testing different combinations, including previous NDVI values, temperature, and other relevant variables, to identify the most informative set for forecasting. While no formal parametric study was conducted at this stage, this iterative approach allowed the model to achieve improved predictive performance despite occasional missing data due to cloud cover or sensor gaps.

The model's output is a predicted 10-day vegetation index composite, starting n days in the future (the forecasting horizon).

Initial results demonstrate promising accuracy while revealing areas for improvement. Fig. 13 presents an example of NDVI and NDWI forecasting results with a 15-day forecasting horizon. As shown, even at the development stage, the model produces reasonably accurate forecasts, with RMSE values of 0.09 and 0.07 for NDVI and NDWI, respectively.

However, visual analysis indicates a tendency for the model to smooth the vegetation index values, meaning it reduces local variability and fine-grained spatial contrasts. This results in a less detailed representation of sharp boundaries, especially

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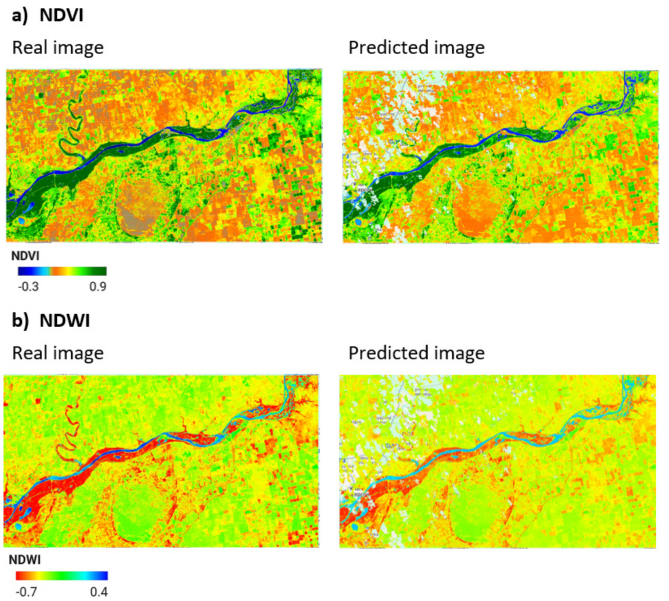


Fig. 13. Example of vegetation index forecasting with a 15-day forecast horizon near the Kakhovka Hydroelectric Power Station (10-day mean composite for 06/15/2024–16/25/2024). a) NDVI forecast, b) NDWI forecast

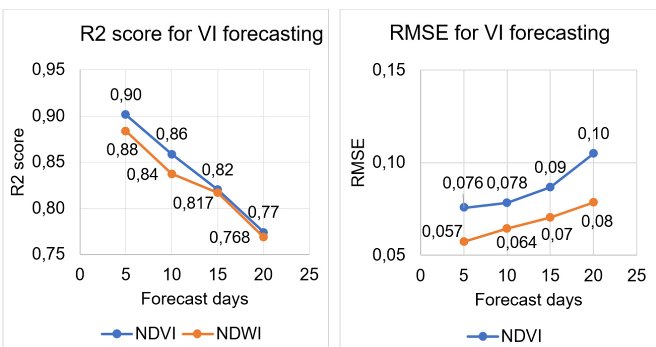


Fig. 14. Dynamics of model accuracy depending on the duration of the forecasting horizon. Averaged results for all available 10-day composites from January 1, 2024, to December 31, 2024

in areas with heterogeneous land cover such as riverbanks or irrigated plots. In both NDVI and NDWI predictions, the overall spatial pattern is retained, but certain features (like narrow vegetation corridors or wetland edges) appear more diffuse compared to the real images. This smoothing effect may be attributed to the averaging behavior of the model during training and could be addressed in future development by incorporating mechanisms that better preserve such details.

Performance analysis reveals predictable degradation with extended forecasting horizons. In Fig. 14, the model's accuracy is shown to change with the length of the forecasting horizon. For instance, at a 5-day horizon, the RMSE and $R^2$ for NDVI were 0.076 and 0.90, respectively. As the forecasting horizon increases, the errors grow consistently, reaching an RMSE of 0.1 and an $R^2$ of 0.77 at a 20-day horizon for NDVI.

Additionally, we considered the test period immediately after the flooding (2023-06-06 to 2023-07-21, 15-day forecast horizon) to evaluate model reliability under extreme events. The model yielded an $R^2$ of 0.705 and RMSE of 0.103 for NDWI, and an $R^2$ of 0.71 and RMSE of 0.12 for NDVI. These results indicate that the model can reasonably capture the immediate impacts of extreme anthropogenic events on vegetation and water indices.

### *B. Monitoring Gradual Land Use Change Through Forest Dynamics in Switzerland and Ukraine*

As part of the implementation of the gradual land use/land cover (LULC) branch of the proposed Digital Twin framework (see Table II), we demonstrate how annual forest dynamics can be monitored to detect spatial hotspots and long-term trends. This functionality builds upon our previous work on large-scale land cover mapping and forest classification using satellite data and advanced machine learning approaches [75], [76]. Annual 10 m resolution forest maps generated for Ukraine and Switzerland provide consistent temporal information on forest extent and composition [77].

The analysis reveals a consistent decrease in total forest area in both Ukraine and Switzerland between 2022 and 2024, although the magnitude and underlying drivers differ substantially. In Ukraine (Fig. 15a), total forest cover declined by 6% over this period, with the most significant hotspots of deforestation located in Donetsk, Luhansk, and Kharkiv regions along the active conflict line. The decline is primarily attributable to direct destruction, fire damage, and the disruption of forest management practices during the war. These results are consistent with previous studies highlighting the vulnerability of forest resources to armed conflict and associated disturbances [72], [78], [79]

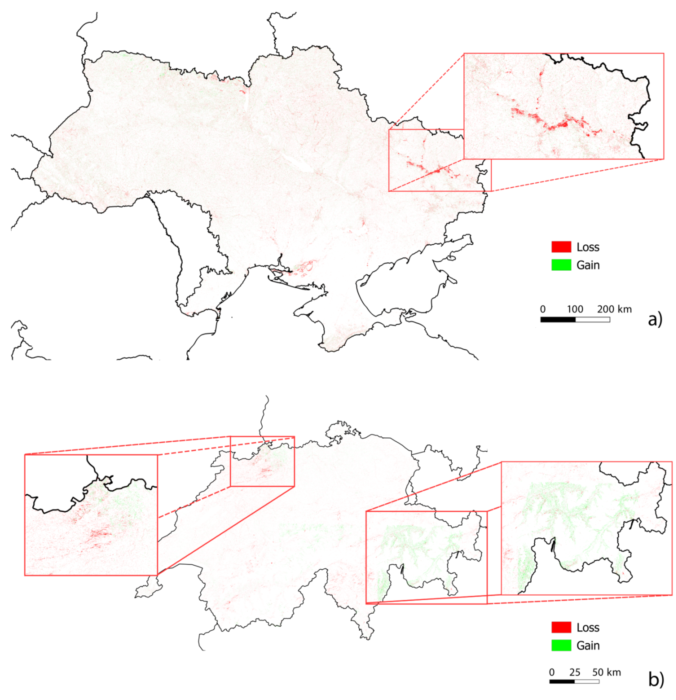


Fig. 15. Annual changes in Ukraine (a) and Switzerland (b) forests, 2024 to 2022

In Switzerland (Fig. 15b), forest cover declined more slowly (–0.9% between 2022 and 2024), and the changes are mainly

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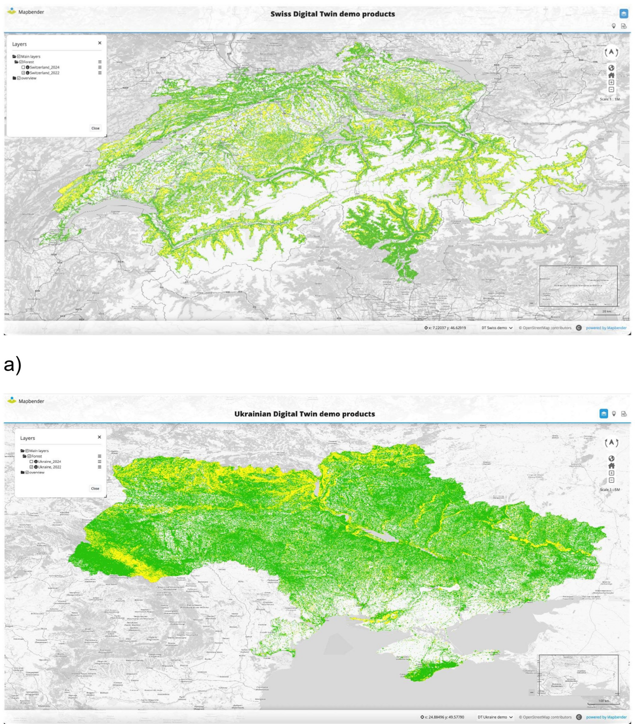


a)

b)

Fig. 16. Forest maps for Switzerland (a) and Ukraine (b) available at the geoportal

associated with climate and anthropogenic drivers. Warming temperatures and land-use pressures contribute to gradual shifts in forest structure, with broadleaved and mixed forests expanding at the expense of coniferous stands. Hotspots of deforestation are primarily observed in the Northern Plain, linked to infrastructure and urban development, while reforestation is evident in the Southeastern mountains, often due to the abandonment of pastures or cropland.

The availability of consistent annual forest maps, combined with change layers at the geoportal (Fig. 16), enables the detection of both deforestation and reforestation hotspots, as well as the attribution of gradual land cover transitions to their drivers. Beyond forest monitoring, the same approach supports broader land cover assessments, including agricultural, urban, and abandoned land transitions. This capacity is essential for pan-European LULC monitoring, ensuring comparability across countries and supporting harmonized policies for environmental management and land use planning.

### *C. Cognitive User Interface for Analysis and Scenario-Based Decision Support*

To ensure effective interaction and information exchange between users and the DT system, we have developed a cognitive web-based user interface using the Streamlit Python library (Fig. 17). This interface is designed to provide non-expert stakeholders with an intuitive tool for uploading their own data — specifically satellite imagery — for a selected area of interest and time period, as well as for viewing and

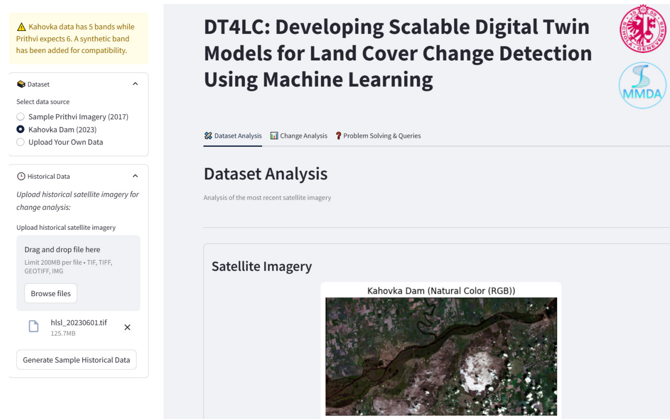


Fig. 17. Example page of the cognitive user interface being developed

interpreting the analysis results generated by the digital twin system.

A key feature of the interface is the integration of artificial intelligence, particularly large language models (LLMs), which serve as intelligent assistants. These assistants help users interpret results, explain possible causes of land cover changes, and offer recommendations for further land use.

The interface architecture reflects a user-centered design approach with modular functionality. The cognitive user interface is logically divided into several modules:

- **Data Upload module** allows users to import their own satellite images in formats such as TIFF, TIF, GEOTIFF, or IMG (limit: 200 MB per file). Users can upload one or two images (for subsequent change detection) and specify the date for each Fig. 18a. The uploaded images are displayed in a dedicated preview window and can be viewed in three modes: Natural Color (RGB), False Color (NIR-R-G), and SWIR Composite (Fig. 18b-d).
- **Data Processing Module**. After data upload, images are sent to the digital twin system for processing, and the results are returned to the interface. Currently, image processing is performed using the Prithvi foundation model.
- **Model Output Visualization Module**. Users can analyze the distribution of land cover classes and vegetation levels (NDVI, at this time) on a single image, or perform change analysis between two images, choosing between the "Dataset Analysis" and "Change Analysis" modes, respectively. Users can view the model results in the form of histograms that display the distribution of land cover classes (Fig. 19). Additionally, numerical and semantic information about the vegetation status is provided.

### *D. AI-Powered Cognitive Support Module*

An integrated intelligent assistant responds to queries related to detected changes, explains their potential causes, and offers practical recommendations for a deeper understanding of the results. At this stage, we are utilising Google's Gemini language model, which is integrated via a free API key.

Furthermore, three specialized cognitive modules have been integrated to enhance analytical precision (Fig. 21).

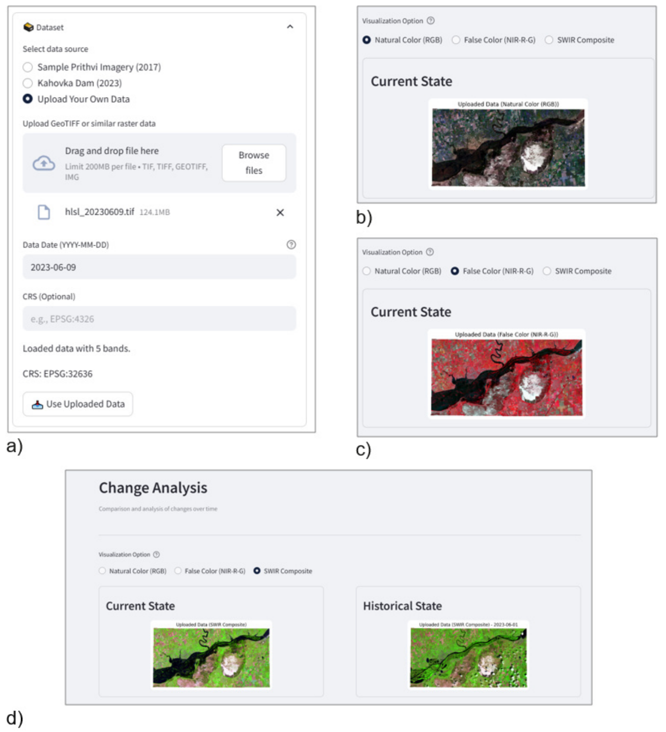


Fig. 18. Example of loading (a) and viewing (b-d) images in the cognitive user interface

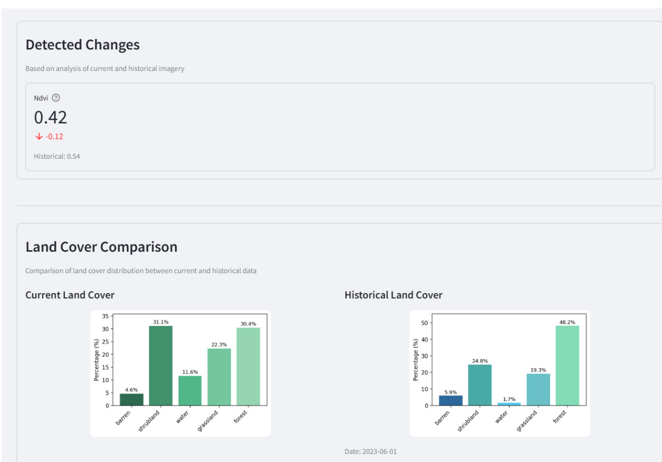


Fig. 19. Example of model output results visualization

Within the "Change Analysis" section, the AI assistant can perform causal reasoning, identifying potential cause-effect relationships underlying the observed environmental changes(Fig. 20). Users can also interact with the AI assistant via natural language queries, submitting questions through the "Problem Solving & Queries" section (Fig. 20b).

## V. Discussion: Challenges, Open Questions, and Future Research Directions

The pilot implementation highlights both the potential and limitations of current Digital Twin (DT) technologies for land use change monitoring. The modular, instance-based architecture presented in this study enables scalable integration

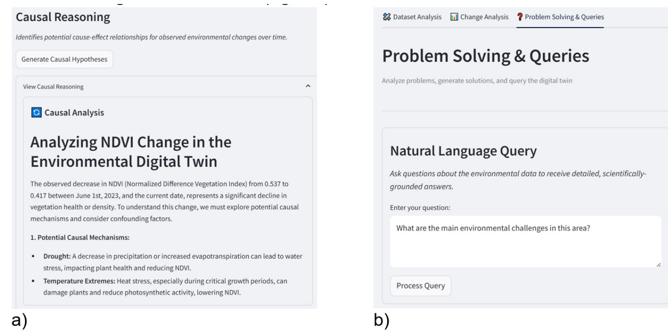


Fig. 20. AI-Powered Cognitive Support Module. a) AI assistant in the "Change Analysis" section performing causal reasoning, b) AI assistant in the "Problem Solving & Queries" section responding to natural language input.

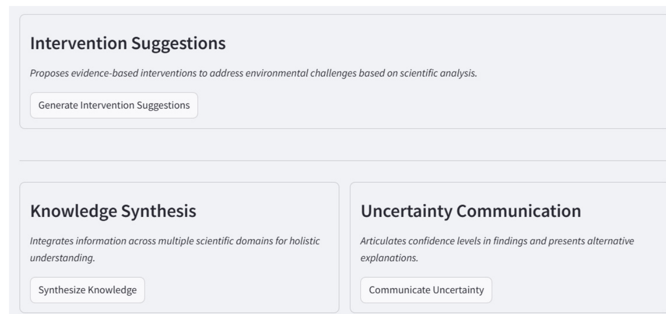


Fig. 21. Specialized AI-modules integrated into the cognitive user interface

of satellite, climate, and in situ data through specialized Digital Twin Instances (DTIs). However, broader operationalization faces significant barriers related to data standardization, model interoperability, validation under uncertainty, and real-world adoption.

One of the central challenges identified in this work is the lack of standardized methods for interpreting satellite and climate data within DT systems. As Earth Observation (EO) foundation models continue to expand—often developed using distinct architectures, datasets, and training strategies—there is a growing need to harmonize how these models process and classify satellite imagery.

In [80], authors emphasize the importance of standardizing Earth Observation Data Cubes (EODCs) to enhance data sharing and interoperability. Without such harmonization, EODCs risk becoming isolated silos that cannot be effectively integrated into broader DT frameworks. Similarly, in [81] researchers stress that semantic interoperability — the ability to interpret the meaning of spectral and temporal patterns consistently across platforms — is just as critical as technical interoperability. Even highly advanced foundation models such as Prithvi, EarthPT, and DOFA may generate incompatible outputs when applied to multi-sensor satellite archives without standardized interpretation protocols.

Temporal standardization presents an additional layer of complexity. Foundation models trained on time series, such as Presto and EarthPT, apply different assumptions in handling temporal dynamics. These differences can lead to inconsistent interpretations of land cover transitions — e.g., identifying gradual vegetation recovery versus abrupt disturbance events,

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which undermines the comparability and reliability of DT outputs.

Moreover, discrepancies in land cover class definitions across datasets and models further exacerbate this challenge. A class labeled as ”forest” in one model may not match the same label in another, creating false indicators of change when aggregating results across sources or time. This is especially critical when monitoring conflict-affected regions, such as Ukraine, where land transformations can occur rapidly and must be detected with high semantic precision.

Our implementation explored the integration of foundation models such as Prithvi and Presto within the DT architecture. While these models offer potential for generalization and transfer learning, preliminary tests revealed unexpected outcomes, including superior performance of simpler classifiers (e.g., Random Forest) in some contexts. This highlights the need for further research into how foundation model encoders interact with downstream tasks and what preprocessing and fine-tuning steps are necessary to leverage their capabilities fully.

Additionally, climate-sensitive forecasting modules such as the Vegetation Dynamics DTI must balance physical plausibility with data-driven flexibility. Incorporating physics-informed neural networks (PINNs) offers a promising path forward, enabling physically consistent simulations even in data-scarce settings. However, challenges remain around training efficiency, generalizability, and the risk of over-constraining models in heterogeneous environmental contexts.

System-level reliability also remains an open challenge. Although individual DTIs (e.g., Vegetation Dynamics) show promising accuracy ($R^2$, RMSE), the propagation and aggregation of uncertainties across modules have not yet been systematically quantified. Input data availability and quality in disaster or conflict zones introduce additional uncertainty, particularly when cloud cover, sensor failures, or infrastructure disruptions reduce temporal continuity.

The framework is currently validated only on selected DTIs, with the Vegetation Dynamics DTI tested on extreme flood events in Ukraine and Land Use Change DTI, tested on forest dynamics monitoring in Swiss and Ukraine. Climate DTI remains conceptual and requires further implementation and benchmarking.

Finally, no systematic parametric study of model or feature selection has been performed. Future work will address this by comparing forecasting methods (e.g., GraphCast, PINNs) and quantifying their effect on overall system performance.

As demonstrated through the Swiss and Ukrainian use cases, DTs hold promise for modeling both long-term environmental trends and sudden land transformations. Realizing this potential will require coordinated progress in data, models, and governance structures.

## VI. Conclusion

This paper presents a modular Digital Twin (DT) architecture designed for land use change monitoring in dynamic and disaster-prone environments. The framework is based on a federated structure of Digital Twin Instances (DTIs), each responsible for distinct components such as land use classification, vegetation dynamics forecasting, and climate-informed modeling. By integrating satellite, climate, and in situ data within a harmonized pipeline, the system enables both gradual and rapid monitoring of land transformation across diverse geographies.

Through the pilot implementation in Ukraine and Switzerland, the study demonstrates how instance-based DTs can be tailored to local data availability, environmental conditions, and governance contexts. In Ukraine, DTIs supported post-conflict recovery monitoring, including the assessment of agricultural land rehabilitation following the destruction of the Kakhovka Dam, as well as the detection of significant forest losses in conflict-affected regions caused by direct destruction, fires, and the disruption of forest management practices. In Switzerland, the framework will be applied to alpine regions, showcasing its adaptability to landscape dynamics and climate regimes.

The case studies presented here should be interpreted as pilot demonstrations rather than full validations. In Ukraine, the Vegetation Dynamics DTI was tested under extreme flood conditions and produced reliable metrics of vegetation response. In both Switzerland and Ukraine, annual-scale forest dynamics were illustrated to highlight the framework’s applicability at gradual temporal scales. However, not all DTIs have been fully deployed, and large-scale, multi-hazard validation remains future work. The contribution of this study lies in defining and prototyping a modular, dual-timescale architecture that explicitly integrates conflict and environmental drivers, while remaining model-agnostic and adaptable. Ongoing efforts will expand the case studies, implement additional DTIs, and quantify system-level uncertainties to progress from proof-of-concept demonstrations toward operational deployment.

Future work will extend the framework to additional hazard types and geographic regions, integrate broader socio-economic datasets, and conduct controlled benchmarking against operational baselines. This transition from pilot demonstrations to multi-hazard, multi-country validation will be a decisive step toward operational Digital Twins for disaster-resilient land governance.

Overall, the proposed DT framework contributes to advancing Earth intelligence systems by supporting real-time and scenario-based decision-making for land governance, disaster response, and climate adaptation. It sets the foundation for future extensions focused on improved scalability, interoperability, and alignment with evolving policy needs under international initiatives such as the EU Green Deal and the Sendai Framework.

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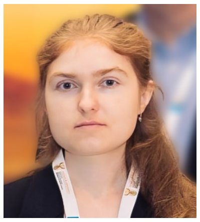

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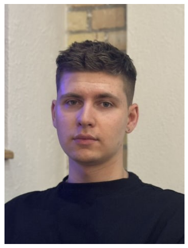

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