Towards a Sustainable Future: AI-Powered Solutions in Agriculture and Green Energy

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Abstract

The urgent need for sustainable development is driving transformative changes in critical sectors such as agriculture and energy. Artificial Intelligence (AI) is playing a pivotal role in this transition by enabling advanced decision-making processes, optimizing resource management, and promoting environmentally sustainable solutions. Our research advances this shift on three cutting-edge fronts: the development of a Digital Twin framework for precision agriculture, which enables real-time crop monitoring and adaptive forecasting; the design of MATNet, a multimodal transformer-based architecture for accurate day-ahead photovoltaic power forecasting; and the application of multi-agent reinforcement learning strategies to optimize energy sharing and management within energy communities, with a focus on operational efficiency and privacy preservation. Collectively, these initiatives demonstrate the transformative potential of AI-driven approaches in advancing sustainable practices across interconnected domains.

Keywords

Artificial Intelligence, Green Energy, Multimodal Learning, Precision Agriculture, Sustainability

1. Introduction

The growing urgency of global challenges such as climate change, resource depletion, and environmental degradation demands an accelerated transition toward sustainability [1]. Agriculture and energy are two critical sectors at the forefront of these challenges. In agriculture, climatic stressors accelerate soil erosion, deplete fertility, and threaten biodiversity, particularly when combined with unsustainable practices like monoculture, poor soil management, and excessive fertilizer use. The energy sector, meanwhile, remains heavily reliant on fossil fuels and faces environmental impacts and instability linked to the intermittent nature of renewables. Addressing these issues is essential for a sustainable, resilient future.

Artificial Intelligence (AI) offers powerful tools to tackle these challenges by enabling smarter decisions, optimizing resource use, and driving innovation. Its versatility has been demonstrated in fields such as healthcare, mobility, and social welfare [2, 3, 4], supporting complex system analysis and data-driven decisions. In agriculture and energy, AI helps process complex datasets, uncover non-linear relationships, and generate accurate forecasts, enhancing efficiency, reducing waste, and enabling adaptation to environmental variability.

Multimodal learning plays a pivotal role in advancing AI-based sustainability solutions. By integrating diverse data sources—such as satellite imagery, climate records, sensor networks, and market data—it enables richer, more accurate predictive models [5, 6, 7, 8, 9, 10]. This is particularly valuable for

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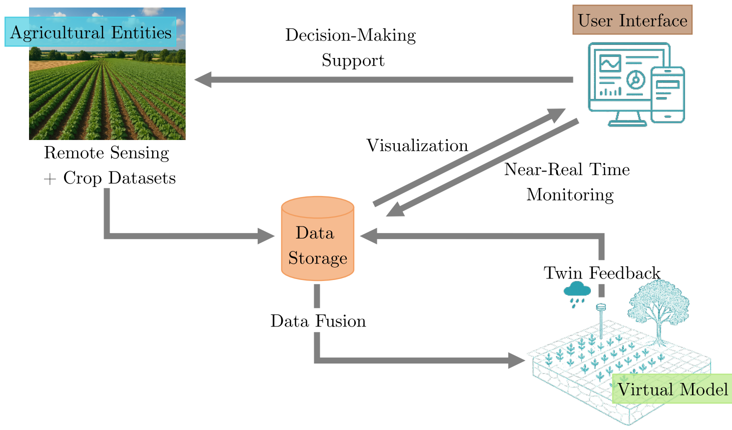

Figure 1: Conceptual workflow of the crop Digital Twin system integrating remote sensing and multimodal data for real-time monitoring, forecasting, and decision support.

sustainability applications, where environmental, economic, and social factors are deeply interconnected. Multimodal models support holistic decision systems capable of delivering tailored, context-aware strategies for sustainable agriculture, renewable energy management, and environmental preservation.

In this context, our research lab develops multimodal AI solutions for sustainability across interconnected projects: a Digital Twin platform for precision agriculture to optimize crop-level resource use and minimize environmental impact; a multimodal deep learning architecture for photovoltaic (PV) energy forecasting that integrates historical PV production, weather history, and forecasted conditions to improve renewable integration and grid stability [11]; and multi-agent reinforcement learning approaches for intelligent energy management to optimize distribution and consumption within Energy Communities (ECs), enhancing local sustainability and reducing energy waste. Together, these initiatives highlight the transformative potential of intelligent systems in advancing sustainable development and building a resilient, eco-friendly future.

2. Advancing Precision Agriculture: The Crop Digital Twin Paradigm

Precision agriculture enables more efficient, targeted, and sustainable crop management. As farming faces increasing vulnerability to climate change and extreme weather, there is growing interest in tools that monitor crops in real time, detect early stress signals, anticipate yield variability, and support timely responses to safeguard food production and reduce environmental impacts.

Among emerging technologies, Digital Twins (DT)—virtual replicas of agricultural entities updated in real time—are gaining recognition as a promising solution. Crop DTs facilitate simulation and prediction of crop dynamics under varying climatic and agronomic scenarios by continuously assimilating new data, allowing models to evolve and reflect the current state of the crop. This makes DTs powerful tools for adaptive, data-driven decision support to enhance productivity, resilience, and sustainability.

Despite their potential, most crop DT applications remain conceptual or experimental [12, 13, 14, 15], with few platforms achieving real-time data integration, accurate modeling of crop dynamics, and responsive feedback. Bridging this gap could transform agricultural decision-making with personalized, actionable insights tailored to local conditions and practices.

In this context, we are developing a framework that combines multimodal data fusion and adaptive AI modeling to monitor, simulate, and forecast crop conditions in near real time, as illustrated in Figure 1. Remote sensing and multimodal datasets are processed into a geodatabase and fused into a dynamic AI-driven virtual model that captures crop spatiotemporal variability and updates continuously through monitoring and feedback. Advanced geospatial tools such as PyTrack [16] enhance spatial data harmonization by integrating mobility patterns and environmental data.

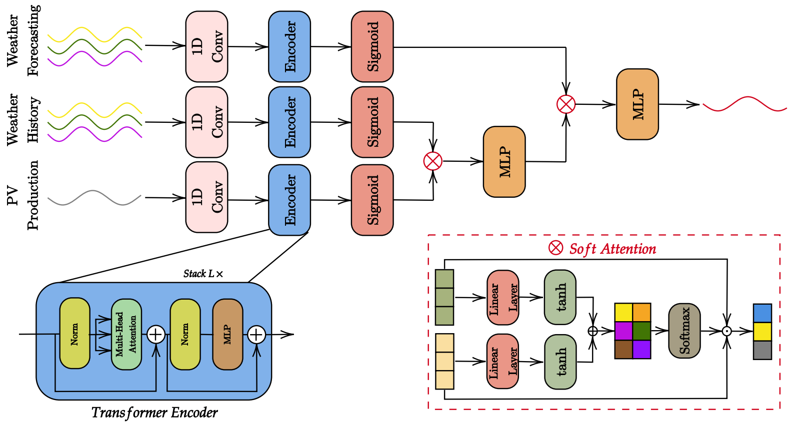

Figure 2: Overall architecture of our proposed MATNet.

At this stage, a geodatabase built on PostgreSQL/PostGIS has been developed to harmonize high-resolution satellite imagery with climate and land use data, integrating vegetation indices from Sentinel-2 imagery (via openEO Hub[1]), climate data [17], and European land use datasets [18, 19]. Vegetation indices [20, 21] are essential for predictive modeling, offering remote insights into vegetation health, vigor, and growth dynamics. This database will support deep learning models for real-time probabilistic forecasts, exploring autoregressive transformer architectures (e.g., Vision Transformers [22]) with masked decoding, and diffusion-based generative models [23]. An intuitive web platform will enable users to explore, visualize, and query forecasts alongside historical data. By supporting timely, data-driven, and adaptive recommendations, crop DTs can significantly enhance sustainability, productivity, and resilience in farming practices.

3. Enabling Renewable Energy Integration: A Photovoltaic Case Study

The integration of photovoltaic (PV) systems is crucial for sustainability, but solar energy's intermittency poses significant grid integration challenges. Accurate day-ahead PV power forecasting is essential to support grid balancing, energy dispatch, and planning of storage and backup resources [24, 25].

Forecasting methods are typically physics-based or data-driven. While physics-based models embed domain knowledge, they are computationally demanding and inflexible. Data-driven approaches, especially AI-based, achieve high predictive accuracy but often overlook the physical principles behind solar generation [26].

To address these limitations, we propose MATNet, a multimodal transformer-based architecture for multi-step, day-ahead PV power forecasting [11]. MATNet combines physics-inspired insights with deep learning's representational power by integrating historical PV production, weather observations, and weather forecasts in a unified model. Its key innovation lies in a multi-level joint fusion mechanism with soft-attention, enabling dynamic weighting of data sources to capture complex temporal and cross-modal dependencies (Figure 2 illustrates the architecture). MATNet also introduces a dense interpolation module, inspired by NLP techniques, to compress high-dimensional attention outputs into compact representations. This design balances predictive power and computational efficiency, making MATNet suitable for real-world deployment.

Experiments on the Ausgrid Solar Home Electricity dataset, combined with meteorological data from OpenWeatherMap and Solcast, showed MATNet outperforming thirteen baselines, including statistical, machine learning, and deep neural network models. MATNet achieved a Root Mean Squared Error (RMSE) of 0.0445—about 10% better than the strongest alternative—and a wMAPE of 16.72%. These improvements were validated using the Diebold-Mariano statistical test. Ablation studies confirmed the

[1]https://openeo.dataspace.copernicus.eu/

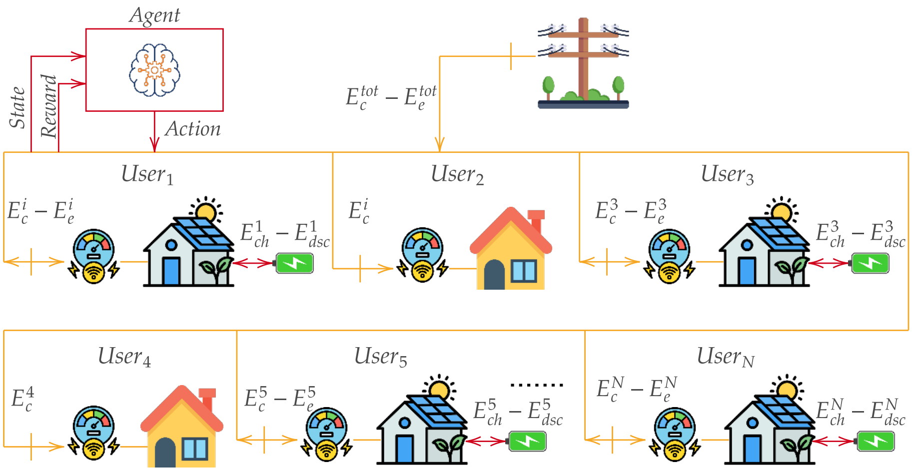

Figure 3: Example of energy community model with multi-agent reinforcement learning control.

benefit of integrating all three data modalities, with weather forecasts proving particularly important during variable conditions. MATNet's attention mechanisms allow it to focus on the most informative features, enabling accurate forecasting even under rapidly changing weather.

In summary, MATNet demonstrates the value of combining heterogeneous data with advanced deep learning for PV forecasting. Future work will explore dynamic fusion weighting and explainable AI techniques to enhance adaptability, transparency, and trust in critical energy infrastructure applications.

4. Optimizing Energy Communities through Multi-Agent Reinforcement Learning

The transition to decentralized energy systems has led to the rise of Energy Communities (ECs)—collaborative groups of producers and consumers that generate, share, and consume renewable energy locally. ECs promote energy self-sufficiency, reduce fossil fuel dependence, and enhance grid resilience, directly supporting decarbonization and sustainable development. However, managing energy flows within ECs is challenging due to the intermittent nature of renewables and the heterogeneous behaviors of participants.

Reinforcement Learning (RL), particularly in deep learning formulations, has proven effective for complex sequential decision-making problems across fields like robotics, finance, and smart mobility [27, 28]. In ECs, RL offers a robust framework for optimizing distributed energy resource management, balancing production and consumption, and coordinating storage and trading activities.

Our project develops a Multi-Agent Reinforcement Learning (MARL) framework to optimize energy sharing and resource management, as illustrated in Figure 3. Multiple intelligent agents—representing community participants—learn cooperative strategies that maximize individual benefits and overall community welfare. Participants are classified as prosumers (producing and consuming energy, typically with PV systems and batteries), consumers (only consuming energy), or producers (dedicated to generation and sharing surplus energy). The MARL framework optimizes key decisions, including battery charging/discharging, intra-community trading, and grid interactions. Modeling the EC as a cooperative multi-agent system enables coordinated energy exchanges and storage use, minimizing waste and costs while boosting self-consumption.

This adaptive, data-driven approach allows agents to respond to fluctuations in renewable production and consumption patterns. Although MARL is not inherently privacy-preserving, decentralized training and local policy updates reduce the need to share raw data [29], supporting cooperation while respecting individual privacy and fostering trust.

Developing intelligent MARL-based control strategies marks a key step toward sustainable, resilient, and decentralized energy systems, empowering communities to actively contribute to the energy transition.

5. Research Vision and Strategy

This work highlights our laboratory's commitment to advancing sustainability through cutting-edge AI solutions. By integrating multimodal learning, deep neural architectures, and reinforcement learning, we address key challenges in precision agriculture, renewable energy forecasting, and intelligent energy communities, demonstrating both technical feasibility and tangible impact. Future research will explore Foundation Models and Generative AI to address challenges such as data scarcity, domain generalization, and adaptive simulation. These models, already demonstrating strong adaptability and efficiency, enable advanced AI solutions for high-fidelity synthetic data generation and critical applications in agriculture and energy systems [30, 31]. Additionally, Explainable AI (XAI) will be central to ensuring transparency and fostering responsible, ethical AI deployment in high-impact decision-making contexts. Through interdisciplinary collaborations and a forward-looking agenda, our lab aims to deliver robust, adaptive AI tools aligned with the goals of ecological transition and digital innovation.

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Declaration on Generative AI

During the preparation of this work, the authors did not use any AI tool.

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