Use of Artificial Intelligence in Soil Nutrient Management and Potato Harvesting

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Nutrient management is a critical component of modern agriculture, serving not only to optimize crop productivity but also to mitigate environmental impacts such as nutrient runoff and leaching. Worldwide, several approaches and techniques are employed to enhance nutrient use efficiency. Traditionally, nutrient recommendations are developed using conventional methods, such as regression models (linear, linear plateau, quadratic, exponential, etc.) to develop yield curves. These models are popular among researchers due to their simplicity and effectiveness. However, the arrival of Artificial Intelligence (AI) presents opportunities to either refine these traditional models or test new AI-based models for their efficacy in comparison to conventional approaches. Ongoing nitrogen management projects in crops such as corn, potatoes, and cotton provide valuable opportunities to explore AI applications in agriculture. Among the commonly used AI models, Random Forest (RF) and Partial Least Square as Regression (PLSR) stand out as robust machine learning algorithms. Both methods analyze the relationship between dependent and independent variables, offering the potential to improve the precision of nutrient management strategies. Beyond nutrient management, AI has promising applications in other agricultural domains. For instance, in potato production, computer vision technology can be employed to estimate tuber mass and detect size grades. This has significant implications for breeders, farmers, and processing units, as it enables the optimization of both technology and manual labor in post-harvest handling. Currently, manual labor is primarily used to discard misshapen potatoes after harvest. However, with rising labor costs and increasing challenges in labor availability, AI-driven solutions could revolutionize this process, offering a more efficient and cost-effective alternative in the near future. This integration of AI into agriculture has the potential to address long-standing challenges while also paving the way for more sustainable and efficient farming practices.

Leveraging AI for Quantifying Soil Hydrology: Applications in Agriculture and Climate Change Mitigation

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Abstract

In-depth understanding of soil hydrologic properties and processes – such as soil moisture, evapotranspiration, soil water retention, infiltration, and evapotranspiration dynamics – is essential for improving water resource management, advancing sustainable agricultural practices, and mitigating the impacts of climate change. However, current modeling approaches struggle with the spatial and temporal heterogeneity of soil systems, especially when integrating datasets from multiple sources, scales, and measurement techniques. Recent advances in Artificial Intelligence (AI) and high-performance computing have opened avenues for novel data-intensive frameworks that can more accurately characterize, estimate and project soil hydrologic properties and processes. Yet, many of these AI-driven methods rely on empirical relationships that often neglect the underlying physical principles and mechanistic relationships that govern soil-water interactions. This limitation reduces the robustness, transferability, and explanatory power of these models and limit their application to new conditions in terms of soil types, land cover, and climate regimes. Our research will integrate AI methods like convolutional and recurrent neural networks with multi-source multi-scale observations including ground-based measurements, national soil survey maps, and proximal and satellite remote sensing observations to identify the spatiotemporal complexity of soil hydrologic properties and processes. By developing physics-informed deep learning models and constraining AI algorithms with physically based water balance principles and soil water retention functions to characterize soil moisture and hydraulic soil properties, we bridge the gap between data-driven predictions and fundamental soil physics. This fusion ensures that our models not only fit observed patterns but also obey established physical rules, which improves their generalizability, interpretability, and application. The outcomes of this integrative approach have the potential to improve water management in agricultural settings by reducing uncertainties in soil moisture and hydraulic soil properties characterization. Additionally, the predictive models can guide climate change adaptation strategies by improving projections of extreme climate events occurrence such as floods, wildfires, and droughts, and reduce the environmental footprint in view of a rapidly changing global climate.

Dr. Nikolaos Tziolas

Bridging the Gaps: Foundation Models and Conversational AI for Scalable Agro-Environmental Monitoring

Recent advancements in artificial intelligence (AI) and the increasing availability of multi-modal data have generated significant opportunities for agro-environmental monitoring. However, critical challenges persist, particularly the high specialization of existing AI models and the limited accessibility of AI-generated products. Many current AI models are developed for highly specific tasks, such as crop yield prediction, soil properties estimation, or land cover classification, and are often tailored to sensor types. This specialization hinders the transferability and scalability of AI applications, preventing their widespread adoption in diverse agricultural settings. In addition, the outputs generated by these models are often difficult to access and interpret for non-expert users.

Despite the availability of rich Earth observation datasets and advanced AI-driven insights, significant barriers remain, including complex data formats, cumbersome interfaces, and a lack of user-friendly tools that enable stakeholders to derive actionable information seamlessly. These limitations reduce the practical value of AI technologies, particularly for farmers, extension agents, and decision-makers operating in resource-constrained environments.

To address these challenges, foundation models, inspired by brain plasticity, offer a transformative solution by dynamically harmonizing diverse data modalities into a unified framework. In this presentation, we will showcase an example of a global-scale foundation model designed to estimate soil properties by integrating data from multiple spectral VNIR-SWIR sensors. Furthermore, we will introduce a novel AI conversational system that provides agronomic services through an interactive chat interface. By integrating large language models with specialized AI models, this system simplifies the processing and analysis of satellite data. It enables users to interact naturally with complex geospatial information, offering solutions such as soil health mapping, cost-optimized soil sampling, and the measurement of degraded land proportions.

This presentation will demonstrate how these cutting-edge AI frameworks—foundation models for multi-modal soil property estimation and LLM-powered interactive systems—can overcome long-standing barriers to data fragmentation, accessibility, and specialization. Through practical examples, we will highlight how these technologies pave the way for scalable, cost-effective, and user-friendly agro-environmental monitoring, fostering smarter and more resilient agricultural systems.