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Precision Regenerative Farming: Using AI to Optimize Soil Carbon Sequestration

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ABSTRACT

The convergence of regenerative agriculture and artificial intelligence (AI) offers a transformative pathway for mitigating climate change while enhancing food security. This article examines the potential of "Precision Regenerative Farming" to optimize Soil Organic Carbon (SOC) sequestration. We explore the biogeochemical underpinnings of the Nitrogen Cycle in low-disturbance systems and the application of machine learning architectures, specifically Random Forest Regressors, to predict carbon stock fluctuations across diverse pedological profiles. By integrating IoT sensor arrays and computer vision with site-specific regenerative practices—such as multi-species cover cropping and no-till management—we demonstrate a robust framework for scalable, AI-verified carbon measurement. The findings suggest that data-driven regenerative systems can effectively pivot global croplands from carbon sources into resilient, high-capacity carbon sinks.

1. Introduction: The Dual Crisis of Soil and Security

As we navigate the mid-2020s, the global agricultural sector faces a localized and systemic dual crisis: the rapid degradation of arable soil and the intensifying pressure of global food insecurity. Conventional industrial agriculture, characterized by intensive tillage and synthetic fertilization, has resulted in the loss of approximately 50-70% of ancestral soil carbon stocks. This loss not only compromises soil fertility and water-holding capacity but also liberates massive quantities of CO_2 into the atmosphere. The "Green Revolution 2.0" must therefore prioritize the restoration of soil health. Regenerative agriculture provides the ecological framework for this restoration, but its success at scale requires the precision and predictive power of modern data science [1].

2. The Regenerative Paradigm in 2026

Regenerative farming is defined by a suite of practices designed to work in harmony with natural biological cycles. In the 2026 landscape, these are no longer fringe concepts but central tenets of sustainable agronomy.

2.1 No-Till and Soil Structure

Mechanical tillage disrupts the fungal-dominant networks (mycorrhizae) essential for nutrient uptake and soil aggregation. By adopting no-till or ultra-low disturbance systems, farmers maintain the structural integrity of the soil, preventing the oxidation of organic matter and reducing erosion [2].

2.2 Advanced Cover Cropping and the Nitrogen Cycle

Traditional nitrogen management relies heavily on the Haber-Bosch process, which is energy-intensive and prone to leaching. Regenerative systems leverage the **Nitrogen Cycle** by integrating leguminous cover crops. These plants facilitate biological nitrogen fixation through symbiotic relationships with *Rhizobium* bacteria. Managing this cycle requires precision; the timing of cover crop termination is critical to ensure that nitrogen mineralization coincides with the nutrient demands of the subsequent cash crop, a process now optimized via AI-driven phenology modeling [3], [4].

3. AI Integration: The Computational Backbone

The transition from general regenerative practices to "Precision Regenerative Farming" is facilitated by the integration of AI at multiple layers of the farm operation.

3.1 Computer Vision and IoT Sensors

Multispectral imaging from drones and satellites, combined with computer vision algorithms, allows for the identification of nutrient deficiencies and pest pressure at a sub-meter resolution. Concurrent with remote sensing, IoT soil probes provide real-time data on moisture, temperature, and electrical conductivity. These data streams feed into decision-support systems that identify optimal planting times, reducing the risk of seedling mortality and maximizing biomass production for carbon input [5], [6].

3.2 Random Forest Regressors for SOC Prediction

Predicting changes in Soil Organic Carbon (SOC) is notoriously difficult due to the high spatial variability of soil properties. **Random Forest (RF) Regressors** have emerged as the gold standard for this task. As an ensemble learning method, RF constructs a multitude of decision trees and outputs the mean prediction. By training on diverse datasets—including slope, historical yield, microbial biomass, and weather patterns—RF models can predict SOC stock changes with a higher degree of accuracy than traditional linear regression models. This allow for the creation of "digital twins" of the soil, enabling farmers to simulate the carbon-sequestration impact of a specific crop rotation before a single seed is planted [7], [8].

4. Quantifying Sequestration: The Measurement Revolution

The primary barrier to large-scale carbon credit markets has been the cost and labor of physical soil sampling. We are currently witnessing a shift toward **Remote, AI-Verified Carbon Measurement**. By correlating high-resolution satellite reflectance data with localized physical samples, AI models can extrapolate carbon sequestration across millions of hectares. This "Monitoring, Reporting, and Verification" (MRV) framework provides the transparency required for carbon finance, turning sequestration into a verifiable commodity for the farmer [9], [10].

5. Conclusion: JARS and the Green Revolution 2.0

The *Journal of Agricultural Research & Sustainability (JARS)* is established at a pivotal moment in human history. The integration of AI and regenerative agronomy is not merely a technical evolution; it is a prerequisite for planetary resilience. By leveraging Random Forest architectures to manage the complexities of the Nitrogen Cycle and SOC dynamics, we can transform agriculture from a climate liability into a primary solution. JARS will serve as the definitive platform for this research, documenting the path toward a future where every acre of land is both a source of life and a guardian of the climate [11].

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