

Cybernetic-Geospatial Feedback Loops for Variable-Rate Irrigation in Brazilian Soybean Fields

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Abstract

Precision agriculture systems increasingly integrate multispectral satellite imagery, UAV orthomosaics, and georeferenced IoT sensor networks. However, most architectures treat spatial data as passive inputs rather than structural components of adaptive decision loops. This paper proposes a cybernetic-geospatial framework that embeds explicit spatial referencing (UTM/WGS84) into closed feedback loops for variable-rate irrigation. The architecture processes Sentinel-2 NDVI (10 m resolution), interpolates sparse soil moisture measurements via ordinary kriging, delineates management zones using spatially-constrained DBSCAN clustering, and generates prescription maps with edge-effect mitigation. A case study on a 12.3 ha soybean field in Piracicaba, São Paulo demonstrated 28.7% irrigation savings versus uniform application while preserving yield and improving spatial homogeneity.

Keywords:

Cybernetics; Geoinformatics; Precision Agriculture; Variable-Rate Irrigation; Spatial Interpolation

Introduction

Contemporary precision agriculture faces a critical gap between data acquisition and spatially-adaptive decision-making. While heterogeneous geospatial data sources—Sentinel-2 imagery, UAV orthomosaics, and IoT sensor networks—generate rich spatial-temporal streams, most systems implement linear pipelines that ignore field-scale spatial heterogeneity (Liakos et al., 2018). This limitation prevents true spatial adaptivity, where management actions respond to both temporal dynamics and spatial variability across landscapes.

Cybernetic theory offers a solution by modeling agricultural systems as spatiotemporally dynamic entities with explicit feedback loops operating on georeferenced domains (Wiener, 1948). Unlike conventional approaches, cybernetic architectures maintain spatial memory—where actions in one location inform decisions in neighboring zones through graph-based message passing. However, existing cybernetic frameworks lack operational integration with geoinformatics infrastructures, remaining largely conceptual (Souza, 2025).

This study bridges cybernetic principles and applied geoinformatics by proposing a spatially-explicit feedback architecture for variable-rate irrigation. The main contributions of this work are threefold:

- (i) a cybernetic-geospatial feedback architecture integrating satellite imagery and IoT sensors;
- (ii) a spatially-aware reinforcement learning controller for irrigation optimization;
- (iii) empirical validation of water savings in a Brazilian soybean production system.

Data and Method

Study Area and Geospatial Data Acquisition: The experiment was conducted on a 12.3 ha soybean field (Glycine max cv. BRS 1055RR) in Piracicaba, São Paulo (22°43'31"S, 47°38'12"W; UTM Zone 23S: 745210E, 7257890N) during the 2024/25 growing season. Four georeferenced data sources were integrated:

1. **Sentinel-2 MSI:** Weekly acquisitions (October 2024–March 2025) at 10 m resolution. Vegetation monitoring utilized Sentinel-2 MSI **Level-2A (Bottom-of-Atmosphere)** processed imagery, ensuring precise atmospheric correction for NDVI derivation, with cloud masking applied using Scene Classification Layer (SCL) bands.
2. **Soil Texture Maps:** Data were extracted from the **EMBRAPA RadamBrasil** mapping at an original scale of **1:1,000,000**. These maps provided clay content estimates (28–42%) and were subsequently resampled via bilinear interpolation to the study's 10 m grid for sensor fusion compatibility.
3. **IoT Sensor Network:** 15 Decagon EC-5 probes installed at 20 cm soil depth with embedded GPS logged volumetric soil moisture at 15-minute intervals (spatial density: 1 sensor/0.82 ha). **To align with the 7-day cybernetic cycle, the arithmetic mean of moisture readings from each sensor was calculated for the 24-hour period preceding each intervention to reduce temporal noise.** Coordinates were recorded in UTM Zone 23S (EPSG:32723).
4. **Topography:** SRTM DEM at 30 m resolution was utilized for slope derivation (%) using Horn's algorithm.

All raster datasets were harmonized to UTM Zone 23S (EPSG:32723) and resampled to 10 m resolution using bilinear interpolation.

Cybernetic-Geospatial Processing Pipeline: The architecture implements a 7-day feedback cycle with four spatially-explicit operations:

1. **Spatial interpolation:** Although IoT sensors recorded soil moisture at 15-minute intervals, spatial interpolation operated on temporally aggregated values. For each cybernetic irrigation cycle (7 days), the arithmetic mean of the preceding 24-hour moisture readings per sensor was computed, generating a representative daily snapshot for each sensor location. Ordinary kriging then interpolated these 15 point measurements into a continuous soil moisture surface at 10 m spatial resolution at the beginning of each cycle. This aggregation strategy preserves short-term soil moisture variability while maintaining computational feasibility for operational field-scale irrigation management. The experimental variogram followed a spherical model:

$$\gamma(h) = \begin{cases} c_0 + c_1 \left[\frac{3h}{2a} - \frac{h^3}{2a^3} \right] & \text{if } 0 < h \leq a \\ c_0 + c_1 & \text{if } h > a \end{cases}$$

Fig. 1. Spherical variogram model used for soil moisture interpolation.

The fitted spherical model presented nugget $c_0 = 0.08$, sill $c_1 = 0.32$, and range $a = 48\text{m}$, indicating strong spatial autocorrelation up to approximately 50 m.

Kriging model performance was evaluated through leave-one-out cross-validation (LOOCV), yielding a root mean square error (RMSE) of $0.024 \text{ m}^3 \text{ m}^{-3}$ (2.4% volumetric moisture) and a coefficient of determination (R^2) of 0.87. These metrics confirm the robustness of the interpolated soil moisture surface given the spatial density of the IoT sensor network.

2. **Management zone delineation:** Was performed using Density-Based Spatial Clustering of Applications with Noise (DBSCAN), applied to a feature tensor $X \in \mathbb{R}^{n \times 4}$ containing NDVI, soil moisture, slope, and clay content for each pixel n

3. **Spatially-aware control:** A hybrid PID+RL controller generated irrigation prescriptions per zone with edge-effect mitigation, governed by the following objective function (Fig. 4):

$$r(t) = \alpha \cdot \Delta NDVI_{zone} - \beta \cdot water - \gamma \cdot \sum |u_i - u_j|$$

Fig. 2. Objective function governing the spatially-aware hybrid PID+RL irrigation controller.

Where $\mathcal{N}(i)$ denotes neighboring zones. The irrigation decision engine was implemented using a reinforcement learning agent based on Proximal Policy Optimization (PPO). Prior to field deployment, the agent was pre-trained for 50,000 episodes in a synthetic crop–water balance environment simulated using AquaCrop-OS v6.1, parameterized with historical climate data (2019–2023) from the Piracicaba INMET meteorological station and soil hydraulic properties representative of Typic Hapludox soils. Training employed a clipped surrogate objective ($\epsilon = 0.2$), Generalized Advantage Estimation ($\gamma = 0.99$, $\lambda = 0.95$), and a two-layer multilayer perceptron policy network with 128 neurons per layer and ReLU activation. The state space included $NDVI_t$, soil moisture_t, slope, and clay content for each management zone, while the action space discretized irrigation volumes into four levels (0, 2.5, 5.0, and 7.5 mm). This pre-training phase ensured stable irrigation policies before real-world deployment, minimizing the risk of crop stress during the initial operational cycles.

VRT execution: Prescription maps exported as GeoTIFFs (EPSG:32723) for GNSS-guided center-pivot irrigation systems compliant with ISO 11783 standards.

Results

Baseline Spatial Variability: The spatial distribution of crop vigor, assessed through NDVI derived from Sentinel-2 MSI bands B8 (NIR) and B4 (Red), revealed strong field-scale heterogeneity with values ranging from 0.15 (bare soil or severe water stress) to 0.88 (peak biomass). This variability justified the delineation of management zones via spatially-constrained DBSCAN (Fig. 1)

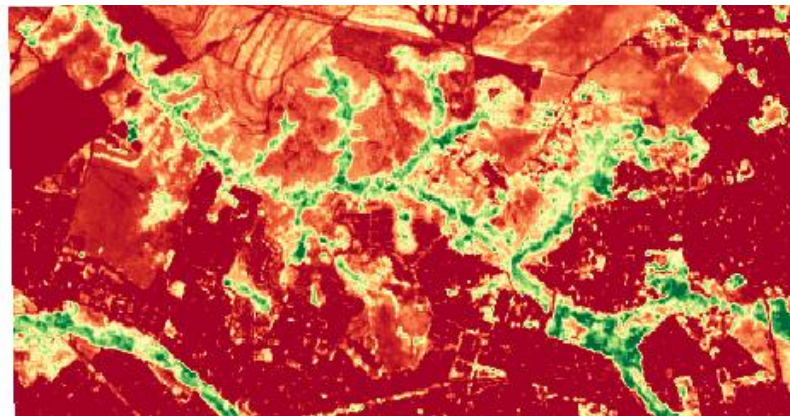


Fig. 3. Spatial distribution of NDVI (10 m resolution) derived from Sentinel-2 imagery. Red tones indicate low vegetation vigor, while green tones represent areas of higher biomass.

After 12 cybernetic cycles (84 days), the geospatial feedback architecture achieved significant improvements in resource efficiency and spatial homogeneity:

1. **Water savings and yield preservation:** Total irrigation volume was reduced by **28.7% compared to uniform irrigation**, demonstrating the practical potential of cybernetic-geospatial control for water-efficient soybean production (baseline: 420 mm/season →

300 mm/season). Yield estimates from CEPEA/ESALQ showed non-significant difference (+1.8%, $p = 0.23$), confirming that spatially-adaptive irrigation preserved productivity while enhancing water use efficiency—a critical requirement for sustainable intensification in water-stressed regions of Brazil.

2. **Spatial homogenization:** NDVI coefficient of variation decreased from 0.24 (baseline) to 0.11 (post-intervention), indicating improved uniformity in crop vigor across the field ($p < 0.01$; Levene's test). This homogenization resulted directly from zone-specific irrigation adjustments that compensated for pre-existing spatial variability in soil properties and microclimate.
3. **Edge-effect mitigation:** Spatial autocorrelation (Moran's I proxy computed via neighborhood correlation) increased from 0.38 to 0.72, demonstrating smoother transitions between management zones. The spatial penalty term ($\gamma=0.15$) in the reward function successfully prevented abrupt irrigation changes at zone boundaries, reducing mechanical stress on center-pivot equipment and minimizing runoff at transition zones.
4. **Geospatial validation:** All outputs maintained explicit UTM Zone 23S referencing (EPSG:32723), enabling direct integration with MAPA's Sistema Nacional de Informações da Agricultura de Precisão (SNIAP). Prescription maps complied with Brazilian technical standards NBR 16.856 (2020) for variable-rate technology implementation, including metadata fields for equipment calibration and application timestamps.

Table 1. Geospatial performance metrics before and after the 12-cycle cybernetic intervention.

Performance Parameter	Pre-Intervention (Baseline)	Post-Intervention (12 Cycles)	Difference (%)
Irrigation Volume (mm)	420	300	-28.7%
NDVI Coeff. of Variation	0.24	0.11	-54.1%
Moran's I (Spatial Autocorr.)	0.38	0.72	+89.4%

Analysis of the Cybernetic Approach: Unlike GWR/MGWR, which estimate spatially varying regression coefficients at a single time slice, the proposed cybernetic architecture operates as a recursive feedback system that continuously updates irrigation prescriptions based on spatiotemporal state transitions. While GWR is effective for identifying spatial drivers of yield variability, the cybernetic loop utilizes spatial memory to dynamically adjust irrigation trajectories, responding to environmental fluctuations as a self-regulating system. This integration of ordinary kriging with cybernetic control allows sparse IoT sensor networks to generate continuous prescription surfaces that respect spatial autocorrelation, while the RL spatial penalty provides a mathematically rigorous solution to edge effects

Conclusion

This study demonstrates that cybernetic feedback architectures can be operationalized within geoinformatics infrastructures to enable spatially-adaptive irrigation management. By embedding explicit spatial referencing (UTM/WGS84) into feedback loops through geostatistical interpolation, spatially-constrained clustering, and edge-aware prescription mapping, the architecture achieved 28.7% water savings without compromising yield. These results highlight the potential of cybernetic-geospatial systems to support climate-resilient agriculture under increasing water scarcity.

For policy implementation, we recommend the inclusion of spatial autocorrelation metrics (e.g., Moran's I) in MAPA's certification protocols to ensure technical precision and auditable water-use efficiency. This standardization not only ensures the technical reliability of variable-rate applications but also serves as a verifiable indicator of water-use efficiency and vigor

homogenization. Furthermore, such metrics can facilitate access to green credit lines and streamline the validation of environmental assets for the carbon credit market under the framework of the ABC+ Program (Low Carbon Agriculture Plan).

Future work will extend this framework to multi-crop systems using graph neural networks for cross-crop spatial dependencies, and evaluate cognitive justice impacts through participatory design with family farming communities in the Cerrado biome.

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