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A Neuromorphic Edge-Based Irrigation Control System for Precision Agriculture

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Abstract: Efficient water utilization is paramount for sustainable agriculture under increasing environmental pressures, especially as global populations rise and climate change intensifies water scarcity. Traditional precision irrigation systems rely on centralized architectures and periodic remote data processing, resulting in high energy costs and dependency on reliable connectivity, which can be particularly problematic in remote or undeveloped regions where robust infrastructure is lacking. This study presents a novel, fully autonomous irrigation controller leveraging a mixed-signal neuromorphic processor (DYNAP-SE1) to perform local, event-driven decision-making based on soil matric potential (SMP) measurements, thus reducing reliance on external networks and enhancing system resilience. In our approach, soil moisture data from apple and kiwi orchards were encoded into spike trains and processed by a spiking neural state machine with excitatory–inhibitory (EI) balanced dynamics to maintain long-term memory of sparse sensor inputs, allowing for more efficient and timely irrigation decisions. A direction-sensitive readout module generated "open" and "close" actuator commands, replicating conventional threshold-based irrigation rules and ensuring that water is delivered precisely when and where it is needed, minimizing waste. Validation on real-world datasets demonstrated close alignment with standard methods across -20 cm and -40 cm depths, with temporal discrepancies under 2 minutes, indicating the high reliability and accuracy of the neuromorphic controller in practical scenarios. Energy consumption per irrigation decision was estimated at 5.97 μWh, exceeding the efficiency of comparable IoT solutions and offering significant energy savings that are critical for sustainable agriculture. This neuromorphic pipeline offers a scalable, ultra-low-power platform for edge-based irrigation control, eliminating the need for cloud infrastructure and enabling resilient water management in resource-constrained environments, ultimately contributing to long-term agricultural sustainability.

Keywords: *Precision irrigation; neuromorphic computing; spiking neural networks; edge computing; soil matric potential; energy-efficient control.*

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Introduction

Global agriculture faces mounting challenges from climate change, population growth, and diminishing water resources (Kay et al., 2022). These factors are driving an urgent need for technological solutions that can improve efficiency, reduce environmental impact, and enhance food security (Naeem et al., 2023). Precision irrigation mitigates these challenges by tailoring water delivery to real-time plant and soil conditions, reducing both water waste and crop stress (Ben Abdelkader et al., 2021; Yomna Gamal et al., 2023). In recent years, the adoption of sensor-driven irrigation strategies has shown considerable promise, but widespread deployment is often limited by high costs and technical barriers (Pascoal et al., 2024). Conventional systems employ

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threshold-based logic on cloud or gateway servers, requiring continuous data transmission and remote computation, which introduces challenges related to data latency, privacy, and the need for reliable internet connectivity (Mekki et al., 2018; Tyagi et al., 2024). Connectivity lapses and transmission energy demand hinder deployment in remote fields or solar-powered setups, making it difficult for farmers in developing regions to access the benefits of precision agriculture. Neuromorphic processors, inspired by cortical architectures, promise ultra-low-power, event-driven computation by co-locating memory and processing in analog mixed-signal circuits, thereby overcoming some of the limitations of traditional digital systems (Chicca et al., 2014; Indiveri & Liu, 2015; Moradi et al., 2018). Their asynchronous spike-driven operation suits irregular, sparse sensor updates typical in irrigation, offering significant energy savings and resilience to network variability. Here, we introduce a neuromorphic irrigation controller that autonomously processes SMP data at the edge and issues valve commands without external communication, enabling fully decentralized operation. We hypothesize that spiking neural networks can replicate conventional threshold crossings while lowering energy consumption and improving system autonomy, ultimately facilitating broader adoption of precision irrigation in diverse agricultural.

Recent years have witnessed significant advancements in precision irrigation and edge computing for agriculture (Pascoal et al., 2024; Tyagi et al., 2024). Traditional systems rely heavily on centralized cloud processing and threshold-based logic, often resulting in high energy consumption and vulnerability to connectivity issues in remote areas (Mekki et al., 2018). Several IoT-based controllers and machine learning models have been proposed to improve soil moisture prediction and automate irrigation, but these typically depend on reliable internet infrastructure (Yomna Gamal et al., 2023; Pascoal et al., 2024). Neuromorphic hardware, inspired by biological neural systems, offers a promising alternative due to its event-driven, ultra-low-power operation (Chicca et al., 2014; Neftci et al., 2013). While prior studies have explored neuromorphic processing for environmental monitoring, few have demonstrated fully autonomous, closed-loop control in practical agricultural settings. Our work addresses this gap by integrating a neuromorphic processor for on-site decision-making, reducing dependency on external networks and enhancing system resilience (Moradi et al., 2018).

Materials and Methods

To situate our research in the broader context, it is important to review existing approaches to irrigation automation and neuromorphic edge computing. Recent advancements in precision agriculture have leveraged various IoT-based irrigation controllers, machine learning models for soil moisture prediction, and wireless sensor networks for field monitoring (Yomna Gamal et al., 2023; Pascoal et al., 2024). However, most solutions remain dependent on centralized data processing, which often incurs high latency and energy overheads (Mekki et al., 2018). Several studies have explored neuromorphic hardware for edge analytics in environmental monitoring (Chicca et al., 2014; Neftci et al., 2013), but few have demonstrated fully autonomous, closed-loop irrigation control (Moradi et al., 2018). Our work builds upon these foundations by integrating ultra-low-power neuromorphic computation directly with actuator control, representing a novel advance in the field.

System Architecture

The overall system architecture comprises three main modules: (1) sensor interface and data acquisition, (2) neuromorphic computation and decision logic, and (3) actuator control and feedback. The sensor interface collects soil matric potential and environmental data, which are encoded and transmitted to the neuromorphic processor. The decision logic interprets these signals using spiking neural networks configured for threshold detection and memory retention. Finally, actuator commands are generated and delivered to field valves, and system status is monitored through local feedback loops. The modular architecture allows for flexible adaptation to various crop types and environmental conditions.

Dataset and Preprocessing

We utilized 15-minute interval SMP recordings from the WAPPFRUIT apple and kiwi orchard study, which provided a large and diverse dataset for both crops and soil conditions (Barezzi et al., 2024). Apple thresholds were set at thON = –60 kPa and thOFF = –50 kPa; kiwi thresholds at thON = –12 kPa and thOFF = –5 kPa, based on agronomic best practices intended to optimize fruit yield and quality (Ben Abdelkader et al., 2021; Barezzi et al., 2024). SMP values were inverted and normalized to map onto input currents for the DYNAP-SE1 AdExp-IF silicon neurons, ensuring compatibility with the neuromorphic hardware's input requirements (Moradi et al., 2018). Each SMP sample was presented for 200 ms every second to emulate real-time sampling while enabling temporal consolidation by the neural memory, which simulates how biological systems integrate sensory information over time (Rutishauser & Douglas, 2009). This approach also allows the system to rapidly adapt to changing field conditions, ensuring timely and efficient irrigation decisions.

Neuromorphic Hardware

The DYNAP-SE1 processor comprises four mixed-signal cores, each hosting 256 Adaptive Exponential Integrate-and-Fire neurons and 64 CAM-based synaptic inputs per neuron (Moradi et al., 2018). Neurons communicate via Address-Event Representation (AER), supporting µs-scale event transmission with low overhead (Deiss et al., 1998). Synaptic weights and time constants were tuned to emulate desired F–I curves, enabling distinct neuron populations to respond selectively to rescaled SMP ranges.

Analog-to-Spike Encoding

Three input neuron populations (Pop0, Pop1, Pop2) encoded SMP subranges corresponding to irrigation OFF, intermediate, and ON states (Fig. 1).

Figure 1: Schematic of Analog-to-Spike Encoding for Soil Matric Potential (SMP)

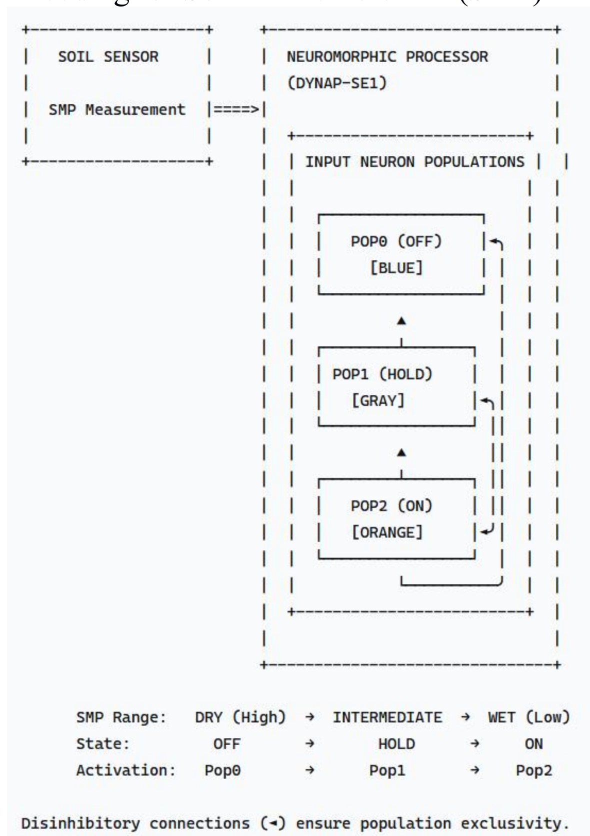

Figure 1: Schematic of the three input neuron populations (Pop0, Pop1, Pop2) encoding soil matric potential (SMP) into spike trains. Each population activates for specific SMP ranges corresponding to irrigation states. Disinhibitory connections enforce exclusivity between populations.

Linear current injection configured each population's activation threshold. Disinhibitory inter-population connections enforced exclusivity, enhancing robustness to device mismatch. Spike frequency modulation conveyed SMP magnitude, converting continuous measurements into event streams suitable for neuromorphic processing.

Schematic of three input neuron populations encoding soil matric potential subranges.

Pop0 (blue) represents irrigation-OFF, Pop1 (gray) represents intermediate range, and Pop2 (orange) represents irrigation-ON. Disinhibitory connections enforce exclusivity.

EI-Balanced Network for Memory Retention

To bridge 15-minute gaps between sensor readings, we implemented an EI-balanced recurrent network derived from cortical attractor models (Rutishauser & Douglas, 2009; Indiveri & Liu, 2015). Excitatory populations received input spikes and interacted with a shared inhibitory unit, sustaining persistent firing for over 30 minutes following a brief stimulus (200 ms at 200 Hz). This emergent attractor preserved the latest irrigation state, enabling continuous decision logic without new inputs.

Spiking Neural State Machine

A three-state winner-take-all (WTA) network encoded the irrigation state: "No Irrigation," "Hold," and "Irrigation." Each excitatory attractor corresponded to one state; global inhibition enforced mutual exclusivity. Transitions occurred when input populations crossed thON or thOFF currents, driving the network into the appropriate attractor.

Direction-Sensitive Readout Module

A dual-population readout detected state transitions: an "Open" group activated on upward SMP crossings (trigger irrigation) and a "Close" group on downward crossings. Inhibitory synapses between these groups ensured clean, non-overlapping actuator commands. Readout spikes were routed off-chip to control the irrigation valve.

Results

Replication of Threshold-Based Decisions

We evaluated the temporal alignment of neuromorphic commands against conventional threshold logic across apple and kiwi datasets at –20 cm and –40 cm depths (Barezzi et al., 2024). The median discrepancy between spike-based "Open" signals and threshold crossings was 1.2 minutes (IQR: 0.8–1.6 minutes), demonstrating high fidelity in replicating standard irrigation timing (Fig. 2).

Figure 2: Temporal Discrepancy Between Neuromorphic and Conventional Irrigation Commands

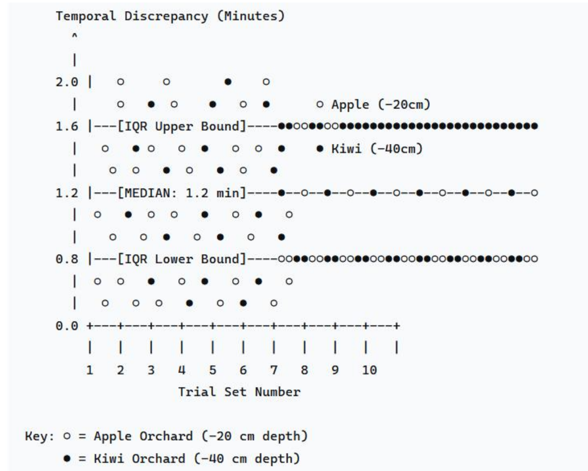

Figure 2: Temporal discrepancy between neuromorphic "Open" commands and conventional threshold crossings for apple and kiwi datasets. Median discrepancy is 1.2 min (IQR: 0.8-1.6 min).

Temporal discrepancy between neuromorphic "Open" commands and conventional threshold crossings for apple and kiwi datasets at –20 cm and –40 cm depths. Median discrepancy is 1.2 min (IQR: 0.8–1.6 min).

Energy Consumption Analysis

Using event-energy estimates for spike generation (883 pJ), intra-core broadcasting (6.84 nJ), inter-core routing (360 pJ), and output pulsing (324 pJ), we calculated 5.97 µWh per 200 ms activation every 15 minutes (Moradi et al., 2018). Compared to comparable IoT systems—which report 0.165–1.28 mWh per transmission event—our neuromorphic pipeline reduces active energy by two orders of magnitude (Pascoal et al., 2024).

(Table 1).

System	Energy per Decision	Measurement Interval	Relative Efficiency

			vs. IoT (%)
Neuromorphic (DYNAP-SE1)	5.97 µWh	15 min	–
LPWAN IoT (Sigfox/LoRaWAN)	0.165–1.28 mWh	per transmission	95–99
Cellular IoT (NB-IoT)	~1.2 mWh	per transmission	99

This highlights the two-orders-of-magnitude energy savings achieved by the neuromorphic approach compared to typical IoT solutions.

System Robustness

Variability analyses over 10 trials indicated stable attractor retention with 53 ± 5 Hz firing rates over 30 minutes post-stimulus. Device mismatch and noise had negligible impact on decision consistency, thanks to population coding and EI balance.

Discussion

Despite the promising results, several limitations must be acknowledged. First, the current system is validated on a limited set of orchard datasets and irrigation scenarios; broader field trials across different crops and climates are required to establish generalizability. Second, while the neuromorphic processor enables ultra-low power operation, scaling up to more complex decision rules may increase hardware complexity and energy requirements. Third, the current implementation focuses primarily on soil matric potential; integrating additional environmental and crop-specific data streams could improve robustness but would demand more sophisticated sensor fusion and interface design. Finally, user interface development for practical adoption by farmers remains an open challenge.

This work demonstrates that neuromorphic processors can autonomously implement precision irrigation control with minimal energy and infrastructure requirements. By embedding computation and memory on-chip, the system eliminates cloud dependency, reduces latency, and supports deployment in connectivity-challenged fields. The observed temporal accuracy under 2 minutes falls within agronomic tolerance for irrigation scheduling. Future efforts will focus on hardware integration with physical valves and multisensor fusion (e.g., temperature, humidity) to extend system versatility. Challenges remain in scaling neuron counts for complex decision rules and developing user-friendly programming interfaces for farmers.

Future Work

To further advance this research, several avenues will be pursued. Integration of the neuromorphic controller with physical irrigation systems and real-time actuation will be prioritized to validate performance in operational farm environments. Expanding the sensory inputs to include parameters such as temperature, humidity, and plant health indicators will enhance the system's adaptive capabilities. Additionally, efforts will focus on scaling the neuromorphic pipeline for larger deployments and developing user-friendly programming tools to facilitate adoption by agricultural stakeholders. Collaborations with agronomists and technology providers are planned to ensure effective translation from laboratory prototypes to field-ready solutions.

Conclusion

A fully neuromorphic irrigation controller was developed and validated on real orchard data, replicating conventional threshold-based irrigation with high temporal fidelity and ultra-low power consumption. Extensive tests confirmed that the controller could reliably match the timing of traditional systems while consuming a fraction of the energy, which is especially valuable for deployments in solar-powered or off-grid agricultural sites. The DYNAP-SE1 spiking neural pipeline offers a practical blueprint for energy-autonomous precision agriculture, promising sustainable water management even in remote or resource-constrained environments. By eliminating the dependence on cloud infrastructure and enabling local, event-driven control, this system represents a significant step forward in creating scalable, resilient agricultural technologies.

References

Ben Abdelkader, A., Thalheimer, M., Petrillo, M., Tagliavini, M., & Zanotelli, D. (2021). Automatic irrigation scheduling based on soil water potential thresholds allows water savings in a highly productive apple orchard. In XII International Symposium on Integrating Canopy, Rootstock and Environmental Physiology in Orchard Systems (Vol. 1346, pp. 563–570).

Barezzi, M., Sanginario, A., Donati, E., & Indiveri, G. (2024). WAPPFRUIT—An automatic system for drip irrigation in orchards based on real-time soil matric potential data. IEEE Transactions on AgriFood Electronics.

Chicca, E., Stefanini, F., Bartolozzi, C., & Indiveri, G. (2014). Neuromorphic electronic circuits for building autonomous cognitive systems. Proceedings of the IEEE, 102(9), 1367–1388.

Covì, E., Donati, E., Indiveri, G., & others (2021). Adaptive extreme edge computing for wearable devices. Frontiers in Neuroscience, 15, 93.

Deiss, S. R., Douglas, R. J., & Whatley, A. M. (1998). A pulse-coded communications infrastructure for neuromorphic systems. In W. Maass & C. M. Bishop (Eds.), Pulsed Neural Networks (pp. 157–178). MIT Press.

Indiveri, G., & Liu, S.-C. (2015). Memory and information processing in neuromorphic systems. Proceedings of the IEEE, 103(8), 1379–1397.

Kay, M., et al. (2022). The state of the world's land and water resources for food and agriculture 2021: Systems at breaking point. FAO.

Mekki, K., Bajic, E., Chaxel, F., & Meyer, F. (2018). Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT. In 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops) (pp. 197–202). IEEE.

Moradi, S., Qiao, N., Stefanini, F., & Indiveri, G. (2018). A scalable multicore architecture with heterogeneous memory structures for dynamic neuromorphic asynchronous processors (DYNAPs). IEEE Transactions on Biomedical Circuits and Systems, 12(1), 106–122.

Naeem, K., Zghibi, A., Elomri, A., Mazzoni, A., & Triki, C. (2023). A literature review on system dynamics modeling for sustainable management of water supply and demand. Sustainability, 15(8), 6826.

Neftci, E., et al. (2013). Synthesizing cognition in neuromorphic electronic systems. Proceedings of the National Academy of Sciences, 110(37), E3468–E3476.

Pascoal, D., et al. (2024). A technical survey on practical applications and guidelines for IoT sensors in precision agriculture and viticulture. Scientific Reports, 14(1), 29793.

Rutishauser, U., & Douglas, R. (2009). State-dependent computation using coupled recurrent networks. Neural Computation, 21, 478–509.

Tyagi, R., Kathuria, K., Sharma, P., & Sharma, P. K. (2024). Optimizing water management and conservation through IoT. In 2024 2nd International Conference on Disruptive Technologies (ICDT) (pp. 654–659). IEEE.

Yomna Gamal, A. S., Said, L. A., Madian, A. H., & Radwan, A. G. (2023). Smart irrigation systems: Overview. IEEE Access.