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22 October 2026

A neuromorphic continuous soil monitoring system for precision irrigation

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***Abstract*—Sensory processing at the edge requires ultra-low power stand-alone computing technologies. This is particularly true for modern agriculture and precision irrigation systems which aim to optimize water usage by monitoring key environmental observables continuously using distributed efficient embedded processing elements. Neuromorphic processing systems are emerging as a promising technology for extreme edge-computing applications that need to run on resource-constrained hardware. As such, they are a very good candidate for implementing efficient water management systems based on data measured from soil and plants, across large fields. In this work, we present a fully energy-efficient neuromorphic irrigation control system that operates autonomously without any need for data transmission or remote processing. Leveraging the properties of a biologically realistic spiking neural network, our system performs computation, and decision-making locally. We validate this approach using real-world soil moisture data from apple and kiwi orchards applied to a mixed-signal neuromorphic processor, and show that the generated irrigation commands closely match those derived from conventional methods across different soil depths. Our results show that local neuromorphic inference can maintain decision accuracy, paving the way for autonomous, sustainable irrigation solutions at scale.**

***Index Terms*—smart irrigation, neuromorphic, spiking neural networks, edge-computing**

I. Introduction

Efficient water management is increasingly critical in agriculture, as climate change, population growth, and resource depletion intensify pressure on food systems [1]. Precision irrigation addresses these challenges relying on timely, localized measurements of plant and soil conditions, minimizing both under- and over-watering, which can harm yield and crop health. Recent studies highlight the effectiveness of real-time, on-site monitoring systems for responsive irrigation control [2–4]. These always-on systems detect early signs of plant stress and trigger prompt corrective actions. Common observables include Soil Matric Potential (SMP) [5], soil moisture [6], and environmental parameters like air temperature and humidity [7]. Different crops and contexts require different sensing strategies and thresholds [8]. A notable example is the WAPPFRUIT project [9], which optimized orchard irrigation using low-power TEROS21 soil matric potential sensors (METER Group, Inc., Pullman, WA, USA) and cloud-connected threshold-based decision logic. This system reduced water usage while maintaining plant health, leveraging LoRaWAN [10] for data transmission and simple rule-based valve control. However, similar to the WAPPFRUIT project, most existing solutions rely on centralized architectures [11], where local sensors transmit data to remote servers via wireless protocols [12]. While effective, these systems face challenges such as unreliable connectivity, high energy consumption, and limited scalability—especially in remote or solar-powered deployments [13]. To address these limitations, neuromorphic computing offers a promising alternative [14, 15]. Inspired by the brain's efficiency, neuromorphic systems process data in an asynchronous, event-driven fashion, integrating memory and computation in analog or mixed-signal circuits [16]. This enables ultra-low-power, real-time processing ideal for edge applications like smart irrigation. In this work, we present a neuromorphic pipeline for real-time irrigation control based on soil moisture sensing. Using a mixed-signal neuromorphic processor and real-world WAPPFRUIT data, we apply the same threshold rules to assess accuracy and responsiveness. By interfacing sensors directly with a biologically inspired, energy-efficient control mechanism, our prototype enables a new class of autonomous, low-power irrigation systems that save water while supporting crop resilience in variable environments.

II. Methods

The proposed neuromorphic pipeline integrates analog sensing and event-driven neural computation within a compact, low-power architecture (Fig. 1). Leveraging the properties of mixed-signal neuromorphic circuits present on the DYNAP-SE1 chip [17], we process slow, analog soil moisture dynamic signals, converted into spike-based representations, by a series of brain-inspired spiking neural networks. The circuits and networks used include an analog-to-spike encoder, a dynamic recurrent network for temporal integration, a winner-take-all neural state machine for stable state retention, and a direction-sensitive readout module that triggers actuator commands. Each stage is carefully designed to operate under the constraints of variable and noisy ultra-low power circuits implementing co-localized memory and computation by mimicking

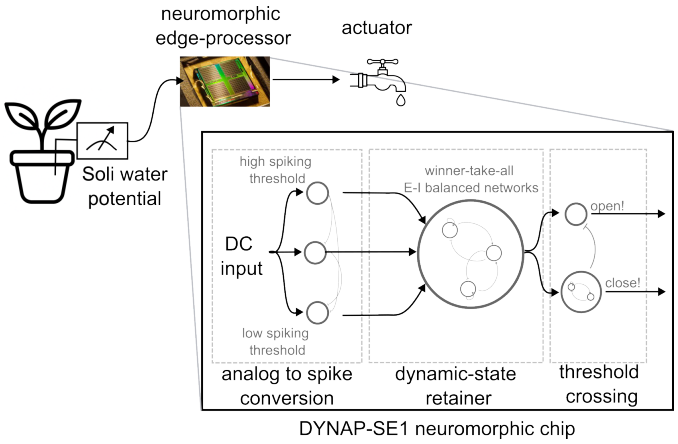

Fig. 1. **Neuromorphic edge-processing pipeline for plant monitoring and water supply management.** A soil-water potential sensor samples the soil's moisture state every 15 minutes and sends an analog signal to the DYNAP-SE1 neuromorphic chip. The signal undergoes analog-to-spike conversion, followed by temporal integration within a dynamic-state retainer—an excitatory-inhibitory balanced, winner-take-all spiking network that preserves slow-varying input dynamics. A readout mechanism is implemented by connecting populations of spiking neurons such that a "close" signal is triggered by downstream threshold crossings, and an "open" signal by upstream threshold crossings. These output signals are sent outside the neuromorphic system to actuate a valve, regulating water delivery accordingly.

cortical processing principles, and to produce robust and reliable event-based control.

A. The dataset

To benchmark our neuromorphic irrigation control system, we used the real-world data presented in the original WAPPFRUIT study [9]. This data consists of a set of time-series measurements of SMP collected from drip-irrigated orchards using TEROS21 SMP sensors. It includes 15-minute interval recordings of SMP values, capturing both natural fluctuations due to environmental conditions and irrigation events. For consistency and reproducibility, we adopted the same irrigation decision thresholds defined in the original paper, where irrigation is triggered, for example in apple orchards, when SMP drops below $-60\,\text{kPa}$ and is stopped when it rises above $-50\,\text{kPa}$, while for kiwi orchards, when SMP drops below $-12\,\text{kPa}$ and is stopped when it rises above $-5\,\text{kPa}$. These thresholds reflect the optimal soil moisture range for maintaining plant health while minimizing water usage. This dataset was inverted and normalized to produce values suitable for application to the chip as input currents to the DYNAP-SE1 silicon neurons. It served as both the input to our neuromorphic network and the ground truth for evaluating the performance of our system in replicating biologically-inspired irrigation decisions.

B. The DYNAP-SE1 chip

The neuromorphic processor used in this study is the DYNAP-SE1, a multi-core asynchronous mixed-signal neuromorphic system designed to emulate spiking neuron dynamics in real time [17]. Each of its four cores contains 256 current-mode silicon neurons [15, 18] that implement faithful models of Adaptive Exponential Integrate-and-Fire (AdExp-IF) neurons [19]. Each neuron can receive up to 64 synaptic inputs, configured by programming 64 corresponding Content Addressable Memory (CAM) blocks with the address of the pre-synaptic input source neuron. Each synapse can be further configured to act as excitatory (positive weight) or inhibitory (negative weight), with a fast or slow time constant. All silicon neurons within the same core share common parameters, including time constants, leak and refractory period values, and support up to 1024 fan-out connections. Communication among neurons is handled via an Address-Event Representation (AER) protocol [20], which enables asynchronous event-driven signaling with microsecond-level precision, even under high-load conditions. In the limit of high input current and with spike-frequency adaptation disabled, the dynamics of the AdExp-IF neuron circuit can be expressed as:

$$\tau \frac{d}{dt} I_{\text{mem}} + I_{\text{mem}} \approx \frac{I_{\text{in}} I_{\text{gain}}}{I_\tau} + \frac{I_a I_{\text{mem}}}{I_\tau}$$

where I_{mem} is the current that represents the membrane potential variable, τ is the neuron time constant, and the second term on the right-hand side models the positive feedback loop characteristic of the AdExp-IF model.

While direct measurement of DYNAP-SE1 power consumption during online operation is not feasible, it can be estimated as the sum of the energy used for spike generation and communication [17, 21], as defined in Eq. II-B:

$$P = \sum_{n=1}^{N} r_n \Big(E_{\text{spike}} + E_{\text{enc}} + N_{\text{cores}} (E_{\text{br}} + E_{\text{rt}}) + N_{\text{cam}} E_{\text{pulse}} \Big)$$

Here, r_n is the firing rate of neuron n, N is the total number of neurons, N_{cores} is the number of cores each neuron's output is sent to, and N_{cam} is the number of postsynaptic neurons receiving the spikes. The energy costs per event, estimated via circuit simulations at 1.8 V [17], are as follows: spike generation (E_{spike}) and encoding with destination tagging (E_{enc}) each consume 883 pJ; intra-core broadcasting (E_{br}) consumes 6.84 nJ; inter-core routing (E_{rt}) consumes 360 pJ; and extending the output pulse (E_{pulse}) adds 324 pJ per match.

C. Analog to spike conversion

To encode SMP levels relative to irrigation decision thresholds, we used pulse-frequency modulation implemented on three distinct populations of AdExp-IF neurons, each deployed on a separate core of the DYNAP-SE1 chip. In particular we linearly mapped SMP values to synaptic currents, such that SMP threshold crossings corresponded to synaptic currents that triggered transitions in our neural system. Indeed, populations were assigned distinct current-injection parameters, tuning their F-I curves to activate within non-overlapping input ranges. Backward inhibition from each group to those responsive to lower inputs enhanced selectivity, ensuring each population responded to a specific subrange of the rescaled

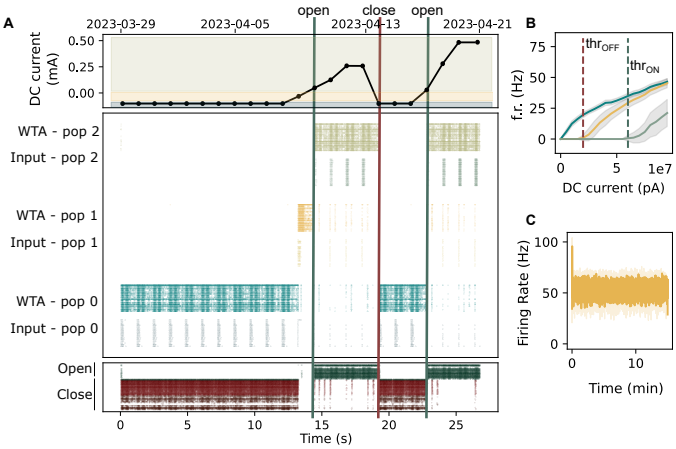

Fig. 2. **Spiking network dynamics for sensor data. A)** *Top row:* Subsampled soil moisture measurements, which serve as inputs to the chip. Each input, originally recorded every 15 min, is presented to the system for 200 ms every 1 s, leveraging the stable state dynamics of the EI-balanced network. For visualization purposes, only one data-point per day has been fed to the network. *Second row:* Raster plots showing spiking activity of the input and Winner-Take-All (WTA) excitatory neuron populations. *Third row:* Activity of the readout layer, indicating the "open" (green) and "close" (red) signals. **B)** Frequency–Current (F-I) curves for three neuron groups, each tuned to get activated at a distinct input DC value. These activation values are used as opening and closing thresholds in the normalized converted data. **C)** Average firing rate of an excitatory WTA population across 10 trials in response to a brief (1 s) stimulus. The sustained activity over a 15-minute period supports the assumption of a stable state during that time interval.

SMP signal. Input signals were linearly rescaled so that transitions between populations aligned with the irrigation activation (th_{ON}) and deactivation (th_{OFF}) thresholds used in WAPPFRUIT [9], as shown in Fig. 2A. Neuron parameters (bias currents and synaptic weights) were adjusted to ensure population-specific activation in response to constant input currents (Fig. 2B). A disinhibitory circuit enforced mutual exclusivity, allowing only the population tuned to the current SMP range to spike robustly, despite variability and device mismatch. The use of entire populations, rather than single neurons, serves two critical purposes: (1) it improves robustness to device mismatch inherent in analog neuromorphic hardware, and (2) it increases the net current delivered to downstream neural state-machine circuits responsible for storing this encoded information in memory.

D. EI balanced dynamics for stable long-term memory

A core challenge of our system lies in the very slow dynamics in the signals and the 15-minute gap between sensor readings. As our neural processor co-localizes memory and computation, unlike conventional digital processors, its individual elements can only retain information over timescales set by the circuit dynamics –wich at most can be configured to be in the order of hundreds of milliseconds. To maintain memory over longer timescales, information must be encoded either in the connectivity of the network or in its emergent dynamics. To address this, we leveraged Excitatory-Inhibitory (EI) balanced dynamics [22, 23], a well-established mechanism in which excitatory and inhibitory populations tightly interact to maintain dynamic equilibrium within stable attractor states [24]. This balance prevents runaway excitation and excessive inhibition, allowing the network to remain stable yet responsive, with fluctuation-driven activity and precise temporal behavior. By tuning the recurrent connectivity and synaptic gains of the EI loop, we configured the network to enter a self-sustaining state. After a brief 1 s, 200 Hz input, the network maintained a stable firing rate (53.3 ± 5 Hz) for over 30 minutes without further input. This emergent activity-based memory bridges the temporal gap between sparse sensor updates and continuous computation. All populations preserved their state for more than 15 minutes, as shown in Fig. 2C.

E. Neural State Machine

To encode distinct soil input levels robustly, we deployed a "neural state machine" [25, 26], a spiking WTA network inspired by cortical microcircuits [27]. Adapted from [28] for this application, the network has three recurrent excitatory populations (e_0, e_1, e_2), each tuned to different input ranges (Fig. 2A). These populations compete via a shared global inhibitory unit (inh) that enforces mutual exclusivity and prevents simultaneous activation. Each excitatory group receives input from a corresponding level-selective neuron (section II-C) and forms a persistent attractor state once activated. EI balance within populations ensures stable, noise-resistant dynamics. Activation of one excitatory population suppresses the others through global inhibition, implementing reliable winner-take-all behavior. For faster testing, input intervals were reduced to 1 second during experiments, based on prior results confirming consistent behavior over longer intervals.

F. Direction-based thresholds crossing detector

Finally, a spiking readout mechanism is implemented using a "close" state, which maintains persistent activity to signal the actuator accordingly. In parallel, a distinct "open" neurons population is activated by strong upward transitions in the input signal and is inhibited by the active "close" population, ensuring mutual exclusivity and direction-sensitive response.

III. Results

A. Network response vs threshold detection

To evaluate the performance of our system, we compared its irrigation control decisions—specifically the open/close signals—with those that would be generated using the threshold-based approach [9] for two different plant types: apples and kiwis. The comparison was conducted at two soil depths, -20 cm and -40 cm. As shown in Fig. 3, the discrepancy between the signals is minimal, and the results are highly comparable. This demonstrates that our edge-based system can reliably replicate the behavior of traditional threshold-crossing methods while avoiding the need for data transmission or remote processing. These findings support the feasibility of performing irrigation decisions locally, offering both energy and infrastructure advantages.

TABLE I
COMPARISON OF IOT IRRIGATION OPTIMIZATION STUDIES

Parameter	This work	Barezzi et al. (2024) [9, 29]	Angelopoulos et al. (2020) [13]
On-the-edge	✓	x	x
Data used	Data from Barezzi et al. 2024 [9]	Apple/Kiwi orchards	Strawberry greenhouses
Energy consumption	5.97 μWh	11.39 μWh	1.44 mWh
Resting energy	5.96 μWh	1.89 μAh @3.6 V = 6.8 μWh	0.05 mAh @3.3 V = 0.165 mWh
Active energy	0.003 μWh	1.28 μAh @3.6 V = 4.59 μWh	0.389 mAh @3.3 V = 1.28 mWh

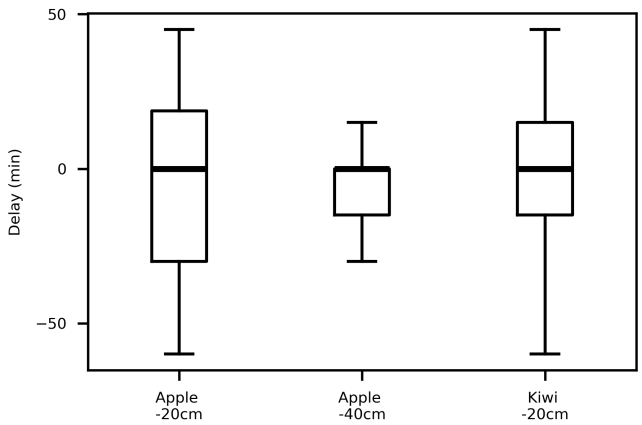

Fig. 3. **Comparison between the open signal of the neuromorphic network and the threshold-based approach.** Time difference between the threshold crossing detected by the neuromorphic system for two different plant species at two different depths. The threshold crossing is defined as the time interval between the sensor signal crossing the activation threshold (th_{ON}) and the moment when the firing rate of the "open" neural population exceeds that of the "closed" population. The line within each box represents the median. Experimental measurements are taken from [9].

B. Power consumption

Based on the approach described in section II-B values, we estimated the energy required to process a single input using the DYNAP-SE1 chip over a 200 ms activation window every 15 minutes. This results in a power consumption of approximately 5.97 μWh per event. Table I presents a comparative analysis of energy consumption across recent IoT-based irrigation optimization studies (without addressing the energy consumption of the sensors). It is important to note that the energy figures reported for the other works account only for the transmission of data and do not include the energy costs associated with the inference processing, which are typically carried out on remote servers.

In contrast, our approach executes the entire inference pipeline directly on the edge device, eliminating the need for data transmission. Communication is required only when a command must be sent to the irrigation system. This design results in drastically lower active energy consumption—only 0.003 μWh—while enabling fast and efficient on-device decision-making. By keeping all processing local, our system not only reduces latency but also achieves significant energy savings, making it highly suitable for large-scale, energy-constrained agricultural deployments.

IV. CONCLUSIONS

We presented a fully neuromorphic, ultra-low-power system for autonomous, edge-based irrigation control, eliminating the need for wireless transmission or cloud inference. Leveraging the DYNAP-SE1 chip, our spiking neural pipeline translates sparse analog inputs into stable actuator commands with only 5.97 μWh total energy consumption. The system integrates memory, computation, and decision-making on a single chip. Tested on real-world soil moisture data, it closely replicates threshold-based irrigation strategies across crop types and depths, demonstrating accuracy and robustness. To handle challenges related to long-timescale processing due to sparse sensor update, we used stable EI-balanced dynamics for memory retention and conservative state transitions, thus ensuring reliable decisions in dynamic conditions. Though already effective as it is, this system can scale to multi-modal data by converting diverse sensor inputs into spikes and processing them locally on neuromorphic hardware—enabling classification and control without cloud resources. This feasibility study highlights the promise of fully local, energy-autonomous control for precision agriculture. Next, we plan to integrate neuromorphic chips with physical sensors and actuators for in-field deployment, validating system performance under real-world variability. We also aim to support multi-sensor integration to enhance system versatility and confirm neuromorphic edge computing as a practical tool for sustainable agriculture.

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