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POSITION PAPER

The promise of neuromorphic edge AI for rural environmental monitoring

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Abstract

Edge AI is the fusion of edge computing and artificial intelligence (AI). It promises responsiveness, privacy preservation, and fault tolerance by moving parts of the AI workflow from centralized cloud data centers to geographically dispersed edge servers, which are located at the source of the data. The scale of edge AI can vary from simple data preprocessing tasks to the whole machine learning stack. However, most edge AI implementations so far are limited to urban areas, where the infrastructure is highly dependable. This work instead focuses on a class of applications involved in environmental monitoring in remote, rural areas such as forests and rivers. Such applications have additional challenges, including failure proneness and access to the electricity grid and communication networks. We propose neuromorphic computing as a promising solution to the energy, communication, and computation constraints in such scenarios and identify directions for future research in neuromorphic edge AI for rural environmental monitoring. Proposed directions are distributed model synchronization, edge-only learning, aerial networks, spiking neural networks, and sensor integration.

Impact Statement

This position article provides a comprehensive analysis of diverse environmental monitoring systems utilized in rural areas, pinpointing prevalent challenges, and evaluates the potential of emerging technologies of edge artificial intelligence (AI) and neuromorphic computing to address these challenges. It also highlights open issues and suggests research directions for the full realization of their potential. The primary goal of the article is to garner the interest of the wider environmental and computational science communities in promising developments in sustainable computing architectures.

1. Introduction

Environmental monitoring plays a crucial role in contributing to the United Nations Sustainable Development Goals, particularly toward *Clean Water and Sanitation*, *Climate Action*, *Life Below Water and on Land*, *Sustainable Cities and Communities*, and *Responsible Consumption and Production.* Indeed, managing the impacts of human activity on the planet necessitates continuous environmental monitoring. Internet-of-Things (IoT) technology enhances environmental monitoring systems by enabling data collection, transmission, and analysis from various sensors and devices. Driven by the exploding number of IoT devices and the amount of data generated at the edge of the network, edge artificial intelligence (AI) (Deng et al., 2020; Zhou et al., 2019) is widely considered the next logical step for real-time distributed data processing. Edge AI arises from the convergence of AI and edge computing (EC) and proposes utilizing the prevalent EC resources for training AI models and inferring based on thereof. Consequently, streaming big data from IoT devices can be processed in close proximity, which could bear various benefits, including bandwidth savings due to reduced amount of transmitted data, high responsiveness due to low latency, and privacy preservation due to local processing. Initial use cases for edge AI, such as traffic control, smart factories, and smart cities, have been almost exclusively located in urban areas (Ding et al., 2022; Peltonen et al., 2020). These environments are characterized by operational utilities (e.g., electric power) and high-bandwidth Internet access. However, we argue that edge AI can also find use in environmental monitoring applications targeted at rural and remote areas. In such a scenario, edge AI has to encounter also the challenges such as data insularity, low computation capability, and limited fan-in.

Another pressing issue that restrains large-scale processing of sensor data is energy consumption. Not to mention the current global energy crisis, electricity use of data centers is already a controversial topic (Katal et al., 2023). In 2019, the city of Amsterdam imposed a moratorium on building new data centers due to their high electricity budget, which was expanded to the whole country by the national government in 2022 (van der Marel et al., 2022). ICT currently accounts for 5% to 9% of global electricity consumption with comparable carbon emissions to air travel. Relying on redundancy (of IoT devices, communication links, and processors) to withstand the data explosion would increase energy consumption exponentially, with estimates exceeding 20% of the global electricity demand by 2030 (Brandic, 2021).

We follow an incremental approach in the rest of this article. Our main contributions can be summarized as follows. First, we define and review three classes of rural environmental monitoring applications (ie, pollution monitoring, disaster warning, and industrial IoT) and outline common characteristics and challenges (Section 2). Then, we introduce edge AI as a promising solution to most of these challenges, which in turn has its own limitations (Section 3). Furthermore, we discuss how neuromorphic computing (NC), a novel non-von Neumann technology, fits into the picture (Section 4) and identify future research directions for its practical use in enhancing edge AI for environmental monitoring use cases in rural areas (Section 5). We conclude the article with final remarks (Section 6).

We define neuromorphic edge AI as *a distributed computing architecture, where brain-inspired, massively parallel, and event-driven hardware is deployed at the edge of the network, close to IoT data sources.* There have been initial studies addressing rural computing from a human-computer interaction perspective, including those by Hardy et al. (2018) and Vázquez-López et al. (2021). Recently, the convergence of edge AI and NC has also been considered (Rubino et al., 2020). However, to the best of our knowledge, this work is the first to identify rural environmental monitoring as a new research direction and also the first to employ neuromorphic edge AI for environmental monitoring. Therefore, we believe it will be highly beneficial for scientists and practitioners in environmental data science alike.

2. State of the art in rural environmental monitoring

In this section, we first identify the most widespread forms of practical monitoring of rural environments. Then, we discuss the defining characteristics and limitations that distinguish them from applications in urban areas, such as the monitoring of noise levels, metropolitan air quality, heat islands, and urban climate. The proposed classification is summarized in Figure 1.

2.1. Classification

2.1.1. Pollution monitoring

Pollution monitoring is a process that involves measuring the ambient level of pollution in various mediums. Increasing global human activity and its consequent impact on the environment make it

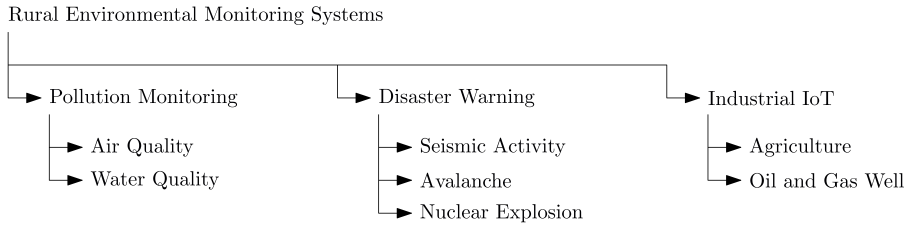

Figure 1. *A classification of the most prominent rural environmental monitoring systems.*

crucial to monitor air and water quality in rural areas. Pollution monitoring is beneficial not only for detecting sudden events such as leakages and enabling countermeasures but also for long-term modeling, which helps environmental scientists better understand the trends, impacts, root causes, etc.

One prominent and long-standing example of such an initiative is the Global Environment Monitoring System (GEMS) (Gwynne, 1982) by the United Nations Environment Program, which is a comprehensive attempt at worldwide pollution monitoring. GEMS focuses on air and water quality monitoring through the combination of low-cost IoT sensors, remote sensing technology, and traditional monitoring methods. GEMS operates through a collaborative network of national governments, research institutions, and nongovernmental organizations, ensuring a wide-reaching and inclusive approach to environmental data collection. By leveraging the latest in satellite imagery, ground-based sensor networks, and extensive data analytics, GEMS delivers an integrated view of the planet's environmental health. The GEMS data portal currently includes more than 20,000 water quality monitoring stations from rivers, groundwaters, lakes, reservoirs, and wetlands, as well as 30,000 air quality monitoring stations globally.

In water quality monitoring, there also exist regional monitoring systems for marine regions and freshwater bodies (both ground and surface water). SWAIN project (Ahmad et al., 2023), supported by the European Innovation Council CHIST-ERA program, focuses on surface waters, particularly rivers. The project aims to detect and locate pollutant sources (eg, industrial leaks or failed wastewater treatment plants) through an unprecedented implementation of EC and IoT for the real-time analysis of water contamination data. Timely decision-making is crucial in this use case as the river water polluted upstream might be used for irrigation or even for municipal water intake downstream. Such a scenario is illustrated by the Ergene River, Turkey, in Figure 2, where the potential health risk is apparent with highlighted heavy industrial development and irrigation areas. Ergene is one of the two use cases in the SWAIN project (the other being the Kokemäki River, Finland).

2.1.2. Disaster warning

Environmental monitoring systems are also widely used to detect and predict natural and anthropogenic disasters. Large-scale deployment of seismic sensors enables effective monitoring of earthquakes, volcanic activities, and avalanches. Two leading organizations for seismic monitoring are the EMSC (European-Mediterranean Seismological Centre) and the USGS (U.S. Geological Survey). The EMSC focuses on providing real-time seismic data and rapid earthquake information, primarily serving the Euro-Mediterranean region. It collaborates with various national seismological agencies to aggregate and disseminate earthquake data, contributing significantly to regional safety and emergency response planning. On the other hand, the USGS, a scientific agency of the U.S. government, plays a pivotal role in monitoring and researching geological phenomena, including earthquakes and volcanic activity, not just in the United States but globally. They employ a comprehensive network of seismic sensors and leverage advanced data processing technologies to analyze seismic events.

Intercantonal Measuring and Information System (IMIS) is the snow meteorology and avalanche warning network covering the Swiss Alps (Oester, 2021). IMIS consists of snow and wind stations to assess snowpack stability and the potential risk of avalanches. Snow stations within the IMIS network are

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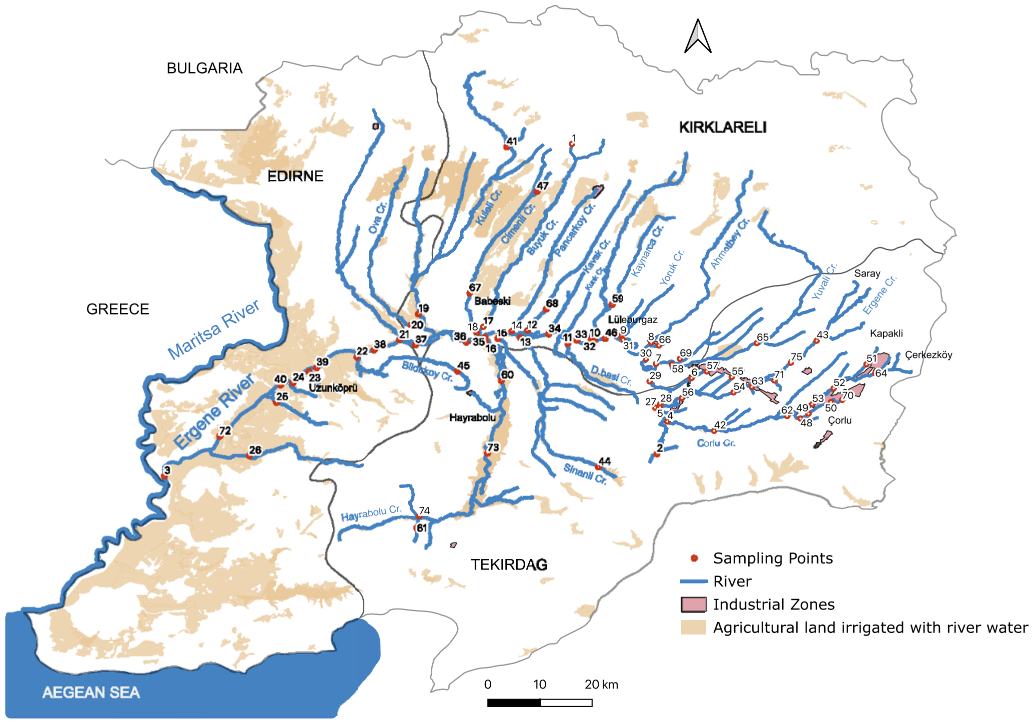

Figure 2. *Geographical overview of the Ergene Watershed located in Northwestern Turkey as a water quality monitoring use case (Image Courtesy of TUBITAK Project 115Y064).*

strategically placed and equipped with advanced sensors that continuously monitor snow depth, air temperature, and surface temperature, whereas wind stations are instrumental in measuring wind speed and direction, which are significant factors in the formation and evolution of snowpacks.

One of the most ambitious disaster warning infrastructures is maintained by the Comprehensive Nuclear-Test-Ban Treaty Office (CTBTO), which monitors the whole planet from more than 300 stations for signs of nuclear explosions. The International Monitoring System (IMS) (Garwin, 2011) uses data from seismic sensors (to monitor shockwaves), hydroacoustic sensors (sound waves in the oceans), infrasound sensors (ultralow-frequency sound waves), and radionuclide sensors (radioactive particles in the atmosphere). Collected data are transmitted to the IMS data center in Vienna, Austria, and processed to detect nuclear explosions, which potentially violate the Comprehensive Nuclear-Test-Ban Treaty adopted by the United Nations.

2.1.3. Industrial IoT

The third and final class of rural environmental monitoring applications that we identify is the industrial IoT systems. Although industries are often located within or near urban areas, e.g., in industrial zones, there exist at least two industrial use cases that are inherently rural. In the agricultural industry, IoT-driven smart farming is increasingly prevalent (Kasera et al., 2024). Here, sensors collect continuous data, including light, humidity, temperature, and soil moisture, to model crop health, yield, and so forth Furthermore, actuators can automate various tasks, including seeding, seedling, pollination, fertilization, irrigation, and harvesting.

The second use case concerns the oil and gas industry, particularly well monitoring systems (Aalsalem et al., 2017). Rural oil and gas wells can be monitored remotely and in real time thanks to IoT

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deployments, which improve safety, productivity, and sustainability. By integrating sensors for temperature, pressure, and other relevant parameters, these systems enable continuous monitoring of well conditions. This constant surveillance is crucial for the early detection of anomalies that could indicate potential safety hazards, such as leaks or pressure build-ups, thereby preventing accidents and ensuring the safety of both the environment and personnel. Moreover, IoT-based well monitoring contributes to improved operational efficiency. Real-time data allow for swift decision-making and timely interventions, reducing downtime and optimizing resource use. This increased efficiency not only boosts productivity but also minimizes the environmental impact of these operations. By closely monitoring and managing well operations, companies can reduce wasteful practices and better comply with environmental regulations.

2.2. Discussion

Table 1 summarizes the general characteristics of the above use cases, as well as the practical challenges in their implementation. The scale and dispersion of the monitoring systems vary significantly from a single field with a few sensors (as in agricultural IoT) to the European-Mediterranean region (as in seismic activity monitoring by EMSC) and even to the whole globe with tens of thousands of sensors (as in air quality monitoring by GEMS/Air). We also observe that real-time requirements in rural environmental monitoring systems are less strict than typical latency-sensitive IoT applications such as industrial control, connected vehicles, digital twins, robotics, and so on, which demand subsecond latency. The sampling frequency and available time for decision-making are both in the range of minutes to a few hours.

While some use cases, such as avalanche monitoring, are exclusively deployed in nonurban environments, others, such as water quality monitoring, include a combination of urban, suburban, and remote deployments. For instance, pollution monitoring stations in the scope of the SWAIN project can be located within cities when the river flows through them. However, other sections of the river in more rural areas have to be monitored, too. All use cases discussed here require a part of the IoT infrastructure to be deployed in remote areas. Consequently, the following new challenges (CH) arise in these use cases compared to urban monitoring. In a similar vein, urban areas can also suffer from these challenges in the aftermath of a disaster and require temporary solutions for data access or analytics (Kamruzzaman et al., 2017).

CH1: Electricity Access In most use cases, the electric utility is unavailable at the measurement locations; therefore, the sensors have limited or no access to reliable power sources. For instance, water and air quality monitoring sensors are usually battery-powered, which makes energy efficiency critical to avoid constant maintenance (Ko et al., 2018). The exceptions are (i) seismic activity sensors, which are not strictly bound to narrow geolocations but can function in nearby settlements almost without loss of accuracy and (ii) oil and gas well sensors since the wells are already powered.

CH2: Internet Access IoT sensors must transmit measurements to computational resources for processing. However, all rural use cases suffer from intermittent or no connectivity to a wide-area network (Ahmad et al., 2023). In theory, satellite-based communication is possible anywhere on the Earth, but in practice, this solution is too costly and energy-intensive. An important trade-off between CH1 and CH2 is the decision to process data locally or transfer it to a remote facility, as both local processing and data transfer are energy-intensive operations.

CH3: Failure Risk Rural deployment of IoT sensors complicates their maintenance and results in failure-prone infrastructures. Although most systems do not collect sensitive data, safety risks are generally high as failures result in undetected pollution or disasters. Moreover, previous research shows

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Table 1. *IoT-driven monitoring use cases in rural environments*

Rural environmental monitoring use case	Number of stations	Dispersion	Real-time constraint	Proximity to urban areas	Potential for electricity access	Potential for Internet access	Safety risk	Data sensitivity
Air quality (GEMS/Air)	≥ 30000	Global	Hour	Any	Moderate	Moderate	Moderate	Low
Water quality (SWAIN)	30–75	Regional	Minute	Any	Low	Low	High	Low
Seismic activity (EMSC)	≥ 2500	Continental	Minute	Any	High	Moderate	High	Low
Avalanche (SLF IMIS)	186	Regional	Hour	Mid to far	Low	Low	High	Low
Nuclear explosion (CTBTO)	337	Global	Hour	Mid to far	Low	Low	High	High
Agriculture	≈ 1 per 2 ha	Local	Hour	Near to mid	Low	Low	Moderate	Low
Oil and gas well	≈ 1 per well	Local	Minute	Mid to far	High	Low	High	High

that such failures in geo-distributed systems can be spatiotemporally correlated, resulting in cascading failures, which might cripple monitoring systems (Aral and Brandić, 2020).

CH4: Sustainability As a direct repercussion of spatially large environments and a wide dispersion of sensors, it is a challenge to achieve good coverage of the target environment. Even on relatively smaller scales, as in river or avalanche monitoring, better coverage requires a higher number of sensors, which undermines sustainability in terms of cost, energy and network use, and ecological footprint. Strategical placement of sensors can improve data quality and reduce the need for an excessive number of sensors (Ahmad et al., 2023).

3. Leveraging edge AI for environmental monitoring

3.1. Background and challenges

In the edge AI paradigm, a part of the computation capacity is deployed at the edge of the network, in the proximity of where the data are generated. Accordingly, the data can be at least partially processed at the edge servers, which have a high-bandwidth local area connection to the IoT devices. The output of preprocessing is usually transferred to the central facility for further analysis (Varghese et al., 2021). Contemporary machine learning algorithms, such as deep neural networks, consist of multiple layers of processing. The size of the data that is required to be transmitted between these layers is multiple orders of magnitude smaller than the raw input data. Therefore, these layers can be partitioned between cloud and edge data centers reducing network overhead significantly and alleviating CH2 (Luger et al., 2023). However, the energy consumption of the processing at the edge servers (CH1) has to be taken into consideration. There also exists federated learning solutions for environmental monitoring such as Nguyen and Zettsu (2021) and Siddique et al. (2024). In such systems, all learning is carried out at the edge of the network, and a central facility is only required as a parameter server that synchronizes learned parameters in distributed locations. This allows to improve the performance of locally trained models using information from other locations without transferring sensor data.

We identify the following additional challenges to achieve effective edge AI for environmental monitoring. The relations between previously introduced CH1–4 and CH5–7 are visualized in Figure 5.

CH5: Insularity Training AI models at the edge results in data scarcity and insularity. Since these models are fed with limited training data from a narrow local area, the models might not generalize well. This is exacerbated by failure-prone IoT sensors (CH3) and unreliable connectivity (CH2), as they make it difficult to fight insularity by transmitting data between edge locations (Aral et al., 2020).

CH6: Computational Capability Compared to the resource-rich cloud environment, EC lacks computational capability and fan-in (the maximum number of input signals) to process streaming data from a high number of sensors, especially under energy (CH1) and cost (CH4) constraints. State-of-the-art edge AI processors range from tiny onboard systems at sensors to system-on-chip devices, such as Raspberry Pi and Jetson Orin.

CH7: Parameter Mismatch There might be a mismatch between the target parameters required by the monitoring goals and parameters that can be sensed under the technical limitations in sensor technology. Additionally, the frequency of the measurements or the geographical diversity of the sensors might not be sufficient for real-time monitoring under sustainability constraints (CH4).

3.2. Case study

Edge AI deployment in the SWAIN project is illustrated in Figure 3 to exemplify the above-listed challenges. The monitoring system consists of measurement stations equipped with various IoT sensors

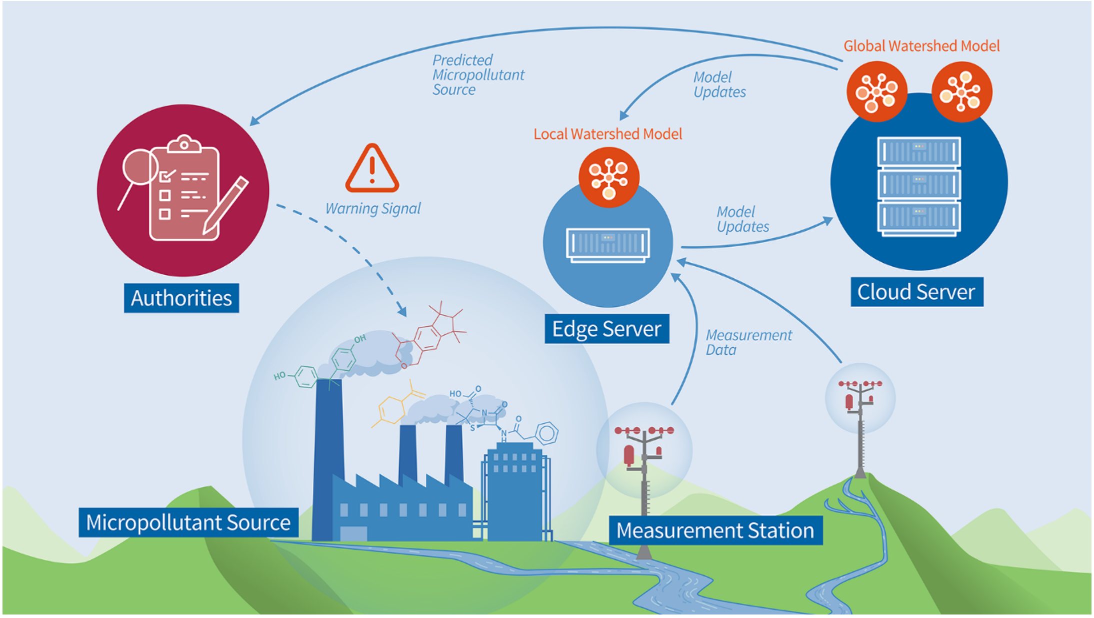

Figure 3. *Information flow in the edge AI architecture for water quality monitoring in the context of the SWAIN project (Ahmad et al., 2023).*

deployed along the river (ie, red circles in Figure 2). Streaming data from these stations are preprocessed through local AI models in nearby deployed EC servers and further analyzed in a remote resource-rich environment (e.g., cloud). Once pollution is detected, corresponding authorities are informed, along with the estimated location of the pollution source.

Here, there exist multiple EC locations (around 70 in one of the use case rivers) considering the size of the area monitored, the lack of network connectivity (CH2), and failure resilience (CH3). Each EC server models a part of the river and lacks a global view of the whole watershed (CH5). This renders source-tracking micropollutants very difficult. Therefore, an effective mechanism that enables servers to communicate and collaborate is required. Furthermore, each EC server can only handle a limited number of measurement stations and a simplified AI model due to computational and I/O constraints (CH6). This necessitates novel hardware with higher computational capabilities yet without higher energy consumption (CH1). Finally, the SWAIN project aims to detect micropollutants in the river water; however, state-of-the-art sensors can only measure conventional water quality parameters, such as pH and turbidity in real time (CH7). Moreover, the environmental impact of the monitoring stations prevents dense deployment (CH4). Accurate AI-driven mapping methods are therefore necessary to resolve the mismatch.

4. The potential of NC

Contemporary computers are almost exclusively based on von Neumann architecture, the main principles of which have remained unchanged since it was first proposed in 1945. This architecture consists of a processing unit and a separate memory that stores data temporarily during processing. The input data has to be transferred to the processing unit and the output data back to the memory through a data path. Moore’s law accurately predicted the growth of the processing speed thus far. However, the steep rise in the processing unit and memory speeds started to increase pressure on the data path capacity, which stopped the already lagging growth (De Maio et al., 2022; Schuller et al., 2015).

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Yet, the requirement for faster computing systems is ever-increasing exponentially. State-of-the-art machine learning algorithms such as Hierarchical Temporal Memory or Generative Adversarial Network entails an unprecedented level of computing resources that cannot be fulfilled by von Neumann-based computers efficiently (Zyarah et al., 2020). Since a single computer cannot be any faster, researchers are developing systems that consist of thousands of processing units to benefit from parallelism. However, this results in extremely high energy consumption, and therefore, such systems are not feasible for widespread use. As an example, the fourth fastest supercomputer currently, Fugaku (Sato et al., 2020), can perform 537 quadrillions (10^{15}) floating point operations per second using 158,976 processing units with an energy budget of 30 to 40 MW, which is comparable to 100,000 average EU households. Considering the proliferation of time-sensitive, streaming, and distributed data sources caused by the IoT revolution, it is of the utmost importance to invent non-von Neumann architectures.

NC (Rubino et al., 2020) is a new disruptive technology providing intelligent systems that imitate human neurobiological processes through massively parallelized computing architectures. NC hardware is not based on von Neumann architecture, as the processing unit and memory are co-located. A pioneer neuromorphic hardware developed by Intel was shown to train deep learning models in up to 81% shorter time than conventional systems (Li et al., 2018). Moreover, massively parallel neuromorphic circuits are event-driven. When the input signal is not present, the corresponding part of the hardware is inactive, which results in immense energy savings. Neuromorphic architecture is based on neurons and synapses, both of which are responsible for processing and memory. As visualized in Figure 4, input neurons are charged with incoming analog inputs (spikes) and eventually fire further spikes through the outgoing synapses, which in turn, charge other neurons. The timing and strength of the spikes (plasticity) can be modulated via synaptic weights. NC hardware facilitates massively parallel event-driven processing since each neuron and synapse is independent, and spikes are asynchronous (Schuman et al., 2022). Such temporal models, also called spiking neural networks (SNNs), are typically implemented using memristors, which are resistive memory devices that can collocate processing and memory (Strukov et al., 2008).

In the specific context of environmental monitoring, where events of interest are infrequent yet critical, NC stands out as an exceptionally energy-efficient solution. The sporadic nature of these events, such as rare seismic activities or unexpected environmental changes, demands a system that is always alert yet consumes minimal energy during periods of inactivity. NC, with its ability to mimic the human brain's efficiency in pattern recognition and anomaly detection, is ideally suited for this task. We propose integrating neuromorphic hardware into the edge servers. This integration would significantly improve the overall monitoring performance in several ways.

1. By increasing the **fan-in**, the system can process a greater volume of environmental data from a multitude of sensors simultaneously. This is particularly useful in complex monitoring scenarios where diverse data types, such as temperature, humidity, and chemical composition, need to be analyzed collectively.

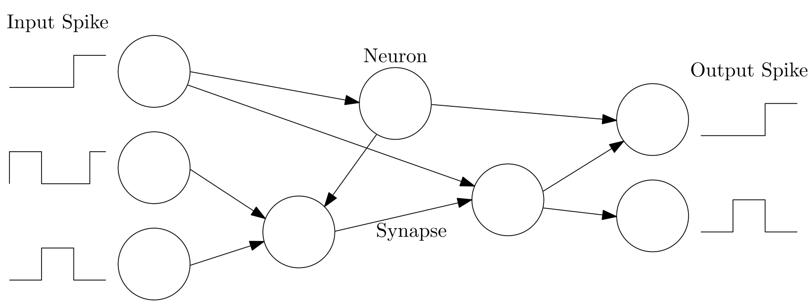

Figure 4. *A simple spiking neural network.*

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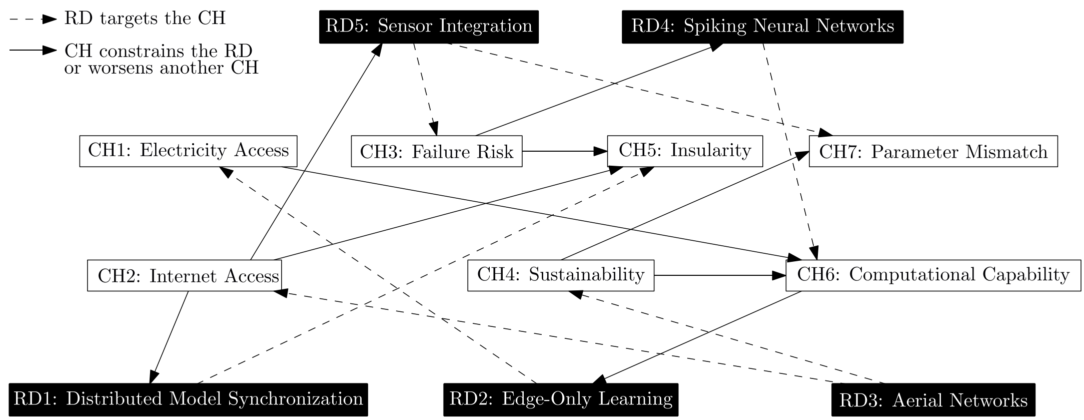

Figure 5. *An overview of the interrelations between challenges (CH) and research directions (RD).*

2. Enhancing **data throughput** is crucial for real-time monitoring and decision-making. Neuromorphic hardware, due to its increased data processing capabilities, can analyze incoming data streams in real time and enable an immediate response to environmental changes or emergencies.
3. NC is inherently **low power**, especially when compared to traditional computing architectures. In environmental monitoring, where power sources may be limited, especially in remote or rural areas, energy efficiency is a critical factor.

5. Directions for future research

Given the emerging nature of neuromorphic edge AI, several future research directions are identified, poised to tackle the challenges outlined earlier. For a visual summary of these challenges and research directions, along with their interconnections, refer to Figure 5.

RD1: Distributed model synchronization Improved fan-in enables more training data and alleviates CH5. However, the challenge of non-independent and identically distributed (non-IID) data in geospatial applications is still a significant issue. Non-IID data are a common scenario in environmental data collected from different geographical locations. This poses a challenge as traditional machine learning models often assume data to be IID, leading to potential biases and inefficiencies when this assumption is violated. Therefore, local models have to intercommunicate either directly or through a parameter server to improve the variety of the data and address the statistical imbalances. Previous work (Aral et al., 2020) demonstrates that complete synchronization is unnecessary and optimized communication can bring significant bandwidth savings. Considering CH2, it is crucial to optimize which and how much data are transmitted between edge nodes. Future research in this area should focus on developing methods that allow for efficient partial synchronization of models. This could involve determining which data are most valuable for transmission and developing algorithms that can efficiently process and integrate these data into local models. Such research could lead to more robust and efficient environmental monitoring systems that can handle the complexities of non-IID data in geospatial applications.

RD2: Edge-only learning Ultralow power operation of neuromorphic hardware could render energy harvesting possible for EC. This means more complex processing tasks can be done locally using ambient power sources, such as solar, wind, or water flow energy, even when the electricity grid is inaccessible (CH1). However, new approaches are required to optimize which data to process locally and which data to offload to remote resources (eg, cloud). It is estimated that transmitting one bit of data requires the same amount of energy as executing 50 to 150 instructions in von Neumann computers (Piotrowski et al., 2006). Considering NC's improved energy efficiency and computational capability, local AI models could come into more prominence.

RD3: Aerial networks Collaborative approaches between edge servers and unmanned aerial vehicles (UAVs), high-altitude platform stations (HAPS), or low-earth orbit (LEO) satellites (Pfandzelter et al., 2021) (Traspadini et al., 2023) are promising to counter CH2 by enabling global network coverage in the future. The improved coverage through these novel technologies would benefit rural environmental monitoring systems primarily in synchronizing local model parameters. However, transmitting massive raw data without preprocessing would consume too much energy in practice. Therefore, we envision that such technologies will complement neuromorphic edge AI rather than replace it, at least in rural scenarios. Aerial networks also promise less ground-based communication infrastructure in natural areas and thus contribute to the sustainability of the monitoring systems (CH4) by reducing their ecological footprint (Sari et al., 2023).

RD4: Spiking neural networks Ensuring that SNN-based systems can scale to cover large geographical areas and integrate seamlessly with existing environmental monitoring infrastructure is a complex task. Another open question is how existing AI models for learning from environmental data can be deployed on NC hardware. The benefits of NC, such as high throughput (CH6), would fully apply only if these models can be converted to SNNs accurately (Wang et al., 2023). This transition poses a significant challenge, as it requires not just a simple transfer, but a fundamental reconfiguration of the models to align with the unique operational dynamics of SNNs.

RD5: Sensor Integration Novel data fusion (Himeur et al., 2022) techniques are needed to cope with unreliable sensors (CH3) and parameter mismatch (CH7) issues in neuromorphic edge AI. They should be capable of identifying and compensating for inconsistencies such as missing data. This is particularly important in neuromorphic edge AI, where the integration of diverse sensor inputs is crucial. Due to technological limitations, parameters of interest in environmental monitoring can often differ from those that can be actually measured. Sensor fusion could help with this challenge by combining data from multiple types of sensors to create a more comprehensive and accurate representation of environmental conditions. Furthermore, integrating sensors can enhance the spatial and temporal resolution of environmental monitoring. Different sensors, deployed in geographically diverse locations or having diverse sensing capabilities, can provide a more detailed and comprehensive understanding of environmental phenomena, capturing changes that might be missed by a single sensor.

6. Conclusion

This article identifies common characteristics and open challenges for IoT- and AI-driven monitoring of rural environments. Furthermore, it presents neuromorphic edge AI as a promising solution to these challenges and proposes directions for future research toward its conception. Compared to other non-von Neumann architectures, NC is arguably the most mature technology; hence, researchers in this area will be the first to face the identified challenges. Therefore, we expect high interest in neuromorphic edge AI research in the following years.

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Data availability statement. This article is a perspective piece that does not involve new empirical data.

Author contribution. Conceptualization: A.A. Methodology: A.A. Writing original draft: A.A.

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Competing interest. The author declares none.

Ethical standard. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

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