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Hypothesis

Ecosystem-based reservoir computing. Hypothesis paper

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ABSTRACT

Reservoir computing (RC) has emerged as a powerful computational paradigm, leveraging the intrinsic dynamics of complex systems to process temporal data efficiently. Here we propose to extend RC into ecological domains, where the ecosystems themselves can function as computational reservoirs, exploiting their complexity and extreme degree of interconnectedness. This position paper explores the concept of ecosystem-based reservoir computing (ERC), examining its theoretical foundations, empirical evidence, and potential applications. We argue that ERC not only offers a novel approach to computation, but also provides insights into the computational capabilities inherent in ecological systems and offers a new paradigm for remote sensing applications.

1. Introduction

In the continuous evolution of computational paradigms, the interplay between the intelligence occurring in nature and evolved after millennia of optimization, and artificial systems built by humans, has given rise to unconventional approaches that transcend traditional algorithmic methods. Among these, reservoir computing (RC) emerges as a flexible framework that exploits the high-dimensional, dynamic properties of physical substrates to process information in ways reminiscent of the human brain. Unlike conventional artificial neural networks, which require extensive training of internal weights, RC has emerged as a "lazy man's" method to train these complicated systems. The approach uses the innate transient dynamics of a complex medium — referred to as the reservoir — to encode and transform input signals into meaningful reservoir states, which in turn are converted into outputs by employing a carefully optimized output layer (Schrauwen et al., 2007). This principle aligns with the broader cybernetic perspective, which information processing is viewed as not just an abstract computational act but as a function emerging from the intrinsic organization of a system and the transition among its states.

Reservoir Computing (RC) operates on the principle that complex, high-dimensional systems can serve as computational substrates, transforming input signals through their intrinsic dynamics without the need for explicit weight optimization. This framework finds its roots in liquid state machines (Maass et al., 2002) and echo state networks (Jaeger, 2001), both of which exploit the transient, nonlinear responses of dynamical systems to encode and process information. While initial implementations relied on artificial recurrent neural networks, subsequent research extended RC into physical systems, including photonic (Duport et al., 2012), mechanical (Dion et al., 2018), colloidal (Fortulan et al., 2024), and quantum (Fujii and Nakajima, 2017) reservoirs. These advancements illustrate the versatility of RC as a paradigm where computation is an emergent property of matter's interaction with energy and information flows (Yan et al., 2024).

Ecosystem-Based Reservoir Computing (ERC) represents a further evolution of this concept, clarified by exploring unconventional reservoirs that manifest at very large spatio-temporal scales, almost impossible to comprehend and hidden in the plain sight such as a part of a forest, a park, a lake, or even something bigger. The idea of using living systems as reservoirs is an attractive one if one has special purpose computation in mind. For example, a colony of bacteria can solve complex computation task via quorum sensing. However, large ecosystems exhibit properties unique only to them. In that sense the phrase "big is beautiful" gains a special meaning. Such systems exhibit key properties that align with RC principles:

- High-dimensional state space, where biotic and abiotic factors interact to produce a diverse range of responses;
- Transient memory effects, as biological networks retain and process past inputs through bioelectric, biochemical, and mechanical signaling;
- Nonlinear transformations, enabling the encoding of complex patterns through self-organized dynamics (Calvo and Friston, 2017).

These system implicitly "monitor" large surfaces and they do it for free. We only need to ask. These features suggest that natural

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ecosystems can function as computational reservoirs, responding to external stimuli with structured, high-dimensional outputs that can be harnessed for computational tasks.

At its core, ERC is informed by cybernetics and dynamical systems theory, particularly the notion that life itself is a network of interrelated control loops (Ashby, 1956). In this framework, computation is not confined to distinct algorithms but emerges from the self-organizing properties of systems far from equilibrium (Prigogine and Nicolis, 1985). This perspective aligns with the enactive approach to cognition (Varela et al., 1991), which posits that intelligence arises from an agent's interactions with its environment rather than from isolated symbolic manipulation. ERC extends this view, proposing that large-scale ecological systems process information through dynamic feedback loops that mirror the functional structure of RC.

One of the key mechanisms enabling ERC is bioelectric communication, a modality through which cells, fungi, and plants transmit information over long distances. Research on plant bioelectricity (Volkov, 2012) and fungal mycelial networks (Adamatzky, 2018) suggests that these biological substrates can be leveraged as computational media, with electrical activity encoding environmental inputs in a manner analogous to artificial reservoirs (Chiolerio et al., 2023). Similarly, chemical signaling in bacterial biofilms (Liu et al., 2017) and metabolic networks (Fondi et al., 2016) exhibit dynamic responses that align with RC's principles of transient, nonlinear information transformation.

The implications of ERC extend beyond theoretical interest, pointing to applications in biohybrid artificial intelligence for environmental monitoring. By treating ecosystems as computational substrates, ERC offers a framework for embedding intelligence within the biosphere itself, merging synthetic cognition with natural systems to create a sustainable, co-evolutionary paradigm for information processing. This shift represents not only a technological breakthrough but also a philosophical realignment, challenging the conventional view of computation as an exclusively human-designed process and instead situating it within the broader evolutionary fabric of life. This brings us to the notion of "accidental computation" and how to recognize it and measure it (Konkoli, 2015), and ultimately exploit it which informs on the question "what is computation" (Adamatzky et al., 2017a).

This paper explores the theoretical underpinnings of ERC, drawing from concepts in cybernetics, nonlinear dynamics, and collective intelligence. Such intelligence can be traced back even to entities like epigenetic memories encoded by histone methylation that depend upon past experiences and drive gene expression regulation (Jarome and Lubin, 2013). We consider that ERC has profound implications for realizing large scale artificial intelligence, and environmental monitoring, proposing a framework that merges computation with ecology in a manner that is both sustainable and fundamentally different from existing silicon-based architectures. By embracing ERC, we move toward a post-digital paradigm where intelligence is no longer confined to silicon-based processors but is instead distributed across natural substrates, leveraging the computational capacity of life itself. This shift has profound implications not only for AI and machine learning but also for our understanding of cognition, adaptation, and the very nature of computation.

2. Theoretical foundations of ecosystem-based reservoir computing

What is the right theory to describe ERC? Can we design a programming language to run an ecosystem as a computer? Every ERC can be viewed as a filter that operates on a time-series input signal $q(t)$ that changes its state $x(t)$ in such a way that the state at a particular time instance t depends on what the system has experienced in the past.

For example $q(t)$ can represent a mathematical representation of environmental conditions, e.g. the amount or rain, the number of rainy days, etc. The meaning of $x(t)$ is harder to grasp. In principle it should be anything we can measure about the system, that is relevant for its overarching dynamics. More examples for what $x(t)$ and $q(t)$ represent will be provided below where we discuss som pioneering efforts to implement this ERC agenda.

In such a way the state of the system contains information of what the system has experienced in the past. Mathematically this can be described as the mapping $x(t) = R[q](t)$ where the notation $R[q](t)$ describes what in the signal processing theory is referred as a filter. A dynamical system driven by an external signal represents a process of collecting information: the information that the system collected about the environmental signal $q(t)$ is accumulated over time whereupon being stored into the state variable $x(t)$. In principle, by studying $x(t)$ one should be able to gain information on $q(t)$.

The variable $x(t)$ is referred to as an observable in statistical physics where it indeed has the meaning of something that we can measure about the system. For example, by connecting electrodes to a tree we can measure voltages that will depend on the state of the environment $q(t)$. An example of a system that realizes the mapping $x(t) = R[q](t)$ is the one that can be described by a differential equation $\frac{dx}{dt} = H(x(t), q(t))$ where $H(x, q)$ describes the dynamic laws that govern the system's behavior. In physics, such an object is referred to as the Hamiltonian of the system.

The state of the system is used to infer about the environmental signal (weather conditions, forest state, etc.) and produce a verdict $y(t) = \psi(x(t))$. The mapping ψ is one of the components of the system that we can hope to control. Together, this chain of mappings, embedded in the ERC realizes a filter $y(t) = \varphi[q](t)$.

More than just a filter, an ERC can be viewed as a database one can query that encodes and retrieves information about its environment. This raises a fundamental question: How can such a system be queried effectively?

A straightforward way would be to simply collect information about the observables $x(t)$. This approach is the most common way to exploit any sensor networks. The information flow is linear. The environment impacts the ecosystem, the system adopts a certain state, and we observe certain features about that state. The obvious appeal of such an approach is its modularity. One can selectively zoom on different parts of the information processing apparatus, building better sensors, information transfer facilities, and increasing the power of the computing center, all to our hearts desire or ability.

However, the most direct approach discussed above does not scale well in terms of the environmental impact. Large-scale monitoring requires widespread sensor deployment, continuous data collection, transmission to a central analysis hub, and subsequent processing. As the environmental impact grows, so does the logistical and computational burden, making this approach inefficient for large, dynamic ecosystems. Further, there might be subtle correlations in the system's behavior that might be lost over time, or significant glitches in the signals that are easily interpreted as noise.

An alternative approach to querying the system draws inspiration from the response theory in physics. The fundamental idea is to expose the system to a weak external signal and infer the state of the system by observing its response. By collecting multiple input-response pairs (u_i, y_i), where u_i represents the applied input and y_i the observed response, one can systematically infer the system's internal state. This method has proven to be highly effective in various problem settings. What is remarkable is that the signal that disturbs the system does not have be necessarily strong to make accurate inference about the systems state.

In reservoir computing, a similar approach has previously been proposed in the form of the SWEET algorithm (Konkoli, 2016). The SWEET algorithm relies on the indirect sensing idea from the linear response theory in physics, but with a heavy modification by trying to actively leverage non-linearities in the system's behavior. The idea is to equip the reservoir with an external auxiliary signal $u(t)$ that the user controls. This signal is used to increase its "intelligence" with a marginal implementation cost. The idea has been successfully employed and tested in a range of information processing scenarios ranging from ECG signal classification (Athanasiou and Konkoli, 2020) to sepsis prediction for intensive care unit patients (Athanasiou and Konkoli, 2019). The accuracy of the prediction with reservoirs consisting of a relatively few non-linear components matched the one obtained by employing deep neural networks.

The suggested implementation of the SWEET algorithm in the context of ERC is as follows. Instead of dissipating many sensors in space, one observes the system over prolonged periods of time while "tickling" it with carefully chosen inputs, drive signals $u(t)$. Formally, one engineers the following filter: $x(t) = R[q,u](t)$ where $u(t)$ denotes the signal provided by the user. One can think of it as a query to the database. Using the language of differential equations, one can describe the newly formed filter as $\frac{dx}{dt} = H(x(t), q(t), u(t))$ where $H(x, q, u)$ describes all the dynamical laws how the user signal interacts with the system. Assume that the goal is perform the query Q on the system, i.e. apply the filter $y(t) = Q[q](t)$. The question is whether we can find the drive signal $u(t)$ such that $Q[q](t) = \psi(R[q,u](t))$. This naturally brings several important questions with increasing degree of complexity. But let us illustrate what is mean but all this abstract theory.

The symbol $Q[q](t)$ represents user's desire to know about the system. For example, one might wish this to represent the question "What is the chance that it will rain tomorrow?". Obviously, we cannot "ask" the forest a direct question like this. Assuming that we treat a hunter moving in the forest as a part of the system we could try to observe their clothes. If they are carrying an umbrella, then it is naturally to expect that the probability of the rain is high. Of course, this would be cheating. We must "ask" the forest somehow and we want to do it over a prolonged period of time by asking small questions and accumulating the answers.

The first question the illustration above motivates is this. What is the right interplay between choosing the readout layer ψ and the drive signal $u(t)$, both of which we fully control, so that we can achieve a one-to-one mapping between Q and (ψ, u). If this were possible this would be ideal. For example, can we for any query Q that we wish to make about the system find the related (drive signal, readout layer) configuration that will realize this query? Of course, the answer depends on what the expressive power of our ecosystem computer is. The real forests probably cannot tell much from scratch, but if queried properly they might.

The second question is about balancing resources. For example, how to choose the best possible drive signal $u(t)$ so that the complexity of the readout layer ψ can be kept at a minimum. Again, it all depends on the complexity of our ecosystem computer. If it has low expressive power, then we have to engineer more intelligent readout-layer, which will likely come with increasing implementation cost in terms of the resources needed of realizing it.

Clearly the choice of the external drive $u(t)$ is central to this novel way of thinking. There is an intrinsic problem to the whole idea due to the scale one wishes to target. Namely, it is not clear that one can find a suitable drive signal $u(t)$ that will have a global effect on the system both in terms of larger spatial and temporal scales. We wish to engineer signals that will propagate through the system and that will no dissipate after causing some local disturbances. For example, an example of a very local input to the system would be to splash a bucket of water on a tree in the forest. One could most definitively affect the tree during the times of drought but this will not alter the system during a heavy rain period. This is one of the key research challenges, to identify which drive signals are the most useful. Several examples already tested in the literature will be discussed in the forthcoming sections.

3. Empirical evidence supporting ERC

The realization of Ecosystem-Based Reservoir Computing (ERC) as a viable computational paradigm requires empirical validation across diverse biological and ecological substrates. Recent research has begun to uncover the computational capacities inherent to natural systems, demonstrating their ability to encode, process, and recall information in a manner analogous to artificial reservoirs. This section examines key experimental findings that support ERC, focusing on bioelectric networks, chemical communication in microbial consortia, and ecosystem-scale information processing.

Fig. 1. Electrodes in Schlumbergera cactus used for reservoir computing (Adamatzky et al., 2017b).

Table 1
Number of gates mined from the frequency responses of the Schlumbergera (Adamatzky et al., 2017b).

Cfg.	Inputs xy				Number of gates	Gate
	FF	FT	TF	TT		
1	F	F	F	F	95 718	Constant False
2	T	F	F	F	366	x NOR y
3	F	T	F	F	304	NOT x AND y
4	T	T	F	F	430	NOT x
5	F	F	T	F	304	x AND NOT y
6	T	F	T	F	430	NOT y
7	F	T	T	F	74	x XOR y
8	T	T	T	F	314	x NAND y
9	F	F	F	T	510	x AND y
10	T	F	F	T	104	x XNOR y
11	F	T	F	T	863	y
12	T	T	F	T	307	NOT x AND NOT y OR y
13	F	F	T	T	863	x
14	T	F	T	T	307	x OR NOT y
15	F	T	T	T	512	x OR y
16	T	T	T	T	94 564	Constant True

3.1. Bioelectric networks as computational reservoirs

Bioelectric signaling, long recognized as a fundamental mechanism in neural networks, extends to non-neuronal tissues, plants, and microbial communities, offering a natural substrate for reservoir computation. Levin (Levin et al., 2017) demonstrated that bioelectric gradients in multicellular systems encode spatial information, guiding morphogenesis in a self-organizing manner. Such bioelectric fields exhibit transient responses to external stimuli, fulfilling the criteria for reservoir computing: high-dimensional state space, nonlinearity, and fading memory. Similarly, Adamatzky (Adamatzky, 2018) explored the electrical activity of fungal mycelial networks, revealing their ability to process environmental data through complex oscillatory patterns. When stimulated with mechanical and chemical inputs, fungal networks exhibited signal propagation and adaptive responses characteristic of reservoir systems.

In 2015 Adamatzky and colleagues (Adamatzky et al., 2017b) demonstrated that living plants make a fruitful substrate for reservoir computing. Eight electrodes, each connected to the digital outputs of

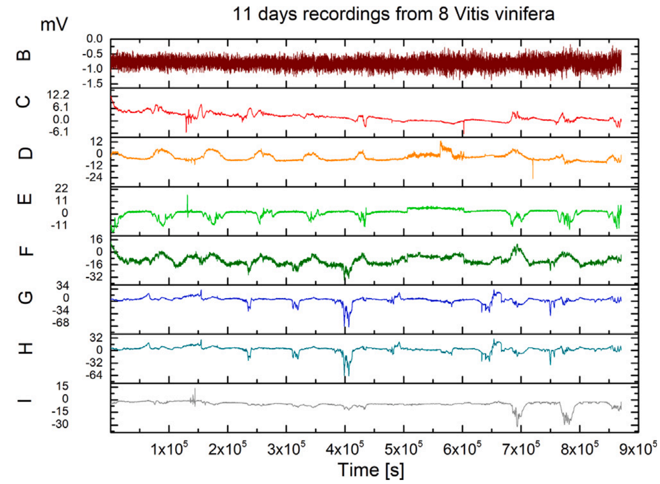

Fig. 2. Eleven days bioelectric potentials recorded from eight different Vitis vinifera individuals, belonging to Barbera variety. B: dead log; C to E: healthy individuals; F to I: different stages of *Flavescence dorée* disease.

the Mecobo via 4.7kOhm resistors, were inserted into a single stem segment of a Schlumbergera (Christmas Cactus) plant, as shown in Fig. 1. An exhaustive search was performed by applying all binary combinations of various frequency pairs (250 Hz, 500 Hz, 1 kHz, 2.5 kHz) to 7 input pins, with one pin used as the output. Each frequency pair, represented by square waves at 3.3 V, was tested to observe plant's response under different input conditions. Table 1, shows a summary for all of the runs. We see that all possible 2 input Boolean gates were implemented.

Plant electrophysiology further supports ERC. Volkov (Volkov, 2012) showed that plants generate action potentials in response to environmental changes, propagating information through vascular tissues. Recent studies (Volkov and Markin, 2015) demonstrated that plant bioelectric responses can be harnessed as computational signals, with artificial neural networks decoding their dynamical states to infer environmental conditions. This is an example of the linear information flow discussed earlier where the system is being observed without any attempt to alter it. These findings suggest that living bioelectric networks function as information-processing reservoirs, dynamically encoding sensory inputs within distributed, nonlinear systems (Chiolerio et al., 2022), proven to be capable of tracking planetary events (Chiolerio et al., 2025). An example of eight collected biopotential recordings from a barbera vineyard (cantina Adorno, Vigliano d'Asti, Italy) is shown in Fig. 2. The reader can appreciate a periodicity in the signals, given by the eleven day/night cycles, as well as a different level of noise, depending on the health conditions of the specific Vitis vinifera individual which has been characterized.

3.2. Microbial chemotaxis and collective information processing

However, one can also look towards micro-scales. Microbial communities exhibit emergent behaviors that mirror the principles of RC, particularly in their ability to adapt to dynamic environments through collective decision-making. Liu (Liu et al., 2017) observed that bacterial biofilms utilize long-range chemical signaling to coordinate metabolic activity, effectively encoding past and present nutrient conditions. The capacity of bacterial populations to integrate multiple stimuli and produce structured, temporally dependent responses aligns with the core mechanisms of reservoir computing.

Beyond bacterial biofilms, engineered microbial consortia have been employed as computational reservoirs. Tamsir (Tamsir et al., 2011) demonstrated that synthetic genetic circuits can process logical operations through quorum sensing pathways, enabling microbes to perform distributed computation. More recently, Fondi (Fondi et al., 2016) reported that metabolic networks in microbial ecosystems exhibit information processing capacities that surpass individual cellular computation. The unicellular organism Tetrahymena thermophila has been used in real-time ecological reservoir computing, where its population dynamics were harnessed to perform computational tasks (Masayuki et al., 2023). These findings support the hypothesis that microbial consortia function as biochemical reservoirs, encoding input signals within dynamic, nonlinear metabolic landscapes.

3.3. Ecosystem-scale information processing

At a larger scale, ecosystems themselves exhibit computational properties. Canarini (Canarini et al., 2021) demonstrated that soil microbial communities' composition change, allowing the formation of ecological memory in soil that may enhance the resilience of ecosystems. Again, this is an example of the linear information flow with well defined observables $x(t)$ responding the environmental changes $q(t)$. Similarly, Braga (Braga et al., 2016) analyzed decentralized, adaptive systems, where nutrient fluxes and microbial populations (representing $x(t)$) encode environmental changes over time.

Forests, as complex adaptive systems, also display computational characteristics. Beiler (Beiler et al., 2010) showed that mycorrhizal networks mediate resource exchange between trees, dynamically adjusting connectivity patterns in response to external stressors. This form of decentralized information processing mirrors RC principles, where mycelial networks serve as substrates for distributed signal transformation.

A study demonstrated that ecological dynamics could be harnessed as a computational resource by developing two frameworks based on reservoir computing. These frameworks utilized the natural interactions within ecological networks to perform computations, highlighting the potential of ecosystems to function as reservoirs (Masayuki et al., 2023).

Taken together, these empirical studies provide compelling evidence that biological and ecological systems naturally implement reservoir-like computation. The observed behaviors — ranging from bioelectric signaling to microbial chemotaxis and ecosystem-scale feedback loops — align with the fundamental properties of RC, reinforcing the feasibility of ERC as a biologically embedded computational framework.

3.4. Dormancy as a source of long-term memory in ERC

A crucial element that can significantly enhance ERC is the phenomenon of dormancy, in other words the ability of certain ecosystem components to enter reversible states of metabolic inactivity. This mechanism could generate an ecological "memory bank", where past environmental experiences are archived and can later influence system dynamics across extended timescales. As highlighted by Lennon et al. seed banks and microbial dormancy are widespread in ecosystems, contributing to the emergence of multiscale complexity by preserving information from prior conditions (Lennon et al., 2021). In the context of RC, dormancy introduces a powerful long-term fading memory: the system's current state may reflect inputs from the distant past which have been incorporated in the genetic structure of seeds, thereby increasing its computational expressivity. Incorporating dormancy mechanisms into ERC enriches the temporal depth of the reservoir, enabling it to handle longer temporal dependencies in input signals. This represents a substantial advancement over earlier biologically inspired approaches, such as Kohonen Self-Organizing Maps or Hopfield networks (Gigante et al., 2023), by providing a natural substrate with intrinsic long-term memory capabilities embedded in ecological dynamics.

4. Potential applications of ERC

The integration of ERC into computational practices offers several promising applications:

- Environmental Monitoring: ERC can be utilized to process complex environmental data, aiding in the detection of ecological changes and the prediction of environmental trends.
- Climate Modeling and Forecast: by leveraging the computational capabilities of ecological systems, ERC can contribute to more accurate climate models, enhancing our understanding of climate dynamics, and allowing for local weather forecasts.
- Bio-inspired Computing: ERC provides a framework for developing bio-inspired computational systems that mimic the adaptive and resilient properties of natural ecosystems.

5. Conclusions

The concept of ERC challenges traditional boundaries between computation and ecology, suggesting a bidirectional relationship where ecological systems can both inspire and implement computational processes. This perspective aligns with the broader field of unconventional computing, which seeks to exploit the computational potential of physical and biological systems.

However, the practical implementation of ERC presents challenges, including the need to accurately model ecological dynamics and to develop interfaces that can effectively harness these dynamics for computation. Addressing these challenges requires interdisciplinary collaboration, integrating insights from ecology, computer science, and complex systems theory.

Ecosystem-based reservoir computing represents a frontier in computational intelligence, leveraging the inherent dynamics of ecological systems for processing information. By exploring the computational capabilities of ecosystems, ERC not only offers novel approaches to computation but also deepens our understanding of the complex interplay between ecological dynamics and information processing. As research in this area progresses, ERC has the potential to inspire innovative applications across environmental monitoring, climate modeling, and bio-inspired computing.

CRediT authorship contribution statement

Alessandro Chiolerio: Writing – review & editing, Writing – original draft, Conceptualization. **Zoran Konkoli:** Writing – review & editing, Writing – original draft, Conceptualization. **Andrew Adamatzky:** Writing – review & editing, Conceptualization.

Declaration of competing interest

We declare that we have no conflicts of interest to disclose relating to this paper.

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