

Predicting the future with magnons

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Forecasting complex, chaotic signals is a central challenge across science and technology, with implications ranging from secure communications to climate modeling. Here we demonstrate that magnons – the collective spin excitations in magnetically ordered materials – can serve as an efficient physical reservoir for predicting such dynamics. Using a magnetic microdisk in the vortex state as a magnon-scattering reservoir, we show that intrinsic nonlinear interactions transform a simple microwave input into a high-dimensional spectral output suitable for reservoir computing, in particular, for time series predictions. Trained on the Mackey-Glass benchmark, which generates a cyclic yet aperiodic time series widely used to test machine-learning models, the system achieves accurate and reliable predictions that rival state-of-the-art physical reservoirs. We further identify key design principles: spectral resolution governs the trade-off between dimensionality and accuracy, while combining multiple device geometries systematically improves performance. These results establish magnonics as a promising platform for unconventional computing, offering a path toward scalable and CMOS-compatible hardware for real-time prediction tasks.

The ability to predict chaotic time series is a longstanding challenge at the crossroads of nonlinear dynamics, machine learning, and physical computing. Chaotic systems, while governed by deterministic rules, exhibit extreme sensitivity to initial conditions, rendering long-term trajectories unpredictable. This combination of determinism and apparent randomness makes them ideal benchmarks for testing new computational architectures aimed at real-time forecasting in complex, high-dimensional systems. Reservoir computing has emerged as a particularly promising approach, offering efficient training and natural suitability for temporal tasks [1–3]. In this framework, a fixed dynamical system projects inputs into a high-dimensional state space, from which a simple linear readout extracts the relevant information. Crucially, this separation of nonlinear dynamics and trainable output enables hardware realizations, where intrinsic material properties can be harnessed directly. Physical implementations have already been demonstrated in diverse platforms, from optical fibers [4–7] and memristive circuits [8–11] to spintronic devices [12–17], nanomagnetic arrays [18–20], skyrmions [21–25], and magnonic systems [26–32]. Each of these leverages unique mechanisms of nonlinearity and memory.

Here we demonstrate chaotic time-series prediction using a magnon-scattering reservoir (MSR) operating with modal multiplexing [33, 34]. The platform consists of a $\text{Ni}_{81}\text{Fe}_{19}$ microdisk in the magnetic vortex state [35, 36], where magnons provide three key advantages: (i) strong intrinsic nonlinear interactions, (ii) temporal memory arising from dispersion and damping, and (iii) compatibility with complementary metal-oxide-semiconductor (CMOS) technology [37]. Harnessing these features, we show that the MSR reliably forecasts the dynamics described by the Mackey-Glass equation, which

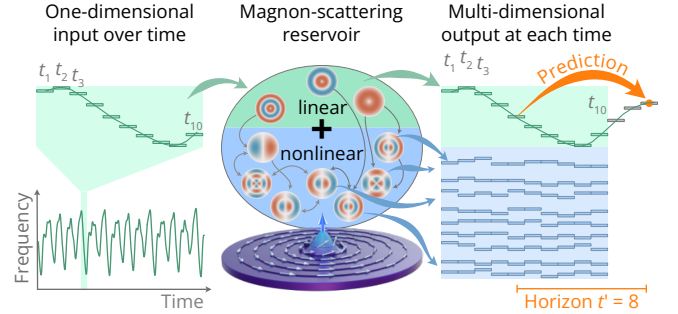


Figure 1. Principle of chaotic time-series prediction based on a magnon-scattering reservoir. A one-dimensional temporal input is encoded in a microwave current and applied to a magnon-scattering reservoir in form of a $\text{Ni}_{81}\text{Fe}_{19}$ microdisk in the vortex state. Nonlinear interactions between various magnon modes transform the one-dimensional input into a multi-dimensional spectral output trained to forecast the future trajectory of the chaotic signal.

produces a cyclic yet aperiodic time series widely used to benchmark machine-learning models. Our MSR exceeds previously reported prediction horizons while maintaining high accuracy [18, 38–40]. This horizon corresponds to approximately six full oscillation cycles of the underlying dynamics. For intuition, these cycles can be viewed analogously to recurrent variations in physiological systems with delayed feedback, such as oscillations in blood cell concentrations governed by the time-delayed response of bone marrow production. Forecasting six cycles ahead in this context would resemble anticipating future phases of over- or underproduction in such a regulatory process. Although purely illustrative, this analogy highlights the temporal depth captured by the magnon reservoir, which reconstructs complex future behavior from the intrinsic memory of its nonlinear dynamics. Our results establish magnon-based reservoirs as a scalable physical com-

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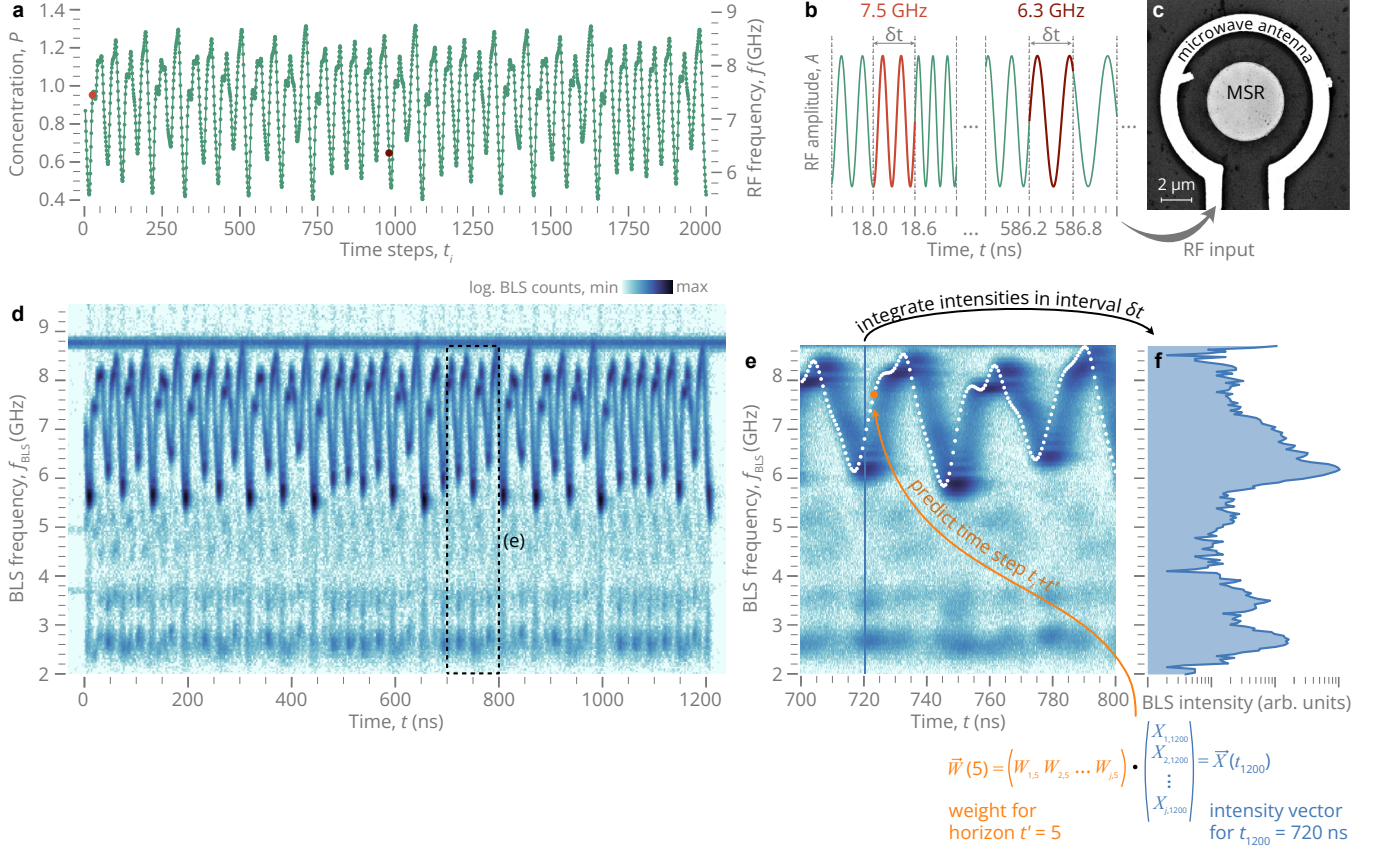


Figure 2. Encoding and reservoir response. **a**, The Mackey-Glass time series is mapped onto a microwave current using continuous-phase frequency-shift keying. **b**, Each microwave frequency is held for a certain time window of $\delta t = 0.6$ ns and injected into an Ω -shaped antenna surrounding the magnon-scattering reservoir (MSR). **c**, Scanning electron microscopy image of the 5 μm -diameter 50 nm-thick reservoir surrounded by the Ω -shaped antenna for microwave excitation. **d**, The time-resolved BLS spectrum reveals both direct responses and nonlinear magnon-magnon scattering, expanding the input into a richer spectral space. **e**, Zoomed in section of the data from panel (d). White dots indicate the input frequencies from the arbitrary waveform generator. The measured magnon intensities persist well beyond the direct input window, providing fading memory. **f**, The integrated spectral intensities form state vectors that serve as inputs for a linear readout used to generate predictions for a given horizon t' .

putting platform for real-time prediction of nonlinear and high-dimensional dynamics.

RESULTS

As a benchmark for our reservoir's prediction capabilities, we use the Mackey-Glass (MG) time series, a prototypical nonlinear model capable of generating chaotic signals, which are widely employed to evaluate reservoir computing systems [41–43]. The MG sequence is based on the biological process modelling the concentration $P(t)$ of mature red blood cells in living organisms mimicking the time delayed production of new cells in the bone marrow. Essentially, the MG sequence is generated from its delay-differential equation

$$\frac{dP(t)}{dt} = \frac{\beta P(t - \tau)}{1 + P(t - \tau)^\alpha} - \gamma P(t), \quad (1)$$

where τ is the delay time, β the production rate, γ the decay rate, and α the nonlinearity parameter. Depending on the choice of parameters the equation yields a periodic oscillation of the output value or a chaotic trajectory when the parameters are chosen for strong nonlinear dynamics. In Fig. 2a, we generated the MG sequence using the parameter set $\beta = 0.2$, $\gamma = 0.1$, $\alpha = 10$, and $\tau = 17$, which yields a chaotic trajectory.

To couple this signal into the magnon reservoir, we employ continuous-phase frequency-shift keying to modulate a microwave current. For each time step t_i the value obtained from the MG equation is mapped onto a microwave signal with a frequency within the 5.5–8.8 GHz band, as shown by the right y -axis in Fig. 2a. This range of excitation frequencies yields the strongest nonlinear response for a 50 nm-thick 5 μm -diameter vortex disk (see supplementary Fig. S1 for details). Each discrete frequency value was represented by a sinusoidal burst of duration $\delta t = 0.6$ ns (Fig. 2b), synthesized by an arbitrary waveform generator and applied to an

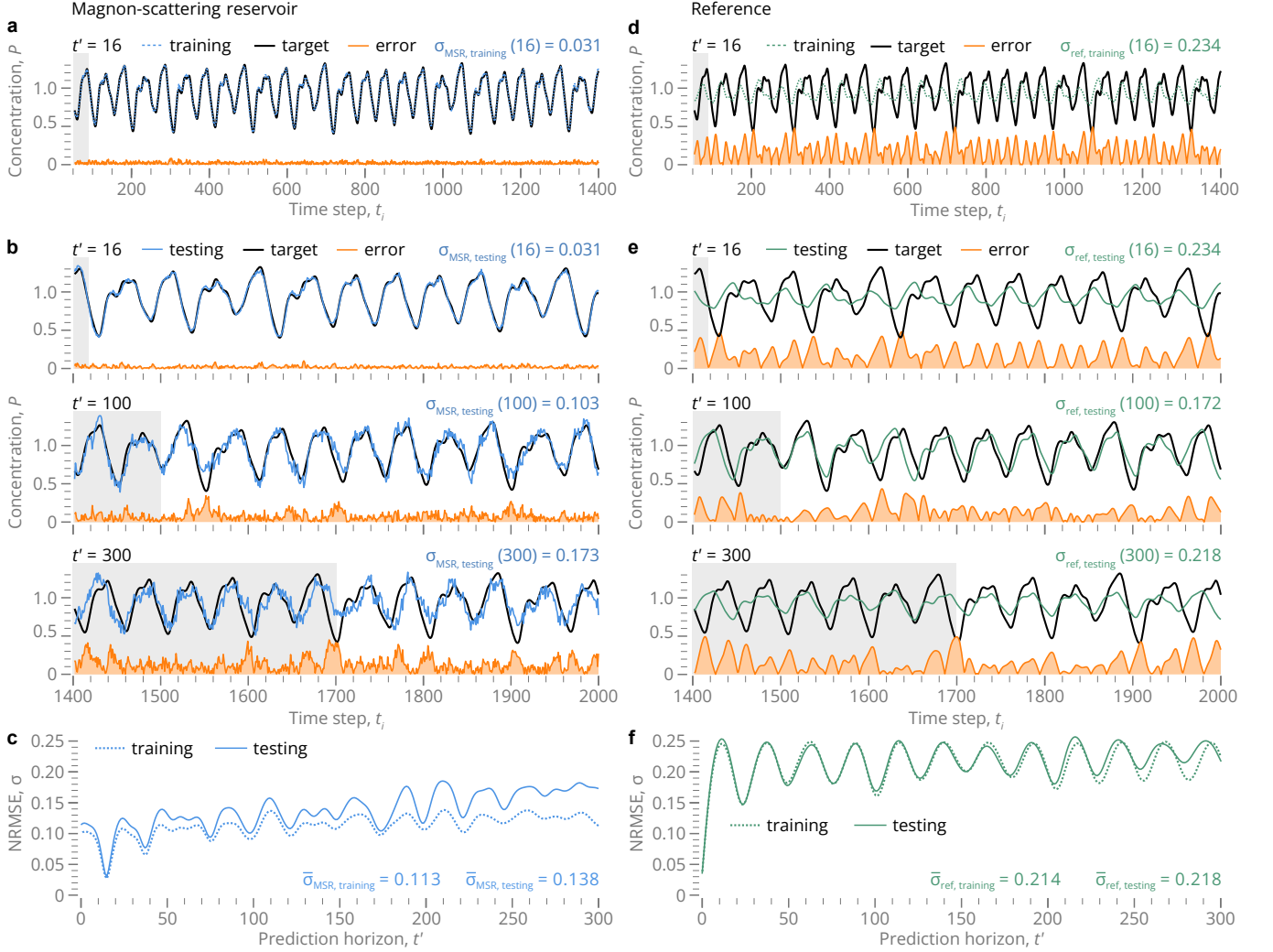


Figure 3. Forecasting chaotic dynamics with and without magnons. **a**, Training data for the MSR when predicting $t' = 16$ steps into the future. **b**, Testing results for the MSR for increasing prediction horizon $t' = 16, 100, \text{ and } 300$ steps. **c**, Normalized root mean squared error (NRMSE) as a function of prediction horizon t' , comparing training (dotted) and testing (solid). Viable forecasts are achieved even up to 300 steps, demonstrating long-range prediction performance. **d**, Training data of the reference prediction task without MSR when predicting $t' = 16$ steps into the future. **e**, Testing results without the MSR for increasing prediction horizon $t' = 16, 100, \text{ and } 300$ steps. **f**, NRMSE as a function of prediction horizon t' , comparing training (dotted) and testing (solid) for the reference task. Note that in panels **a**, **b**, **d**, and **e** the displayed errors correspond to the deviation of the training and testing outputs from the target MG data and are therefore larger than the NRMSE shown in the lower panels.

Ω -shaped antenna surrounding the MSR (Fig. 2c). To ensure a continuous waveform, the relative phase between consecutive bursts was adjusted during synthesis. A continuous-wave drive at 8.8 GHz, above the nonlinear threshold, was superimposed to increase the number of active magnon modes.

The reservoir's response is probed magneto-optically by time-resolved Brillouin light scattering (BLS) (see Methods for details). Figure 2d shows the spectral intensity during the MG sequence. Within the direct excitation band, the response follows the input frequencies, but crucially, strong signals also appear in the 2-5.5 GHz range due to nonlinear three-magnon splitting [44, 45]. This intrinsic nonlinear mode coupling is essential the MSR's performance. The nonlinearity not only

depends on the system's history and provides a unique fingerprint of the dynamic state in which the system is evolving, it also projects the one-dimensional input into a much higher-dimensional spectral output. In addition, the zoomed in spectrum in Fig. 2e highlights that the magnon responses to the microwave excitation signal persist well beyond the 0.6 ns input window, contributing to the fading memory. These two features – nonlinear expansion and memory – are the fundamental ingredients for reservoir computing.

To extract reservoir states, the BLS intensity is integrated within each 0.6 ns time window. Covering the frequency range from 2-8.8 GHz this yields a spectral vector $\vec{X}(t_i)$ (Fig. 2f) with the number of entries $j = 182$ determined by the spec-

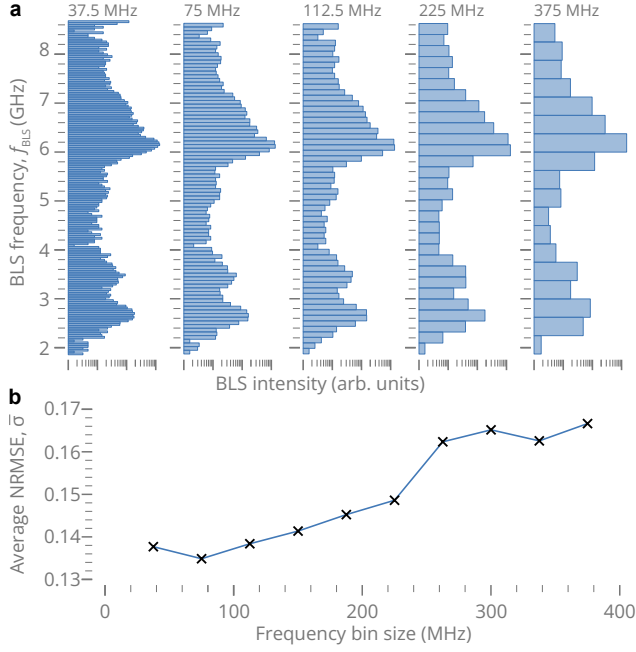


Figure 4. **Influence of spectral binning on prediction accuracy.** **a**, BLS spectra extracted with different frequency bin sizes. **b**, Average NRMSE as a function of bin size, showing an optimal performance at twice the natural BLS spectral resolution. Excessive binning reduces spectral richness and degrades forecasting accuracy.

tral resolution of the BLS measurement of 37.5 MHz. The sequence of vectors forms a state matrix $\mathbf{X}$ representing the reservoir's transformation of the input. This representation is then used to train a linear readout layer.

We task the magnon reservoir with predicting the MG signal at $t_i + t'$ time steps into the future. A linear regression model is trained on a subset of 1350 time steps ($51 \leq t_i \leq 1400$, discarding the first 50 steps to allow the system to reach steady operation) to determine the weight vectors $\vec{W}_{t'}$ for each prediction horizon t' :

$$\vec{y}_{\text{training}}(t') = \vec{W}_{t'} \cdot \mathbf{X} + \text{const.} \quad (2)$$

with $\vec{y}_{\text{training}}(t') = (P(51 + t'), P(52 + t'), \dots, P(1400 + t'))$. The result of this training is plotted in Fig. 3a.

The performance is evaluated on the 600 remaining unseen time steps ($1401 \leq t_i \leq 2000$). Figure 3b shows successful forecasts for $t' = 16, 100$, and 300 steps, with errors increasing gradually with horizon length. Determining an average normalized root mean squared error for each prediction horizon t' (Fig. 3c) shows that the error remains low even predicting 300 steps into the future.

To put the MSR's performance into perspective, we follow the same training routine directly on the MG data $P(t_i + t') = w_{t'} P(t_i) + \text{const.}$ with weights $w_{t'}$, assuming a scenario without the MSR projecting the time-series input to the higher-dimensional spectral output space. The results are summarized in Fig. 3d-f. Overall, the errors for this reference task remain well above the ones achieved with the MSR across all

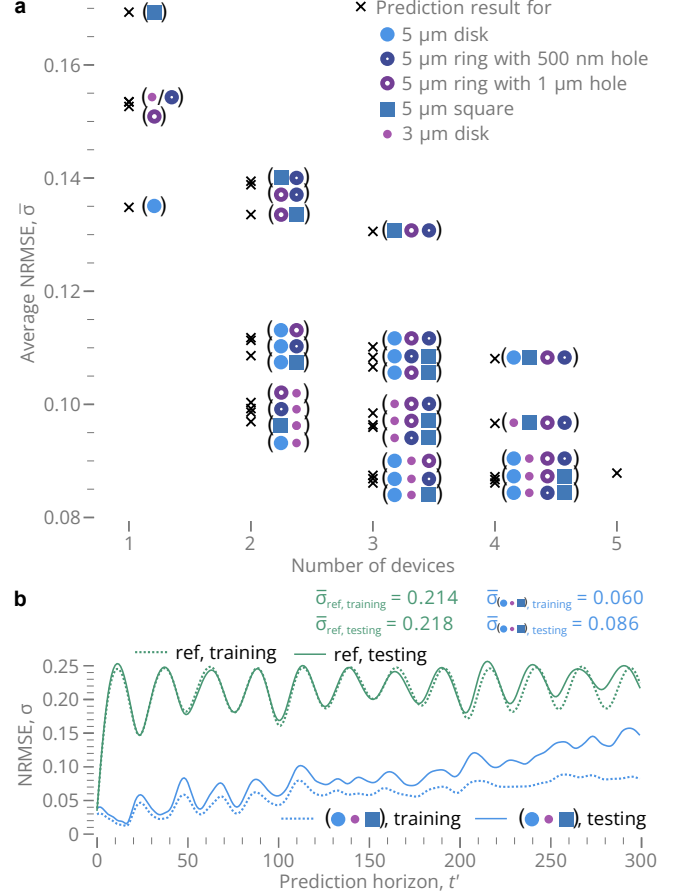


Figure 5. **Increasing reservoir depth improves prediction.** **a**, Average NRMSE for different MSR geometries and their combinations. Appending outputs from multiple devices systematically reduces error, showing that greater reservoir depth enhances forecasting performance. **b**, NRMSE as a function of prediction horizon t' , comparing training (dotted) and testing (solid) for the optimum combination of devices and the reference task.

prediction horizon.

The dimensionality of the reservoir state is determined by the spectral resolution of the BLS output. To evaluate its impact, we applied additional binning to the spectra, effectively reducing the number of features per time step as shown in Fig. 4a. Within each frequency bin, the detected BLS intensity is averaged. Smaller state dimensions simplify the regression task by lowering the number of trainable parameters, which can improve stability during training and mitigate overfitting for limited datasets, as can be seen in Fig. 4b when doubling the bin size from the BLS inherent 37.5 MHz to 75 MHz. However, excessive binning discards spectral detail, thereby reducing the richness of the nonlinear mapping and degrading prediction performance. We find that moderate binning yields a favorable compromise between computational efficiency and accuracy, whereas large bin sizes significantly diminish the forecasting horizon. This highlights the importance of tuning the reservoir dimensionality to balance training efficiency and predictive power.

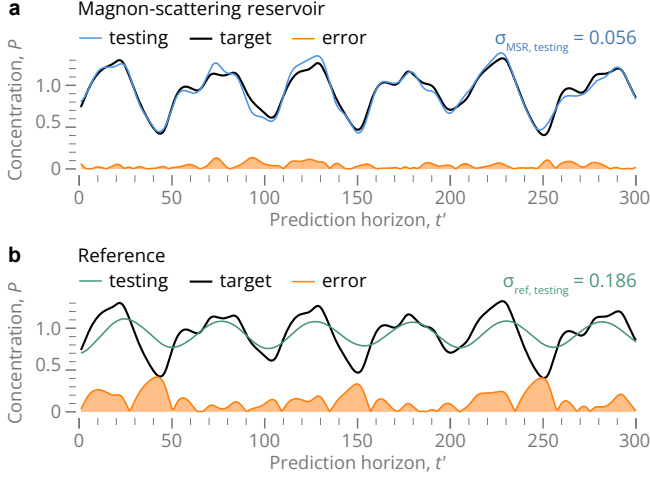


Figure 6. **Forecasting the future from a single spectrum.** **a**, Predicting 300 steps of the MG series directly from one unseen spectrum of the MSR by concatenating 300 individually trained prediction models into a single weight matrix. This approach yields consistently low errors across all horizons. **b**, In stark contrast, models trained only on MG data show much lower accuracy.

Thus far, our predictions were obtained from a single 50 nm-thick 5 μ m-diameter vortex-state MSR. To explore how reservoir richness influences performance, we extended the approach including four other distinct device geometries, all excited via Ω -shaped antennas: a 3 μ m-diameter disk, two rings of 5 μ m outer diameter with hole widths of 525 nm and 800 nm, and a 5 μ m square. On the one hand, additional geometries were chosen similar to the previously studied 5 μ m disk to yield adequate nonlinear response when excited with microwave currents in the same frequency range. On the other hand, adding smaller disks and other shapes increased diversity. However, we want to point out that the choice of additional geometries was not optimized yet but already demonstrates the feasibility of increasing the reservoir complexity. The input waveform was identical across devices, designed based on the spectral properties of the 5 μ m disk, and the outputs were measured using the same BLS setup (see Fig. S2 in supplementary material).

To construct an enlarged reservoir state, the frequency-intensity vectors (with 75-MHz binning) from different geometries were combined, forming larger state vectors $\vec{X}(t_i)$. As summarized in Fig. 5a, prediction performance systematically improves with the number of devices included. In particular, the combination of the 3 μ m and 5 μ m disks with the 5 μ m square yields the lowest average normalized root mean squared error (NRMSE) across the entire prediction horizon, as highlighted in Fig. 5b.

Ultimately, we concatenate the 300 individually trained prediction models $\vec{W}_{t'}$ for the optimal device combination (3 μ m and 5 μ m disks with the 5 μ m square) into a single weight matrix $\mathbf{W}$. This allows forecasting up to 300 future steps directly from one unseen spectrum $\vec{X}(t_i = 1401)$:

$$\vec{y}_{\text{testing}} = \mathbf{W} \cdot \vec{X}(1401) + \text{const.} \quad (3)$$

with $\vec{y}_{\text{testing}} = (P(1402), P(1403), \dots, P(1701))$. As shown in Fig. 6, this approach yields consistently low errors, much lower compared to the reference prediction model without the magnon reservoir.

Beyond enhancing accuracy, this approach also changes the prediction paradigm. Instead of relying on long sequences of MG input data, the concatenated models extrapolate far into the future from a single reservoir state. This ability to forecast hundreds of steps from a single reservoir state underscores the richness of the magnonic representation and illustrates a fundamentally new prediction paradigm, where the future trajectory can be reconstructed from a single snapshot rather than a continuous input stream.

DISCUSSION AND OUTLOOK

Our results demonstrate that a magnon-scattering reservoir can reliably forecast the Mackey-Glass time series over hundreds of time steps, establishing magnons as a viable substrate for physical reservoir computing. A prediction horizon of $t' = 300$ corresponds to approximately six full oscillation cycles of the Mackey-Glass sequence, indicating that the magnon reservoir can reliably capture long-term variations, substantially exceeding previously demonstrated magnetic reservoirs based on artificial spin-ice arrays [18, 39, 40], which achieved short-term prediction over one to two characteristic cycles with comparable errors. This improvement arises from the continuous, GHz-frequency dynamics of magnons, which provide both stronger nonlinearity and intrinsic fading memory on nanosecond timescales.

Beyond benchmarking on the Mackey-Glass system, the intrinsic properties of magnons suggest several directions for future exploration. First, strong nonlinear interactions and long-lived excitations provide a natural resource for tackling tasks that require both high-dimensional feature spaces and fading memory, such as speech recognition or real-time sensor data processing. Second, the frequency-tunable nature of magnons opens pathways toward multiplexing and parallelism, potentially enabling multi-channel prediction on the same chip. Third, compatibility with CMOS processes points toward scalable integration, where arrays of magnetic microdisks could be co-fabricated with conventional electronics.

An additional design principle emerges from our analysis of spectral binning. While reducing dimensionality can simplify training and lower computational cost, excessive compression comes at the expense of predictive accuracy. This trade-off underscores the importance of tailoring the effective state dimension of the reservoir to the specific task at hand. In scalable architectures, such control could be realized by dynamically adjusting spectral resolution or by combining multiple reservoirs with complementary dimensionalities. More broadly, this highlights that not only the physical substrate but also the way its output is encoded plays a crucial role in optimizing performance.

From a broader perspective, our work connects nonlinear magnetism with machine learning and neuromorphic computing, demonstrating how fundamental spin-wave physics

can be leveraged for tasks traditionally reserved for artificial neural networks. The demonstrated ability to map a simple one-dimensional input into a rich spectral output illustrates how magnonic devices can function as compact, intrinsically energy-efficient reservoirs, where nonlinear transformation and memory emerge naturally from low-loss spin dynamics instead of being emulated through large numbers of active electronic elements. Looking ahead, combining magnon reservoirs with other spintronic or photonic elements may yield hybrid architectures that exploit the strengths of multiple substrates. Such advances could bring physical reservoir computing closer to deployment in edge devices, where real-time prediction and low power consumption are critical.

In summary, the use of magnons for chaotic time-series prediction highlights the potential of magnonics as a platform for unconventional computing. By uniting the fields of nonlinear dynamics, magnetism, and machine learning, this approach opens new avenues for scalable, real-time information processing in both scientific and technological contexts.

METHODS

Sample preparation

The standard magnon-scattering reservoir (MSR) consists of a 5 μm -diameter magnetic disk patterned on a SiO_2 substrate. Fabrication employed a polymethyl methacrylate (950PMMA A4) resist mask, electron beam lithography, sputter deposition, and lift-off. To suppress anisotropy in the magnetic film, the $\text{Ni}_{81}\text{Fe}_{19}$ (50 nm)/Ta (4 nm) bilayer was sputtered in a 1 mT rotating magnetic field [46].

To excite magnetization dynamics, an Ω -shaped microwave antenna was patterned using a double-layer resist stack (ethyl lactate EL11 and PMMA 950 A4), followed by electron beam lithography, deposition of Cr (5 nm)/Au (150 nm), and lift-off. The antenna inner and outer diameters are 8.7 and 11 μm , respectively. Microwave currents in the GHz range excite well-defined magnon eigenmodes of the vortex-state disk.

Additional MSR geometries, including 3 μm -diameter disks, rings (5 μm outer diameter, hole widths of 525 nm and 800 nm) and squares (5 μm edge length), were fabricated simultaneously on the same substrate and each embedded in an individual Ω -shaped antenna.

Three-magnon splitting

At microwave powers above threshold, nonlinear three-magnon splitting occurs [44, 45]. A magnon mode ($n_{\text{initial}}, 0$) initially excited at frequency f_{initial} splits into two secondary magnons under conservation of energy ($f_{\text{initial}} = f_+ + f_-$) and angular momentum ($m_{\text{initial}} = m_+ + m_-$). This is exemplary depicted in supplementary Fig. S1a for the splitting process $(0, 2) \rightarrow (2, \pm 4) + (0, \mp 4)$.

As shown previously [33, 34], the coexistence of multiple splitting channels leads to non-reciprocal mutual stimulation, such that different secondary modes are populated depending

on the temporal order of various frequency components in a multitone excitation signal. This mechanism underpins the nonlinear expansion and temporal memory essential for the reservoir's predictive capability.

Mackey-Glass benchmark generation

The Mackey-Glass (MG) time series is a standard benchmark for reservoir computing [41, 42]. Initially, it was derived to describe fluctuations in the concentration $P(t)$ of red blood cells over time using a time delayed differential equation:

$$\frac{dP(t)}{dt} = \frac{\beta P(t - \tau)}{1 + P(t - \tau)^\alpha} - \gamma P(t), \quad (4)$$

where τ is the delay time, β the base level production rate, γ the decay rate, and α the nonlinearity parameter.

In our study, we generated the MG sequence using the parameter set $\beta = 0.2$, $\gamma = 0.1$, $\alpha = 10$, and $\tau = 17$, which yields a chaotic trajectory. The equation was solved using the python package *BrainPy* [47]. From the resulting trajectory, we extracted 2000 discrete points $P(t_i)$, which served as the input sequence for the magnon reservoir.

Data preprocessing

To couple the MG sequence into the magnon reservoir, each value $P(t_i)$ was linearly mapped $f_{t_i} = kP(t_i) + c$ to a microwave frequency in the 5.5–8.8 GHz band, where nonlinear three-magnon scattering is strongest. The mapping constants k and c were chosen such that the full dynamic range of the MG sequence matched this frequency interval.

Each discrete point was represented by a sinusoidal burst of duration $\delta t = 0.6$ ns, synthesized by an arbitrary waveform generator and applied to the Ω -shaped antenna using a ground-signal-ground microwave probe. To ensure a continuous waveform, the relative phase between consecutive bursts was adjusted during synthesis. The effect of choosing different time windows is discussed in Fig. S3 in the supplementary material.

A continuous-wave drive at 8.8 GHz, above the nonlinear threshold, was superimposed to increase the number of active magnon modes.

Experimental Setup

We used an arbitrary waveform generator (AWG7000 Tektronix) to generate the Mackey-Glass signal at a sampling rate of 25 GS/s and V_{pp} of 500 mV. This signal is transmitted through a series of amplifier (23 dBm), attenuator (−5 dBm), and amplifier (16 dBm) before combining it with the continuous-wave (CW) microwave signal using a frequency combiner. The CW signal at 8.8 GHz at 25 dBm is provided by a signal generator (*Keysight N5173B*). The combined signal is then applied to the Ω -antenna via a ground-signal-ground microwave probe.

Time-resolved Brillouin light scattering microscopy

The MSR response to the input waveform was probed using time-resolved micro-focused Brillouin light scattering (TR- μ BLS) spectroscopy [48]. A continuous-wave laser (532 nm) was focused onto the sample surface using a 100 $\times$ objective lens (NA = 0.75), yielding a spatial resolution of approximately 300 nm. The backscattered light was analyzed in a Tandem Fabry-Pérot interferometer (TFPI) [49], which resolves the frequency shift due to inelastic photon-magnon scattering with a spectral resolution of 37.5 MHz.

Photon counts, interferometer control signals, and a synchronized clock reference from the arbitrary waveform generator were recorded by a time-to-digital converter (Timetagger 20, Swabian Instruments) with 200 ps resolution. By synchronizing to the arbitrary waveform generator excitation, the temporal evolution of the magnon spectra was reconstructed.

Sample drift was actively compensated using image recognition of in-situ CCD images of the structure, with corrections applied via high-precision piezo stages (Newport XMS series).

To access modes with different spatial profiles, μ BLS spectra were averaged over 25 positions covering one quarter of the disk (five azimuthal angles at five radial positions).

All measurements were performed at room temperature.

Training procedure

The transient spectral response of the magnon reservoir was recorded using TR- μ BLS as explained above. To define the reservoir states, the BLS intensity was integrated within each 0.6 ns input window across the entire frequency range. The resulting intensities were assembled into a spectral vector $\vec{X}(t_i)$ for each time step. Concatenation of all vectors yielded the reservoir state matrix $\mathbf{X}$, which represents the nonlinear transformation of the MG input.

Additional dimensionality control was implemented by binning the spectral output into larger frequency intervals, allowing systematic evaluation of the trade-off between feature richness and regression complexity.

The prediction task was formulated as learning a linear mapping between reservoir states and future MG values:

$$\vec{y}_{\text{training}}(t') = \vec{W}_{t'} \cdot \mathbf{X} + \text{const.} \quad (5)$$

with $\vec{y}_{\text{training}}(t') = (P(51 + t'), P(52 + t'), \dots, P(1400 + t'))$ and $\vec{W}_{t'}$ the weight vector trained for each prediction horizon t' . Training and testing sets were created by splitting the MG sequence into non-overlapping subsets of 1350 ($51 \leq t_i \leq$

1400) and 600 ($1401 \leq t_i \leq 2000$) time steps, discarding the first 50 steps to allow the system to reach steady operation.

The weight vector and constant were found using the *LinearRegression* model from *scikit-learn* [50], where the model only uses an analytical method to find the suitable parameters without any iterative optimization. This also means that the training time is very short.

For the reference task, we follow the same training routine directly on the MG data $P(t_i + t') = w_{t'} P(t_i) + \text{const.}$ with weights $w_{t'}$. Therefore, we again use the *LinearRegression* model from *scikit-learn* [50].

For experiments involving several MSR geometries, the frequency-intensity vectors from different devices were combined to form an enlarged state vector $\vec{X}(t_i)$. The same training and testing protocol was applied, enabling direct comparison of predictive performance across different reservoir depths.

Error metrics

Prediction accuracy was quantified using the root mean squared error (RMSE) between the predicted $\hat{y}_i(t')$ and target $y_i(t')$ values:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i(t') - \hat{y}_i(t'))^2}. \quad (6)$$

To allow comparison across different signal amplitudes, the RMSE was normalized to the dynamic range of the MG sequence, yielding the normalized RMSE (NRMSE):

$$\text{NRMSE} = \sigma(t') = \frac{\text{RMSE}}{y_{\max} - y_{\min}}. \quad (7)$$

A smaller NRMSE indicates higher predictive accuracy. For each prediction horizon t' , the error was computed separately for the training and testing sets to monitor potential overfitting. In addition, the mean prediction error $\bar{\sigma}$ was defined as the average NRMSE over all horizons from 1 to 300 steps, providing a single figure of merit for overall forecasting performance.

$$\bar{\sigma} = \frac{1}{300} \sum_{t'=1}^{300} \sigma(t') \quad (8)$$

DATA AVAILABILITY

The data that support the findings of this study are openly available in Ref. [51].

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Competing interests

The authors declare no competing interests.

SUPPLEMENTARY MATERIALS FOR PREDICTING THE FUTURE WITH MAGNONS

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Time-resolved BLS spectra for different geometries

For increasing the reservoir dimensionality, we input the same frequency-modulated MG data into five different devices: two disks of 5 μm and 3 μm diameter disk, two rings of 5 μm outer diameter with hole widths of 525 nm and 800 nm, and a 5 μm square. Scanning electron microscopy images of all devices are shown in Fig. S2a-e. On each individual device we recorded time-resolved BLS spectra, integrated over multiple scan positions. The spectra are plotted in Fig. S2f-j. Since the frequency range for the MG input was designed to yield the maximum nonlinear response for the 5 μm disk, the spectra for other devices show less nonlinearity, the more their geometry diverges from the 5 μm disk. This also explains why the 5 μm disk gives the best accuracy among all individual predictions (see Fig. 5a in the main manuscript).

Influence of input duration

The MSR's response to the MG sequence clearly depends on the time scale with which the frequency-modulated microwave current is applied. Therefore, we tested different signal duration δt between 0.2 ns to 1 ns to find the time scale optimal for future prediction. The resulting time-resolved BLS spectra are summarized in Fig. S3. By comparing NRMSE values for different spectrum tests, 0.6 ns is the most suitable time duration for MG input data. This relates to the balance between reaction time – given by the onset of nonlinearity – and memory capacity in our system – mostly determined by the intrinsic magnon lifetime.

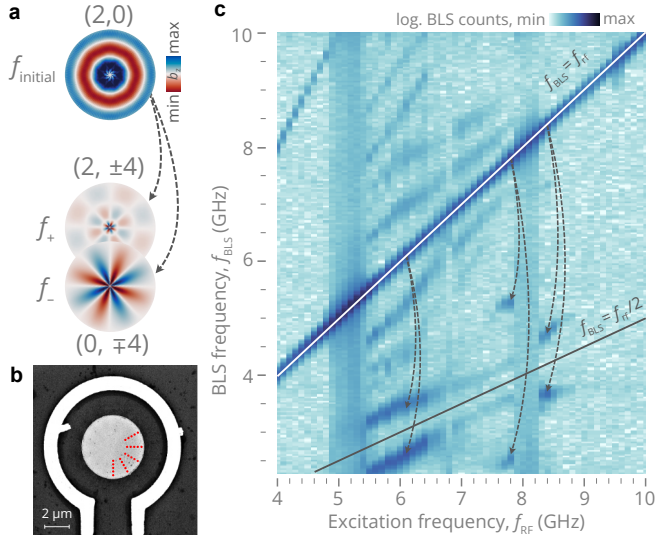


Figure S1. Nonlinear magnon splitting and device characterization. **a**, Schematic of a three-magnon splitting process: a directly excited mode $(2,0)$ at frequency f_{initial} decays into two secondary modes $(2, \pm 4)$ and $(0, \mp 4)$ with frequencies f_+ and f_- , conserving both energy and momentum. **b**, Scanning electron microscopy image of the $5 \mu\text{m}$ -wide 50 nm thick NiFe disk embedded in the Ω -shaped antenna. Red dots indicate the measurement positions used for spatial averaging of the BLS signal. **c**, BLS spectra measured on the device in (b) at an excitation power of 23 dBm , i.e. above the threshold for nonlinear three-magnon splitting. Each column corresponds to a spectrum recorded at a fixed excitation frequency f_{RF} , with intensity color coded on a logarithmic scale. The strongest nonlinear response is observed for excitation frequencies between 5.5 and 8.8 GHz .

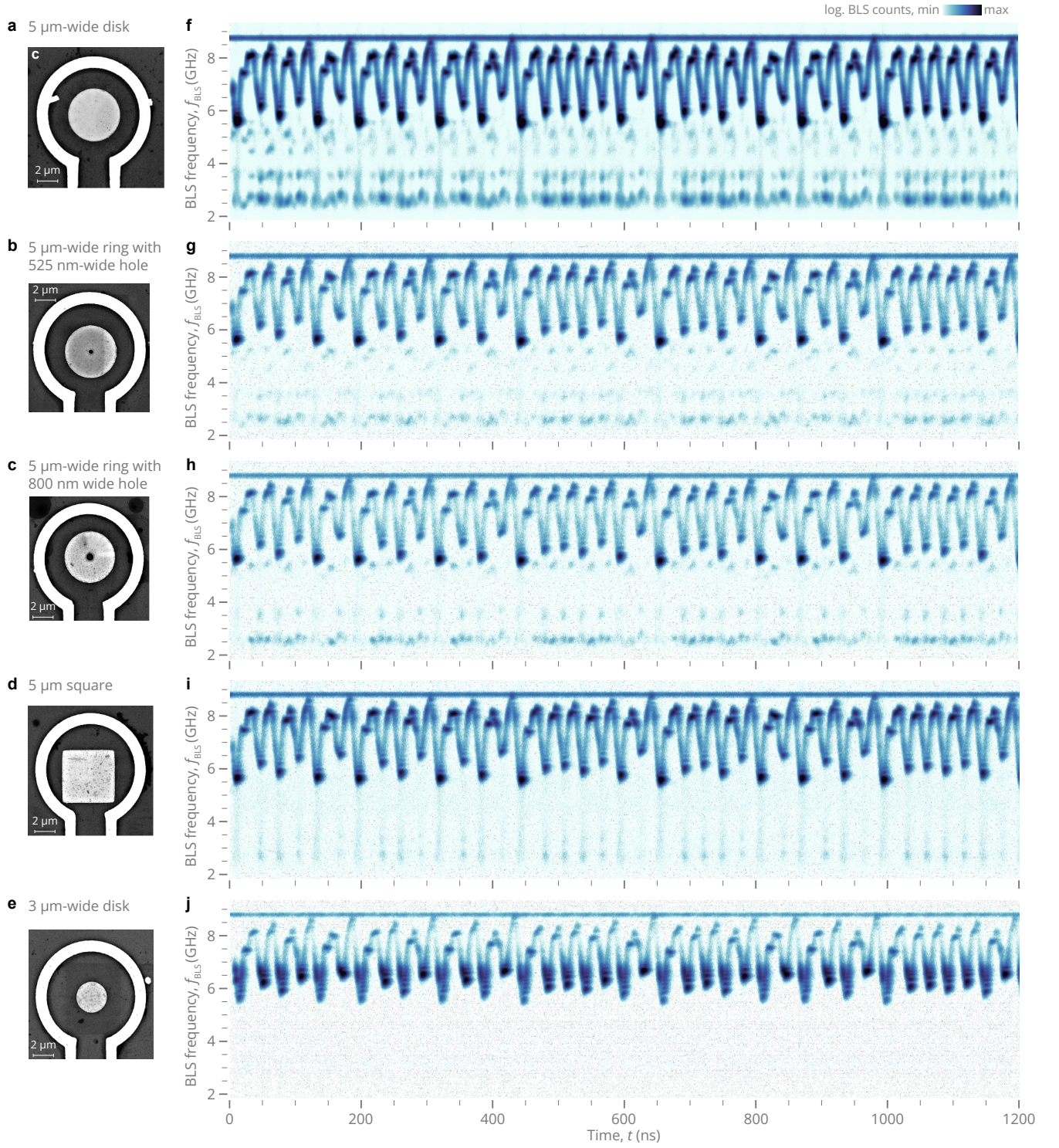


Figure S2. **Comparing different devices.** **a-e**, Scanning electron microscopy images of magnon reservoirs with different geometries. **f-j**, Time-resolved BLS spectra measuring the different reservoirs' response to the complex MG time-series sequence. The nonlinear response recorded for BLS frequencies between 2 GHz and 5.5 GHz gets weaker the more the geometry diverts from the 5 μm -diameter disk. This is to be expected since the frequency range for the microwave current inputting the MG sequence was optimized to address the fundamental modes in the 5 μm -diameter disk.

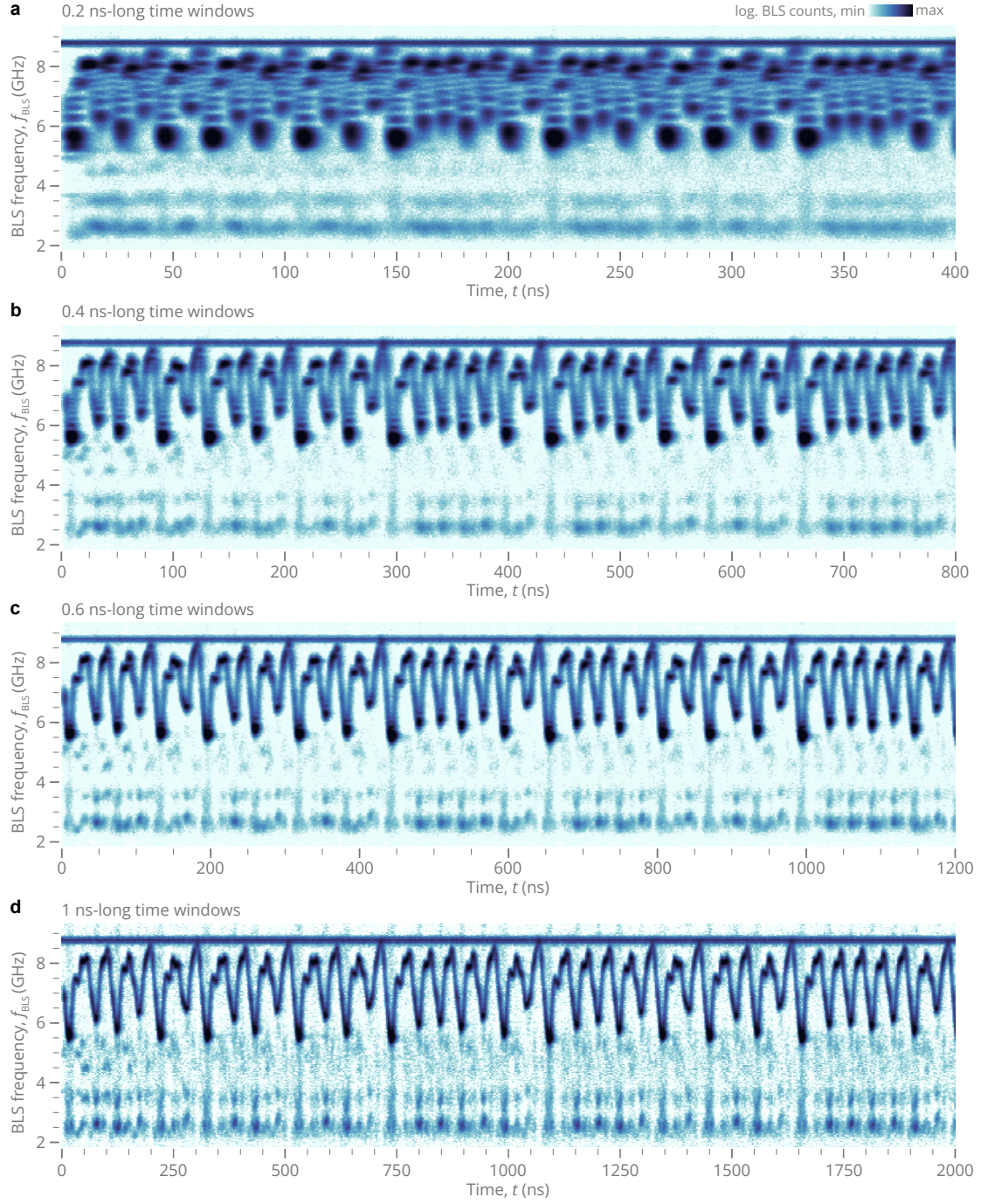


Figure S3. **Comparing different time scales for inputting the MG sequence.** Time-resolved BLS spectra measured for the MG sequence encoded using different time windows $\delta t = 0.2, 0.4, 0.6$, and 1 ns. The 0.2 ns-long input is too fast to allow the magnon system to evolve a clear dynamic response. With increasing δt , more nonlinear scattering sets in. However, if signals are too long, they have less overlap with past data due to the limited lifetime of magnons. Thus, the balance between system response and enough data overlap has to be found. By comparing their average NRMSE values without binning, we determined $\delta t = 0.6$ ns to be the optimal duration for inputting the microwave current via continuous-phase frequency-shift keying.