

# Spin-wave Reservoir Computing in Artificial Spin Systems: *Conventional, Deep & Parallel Architectures*

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Tianyue Wang<sup>1</sup>, Tingjung Zheng<sup>1</sup>, Francesco  
Caravelli<sup>3</sup>, Daan M. Arroo<sup>1</sup>, Hidekazu  
Kurebayashi<sup>2</sup>, Will R. Branford<sup>1</sup>

**Imperial College London<sup>1</sup>  
University College London<sup>2</sup>  
Los Alamos National Lab, USA<sup>3</sup>**

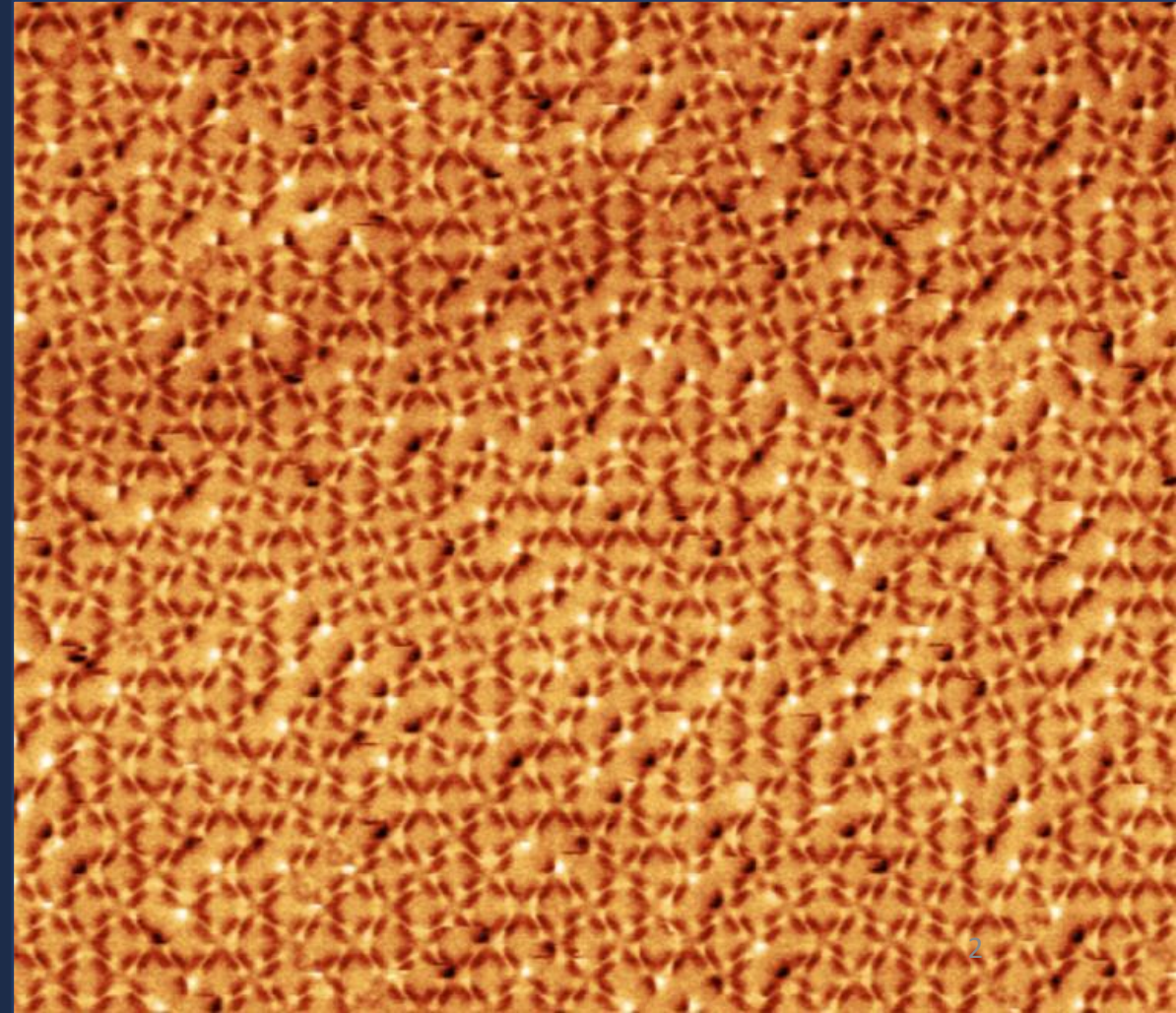
# Spin-wave Reservoir Computing in Artificial Spin Systems: *Conventional, Deep & Parallel Architectures*

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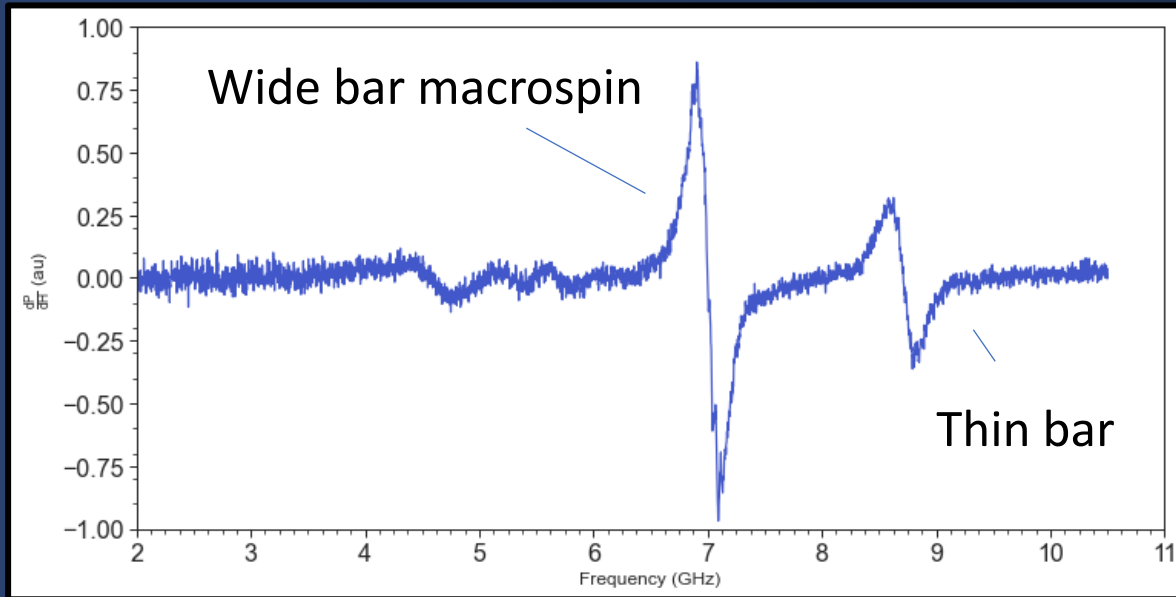
## What we'll learn:

- ASVI – Magnetic nanoarray engineered for Vortex/Macrospin bistability
- Ratchet-like Vortex creation
- FMR signatures of Vortex & Macrospins
- Non-linear mode dispersion
- Long-term training up to 60 field loops
- Reservoir computing

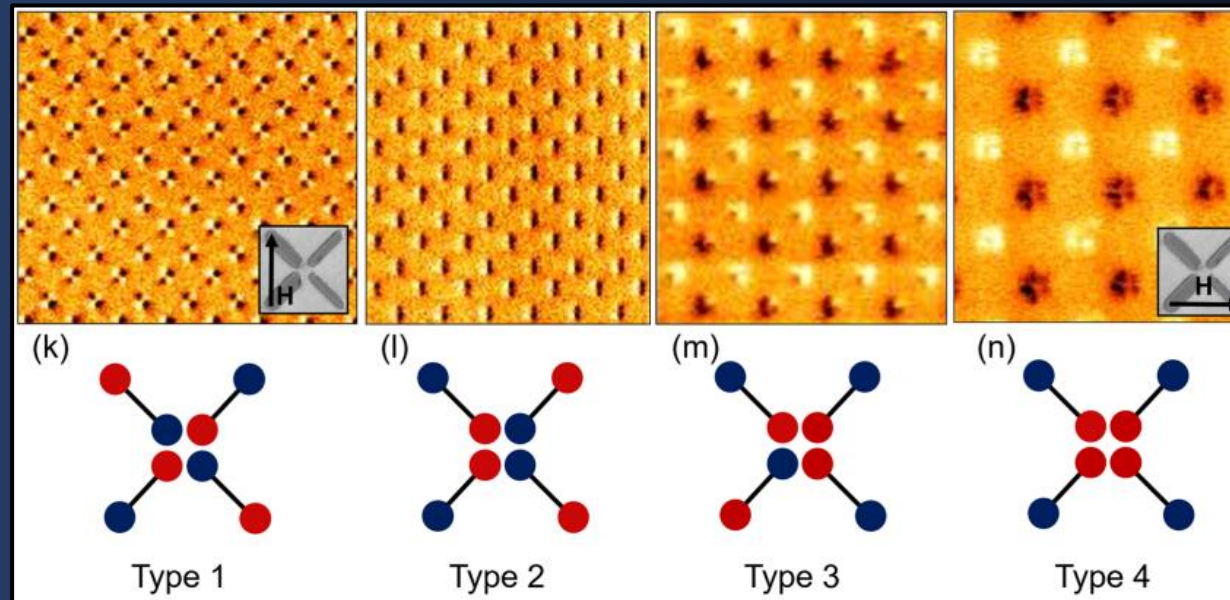
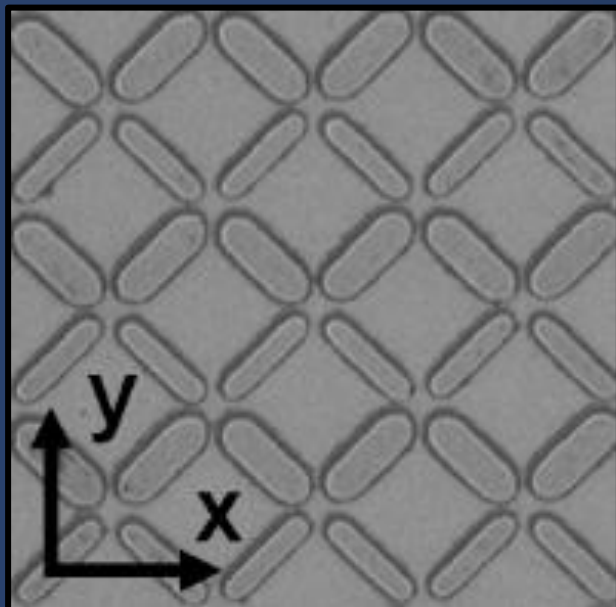
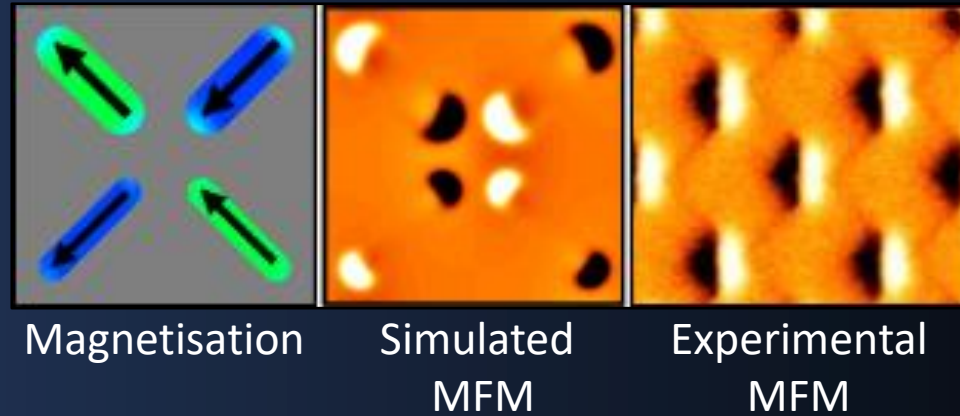
Gartside, Jack C., Stenning, Kilian D. et al. “Reconfigurable Training, Vortex Writing and Spin-Wave Fingerprinting in an Artificial Spin-Vortex Ice.” *Nature Nanotechnology* (2022)



# ASVI– Beyond a single magnetic texture

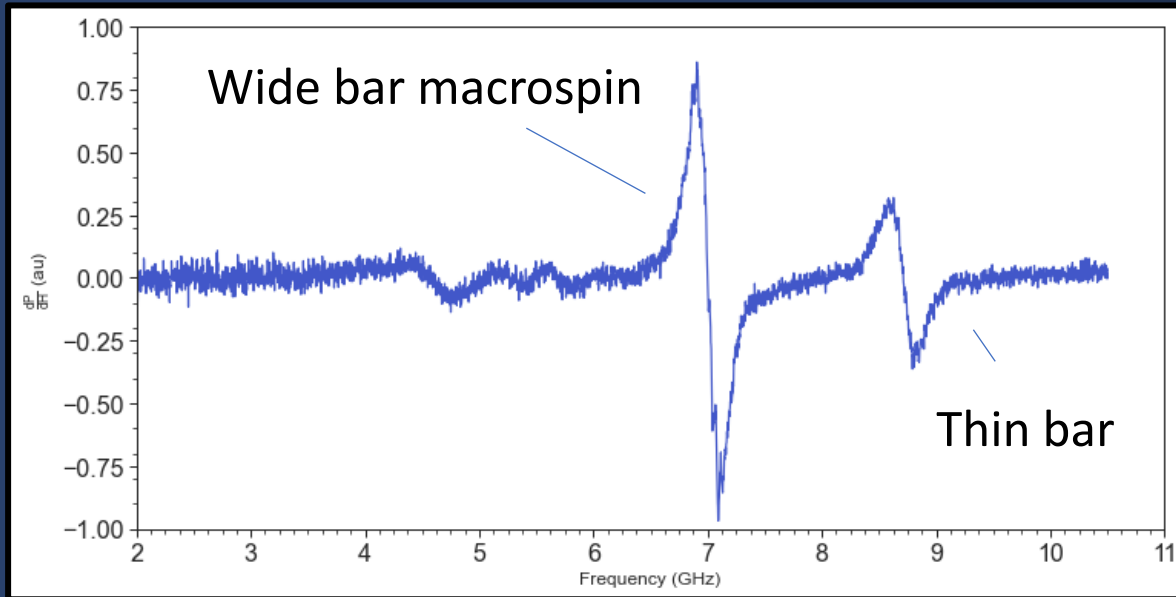


## Normal saturated ASI spectra

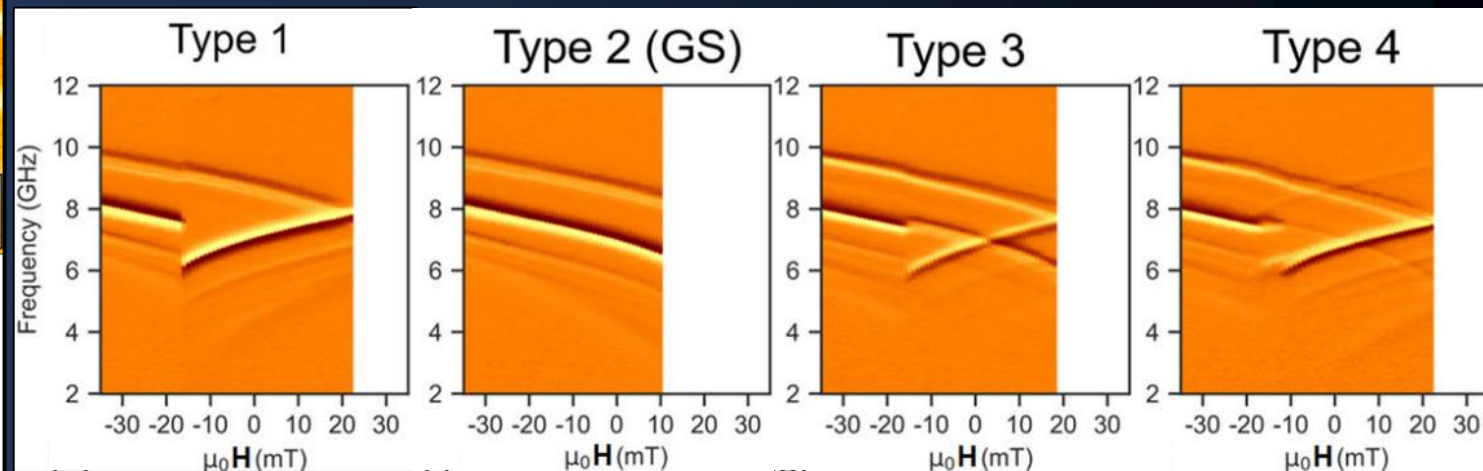
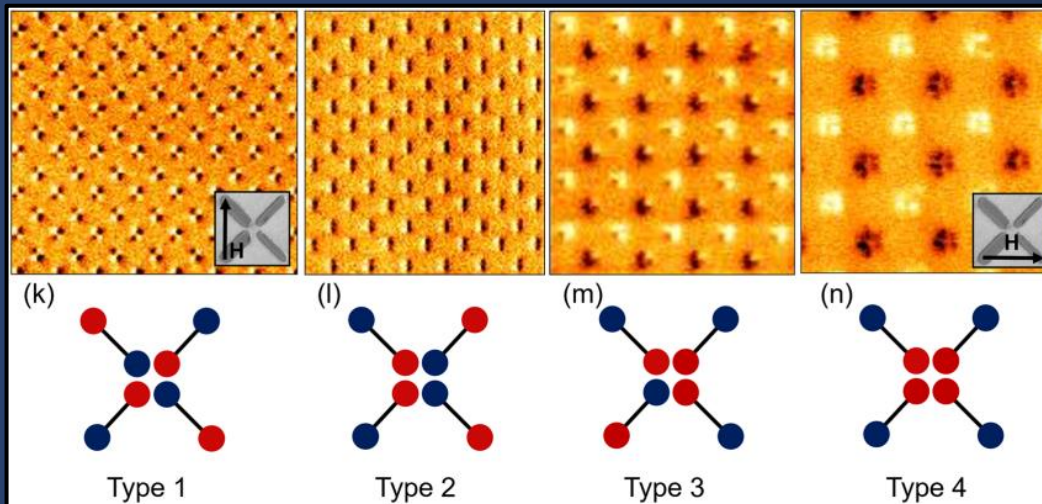
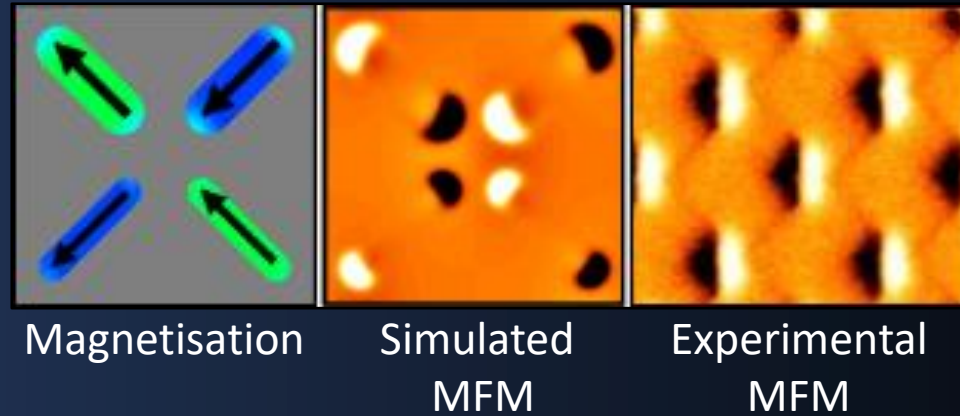


Gartside, Jack C., et al.  
 "Reconfigurable magnonic mode-hybridisation and spectral control in a bicomponent artificial spin ice."  
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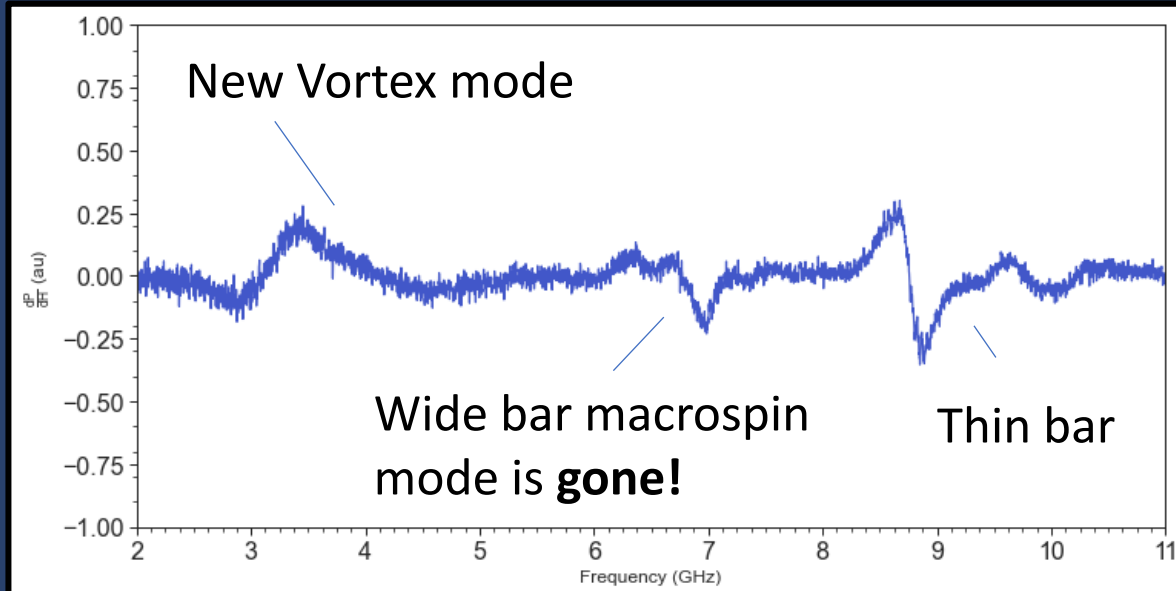
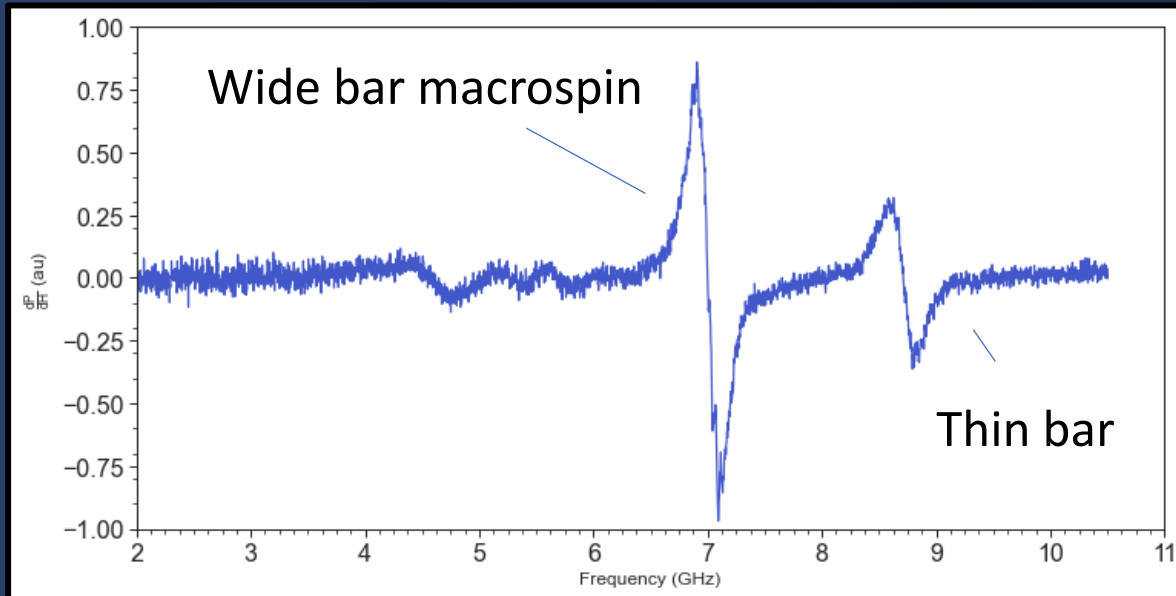
# ASVI– Beyond a single magnetic texture



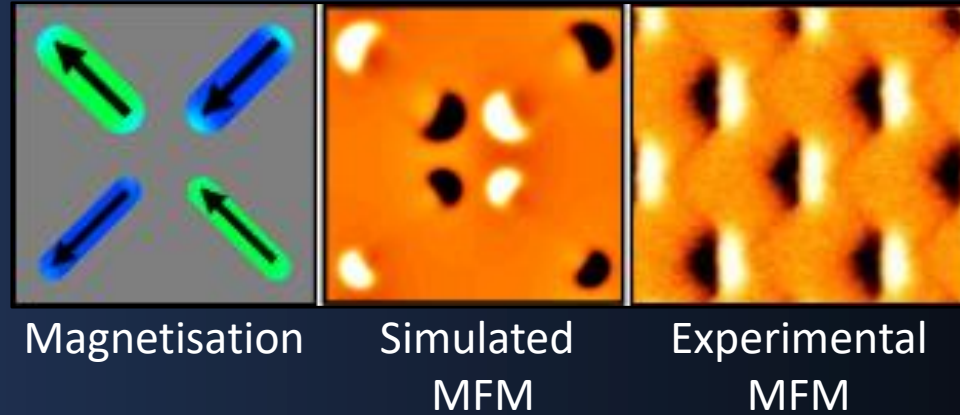
## Normal saturated ASI spectra



# ASVI– Beyond a single magnetic texture

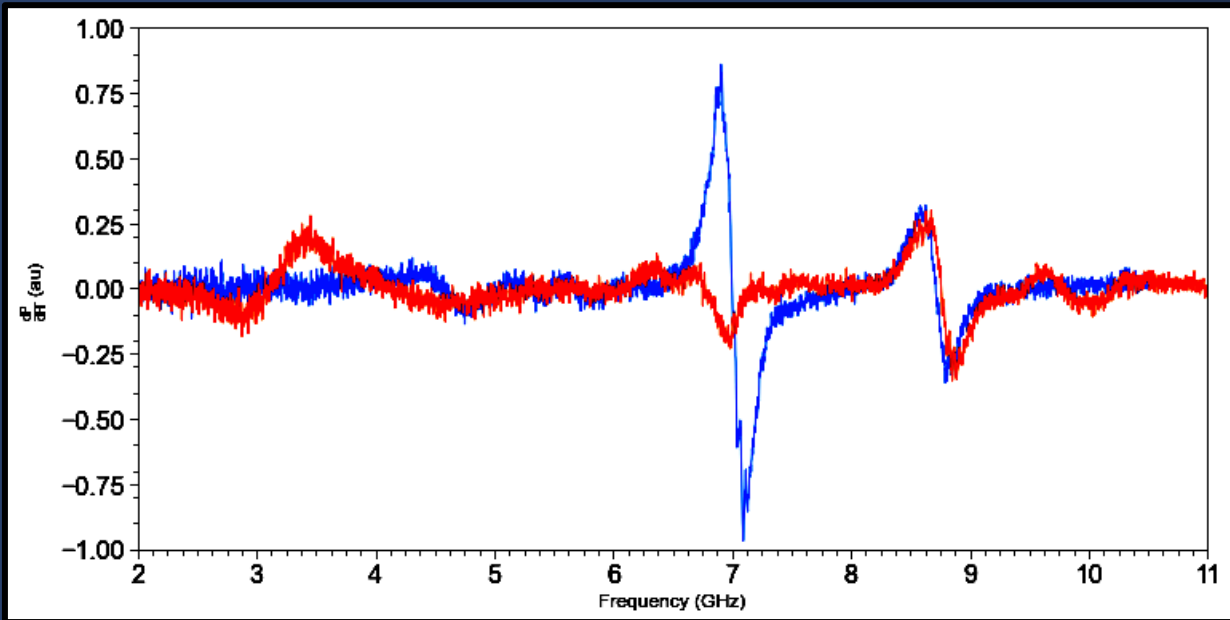


## Normal saturated ASI spectra

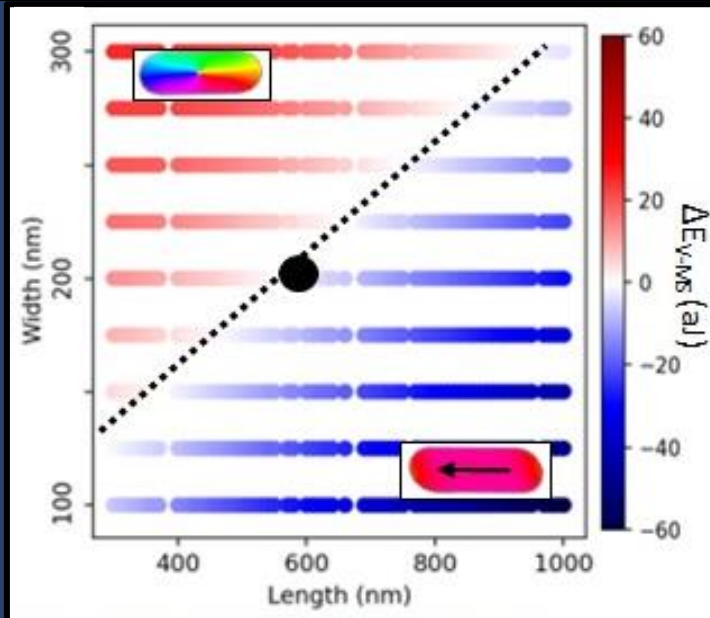


## Spectra after 30x 18 mT field loops (wide bar $H_c = 16$ mT)

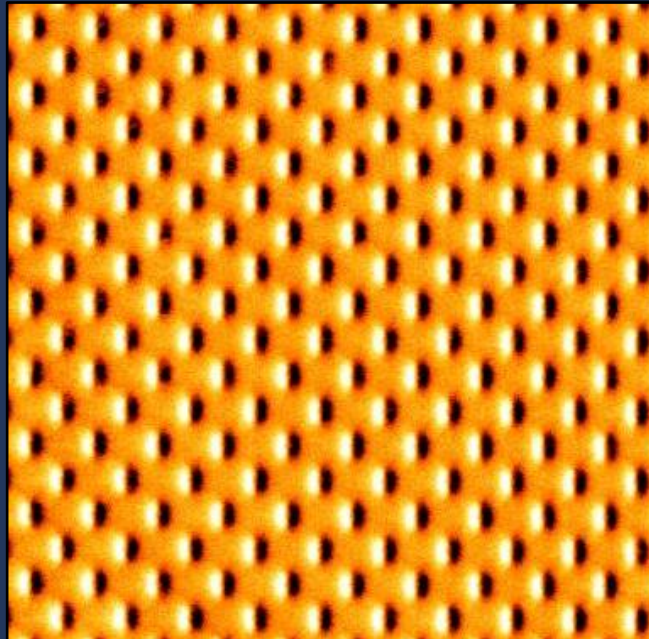




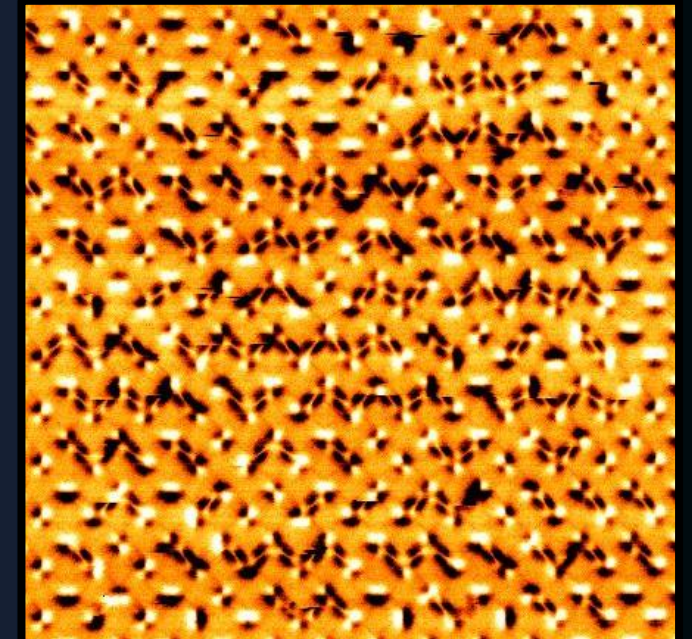
Blue = Initial -200 mT saturated  
 Red = After 30x 18 mT training loops



Vortex/Macrospin Demag  
& Exchange Energy

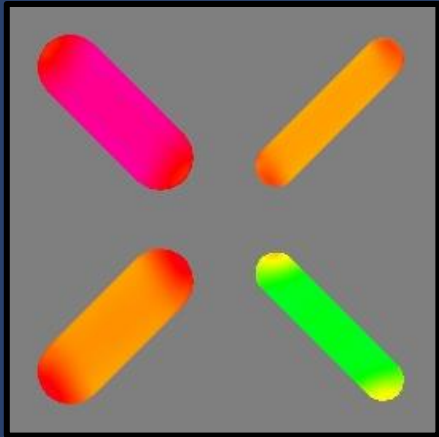


MFM: Saturated initial state

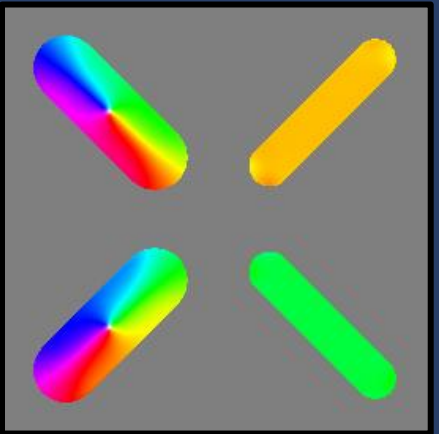


MFM: 30x Field-loops state

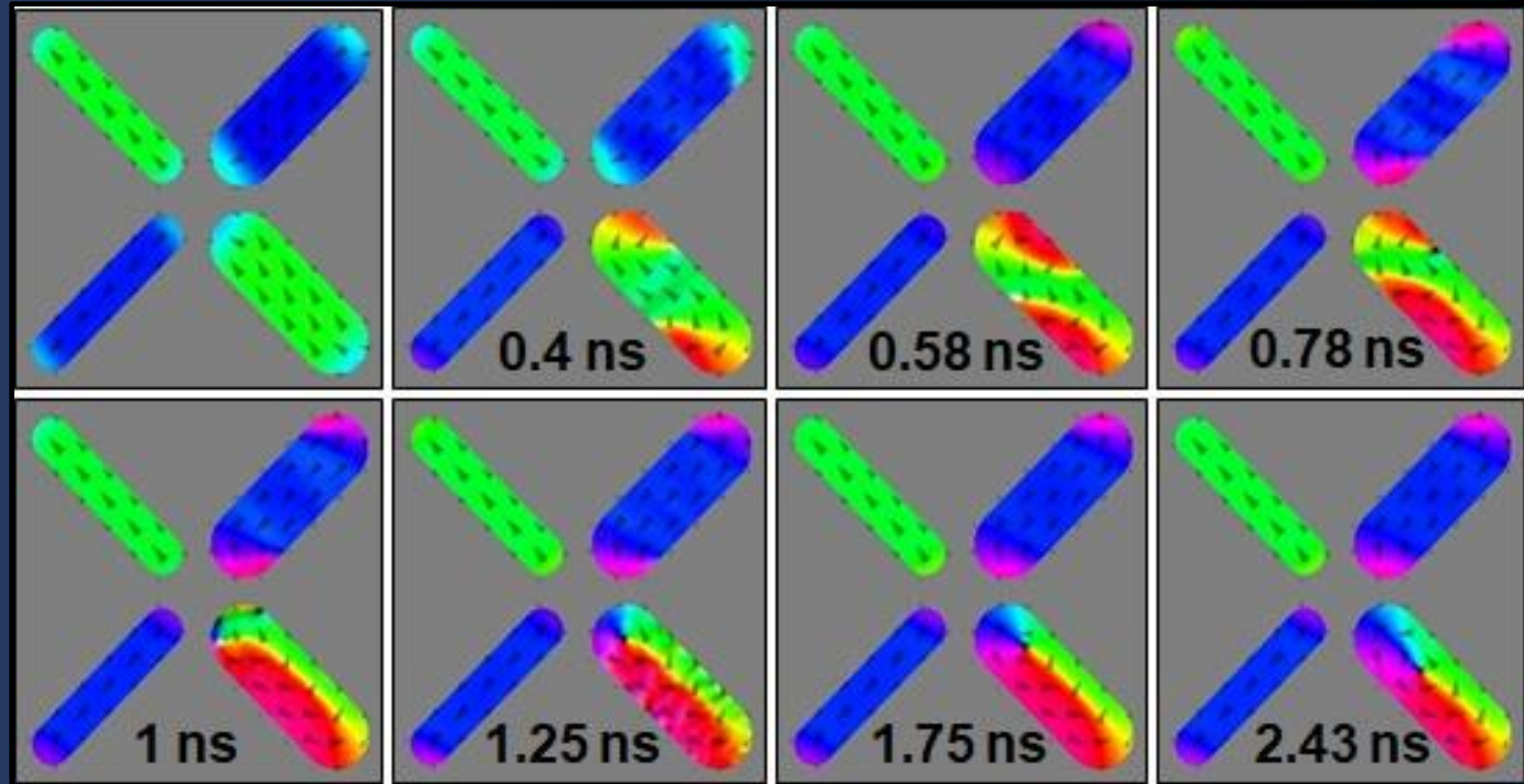
# Simulating vortex formation – Troy Dion



Saturated initial state

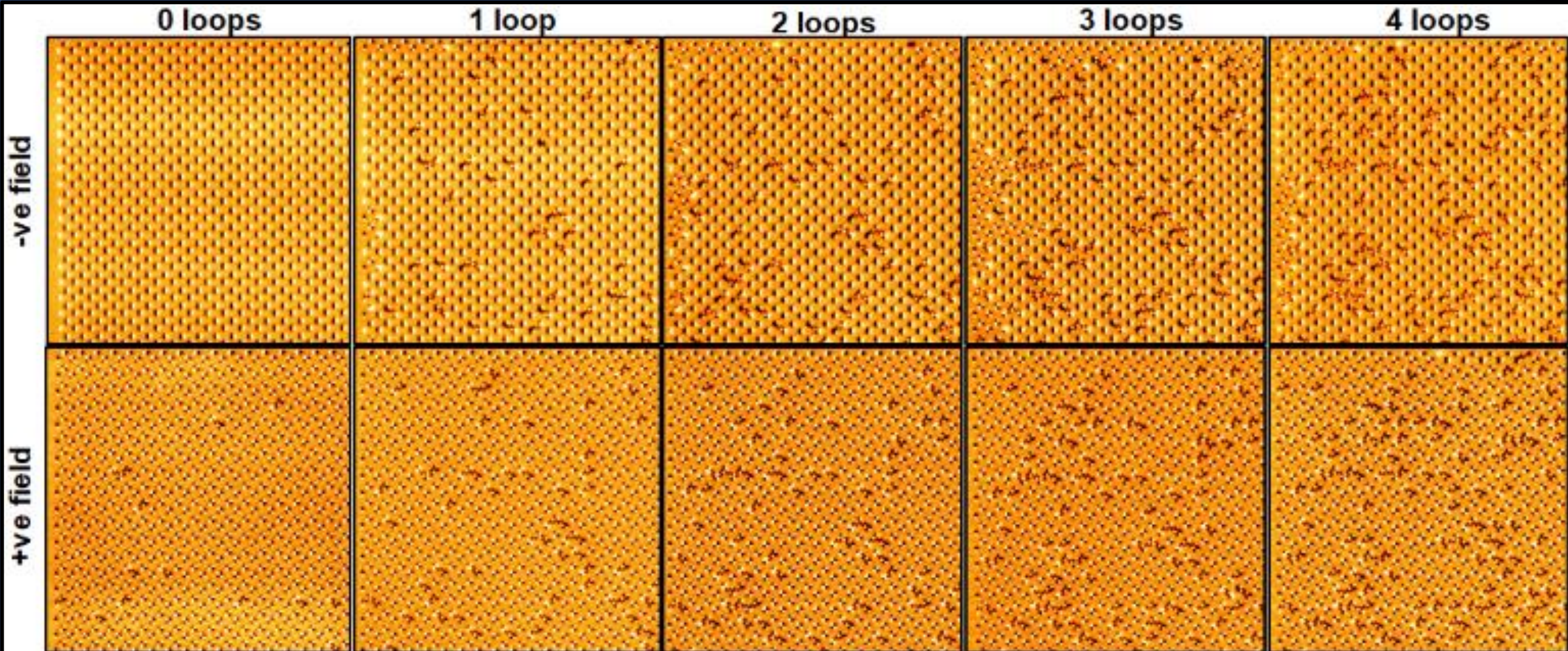


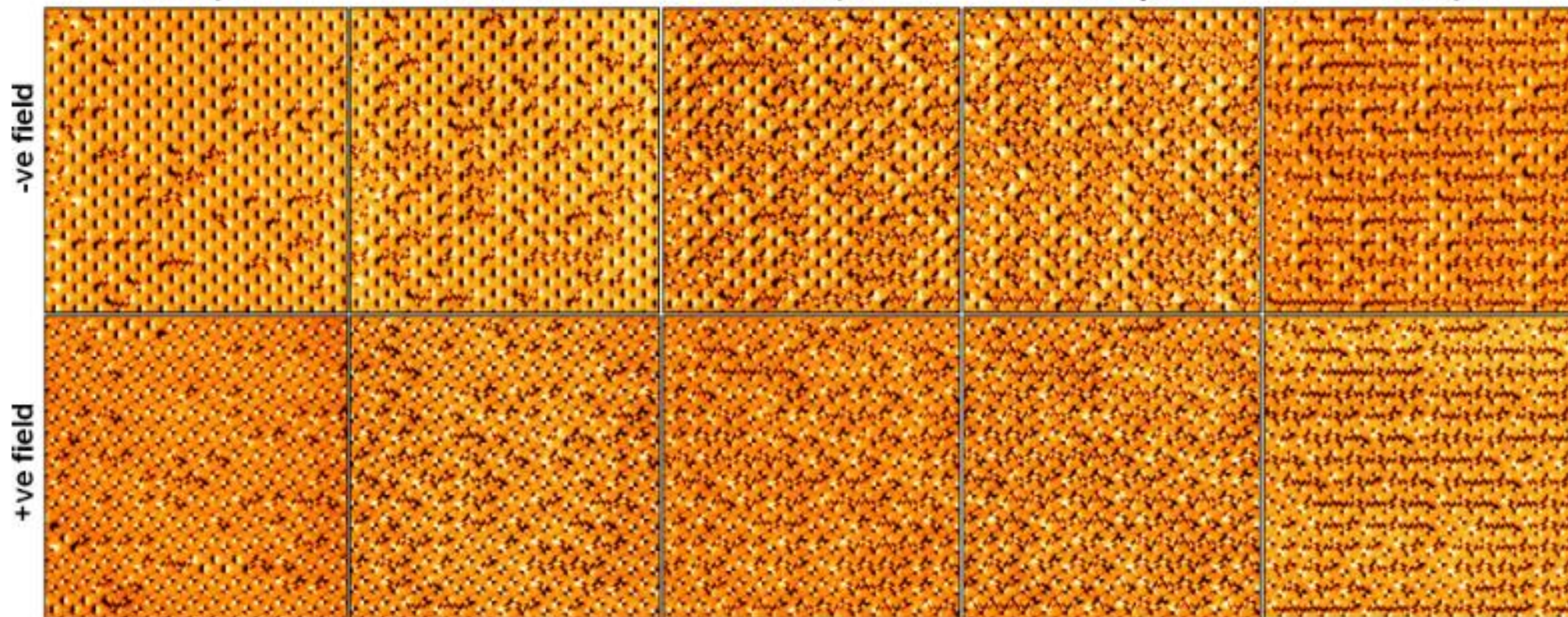
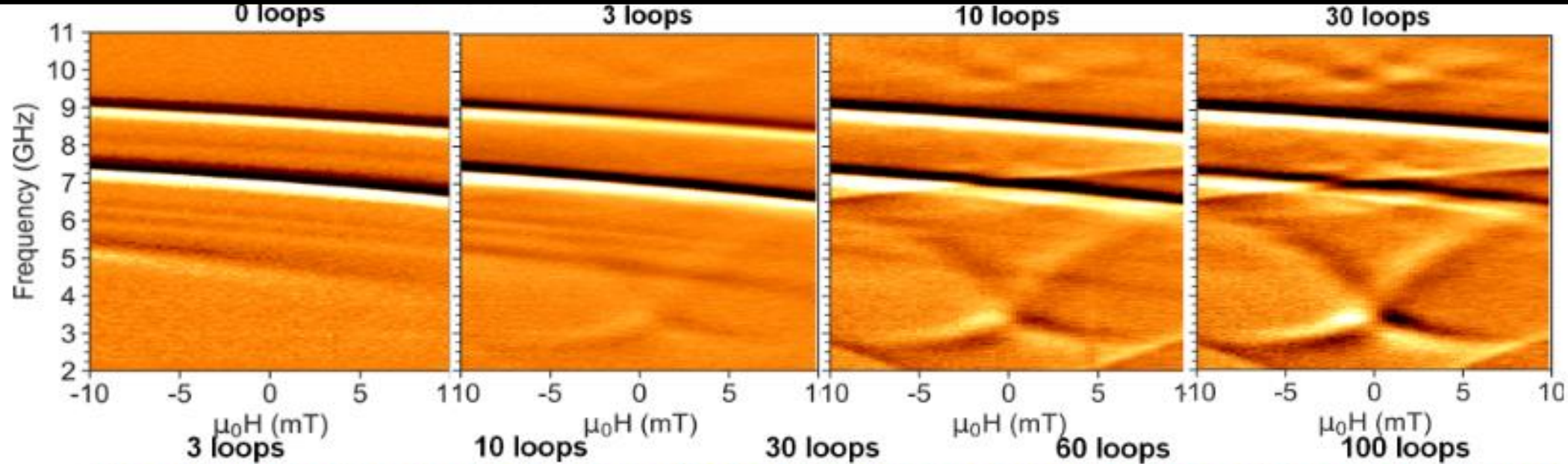
Trained state:  
Vortices in wide bars



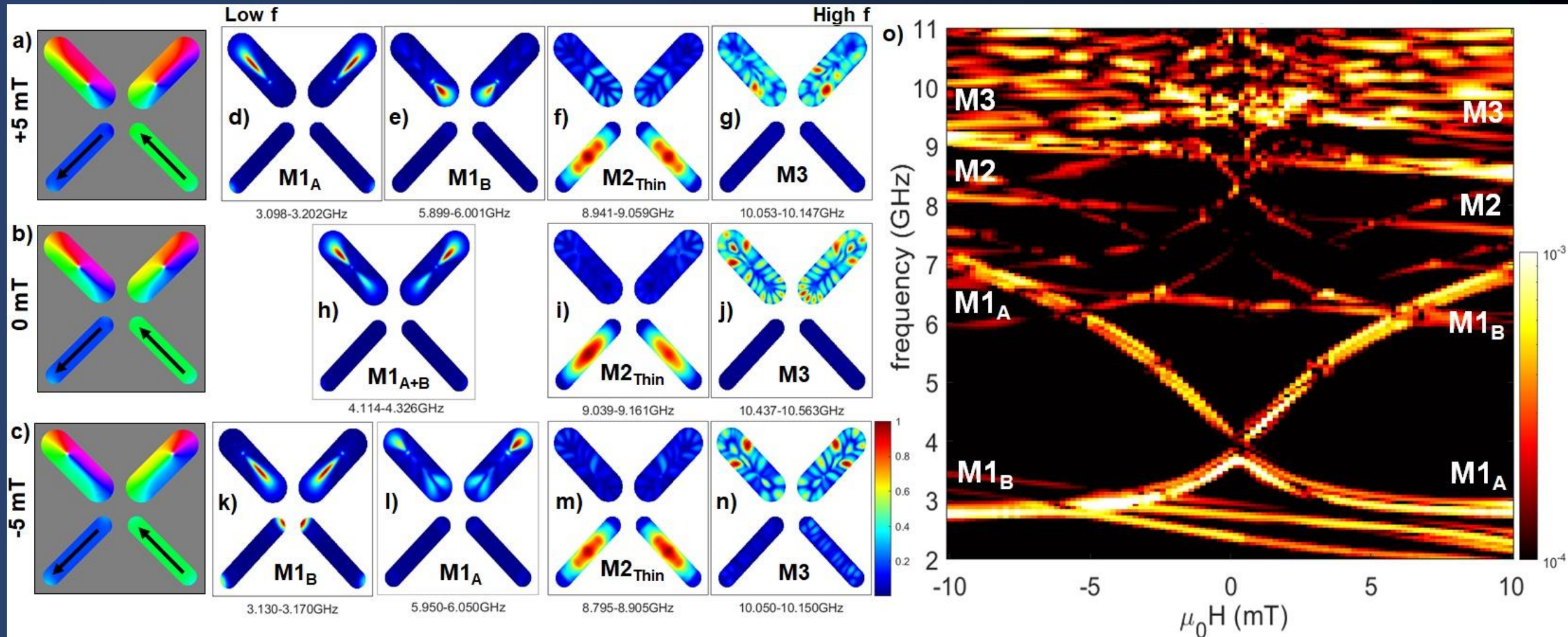
Vortex formation time-series – MuMax3

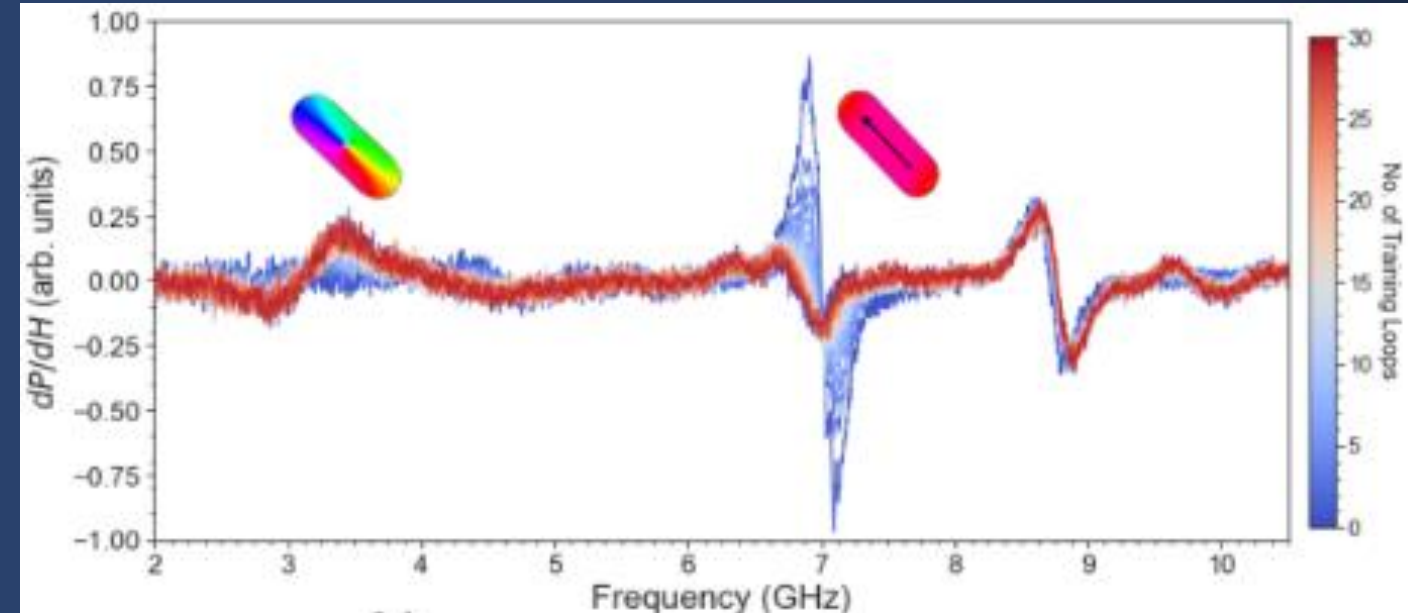
# MFM Imaging of Vortex Training: Domain formation



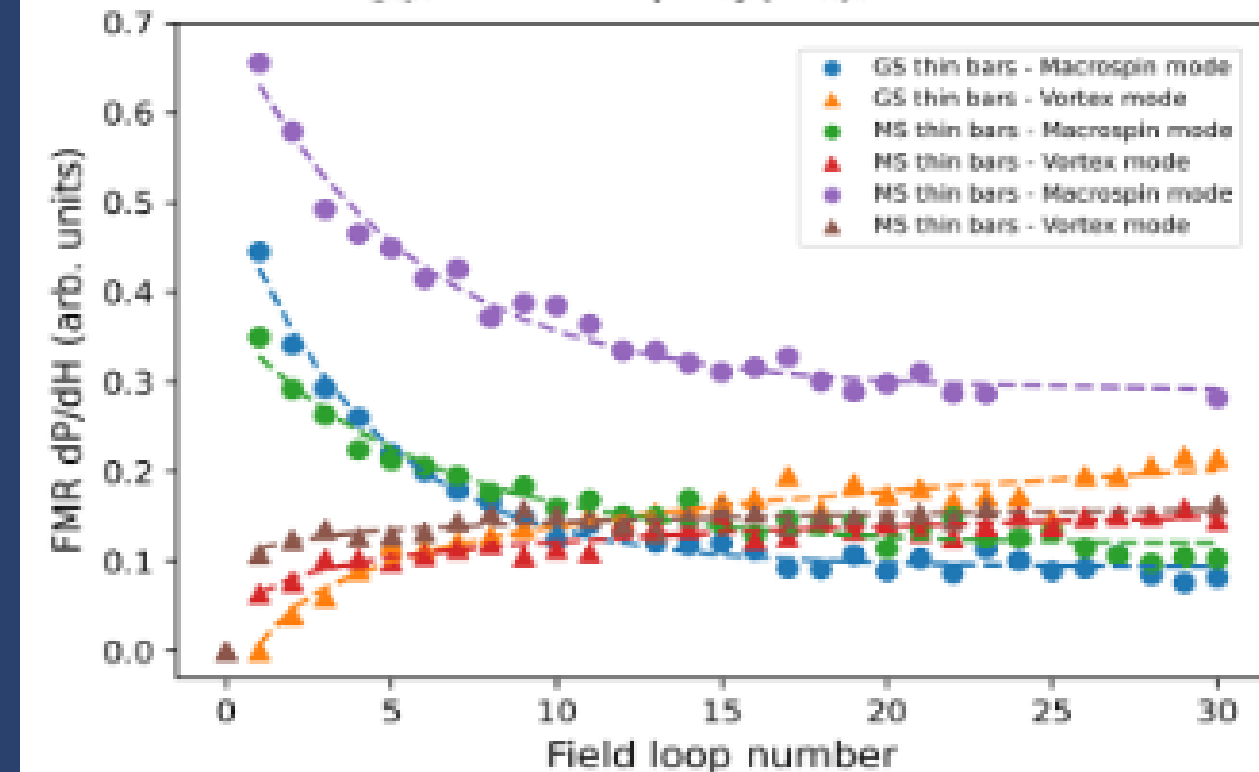


# Micromagnetic simulation of FMR response – T. Dion

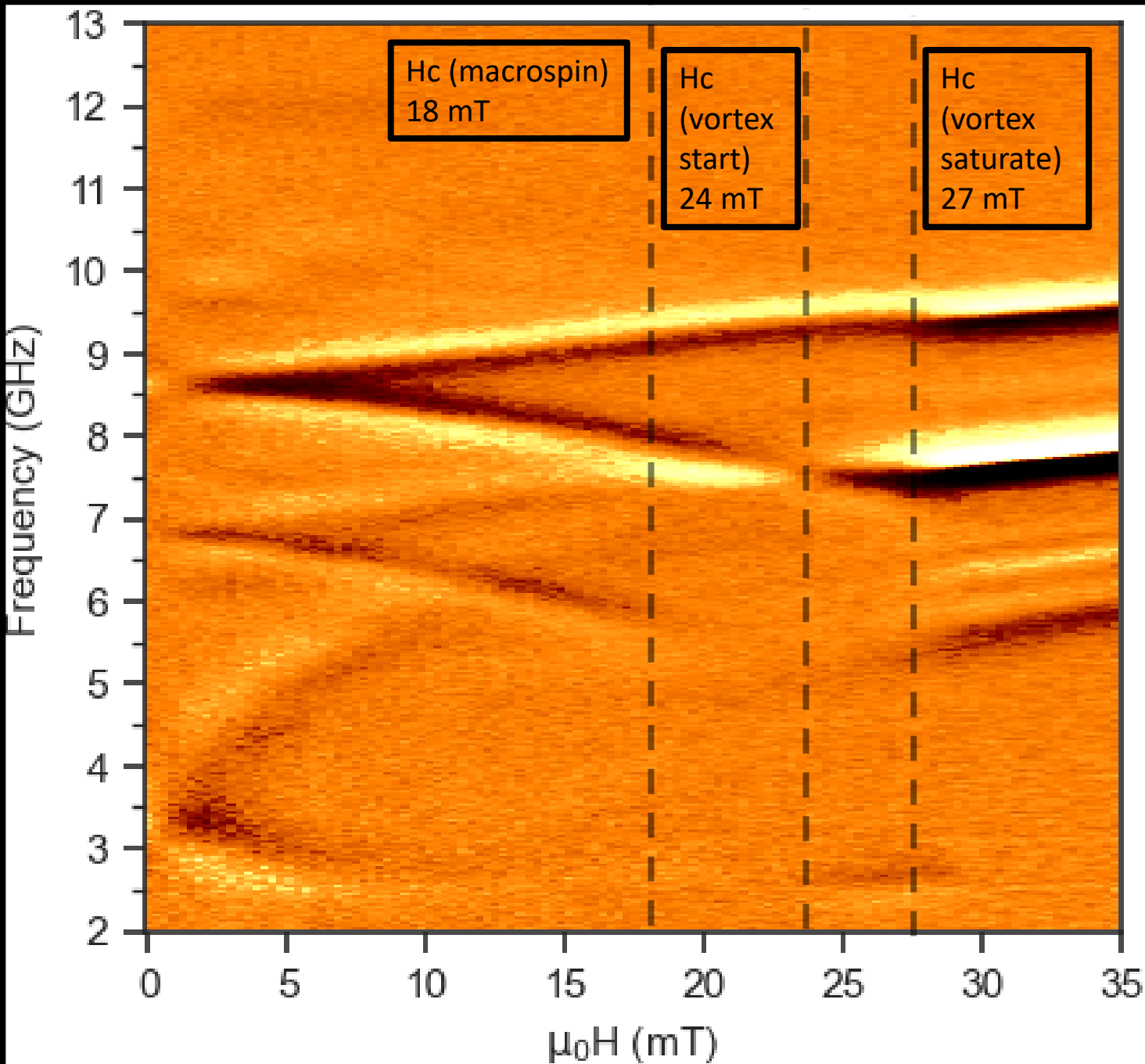




- ‘Waterfall’ spectra taken at - 1.2 mT after each training field loop.

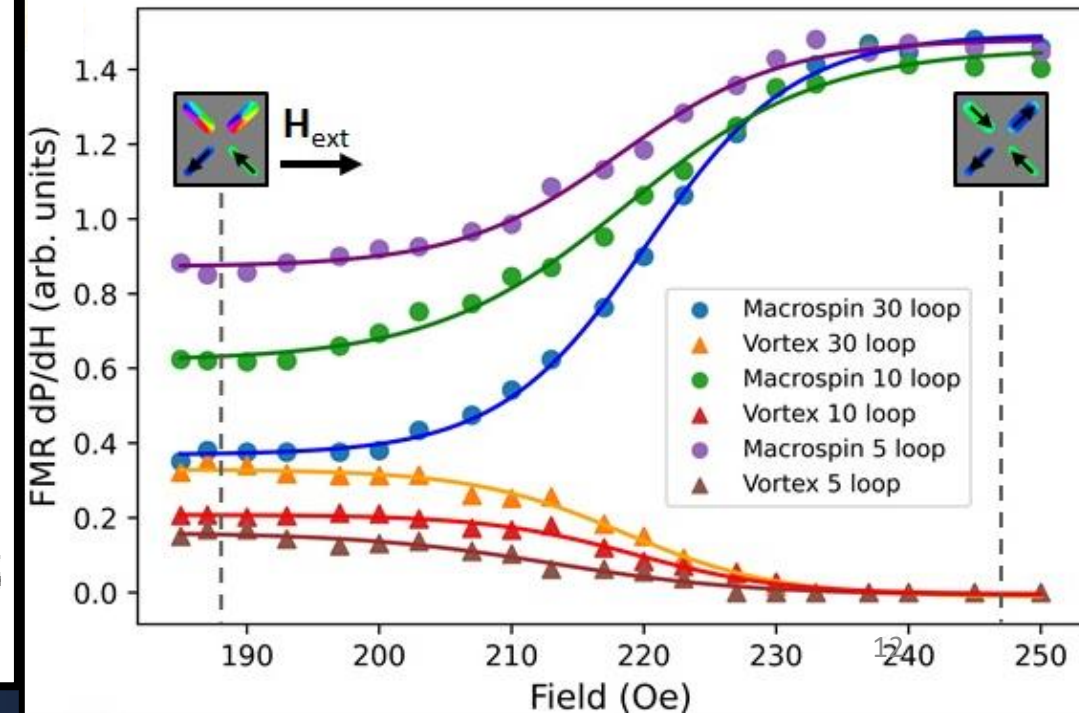


- Macrospin & vortex mode amplitudes throughout training for different thin-bar magnetisations.
- Thin-bar magnetisation state controls **training rate** & final **state populations**.



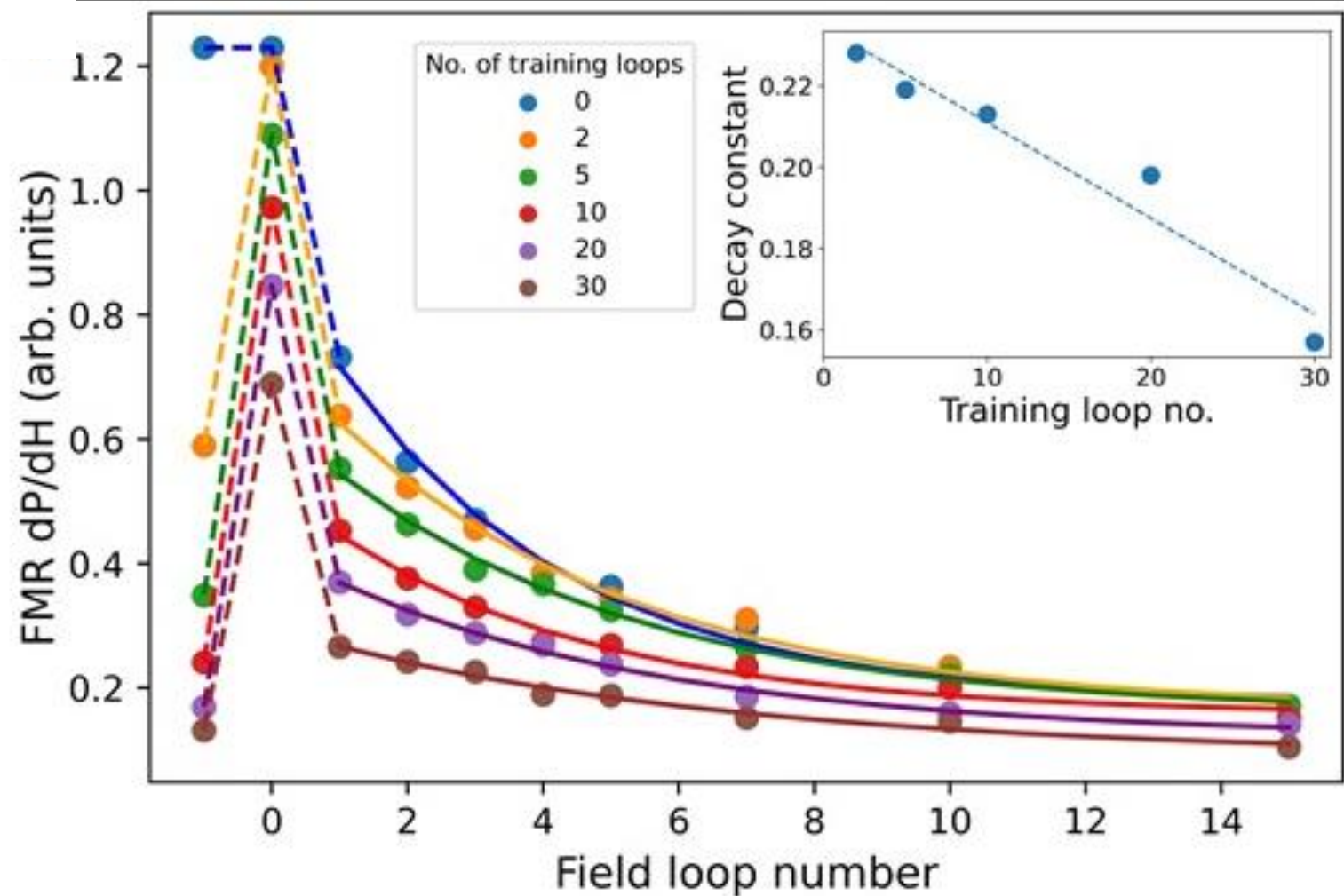
## Vortex to Macrospin Conversion

- Prepare initial high-vortex state
- Sweep  $H$  0-35 mT
- Reach saturated macrospin state at **27 mT**
- Thin bar biasing controls saturation field,  $H_c$  vortex = 27 mT for  $y$  magnetised thin bars, 23.5 mT for  $x$  magnetised thin bars:



# Training ASVI

Higher field application after different training lengths

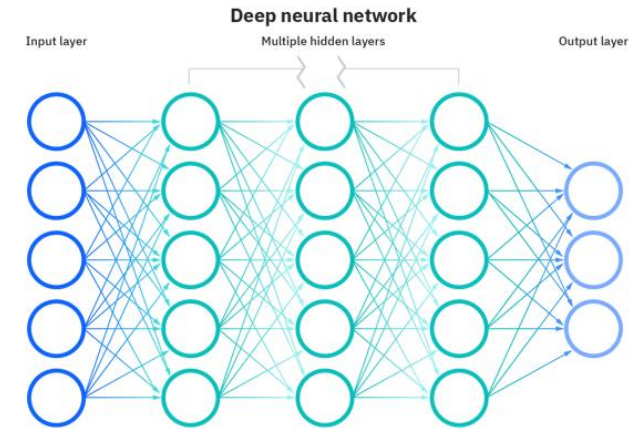


Echo-state property:  
'Fading Memory'  
System converges from  
different initial states when  
driven through same input  
sequence

# Reservoir Computation

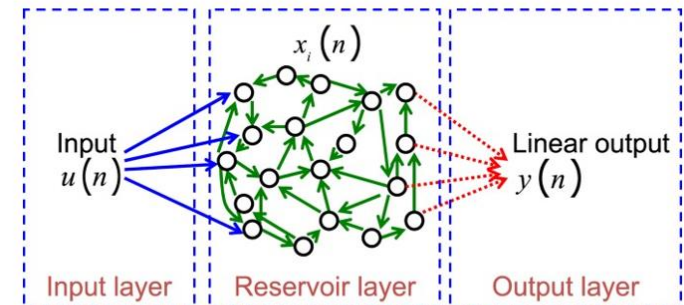
- **Aim:** Map complex problems onto simple linear ones
- Reservoir has huge number of strongly-interacting hidden connections
- Train small number of outputs ( $300$  vs  $10^8$ )
- Strengths: Time series prediction, transforms & classification
- Huge energy savings possible vs. deep neural networks
- Energy cost of global Machine Learning doubling every 3.5 months (!) *OpenAI white paper (2019)*

## Neural network



Train all of the weights  
Costs time and energy

## Reservoir computing

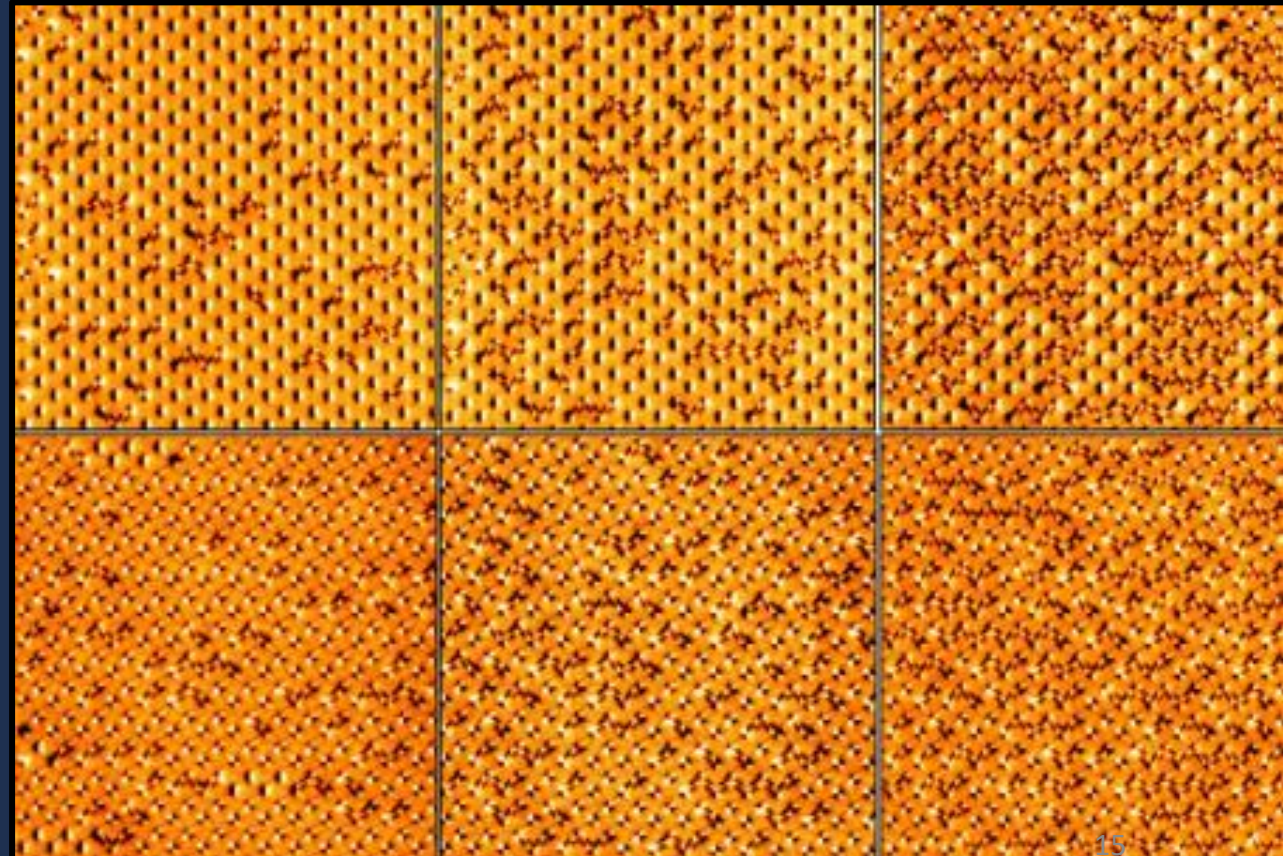


Only train output weights  
Much simpler and still competitive

# Reservoir Computation

Prerequisites for good reservoir computation:

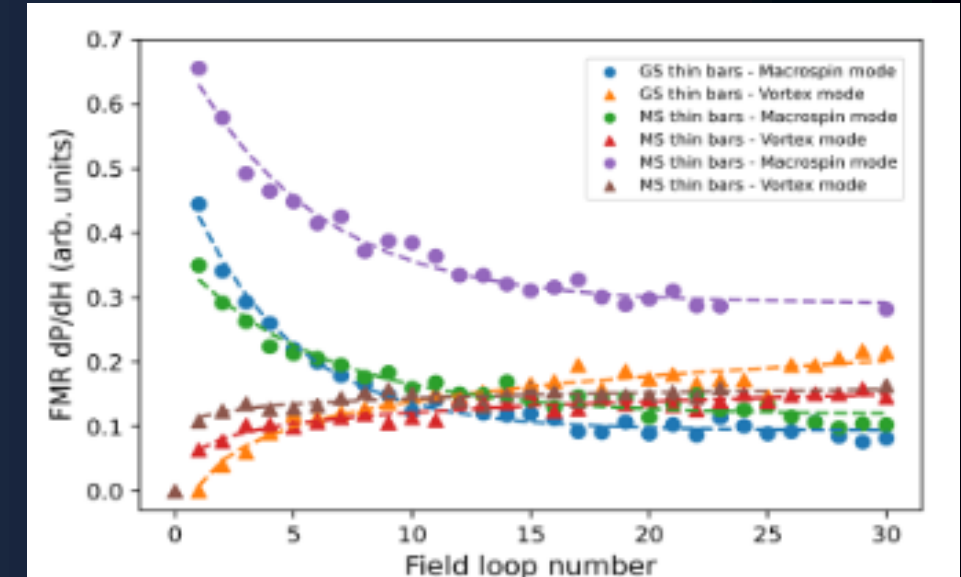
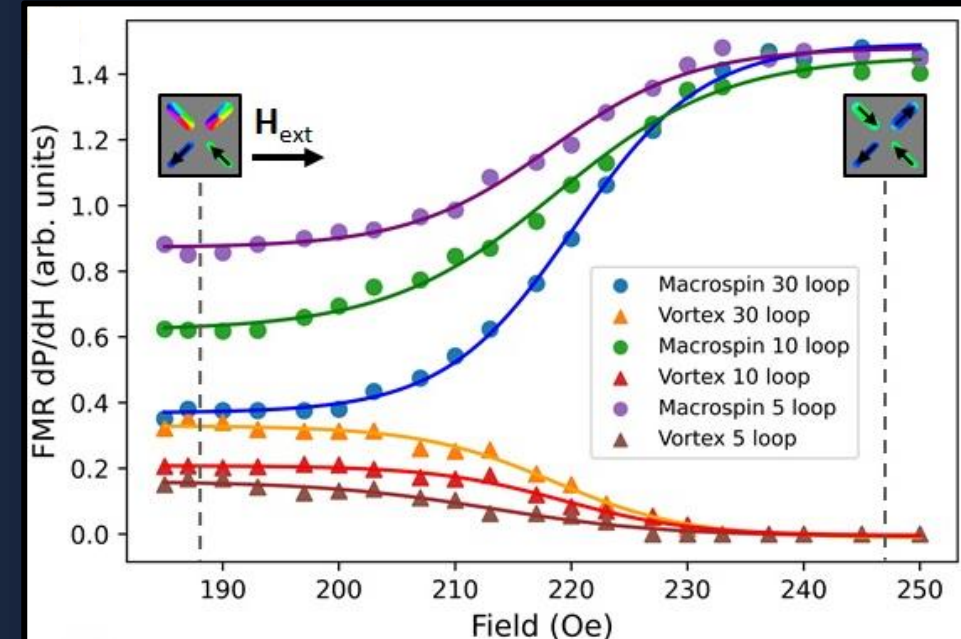
- ✓ Wide range of distinguishable states
- ✓ Strong inter-element coupling



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Prerequisites for good reservoir computation:

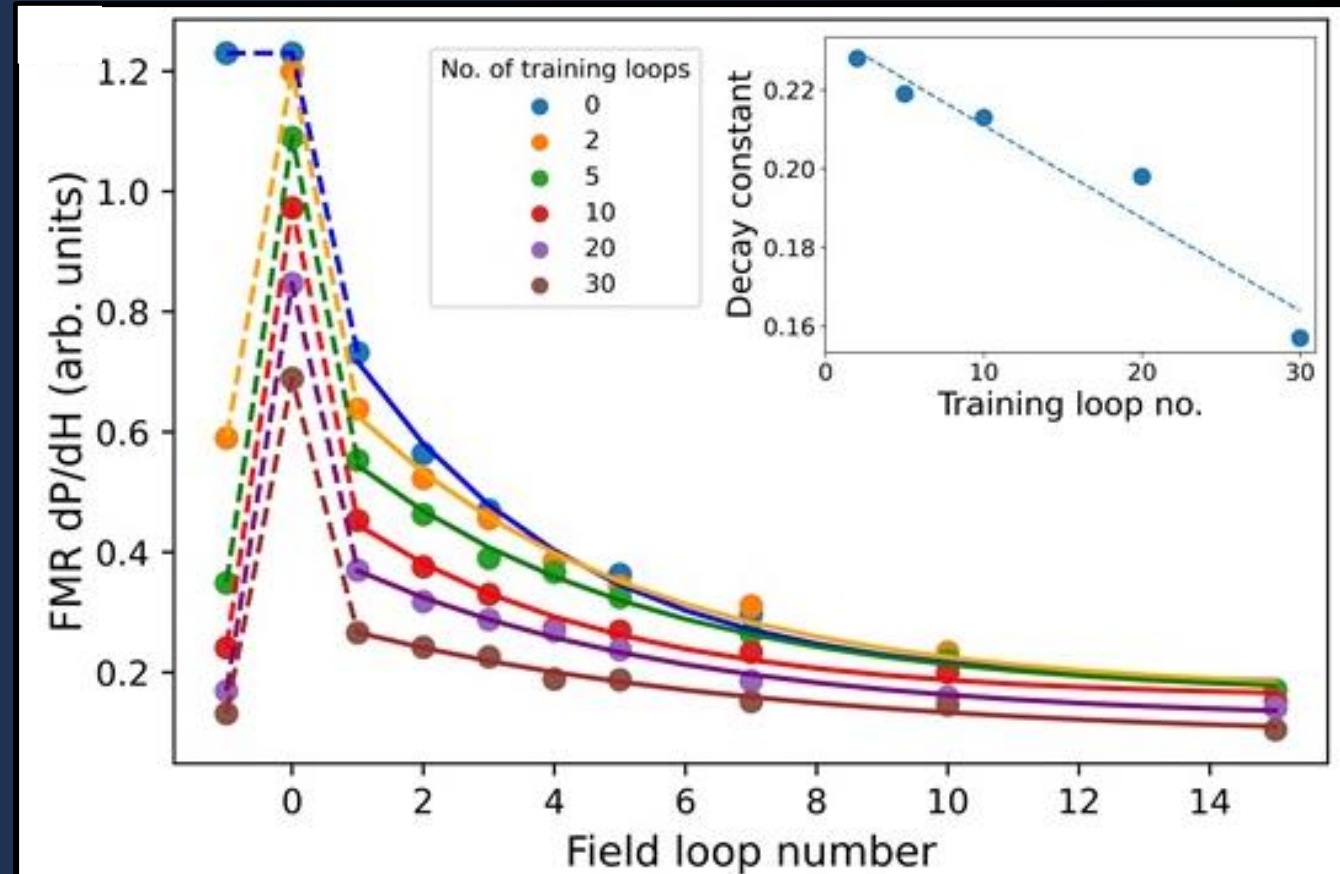
- ✓ Wide range of distinguishable states
- ✓ Strong inter-element coupling
- ✓ Highly-nonlinear response to input



# Reservoir Computation

Prerequisites for good reservoir computation:

- ✓ Wide range of distinguishable states
- ✓ Strong inter-element coupling
- ✓ Highly-nonlinear response to input
- ✓ Gradually fading memory



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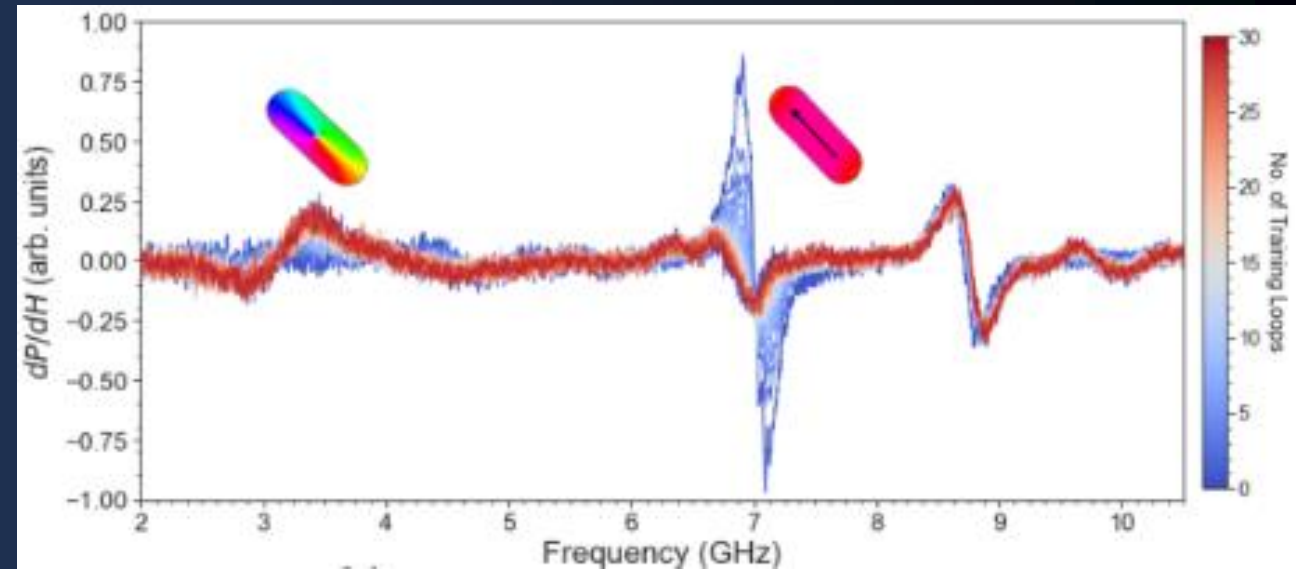
ASVI appears to tick boxes well

Implement ASVI reservoir!

PhD student **Kilian Stenning** lead our implementation

**Key breakthrough: Frequency domain readout**

Each FMR freq. bin assigned training weights



# Reservoir Computation

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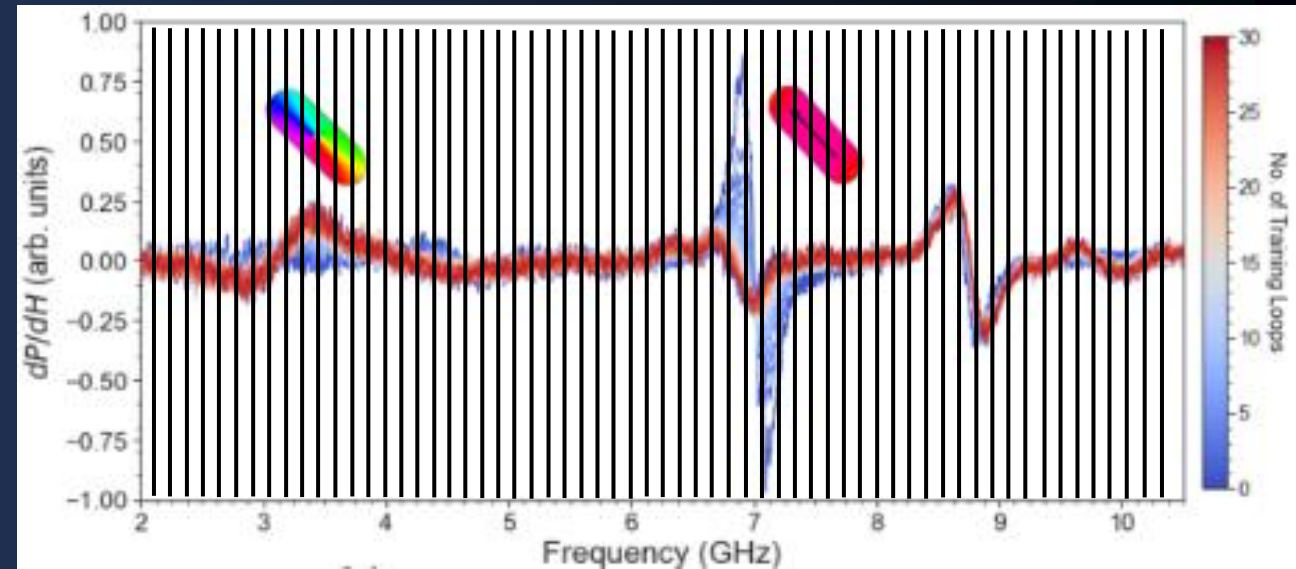
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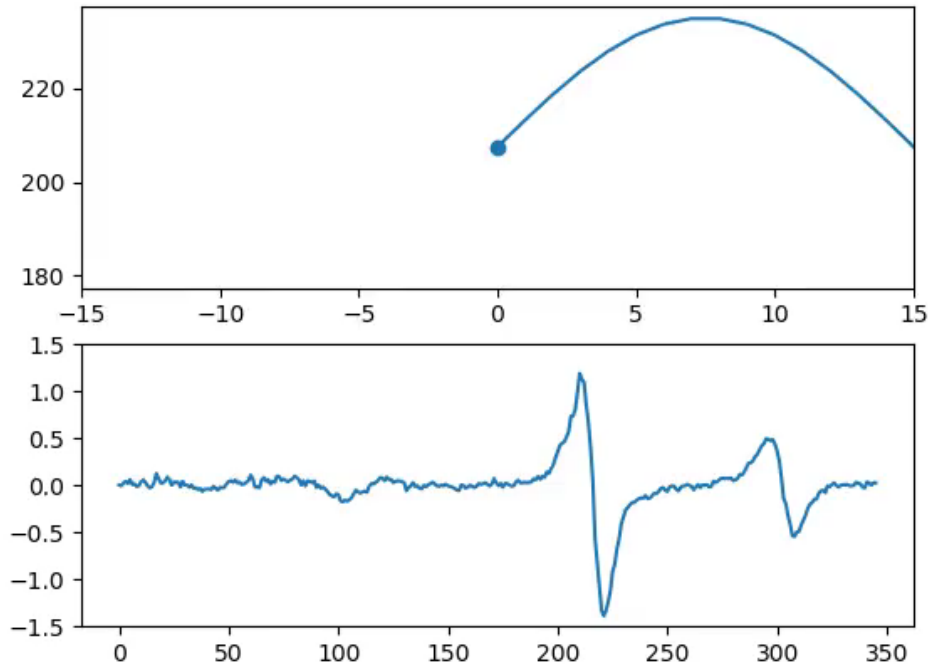
**Key breakthrough: Frequency domain readout**

Each FMR freq. bin assigned training weights



Reservoir outputs = 300 FMR frequency bins  
Measure  $10^8$  nanomagnets in 2-10 s

# Reservoir Computation



- Encode sine wave input as sequence of field-loop amplitudes
- Use reservoir FMR outputs to 'learn' transforms

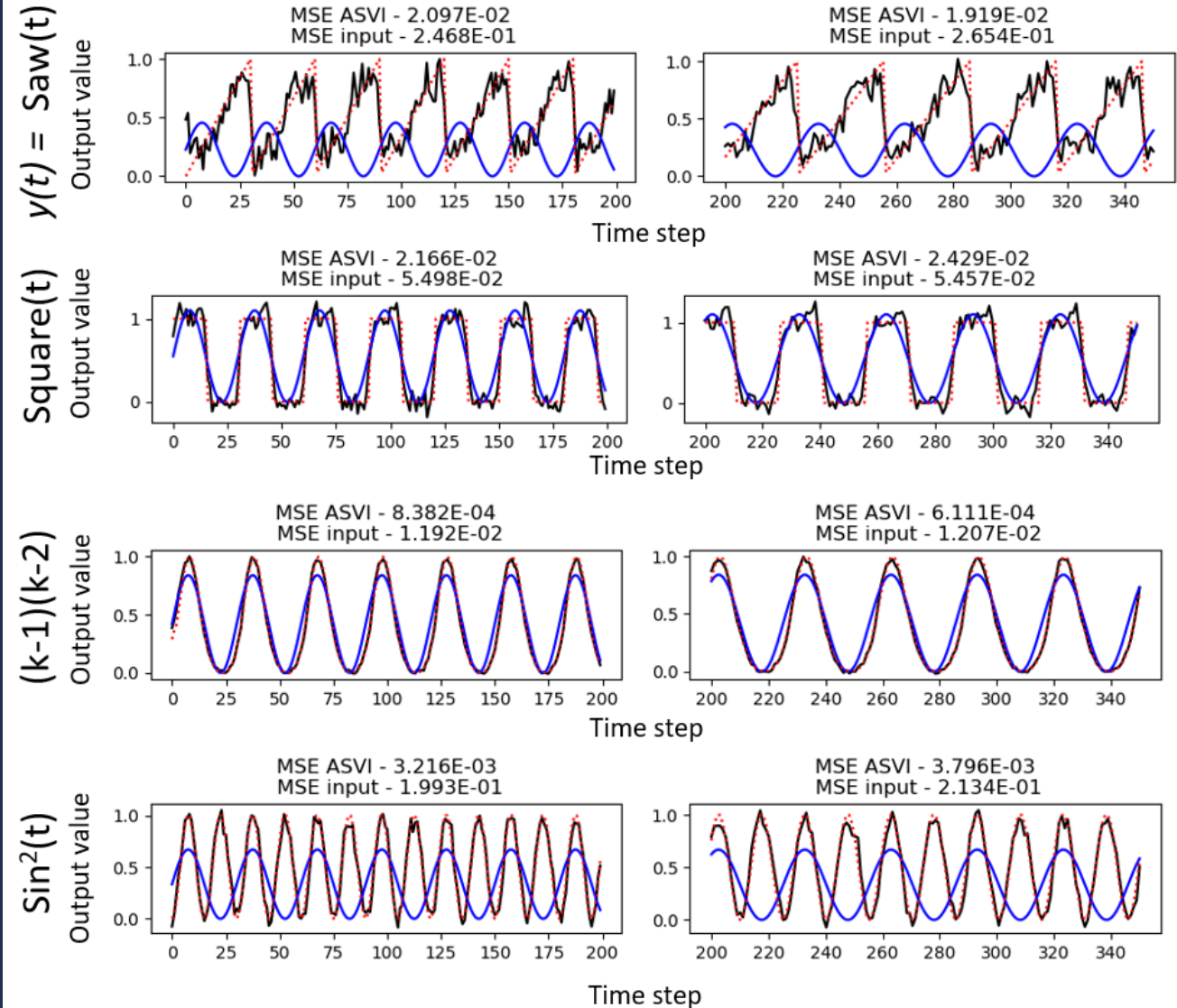
## Waveform transformation

..... Target — ASVI prediction — Raw input prediction

$$I(t) = \sin(t)$$

Train

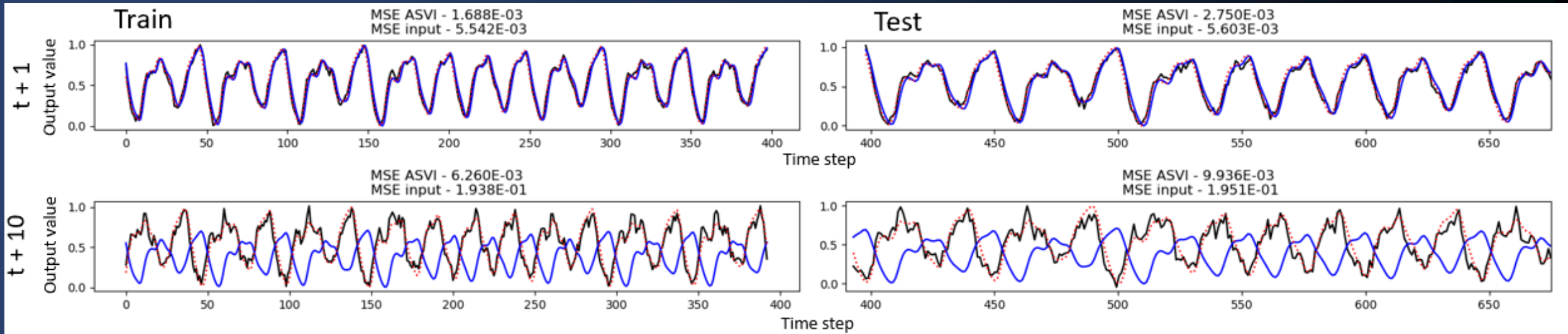
Test



# Reservoir Computation

- Chaotic time-series prediction – ‘Mackey-Glass’ equation

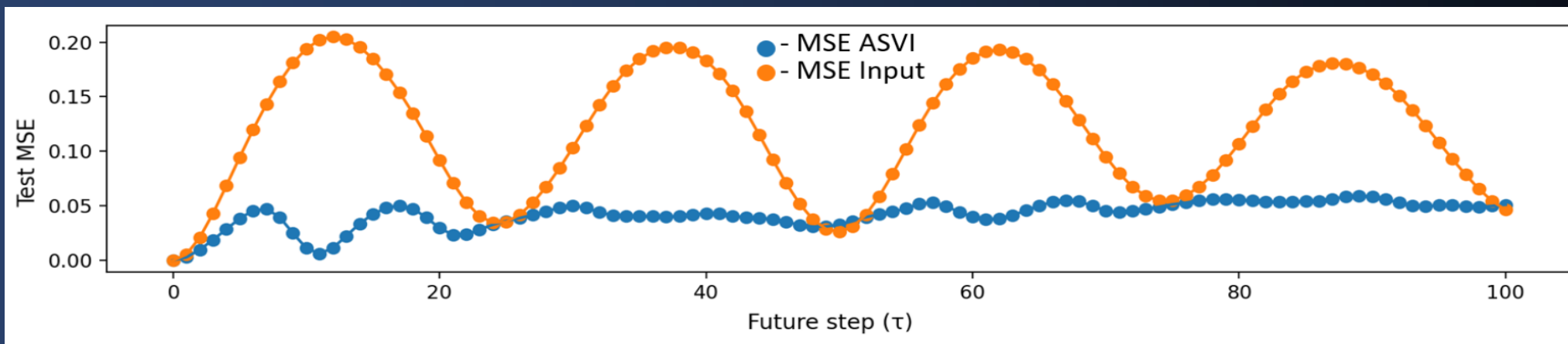
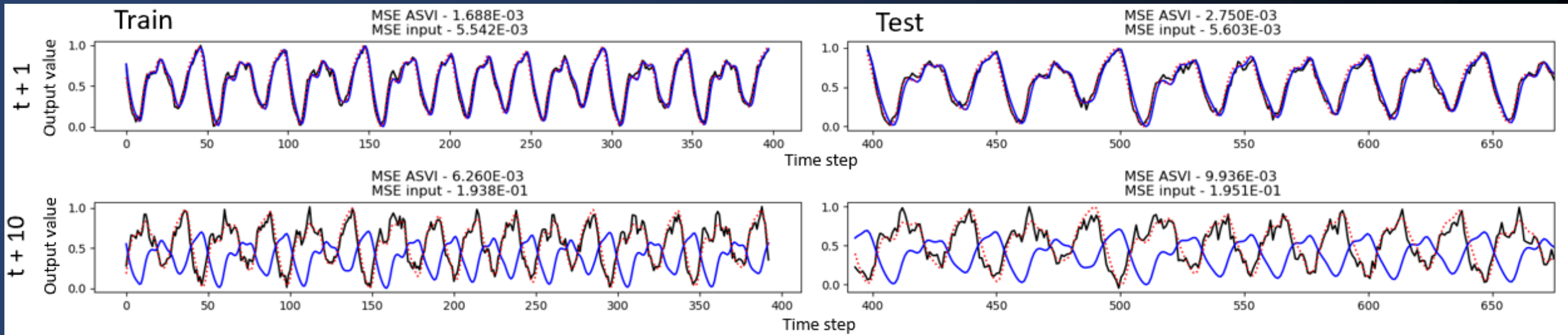
..... Target    — ASVI prediction    — Raw input prediction



# Reservoir Computation

- Performance weaker for harder predictions! *Stay Tuned ;)*

- - - Target   
 — ASVI prediction   
 — Raw input prediction



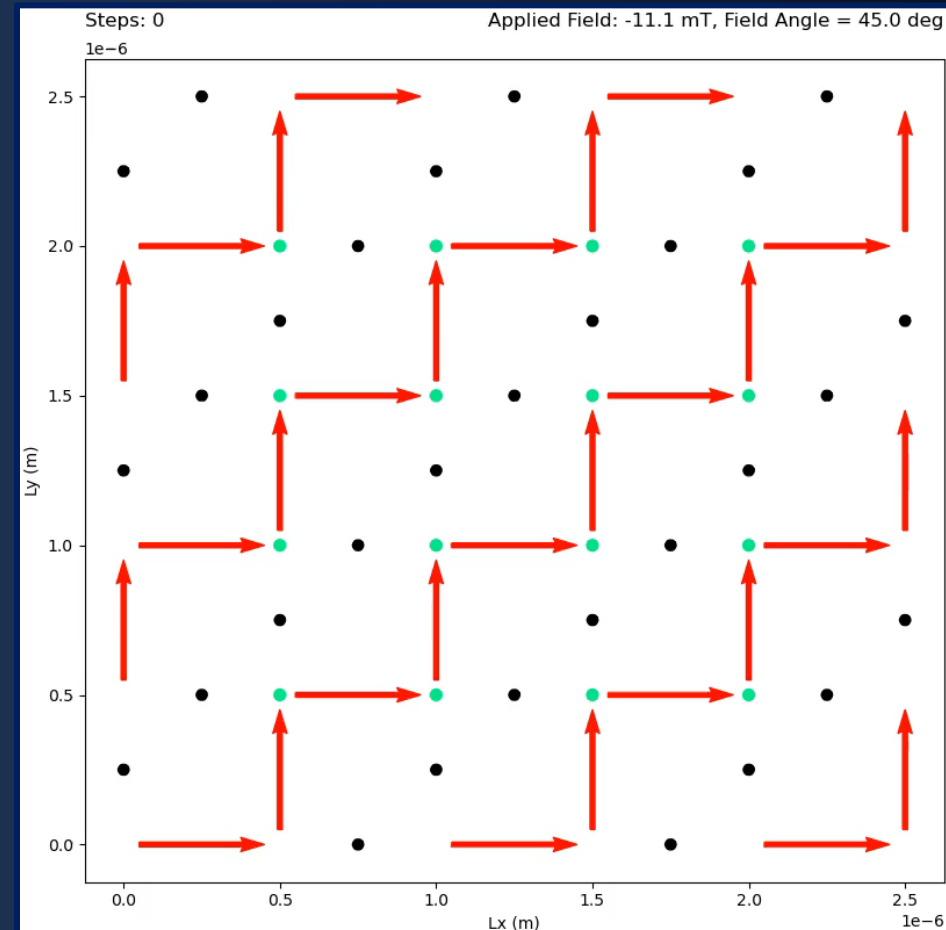
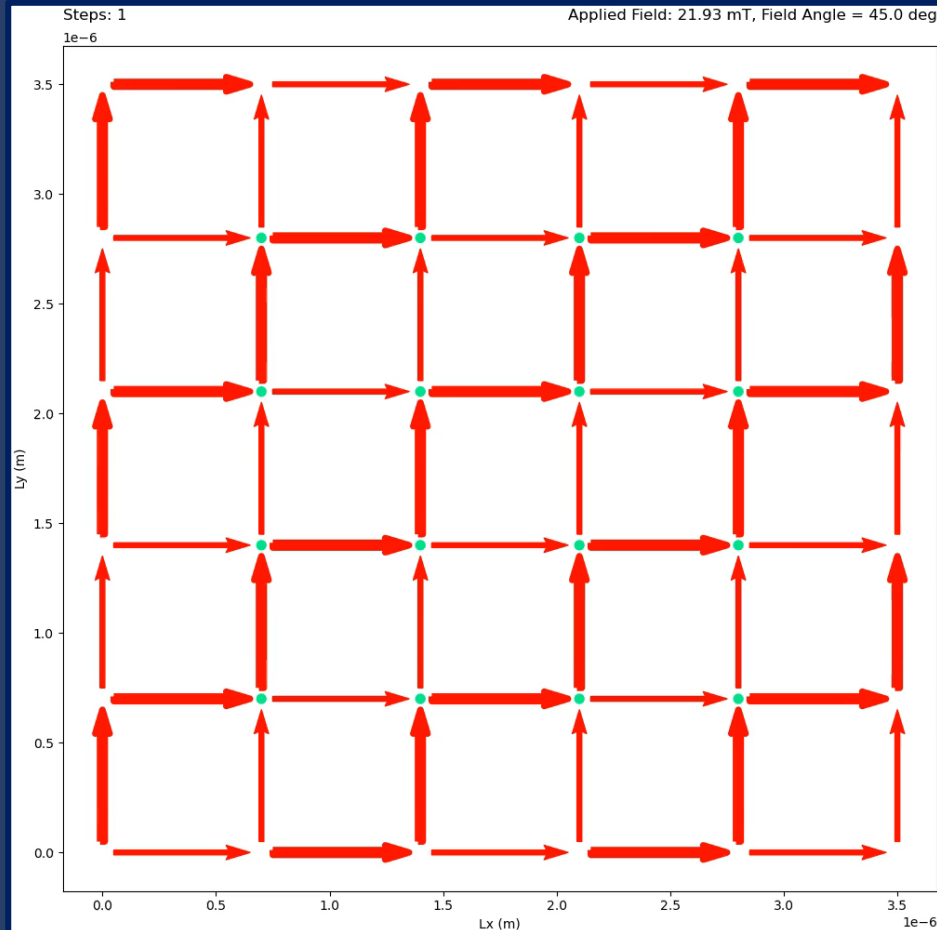
# Reservoir Computation: Exploring Different Arrays

- Bit of honesty! – this sample was not originally designed for computation 😊
- **Huge** parameter space to explore for improvements:
  - Vortex training rate?
  - Bar Dimensions
  - Array Geometry
  - Inter-Bar Interaction Strength
  - Etc!
- Need **simulation framework** to explore

# Reservoir Computation: Exploring Different Arrays

- Introducing our new dipolar simulation framework
- Development: **Alex Vanstone, Tianyue Wang, Tingjung Zheng**

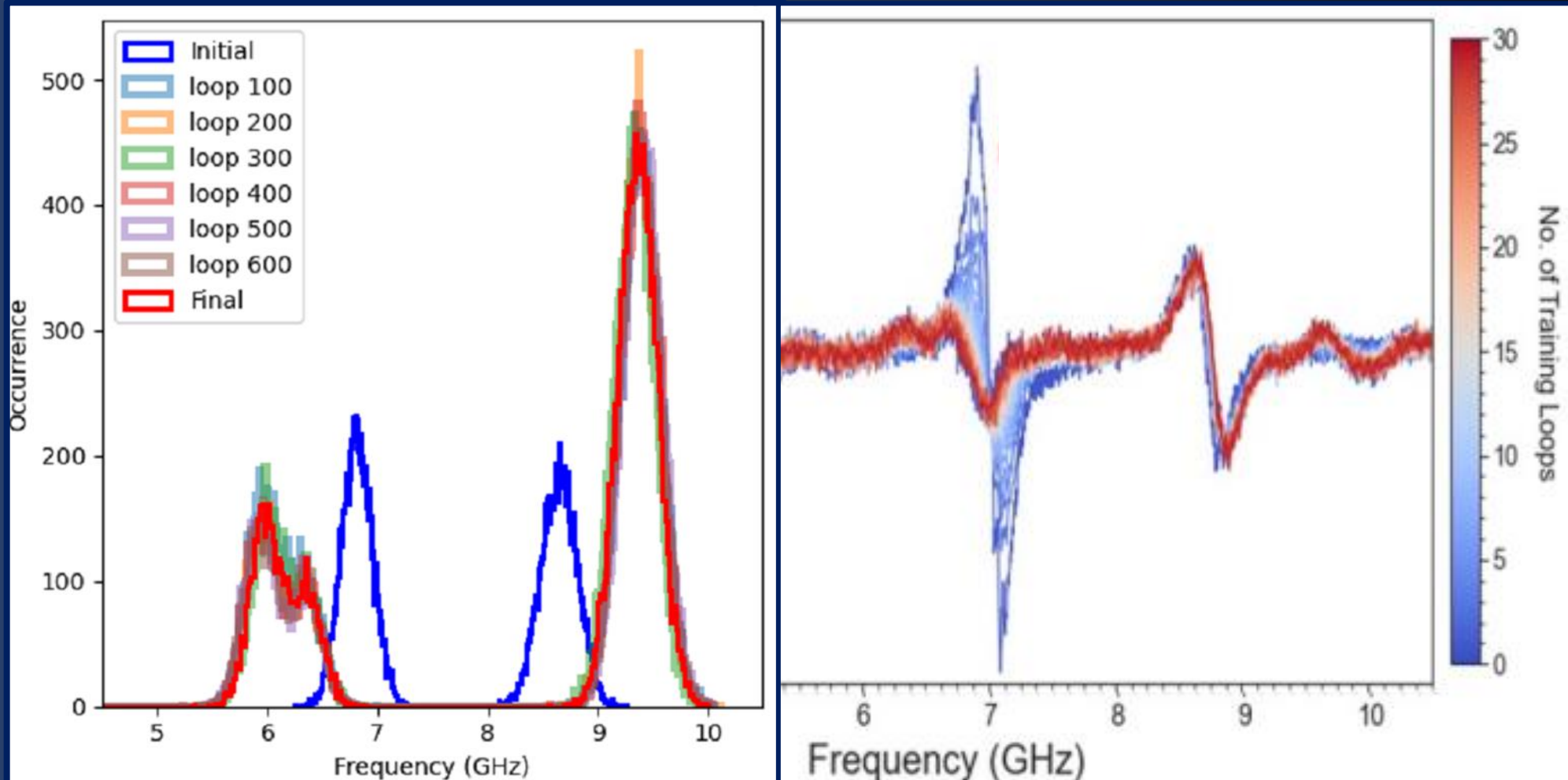
Macrospin  
Initial state  
Sine dataset  
field input



Vortex  
Initial state  
Apply field &  
saturate to  
macrospins

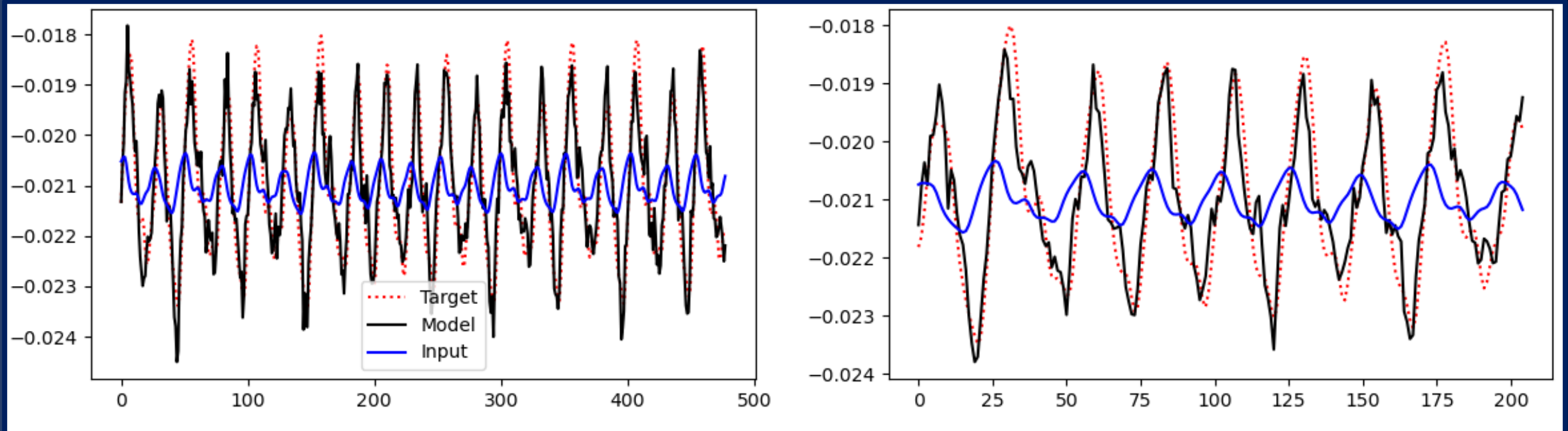
# Reservoir Computation: Exploring Different Arrays

- Convert spatial island state & local field distribution to FMR spectra:



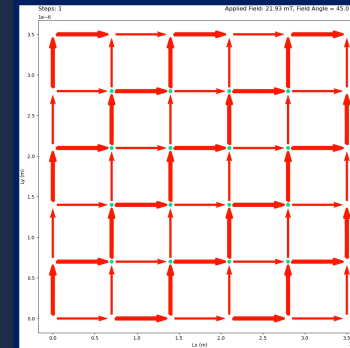
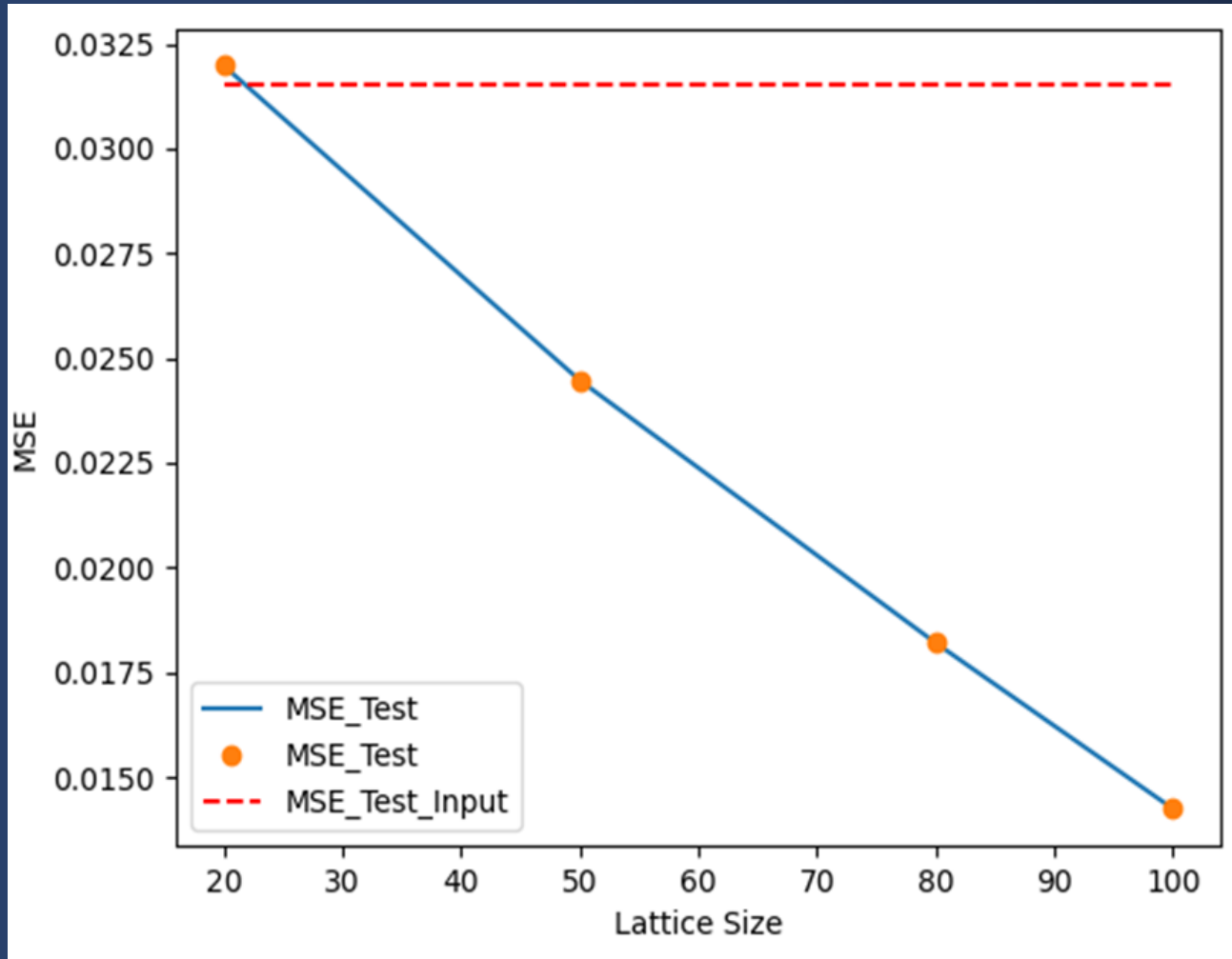
# Reservoir Computation: Exploring Different Arrays

- Models experimental task performance well: Mackey-Glass prediction

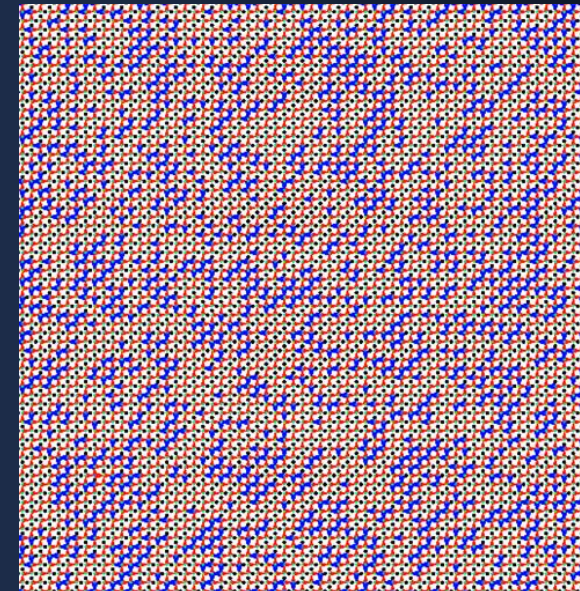


# Reservoir Computation: Simulated Lattice Size vs. MSE

- Bigger system = Better performance (Mackey-Glass task)



5x5 lattice



100x100  
lattice

# Reservoir Computation: Alternative Geometries - Pinwheel

**Flashing Image Warning**

Pinwheel  
ASVI:  
Sine field  
input,  
100x100  
lattice

# Conclusions

- Developed new artificial spin system 'ASVI'
- Controlable bistable vortex/macrospin textures
- Leads to strong **memory** (vortex nucleation) & **non-linearity** (spin-wave mode dispersion)
- Leverage for reservoir computing scheme

## Future Work

- Upcoming paper on combining multiple reservoirs – **over to Kilian!**
- Development underway on higher dimensional input
- Beyond reservoirs – recurrent & convolutional nets

## Thanks

- Prof Karin Everschor-Sitte & Jake Love for helpful discussion
- All co-authors and collaborators