

# Reconfigurable Training and Reservoir Computing via Spin-Wave Fingerprinting in an Artificial Spin-Vortex Ice

**Jack C. Gartside**

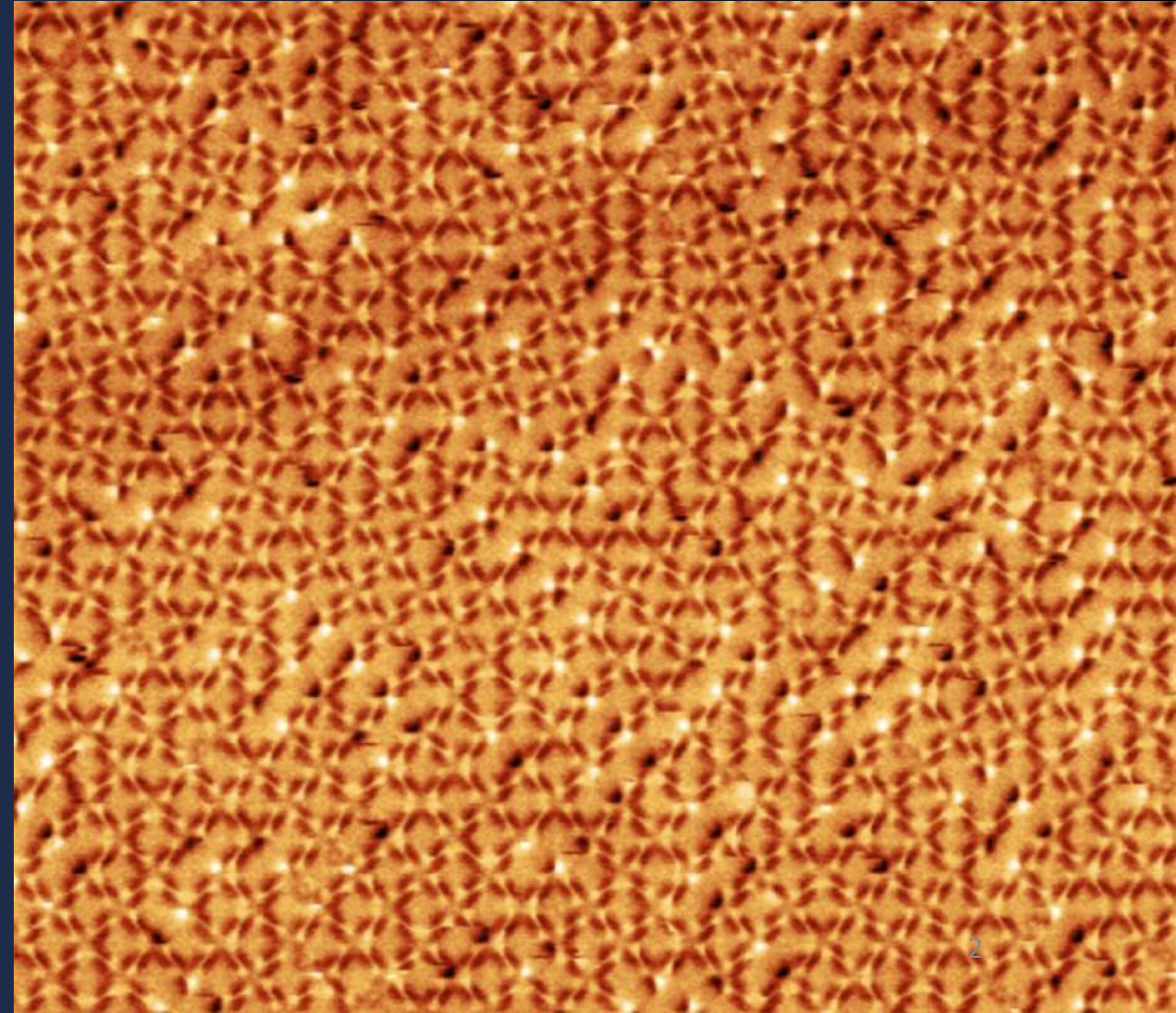
Kilian D. Stenning, Alex Vanstone, Troy Dion,  
Holly H. Holder, Francesco Caravelli, Daan M.  
Arroo, Hidekazu Kurebayashi, Will R. Branford

**Imperial College London, UCL, Los Alamos  
National Lab**

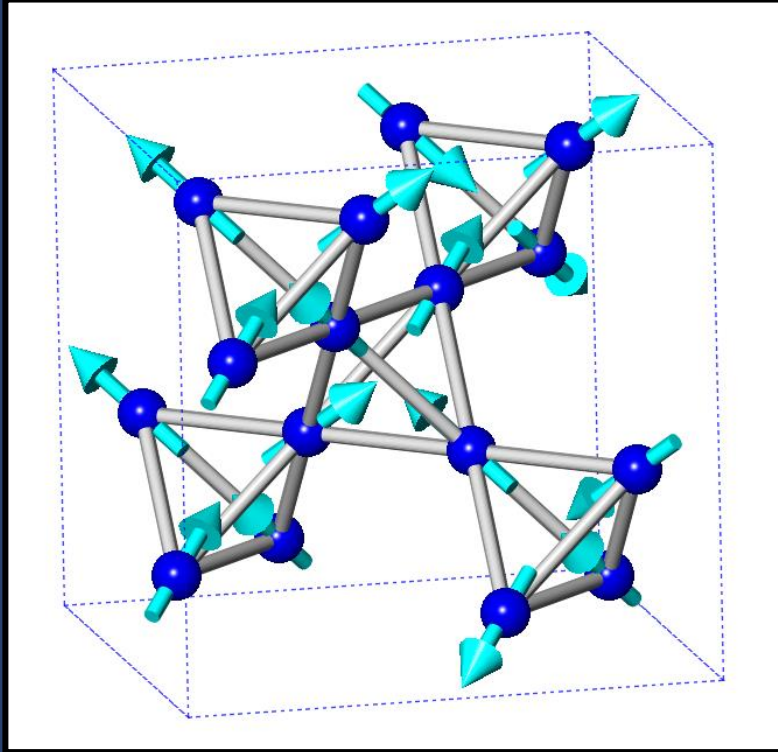
# Reconfigurable Training and Reservoir Computing via Spin-Wave Fingerprinting in an Artificial Spin-Vortex Ice

Jack C. Gartside, Kilian D. Stenning, Alex Vanstone, Troy Dion, Holly H. Holder, Francesco Caravelli, Daan M. Arroo, Hidekazu Kurebayashi, Will R. Branford

- Introduction to Artificial Spin Systems
- Microstate control
- ASVI - Artificial Spin System engineered for Vortex/Macrospin bistability
- Ratchet-like Macrospin to Vortex conversion
- FMR signatures of Vortex & Macrospin modes
- Long-term training up to 60 field loops
- Targeted vortex writing via MFM tip
- Reservoir computation scheme
  - Waveform transformations
  - Chaotic time-series prediction

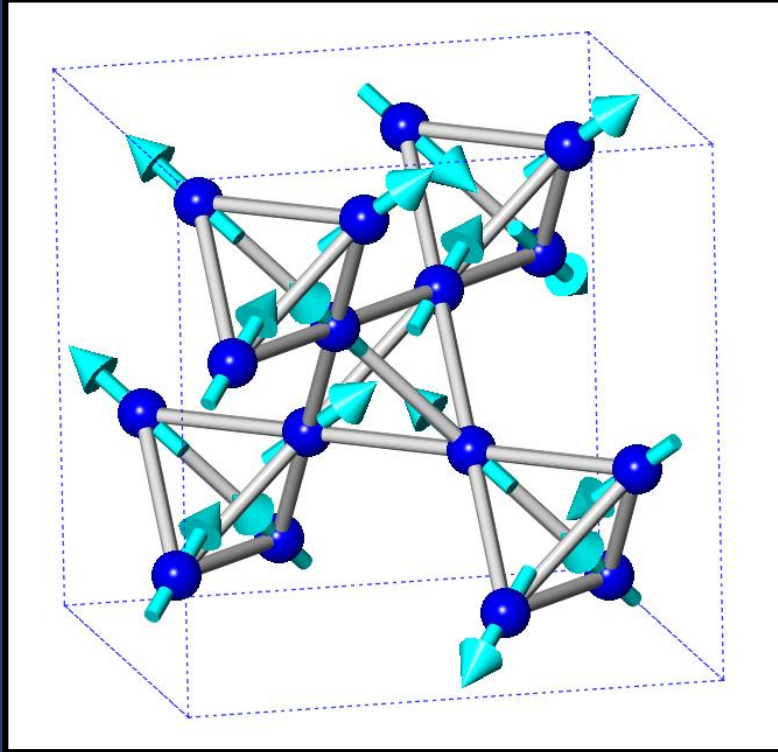


# What is an artificial spin system?

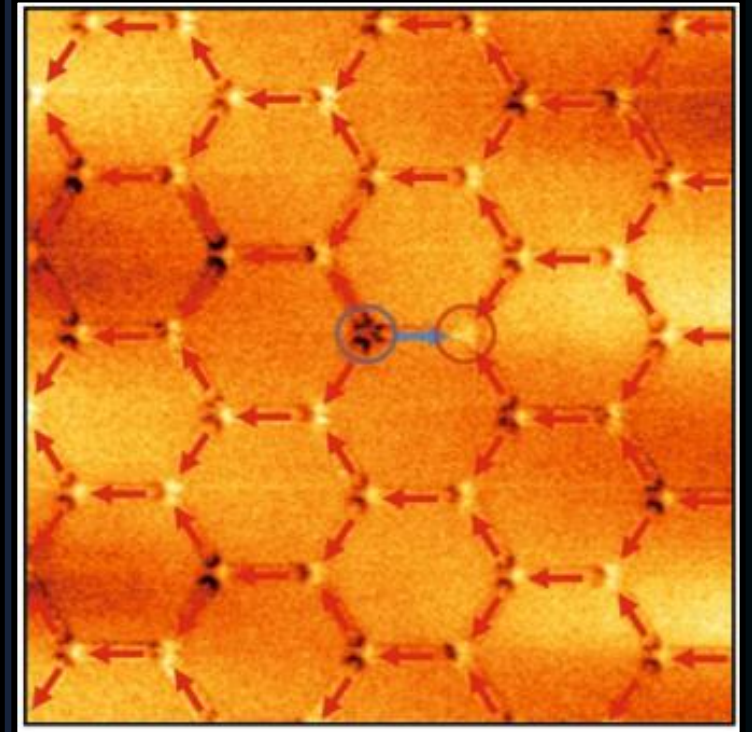
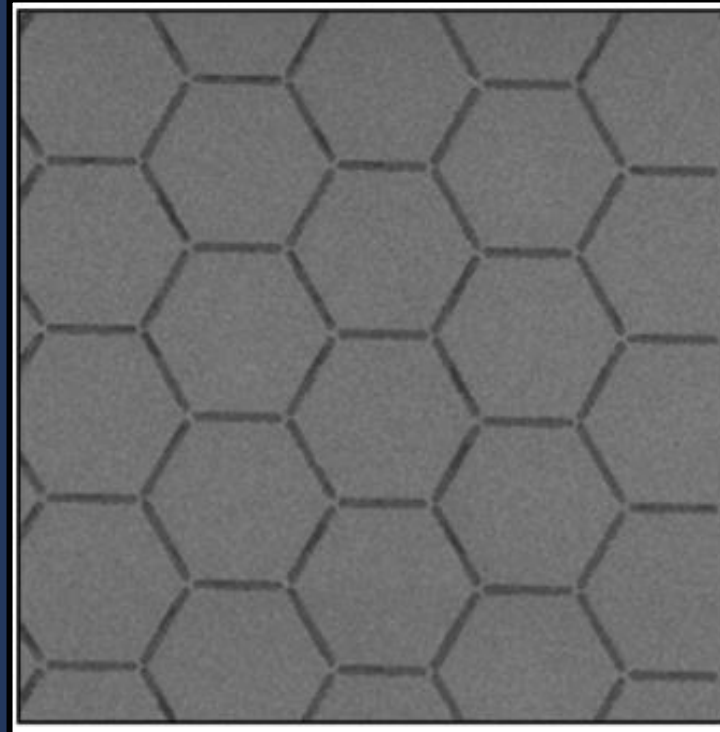


Dysprosium titanate

# What is an artificial spin system?



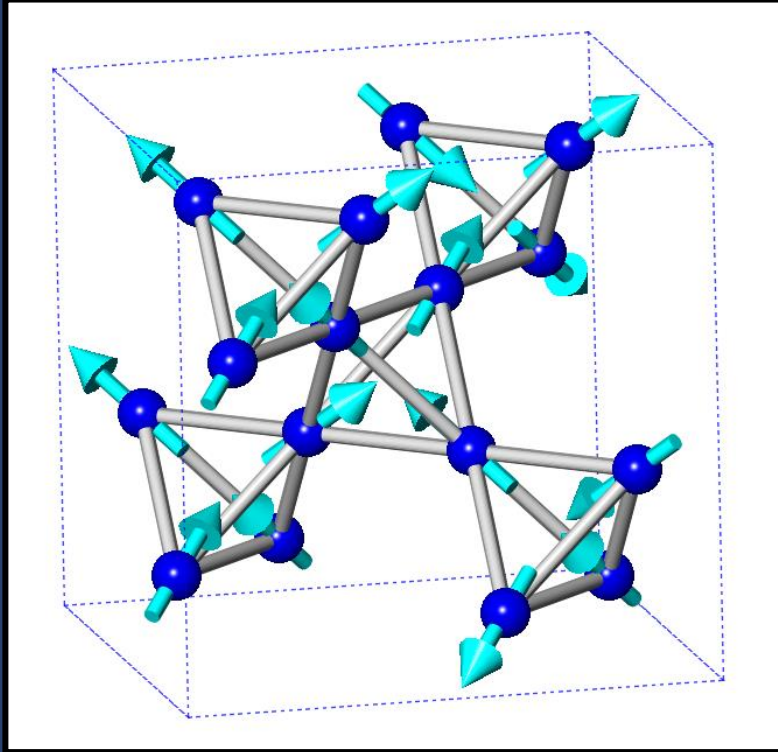
Dysprosium titanate



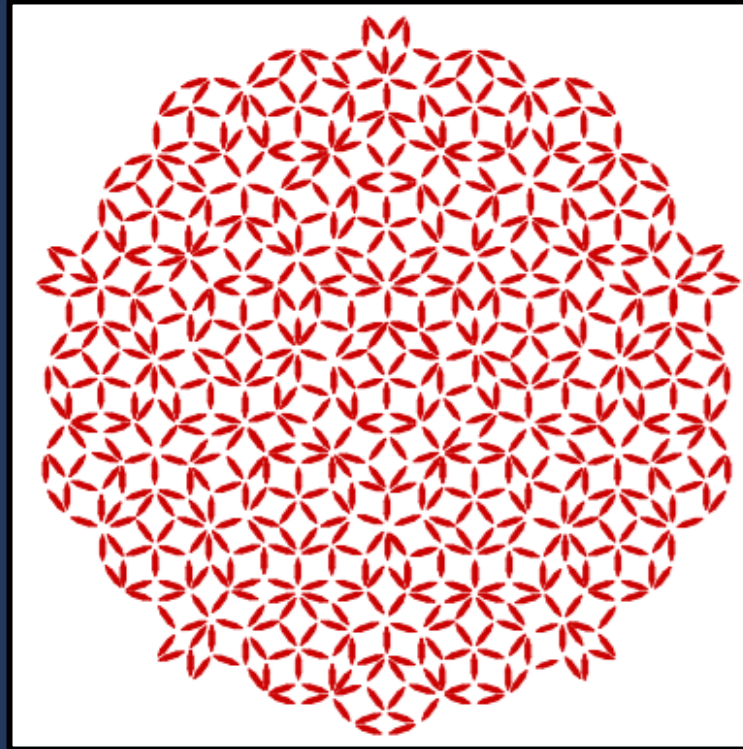
Artificial Spin Ice – Nanopatterned analogue

Gartside et al – *Nature Nanotechnology* (2018)

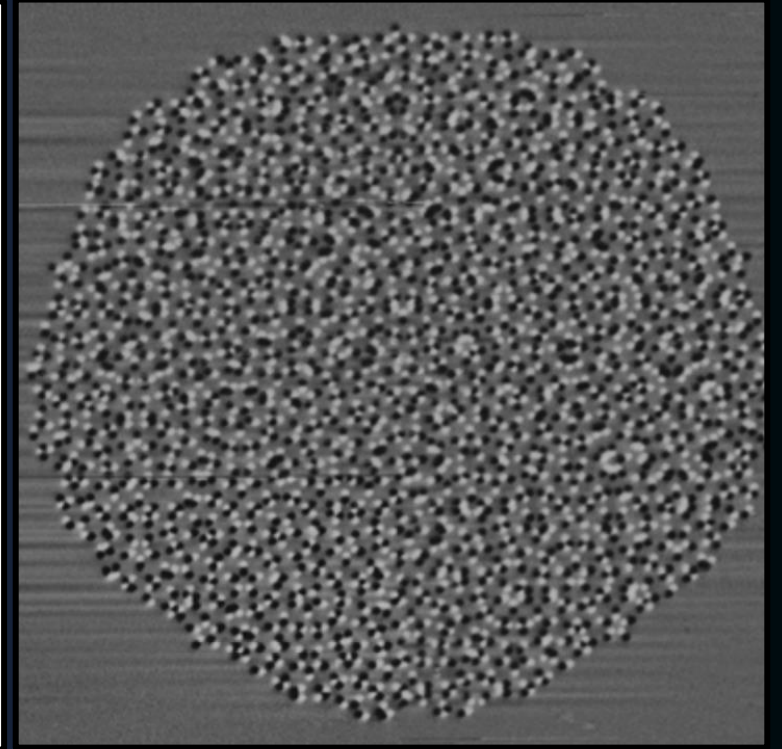
# What is an artificial spin system?



Dysprosium titanate



Artificial Spin Ice – Nanopatterned analogue

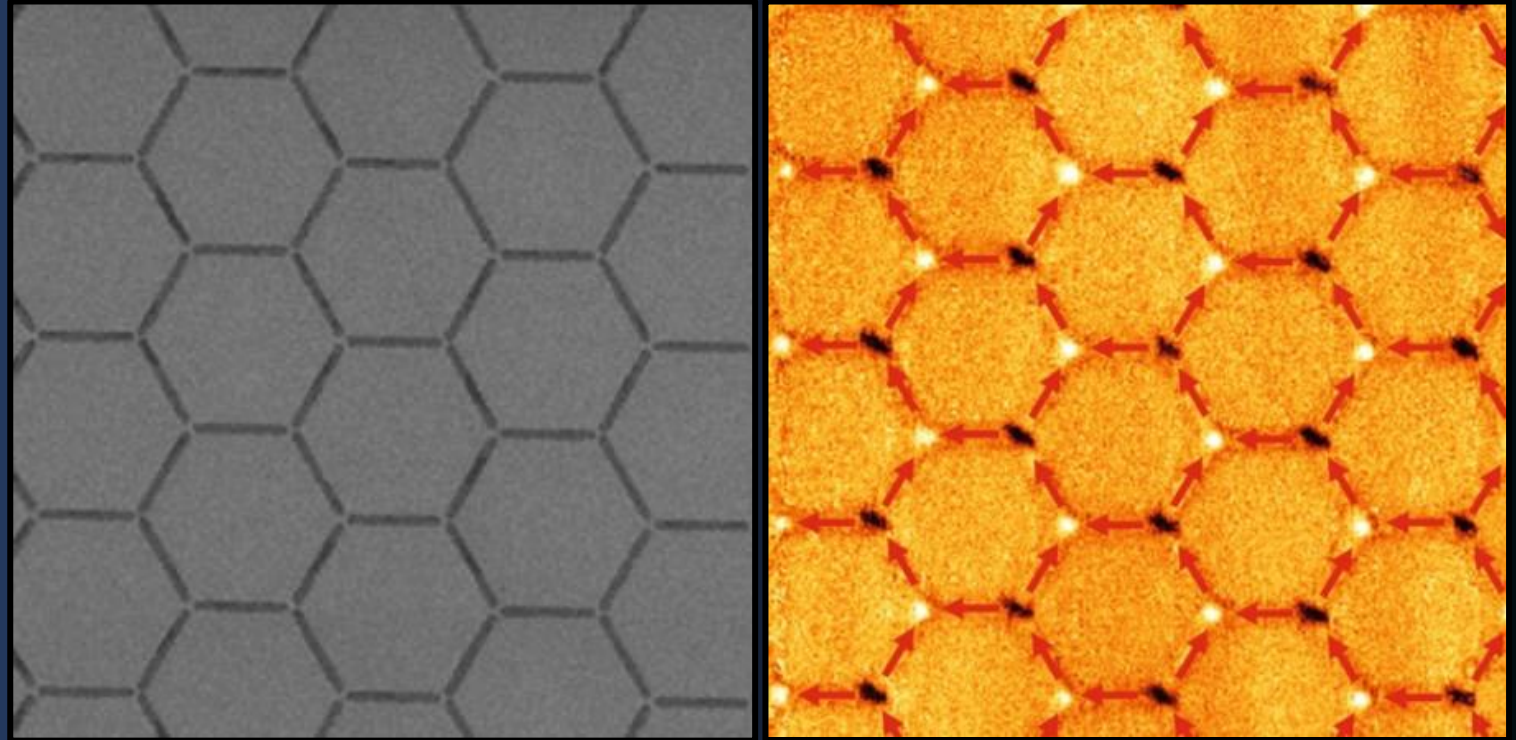


Shi et al – *Nature Physics* (2018)

# What is an artificial spin system?

## Microstate control

- Great promise of huge microstate space
- Problem: How to access?
- Few states possible:
- Typically all macrospins aligned by field
- Randomised/AC demagnetised
- Thermally annealed



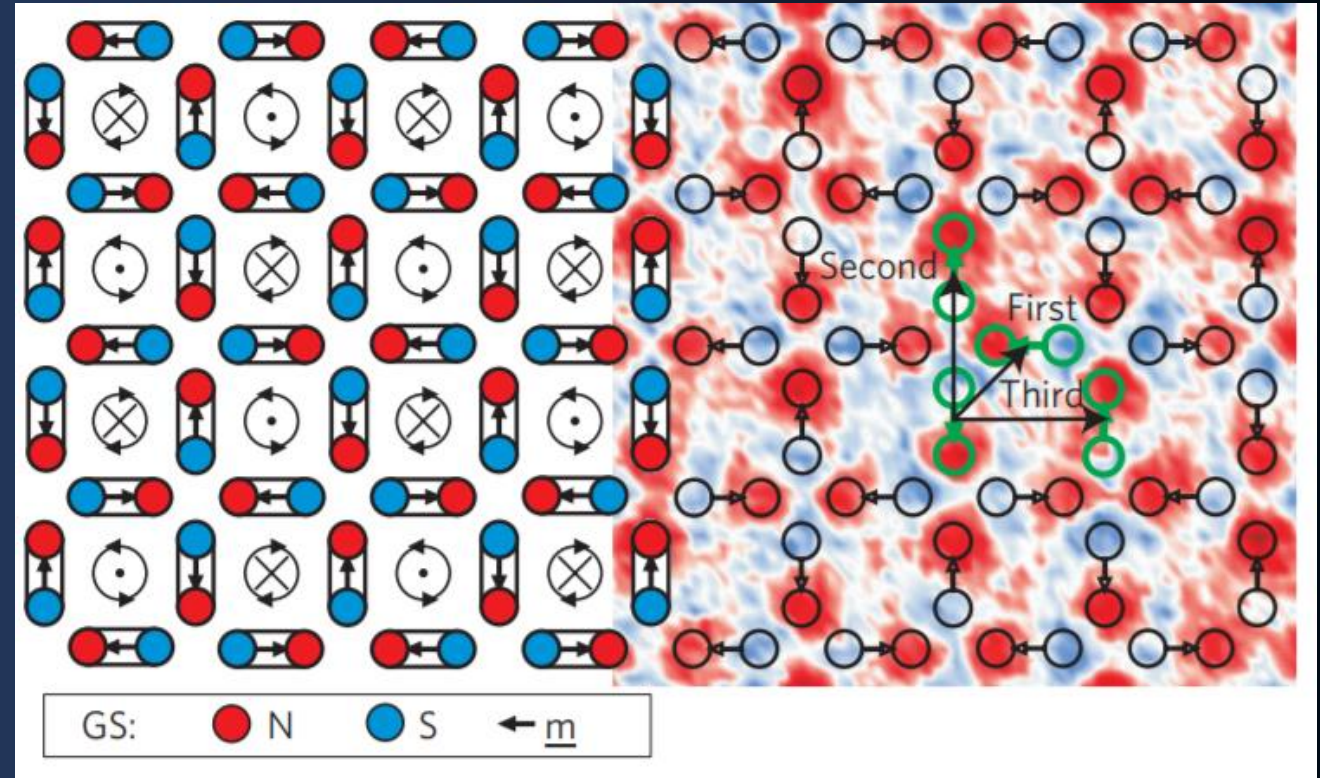
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# What is an artificial spin system?

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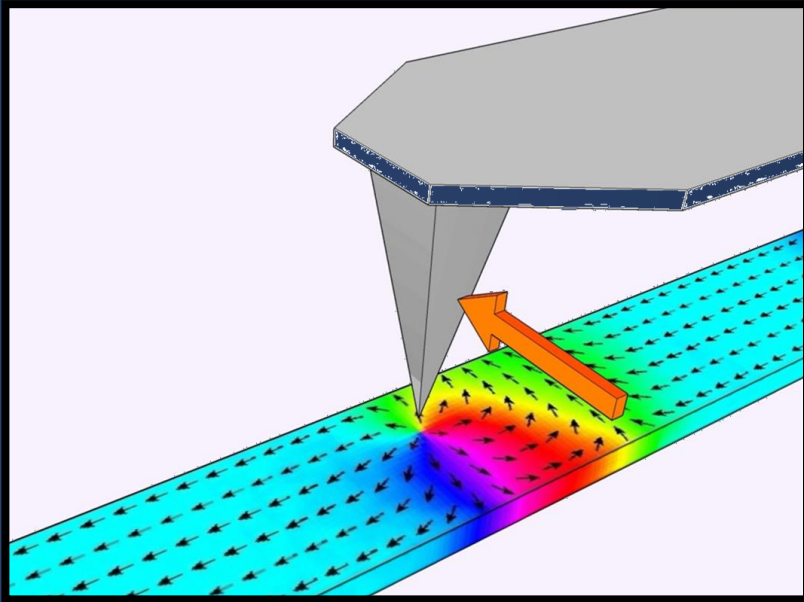


Artificial Spin Ice – Thermally-annealed ground state

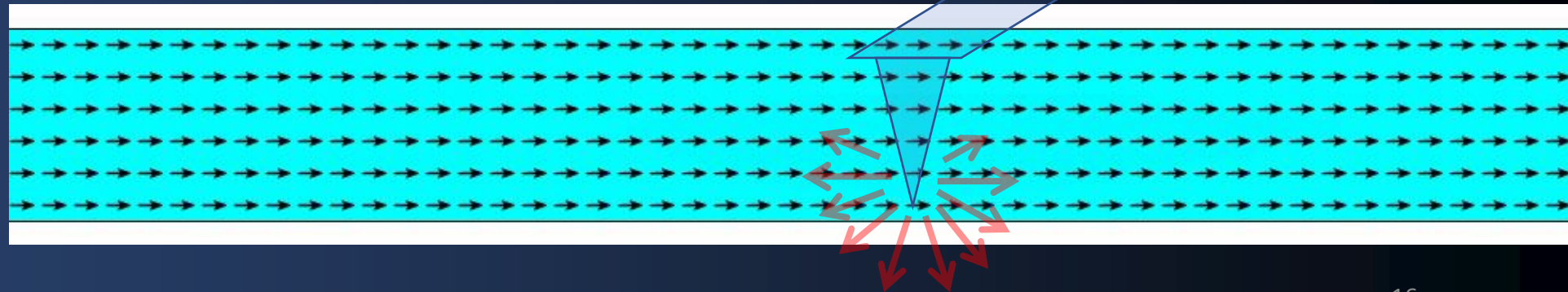
Morgan et al – *Nature Physics* (2010)

# Microstate control

## Developing a tip-based approach



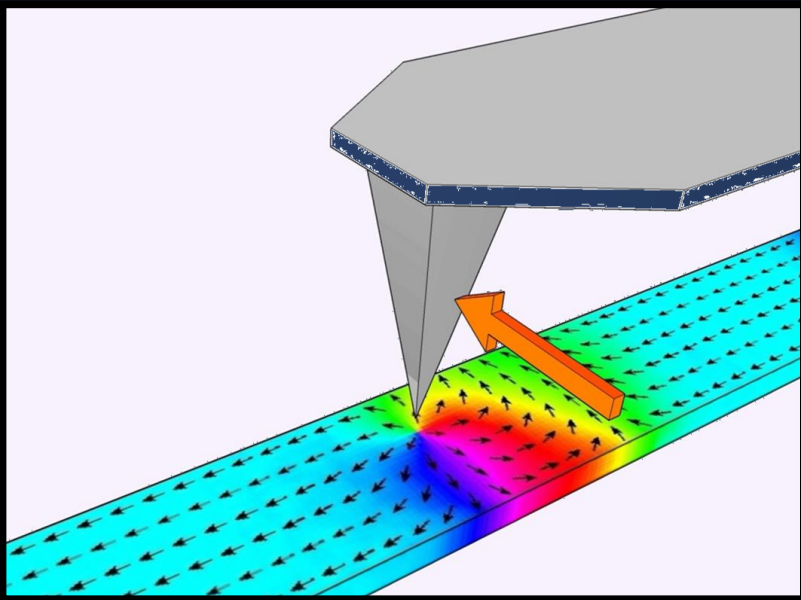
Direction of tip motion





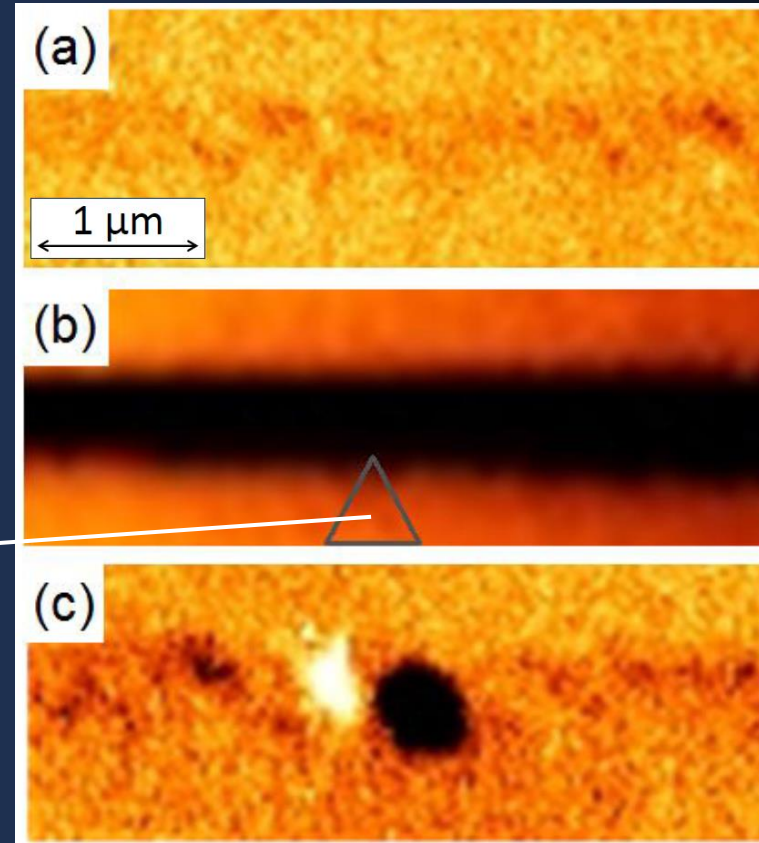
# Microstate control

## Developing a tip-based approach



Tip-retraction  
point

### MFM data



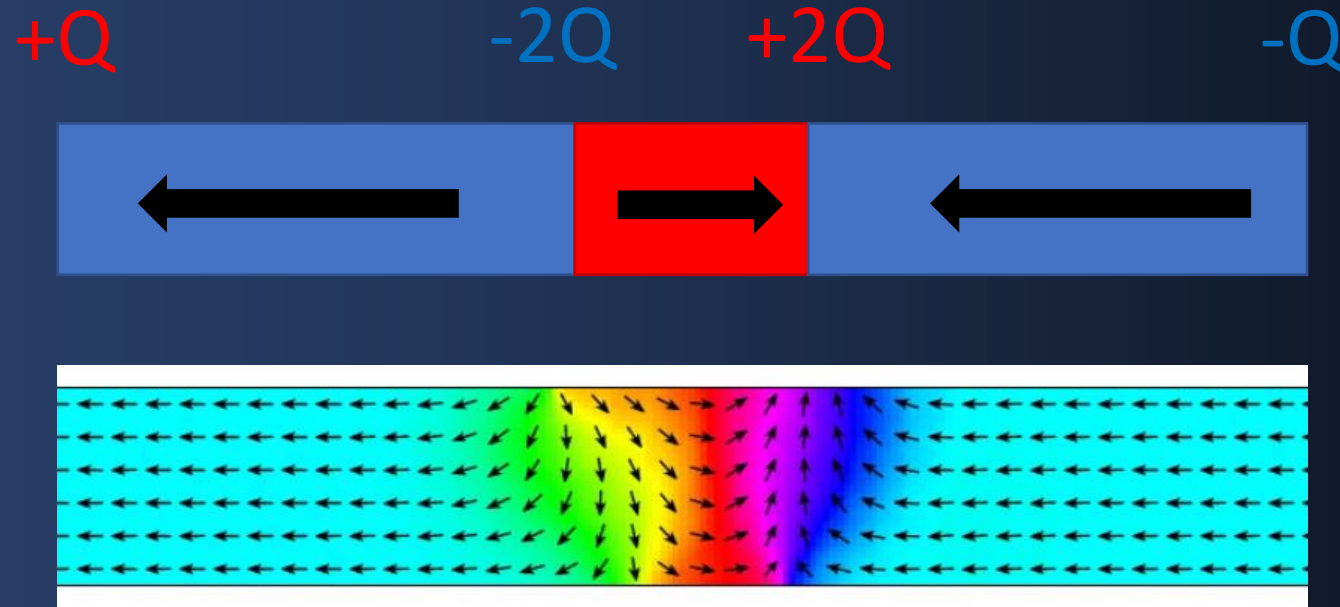
Low-moment tip  
( $0.3 \times 10^{-13}$  emu, 320 Oe)

High-moment tip  
( $3 \times 10^{-13}$  emu, 690 Oe)

Low-moment tip  
( $0.3 \times 10^{-13}$  emu, 320 Oe)

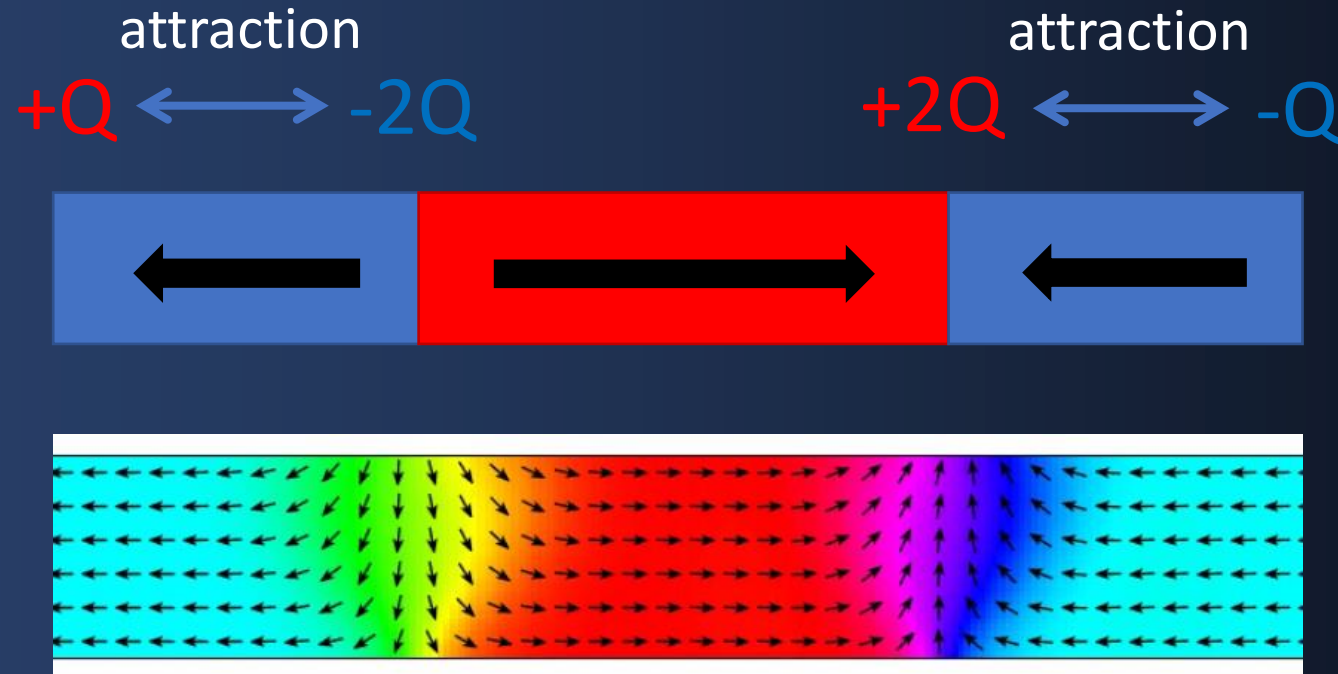
# Microstate control

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# Microstate control

## Developing a tip-based approach



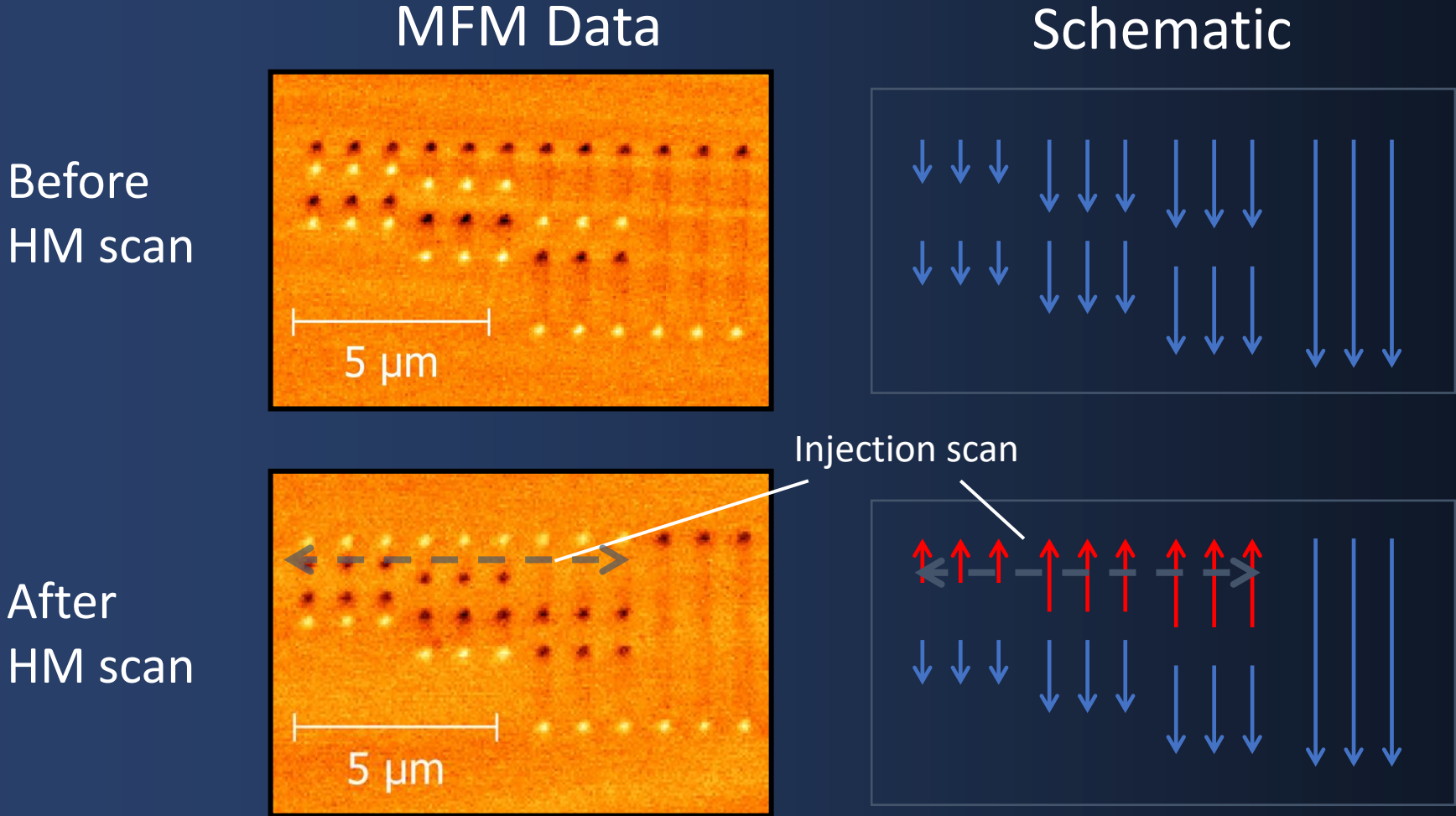
# Microstate control

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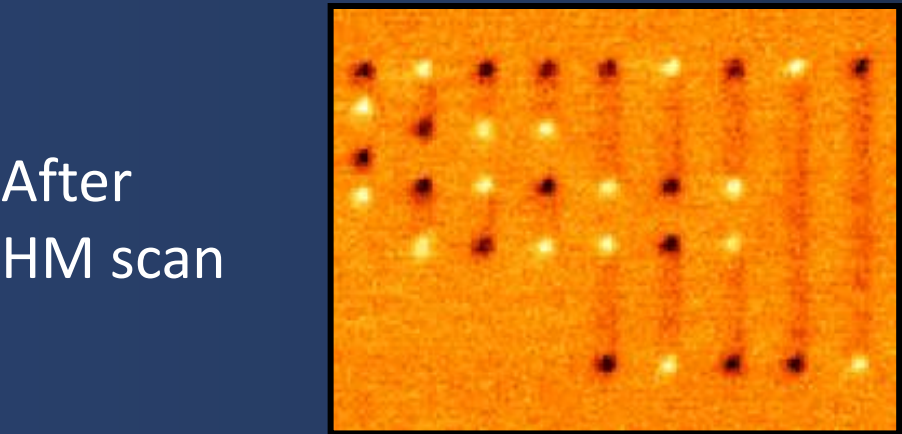
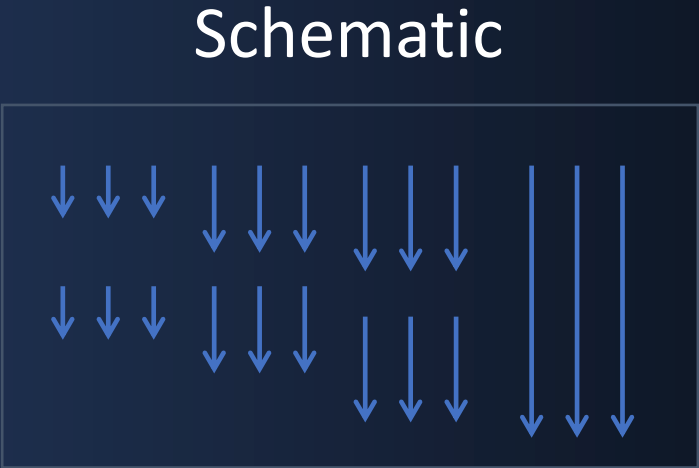
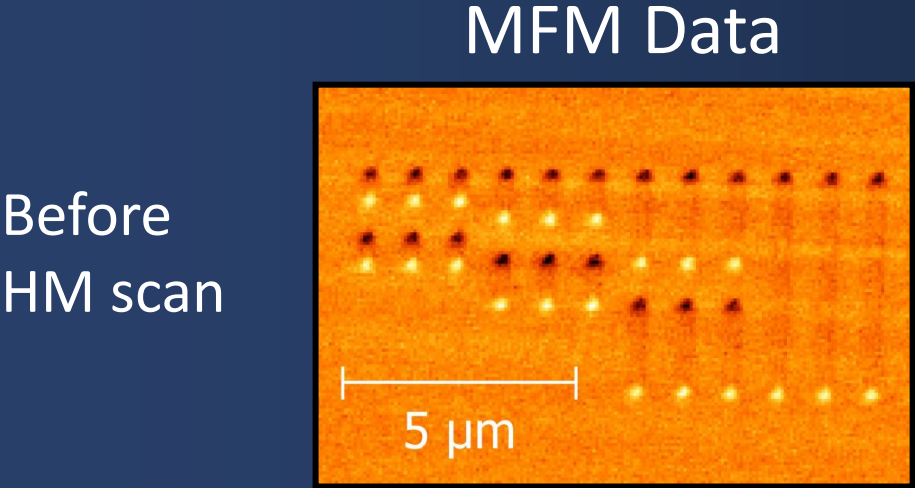
# Microstate control

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# Microstate control

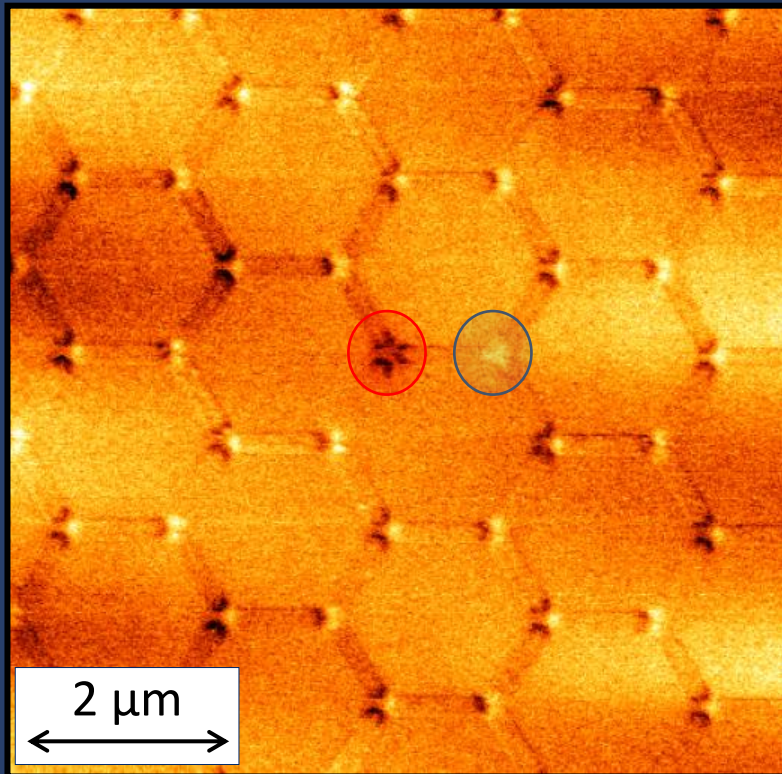
## Developing a tip-based approach



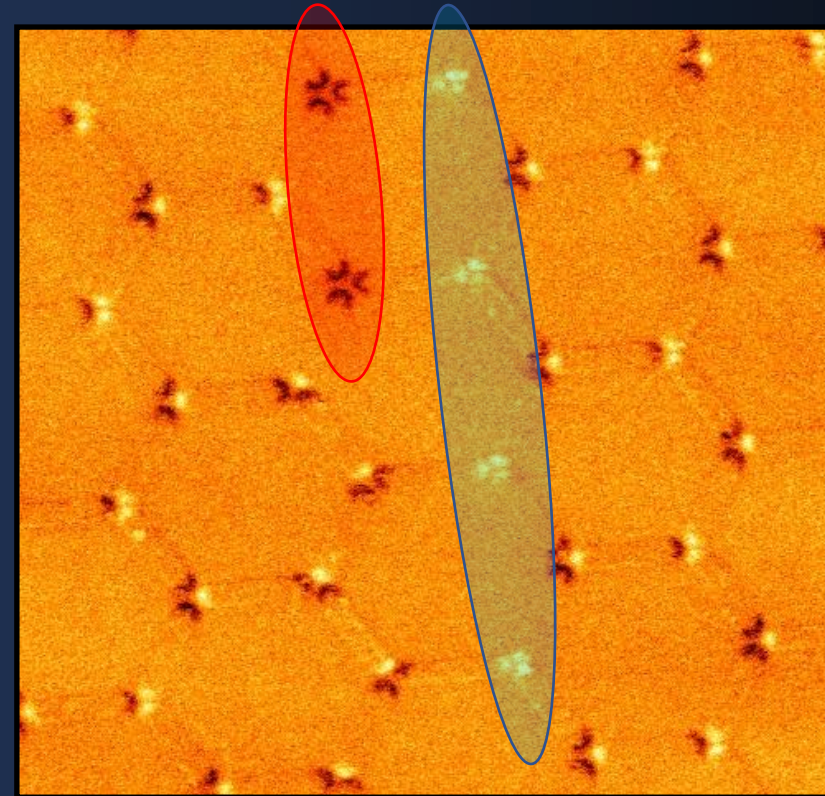
# Microstate control

## Developing a tip-based approach

Single 'monopole' defects



'monopole' chains

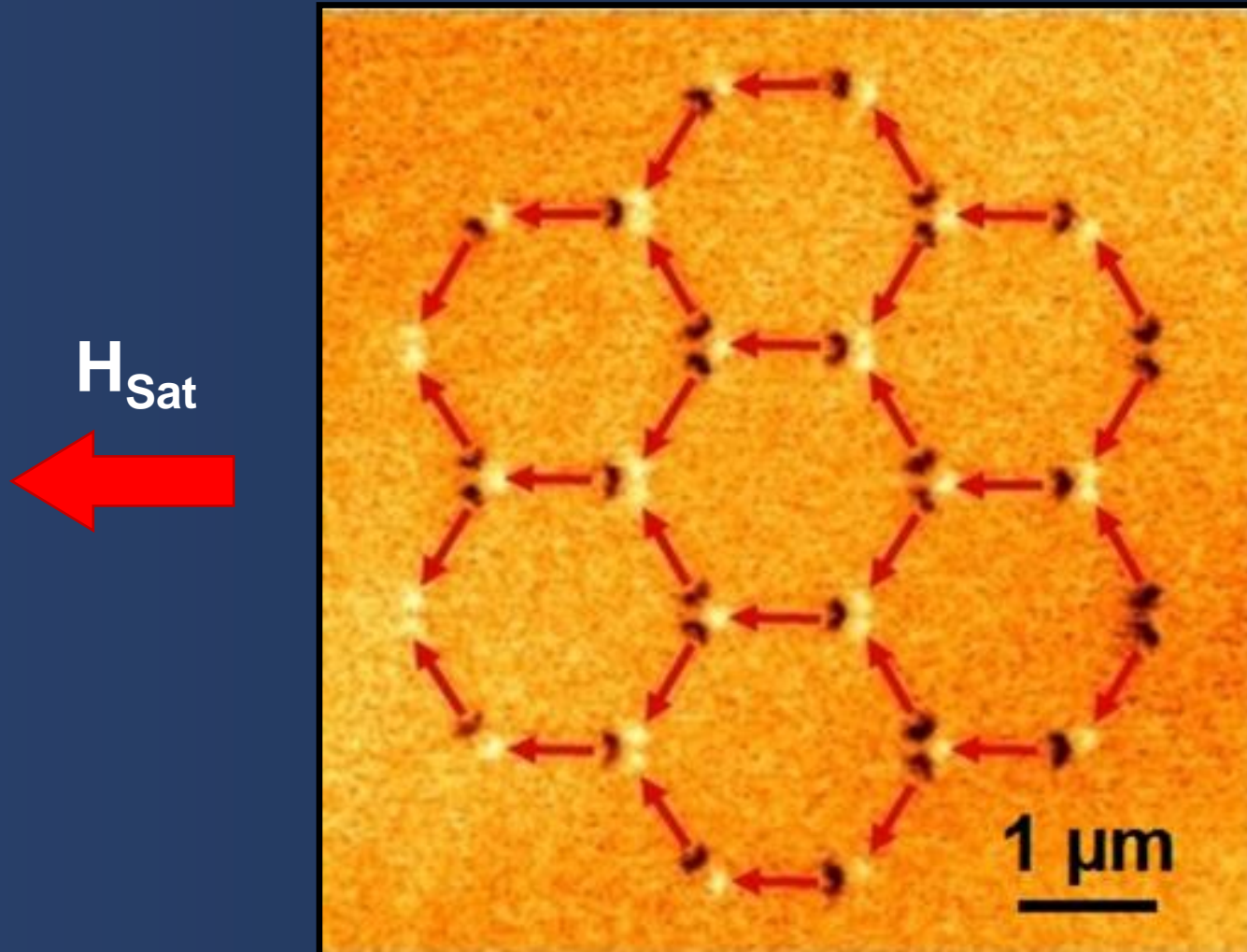


Gartside et al – *Nature Nanotechnology* (2018)

# Microstate control

## Developing a tip-based approach

Ground state of kagome ASI

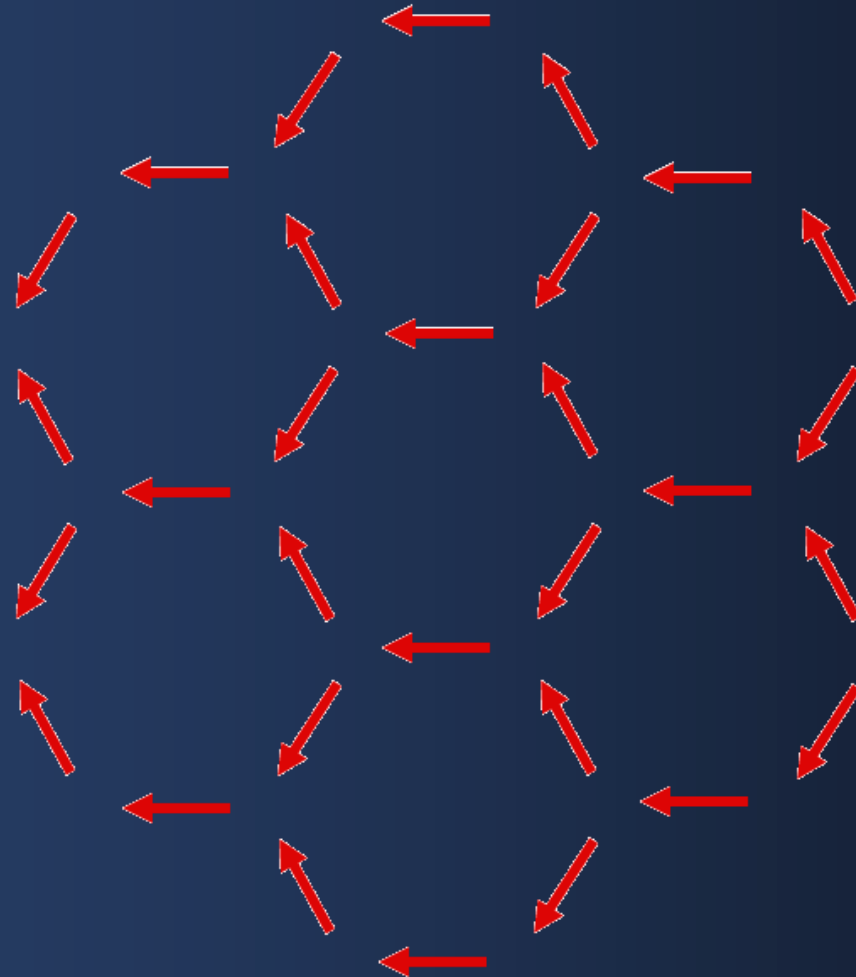




# Microstate control

## Developing a tip-based approach

Ground state of kagome ASI

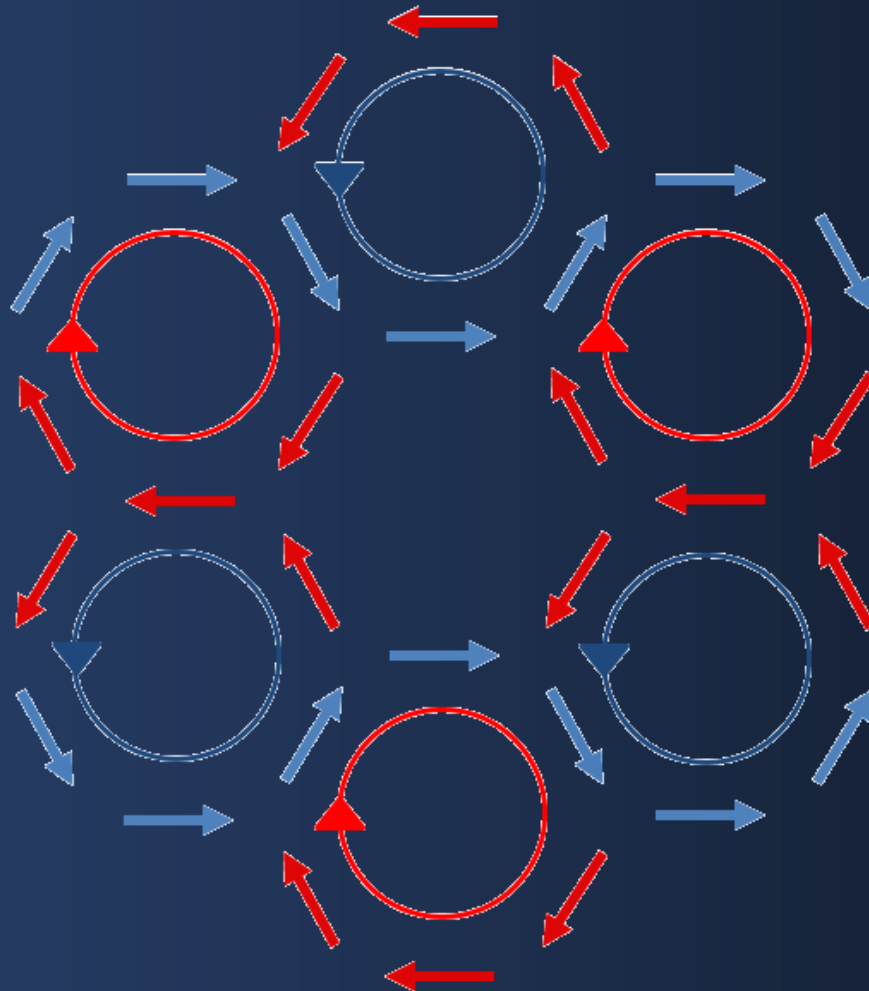


# Microstate control

## Developing a tip-based approach

### Ground state of kagome ASI

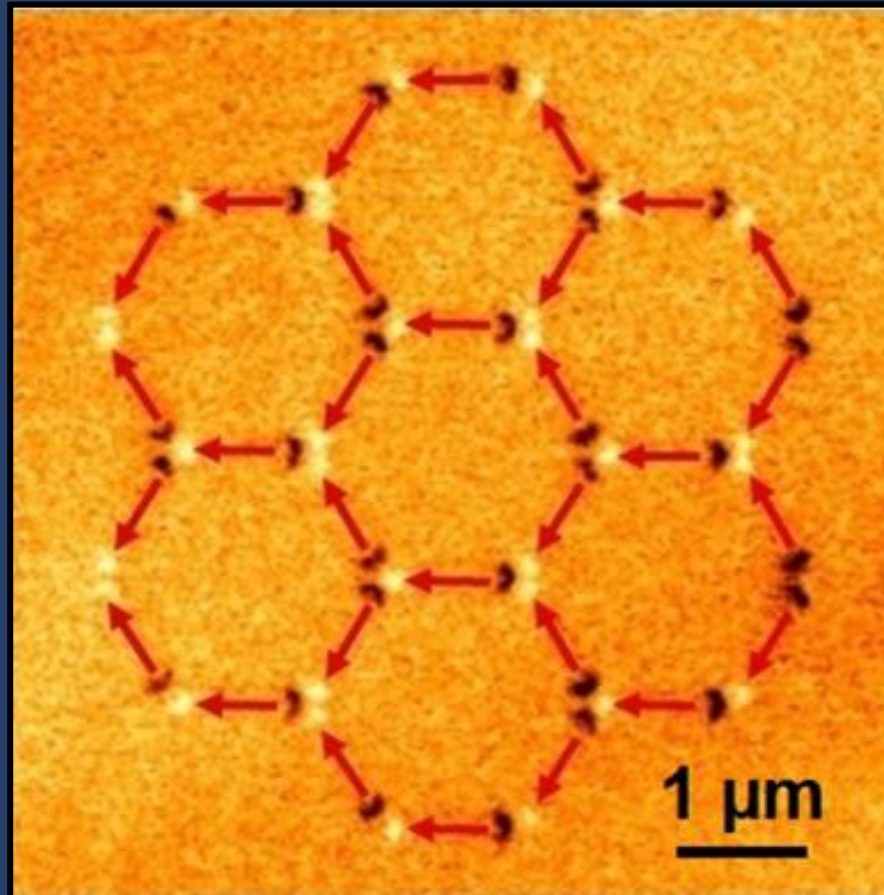
Flux-closure  
loops lower  
system energy



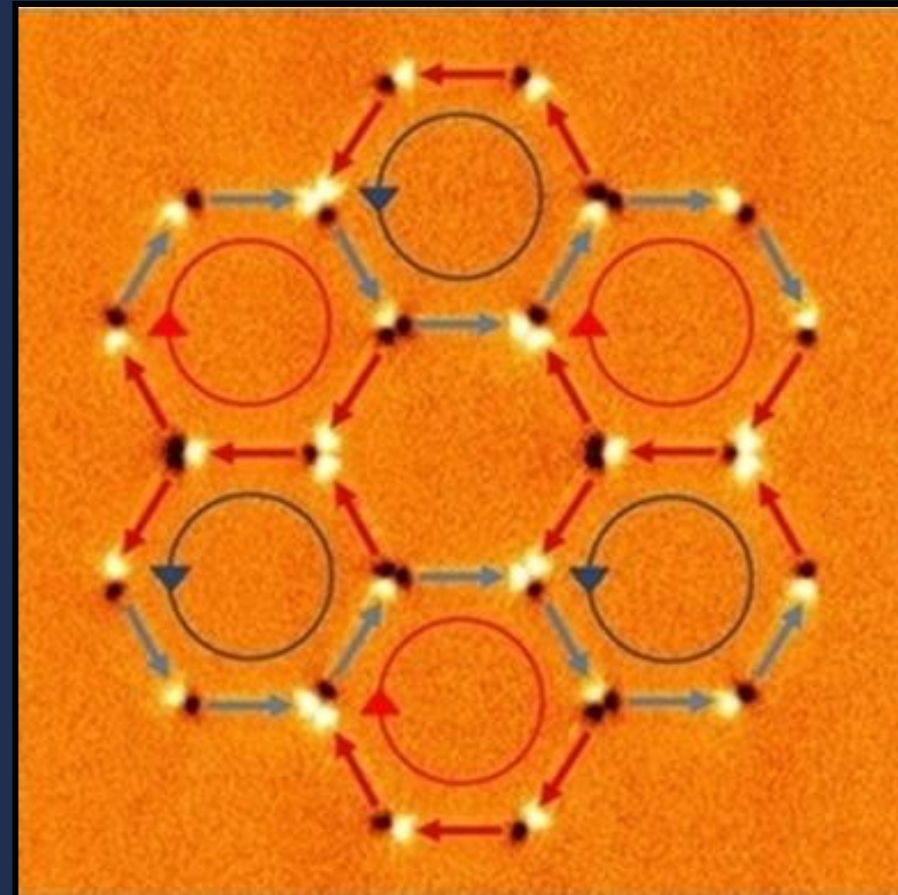
# Microstate control

## Developing a tip-based approach

Before

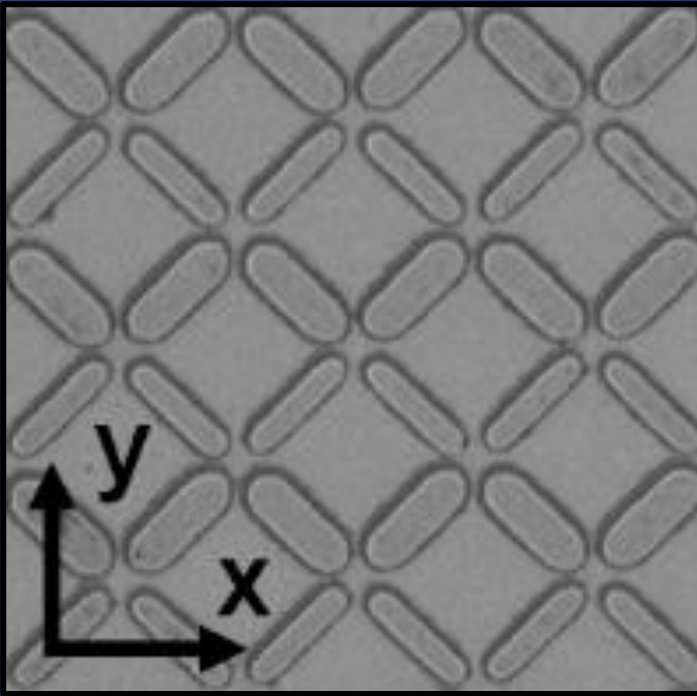


After

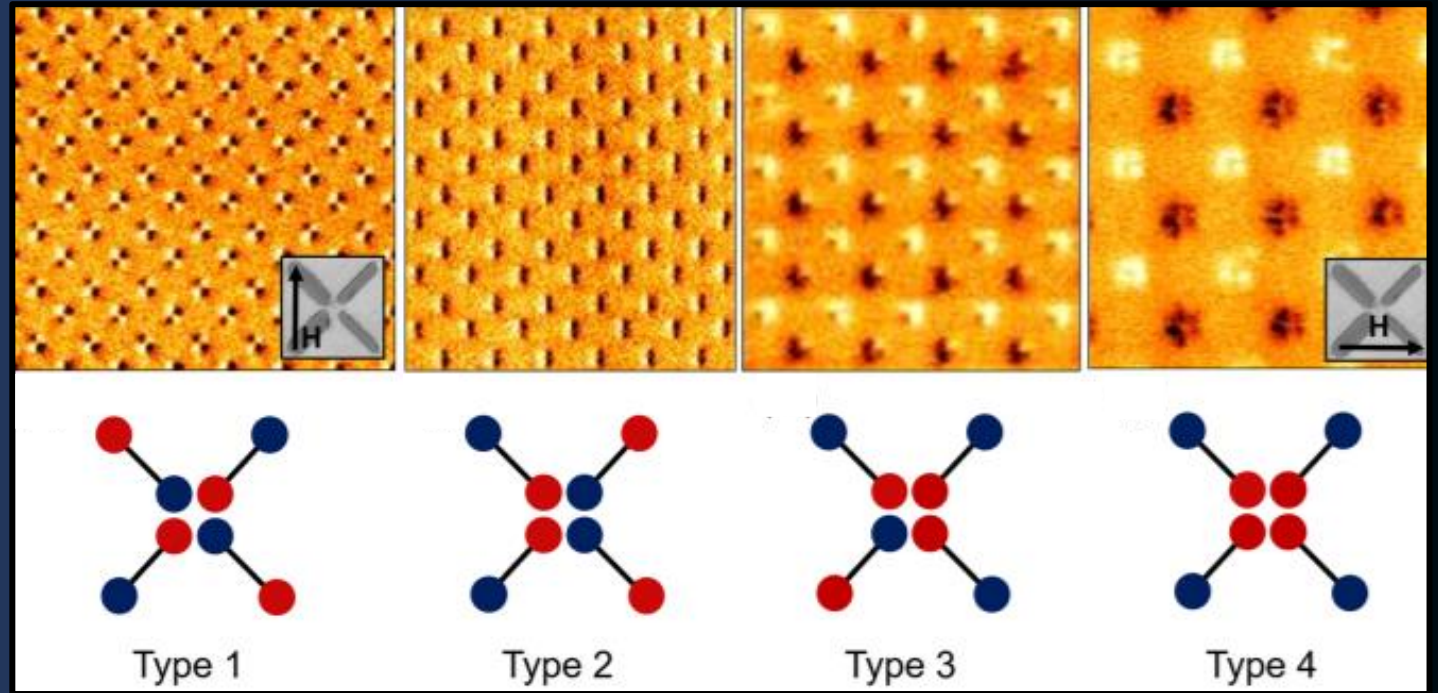


# Microstate control

## A global-field approach



Break nanoelement symmetry

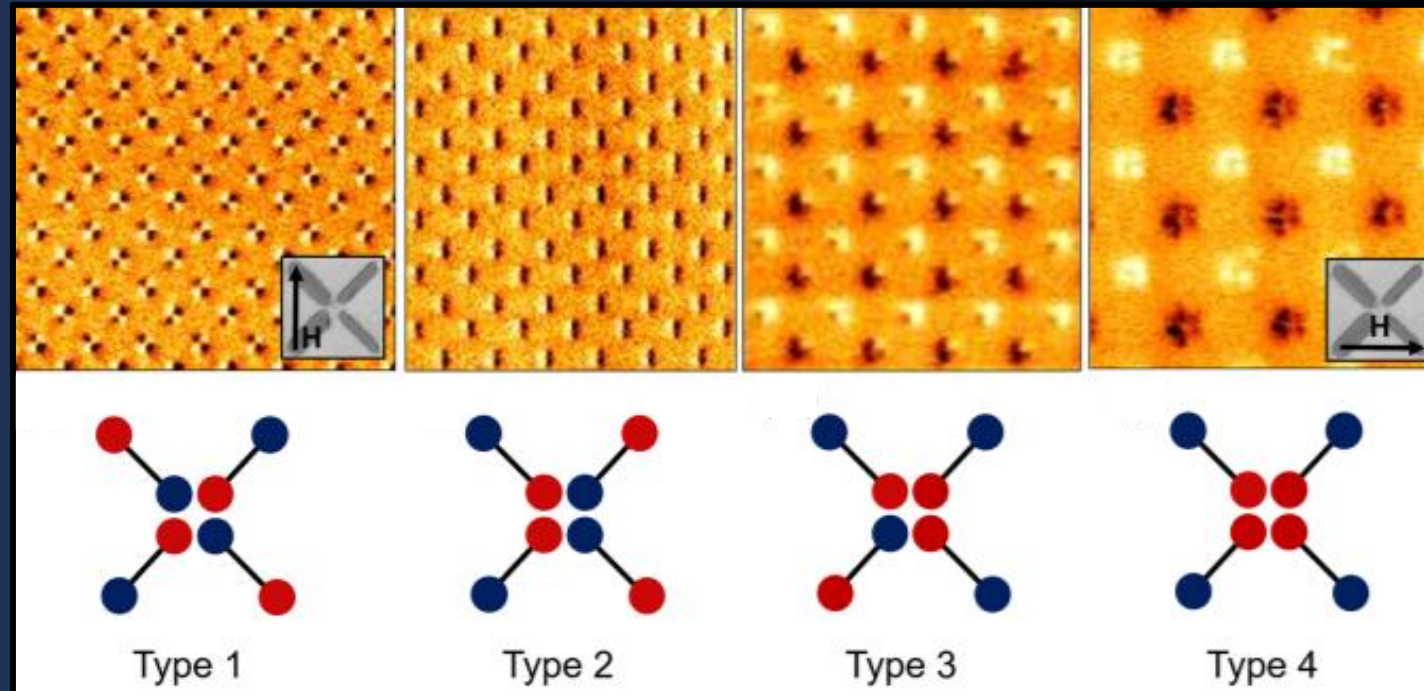
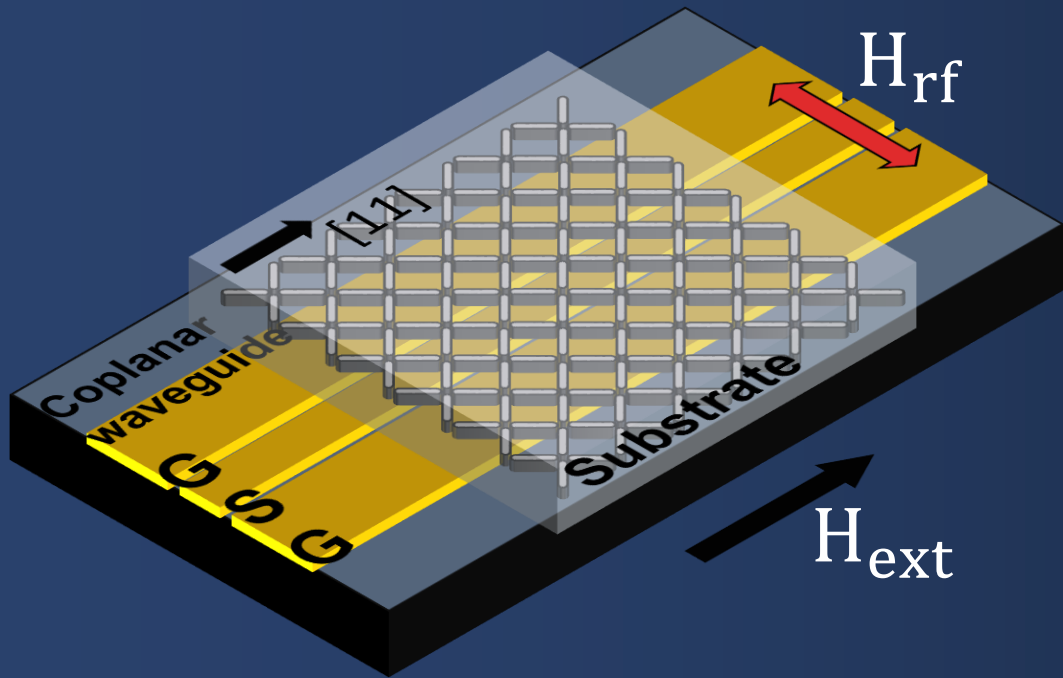


Allows access to otherwise elusive states

Gartside et al – *Nature Communications* (2021)

# Microstate control

## A global-field approach

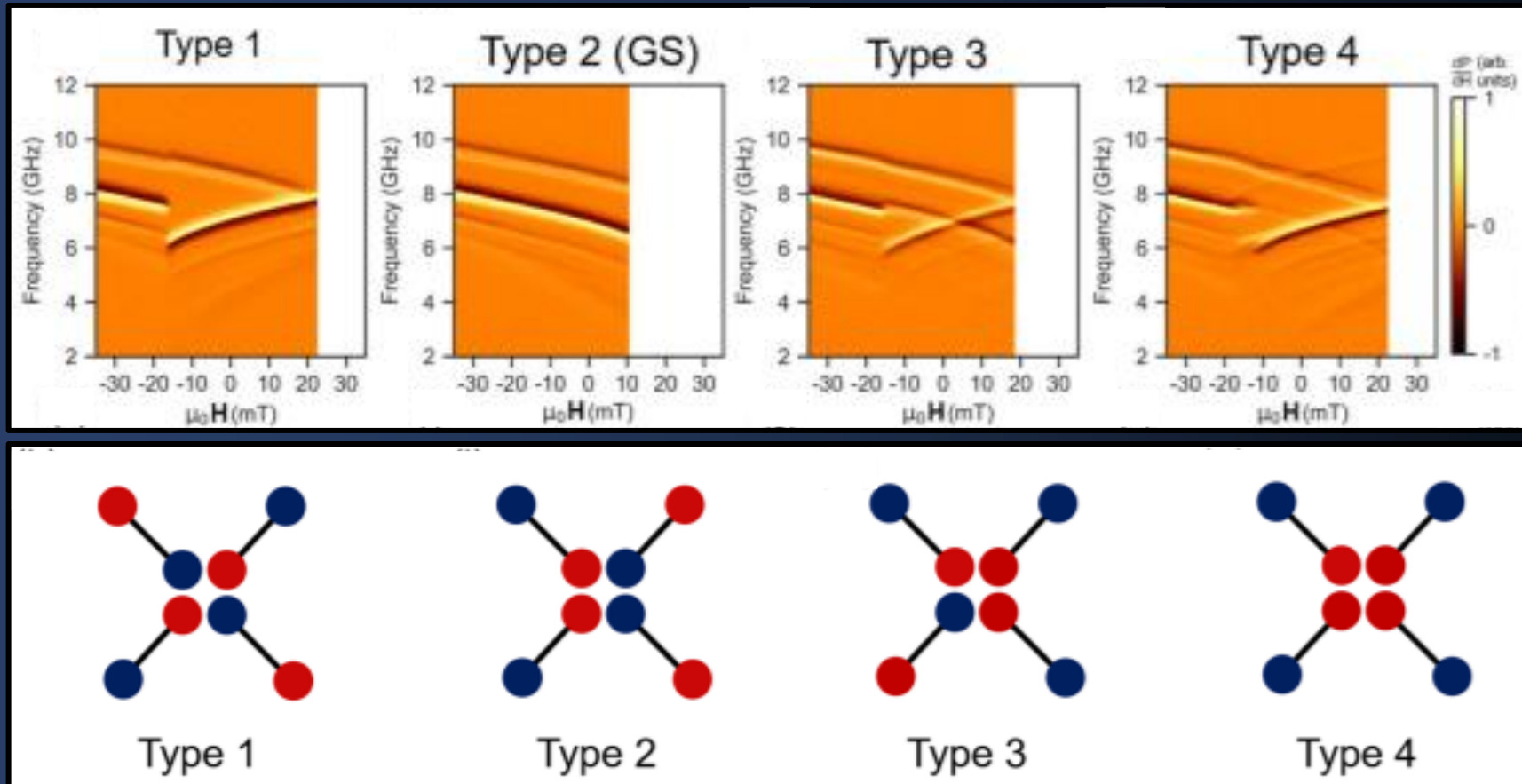


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# Microstate control

## A global-field approach



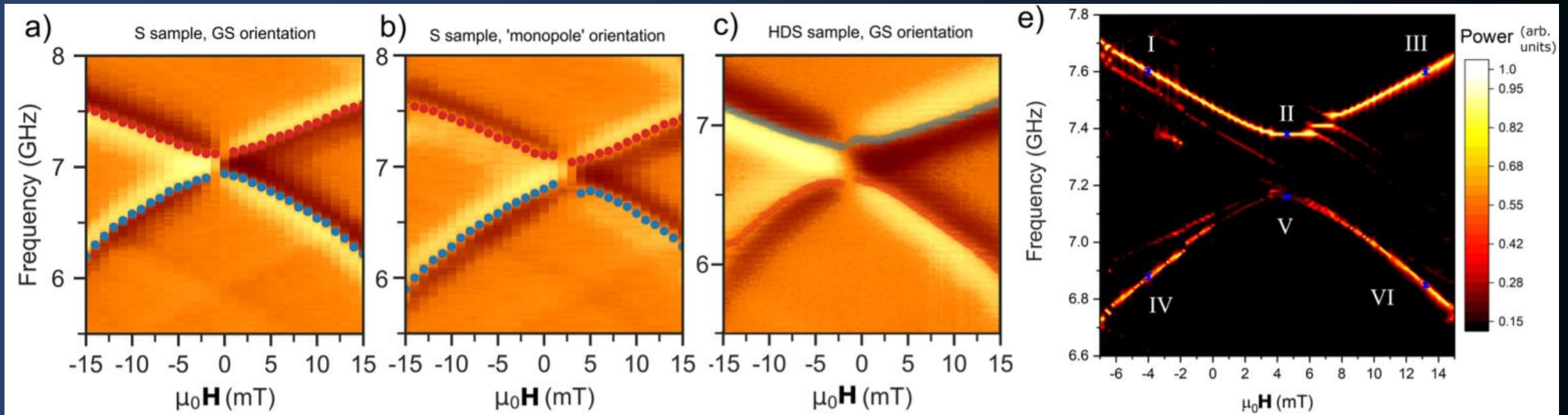
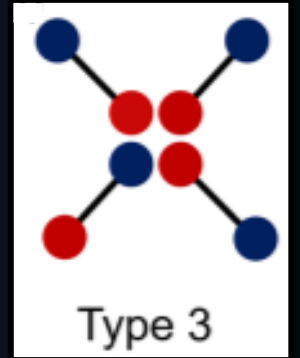
Explore magnonic properties of diverse states

Gartside et al – *Nature Communications* (2021)

# Microstate control

## A global-field approach

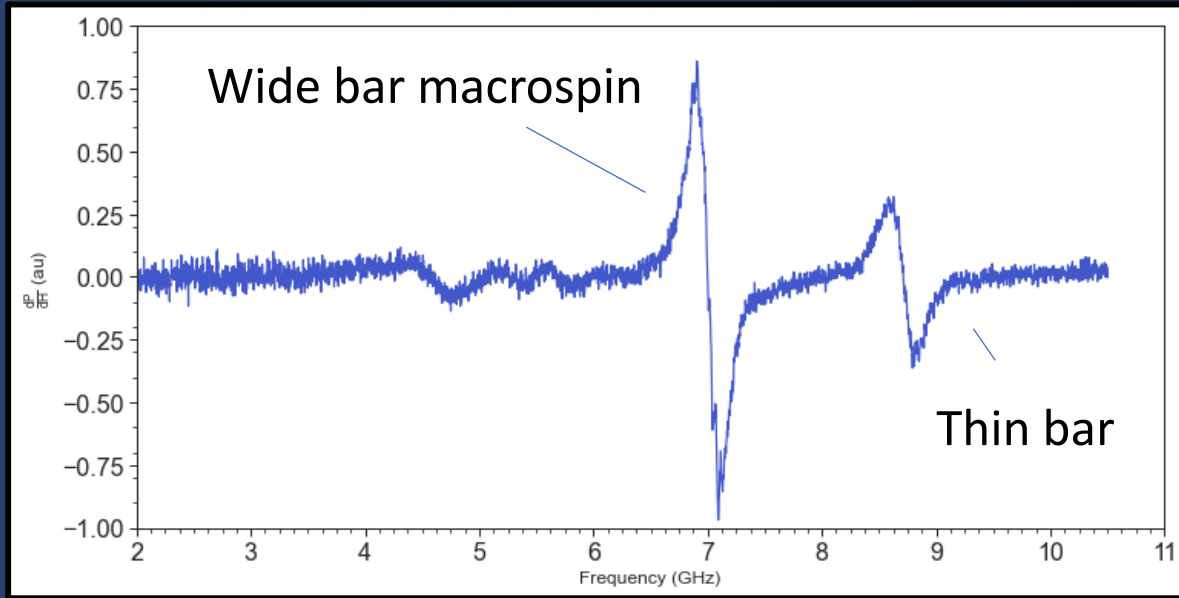
Use elusive 'Type 3' ASI state to observe dipolar coupling induced spin-wave mode anti-crossing



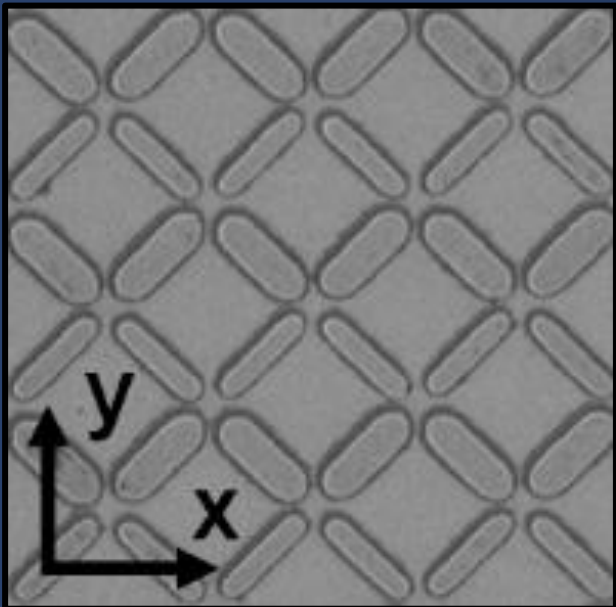
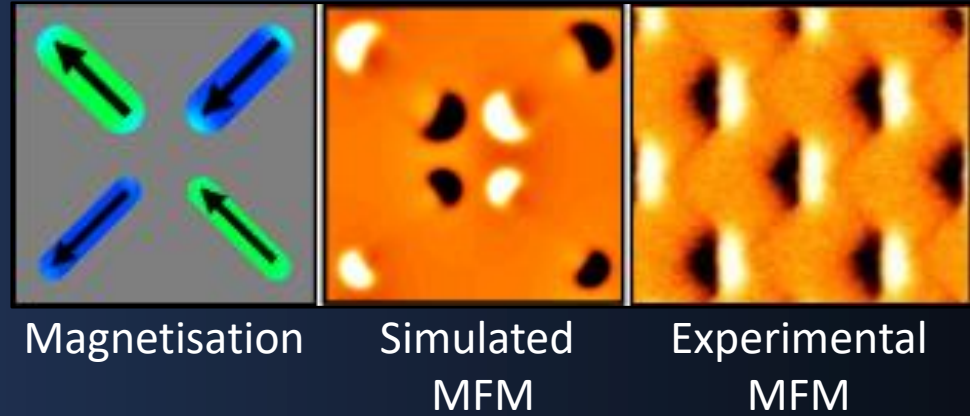
FMR experiment

Simulation

# Microstate control – Beyond a single texture

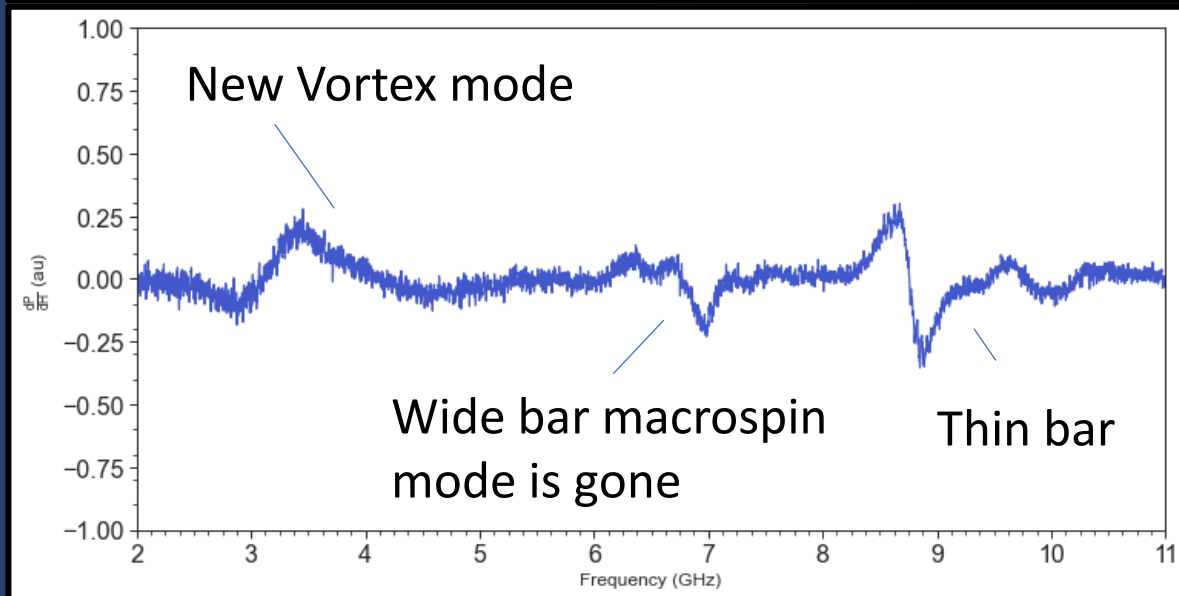
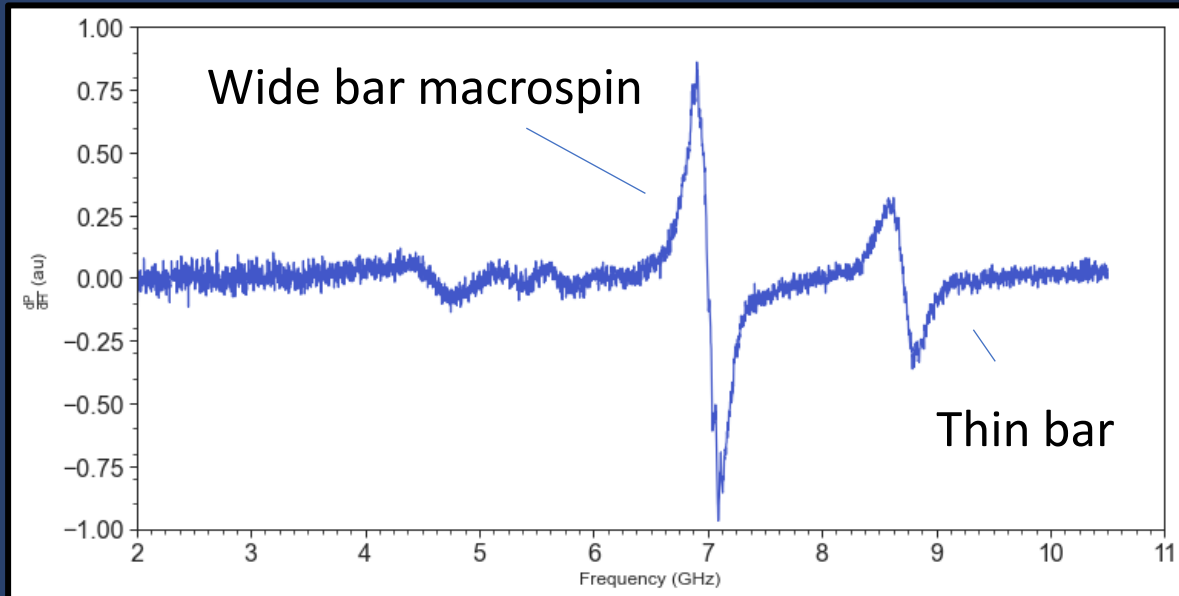


## Normal saturated ASI spectra

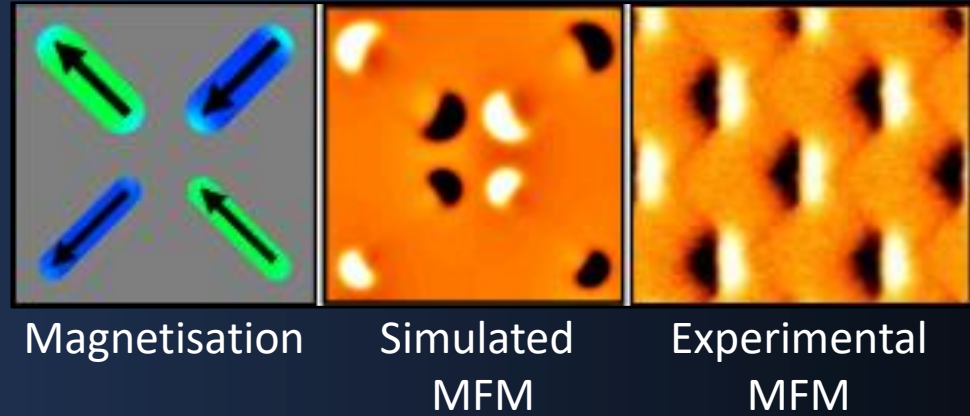




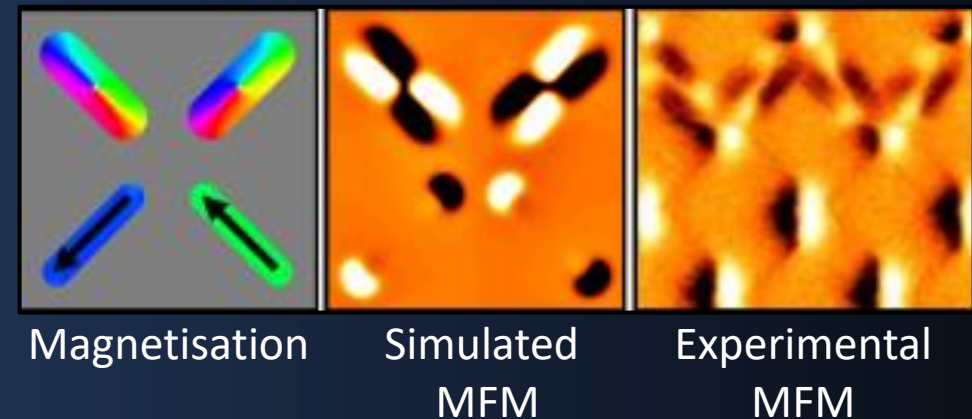
# Microstate control – Beyond a single texture

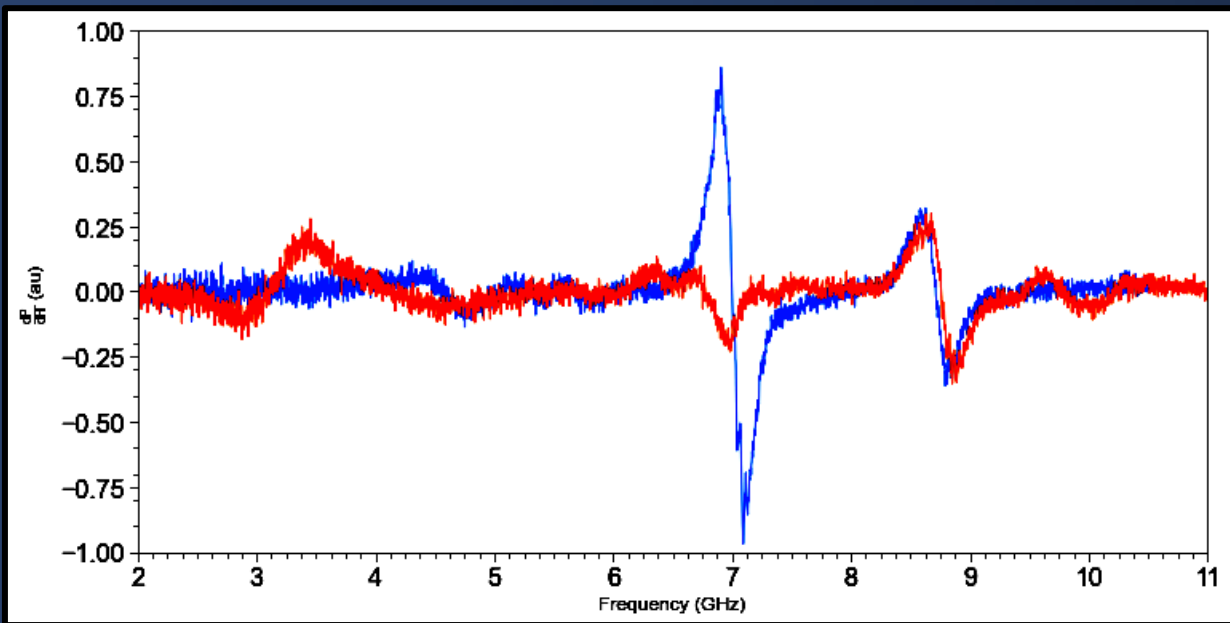


## Normal saturated ASl spectra

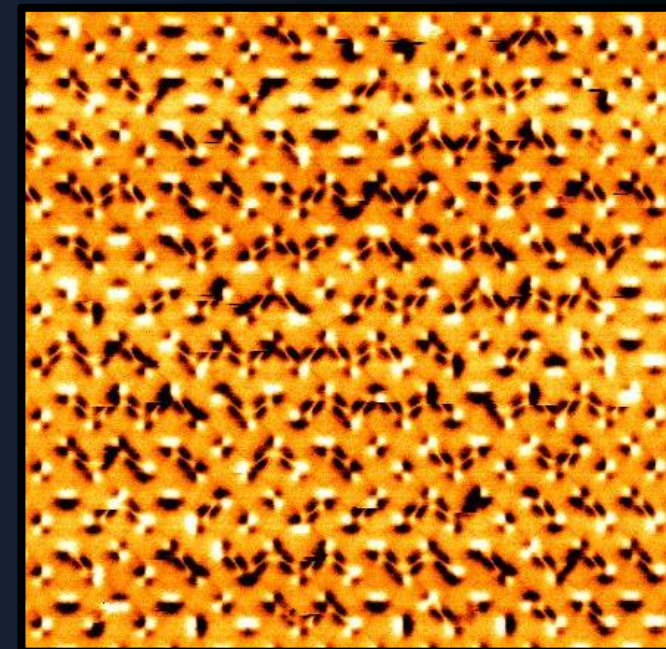
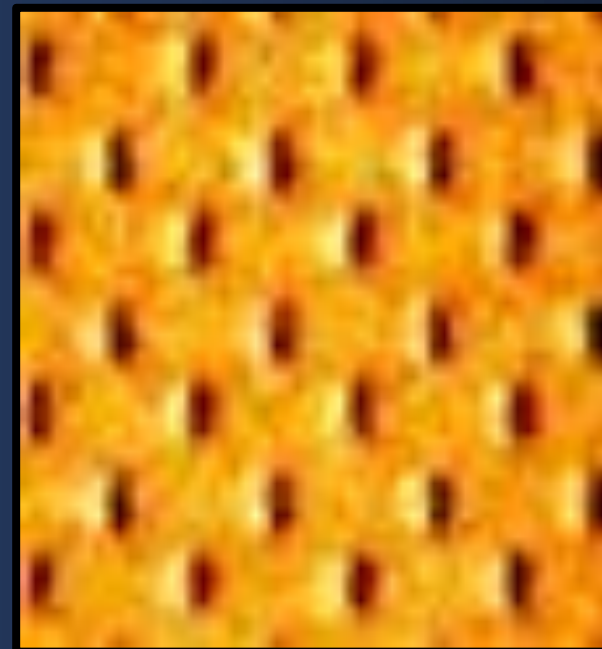
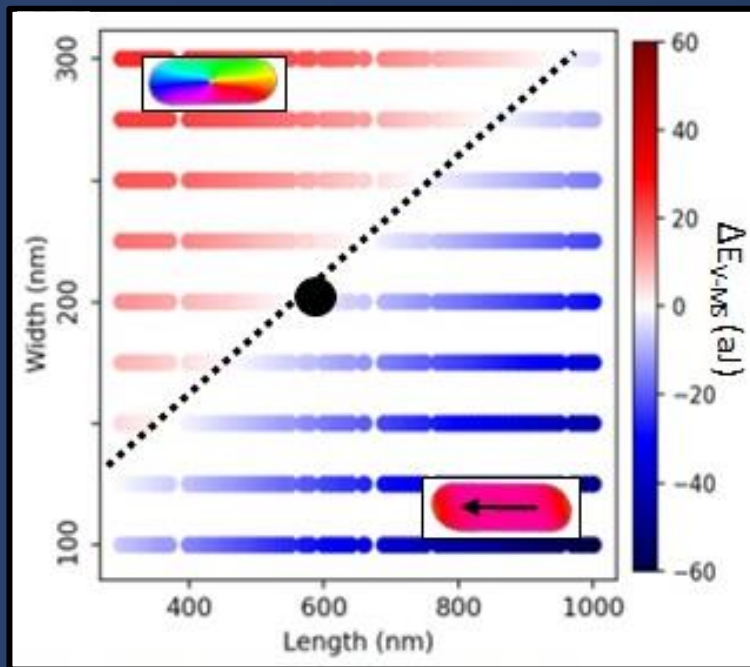


## Spectra after 30 training cycles at 18 mT (wide bar $H_c = 16$ mT)





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

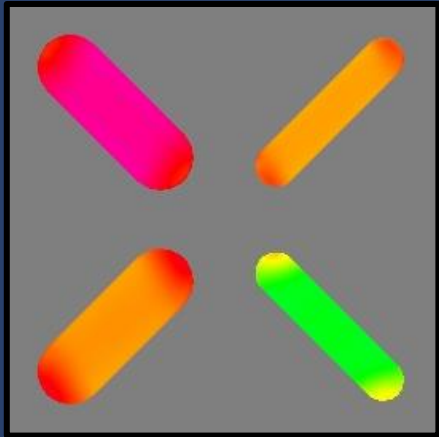


Vortex/Macrospin Energy

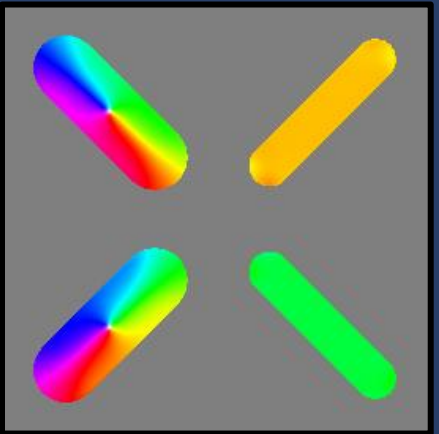
Saturated initial state

Field-Trained state

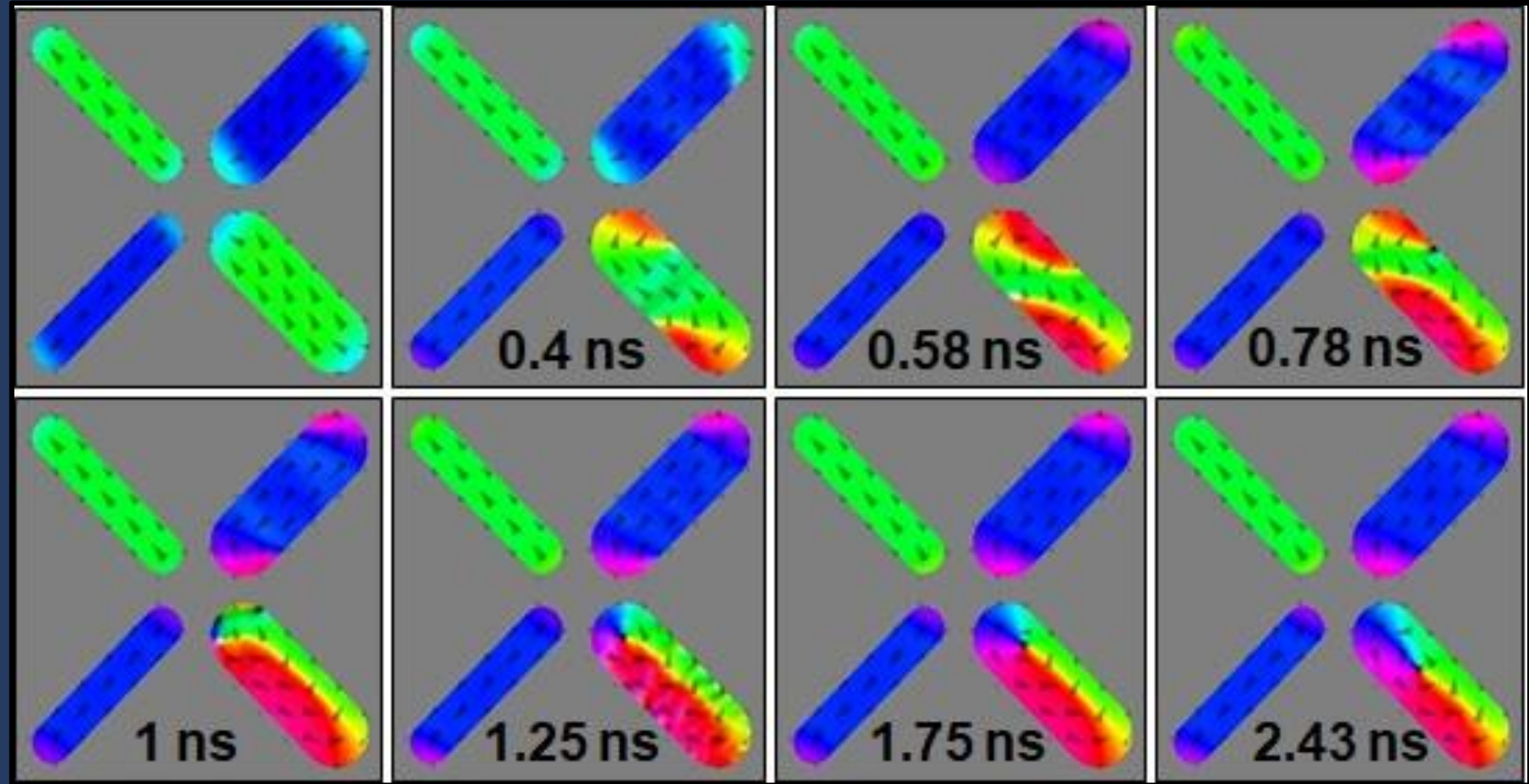
# Simulating vortex formation



Saturated

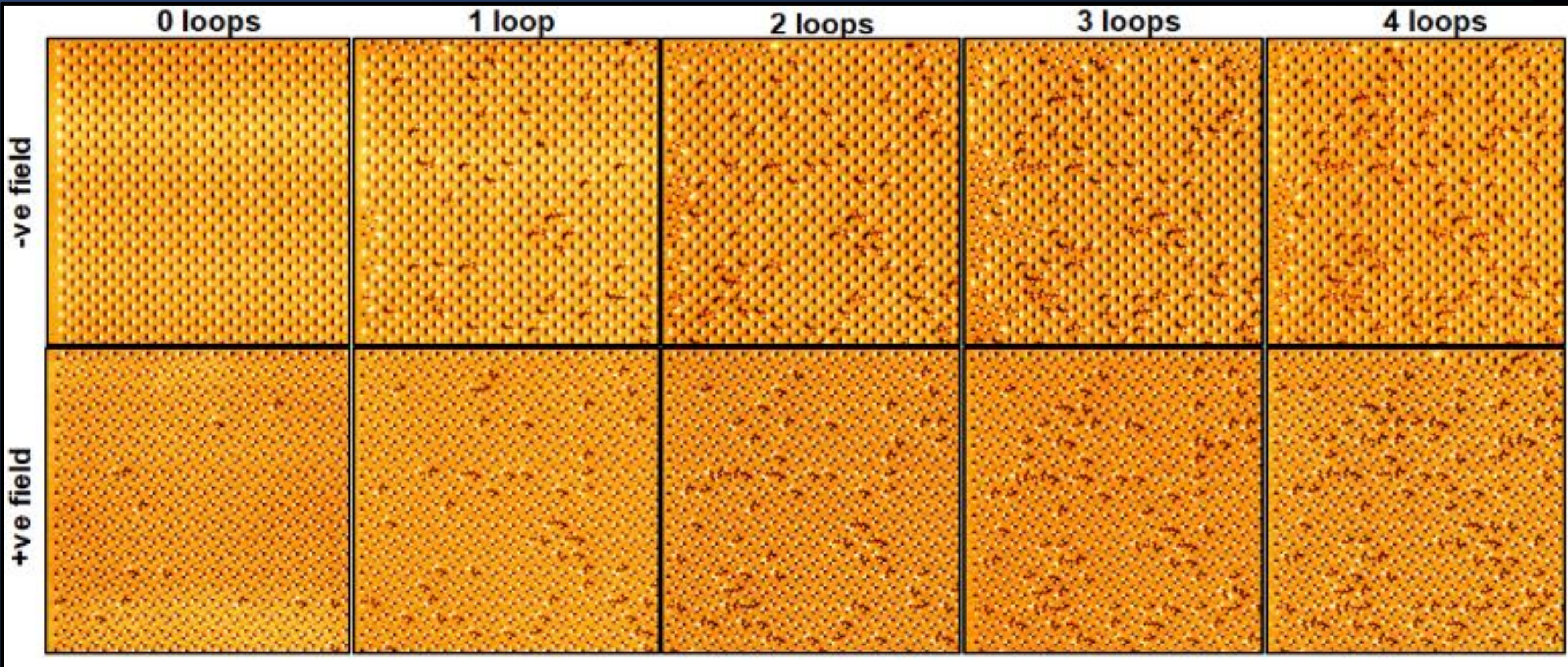


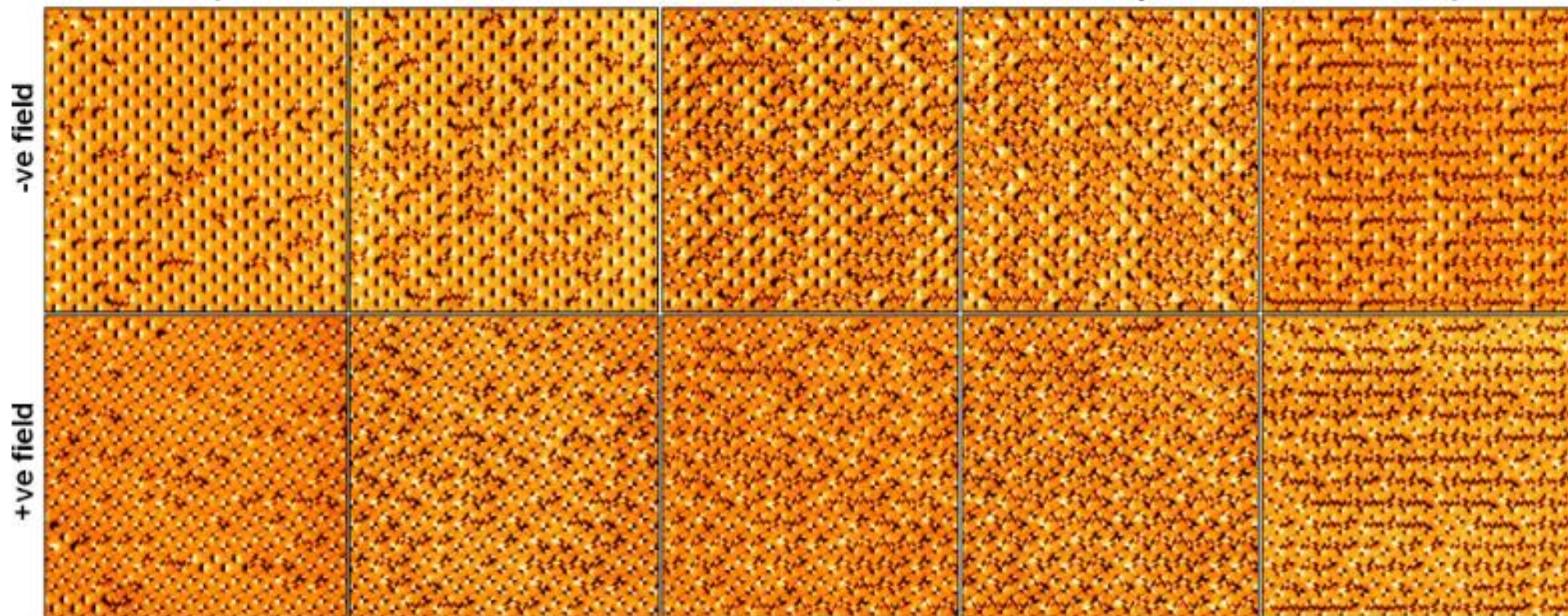
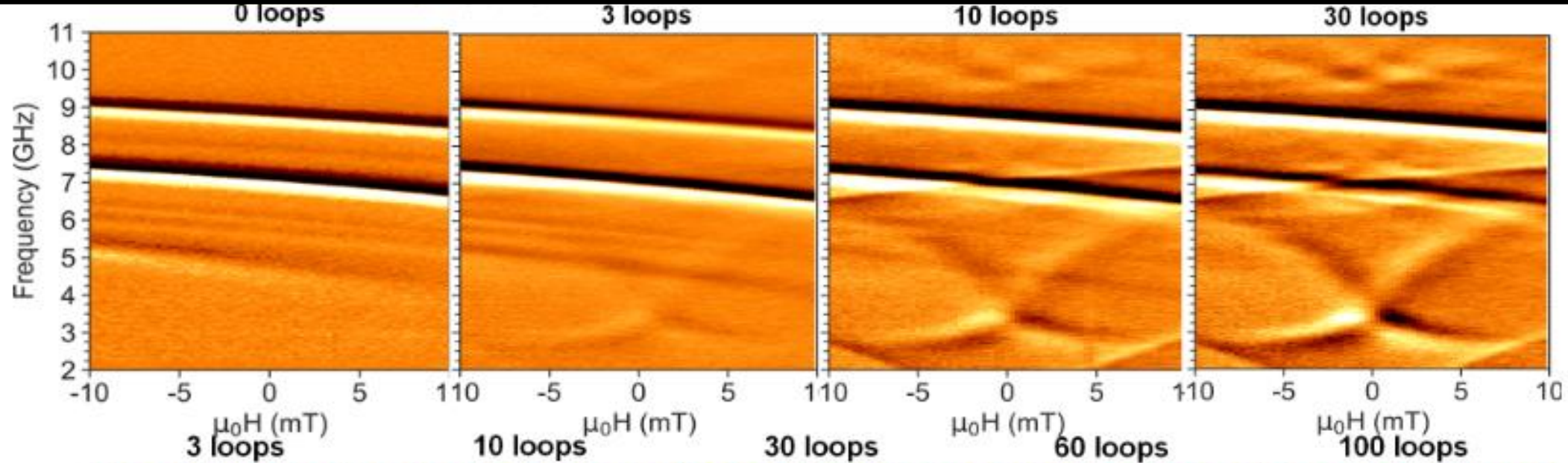
Trained – Vortices in wide bars



Vortex formation time-series – MuMax3

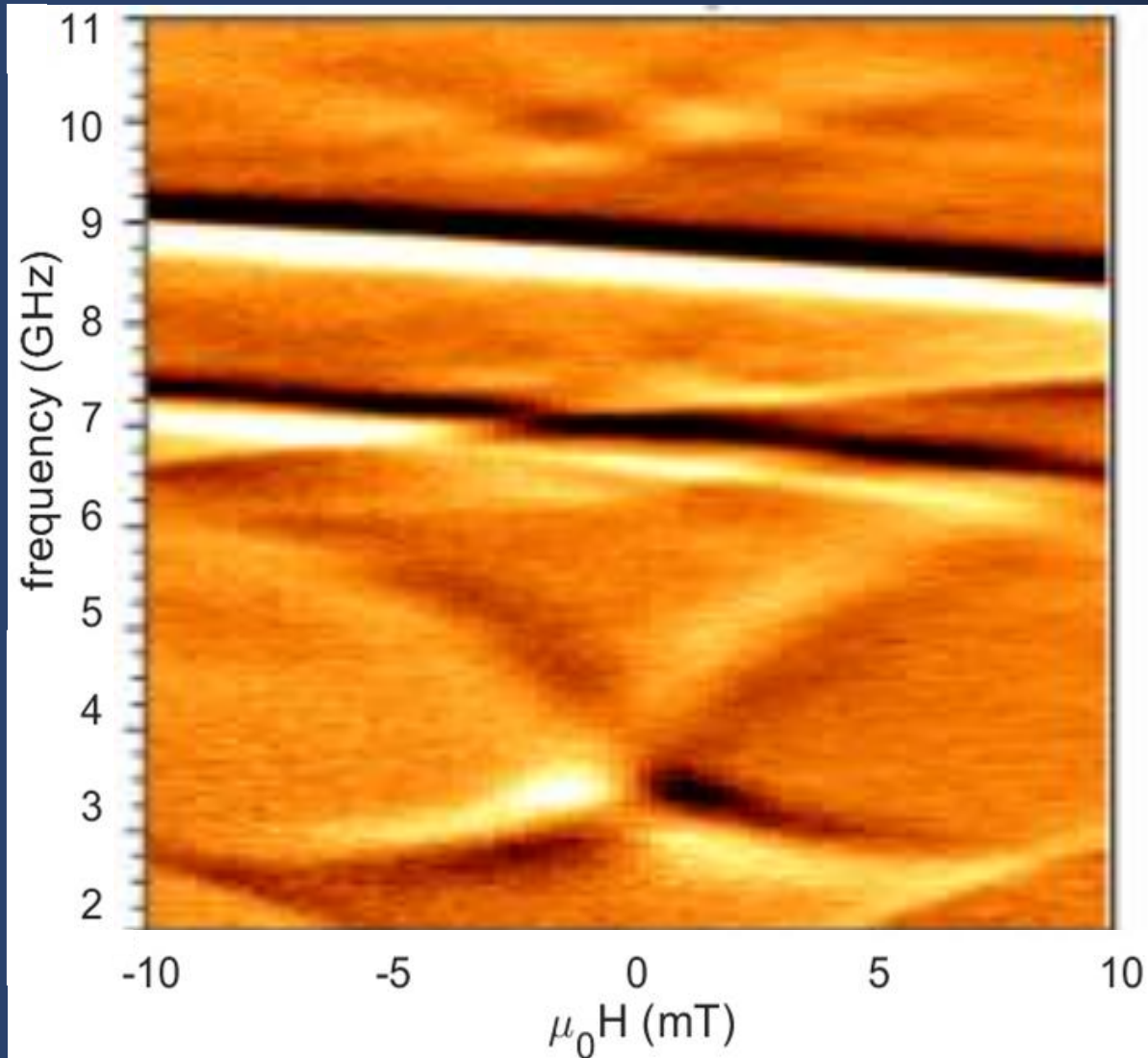
# MFM Imaging of Vortex Training



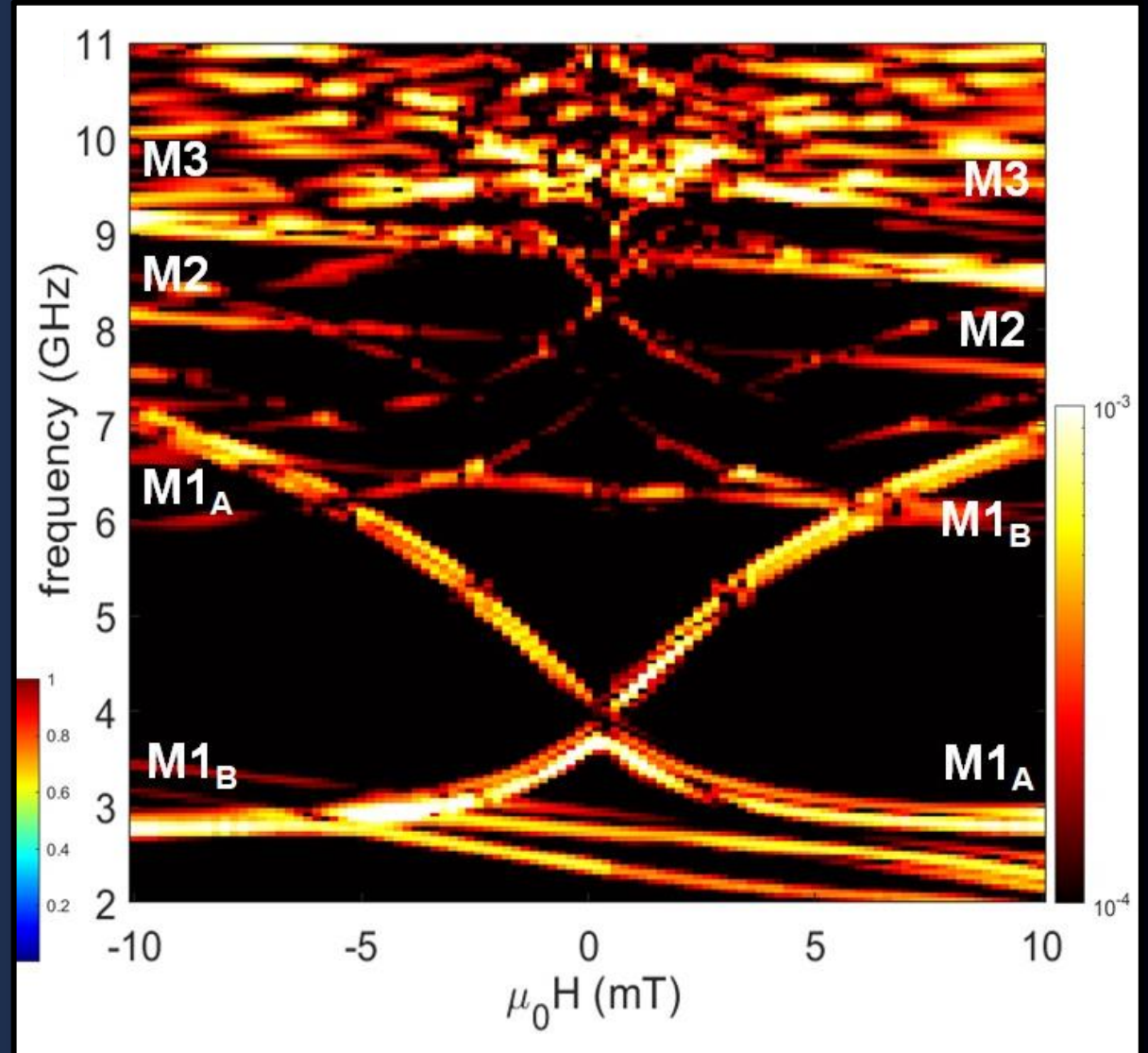


# Micromagnetic simulation of FMR response

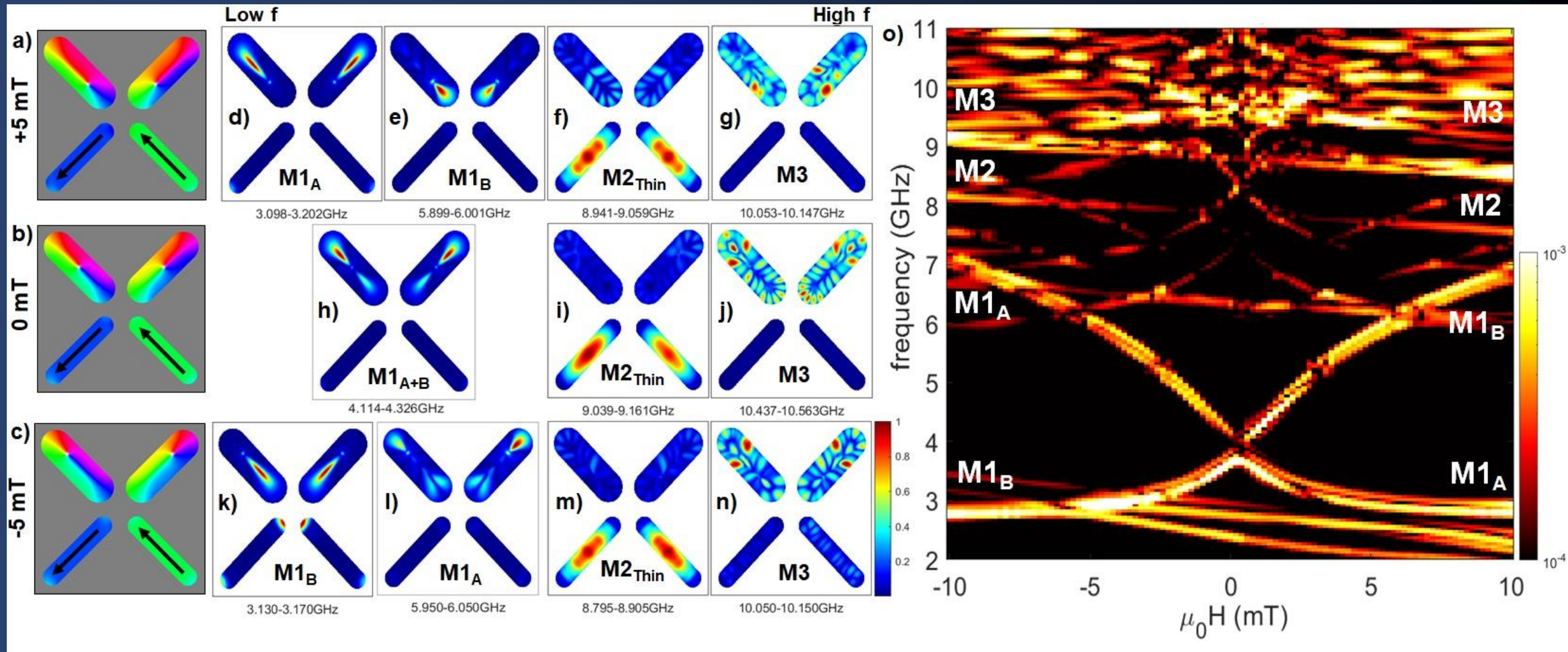
Experiment

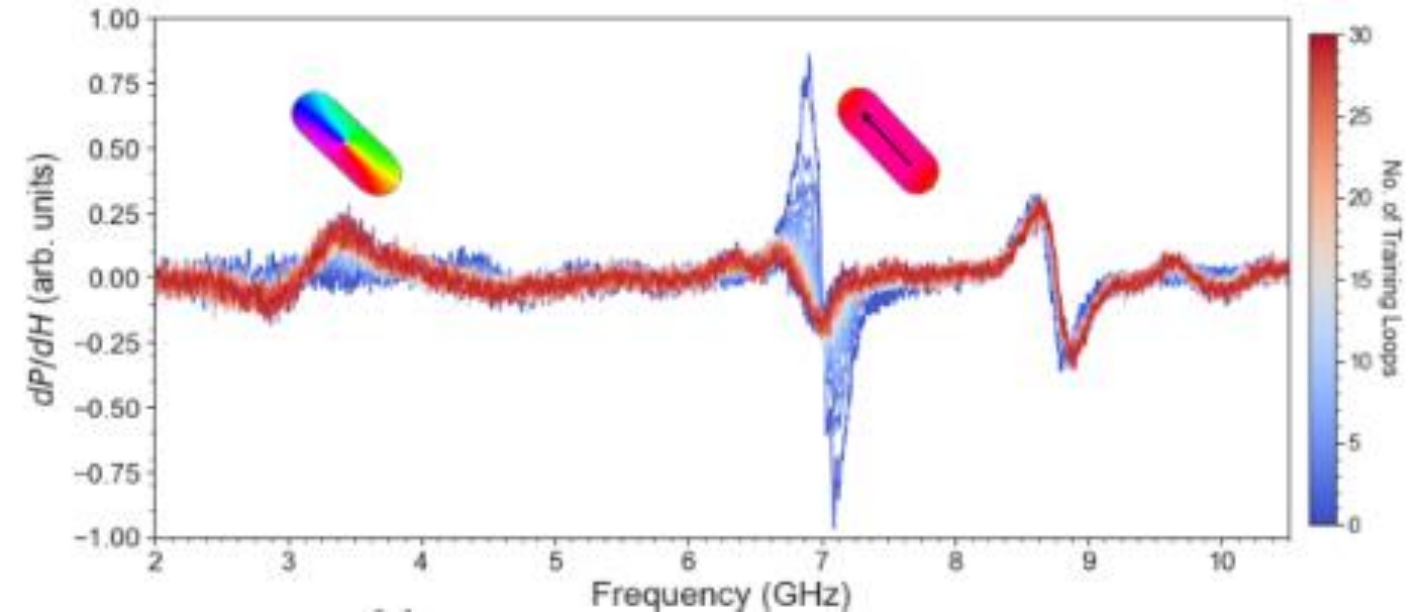


Simulation

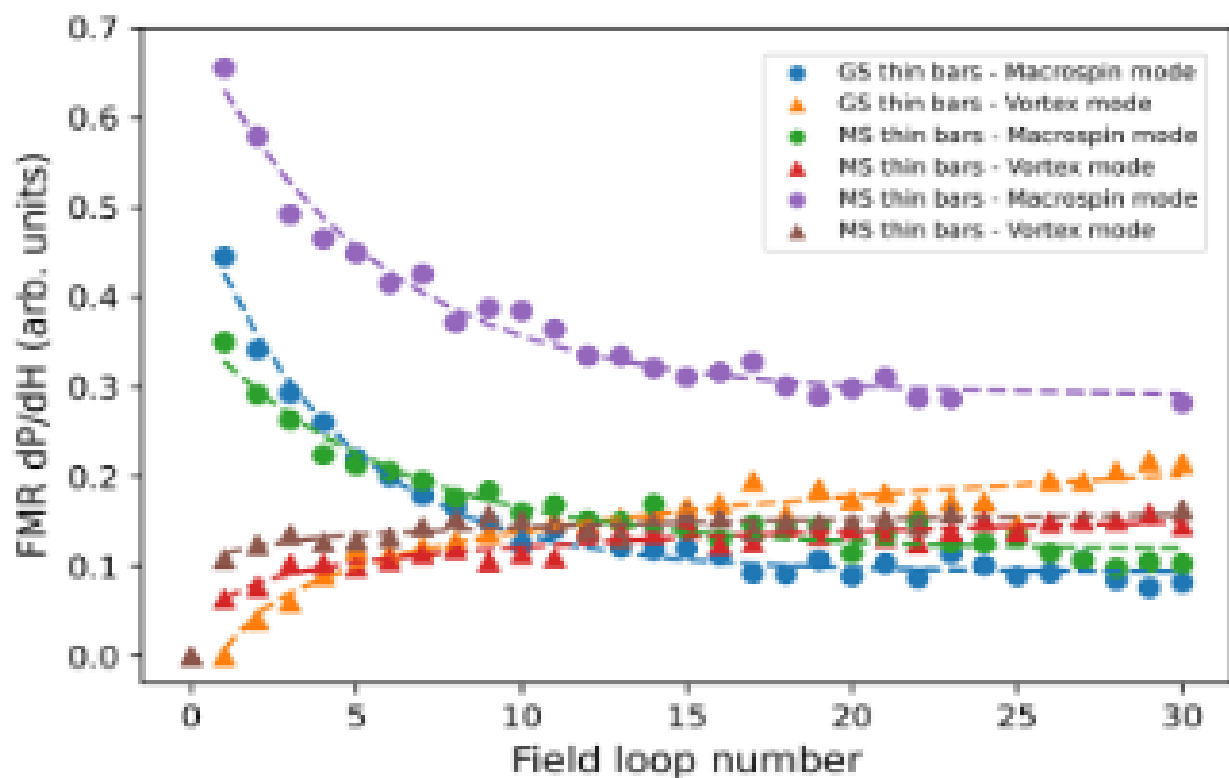


# Micromagnetic simulation of FMR response



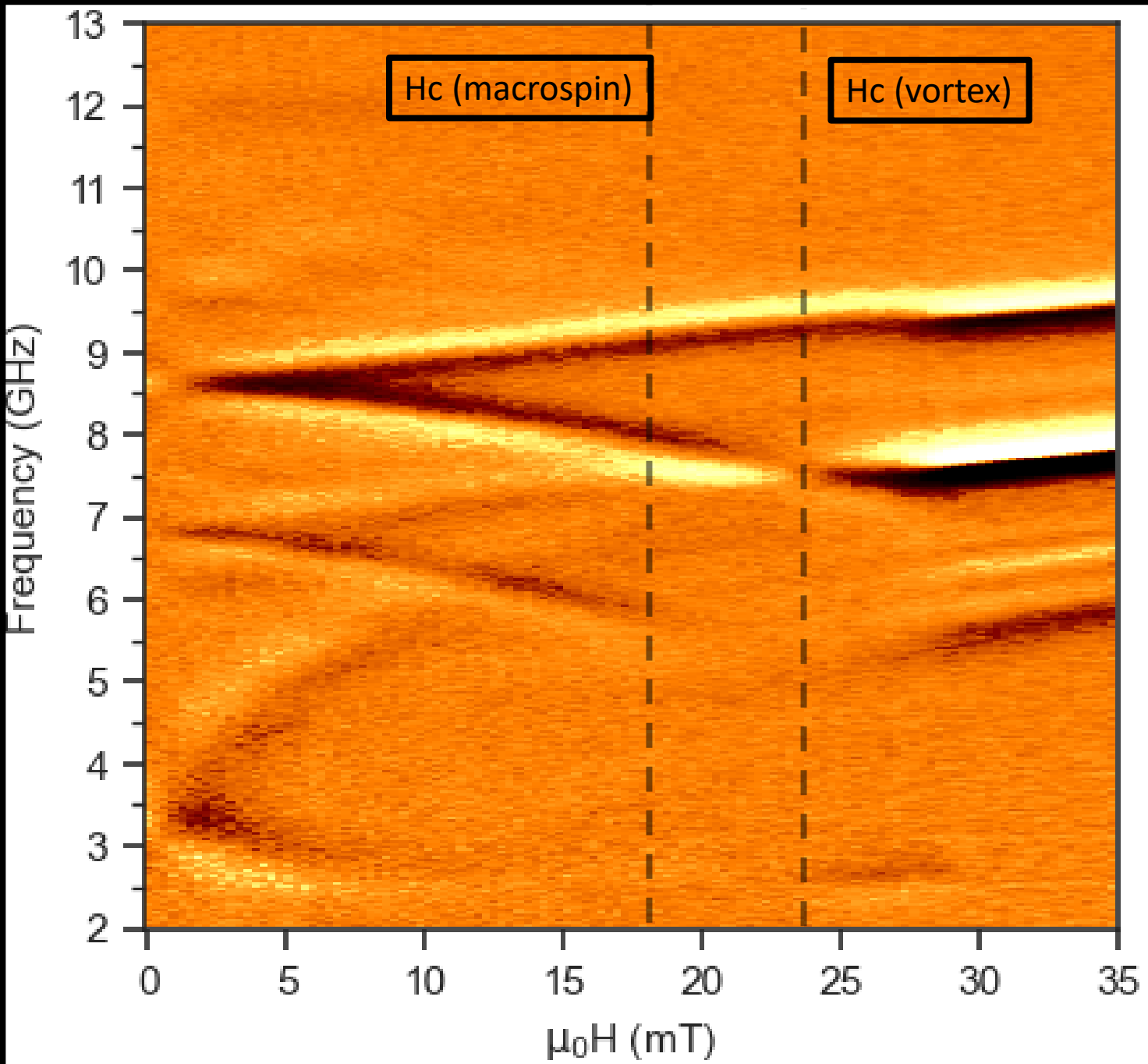


Waterfall spectra taken after each training field loop



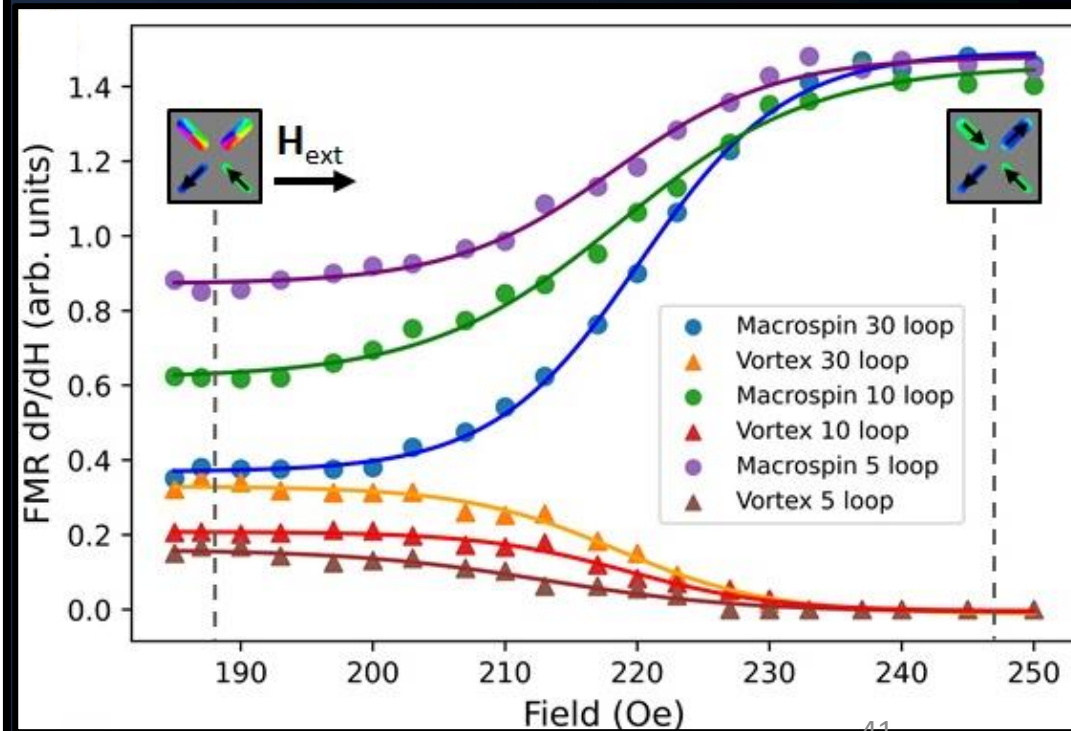
Macrospin & vortex mode amplitudes throughout training for different thin-bar biasing





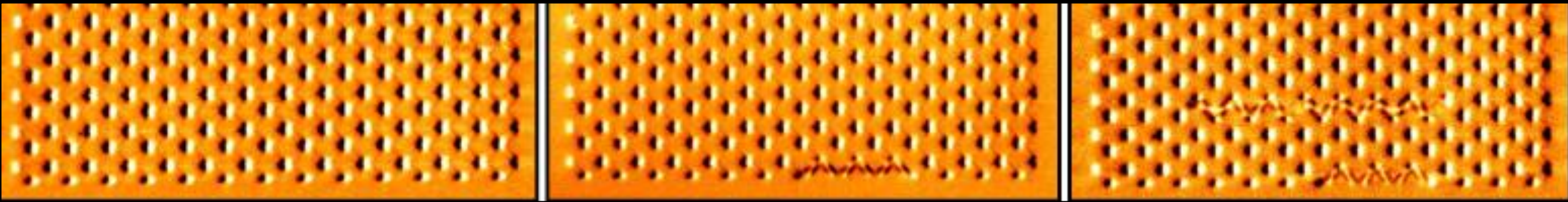
## Vortex to Macrospin Conversion

- Initial high-vortex state
- Sweep H 0-35 mT
- Reach saturated macrospin state at 27 mT
- Thin bar biasing controls saturation field



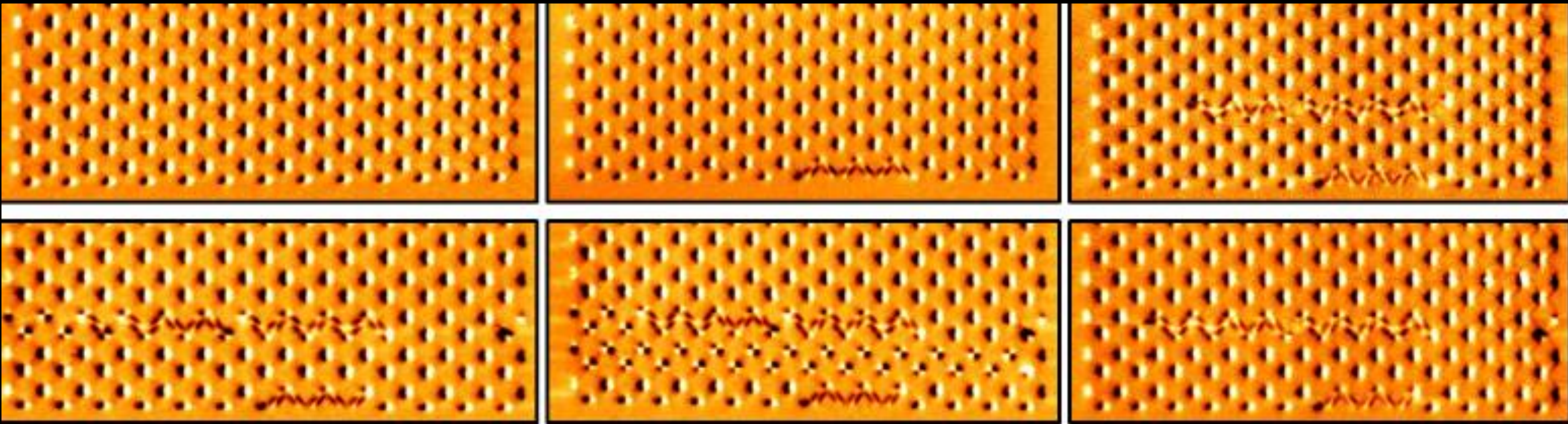
# Vortex Writing via MFM Tip

Top Frames (1-3): Tip-written vortices



# Vortex Writing via MFM Tip

Top Frames (1-3): Tip-written vortices

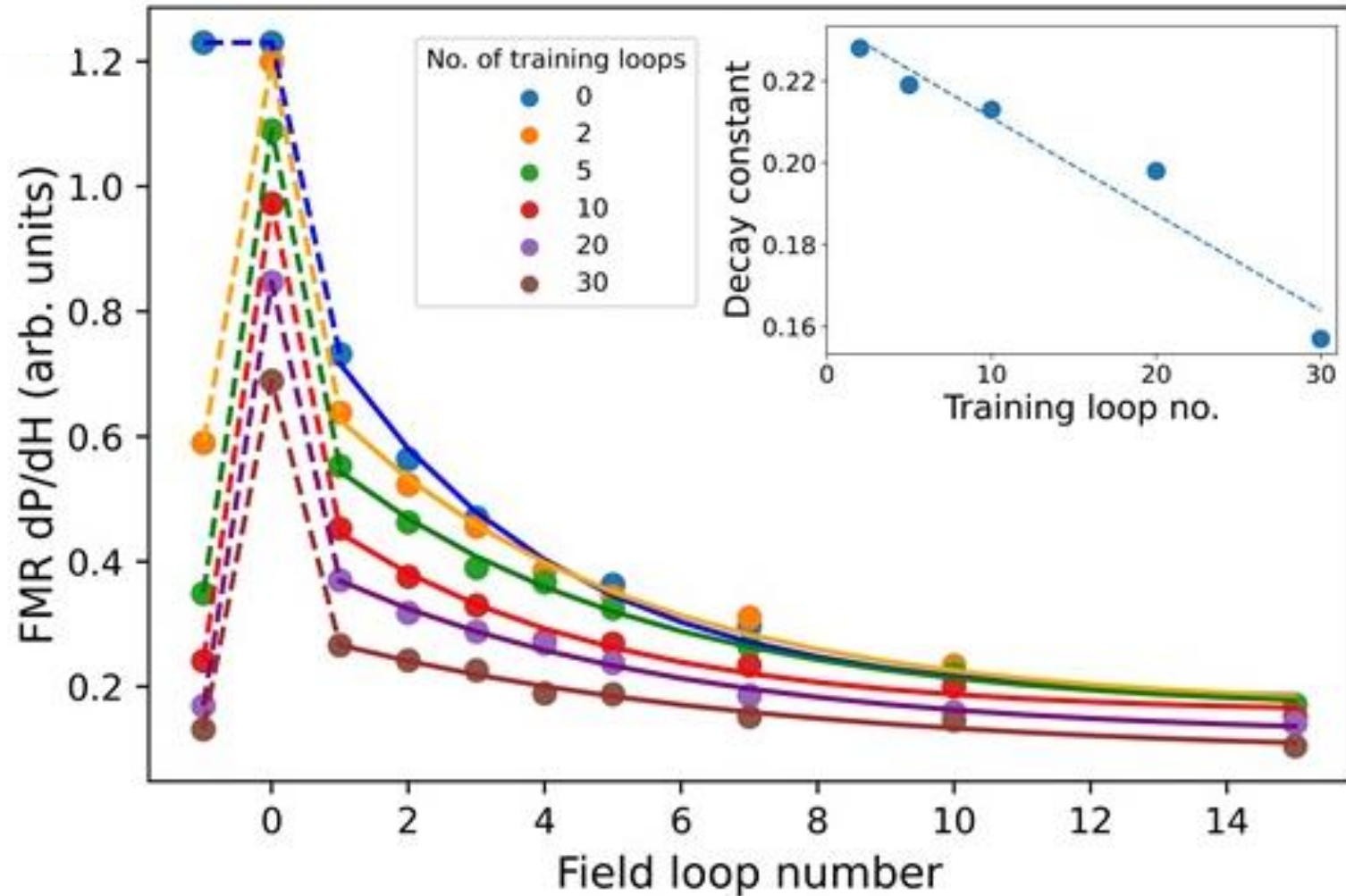


Bottom Frames (4-6):

Field looping of vortex line states at 13 mT ( $H_c = 16-17$  mT)

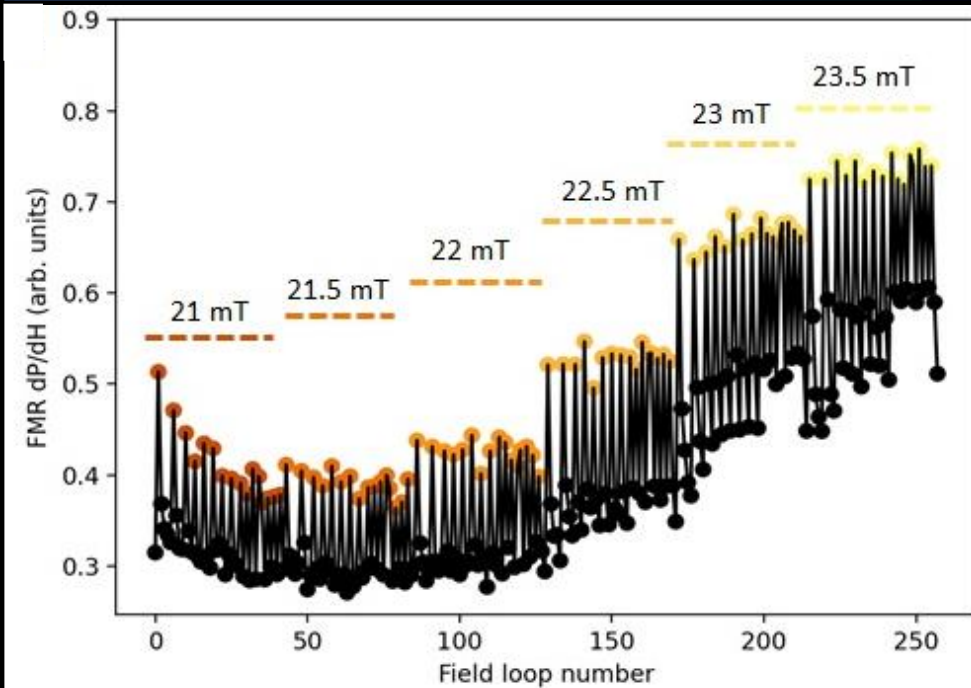
# Training ASVI

Higher field application after different training lengths



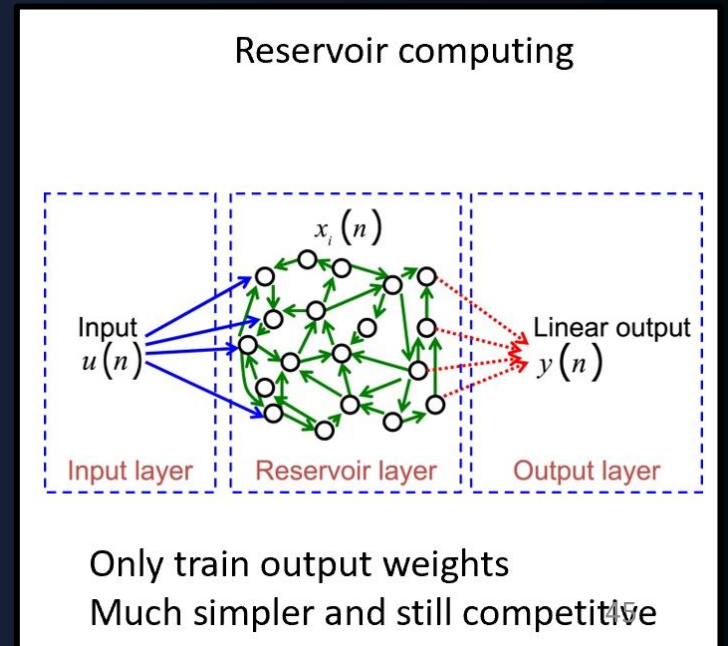
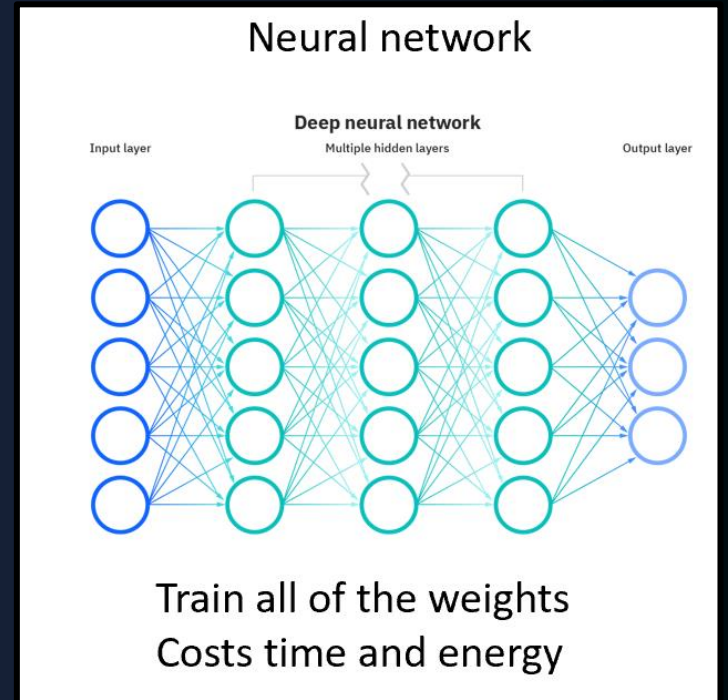
Echo-state property:

System converges from different initial states when driven through same input sequence



# Reservoir Computation

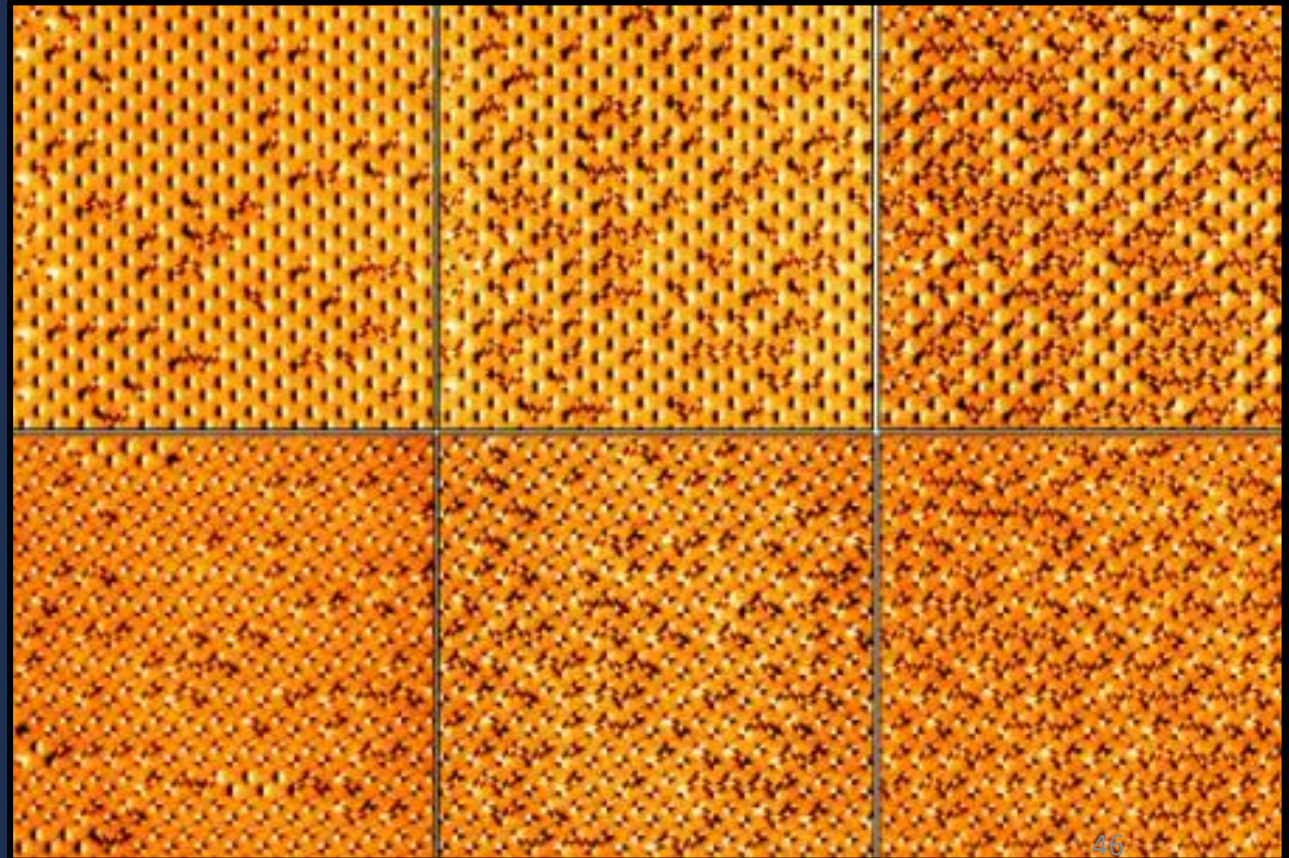
- **Aim:** To map complex problems onto linearly-solveable ones
- Reservoir has huge number of strongly-interacting hidden connections
- Only need to train small number of outputs
- Strengths are temporal data prediction, transformation and classification
- Huge energy savings possible vs. deep neural networks as only train small subset of weights
- Energy cost of global Machine Learning doubling every 3.5 months (!) *OpenAI white paper (2019)*



# Reservoir Computation

Prerequisites for good reservoir computation:

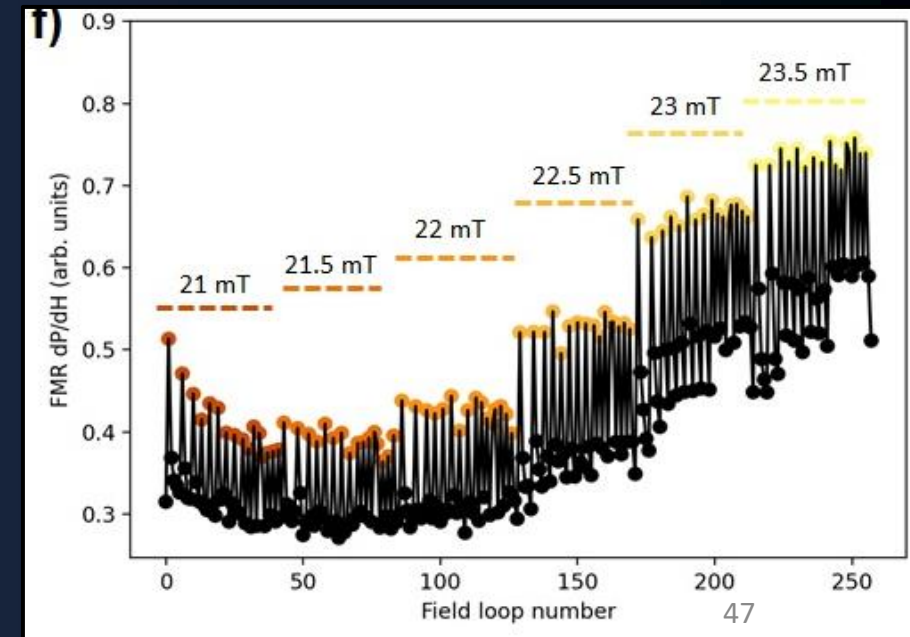
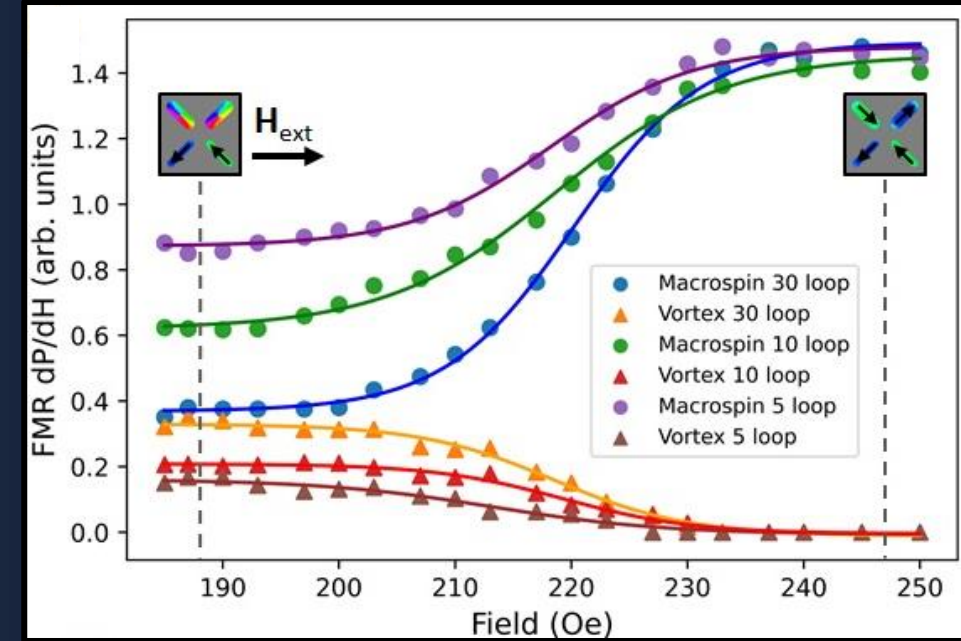
- ✓ Wide range of distinguishable states



# Reservoir Computation

Prerequisites for good reservoir computation:

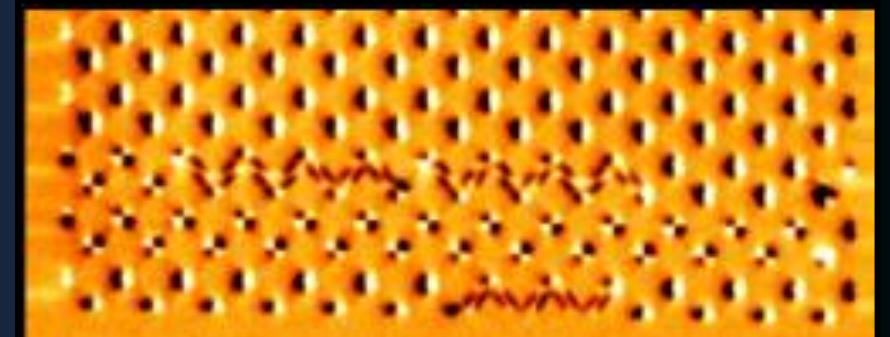
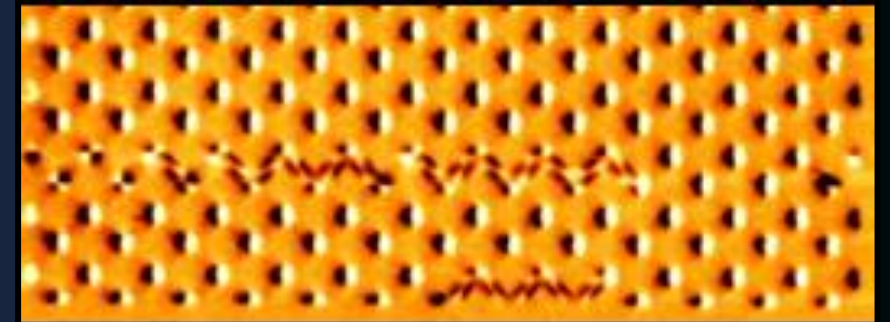
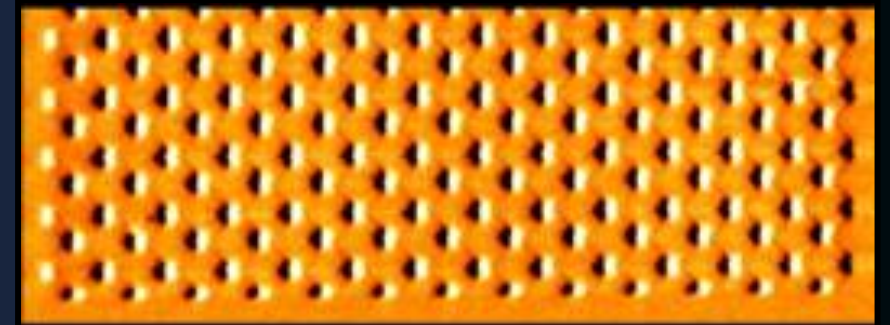
- ✓ Wide range of distinguishable states
- ✓ Highly-nonlinear response to input



# Reservoir Computation

Prerequisites for good reservoir computation:

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

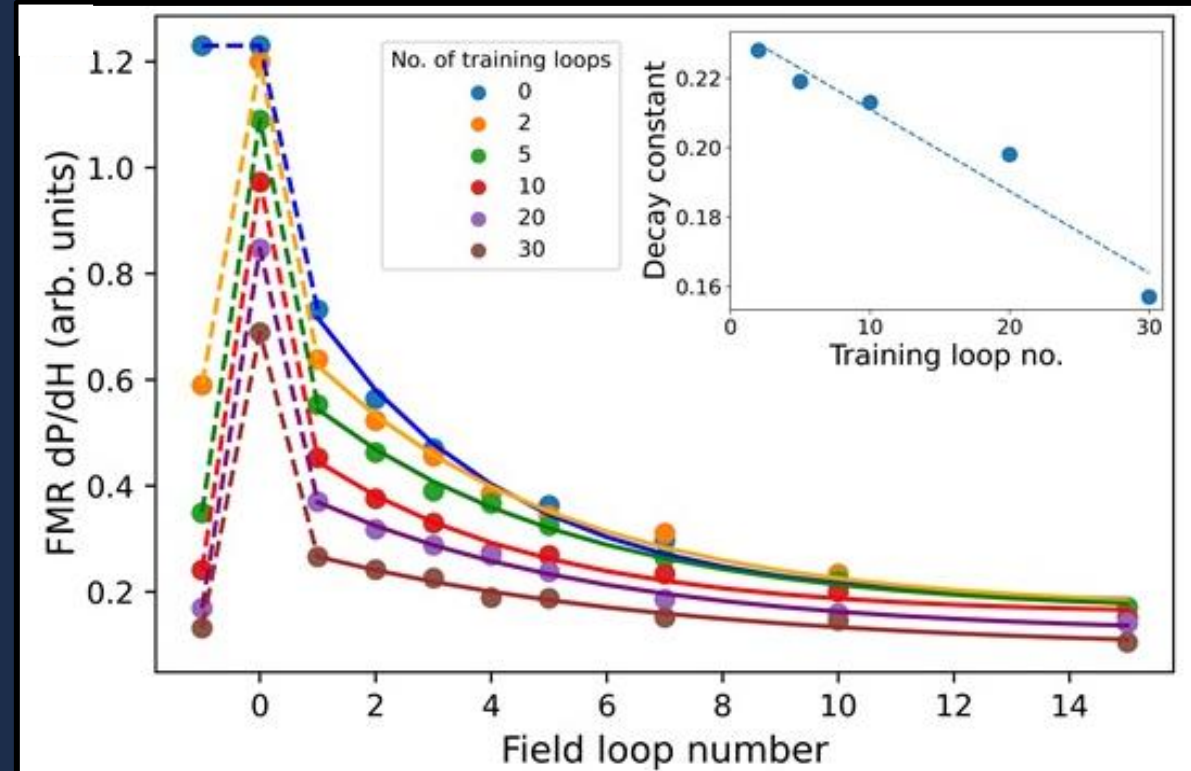




# Reservoir Computation

Prerequisites for good reservoir computation:

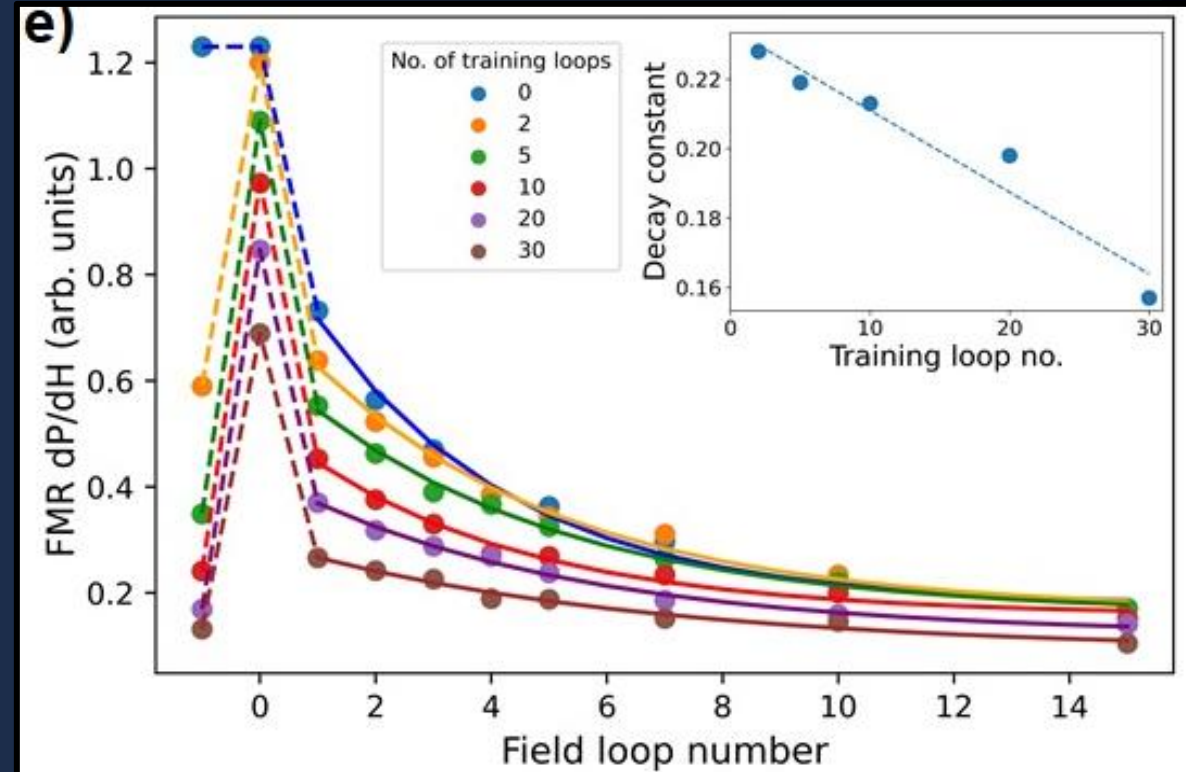
- ✓ Wide range of distinguishable states
- ✓ Highly-nonlinear response to input
- ✓ Strong inter-element coupling
- ✓ Short-term memory of input sequences
- ✓ Ability to gradually 'forget' – Echo-state property



# Reservoir Computation

Prerequisites for good reservoir computation:

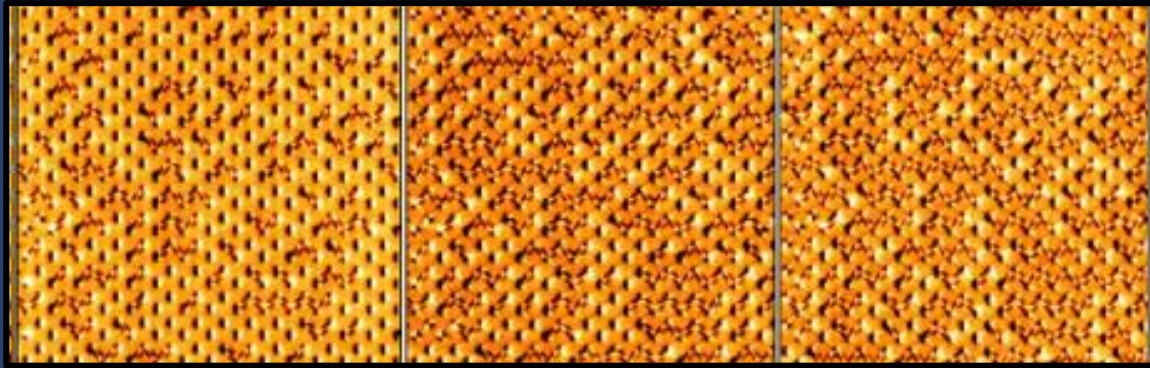
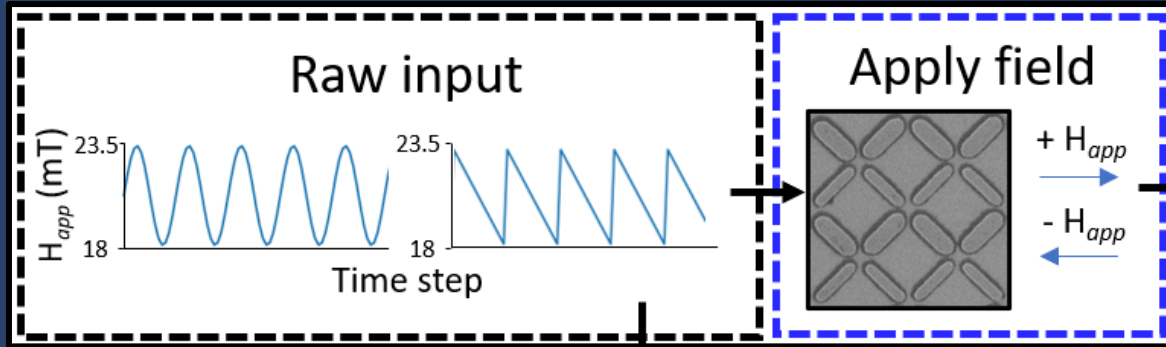
- ✓ Wide range of distinguishable states
- ✓ Highly-nonlinear response to input
- ✓ Strong inter-element coupling
- ✓ Short-term memory of input sequences
- ✓ Ability to gradually 'forget' – Echo-state property



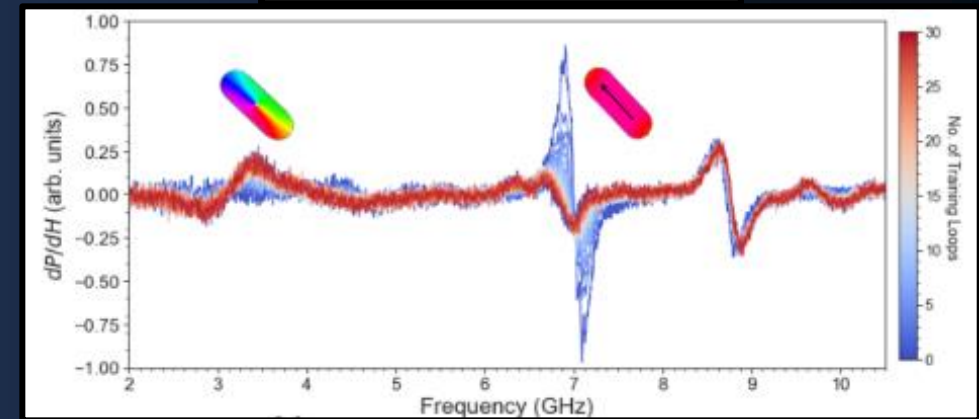
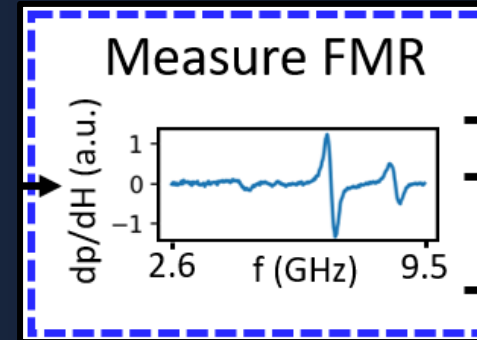
ASVI appears to tick boxes well – Implement ASVI reservoir!  
PhD student Kilian Stenning lead our implementation

# Reservoir Computation with ASVI

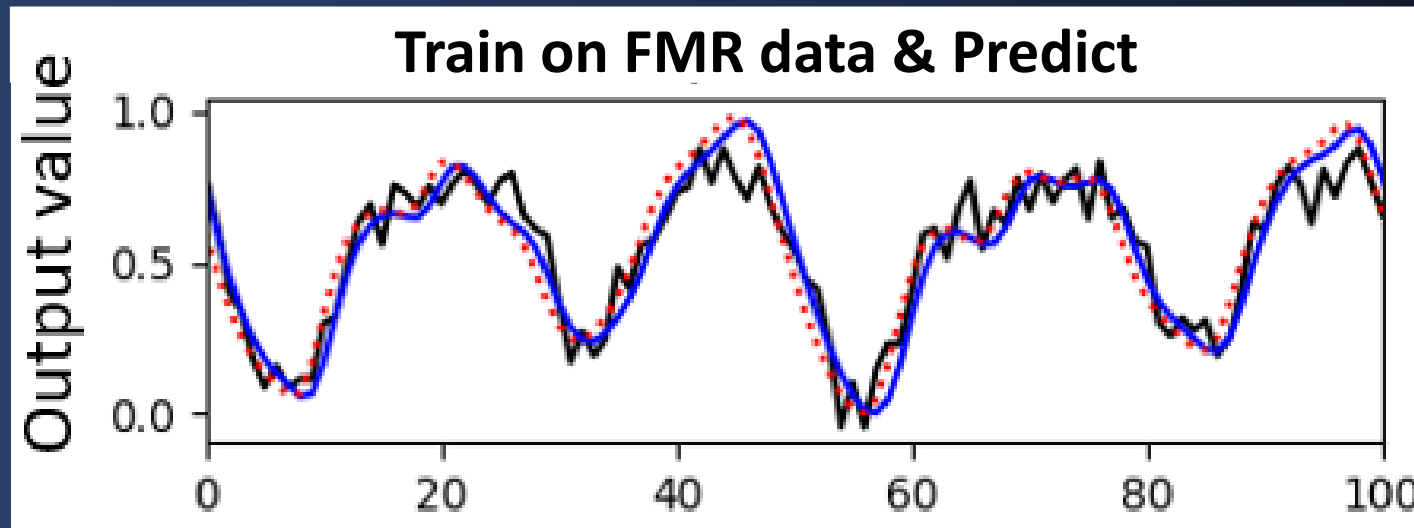
1)



2)



3)

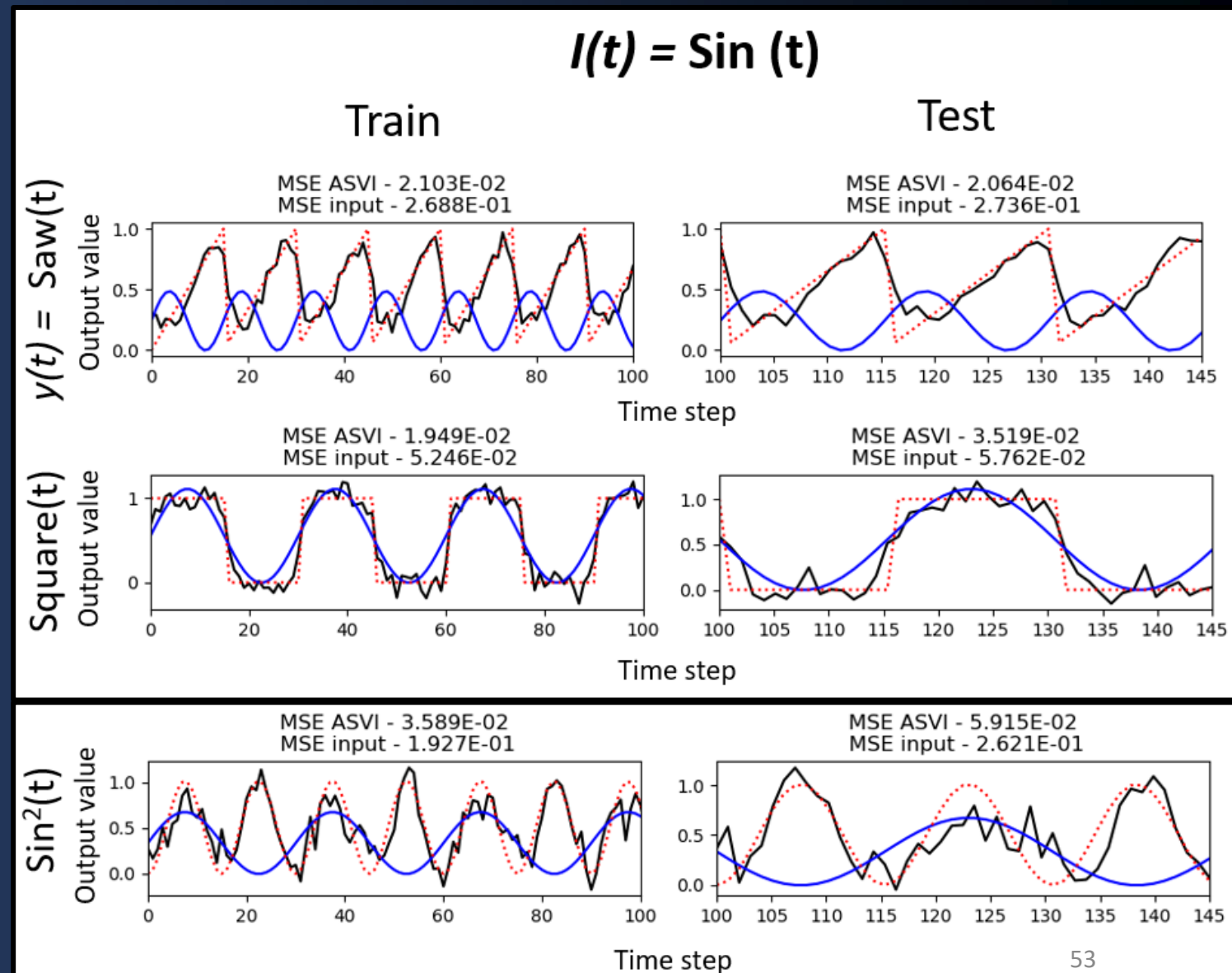


# Waveform transformation

## Waveform transformation

- Input  $I(t)$  dataset as field-sequence
- Transform output data to desired waveform  $y(t)$  via Ridge-Regression
- Unknown transformation relation, challenging benchmarking task
- Short 100 datapoint training to reflect real-world embedded device use cases

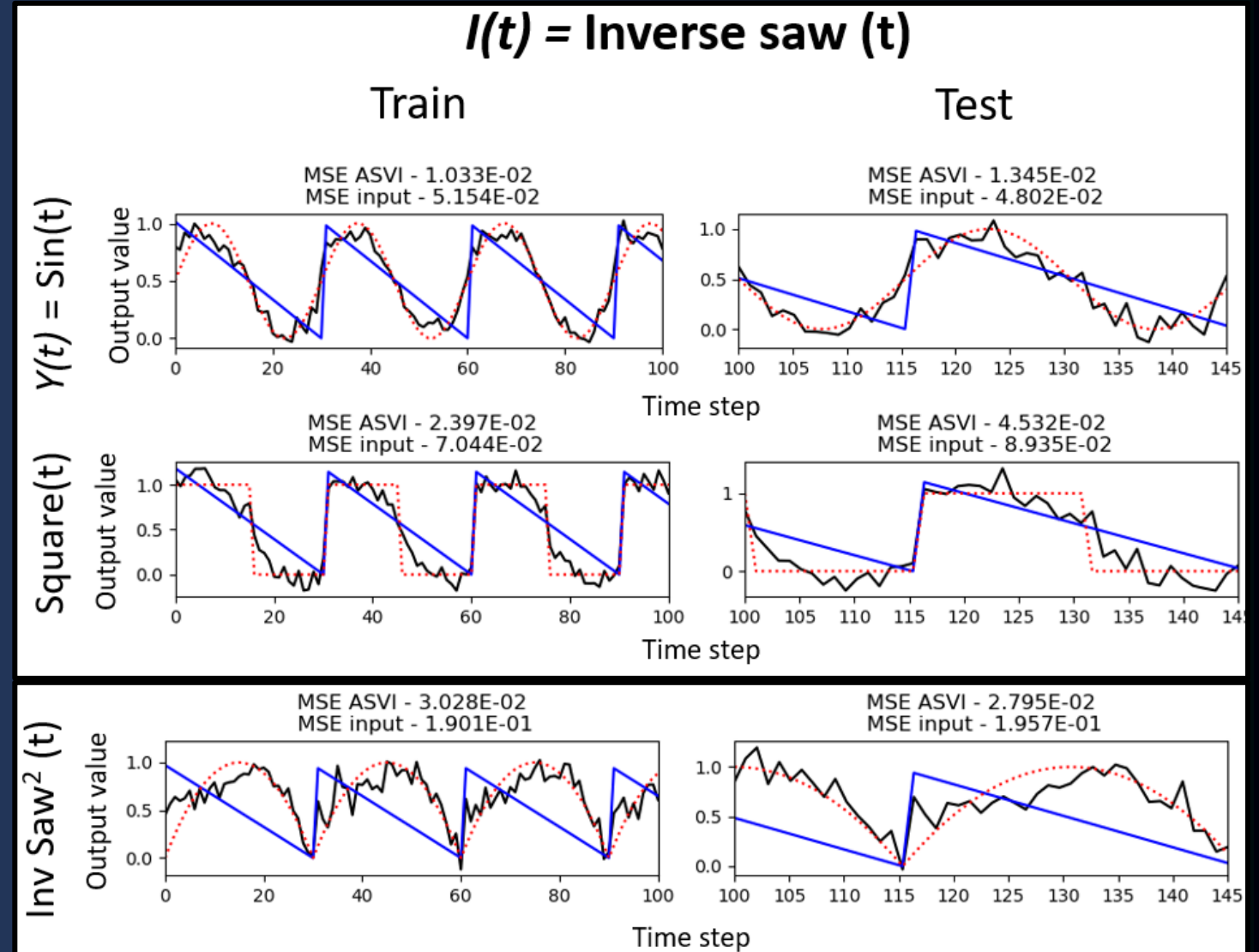
--- Target — ASVI prediction — Raw input prediction



# Waveform transformation

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

- Input  $I(t)$  dataset as field-sequence
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# Waveform transformation

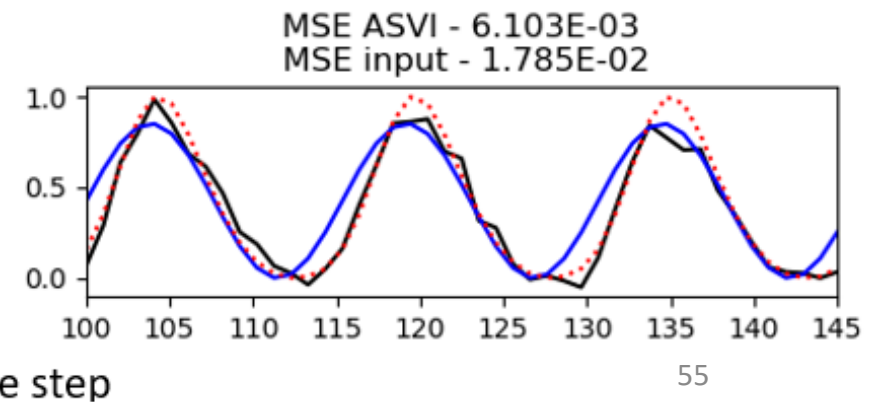
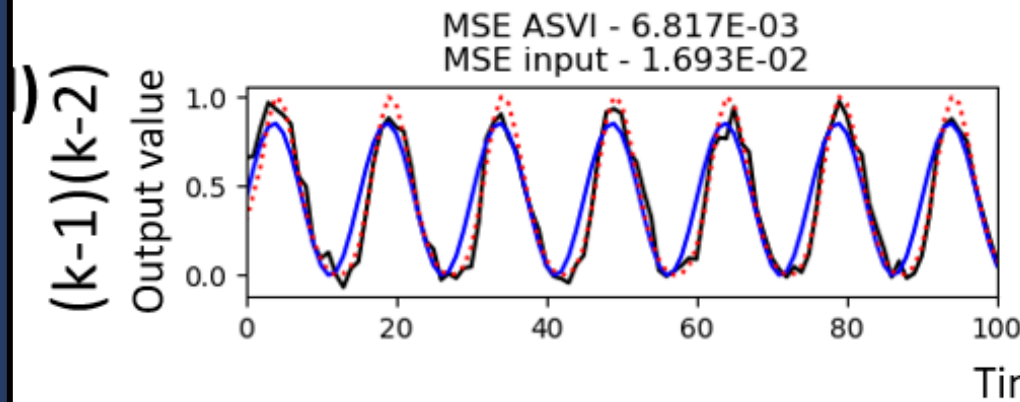
- Hysteretic Non-Linear Transformation task
- $y(t) = 0.4y(t-1) + 0.4y(t-1)y(t-2) + 0.613(t)$
- Challenge of training to prior steps in addition to higher-order
- Function after Du et al, *Nat Comms* (2017)

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

$$I(t) = \text{Sin}(t)$$

Train

Test



# Time-Series Prediction

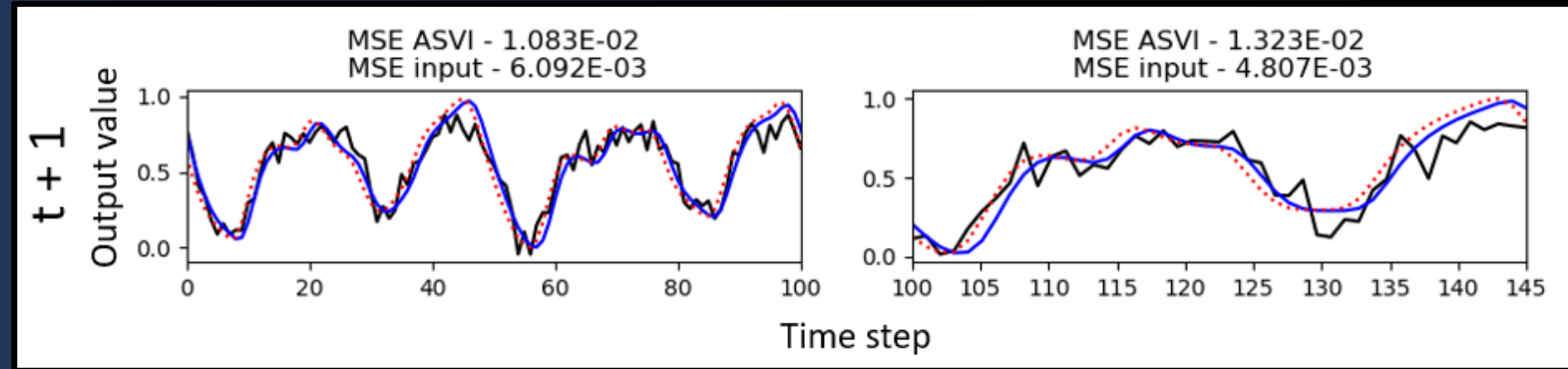
- Input training waveform as field-sequence
- Train on FMR output to predict future behaviour
- Employ chaotic oscillatory 'Mackey-Glass' time series
- ASVI performs increasingly well vs. no reservoir case as prediction moves further into future

## Mackey Glass future prediction

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

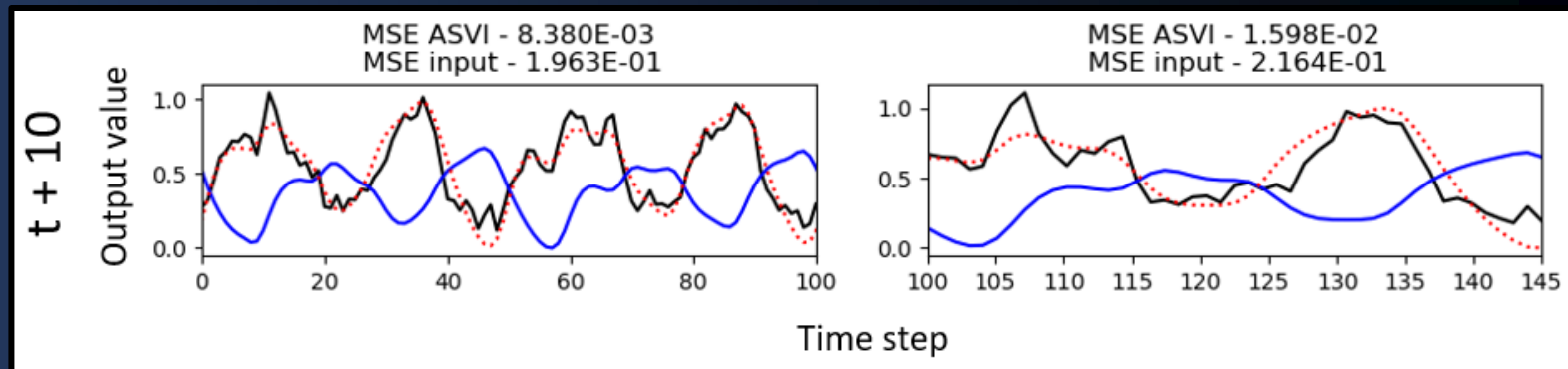
Train

Test



Train

Test



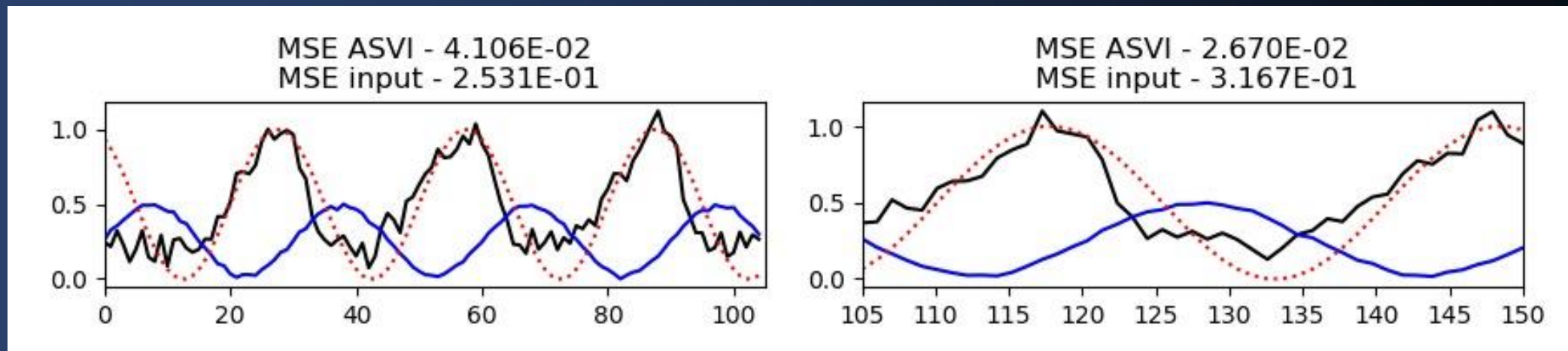
# Time-Series Prediction – Noise Tolerance

- Inject white noise to input signal
- ASVI retains good future prediction

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

Train

Test



Sin(t) future prediction, t+10



# Conclusions & Future Work

- Designed & tested a new artificial spin system with controllable bistable magnetic textures
- Exhibits ratchet-like macrospin-to-vortex training & emergent physical memory behaviour
- Rich spin-wave spectra with analogue-style mode amplitude tuning via training
- Tip-written vortices allow local control of training behaviour
- Potential as a new versatile platform for reconfigurable magnonics & neuromorphic computation
- Leverage Vortex-writing for directed reservoir computation
- Multiple nanoscale FMR pickups for reservoir scheme

# Thanks & Acknowledgements

- Thanks to Prof. Karin Everschor-Sitte & Jake Love for reservoir discussions
- Thanks again to all co-authors and collaborators:
- Kilian D. Stenning, Alex Vanstone, Troy Dion, Holly H. Holder, Francesco Caravelli, Daan M. Arroo, Hidekazu Kurebayashi, Will R. Branford
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  - Alex Vanstone – Establishing FMR readout of microstates
  - Troy Dion – Simulation of spin-wave modes & spatial profiles