Deep-Learning-Enhanced Electron Microscopy for Accelerated Super-Resolution Imaging in Solid Earth Research

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WHY: *Accelerate electron microscopy imaging*

Given the inherent heterogeneity of Earth materials, there exists an acute need for a multiscale imaging approach to systematically analyse microstructural variations across relevant length scales. However, addressing the need for statistical representativeness often requires imaging numerous samples at high magnification.

WHAT: *The DLE-EM workflow*

A Deep-Learning-Enhanced Electron Microscopy (DLE-EM) workflow (Fig. 1), achieving a six- to sixteenfold acceleration of the imaging process by capturing one or more high-resolution (HR) regions within a low-resolution (LR) area. The overlapping HR and LR data is then used to enhance the resolution of LR data for which no HR counterpart is available.

HOW: *Integrated image registration and DL upscaling workflow*

The workflow involves capturing one or more HR regions within a LR area. Precise image registration is achieved in two steps: first, determining the HR region's location within the LR region using a Fast Fourier Transform algorithm [1], and second, refining image registration through iterative calculation of a deformation matrix. This matrix, utilizing Newton's optimization method, aims to minimize differences between both images [2]. Subsequently, paired HR and LR images undergo processing in a Generative Adversarial Network (GAN), comprising a generator and a discriminator. This GAN learns to generate HR images from LR counterparts through joint training in an adversarial process.

PERFORMANCE:

Fig. 2 depicts results from models trained using Mean Squared Error (MSE) and Mean Absolute Error (MAE) loss functions. These models were evaluated using random LR tiles, juxtaposed with their corresponding *ground truth* HR tiles.

Fig. 3 provides a quantitative analysis on a binary segmentation of a sandstone dataset, validating both models' ability to reproduce realistic spatial distributions of pores of different sizes.

Fig. 4 illustrates the Structural Similarity Index Measure (SSIM) score distribution for MSE-trained model data and LR data vis-à-vis HR data, highlighting the models' ability in replicating high-similarity HR data from dissimilar input data.

Acknowledgements:

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References:

[1] Lewis, J. P. "Fast normalized cross-correlation, Industrial Light and Magic." unpublished (2005).
[2] Tudisco, Erika, et al. "An extension of digital volume correlation for multimodality image registration." Measurement Science and Technology 28.9 (2017): 095401

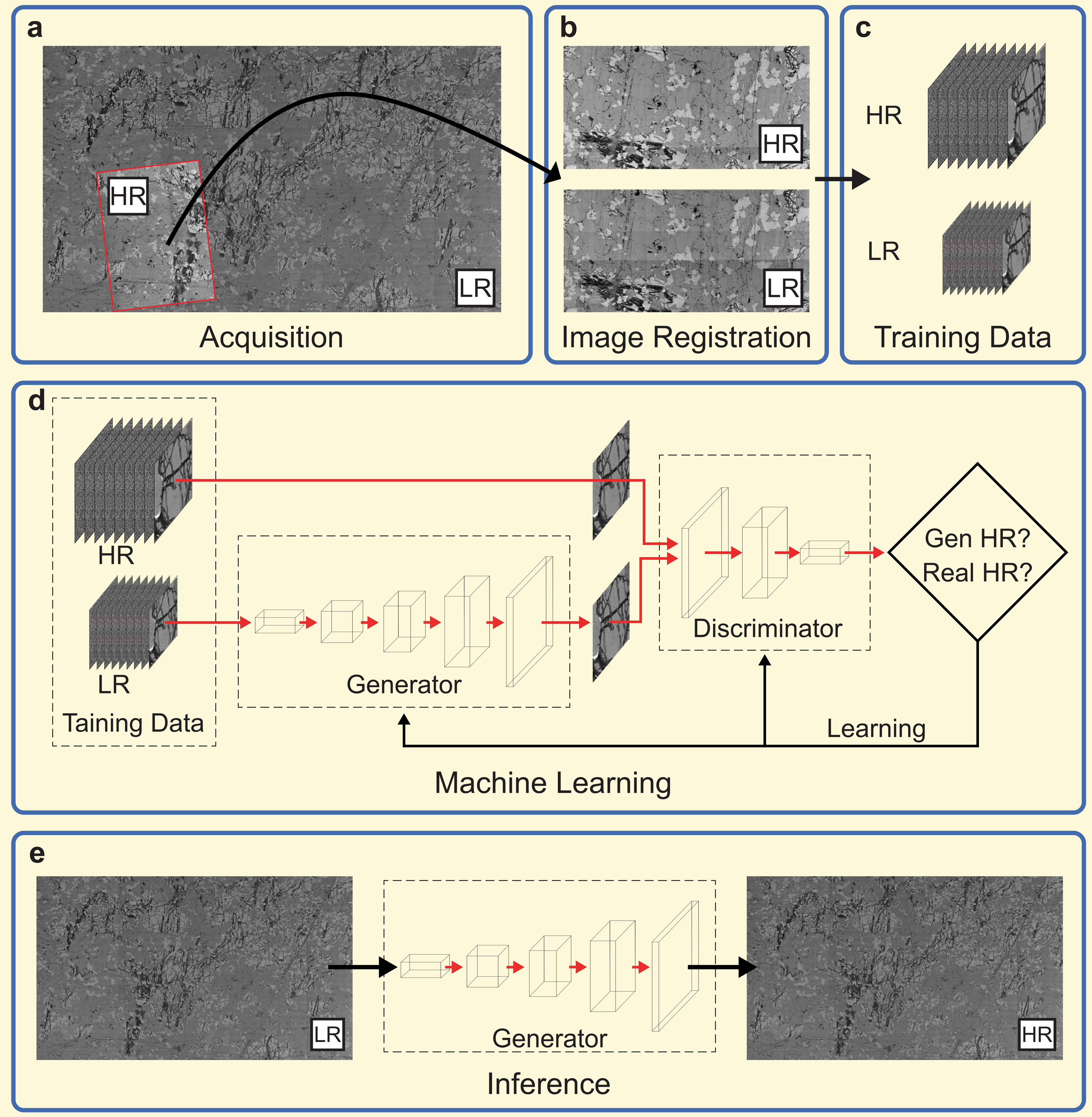

Fig. 1: Overview of DLE-EM workflow.

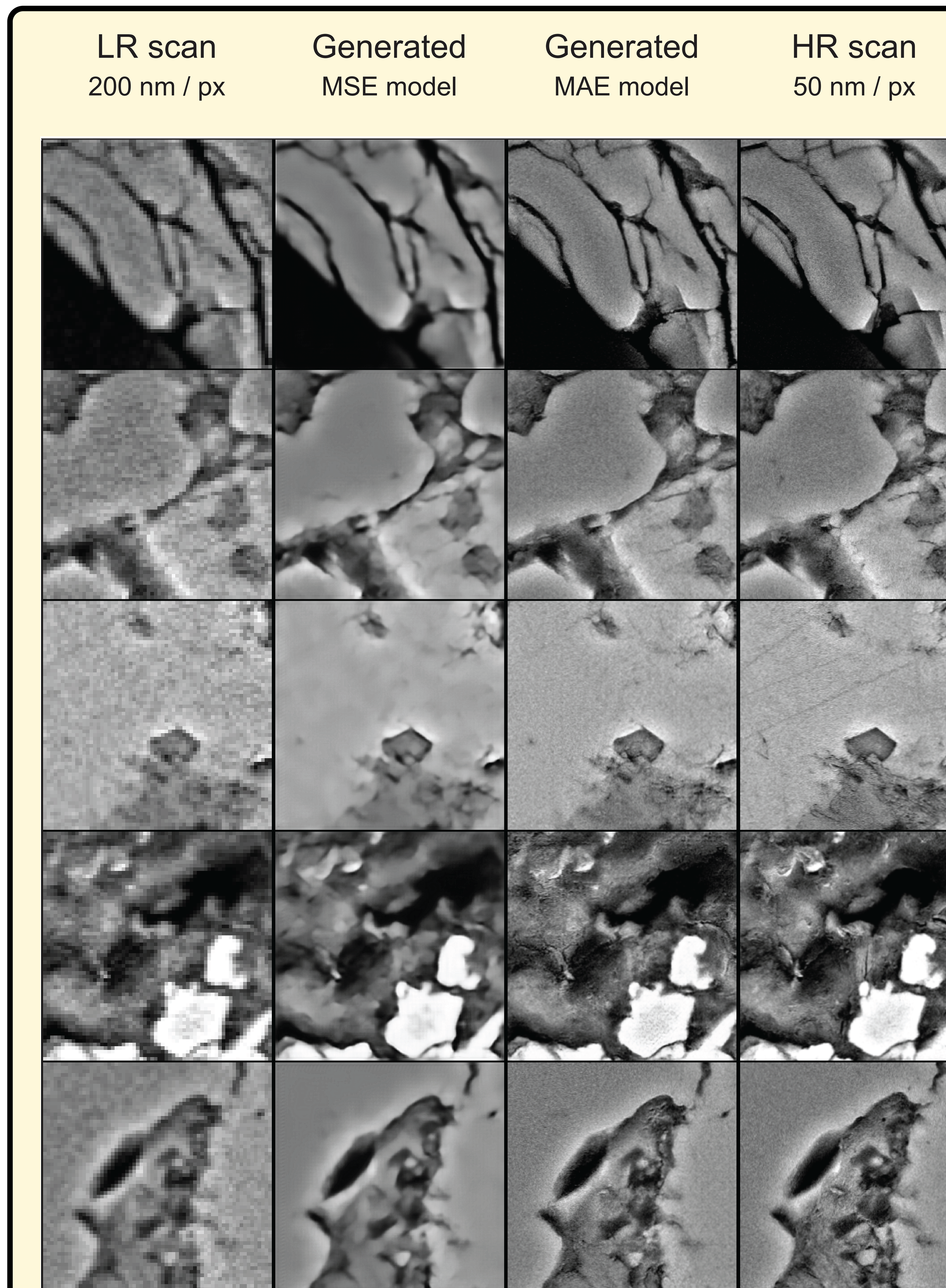

Fig. 2: From left to right: LR tiles that have been resized from 64x64 to 256x256 pixels using bicubic interpolation to match the HR tile size, generated data using a model that was trained using MSE (50 epochs) and MAE (150 epochs) loss functions, respectively, and the corresponding HR tiles.

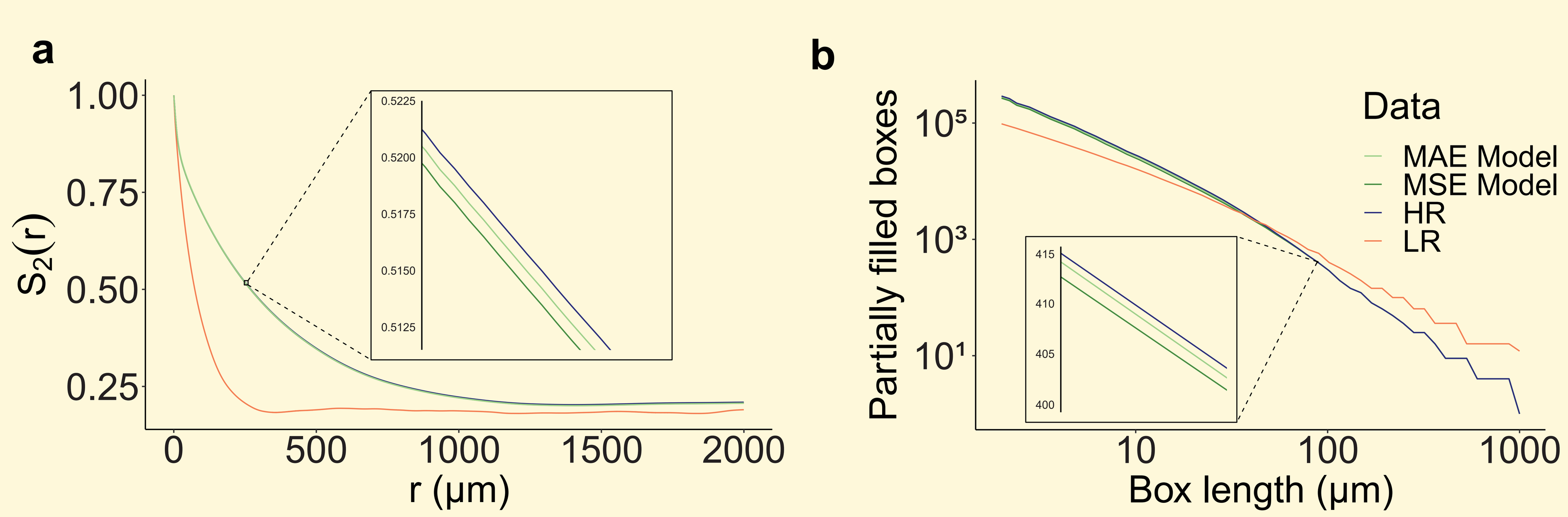

Fig. 3: **a,** Comparison of two-point correlation functions S_2, quantifying the probability that two points separated by an arbitrary distance lie within the same phase, among high-resolution (HR), low-resolution (LR), and model-generated datasets. **b,** Evaluation of the fractal dimension for HR, LR, and model-generated data using the box-counting method.

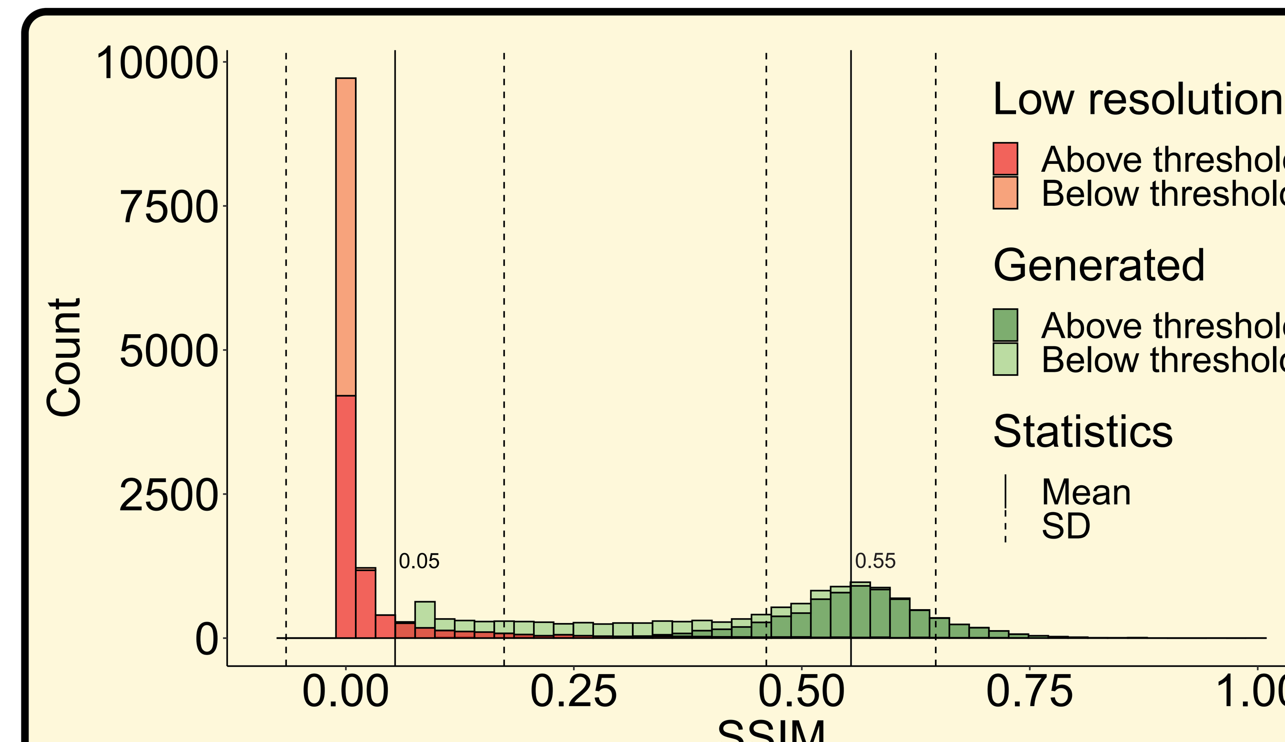

Fig. 4: Structural Similarity Index Measure (SSIM) scores for the MSE-trained model compared against LR data.

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