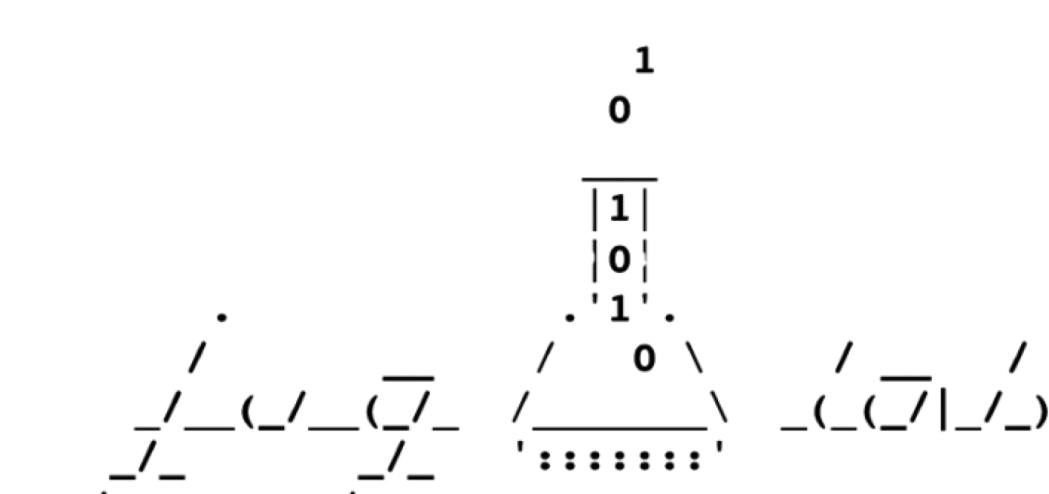


Computational Dehazing and Super-resolution in Fluorescence Microscopy via Guided Conditional Flow Matching

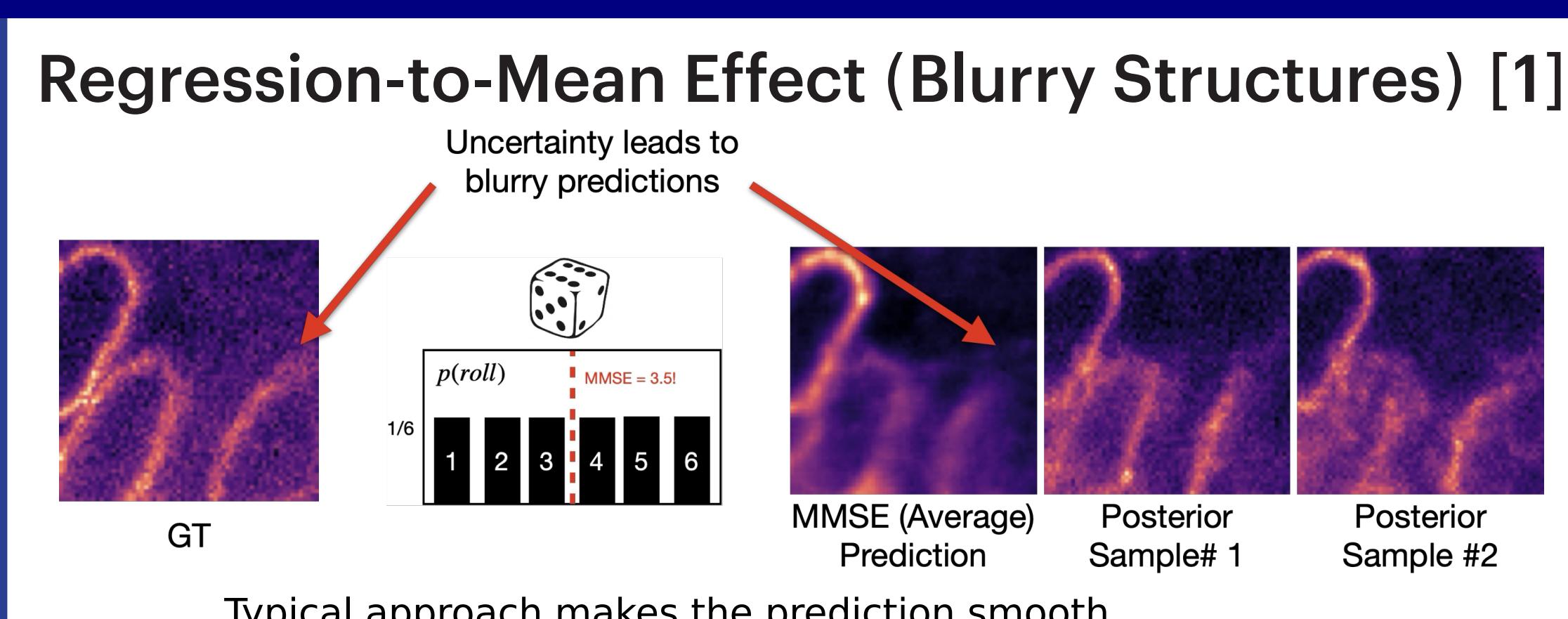
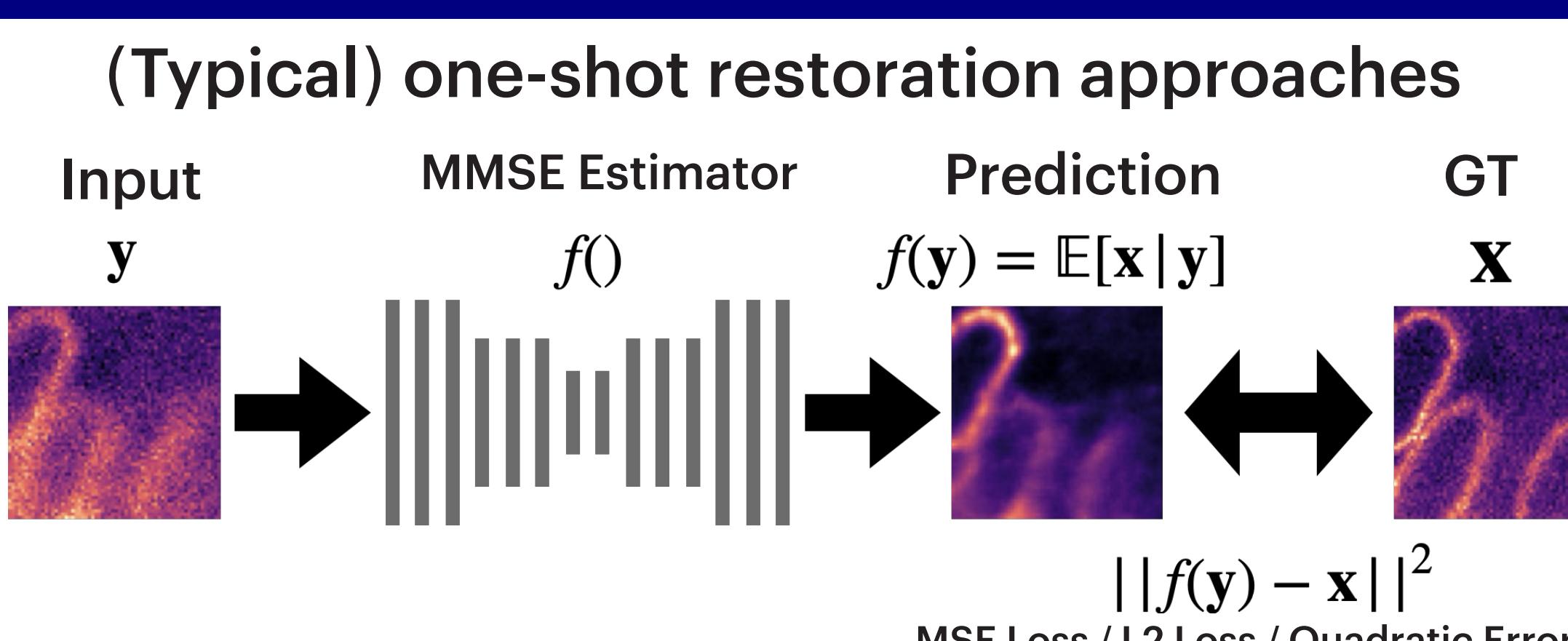
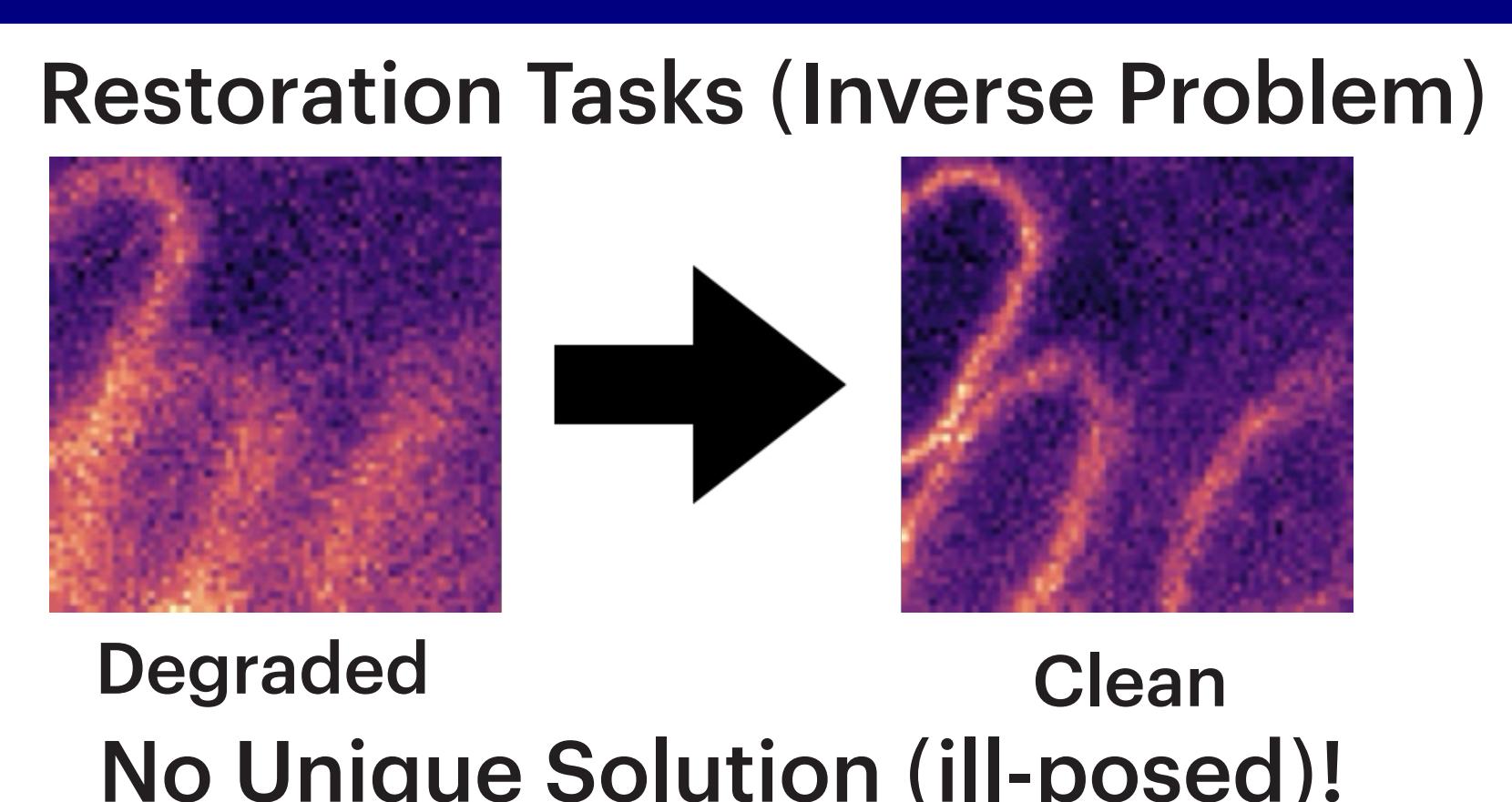
Anirban Ray^{1,2}, Ashesh Ashesh^{1,2}, Vera Galinova¹, and Florian Jug¹

¹Human Technopole, Milan, Italy

²Technische Universität Dresden, Germany

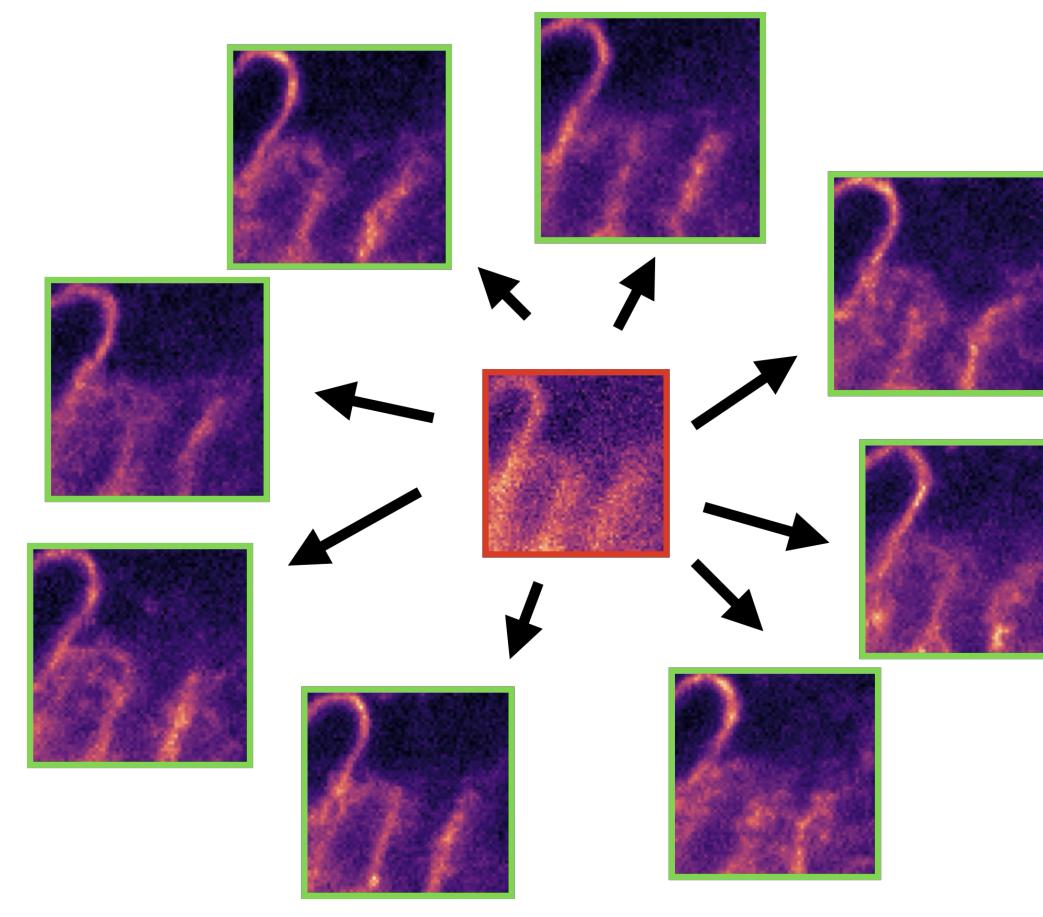


Background of the Problem

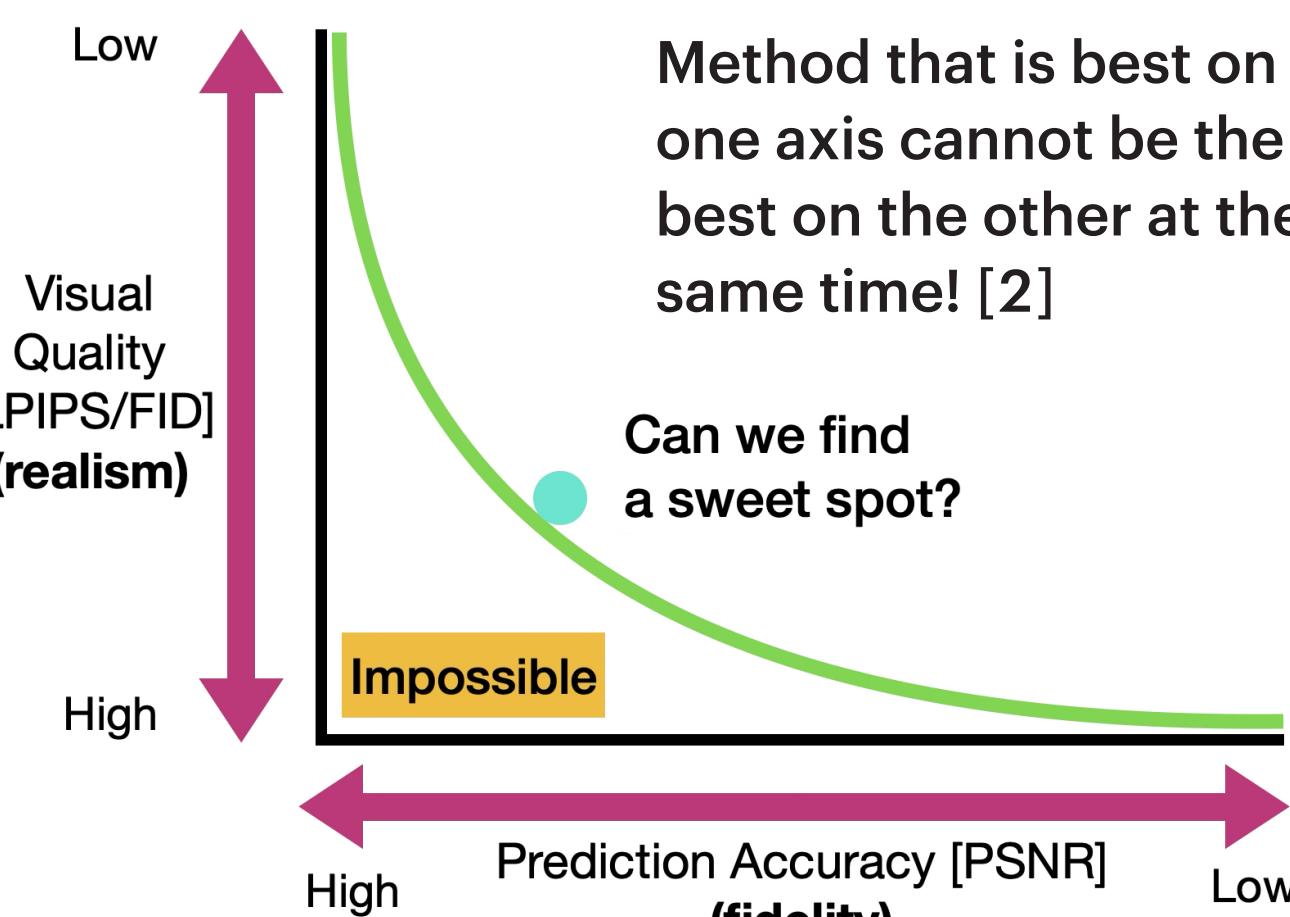


Why it happens and how can we address this issue?

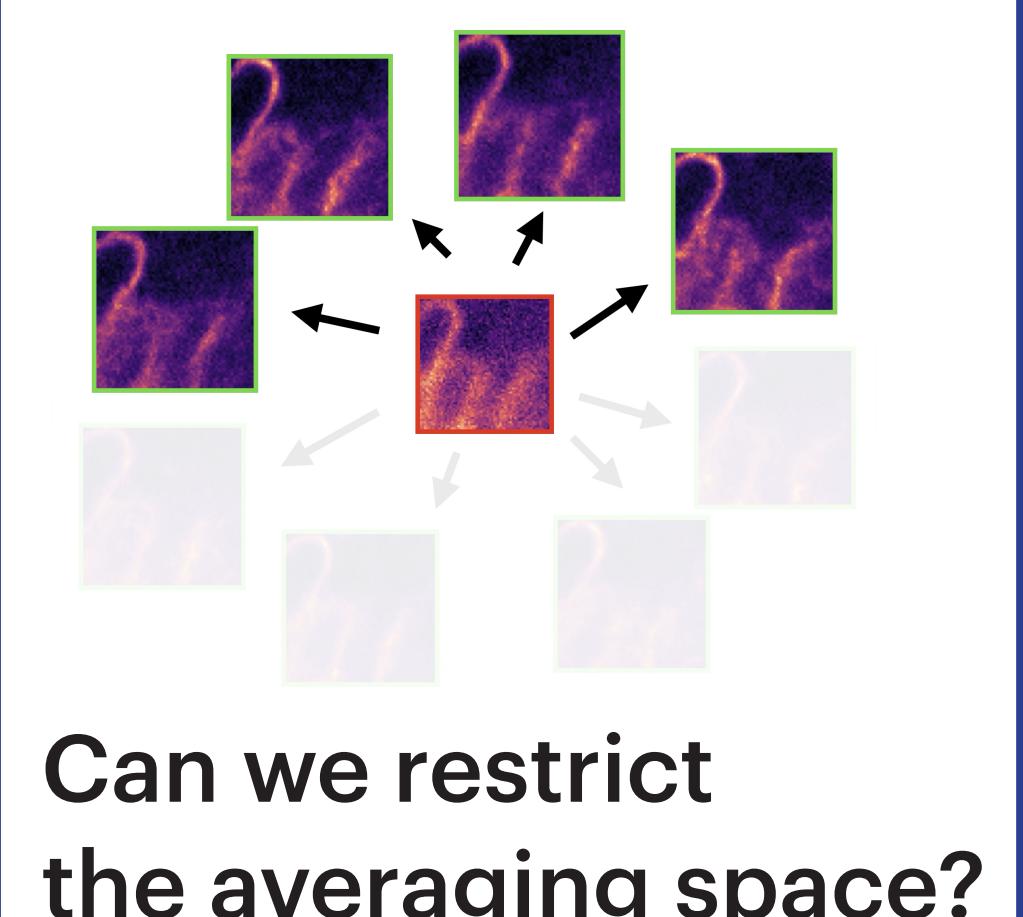
Many plausible solutions



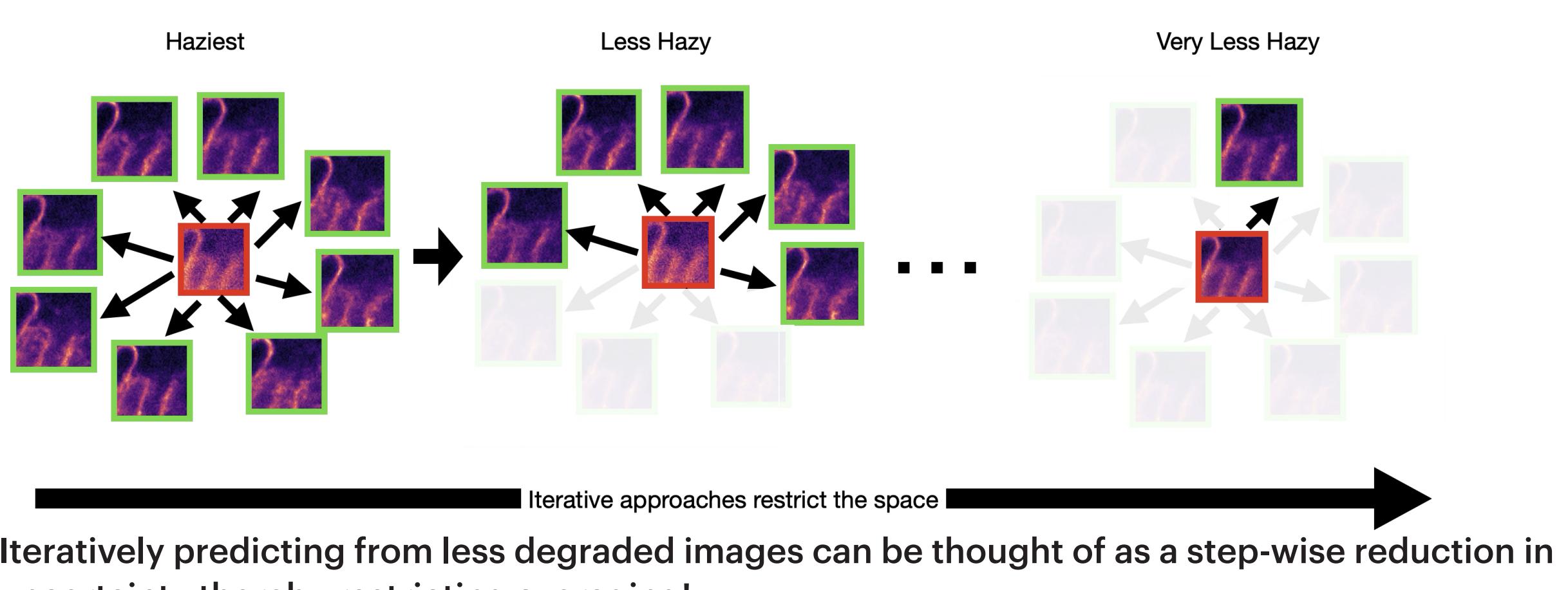
Perception-Distortion Tradeoff



Restricting Averaging

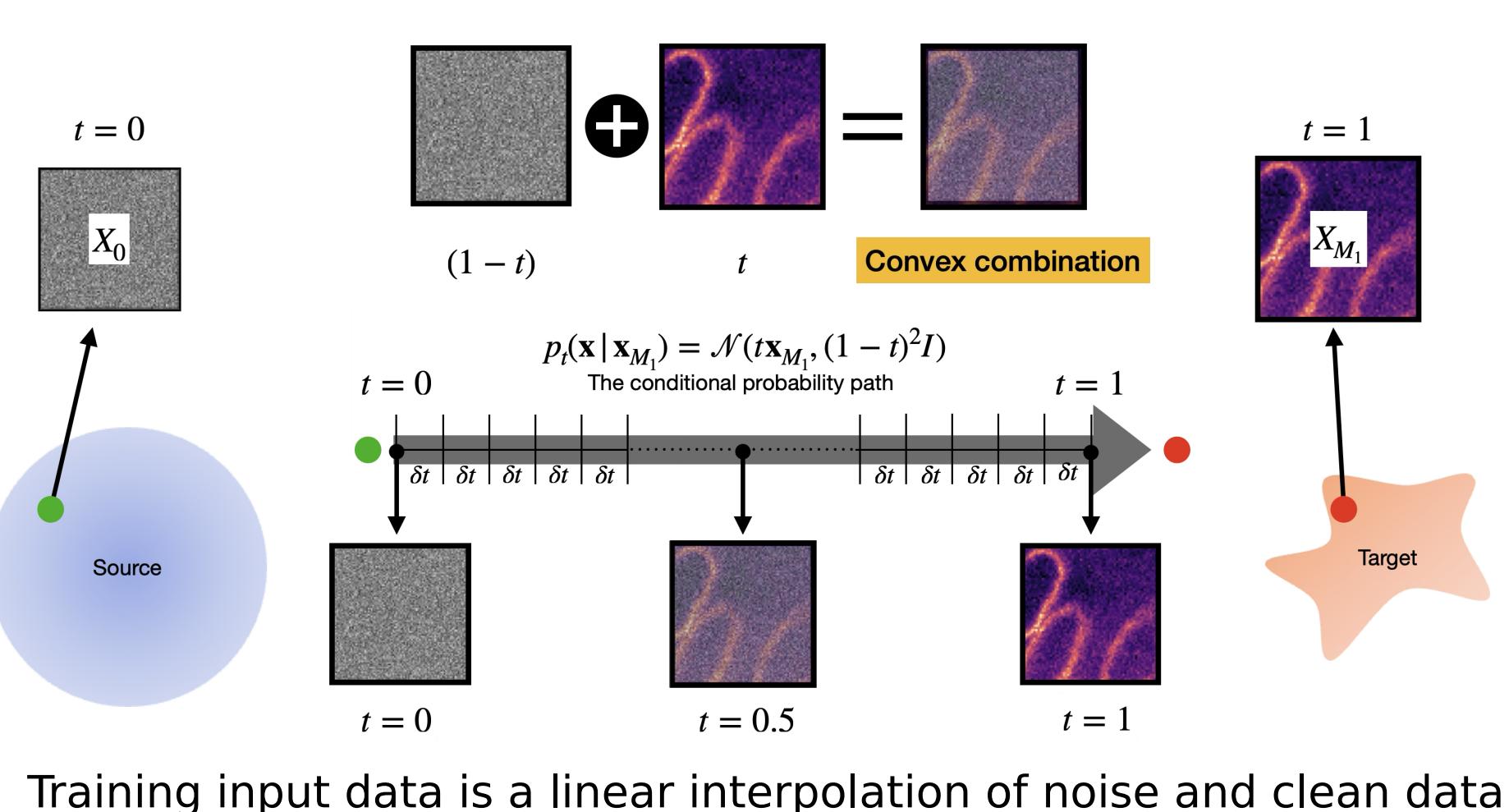


Iterative Prediction reduces averaging effect



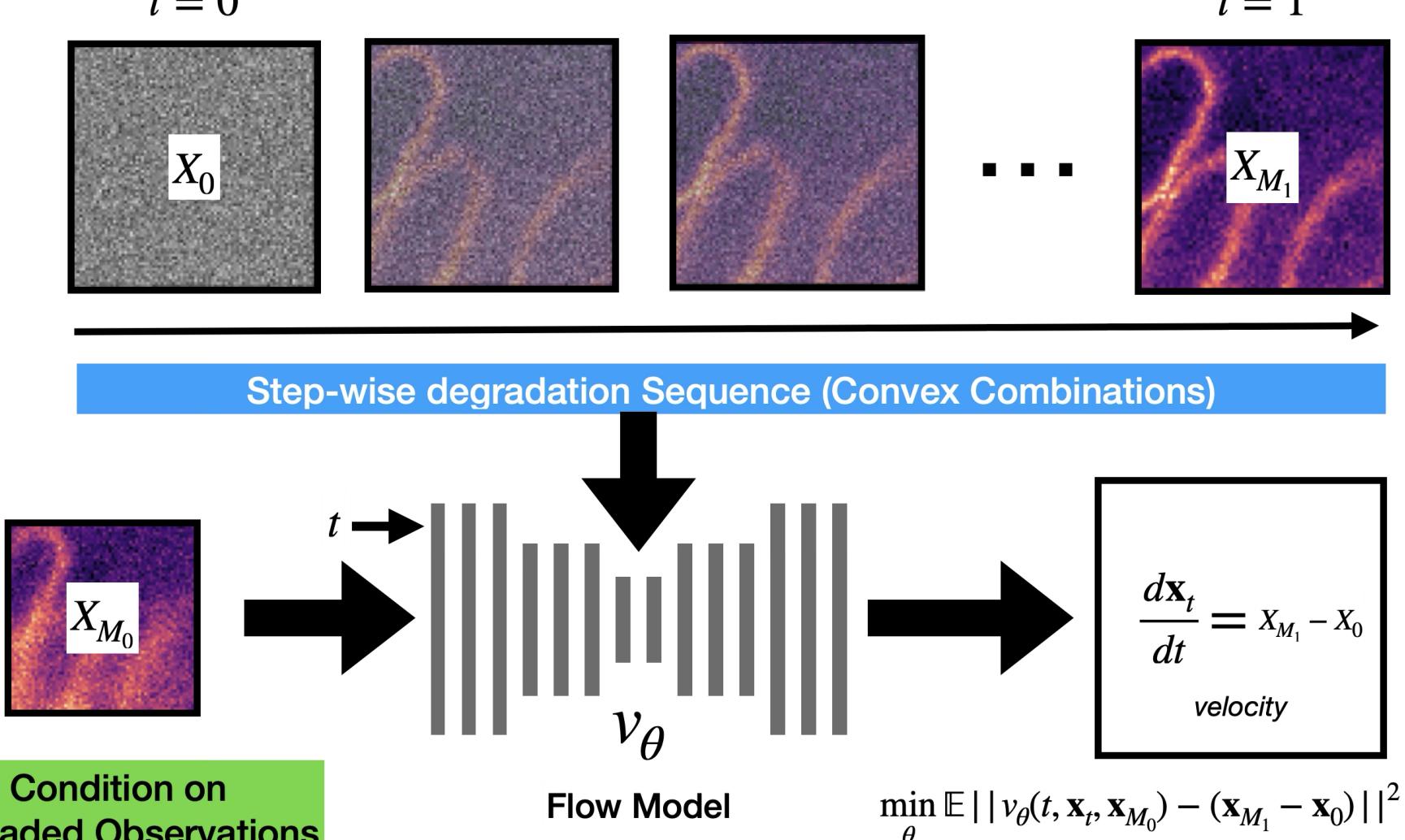
Solution: Guided Conditional Flow Matching — an ODE based iterative restoration approach

Training Data Generation

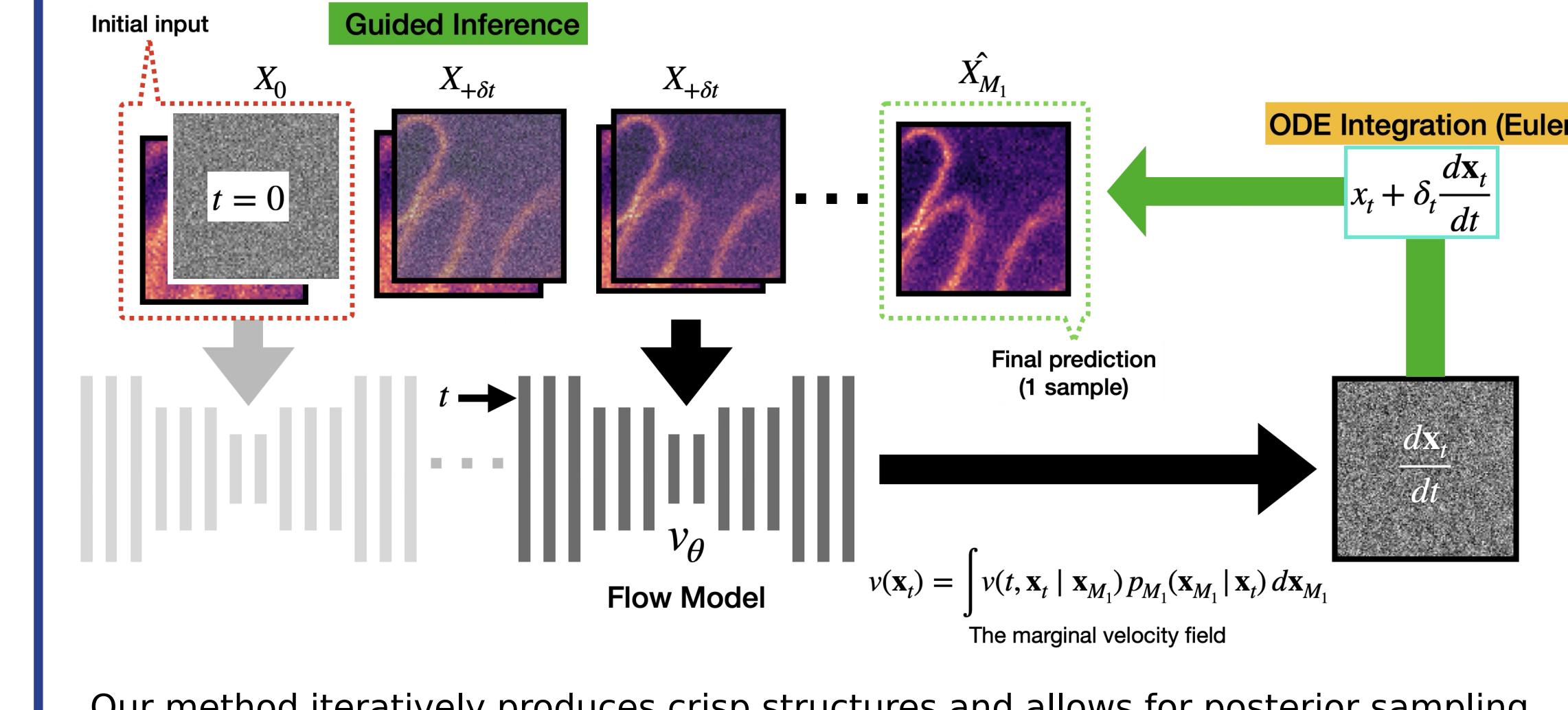


Training input data is a linear interpolation of noise and clean data

Training Scheme



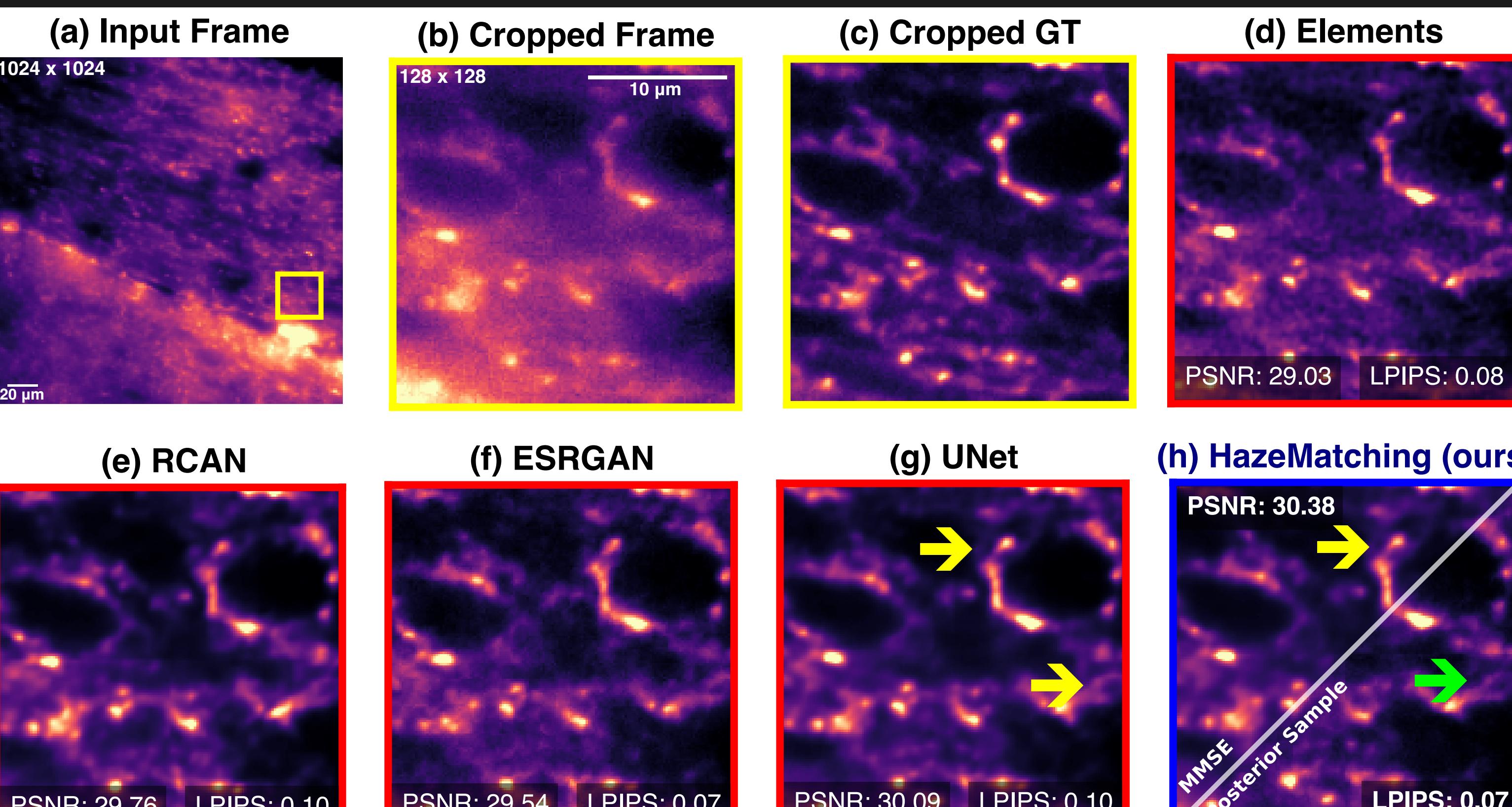
Iterative Inference Scheme



Our method iteratively produces crisp structures and allows for posterior sampling

Application to Widefield Image Dehazing and Computational Super-resolution (CSR)

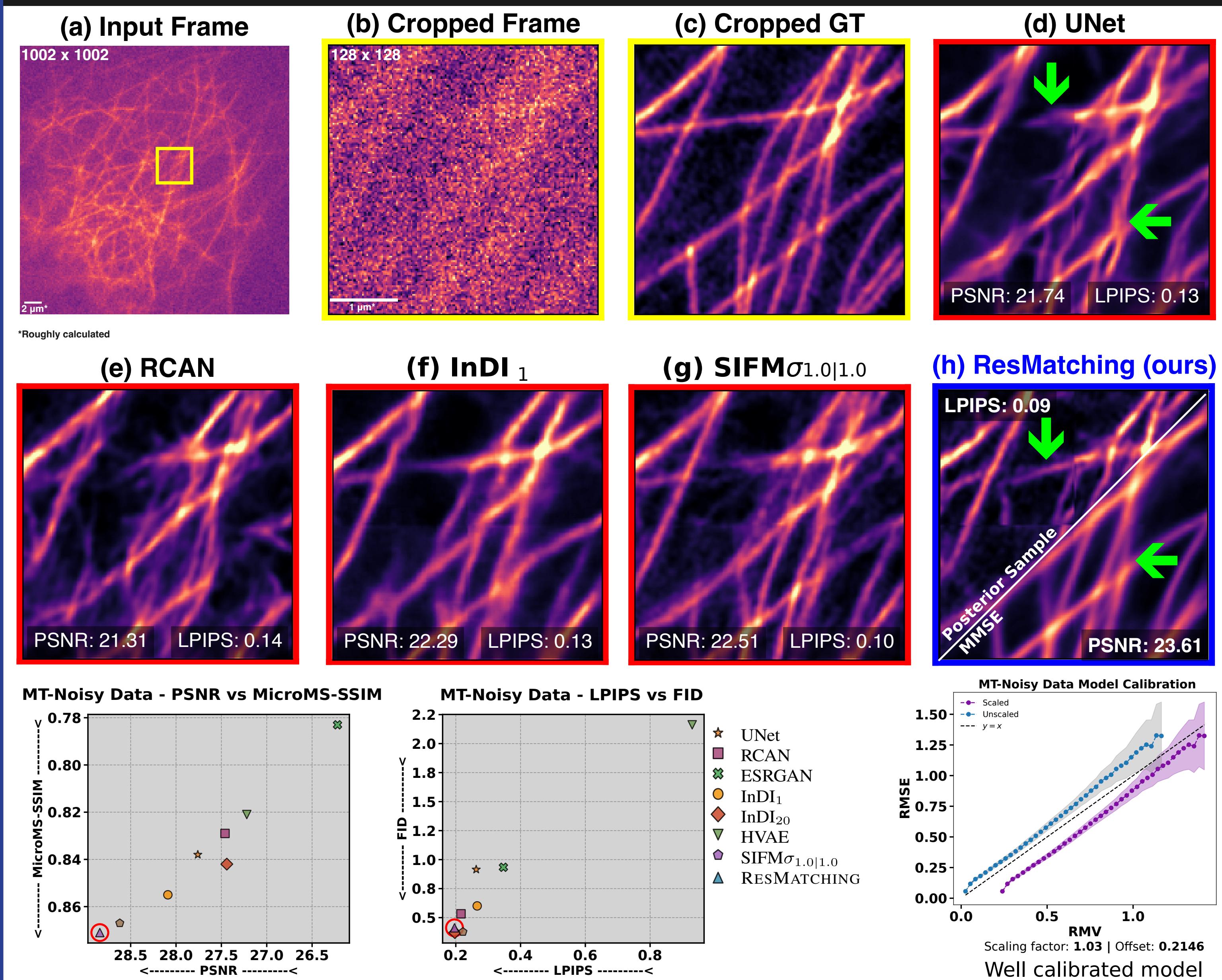
HazeMatching: Widefield Image Dehazing [3]



Results on the Organoids1 dataset: This dataset was acquired using a widefield microscope, with training pairs consisting of images captured with and without the disk.

Evaluating PSNR against LPIPS and FID, HazeMatching finds the "sweet spot" that one-shot baselines miss, maximizing visual quality (of samples) without sacrificing prediction accuracy (in the MMSE).

ResMatching: CSR under extreme noise [4]



Results on the MT-Noisy dataset: The MT-Noisy dataset consists of Microtubule (MT) data from the BioSR dataset [5]. We added additional noise to make the problem more challenging.

Evaluating PSNR and MicroMS-SSIM shows that ResMatching outperforms baselines in fidelity metrics (of the MMSE), while being competitive in the perceptual metrics (of the samples), making ResMatching especially powerful under extreme uncertainty.

Conclusions

- We introduce Guided Conditional Flow Matching, an ODE-based iterative method for ill-posed microscopy image restoration that successfully restricts the averaging space to navigate the perception-distortion tradeoff for clearer dehazing and super-resolution.
- Flow Matching models are especially useful where there is extreme uncertainty in the data such as in the CSR problem.
- This improved visual fidelity comes with the inherent challenge of higher computational costs compared to standard one-shot inference methods. Future work may optimize for throughput.
- Stitching artifacts continues to be a problem and additional method development will be required (a work in progress at JugLab!).

- [1] Delbracio, M. and Milanfar, P. (2023). Inversion by direct iteration: An alternative to denoising diffusion for image restoration. TMLR 2023.
- [2] Blau, Y. and Michaeli, T. (2018). The perception-distortion tradeoff (CVPR 2018)
- [3] Ray, A., Ashesh A., and Jug F. (2026). HazeMatching: Dehazing Light Microscopy Images with Guided Conditional Flow Matching. CVPR 2026 (Findings).
- [4] Ray, A., Galinova, V., and Jug, F. (2025). ResMatching: Noise-Resilient Computational Super-Resolution via Guided Conditional Flow Matching. IEEE ISBI 2026
- [5] Qiao, C. et al. (2021). Evaluation and development of deep neural networks for image super-resolution in optical microscopy," Nature Methods

References