The Impact of a Deep Learning Self-Adaptive Colour Restoration Pipeline for Deep Underwater Images in 3D Reconstruction

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3D Underwater Mapping from Above and Below: Wien July 8-11, 2025

CIPA Heritage Documentation

isprs information from imagery

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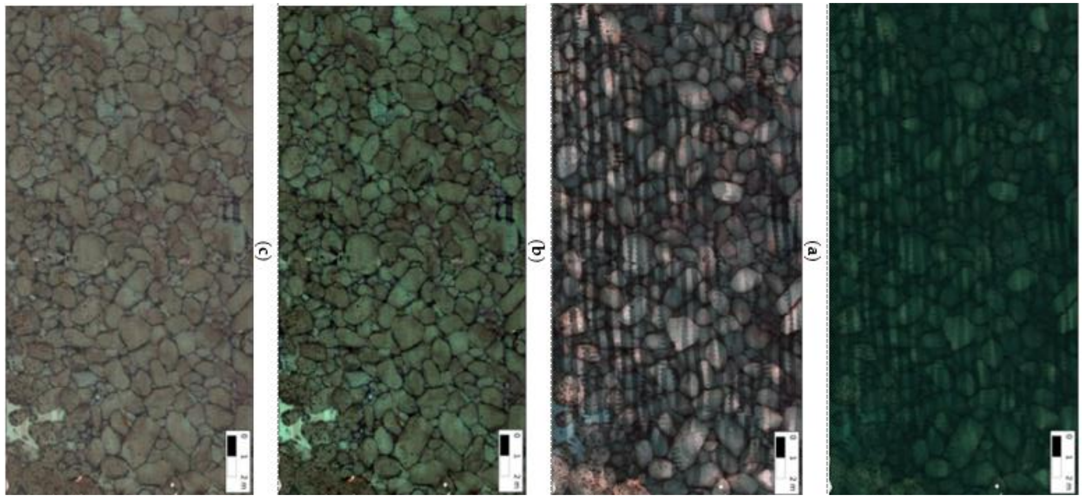

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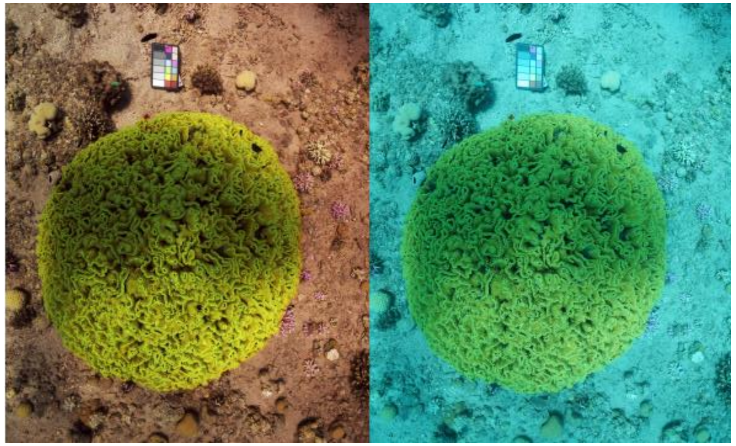

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Motivation

Does Colour Accuracy Matters in Underwater 3D documentation

- Underwater images suffer from blue-green colour casts and poor contrast.
- Light absorption and scattering degrade image quality.
- Does this affect feature matching and 3D reconstruction fidelity?
- In some applications colour is important (biology, environmental monitoring, archaeology, VR, etc)
- Aim: Restore colour before 3D processing to enhance outcomes.

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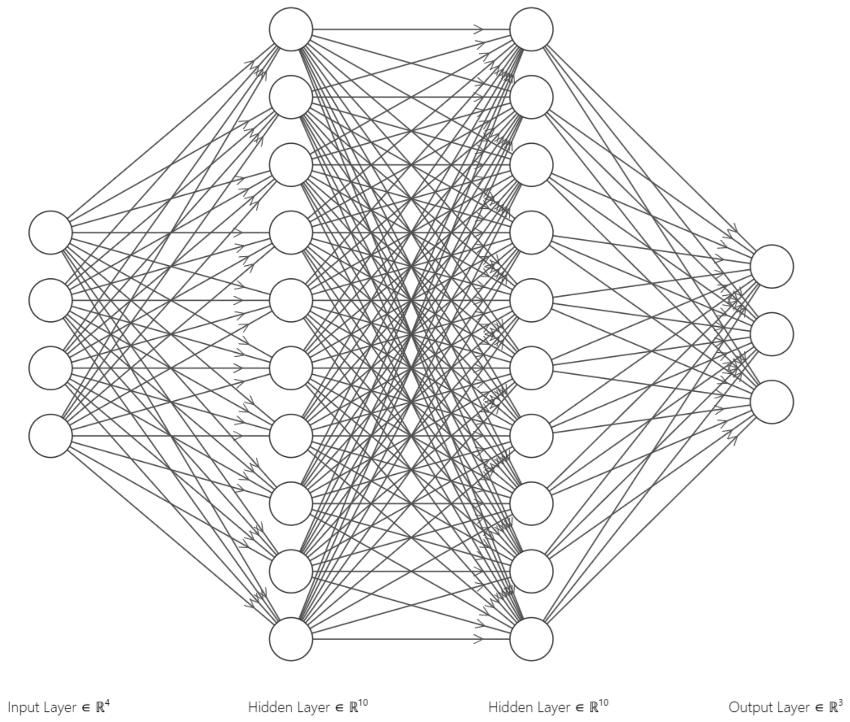
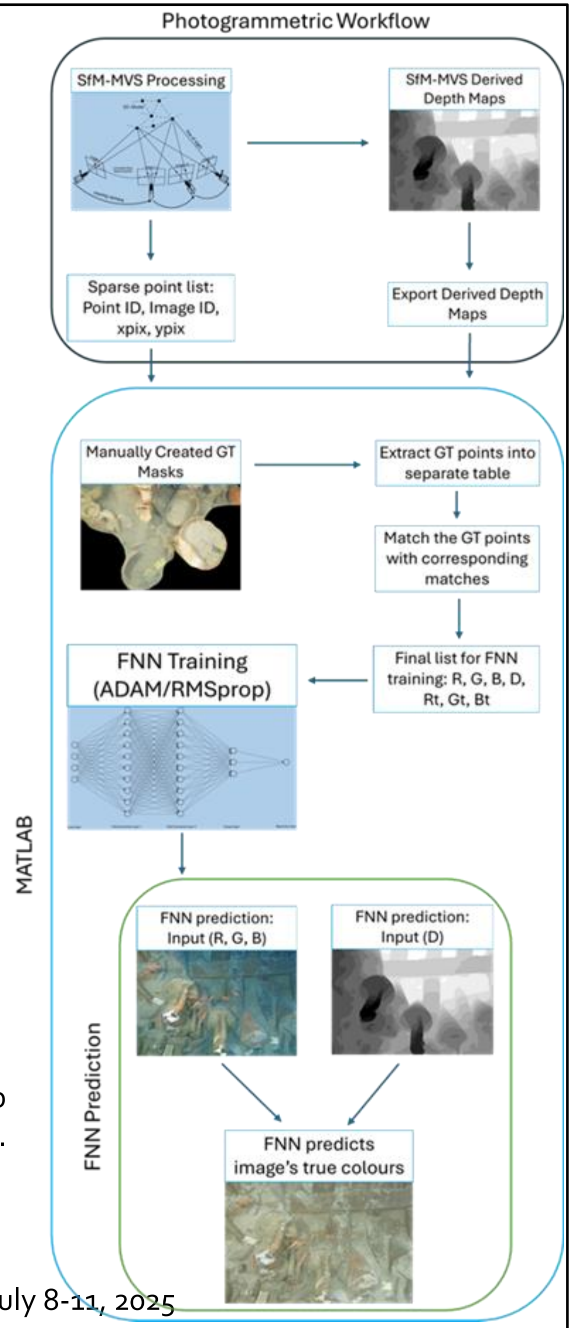
Colour Restoration Pipeline

- Inputs: R, G, B, Camera-to-Object Distance
- Architecture:
  - Input layer (4 neurons)
  - 2 hidden layers (10 ReLU neurons each)
  - Output: Rtrue, Gtrue, Btrue
- Optimized using Adam optimizer
- Code implementation: MATLAB

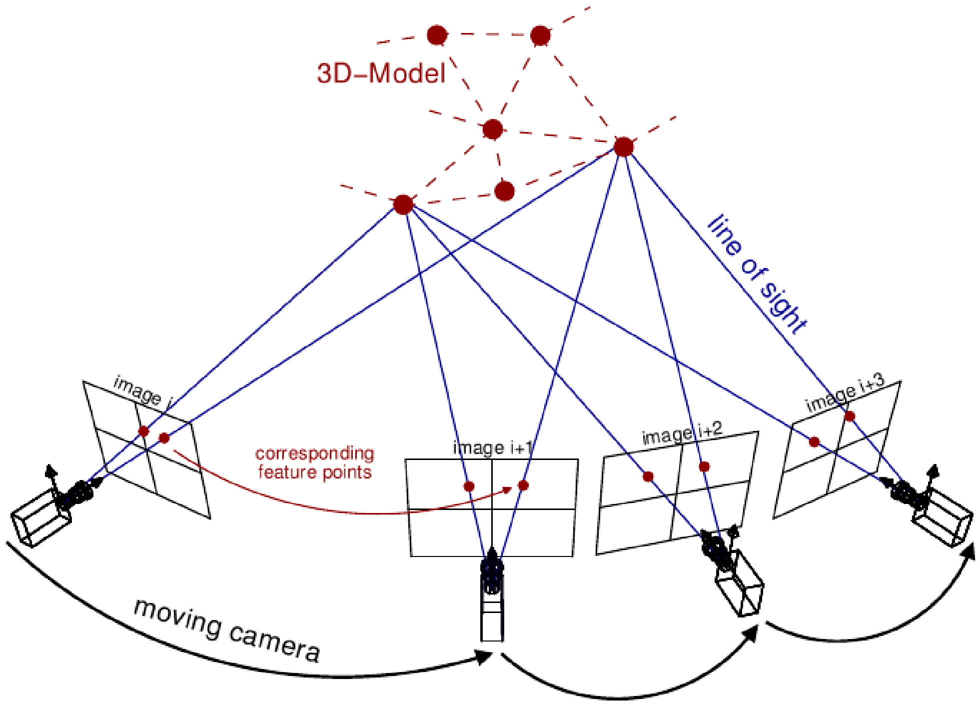


Vlachos, M., & Skarlatos, D. (2024). Self-Adaptive Colour Calibration of Deep Underwater Images Using FNN and SfM-MVS-Generated Depth Maps. Remote Sensing, 16(7), 1279. https://doi.org/10.3390/rs16071279



Objectives

- New approach: Use the SfM process to correlate colour absorption to camera-to-object distance [*]
- Evaluate the Self-Adaptive Colour Restoration Pipeline [*]
- Use of a Feedforward Neural Network (FNN) trained on image colour-distance input
- Assess performance in regards to:
  - Image Feature Matching (SIFT/SURF)
  - Sparse SfM Reconstruction
  - Dense Point Cloud Accuracy

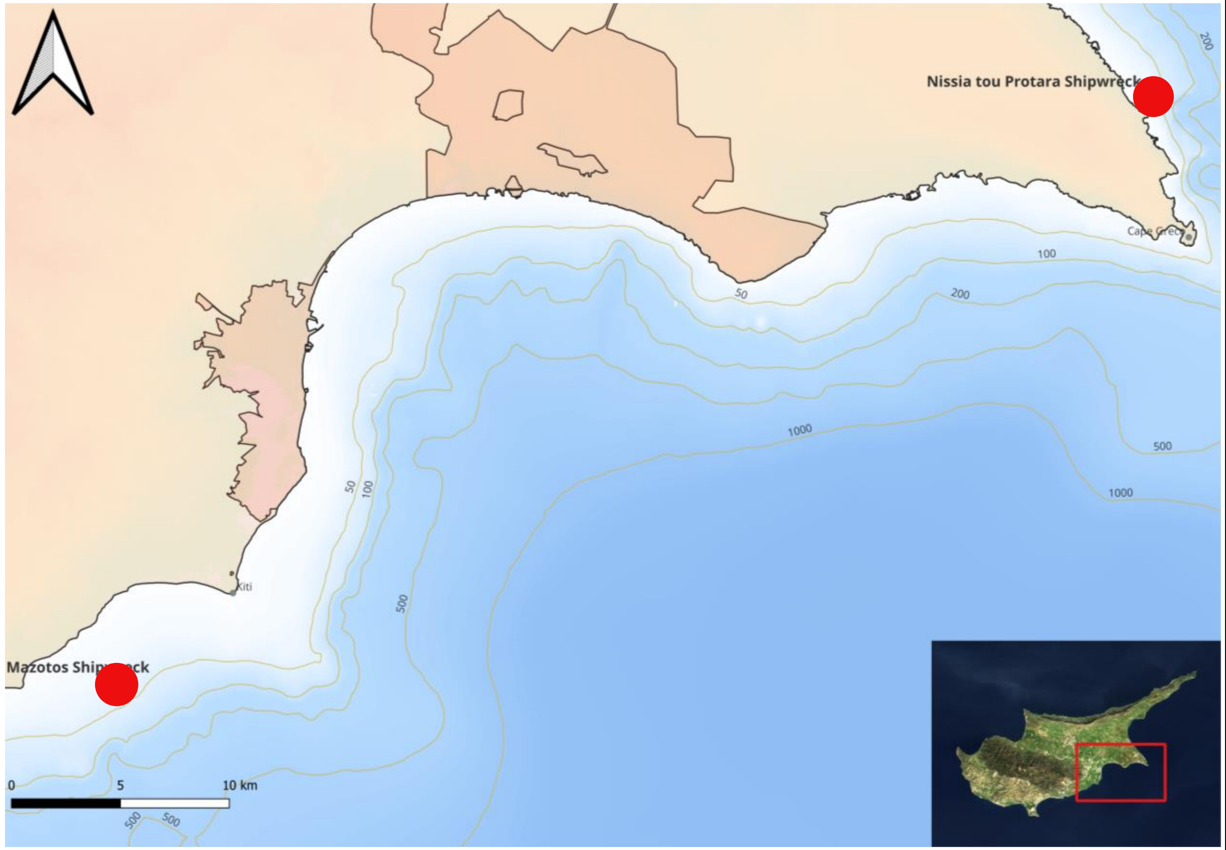


Structure from Motion (SfM) photogrammetric principle. Source: http://www.theia-sfm.org

[*]Vlachos, M., & Skarlatos, D. (2024). Self-Adaptive Colour Calibration of Deep Underwater Images Using FNN and SfM-MVS-Generated Depth Maps. Remote Sensing, 16(7), 1279. https://doi.org/10.3390/rs16071279

Underwater Sites & Data Collection

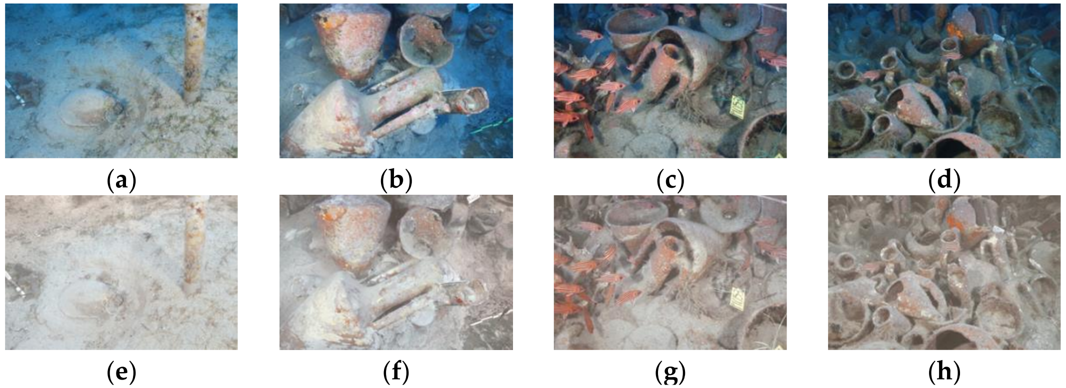
- Mazotos Shipwreck (45m depth)
  - Canon EOS 7D (2018)
  - Sony SLT-A57 (2019)
- Nissia Shipwreck (28m depth)
  - Nikon D610 (2024)
- Campaigns span from 2018 to 2024, offering temporal and spatial variability
- All cameras used strobes
- Sites present different turbidity, depth, and environmental challenges
- Data supports testing robustness across various equipment and conditions



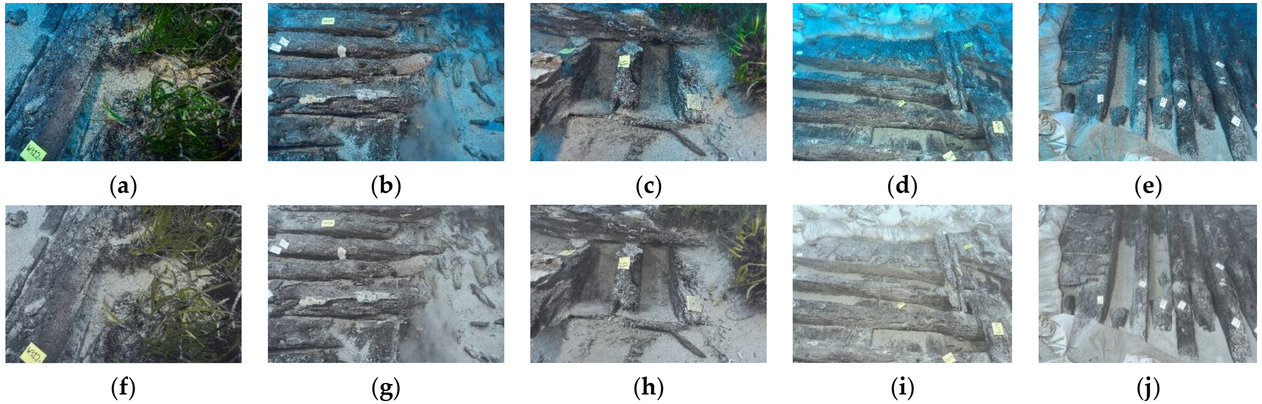
Approximate locations of Mazotos and Nissia shipwreck sites.

Colour Restoration Pipeline

- Inputs: R, G, B, Camera-to-Object Distance
- Canon EOS 7D (2018) & Sony SLT-A57 (2019)
- Architecture:
  - Input layer (4 neurons)
  - 2 hidden layers (10 ReLU neurons each)
  - Output: Rtrue, Gtrue, Btrue
- Optimized using Adam
- Code implementation: MATLAB



Training results on 4 images with Adam optimizer ((a–d) Original images, (e–h) Adam optimizer-based prediction results). Dataset A, Camera: Canon EOS 7D. Images acquired at the Mazotos shipwreck site. Credits: MARELab, © University of Cyprus. Photographer: Andreas C. Kritiotis.



Training results on 5 images with Adam optimizer ((a–e) Original images, (f–j) Adam optimizer-based prediction results). Dataset C Camera: Nikon D610. Images acquired at the Nissia shipwreck site. Credits: MARELab, © University of Cyprus. Photographer: Andonis Neophytou.

Effect on image pair Feature Matching (SIFT & SURF)

Nine selected pairs (three from each site), Brute force matching, RANSAC filtering, MATLAB implementation:

- Majority of image pairs showed improvement:
  - Up to 26% gain with SIFT
  - Up to 24% gain with SURF
- 7 out of 9 image pairs improved for both algorithms
- SIFT more sensitive to colour contrast and gradient improvements
- SURF showed smaller but consistent gains
- Performance drops in a few cases, likely due to overcorrection or texture loss
- Fuzzy results, do not support a definitive gain

Image Pairs	SURF			SIFT		
	# of valid matches original	# of valid matches colour corrected	% improve ment	# of valid matches original	# of valid matches colour corrected	% improve ment
P_A1	15	17	13%	430	467	9%
P_A2	224	277	24%	1957	2086	7%
P_A3	54	47	-13%	150	134	-11%
P_B1	91	97	7%	673	754	12%
P_B2	128	140	9%	766	966	26%
P_B3	719	746	4%	324	378	17%
P_C1	11697	13008	11%	18025	20350	13%
P_C2	1426	1512	6%	4493	5262	17%
P_C3	8321	8196	-2%	15197	13602	-10%

Sparse SfM Point Cloud Evaluation

SfM in Agisoft Metashape v2.0.2, high accuracy, ≥3 images matches, common reconstruction uncertainty and projection accuracy filters:

- Mazotos 2018: +8% SfM points
- Mazotos 2019: -9%
- Nissia 2024: -5%
- Declines is not correlated to gross errors
- Gains aligned with improved feature matching in Dataset A
- Fuzzy results, do not support a definitive gain

Dense Cloud		# of SfM points	% gain / loss
Dataset A (Mazotos 2018)	Original	61.0K	8%
	FNN	66.2K	
Dataset B (Mazotos 2019)	Original	13.8K	-9%
	FNN	12.6K	
Dataset C (Nissia 2024)	Original	46.7K	-5%
	FNN	44.4K	

Dense Point Cloud Evaluation

Consistent alignment and calibration parameters ensured fair evaluation

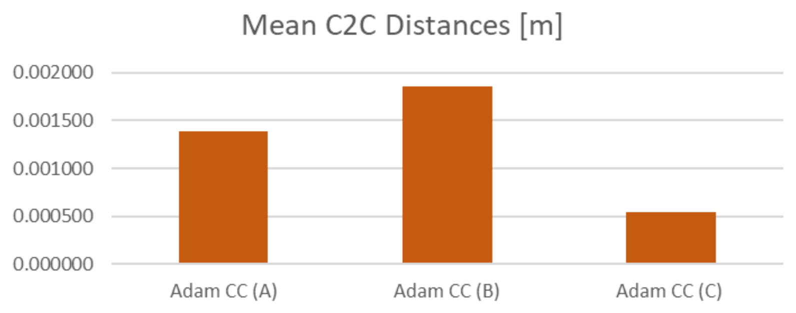
CloudCompare used for dense point comparisons:

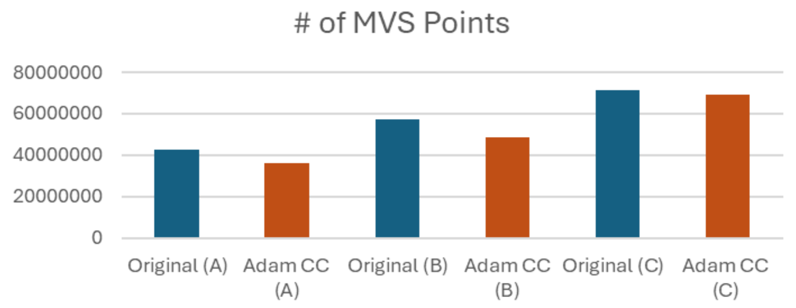
- (-) Slight increase in roughness observed across all datasets (e.g., +0.01 mm)
- (-) Lower total MVS point counts in corrected datasets (up to -15%)
- Nissia 2024 had the smallest geometric deviation (Mean C2C = 0.544 mm)
- (-) Surface density declined slightly in most corrected models
- (+) Minor deviations indicate preserved geometric structure, despite point reduction
- Fuzzy results, do not support a definitive gain

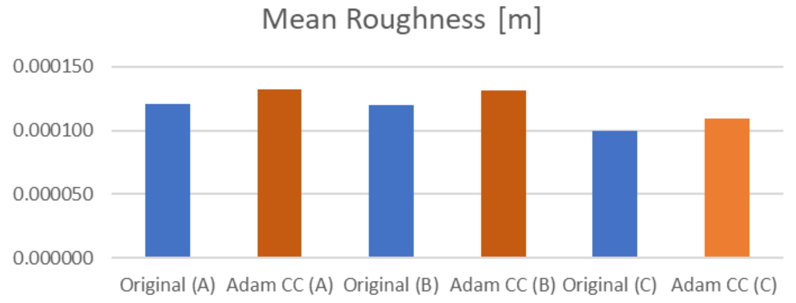
Dense Cloud		Mean C2C Abs Dist. (mm)	Mean Roughness (mm)	Mean Density	# of MVS Points
Dataset A (Mazotos 2018)	Original	----	0.12	5.7M	42.6M
	FNN	1.39	0.13	5.4M	36.3M
Dataset B (Mazotos 2019)	Original	----	0.12	2.3M	57.2M
	FNN	1.86	0.13	2.2M	48.6M
Dataset C (Nissia 2024)	Original	----	0.10	2.0M	71.3M
	FNN	0.54	0.11	2.0M	69.4M

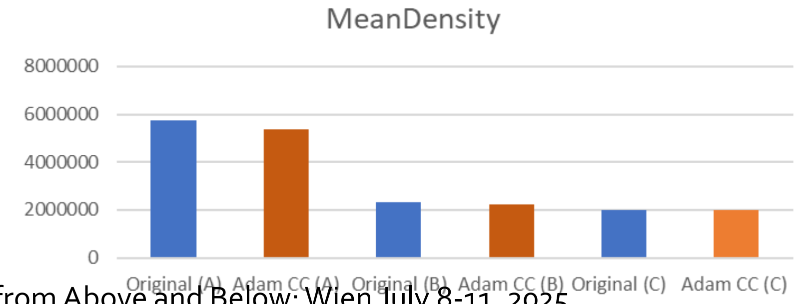
Key Findings

- Visual clarity and colour fidelity improved significantly, although this is subjective
- Overall, feature matching is enhanced, especially with SIFT descriptors
- Sparse and dense reconstruction results were unresolved
  - Improvement in some cases, declines in others
- Neural network correction improved perception, but not always geometry
- Best suited for interpretation, visualization, and documentation
- **Original data captured, are indispensable**









Future Work & Acknowledgements

- Investigate effects on semantic segmentation and object recognition in underwater imagery
- Future development: hybrid models combining physics-based and learning-based methods for colour restoration
- Extend testing to more environments and imaging setups (e.g., deeper sites, low-light)

Acknowledgements:

- MARELab, University of Cyprus
- Photographers: Dr. Massimiliano Secci, Andreas Kritiotis, Andonis Neophytou

- **Questions?**

THANK YOU