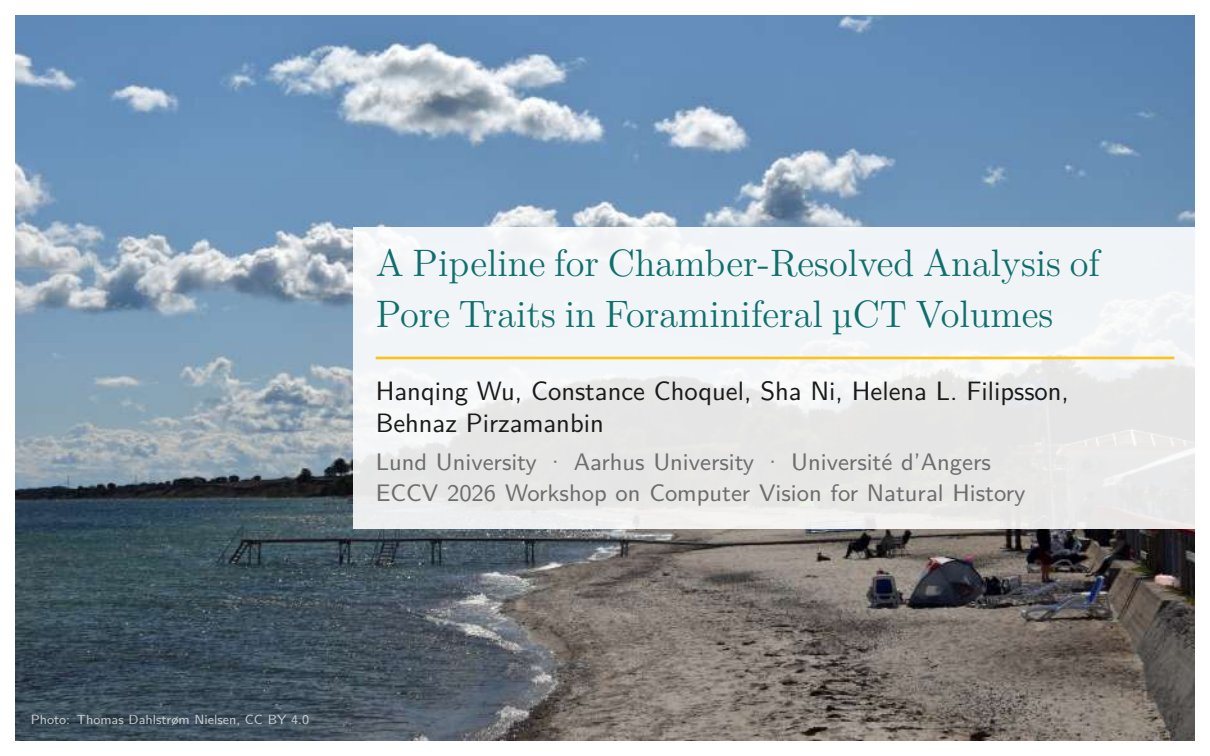




A Pipeline for Chamber-Resolved Analysis of Pore Traits in Foraminiferal μ CT Volumes

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Pore traits can record palaeoenvironmental change

- Foraminiferal shell morphology, which includes pore traits (pore number, size, density and porosity) and shell thickness, can reflect physiological responses to the environmental conditions under which the organism calcified¹.
- Morphological characteristics of foraminifera are increasingly being investigated as complementary proxies for bottom-water oxygenation, carbonate chemistry, and ecological stress.
- 3D μ CT measures the whole shell, across which pore patterns and shell thickness can vary. Conventional 2D measurements can miss that variation².

¹Richirt et al. (2019); Fox et al. (2020); Glock et al. (2022); Hoogakker et al. (2025)

²Choquel et al. (2023); Ni et al. (2025)

A gap remains in chamber-resolved pore analysis

- Foraminiferal shells exhibit complex 3D morphologies, yet segmentation in foraminiferal studies has historically relied on manual or semi-manual methods that do not scale to large datasets³.
- Even in recent work, pores are generally quantified at the specimen level, and the few studies⁴ that segment chambers do not associate them with their constituent pores.
- Deep learning, and specifically the U-Net architecture, is well established for segmentation of complex images, particularly in medical settings⁵.
- No previous work assigns pores to individual chambers, so chamber-resolved pore traits have never been measured.

³Kellner et al. (2019)

⁴Lin et al. (2025); Trend et al. (2026)

⁵Siddique et al. (2021); Zhou et al. (2021); Neha et al. (2025); Laprade et al. (2025)

Dataset and annotation interface

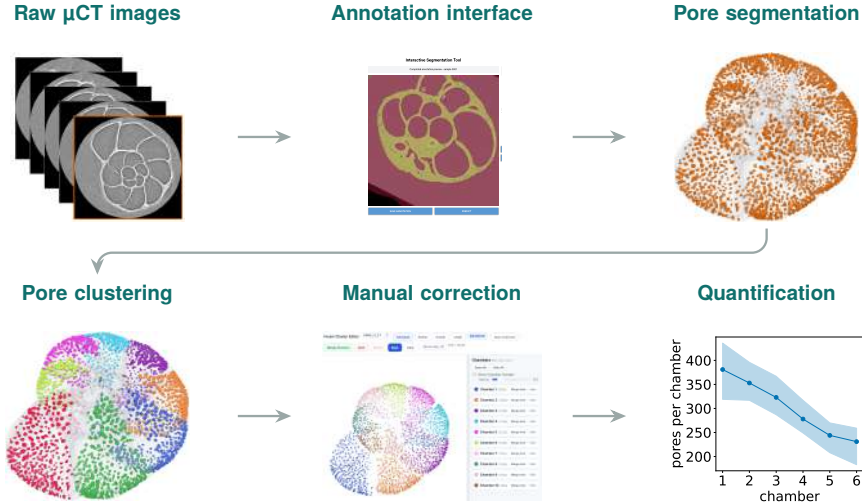
- We analyzed a dataset comprising 122 Synchrotron Radiation X-ray micro-computed tomography (SR μ CT) volumes of *Elphidium clavatum* specimens from the Mommarm site in southern Denmark.
- The raw projection data were reconstructed into 3D image volumes for subsequent analysis.
- We generated annotations using an adapted browser-based annotation tool⁶. 20 specimens were randomly selected, and 211 slices were annotated, of which 171 were used for model training and 40 were reserved for validation and model selection.

Severe class imbalance

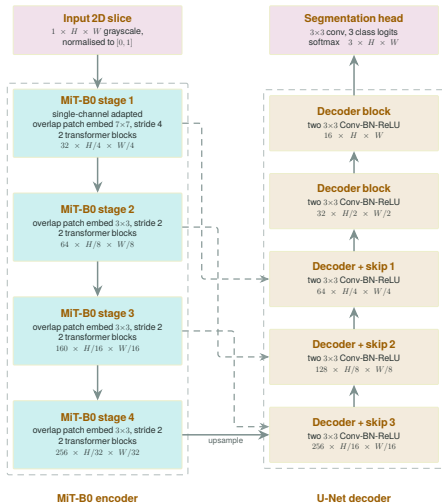
Among 211 slices, only 0.61% of the pixels are annotated as pores.

⁶Laprade et al. (2025); Laprade (2026)

An overview of the chamber-resolved analysis of pore traits



Multi-planar U-Net for voxel classification



We adopt a multi-planar 2D U-Net architecture with an MiT-B0 encoder pretrained on ImageNet.

To address the extreme class imbalance, we use the Tversky loss:

$$TI_c = \frac{TP_c}{TP_c + \alpha_c FP_c + \beta_c FN_c}.$$

$$\mathcal{L} = 1 - \frac{1}{|C|} \sum_{c \in C} TI_c$$

where TP_c , FP_c and FN_c are soft counts over voxels. For pores we set $\alpha_c = 0.3$, $\beta_c = 0.7$ to penalize false negatives more.

The final predictions are generated via a 12-view test-time augmentation.

From pores to chambers

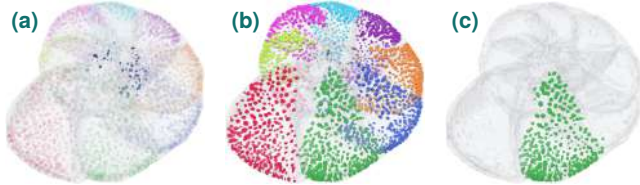
- A statistical clustering method is a promising route to achieve a chamber-resolved pore assignment in an unsupervised manner.
- Each pore object was represented by its centroid for scalability while retaining spatial location.
- To untangle the 3D geometry of foraminiferal shells, we embedded the pore centroids into a 2D space using t-SNE⁷ for the downstream clustering task.
- 2D-embedded pore centroids were grouped into putative chamber groups via HDBSCAN⁸, which accommodates local variation in cluster density.

⁷van der Maaten and Hinton (2008)

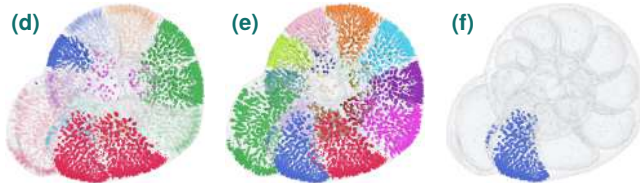
⁸Campello et al. (2013)

Clustering results and the manual correction interface

Little correction needed 1.6 % of pore volume reassigned

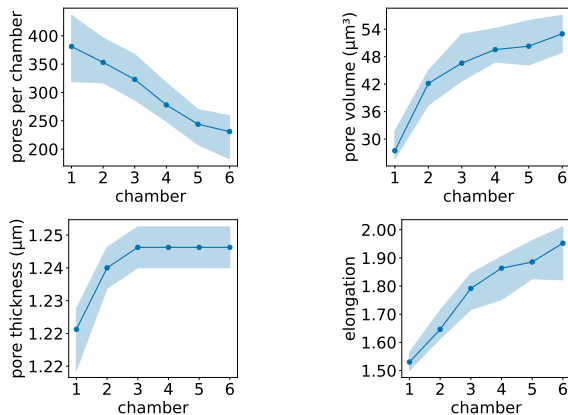


Adjacent chambers merged 47% reassigned



Panels (a,d) show automated assignments, (b,e) corrected assignments, and (c,f) isolated penultimate chambers. Colors denote chamber labels ranked by pore count within each specimen and are not comparable between rows.

Quantification: a gradient across the final whorl



(a) Pore count · (b) mean pore volume · (c) pore thickness · (d) elongation; medians with bootstrap 95% CIs. Pore count decreases while pore volume and elongation increase toward older chambers. Pore thickness varies only weakly and lies near the scan resolution.

Conclusions

In this work, we propose a semi-automated pipeline that provides a chamber-resolved analysis of foraminiferal pore traits. It

- enables chamber-resolved measurements that are not available from conventional 2D analyses or whole-shell summaries.
- provides a practical basis for linking pore morphology to environmental conditions, and extends readily to other taxa and datasets.

Thank you for listening



Paper



Code & pipeline



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