Understanding Complex Dynamic Response Through New Diagnostic and Analysis Methods

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DyCoMaX

STREAMLINE

ESRF-EBS
Extremely Brilliant Source

ACO-CHOCOLAS
Matériaux sous
Hautes Vitesses de Déformation
Groupe de recherche cnrs

"Complex Dynamic Response" is all the messy and complicated physics we don't have great models for (yet)

- Standards in the field show where our strengths lie:
  - Al, Cu, Ta
- Easy to
  - Machine
  - Measure/characterize
  - describe with conservation equations and bulk variables

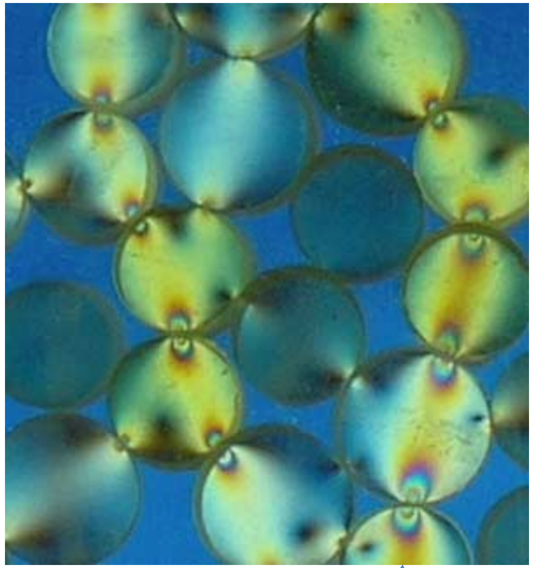
- Contrast: all the fun, cool stuff we don't understand
  - Chemistry, Kinetics, Temp.
  - Heterogeneous materials
    - Grains, additive manufacture
  - Strength, shear, failure
- Probing these topics means we need inside knowledge

Most models are built around idealized, bulk materials. Most materials are not ideal. Beam lines are great tools for improving our understanding!

Granular systems are a special case of heterogeneous media

Allende
Britannica.com

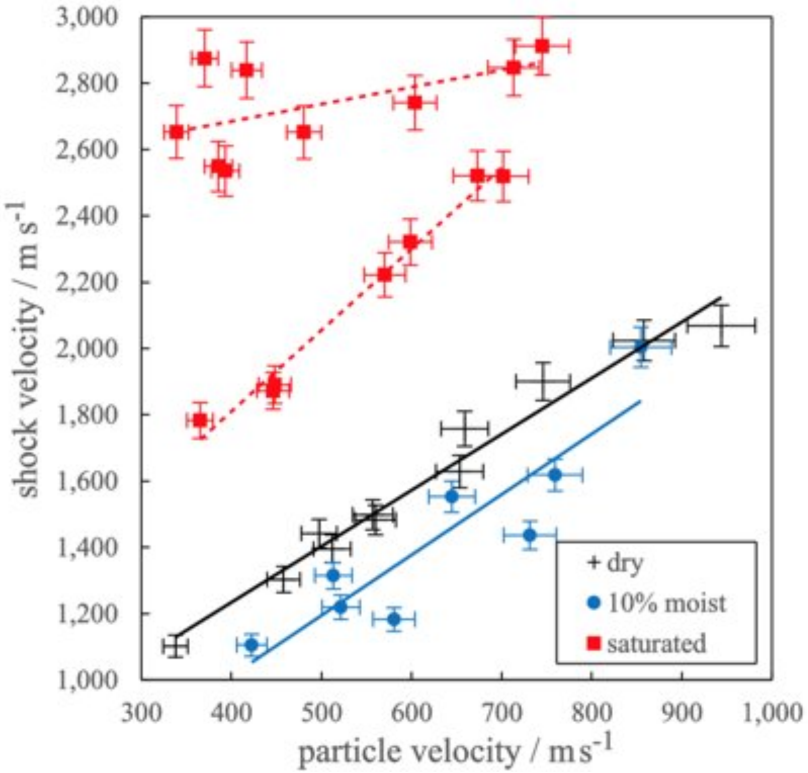
- Metamaterials
  - Additive manufacturing
- Foams
- Aggregates
  - concrete, raisin bran, most rocks
- Fibers
  - Felts, fiberglass, woven materials



Force chain, shown in plastic disks Behringer et al

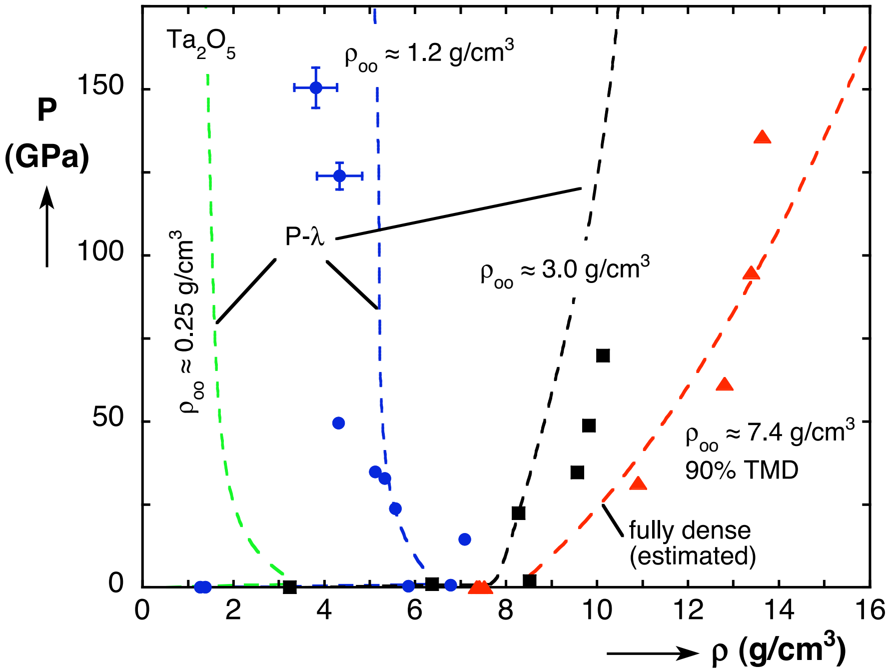
Knowledge of bulk material does not mean we can predict its discontinuous forms' response

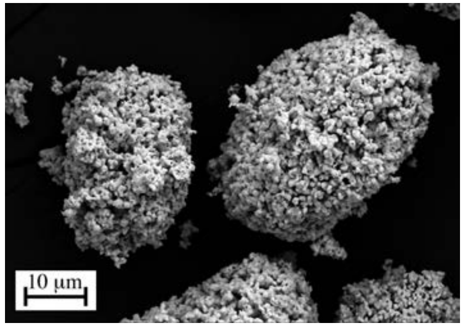
Granular response is complex; current models are inadequate

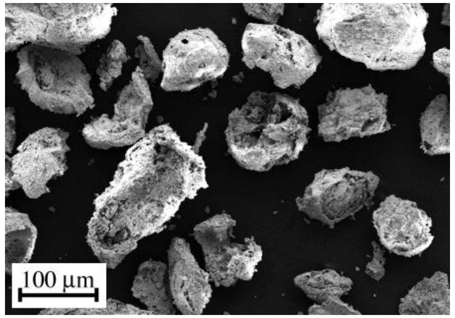


Small changes in initial properties lead to large changes in response

Perry et al, 2015







Ta_2O_5 Hugoniots of different initial density with best P-λ **fits.**

Vogler et al., SAND2011-6770

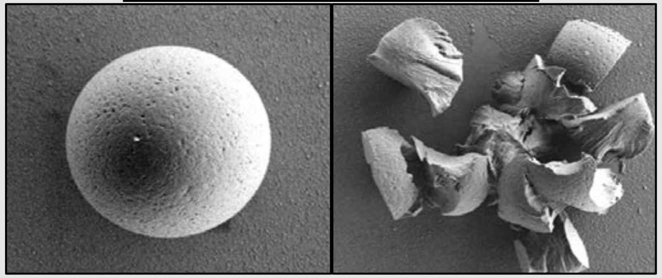
Grain scale data are missing, and we need them to advance predictive ability.

Key questions about heterogeneous materials remain

Grain Properties

Grain Arrangement

Grain Dynamics

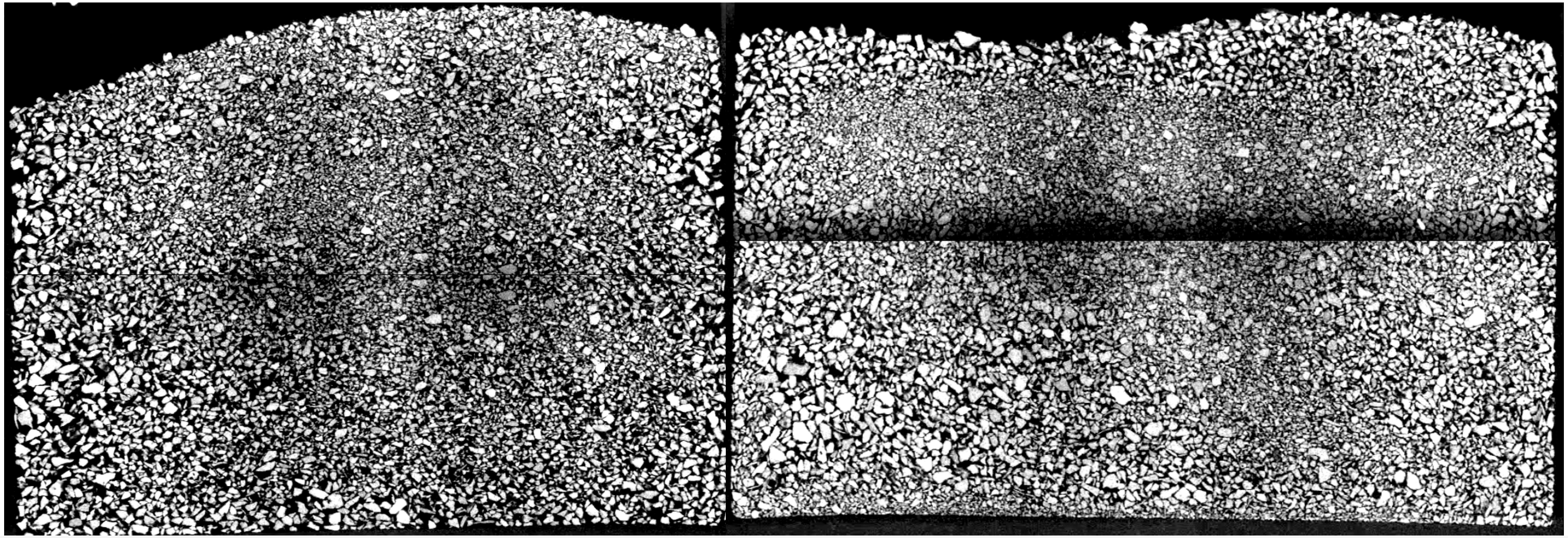


- Scatter sources?
- When are data good/trusted enough?
- What’s going on inside?
- Can we avoid measuring every single form?

We need data to build internal micromechanical models to combine with bulk material models

Vertical and radial packing variation violate assumptions made in bulk measurements

- Not uniform
- How thick is a boundary? How big does a sample need to be to not be dominated by boundary effects?
- If the sample is small enough, it will be all boundary and more uniform. Is this preferable? Sometimes…



GSECARS computed tomography

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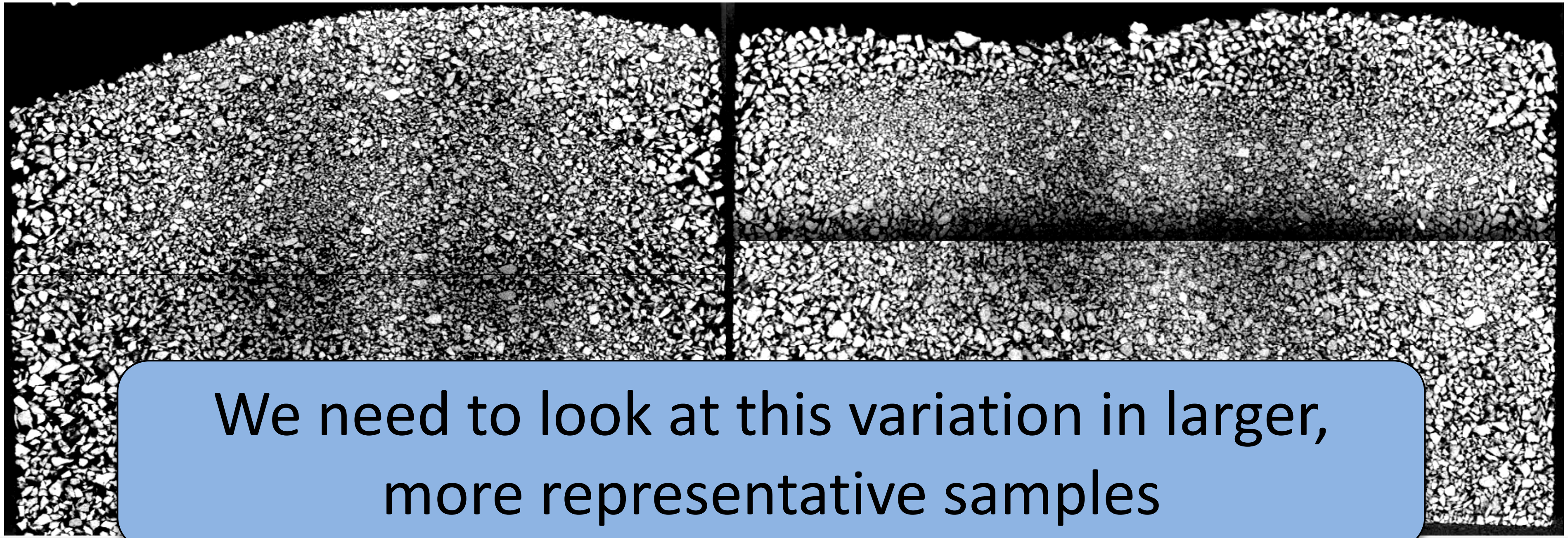
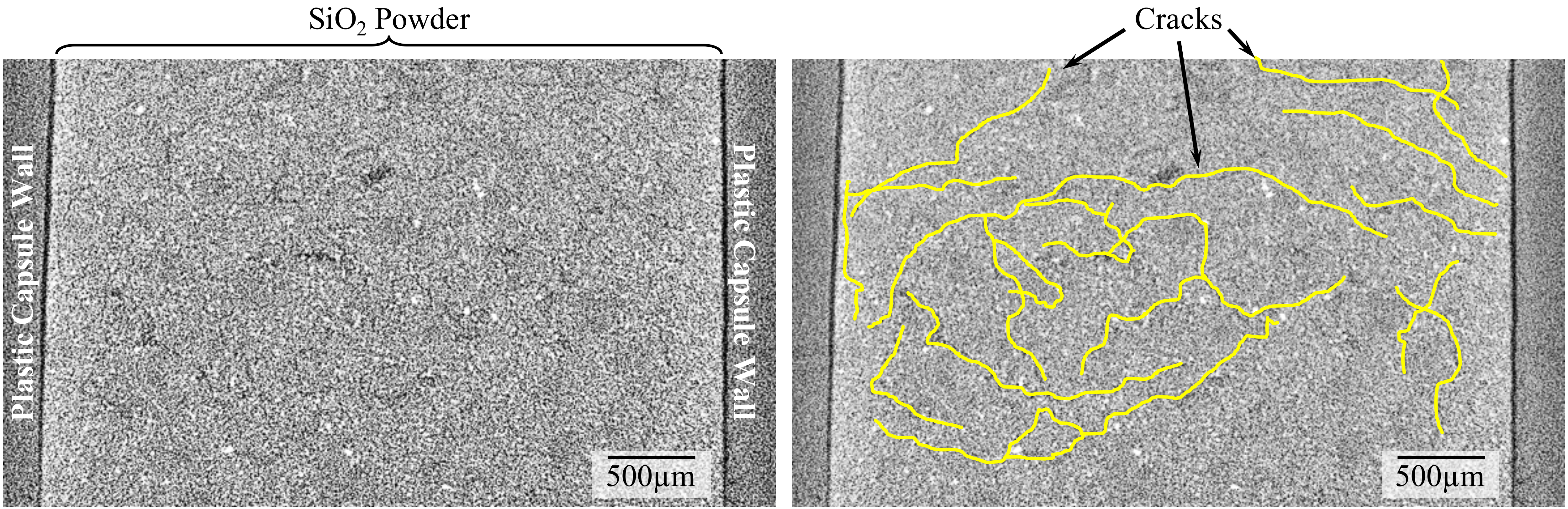


We need to look at this variation in larger, more representative samples

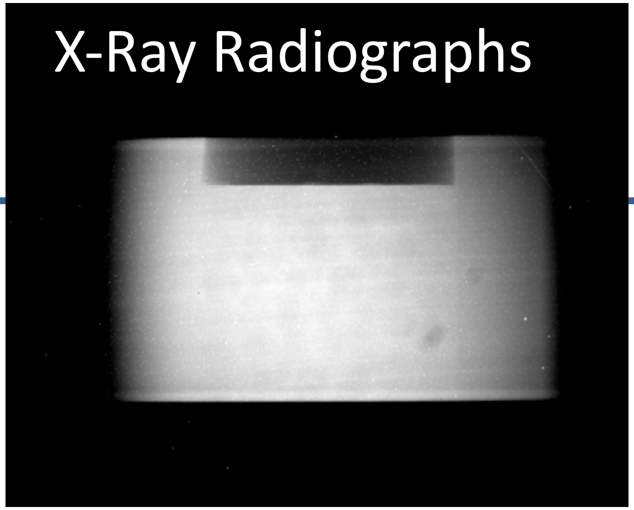
GSECARS computed tomography

Larger samples also show lots of variation. We need to determine how much packing variation is present

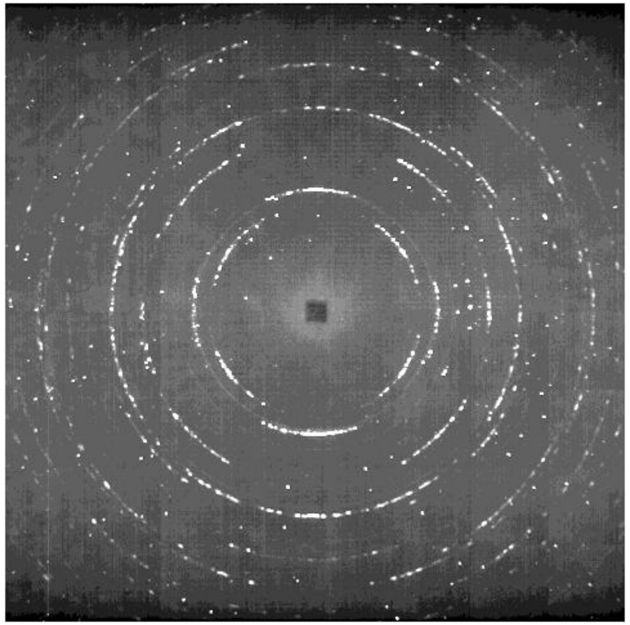


In this measurement, crack volume can be up to 7%

Combined Topology and Stress Analysis gives a rich data set

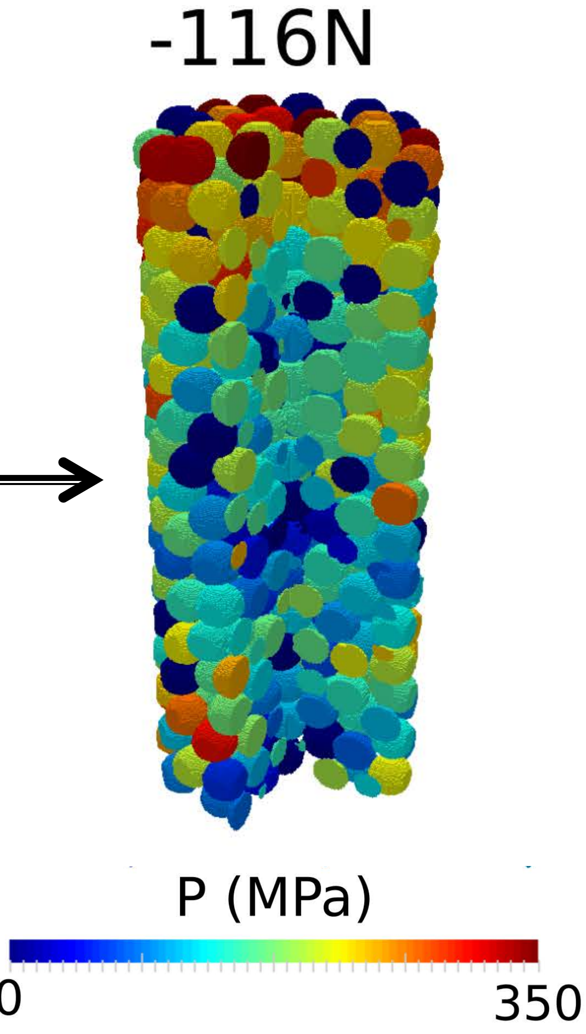


Far Field Diffraction Data

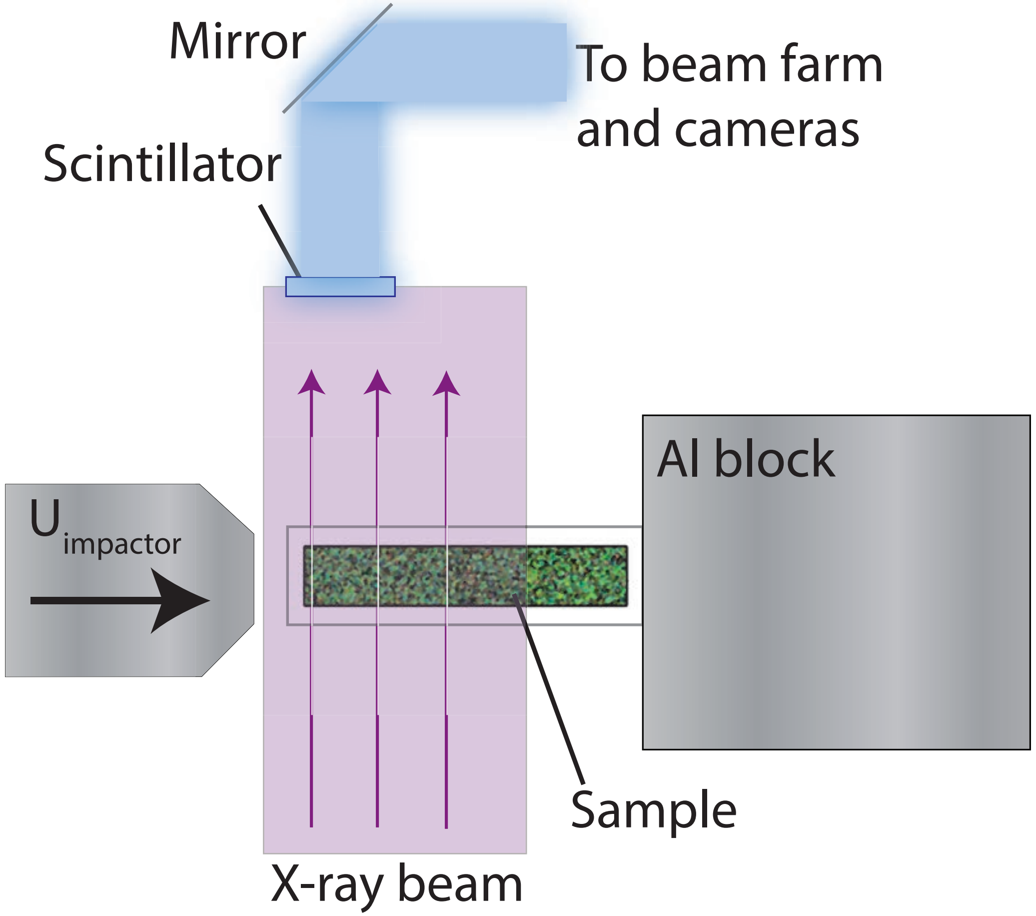


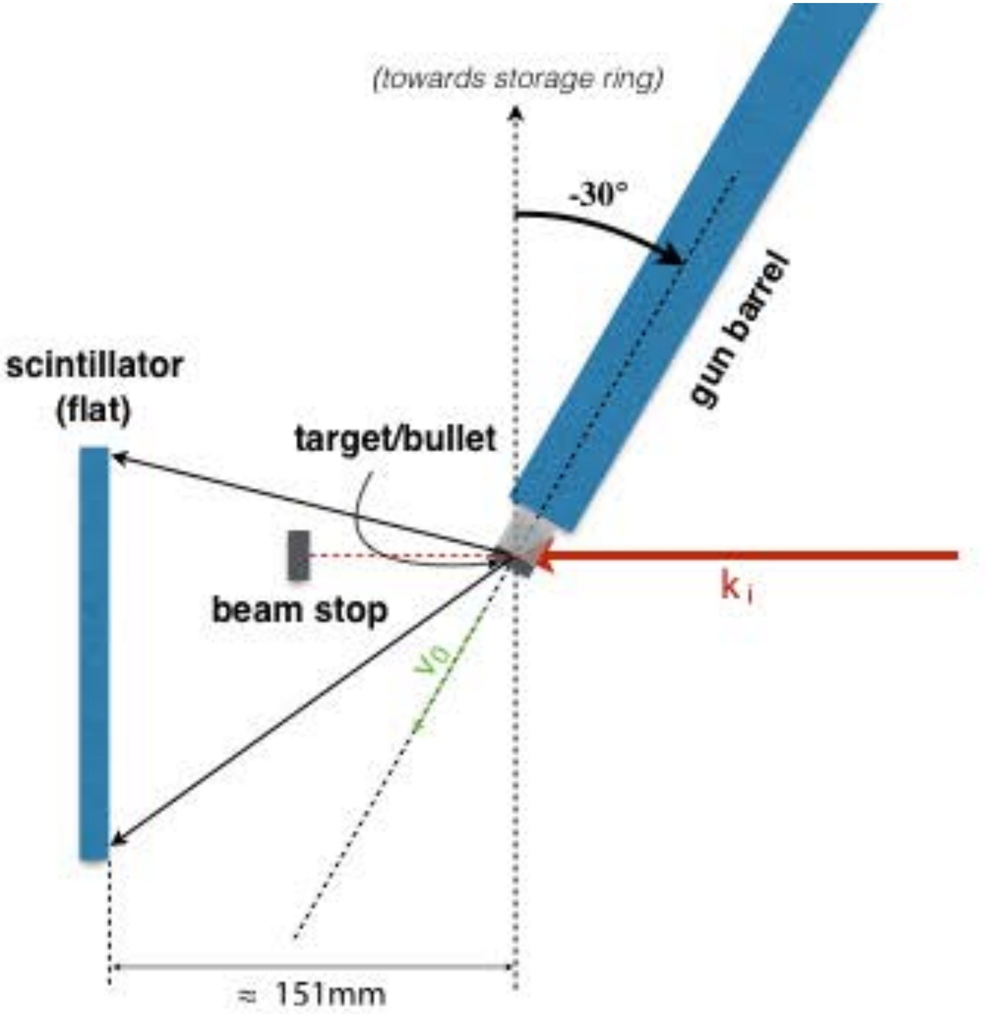
Micro Computed Tomography

Grain Position, Lattice Orientation, and Lattice Strain Analysis

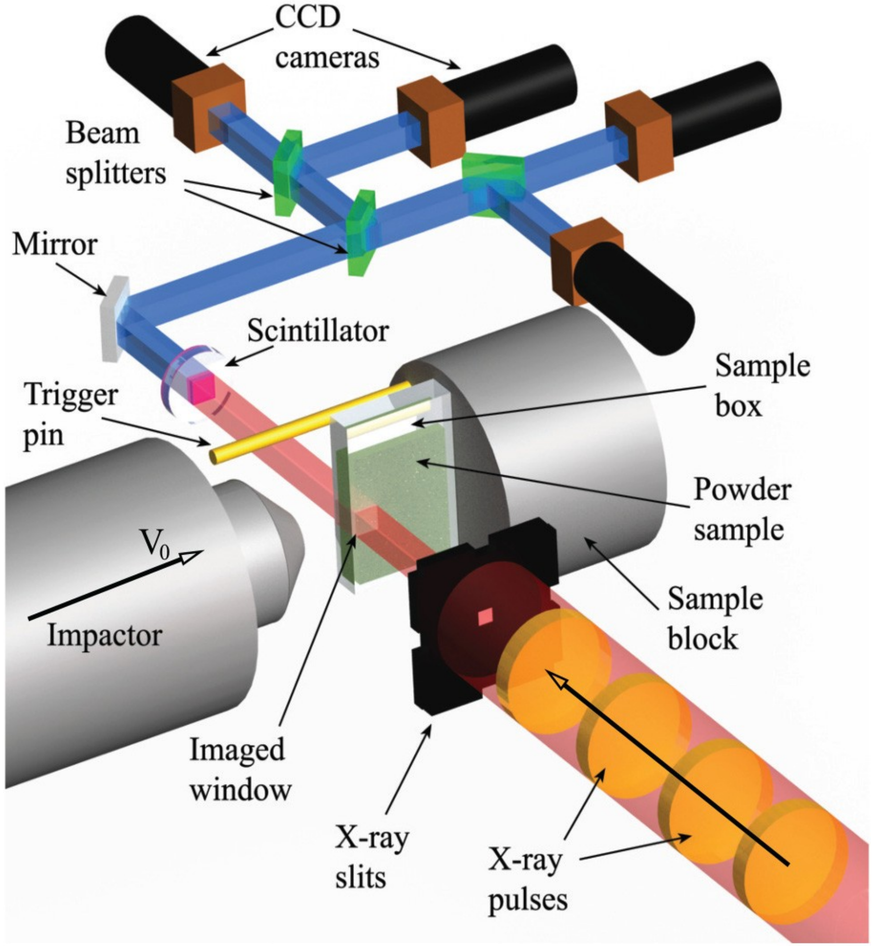


Imaging and diffraction setups constrain experimental design

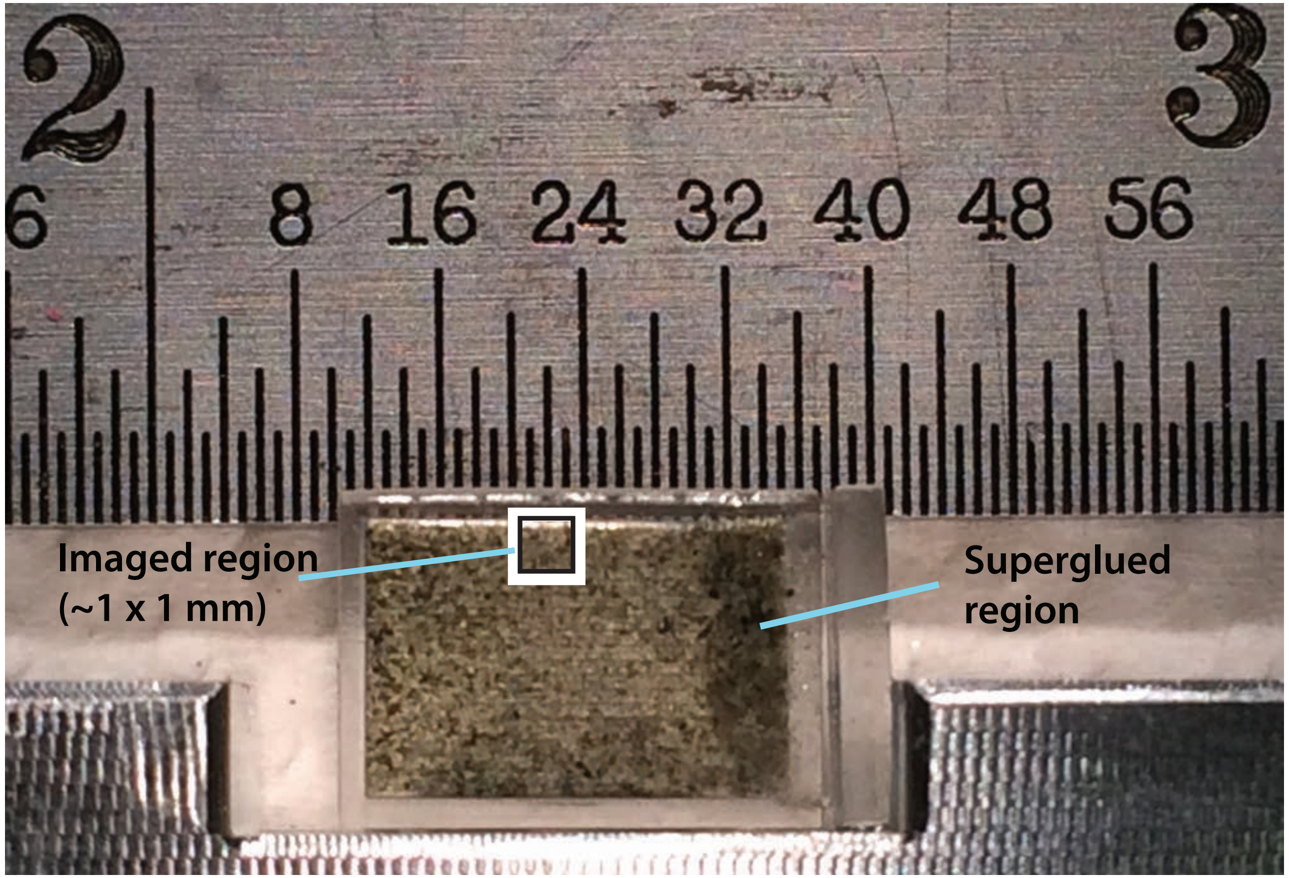




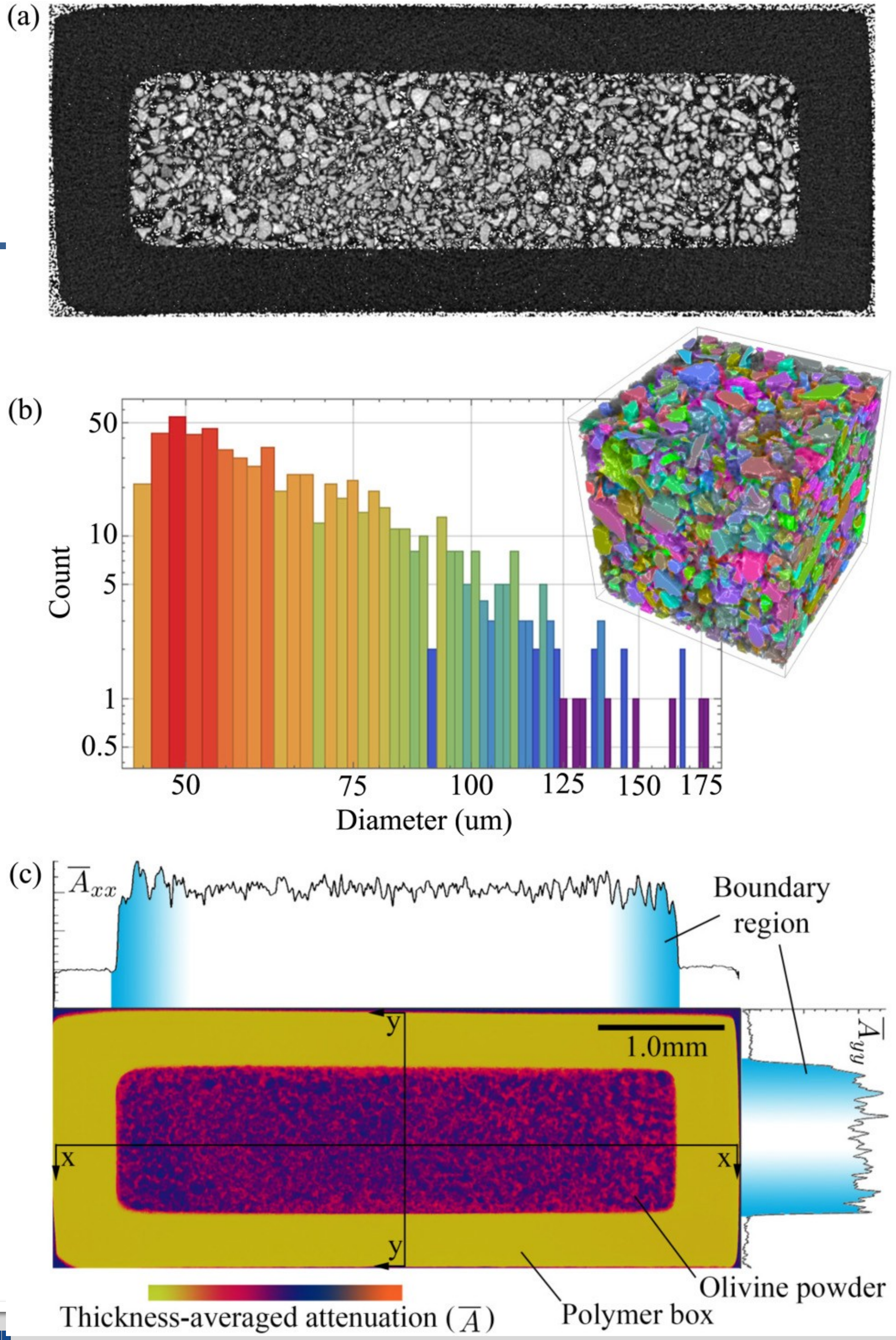
Dynamic imaging experiments are designed to be close to 1D



IMPULSE imaging setup at DCS



Crum et al., J. Appl. Phys. 125, 025902 (2019); https://doi.org/10.1063/1.5057713

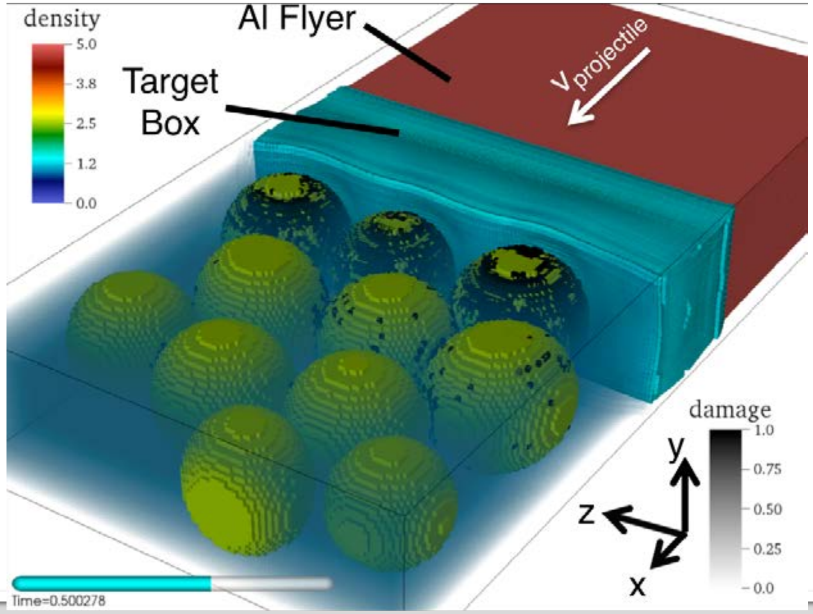


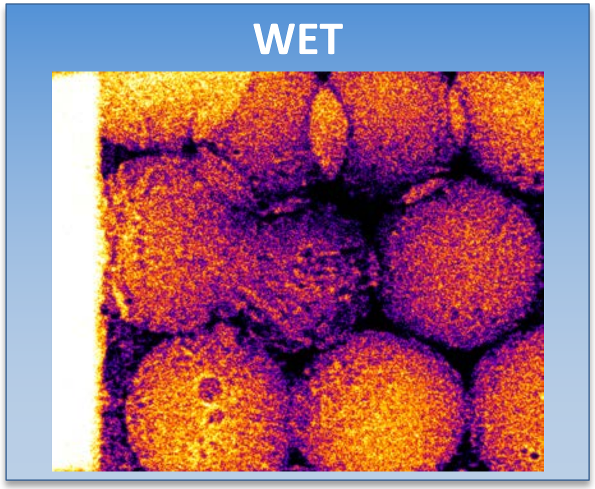
Detailed data are extracted to improve models and analysis

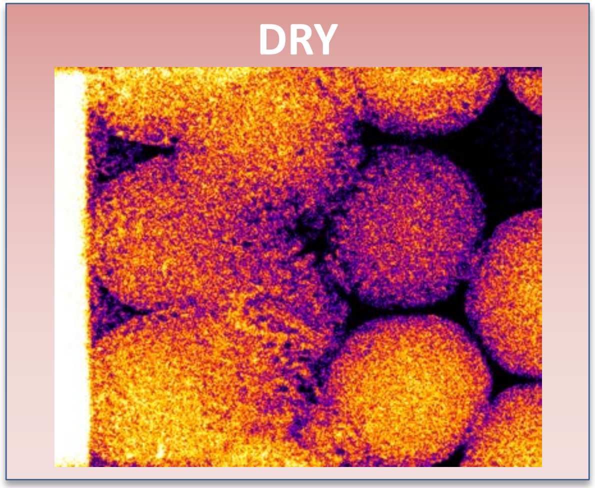
- Reconstructed CT of sample
- Segmented to find sample properties
  - —particle size distribution
  - —thickness averaged attenuation of the sample.
- Used to inform models and calculations

Fracture and compaction response differ in wet vs. dry media

- X-ray phase contrast imaging of shocked glass spheres
- Deformation mechanisms of dry and water-saturated samples are not the same
  - consistent with shock recovered samples
- We update our models using these data

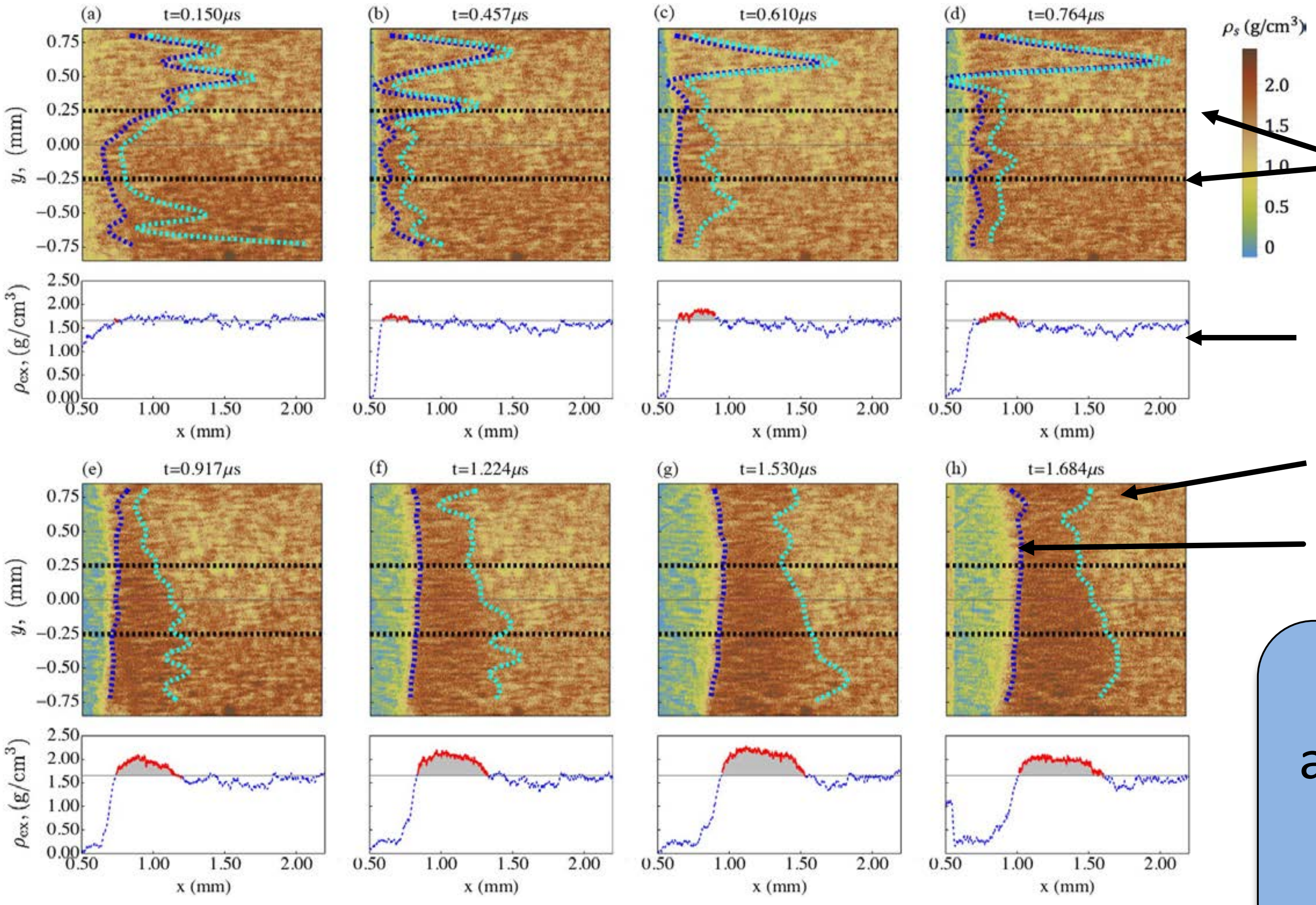






Packing variation seeds variation in compaction front in sand

465 m/s impactor



middle region = between black bands

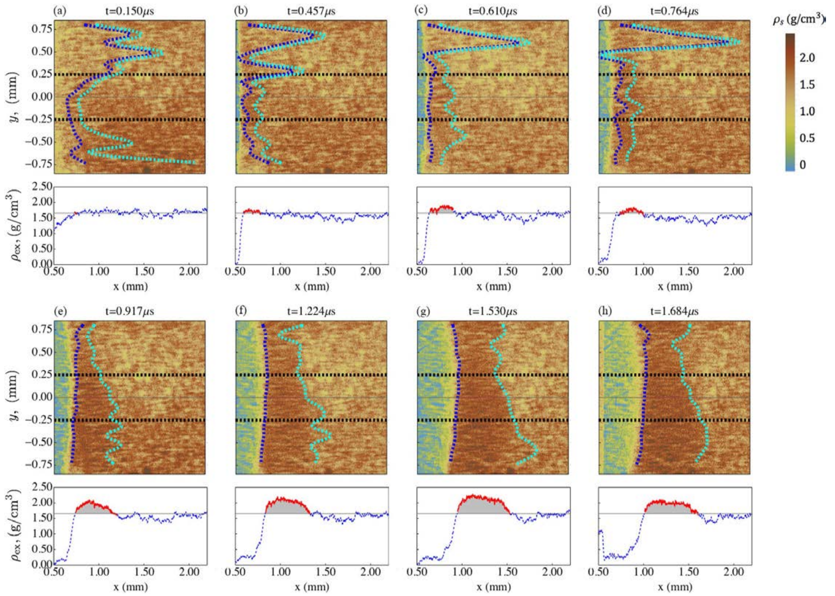
Mean density profiles of middle region; red = density compaction front

compaction front (cyan)

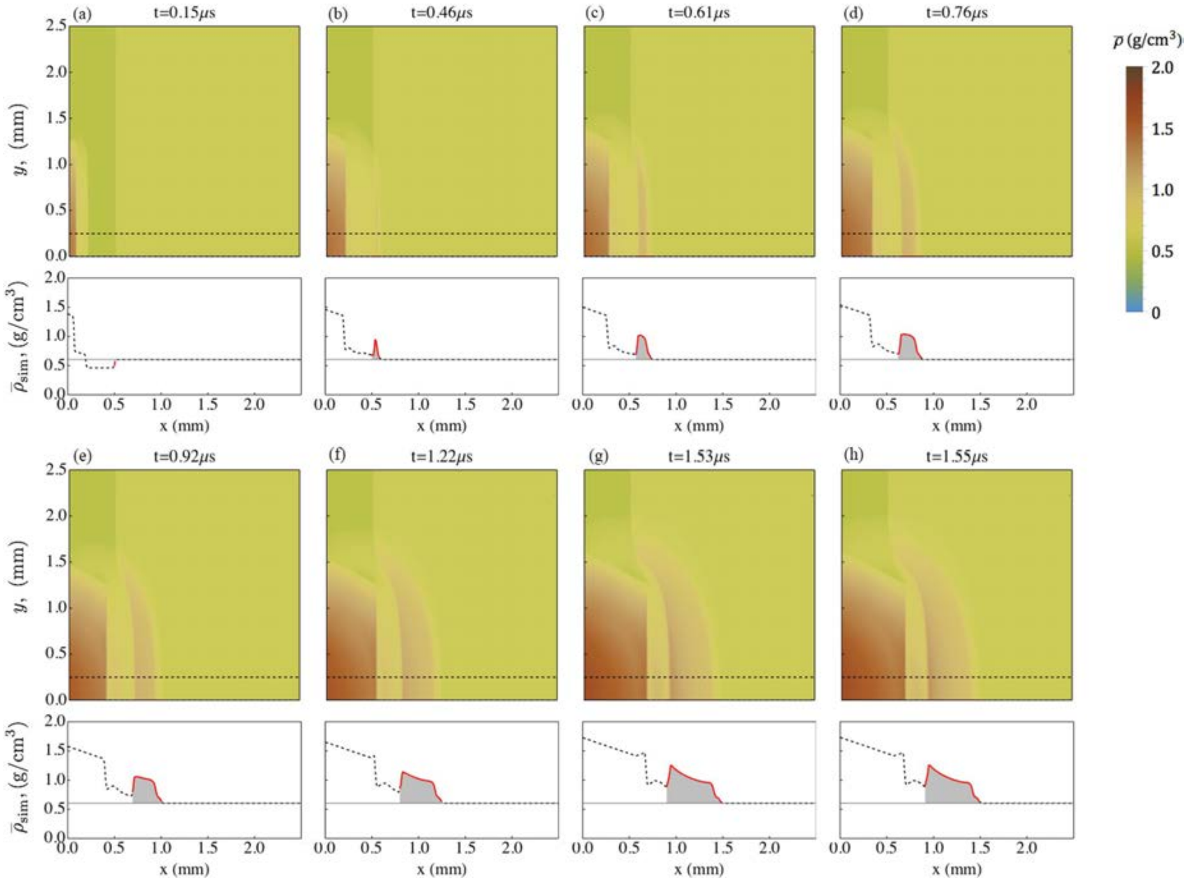
Sample-polymer interface (blue)

Length scale of variation depends on analysis method. Density variation finds a length scale of ~30 grains. Local filtering reduces this to a few grains.

Packing variation seeds variation in compaction front



Simulation results qualitatively agree but can be improved

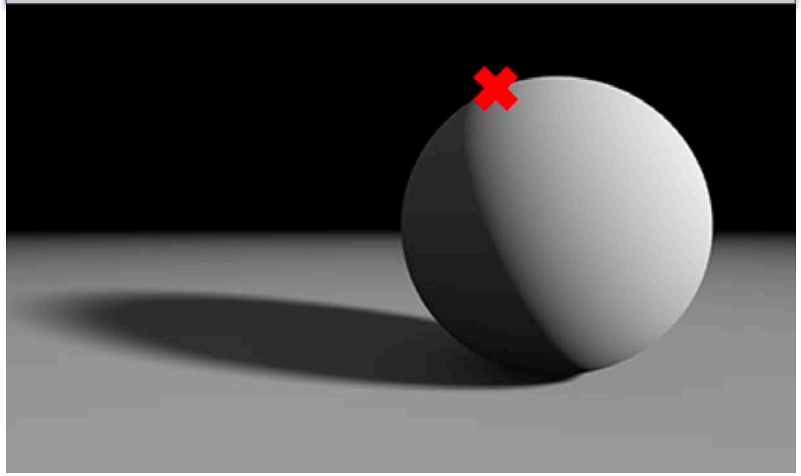


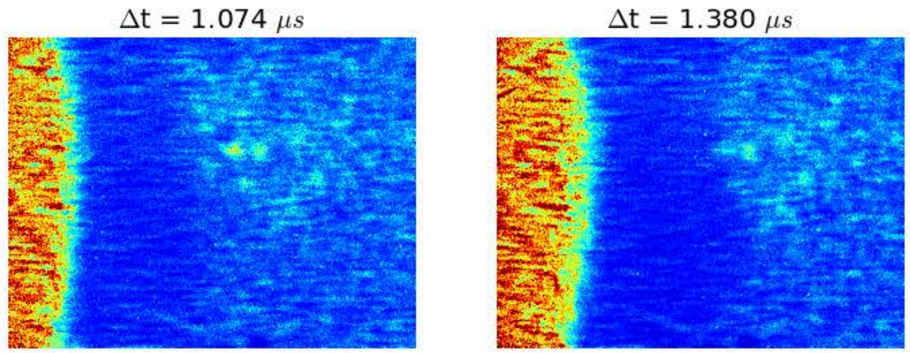
Simulation results showing thickness-averaged density in the *x* - *y* plane for the granular material impacted at 465 ms^{-1}.

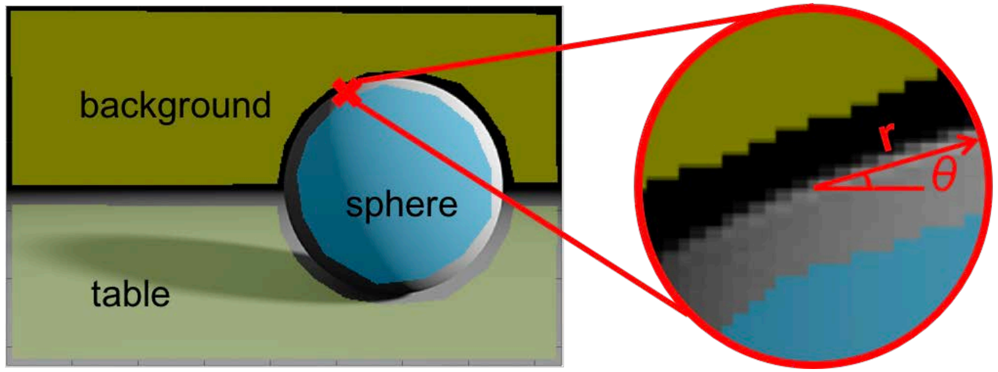
Identifying shock boundaries and densities can be done with machine learning (ML)

- As throughput increases, analysis becomes more time consuming
- Identifying shock boundaries in images is a challenge
  - Want to avoid subjective assignment
  - Can be slow

Machine learning can be challenged to determine if X is ball or table

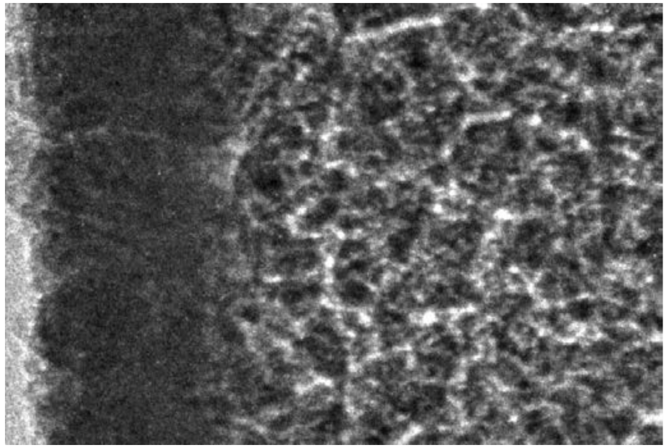




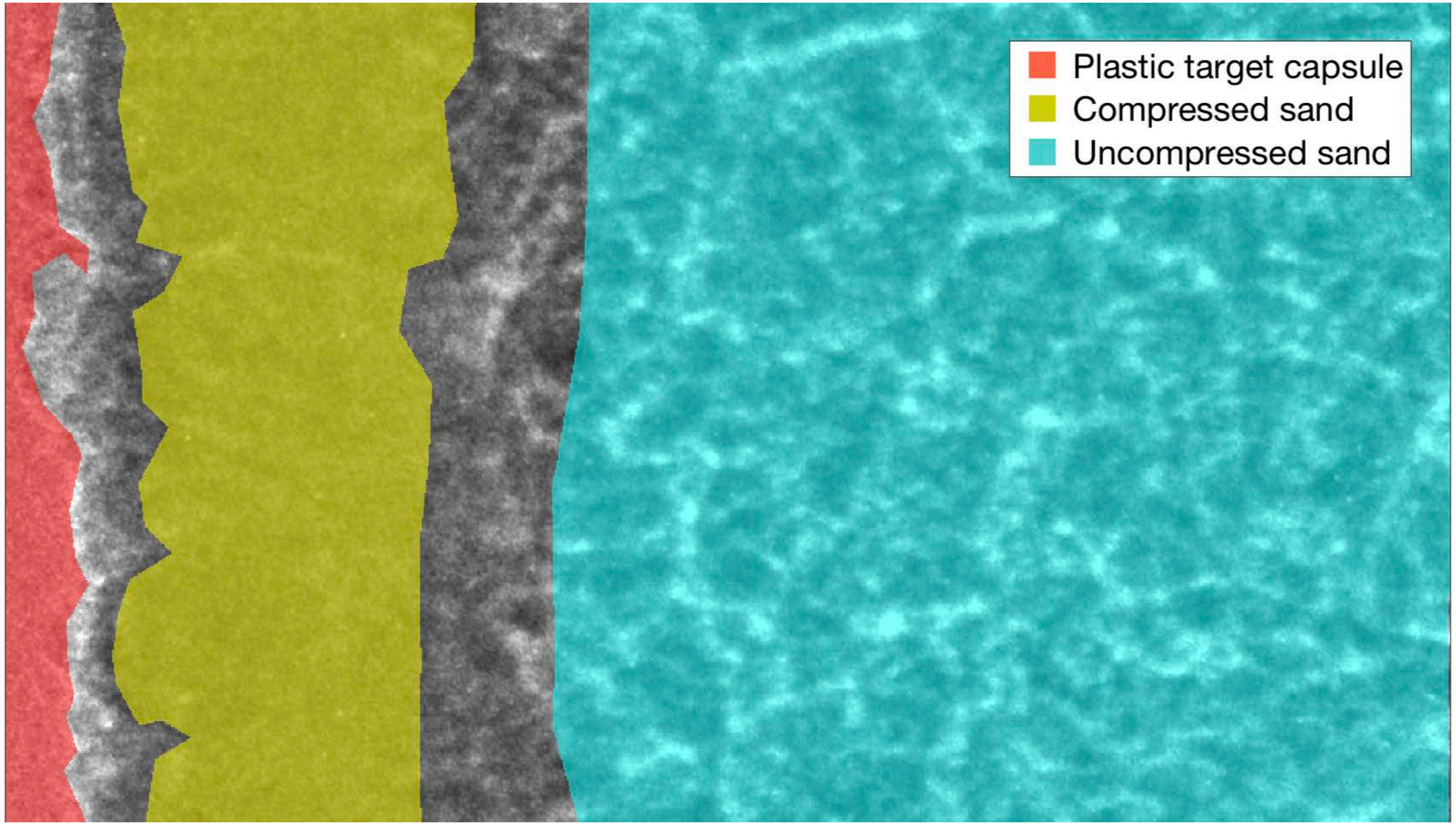


Lund et al in press

We apply the ML algorithm to train each image and find boundaries



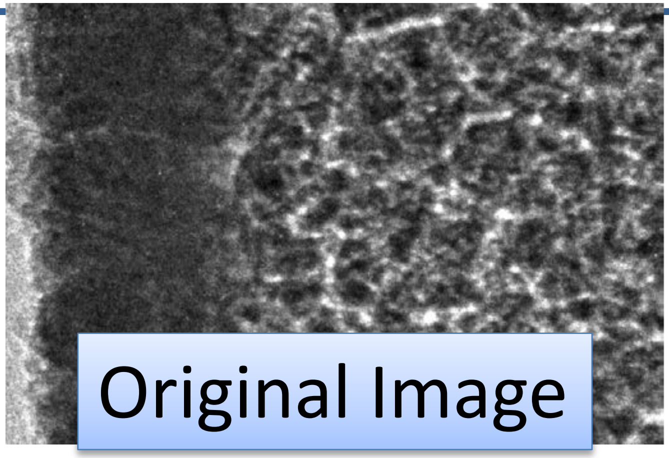
Original Image

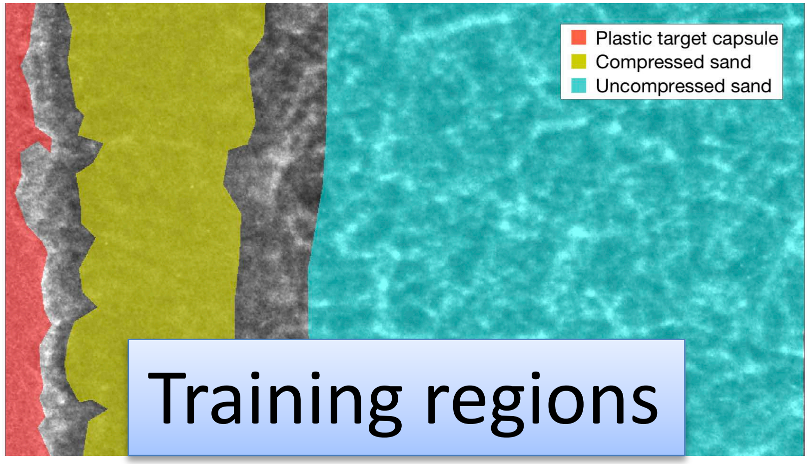


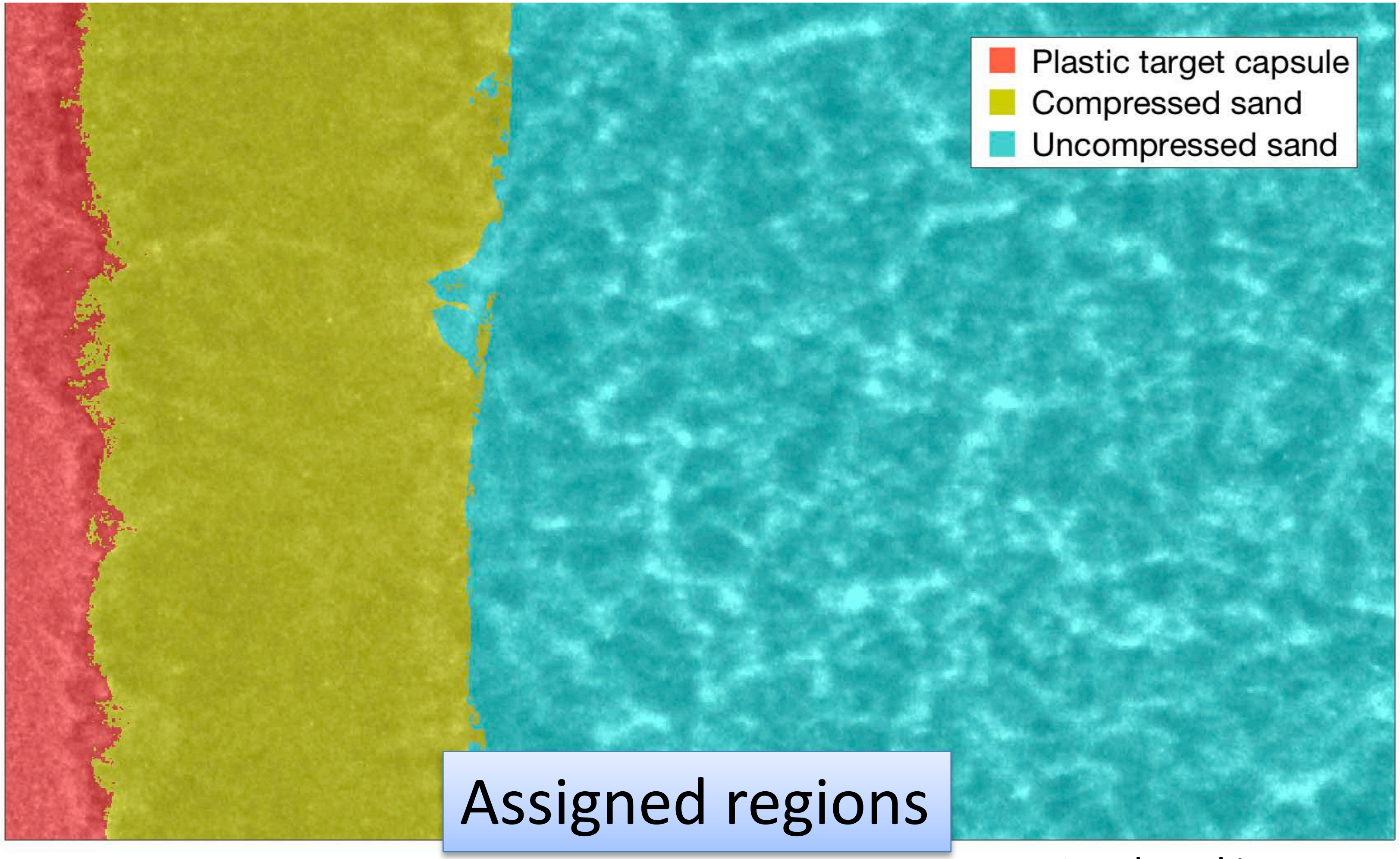
Training regions

Lund et al in press

We apply the ML algorithm to train each image and find boundaries

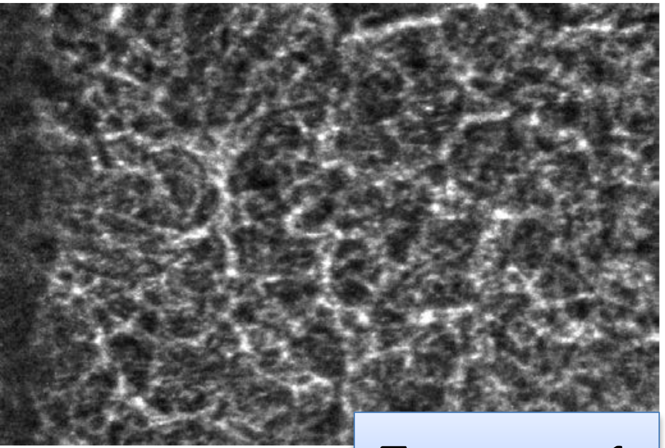


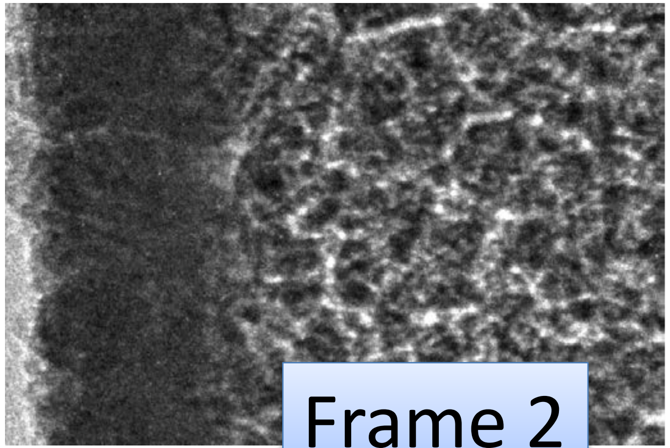


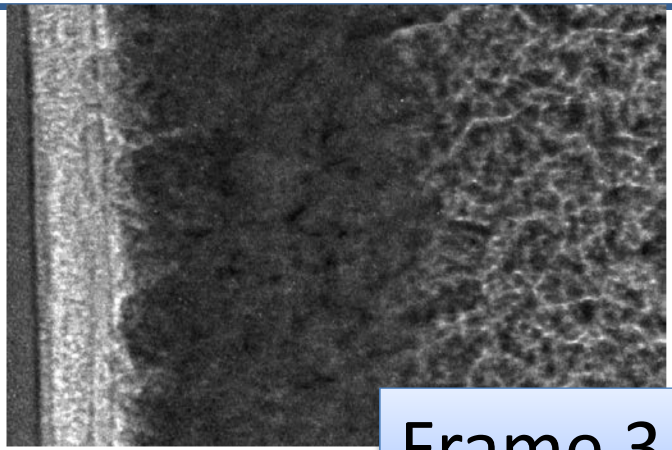


Lund et al in press

Repeating for each image, we can find the boundary evolution



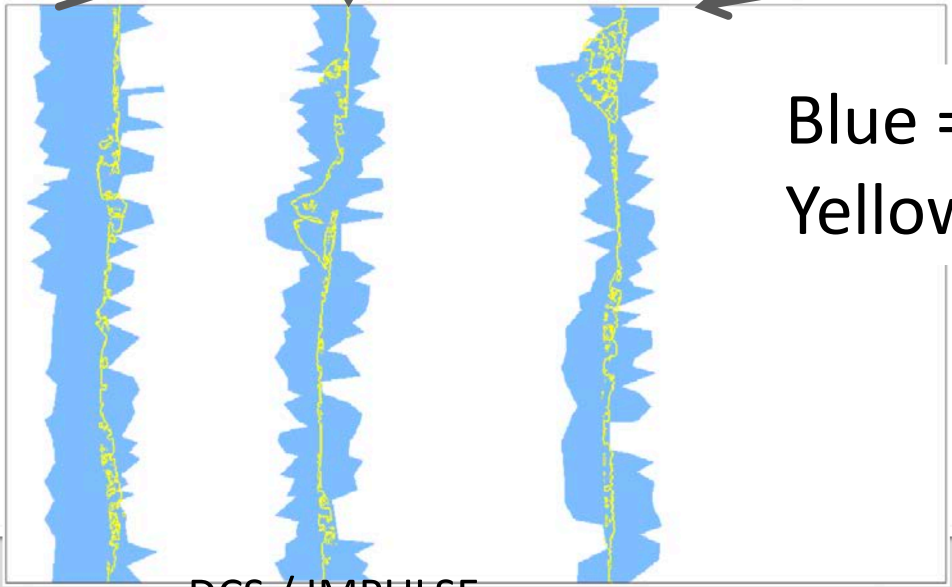




Frame 1

Frame 2

Frame 3

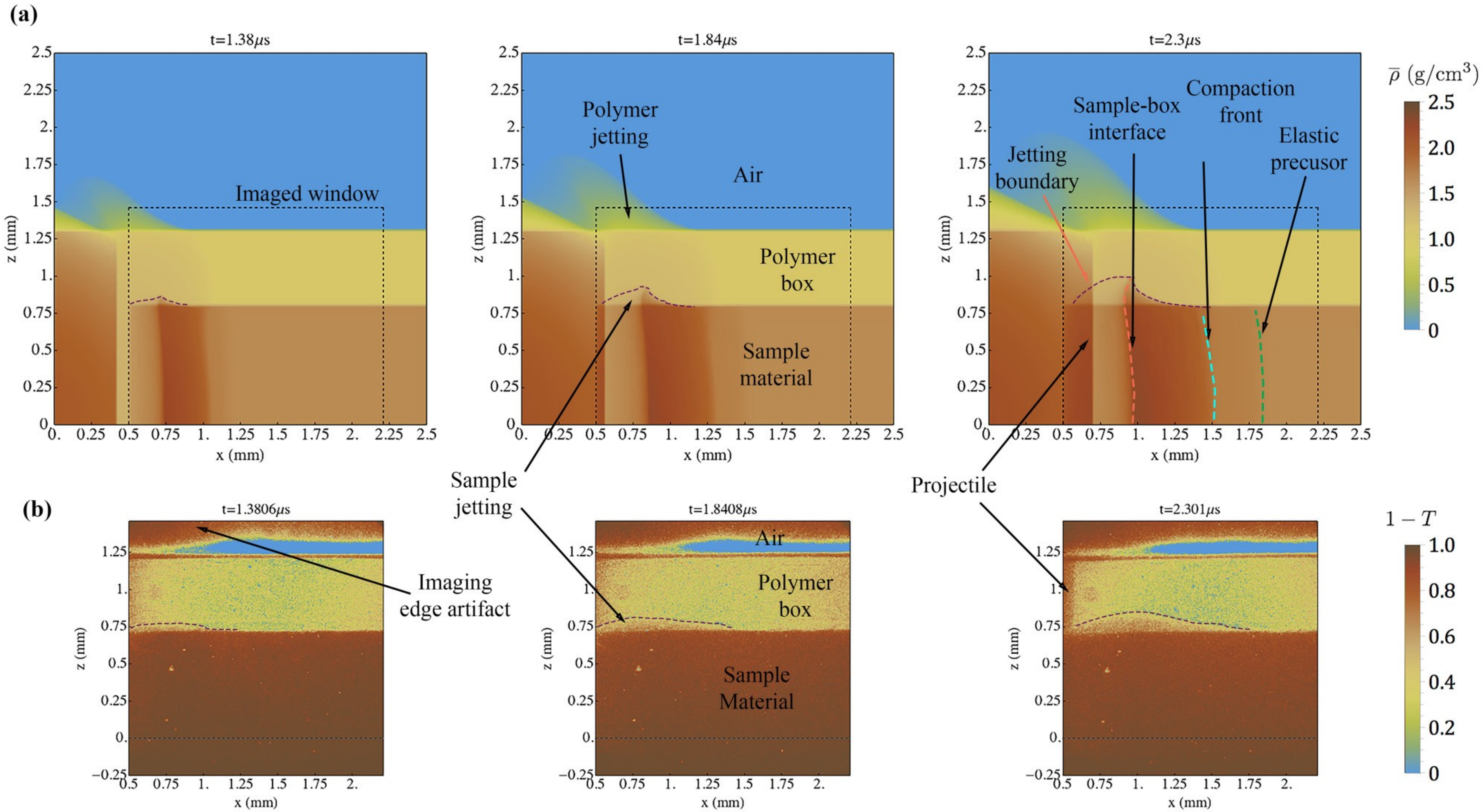


Blue = region of uncertainty
Yellow = boundary

Lund et al in press

DCS / IMPULSE

Out-of-plate deformation must be accounted for; we built new models to do so



Conclusions

- We need to understand/characterize samples at detailed level
  - Not just bulk EOS/strength, but also local variations in density and network
  - Local structures may imprint
  - Wetting (water or container) changes both contact type and friction
- Analysis methods can give different results
  - When are we over-filtering?
- Multiple length, pressure, and time scales apply
  - At grain/grain or grain/liquid contact
  - Within grain
  - Between grains/across network
  - At boundaries
- Improving model capabilities for packing, local stress-strain, friction, and strength has led to better models that can capture some of the response

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