

Disease progression patterns in COPD

Felix Bragman, Alexandra Young,
David Hawkes, Daniel Alexander and John Hurst

alexandra.young@ucl.ac.uk

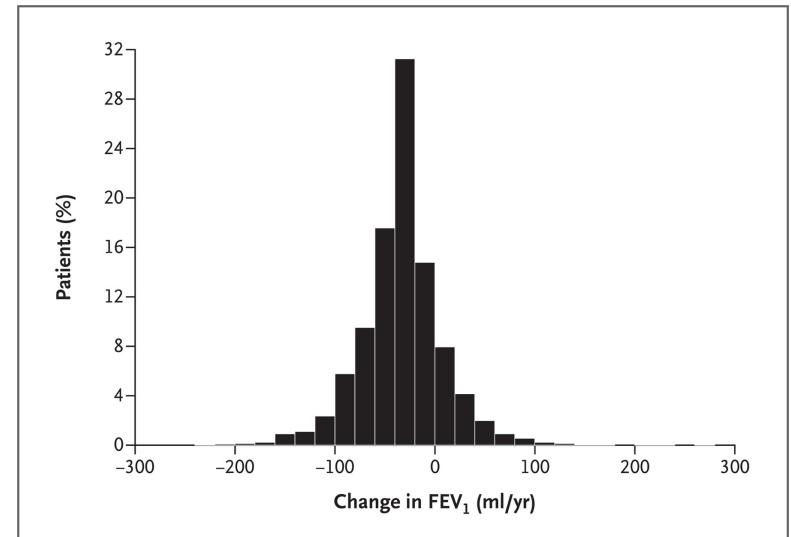
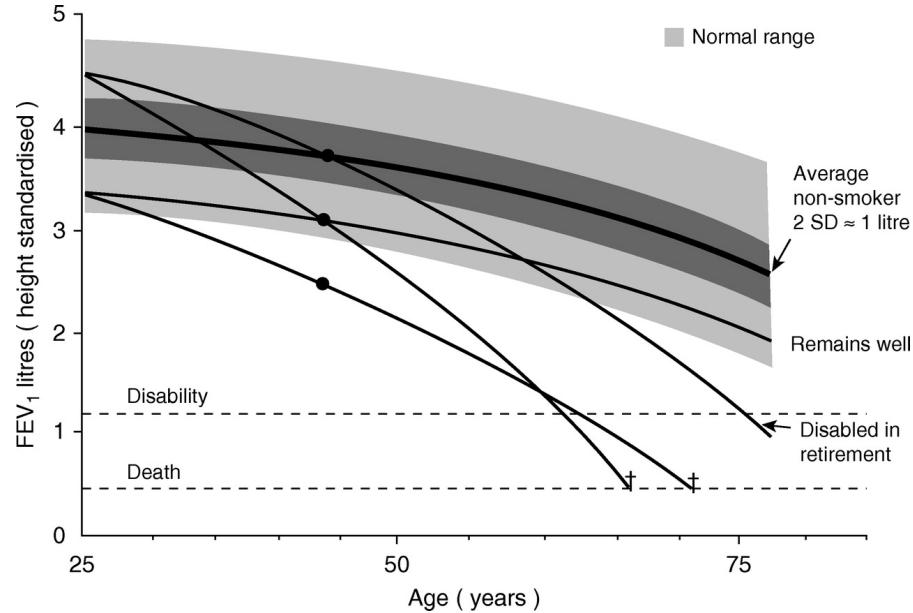


Centre for Medical Image Computing



No disclosures

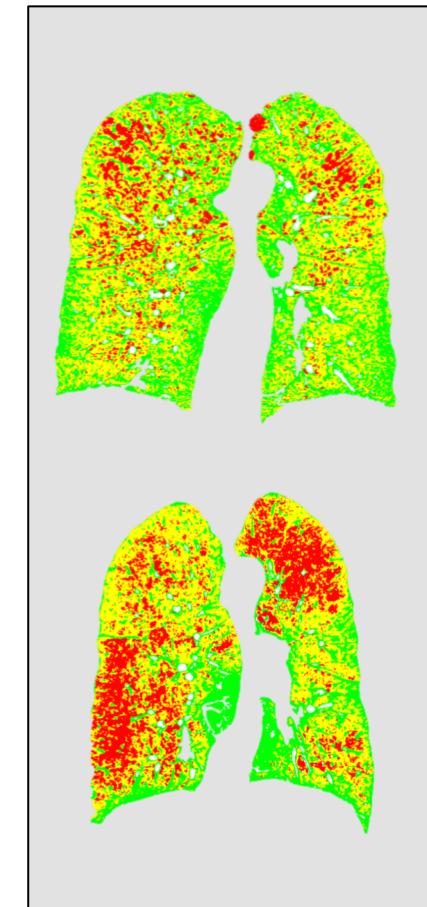
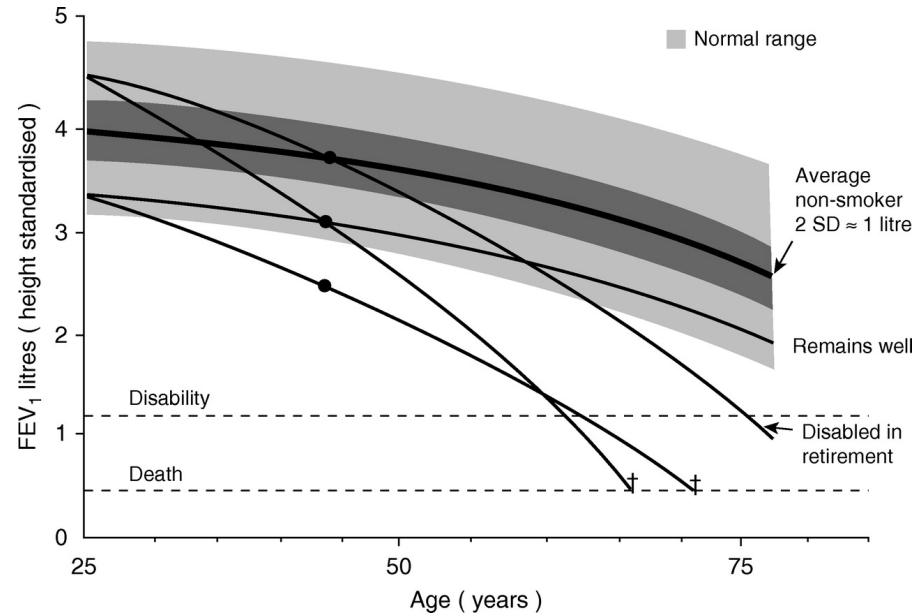
COPD is heterogeneous and has a long-term progression that spans several decades



Fletcher-Peto, 1977

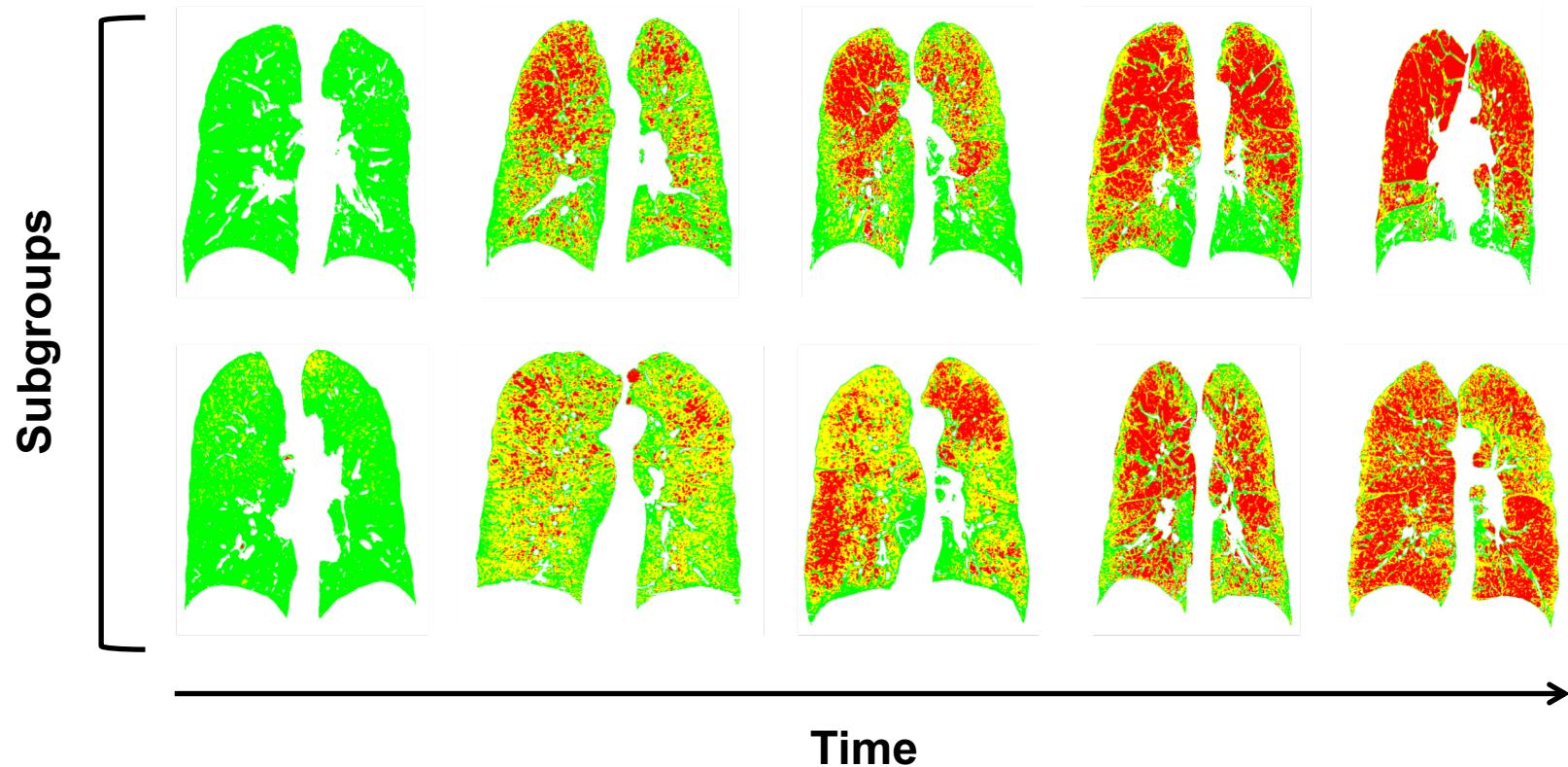
Vestbo, 2011

Lung function decline is a non-specific measure that can correspond to a range of underlying pathologies

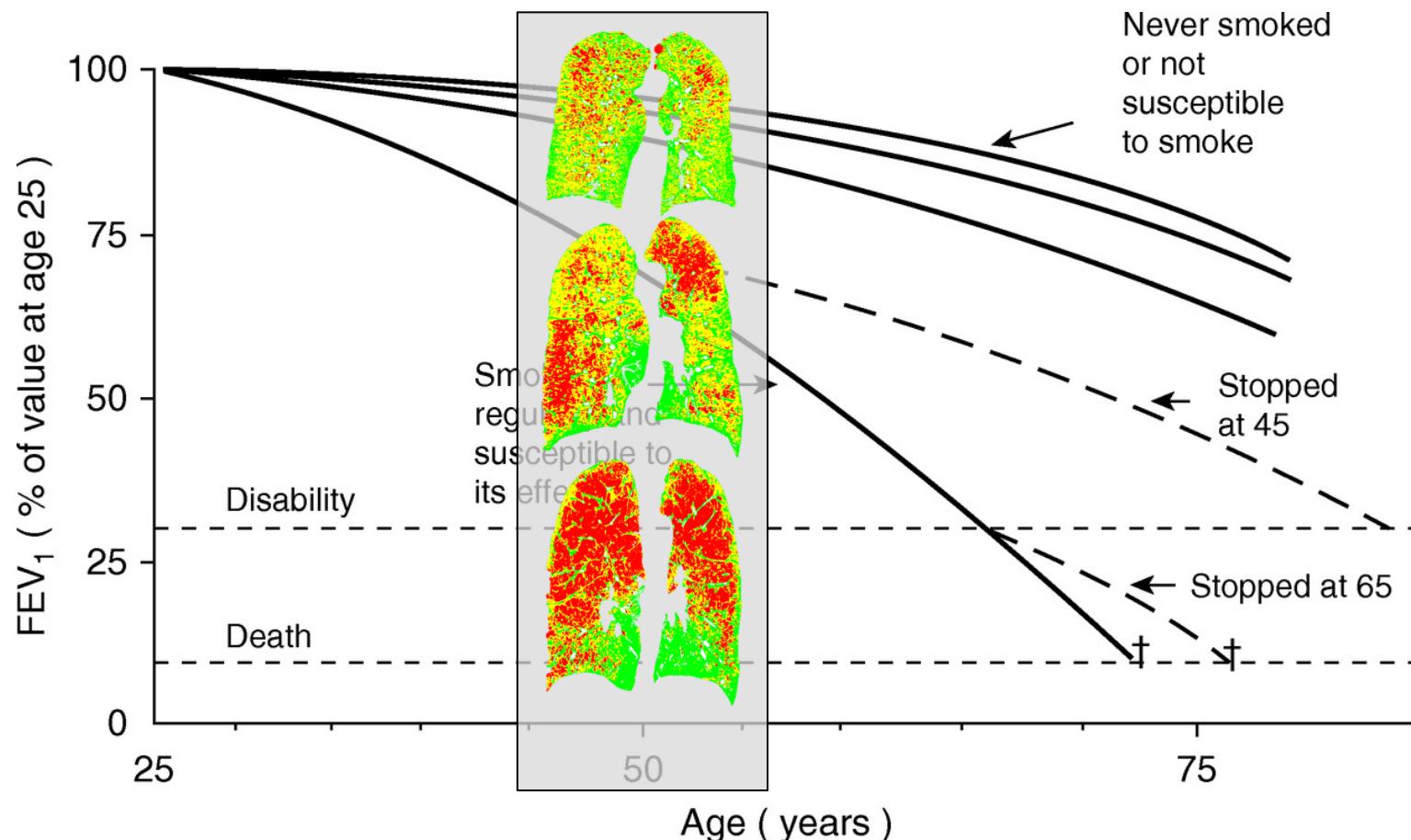


Fletcher-Peto, 1977

Hypothetical description of COPD progression



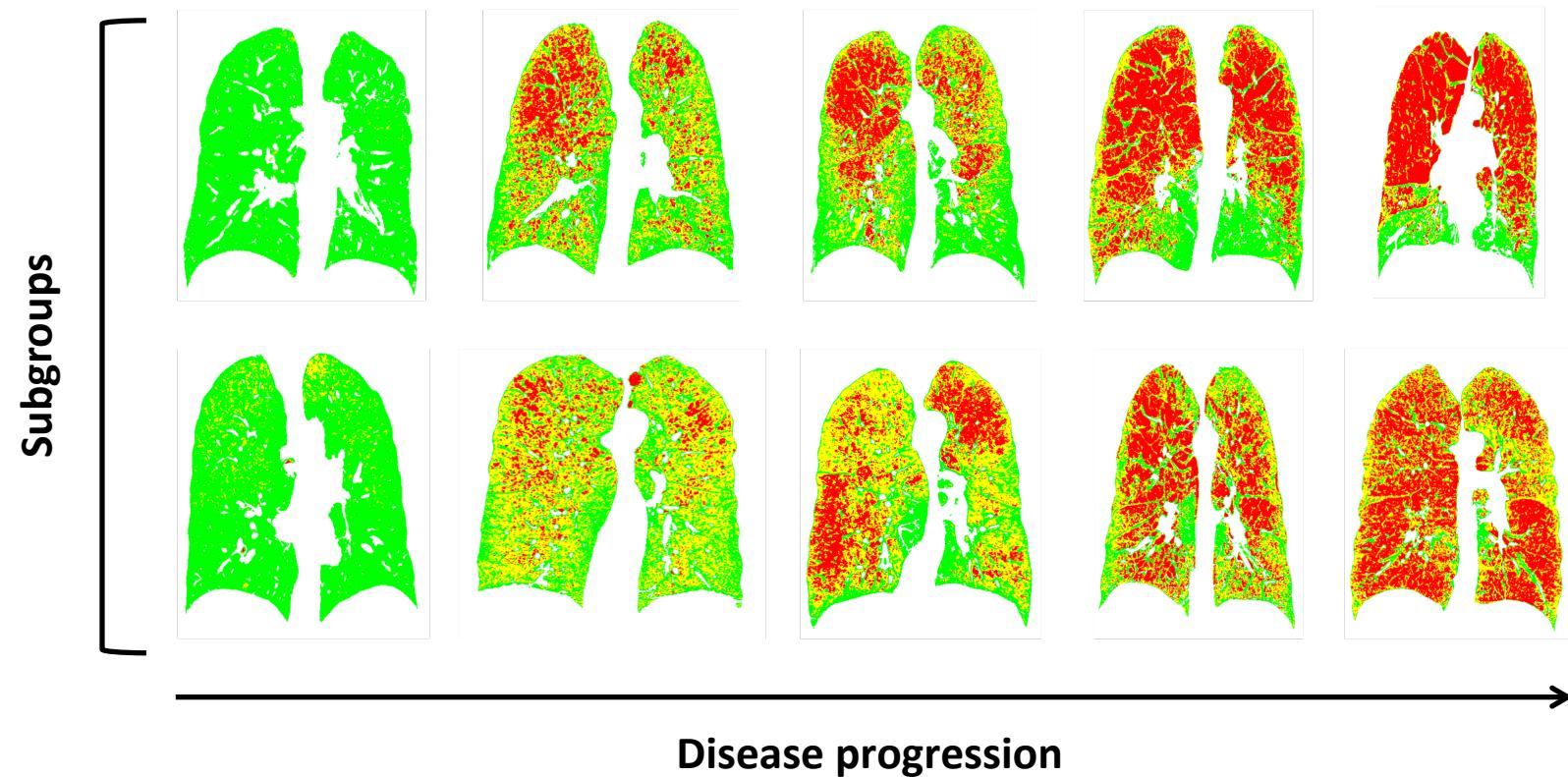
Disentangling imaging trajectories is complicated by long-term natural history of COPD



Fletcher-Peto, 1977

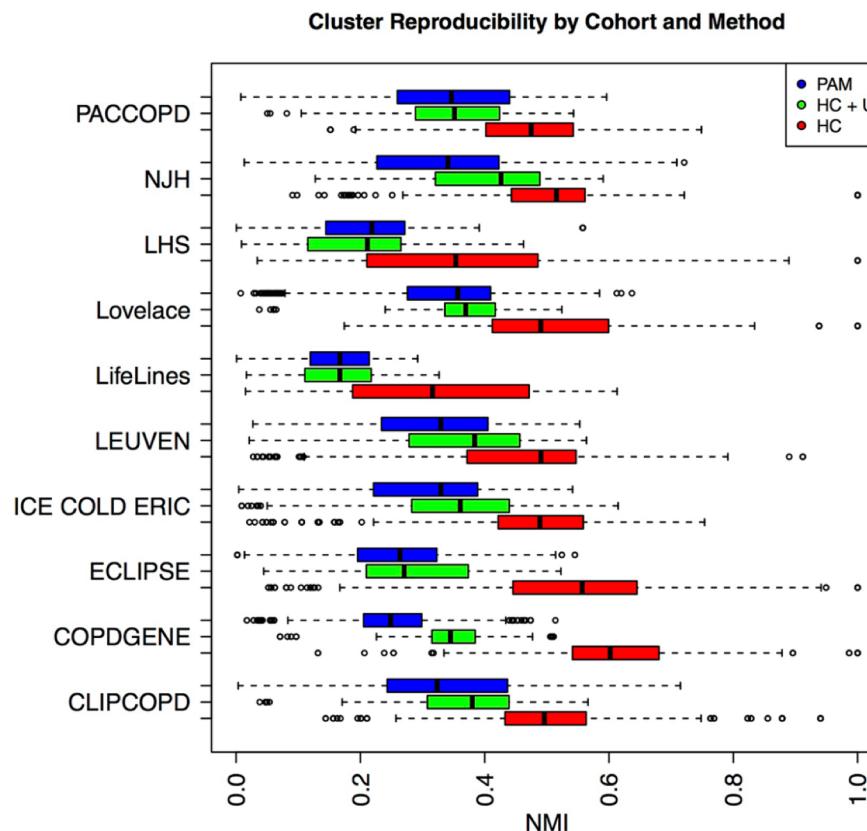
Objectives

- Demonstrate use of a novel machine learning technique to identify subgroups of COPD with distinct progression patterns
- Apply technique to image-based markers from COPDGene study

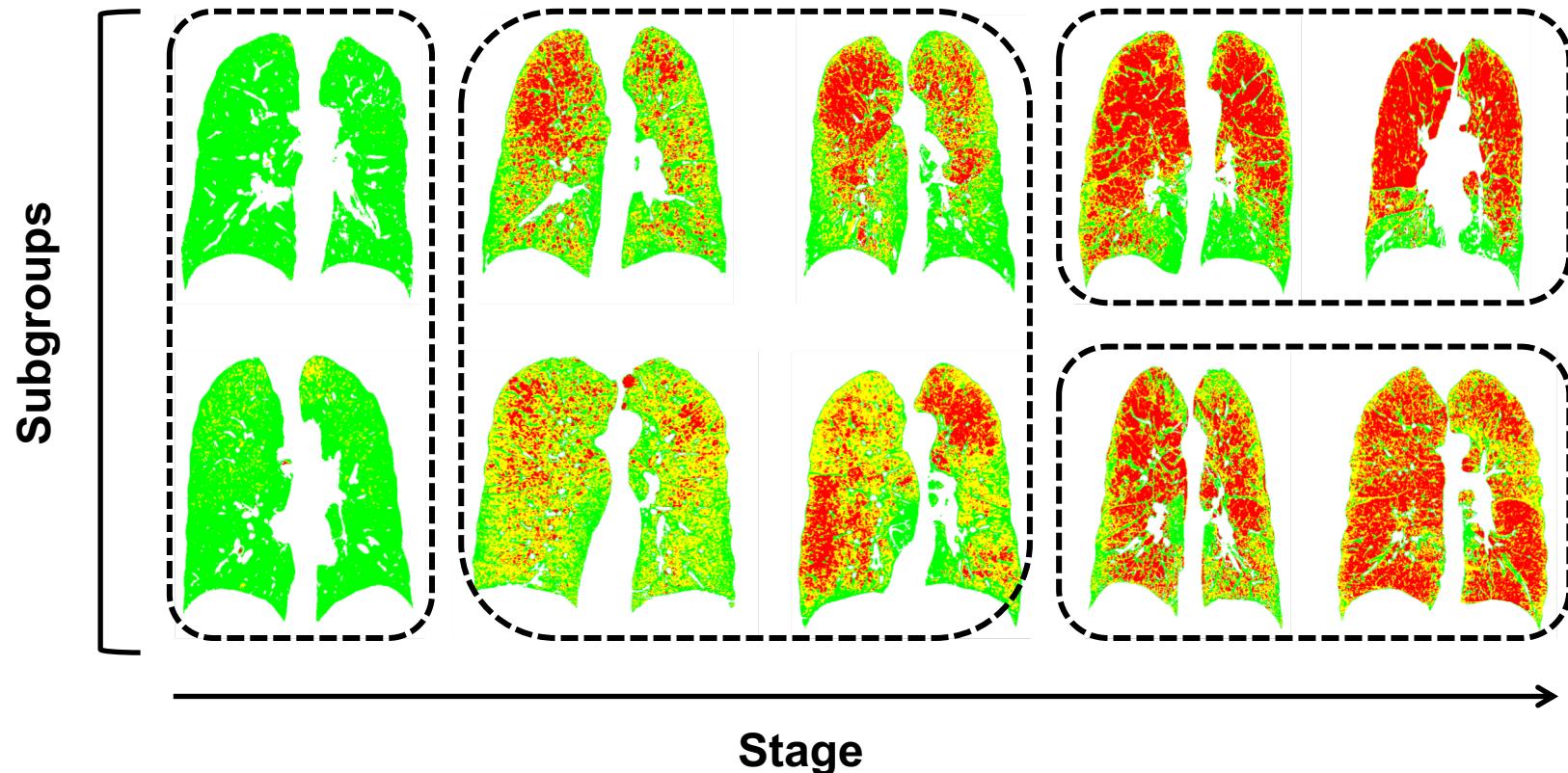


Previous studies investigating heterogeneity use clustering

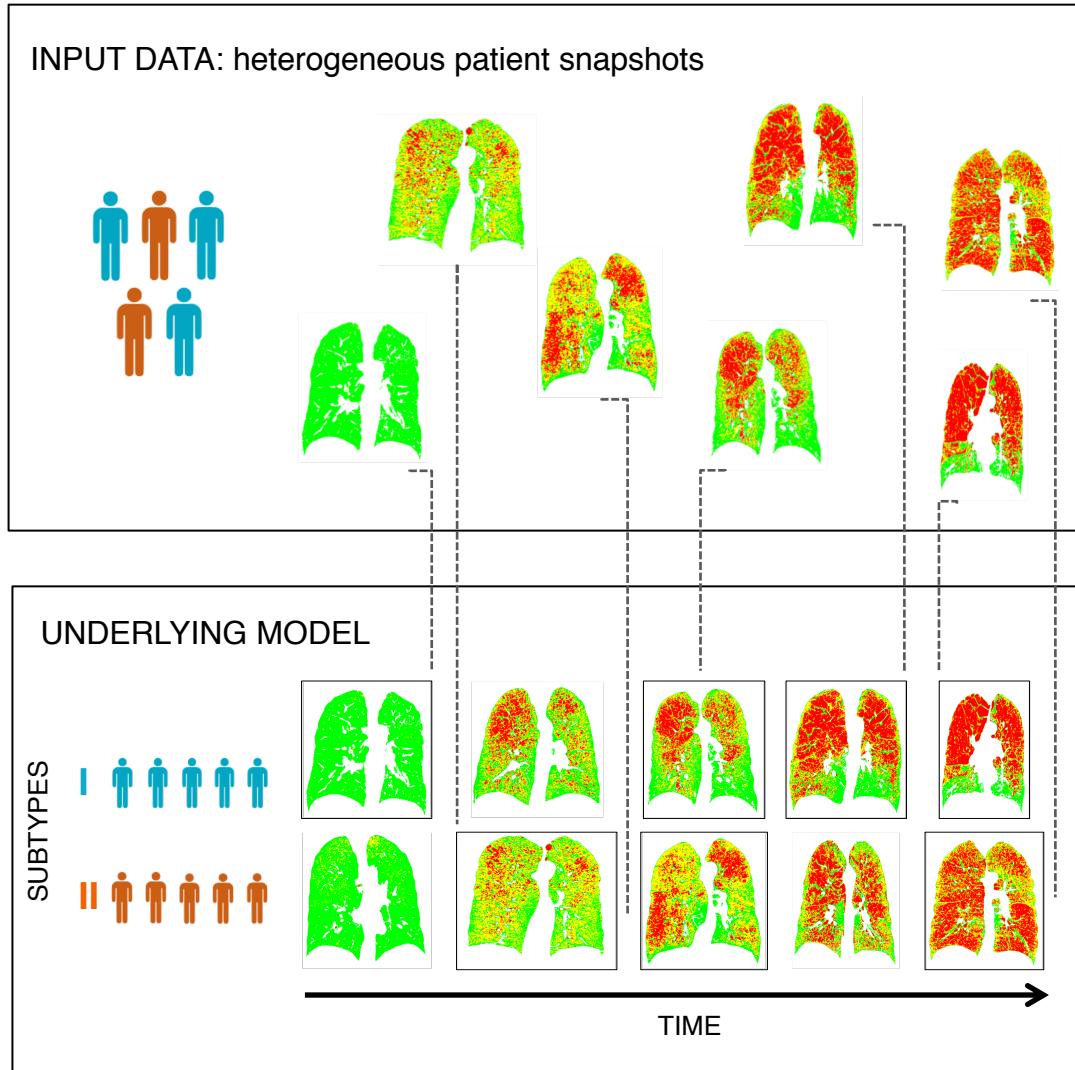
- Clustering associates individuals with similar biomarker profiles
- Doesn't describe the progression of the disease
- Results highly variable (Castaldi et al. 2017)



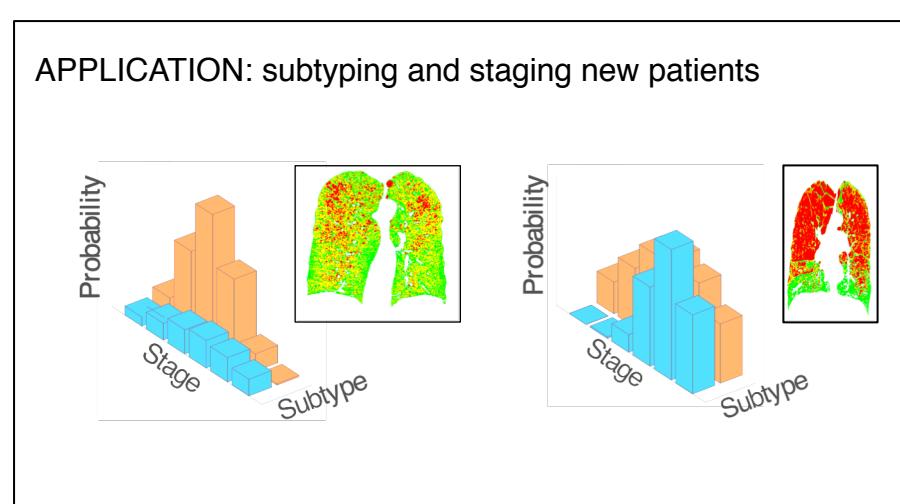
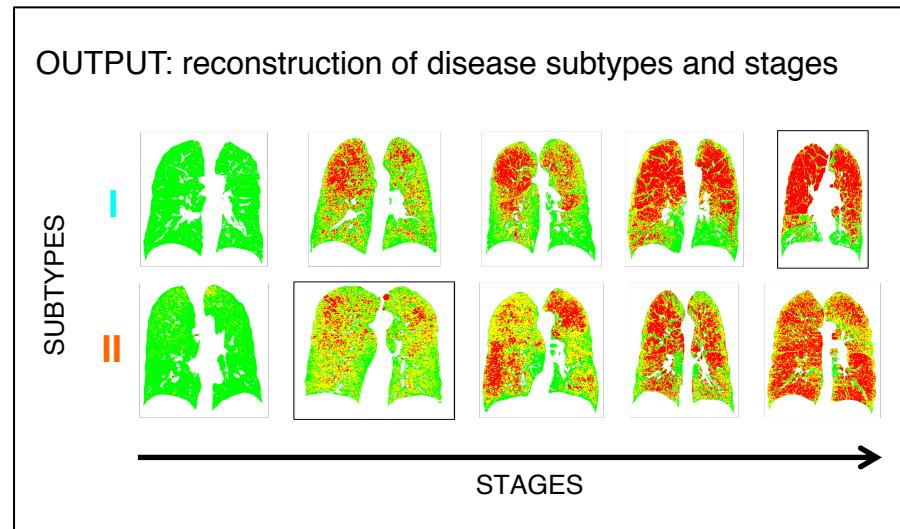
Clustering conflates disease subtypes and stages



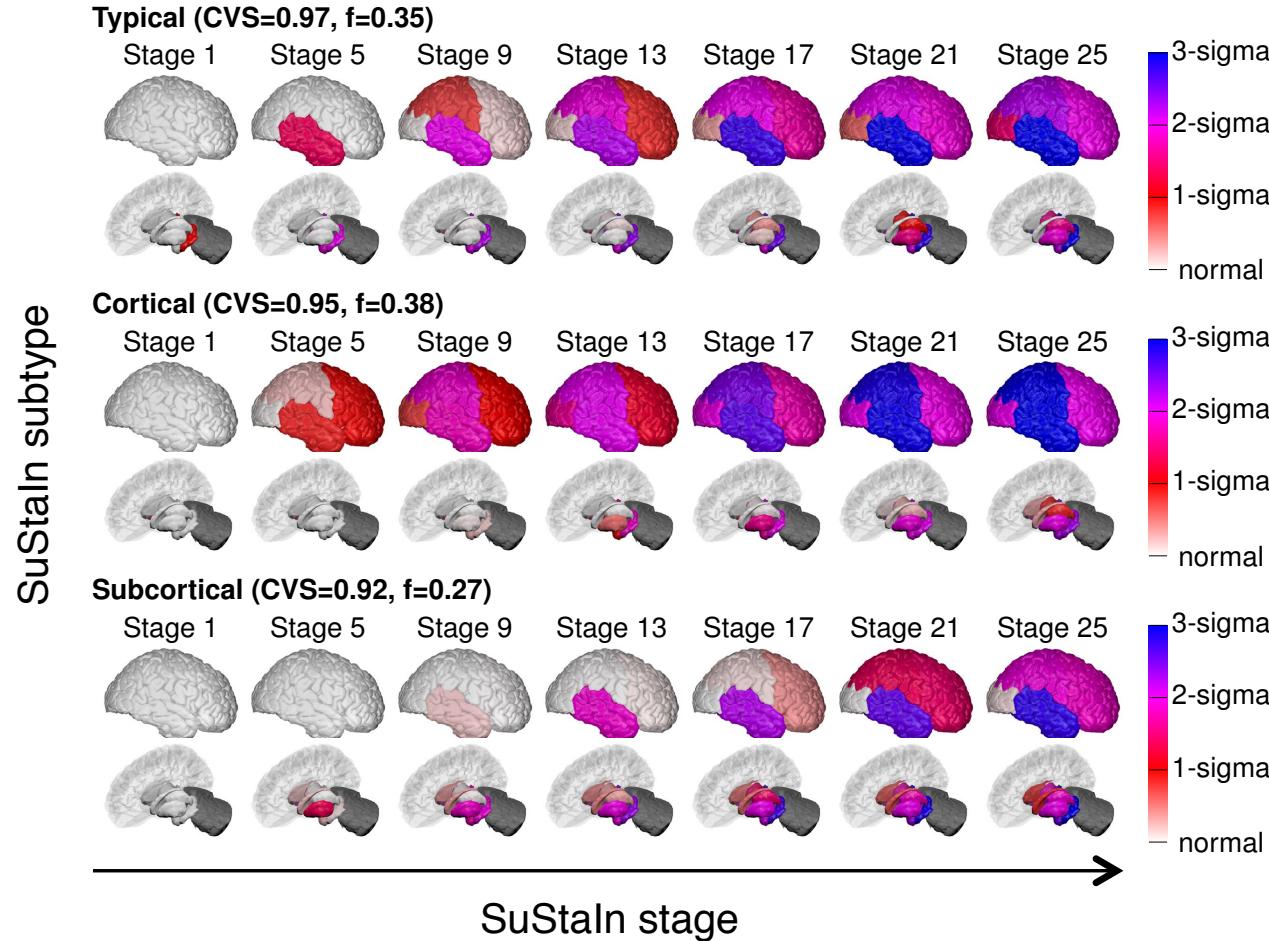
Subtype and Stage Inference (SuStIn)



Subtype and Stage Inference (SuStIn)

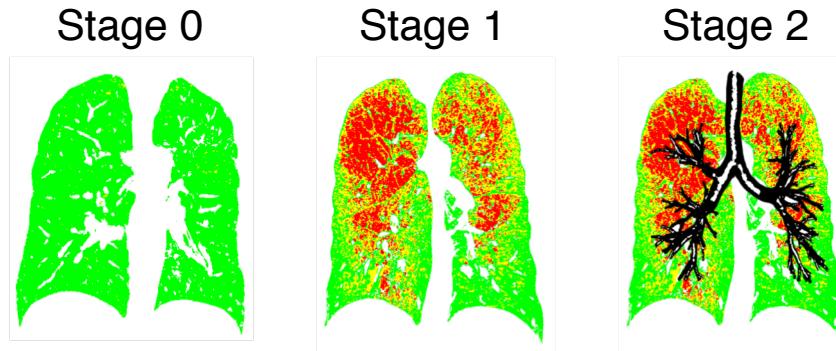


SuStaln initially developed for Alzheimer's disease, but naturally extends to COPD



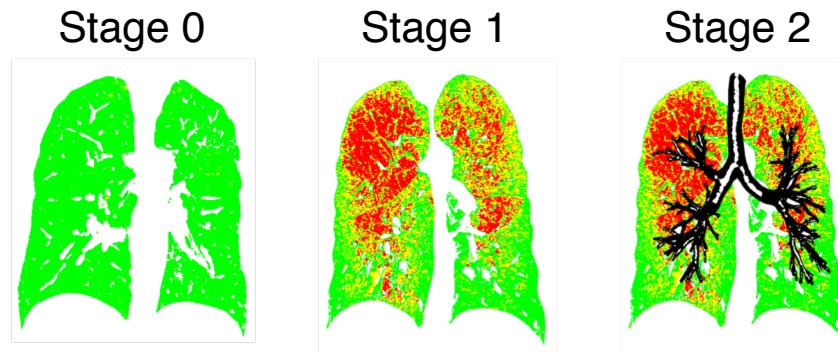
Reconstructing temporal progression from cross-sectional data

A

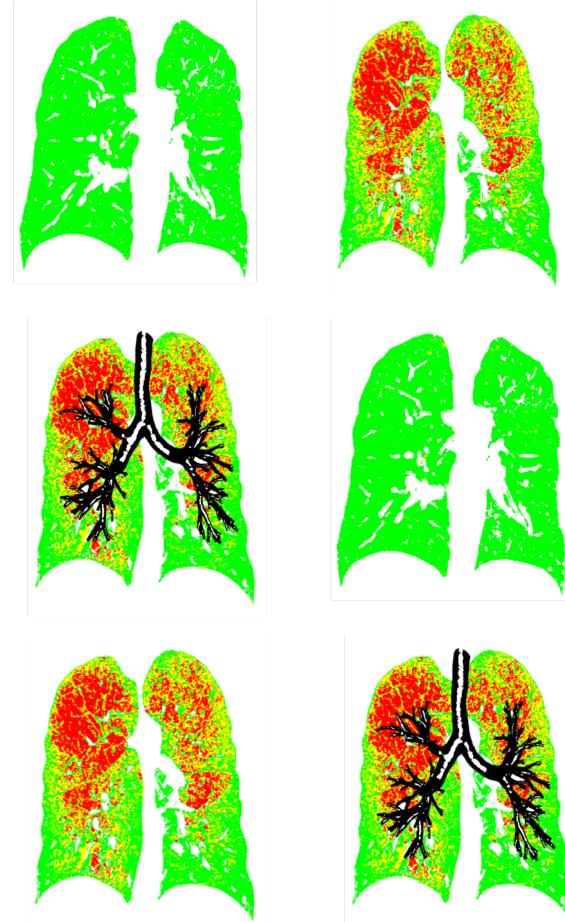


Reconstructing temporal progression from cross-sectional data

A

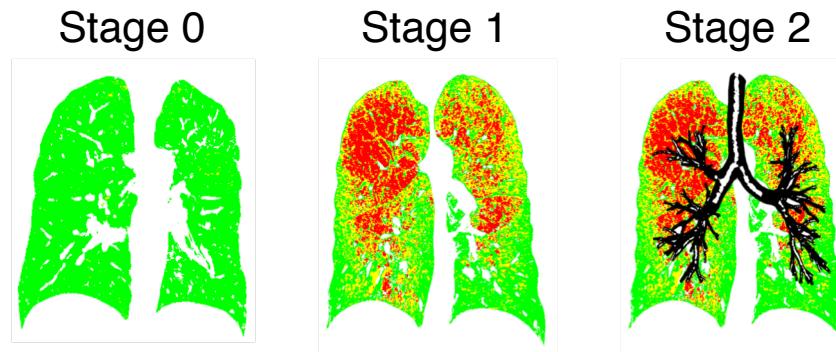


Cross-sectional samples

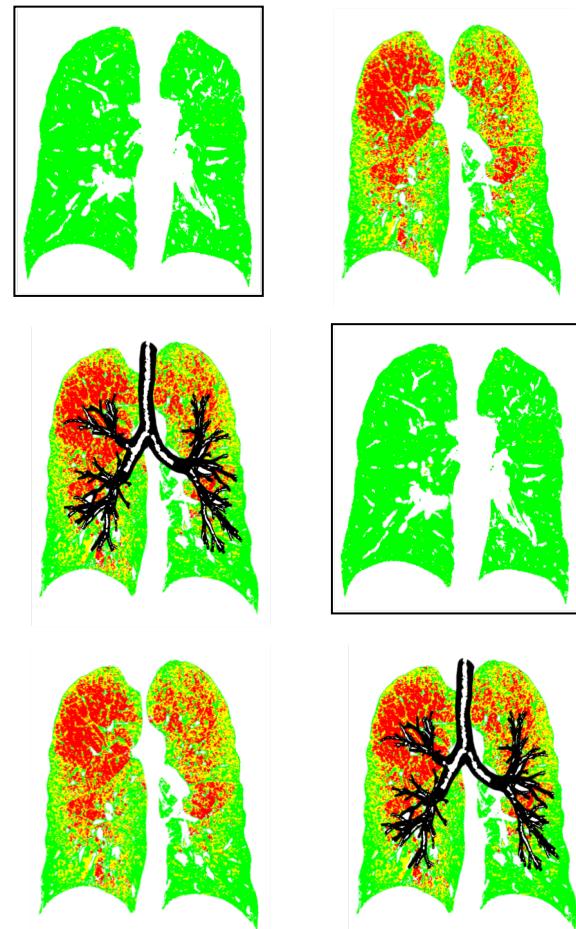


Reconstructing temporal progression from cross-sectional data

A

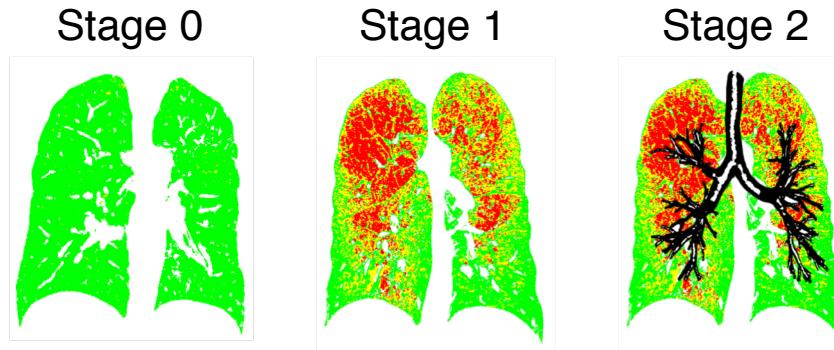


Cross-sectional samples

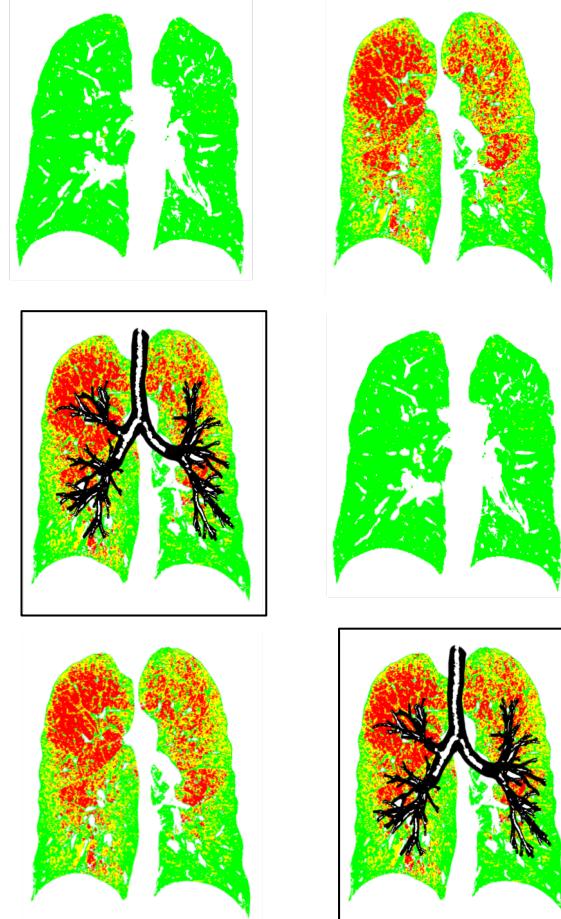


Reconstructing temporal progression from cross-sectional data

A

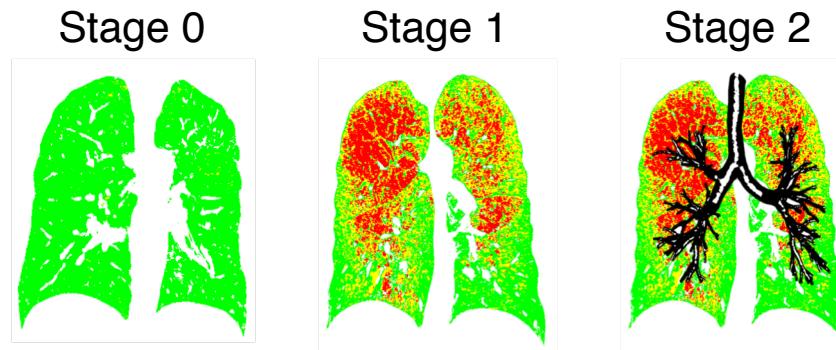


Cross-sectional samples

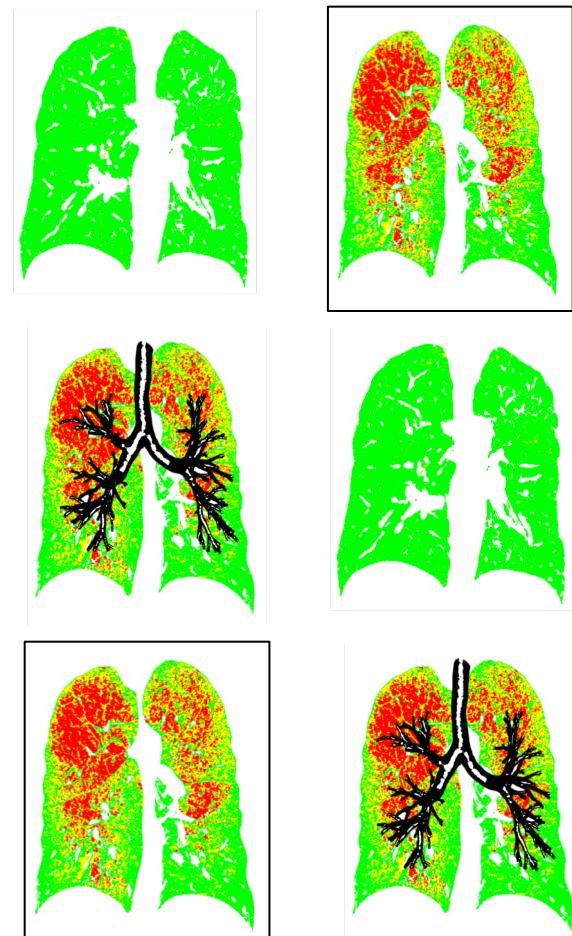


Reconstructing temporal progression from cross-sectional data

A

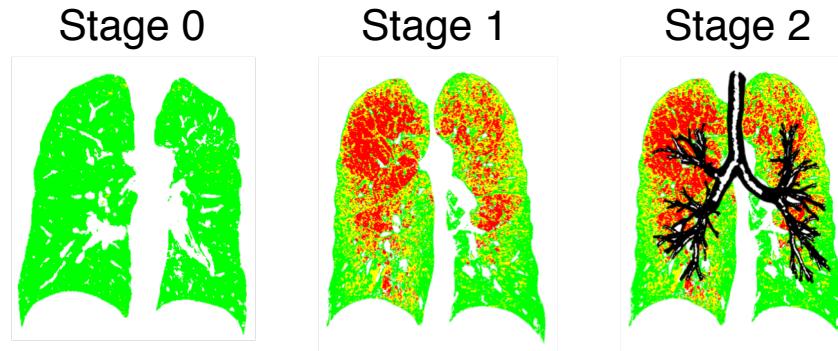


Cross-sectional samples

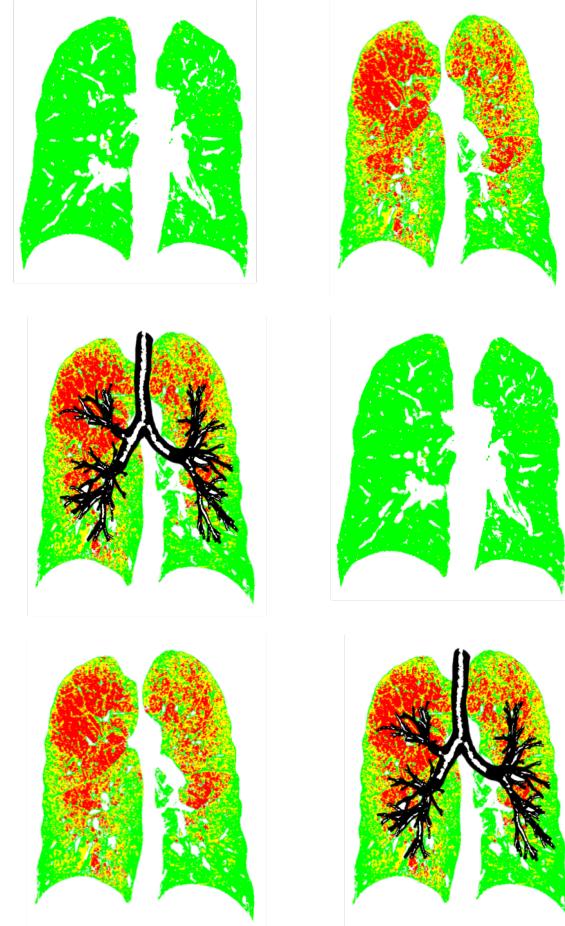


Reconstructing temporal progression from cross-sectional data

A

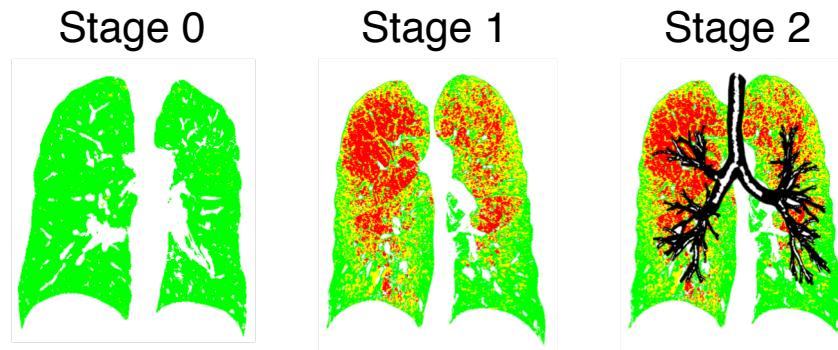


Cross-sectional samples



Reconstructing temporal progression from cross-sectional data

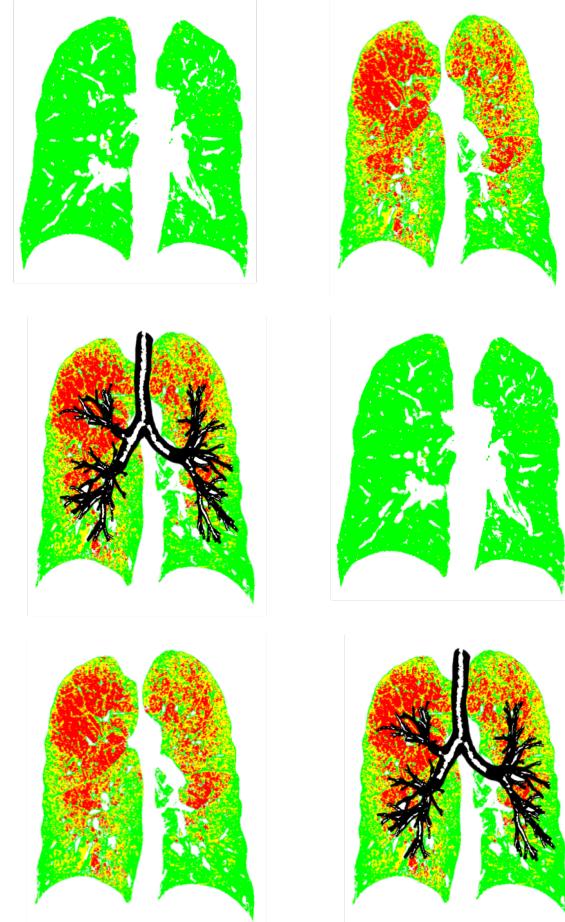
A



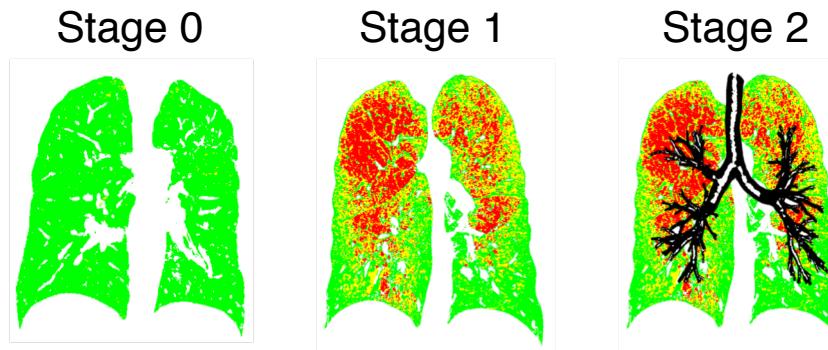
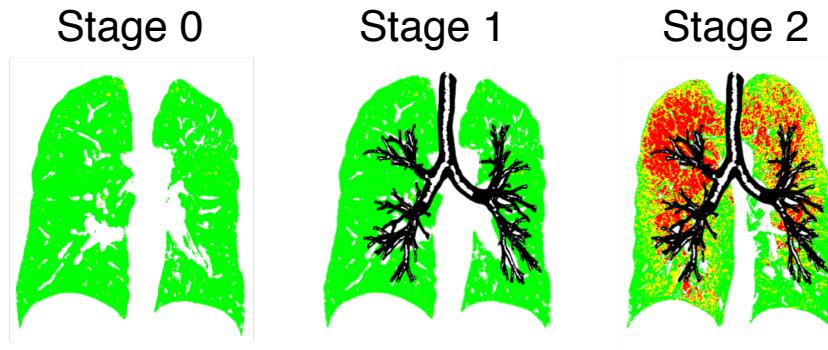
Emphysema precedes airway wall thickening



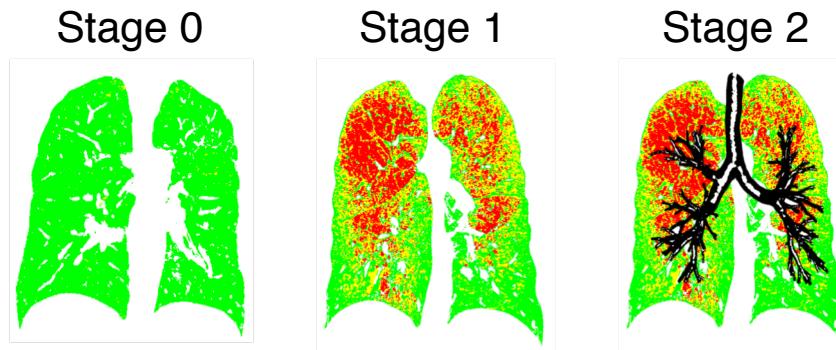
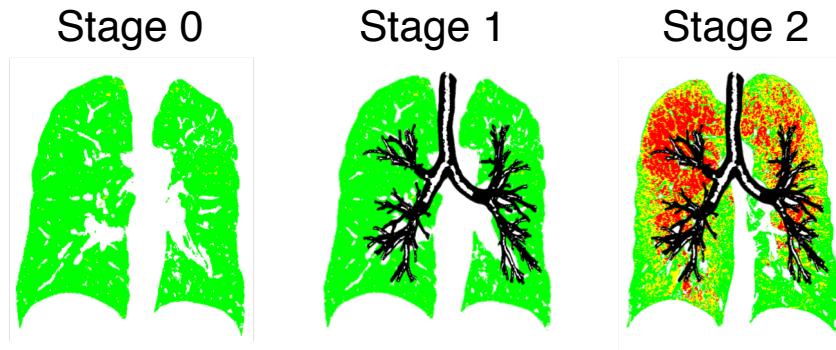
Cross-sectional samples



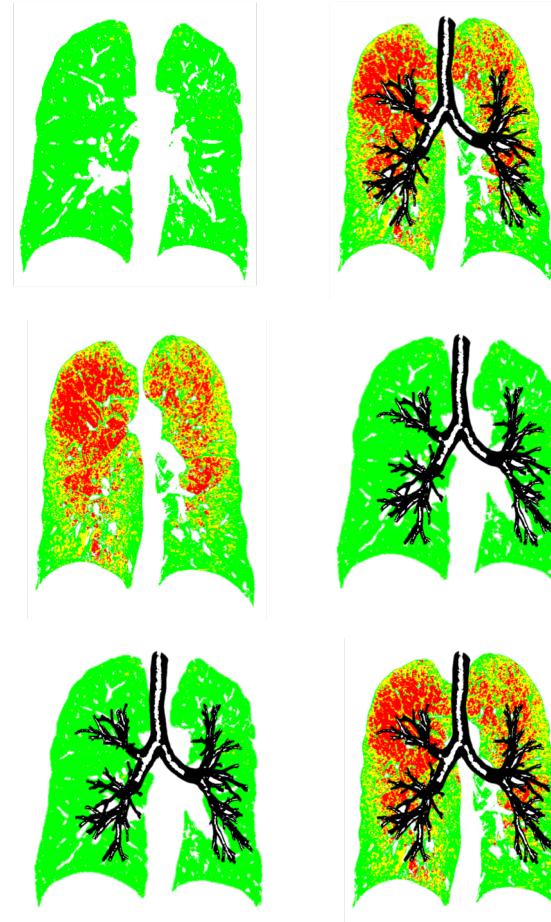
Reconstructing temporal progression from cross-sectional data

A**B**

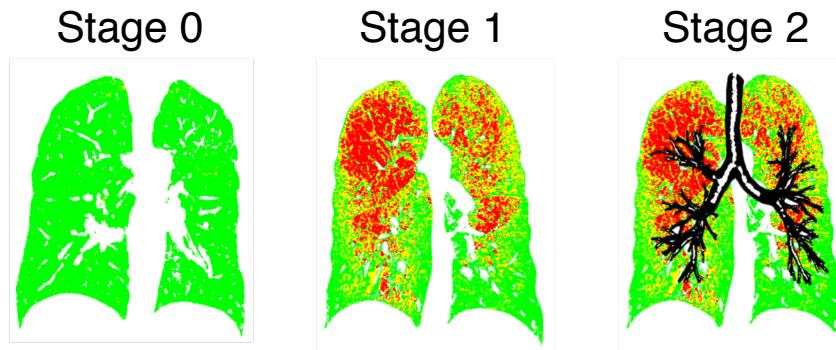
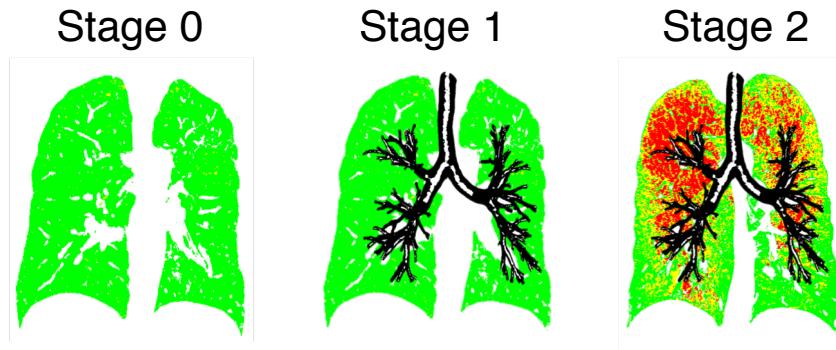
Reconstructing temporal progression from cross-sectional data

A**B**

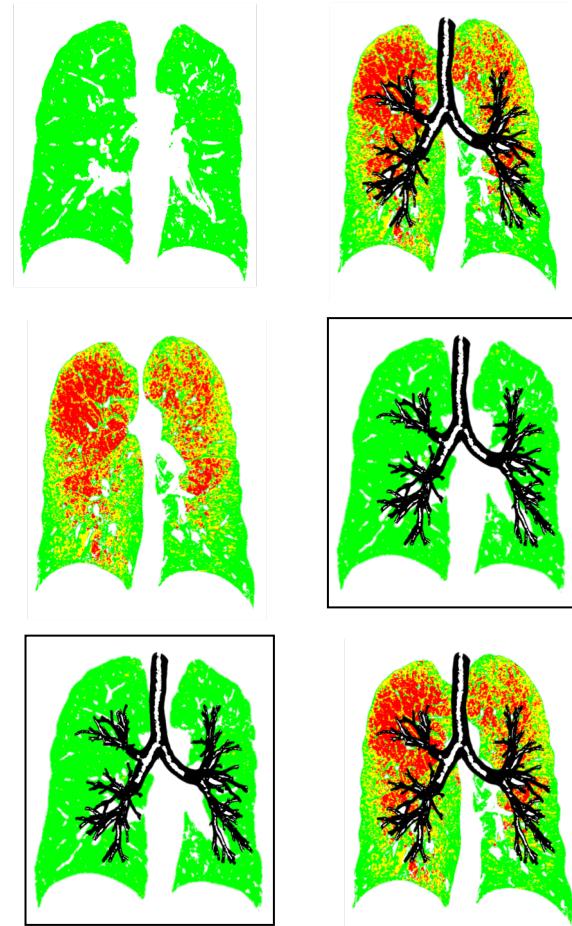
Cross-sectional samples



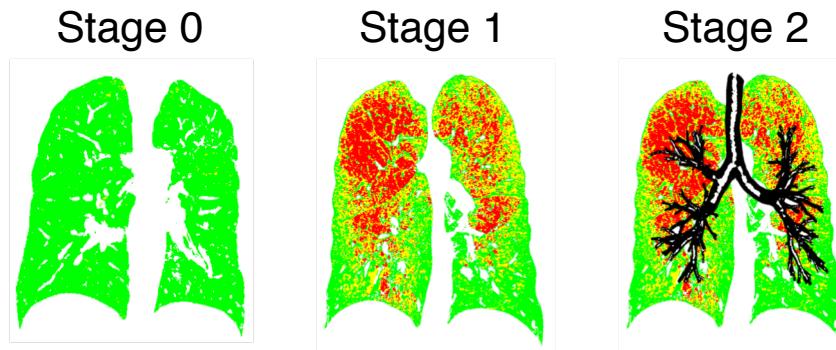
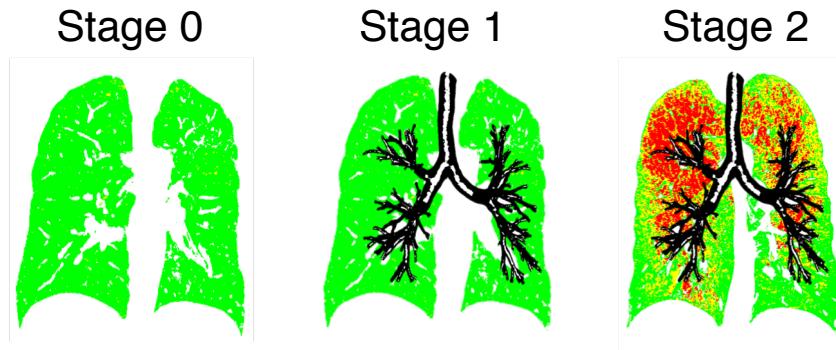
Reconstructing temporal progression from cross-sectional data

A**B**

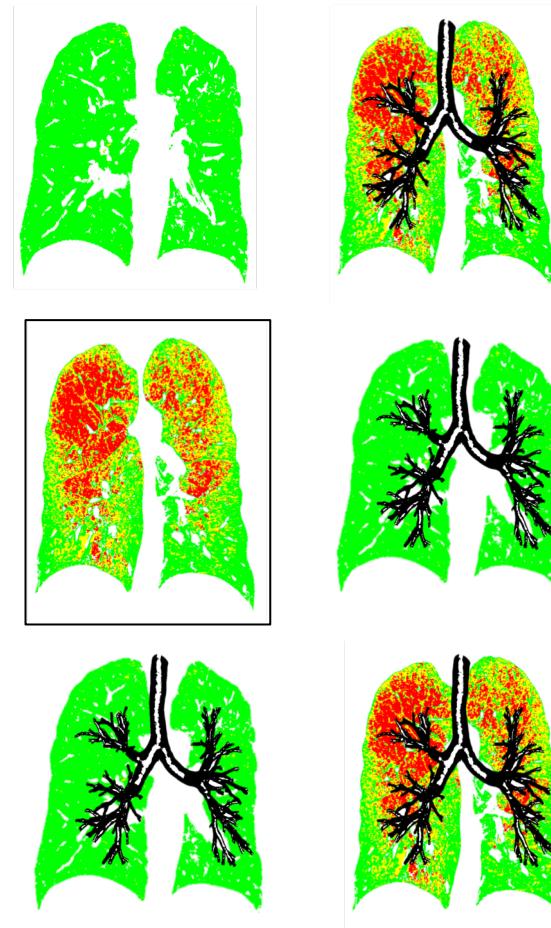
Cross-sectional samples



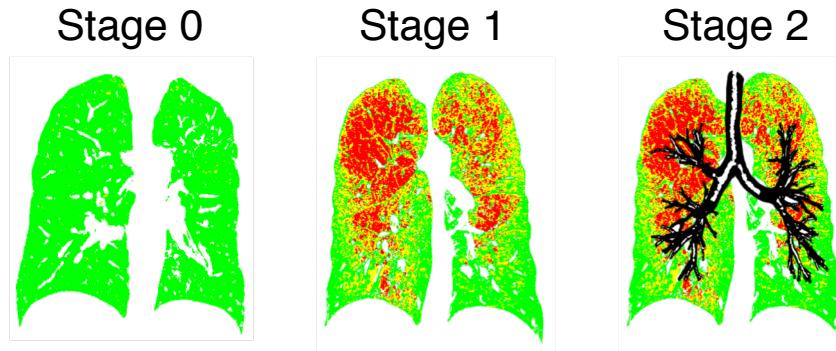
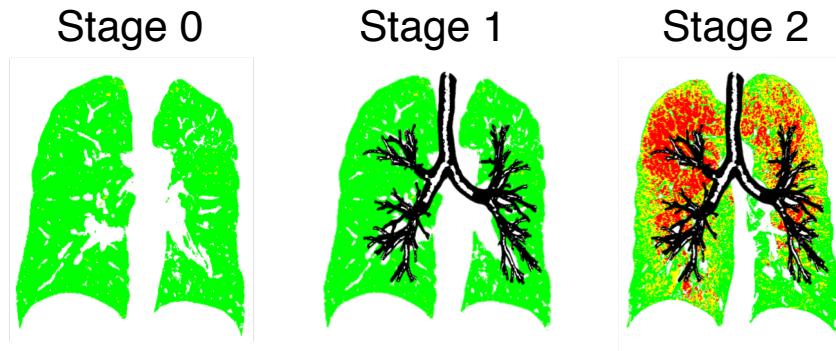
Reconstructing temporal progression from cross-sectional data

A**B**

Cross-sectional samples

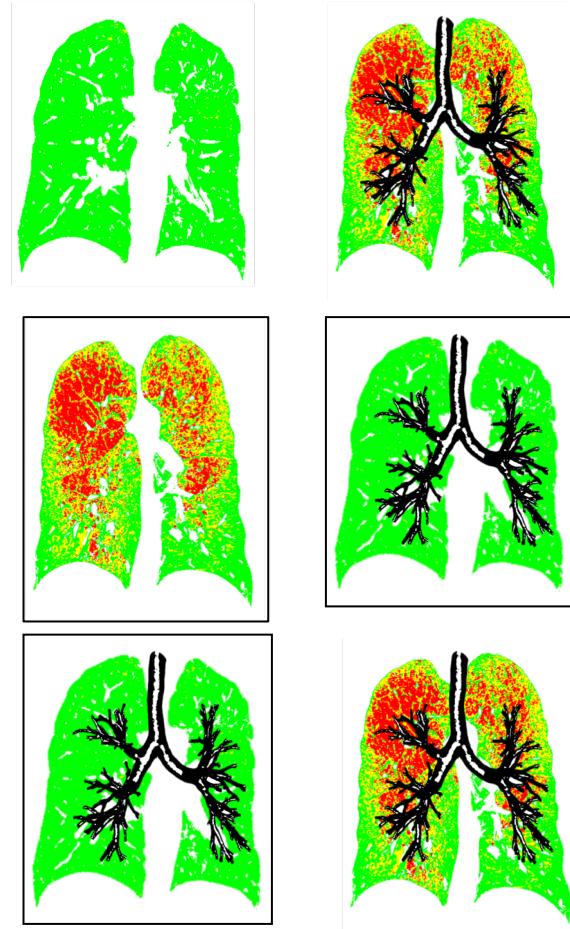


Reconstructing temporal progression from cross-sectional data

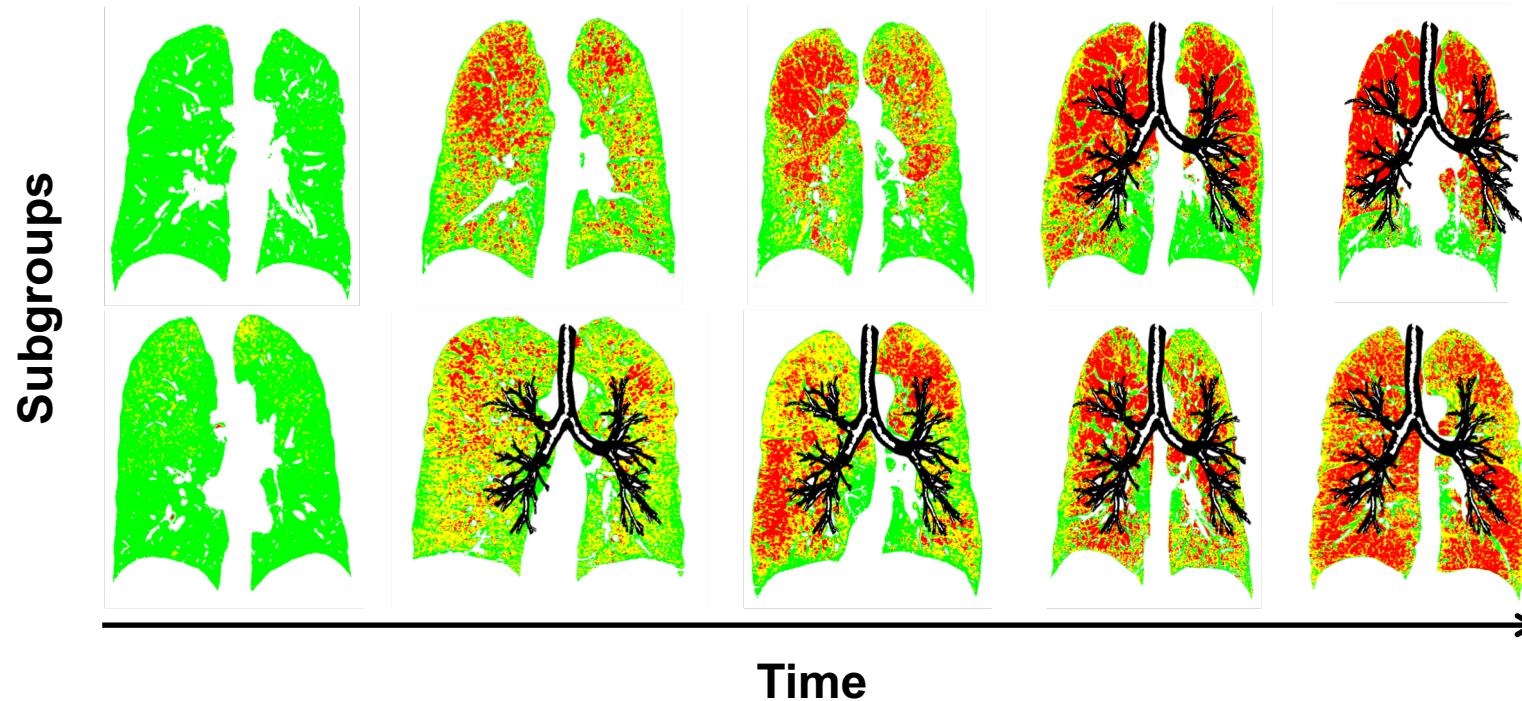
A**B**

Two subtype progression patterns:
Emphysema precedes airway wall thickening
Airway wall thickening precedes emphysema

Cross-sectional samples



SuStaln formulates this idea mathematically and generalises it to multiple subtypes and biomarkers



- Stages are indexed as a biomarker reaching a new z-score relative to a control population
- SuStaln estimates the optimal number of subtypes

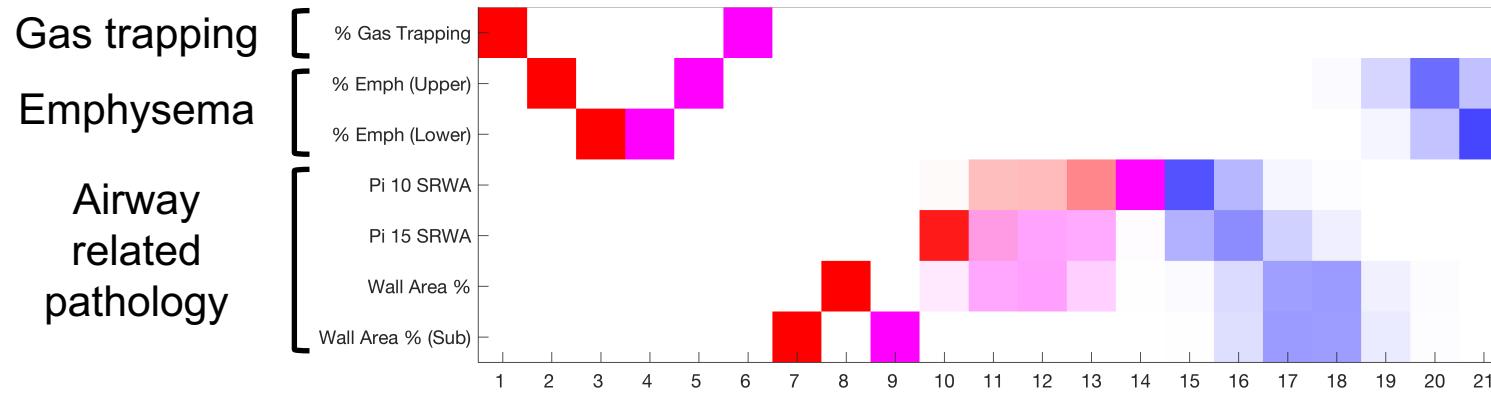
Application of SuStaln to COPDgene dataset

- Selected a set of 1349 patients (GOLD stage 1-4) with cross-sectional CT imaging measures available
- Seven image based-markers
- Measured relative to a set of 1151 smoking controls

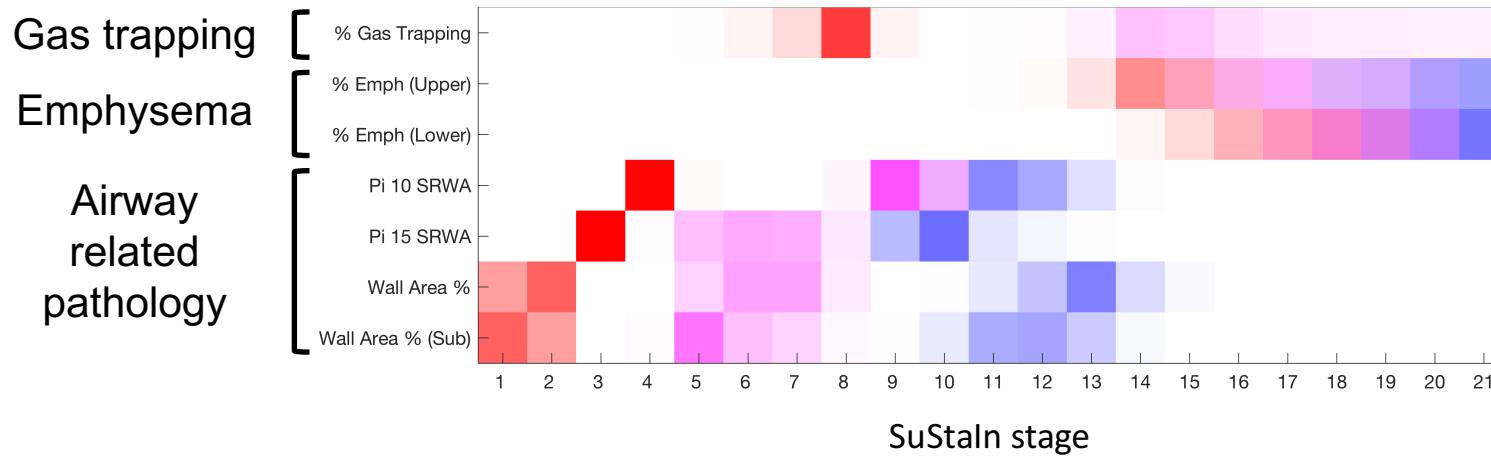
Tissue	Airway		
Gas trapping	Emphysema	Airway related pathology	
<ul style="list-style-type: none">• % Gas trapping	<ul style="list-style-type: none">• % Upper lobe emphysema• % Lower lobe emphysema	<ul style="list-style-type: none">• Pi10 square root airway wall area• Pi15 square root airway wall area• % Segmental wall area• % Sub-segmental wall area	

SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%



Airway-Tissue 23.7%

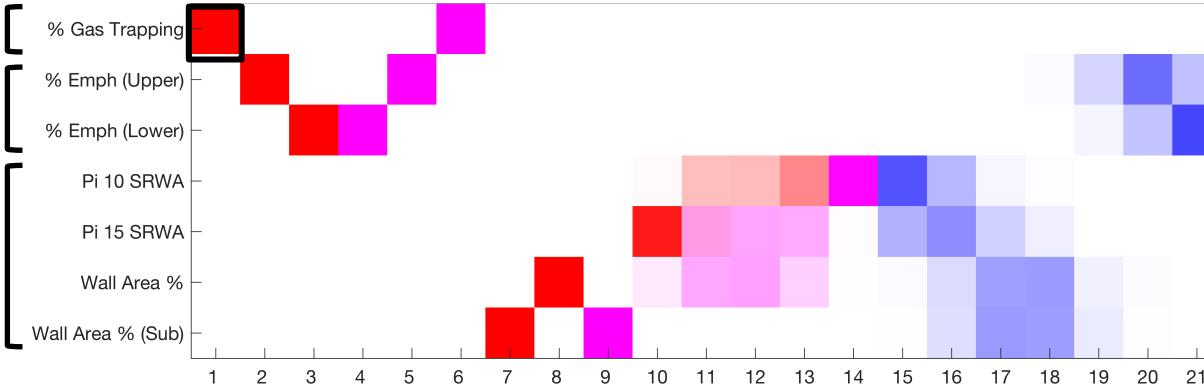


SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%

Gas trapping

Gas trapping

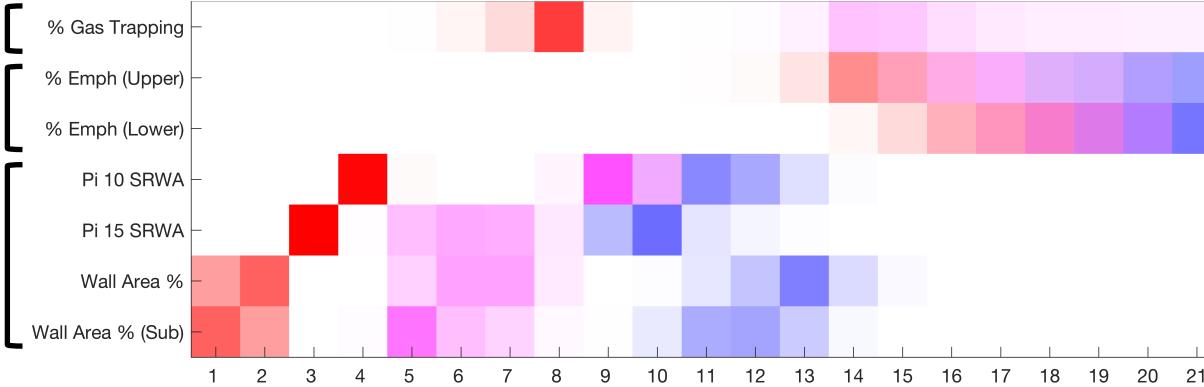


1
2
3

Airway-Tissue 23.7%

SuStaln stage

Gas trapping

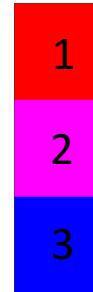
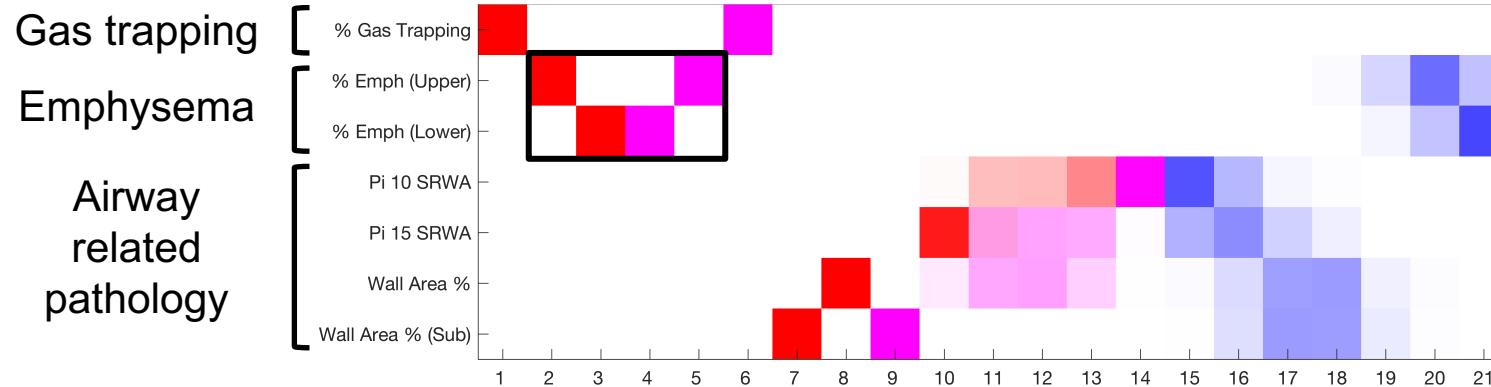


1
2
3

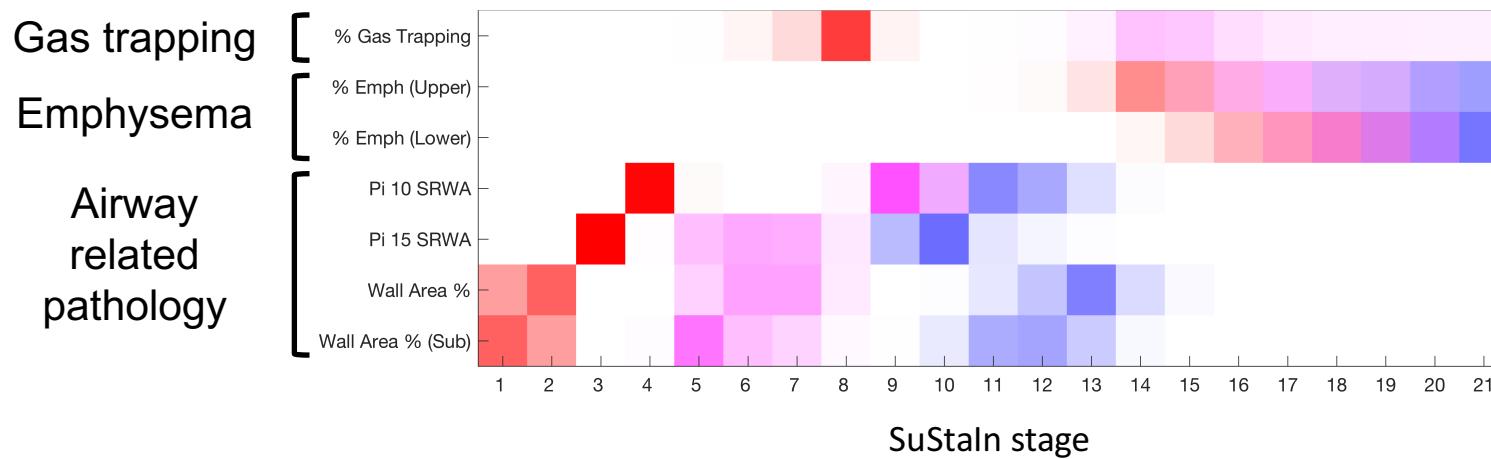
SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%

Gas trapping → Emphysema



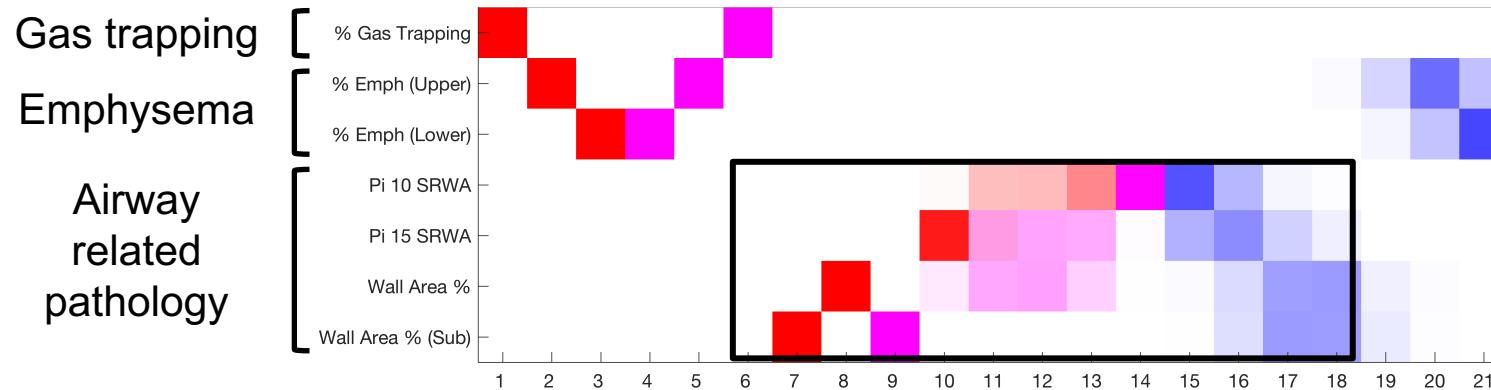
Airway-Tissue 23.7%



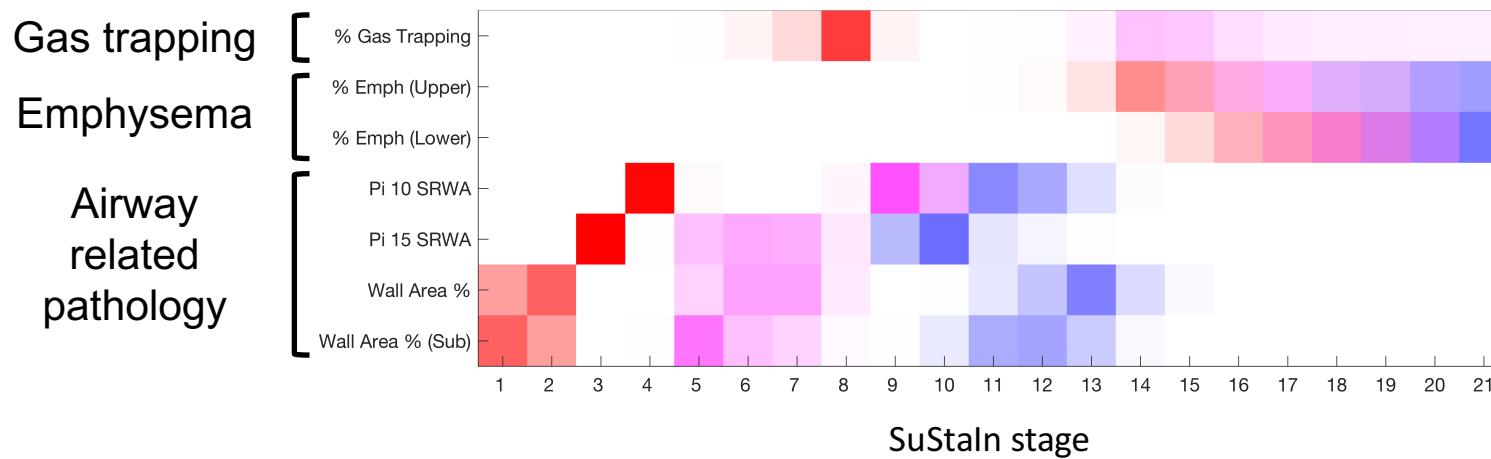
SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%

Gas trapping → Emphysema → Airway related pathology



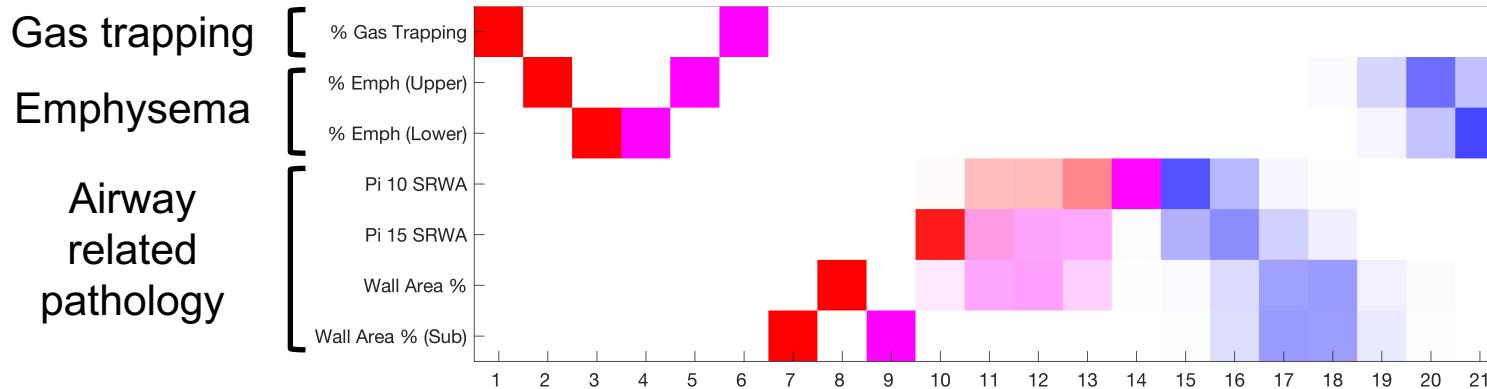
Airway-Tissue 23.7%



SuStaln identifies a Tissue-Airway and an Airway-Tissue group

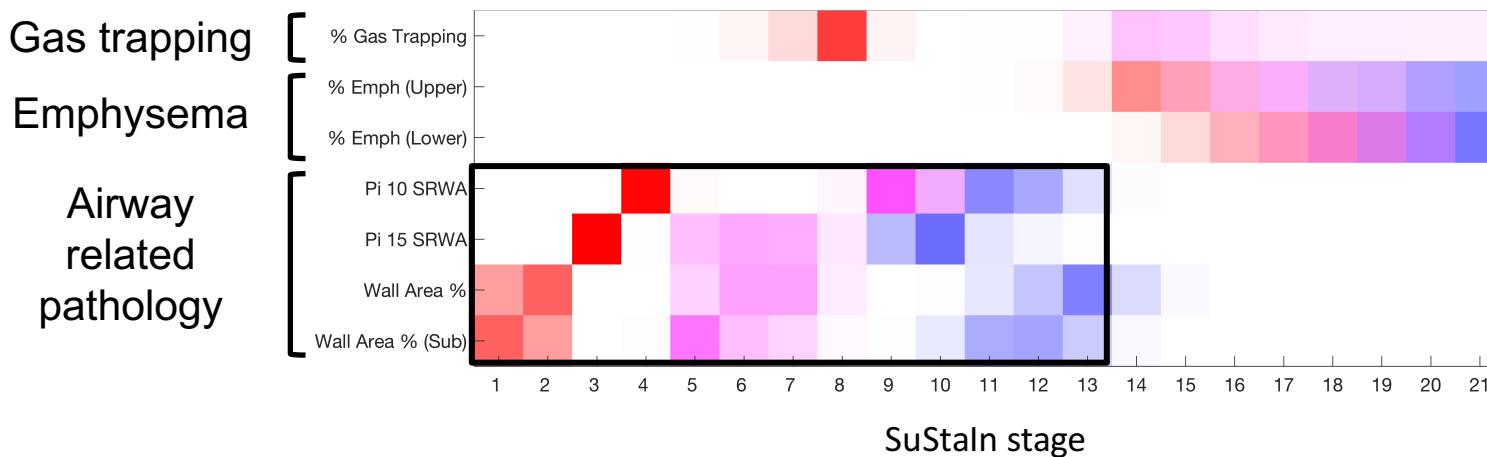
Tissue-Airway 76.3%

Gas trapping → Emphysema → Airway related pathology



Airway-Tissue 23.7%

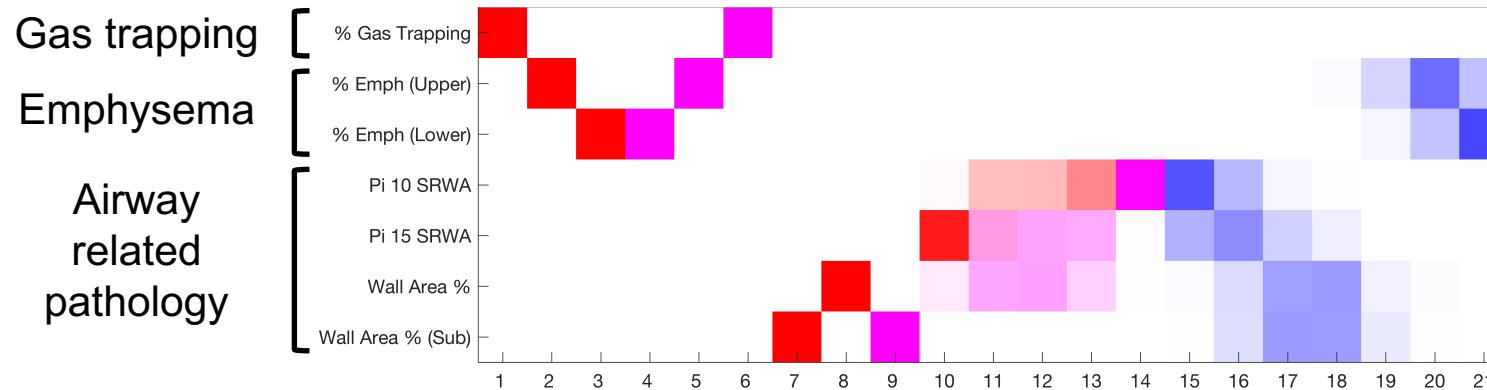
SuStaln stage
Airway related pathology



SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%

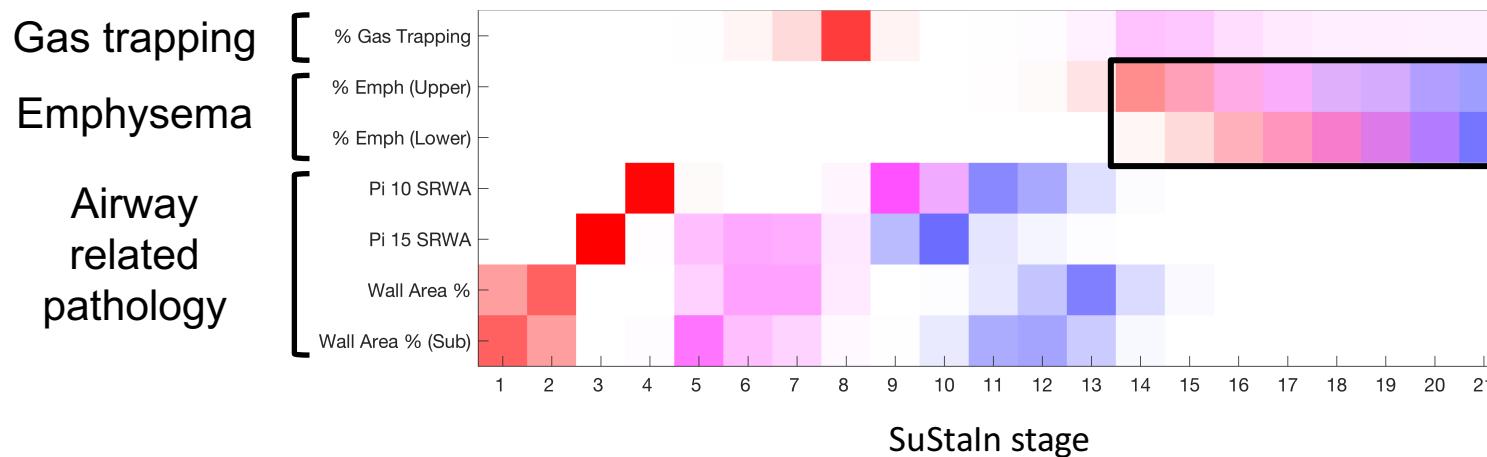
Gas trapping → Emphysema → Airway related pathology



1
2
3

Airway-Tissue 23.7%

SuStaln stage
Airway related pathology → Emphysema

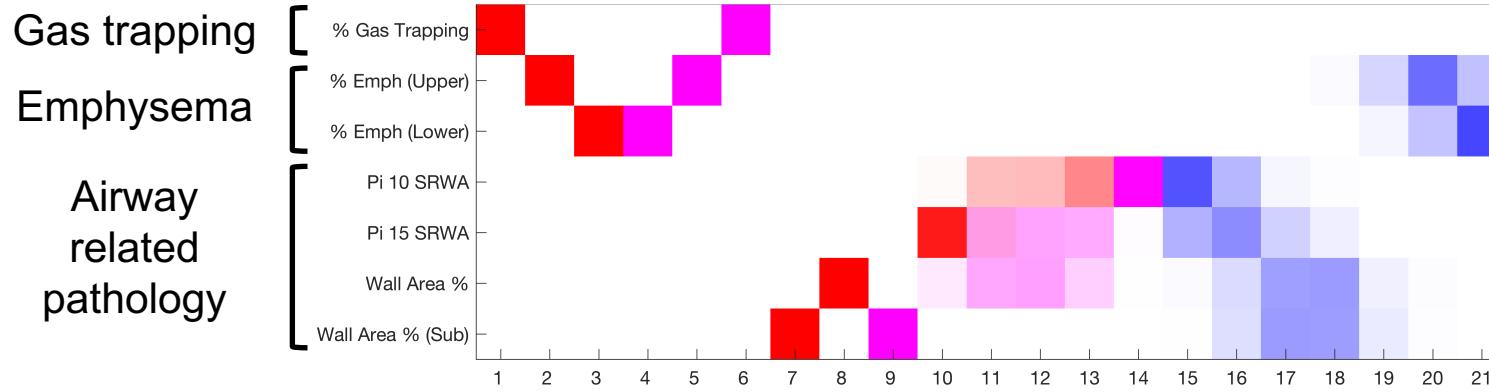


1
2
3

SuStaln identifies a Tissue-Airway and an Airway-Tissue group

Tissue-Airway 76.3%

Gas trapping → Emphysema → Airway related pathology

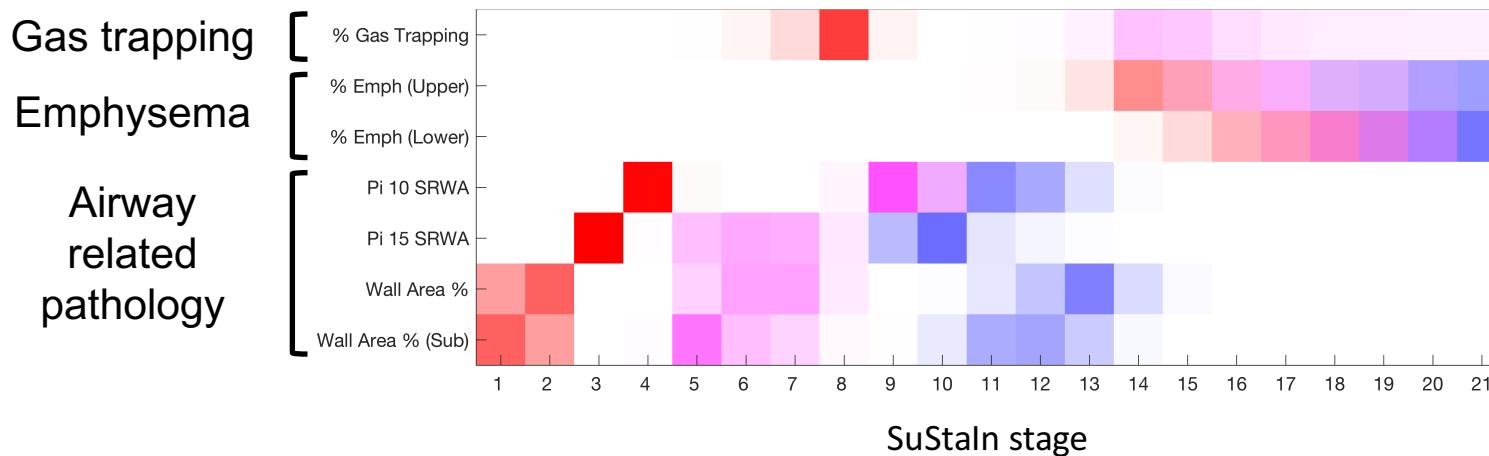


More men
Older
Lower BMI



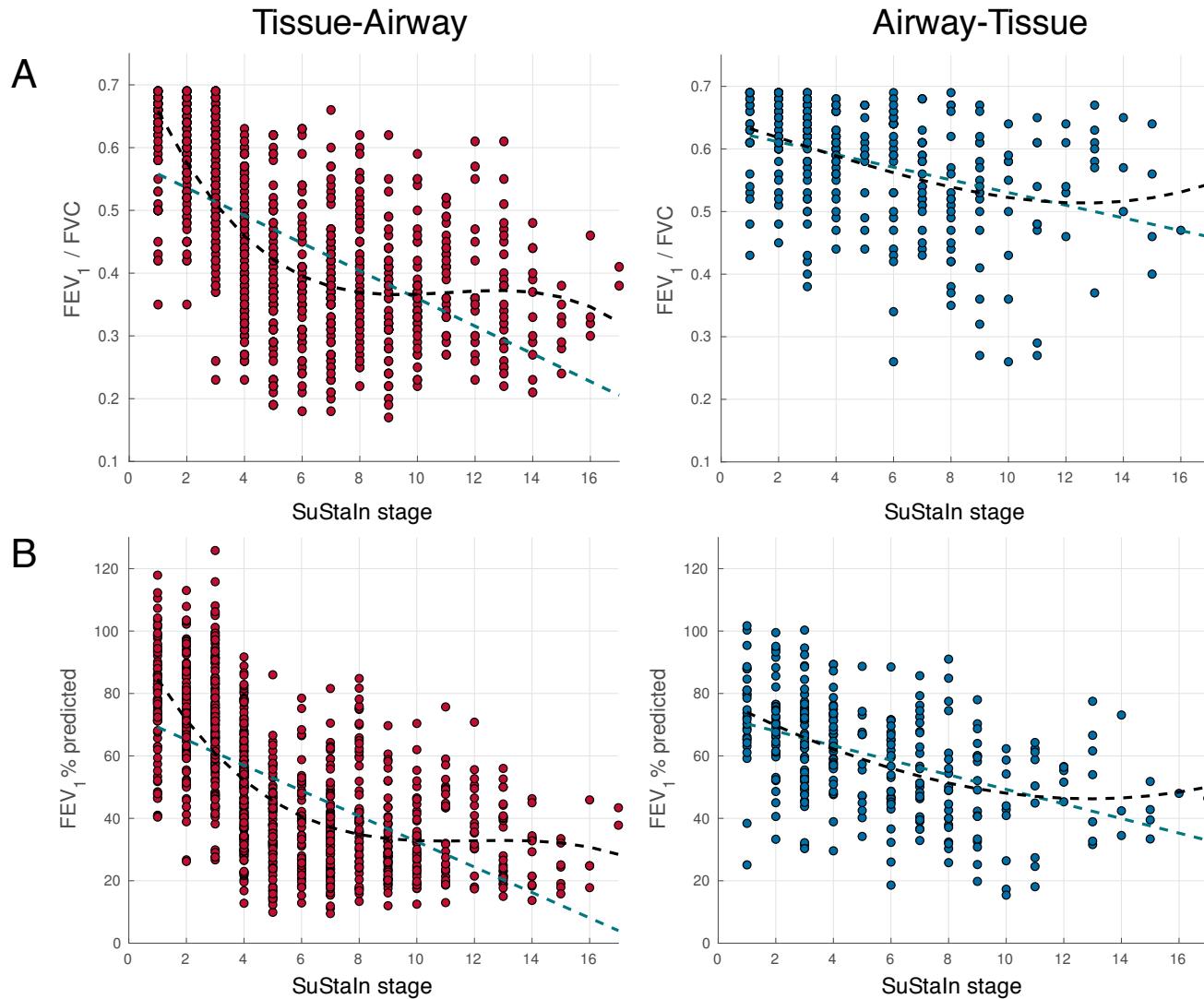
Airway-Tissue 23.7%

SuStaln stage
Airway related pathology → Emphysema



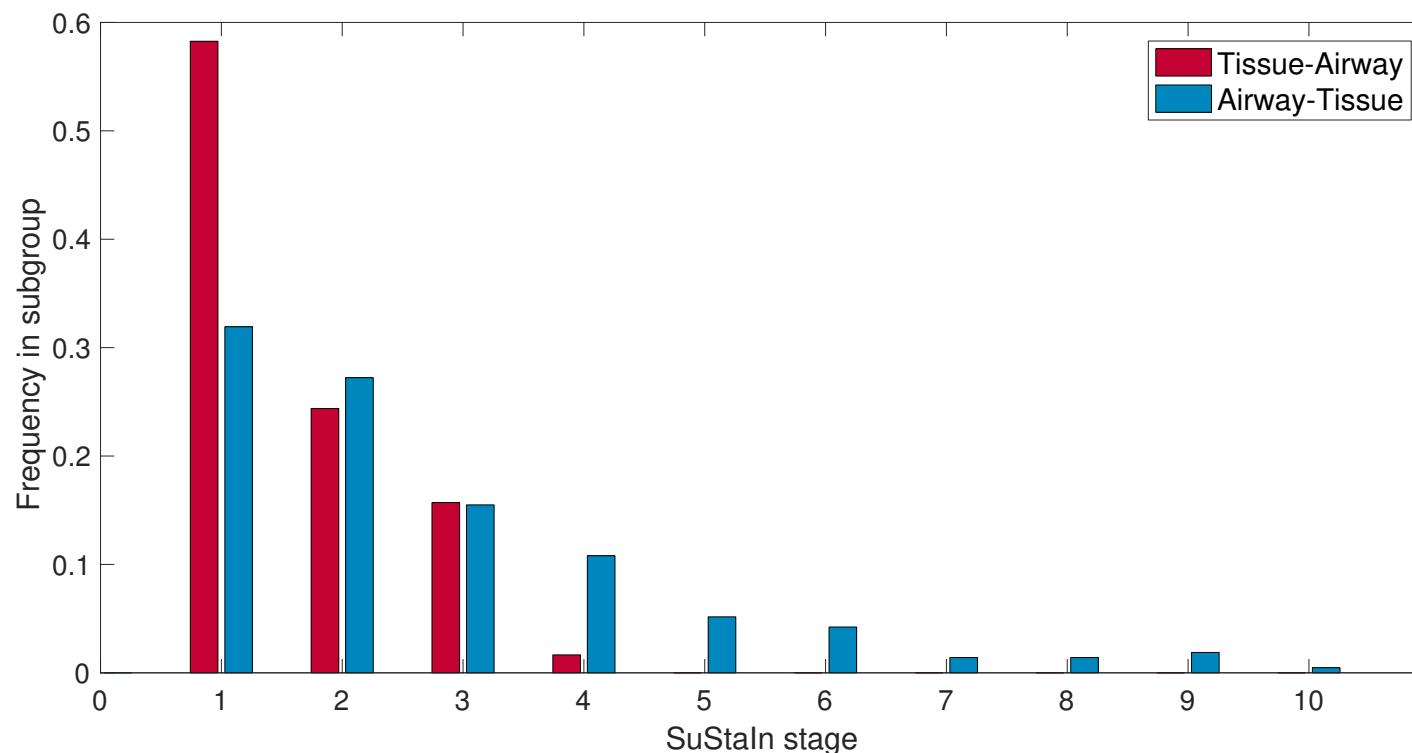
More women
Younger
Higher BMI

Subtypes correlate with decline in lung function



Early stages of COPD may be identifiable in a group of smoking controls

61% Stage 0 (no abnormalities)
39% Stage 1+
11% Stage 3+



Summary

- Identify two COPD subgroups that mirror classical descriptions of COPD phenotypes
- **Tissue-airway:** emphysema and low BMI
- **Airway-tissue:** chronic bronchitis and high BMI
- In each subgroup, SuStaln stage is significantly correlated with lung function decline
- Early stages may be identifiable in a fraction of smoking controls

Acknowledgements

Felix Bragman

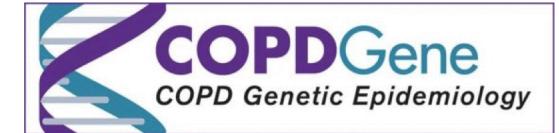
John Hurst

Daniel Alexander

David Hawkes



Engineering and Physical Sciences
Research Council



Pre-print SuStain Nature Comms

alexandra.young@ucl.ac.uk

bioRxiv <https://doi.org/10.1101/236604>



Centre for Medical Image Computing

