

# Single-molecule genomics data delineate patient-specific tumor profiles and cancer stem cell organization

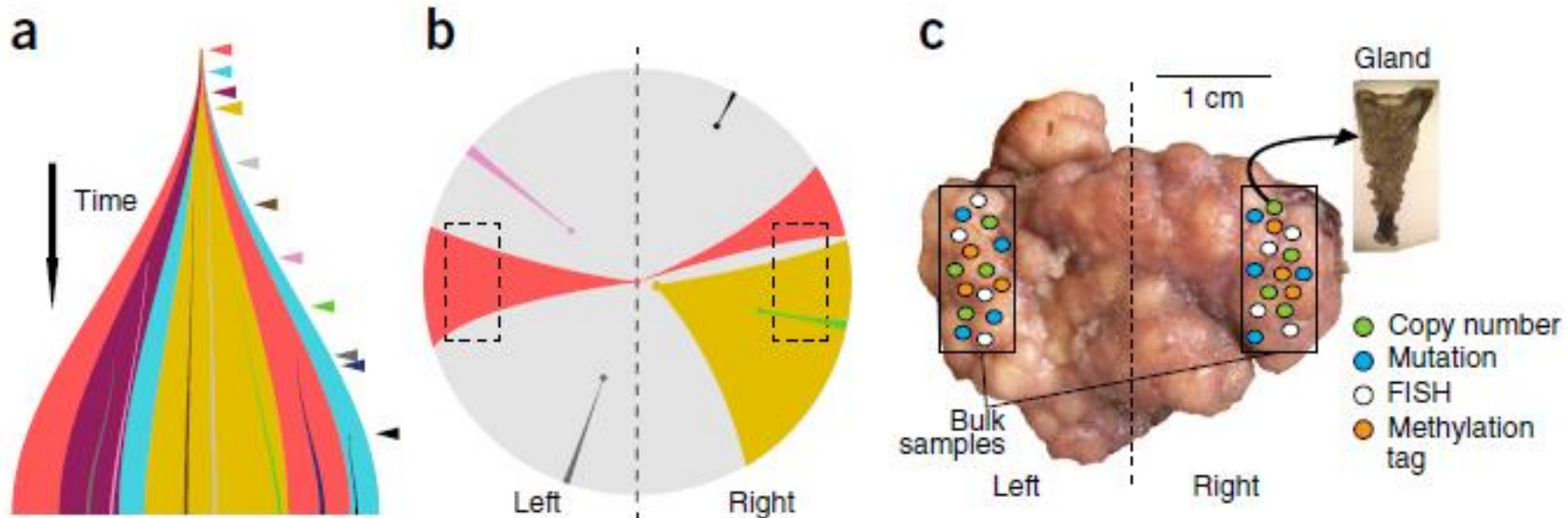
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2015-3-2

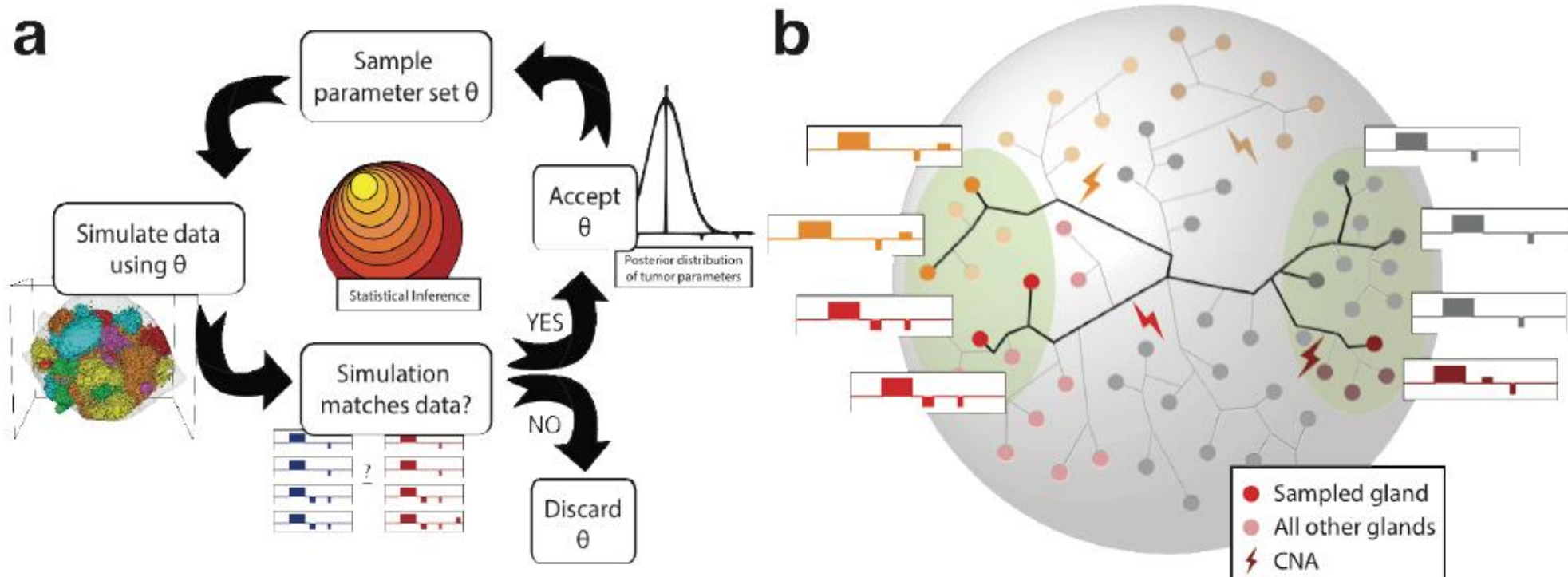
- <https://www.synapse.org/#!Challenges:DREAM>

# A big bang model of colon tumor growth

- “It’s like going back in time. The history of each tumor is written in its genomes. To prevent tumors, you want to see what happened early on and how to stop their first cell divisions.”



# Aim: How to model tumor growth considering the heterogeneity



Data:

Table 1. Patient clinical information

| <b>Patient</b> | <b>Age</b> | <b>Tumor<br/>size (cm)</b> | <b>Stage</b> | <b>MSI+</b> |
|----------------|------------|----------------------------|--------------|-------------|
| CT             | 53         | 4.5                        | 3            | N           |
| CU             | 50         | 4.5                        | 1            | Y           |
| CX             | 44         | 9                          | 3            | N           |
| HA             | 61         | 7.5                        | 3            | N           |
| Z              | 83         | 6                          | 3            | NA          |

# Method: Three building blocks

- The patient molecular data (the history of tumor evolution)
  - somatic point mutation
  - microsatellites
  - neutral methylation
- The mathematical/computational model
  - simulate tumor growth in a spatial fashion
  - mutation rate, apoptosis, etc
- The statistical inference
  - probability distribution of parameters.

# Block 1: The patient molecular data

- Choose a clock: Neutral somatic mutation
- This measurement is used to indicate the historical mutation/changing during tumor growth, also related to tumor status.
- DNA methylation of IRX2
- 8 CpG islands :  $2^8 = 256$  patterns (binary representation)
- Low methylation: non-dividing tissues (differentiated)
- High methylation: dividing tissues (proliferative)

# Block 2: simulate tumor growth in a spatial fashion

- Dynamic models (numerous)
- Build a phylogenetic tree (spatial property)
- Go to Pseudocode 1 (crecspace)
- Go to Pseudocode 2 (crecmeth)



# Block 3: statistical inference

- Rejection sampling
  1. Sample the parameter  $\theta$  from the prior distribution  $P(\theta)$ .
  2. Simulate the data  $D'$  from the computational model with input  $\theta$ .
  3. If  $\rho(S[D], S[D']) < \varepsilon$  accept  $\theta$ .
  4. Go to 1.

# Results 1: Cancer glands are heterogeneous

**A**

Tumor CT, gland R1



Tumor CU, gland R4



Tumor CX, gland L3



Tumor HA, gland L5



Tumor Z, gland R3

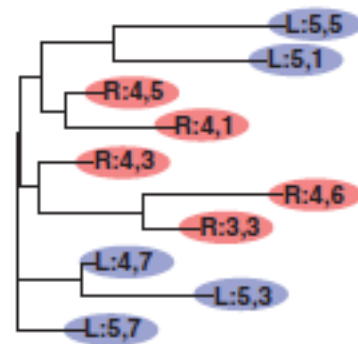


Tumor Z, gland L2

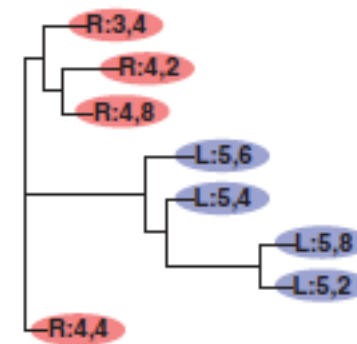


**B**

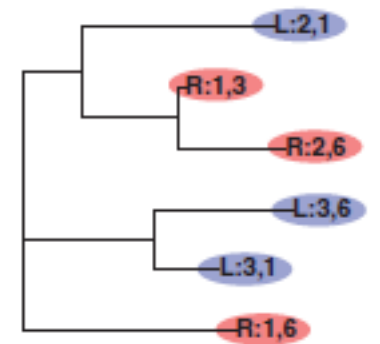
Tumor HA (1402 reads/gland)



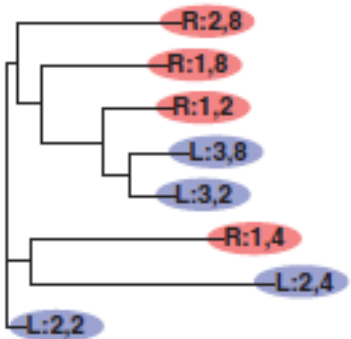
Tumor CU (2076 reads/gland)



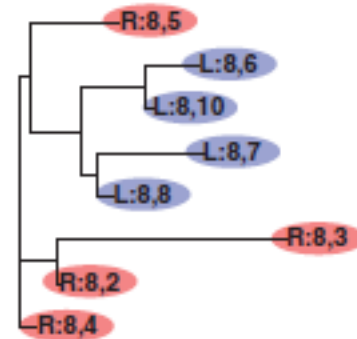
Tumor CX (1006 reads/gland)



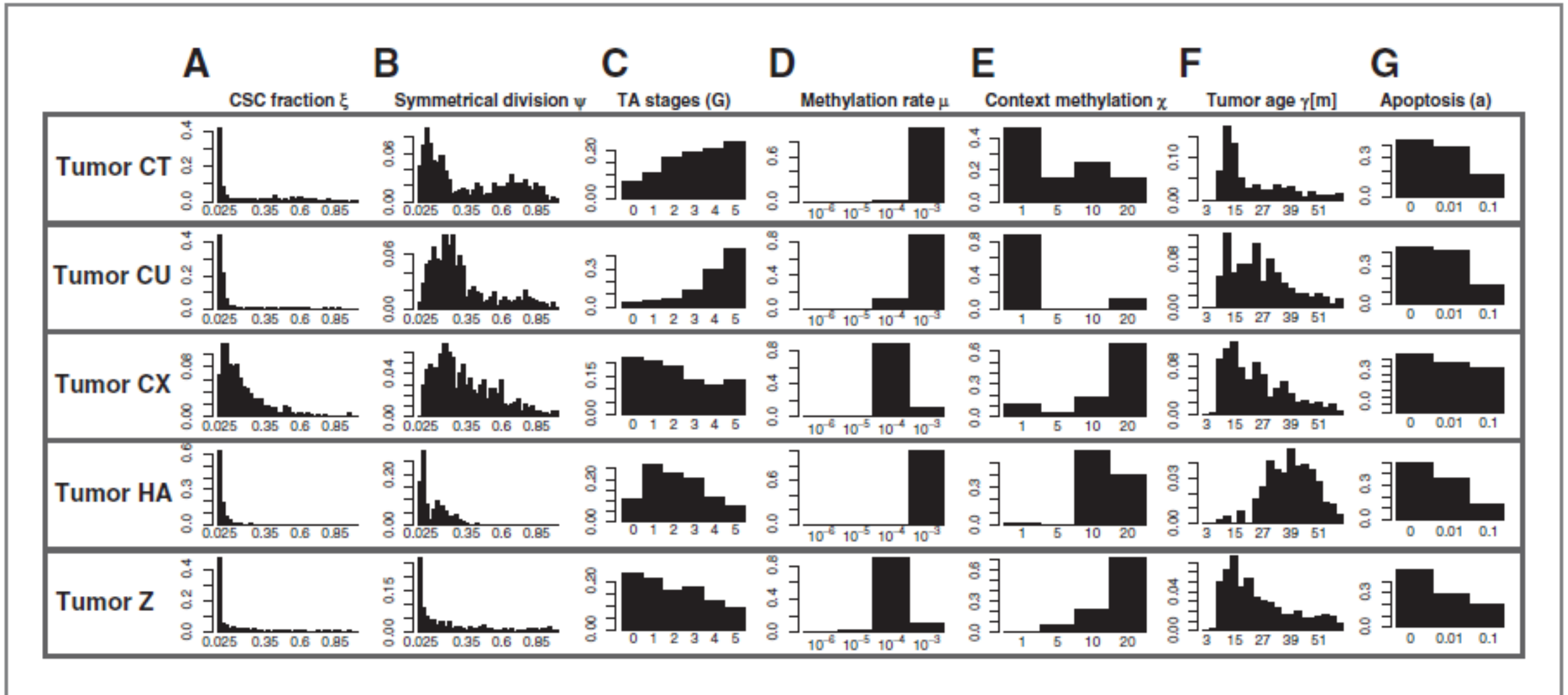
Tumor CT (2430 reads/gland)



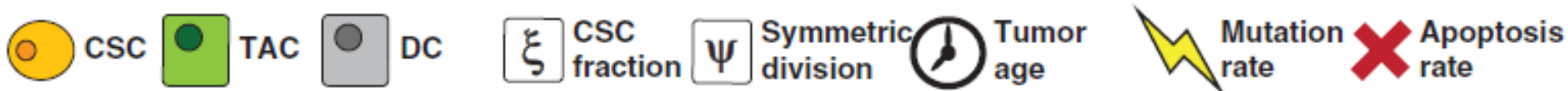
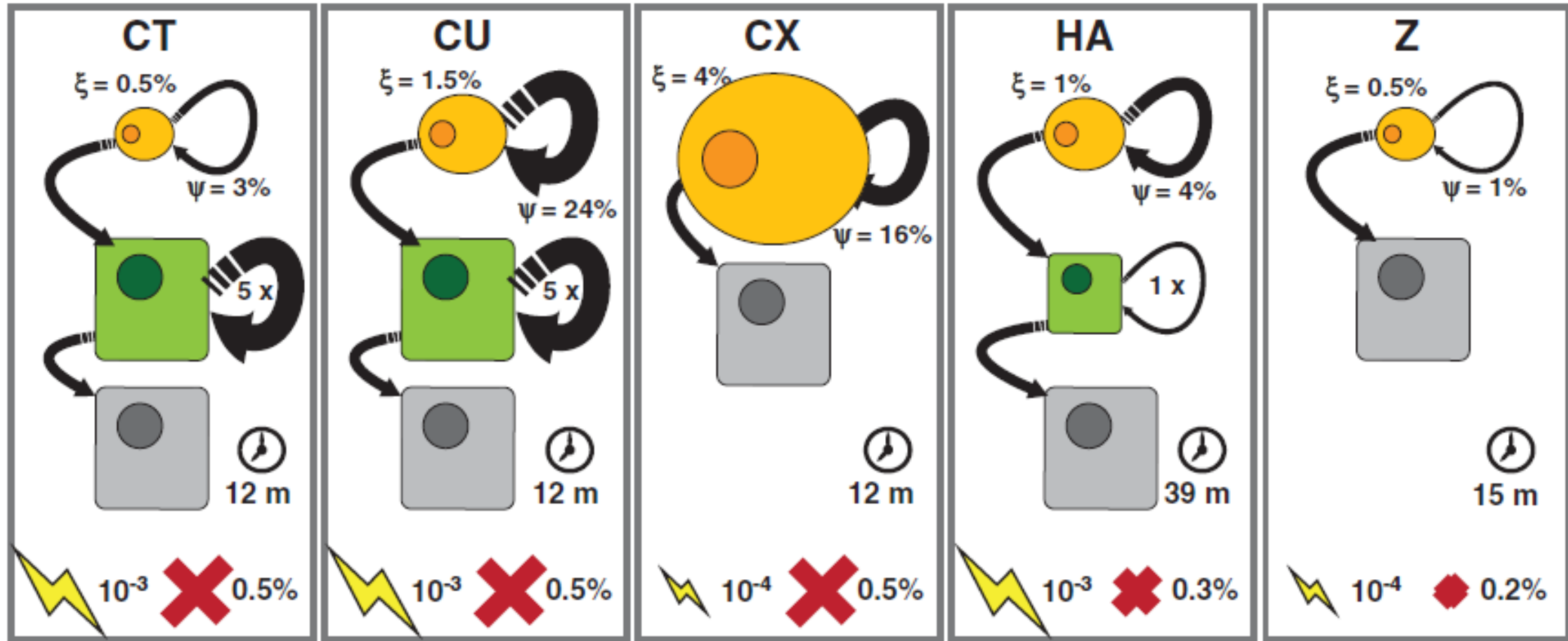
Tumor Z (1703 reads/gland)



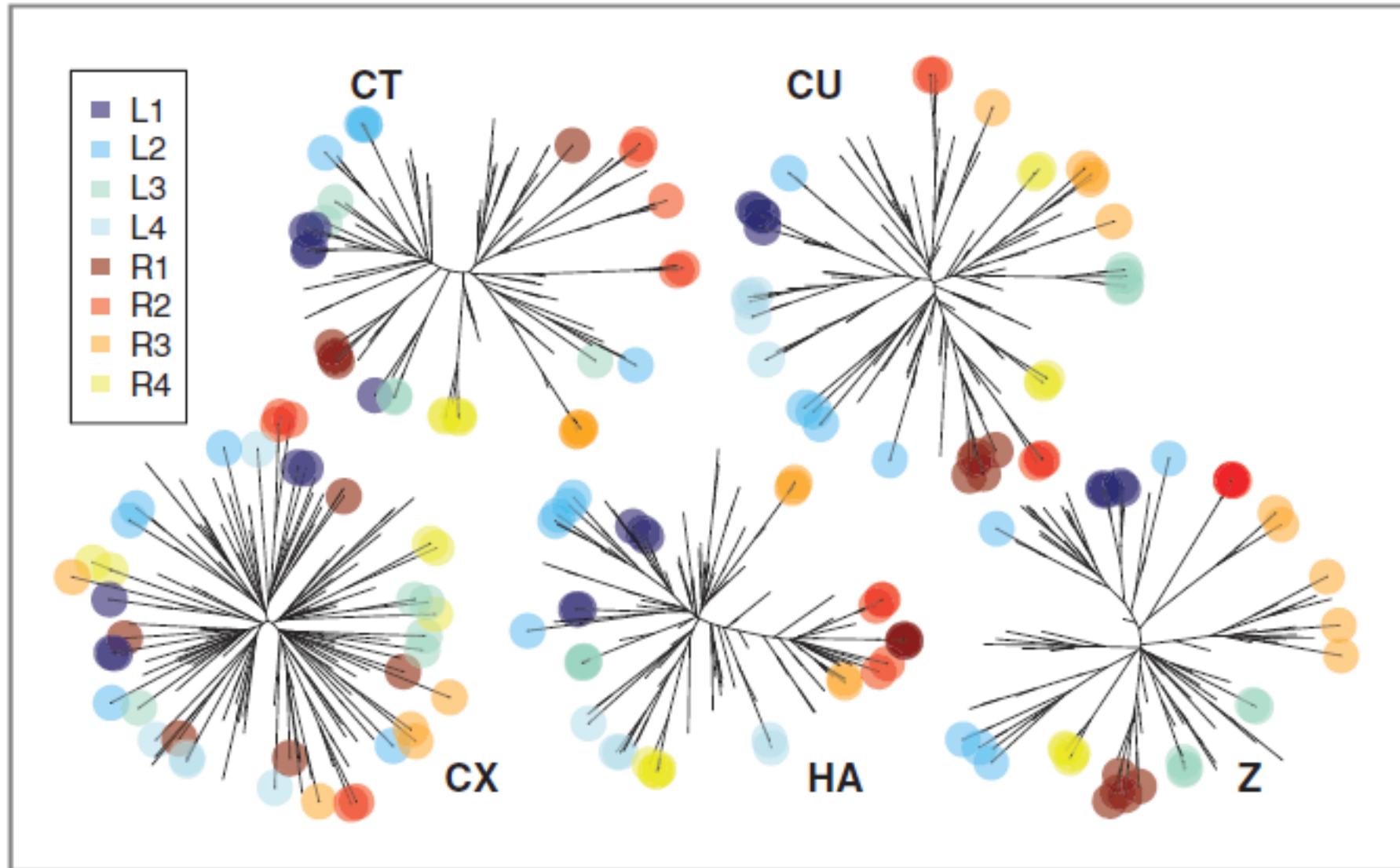
# Results 2: parameters summary for each patient



# Results 3: Cartoon representation of the tumor growth characteristics for each patient



# Results 4: reconstructing tumor ancestral tree



# Discussion:

- Deep sequencing technologies have enable the generation of high-throughput molecular data, which coupled with careful tumor sampling schemes, can provide new insight into tumorigenesis.
- Using our model, we simulated the entire history of a tumor using the inferred parameters to generate a representation of a phylogenetic tree.

- How to decide the number of subclones in a tumor?
- How to utilize molecular data (multi-genes? RNA-seq data? Meta-data?) to retrieve the tumor growth history?
- How to simulate tumor growth considering single-cell heterogeneity?