



Using High-Content Imaging to Analyze Toxicological Tipping Points

International Conference on Toxicological Alternatives &
Translational Toxicology

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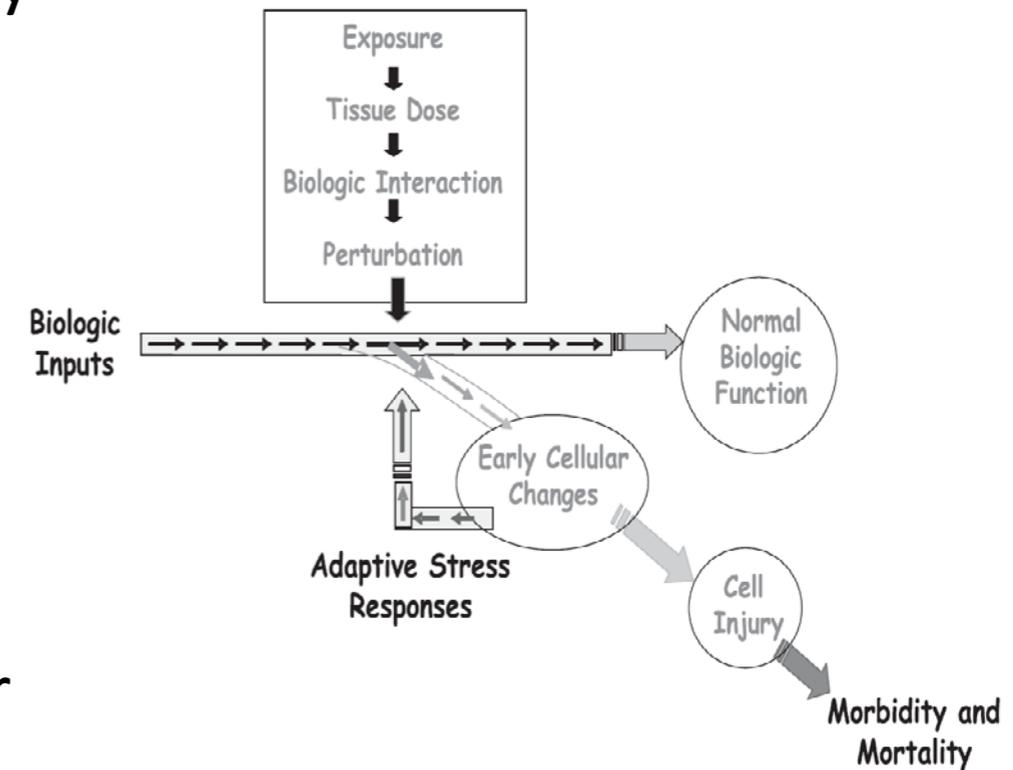
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National Center for Computational Toxicology

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Toxicological Tipping Points

- ❑ Current toxicological tests use apical *in vivo* adversity to define a point of departure (PoD) for risk assessment
- ❑ Biological systems are resilient and adapt to environmental perturbations
- ❑ Threshold between adaptation and adversity:
“Tipping point”
- ❑ Could toxicological tipping points be used as PoD for risk assessment ?
- ❑ ***How can we use high-content imaging (HCI) data to find tipping points ?***



High Content Imaging (HCI)

□ Study

- HepG2 cell culture
- 967 chemicals (ToxCast)
- 10 conc

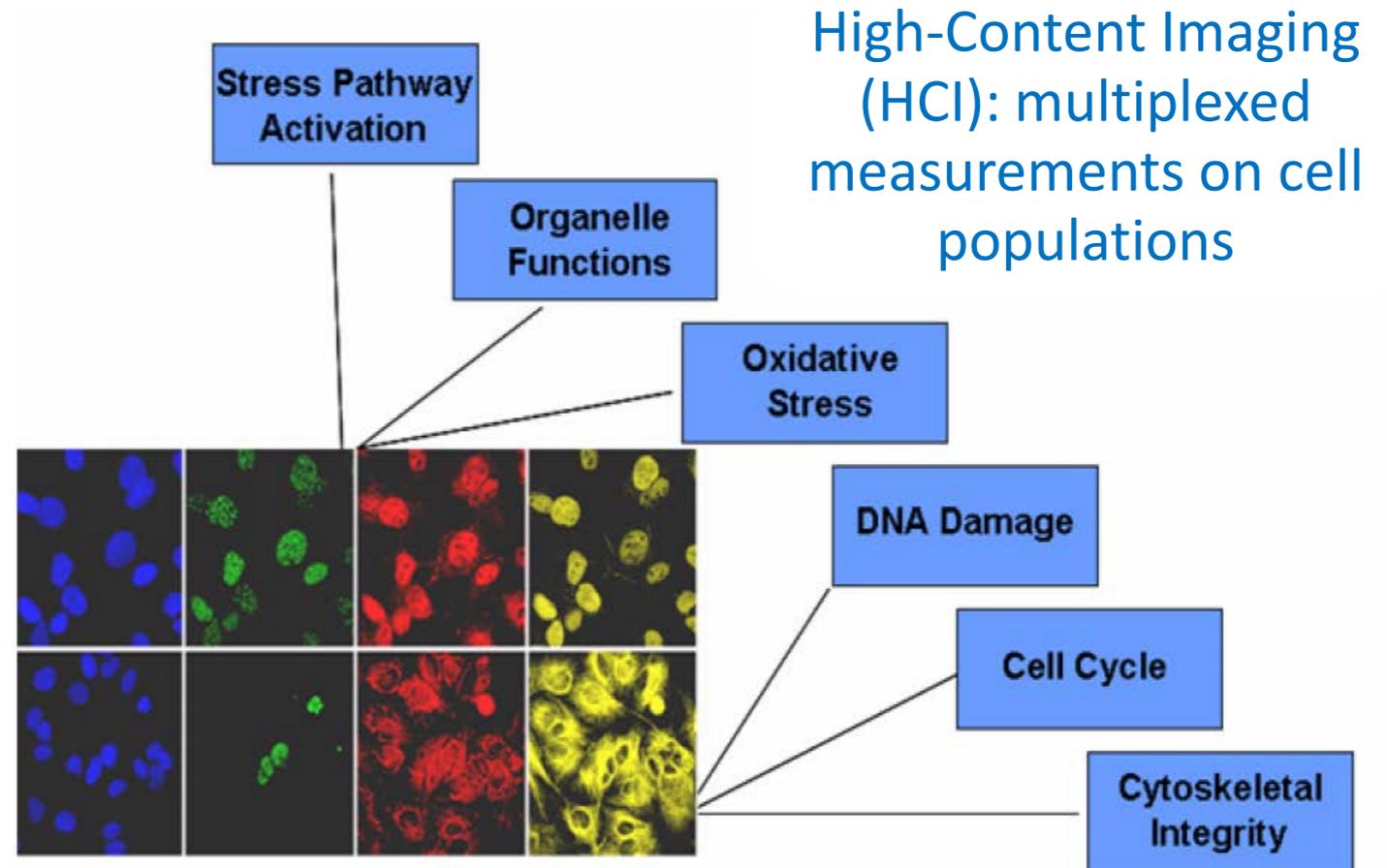
□ HCI Assays

- Health
- Stress
- Cellular perturbations

□ Dynamic phenotypic response of cells to chemicals

□ Large-scale data

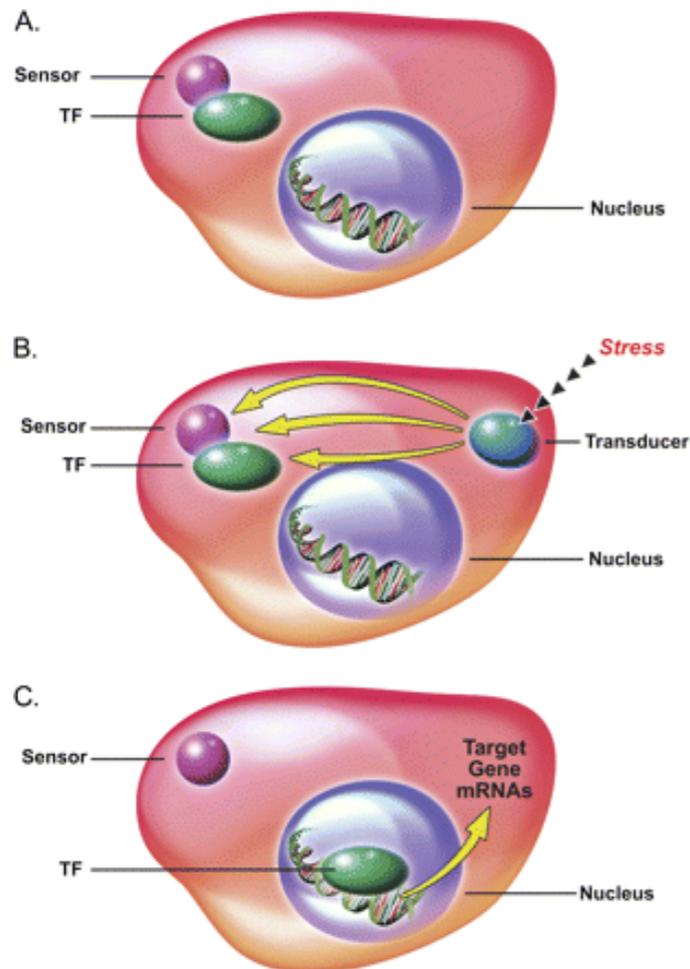
- ~400 plates
- ~100,000 wells
- ~2,400,000 images



HCI Conducted by Cyprotex, Inc.

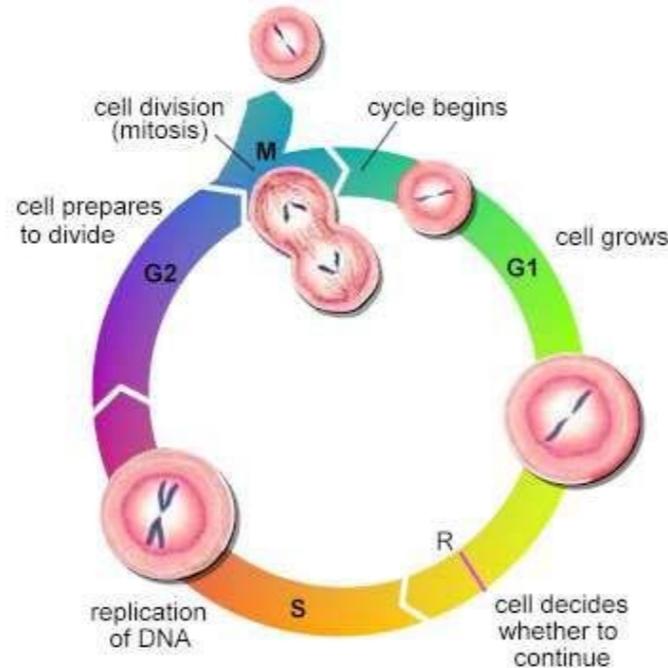
HCI Endpoints: Cell State

Stress Response Pathways



Simmons et al 2009

Cell Cycle Progression



www.flowcytometry.us

- P53: p53 activity (**p53**)
- c-Jun: stress kinase (**SK**)
- H2AX: oxidative stress (**OS**)
- MitoTracker Red: mitochondrial mass (**MM**), mitochondrial membrane potential (**MMP**)
- Tubulin: microtubule organisation (**Mt**)
- Hoechst33342: nuclear size (**NS**), cell cycle arrest/progression (**CCA**), cell number (**CN**)
- PH3: mitotic arrest (**MA**)

Cell-State Data from Images

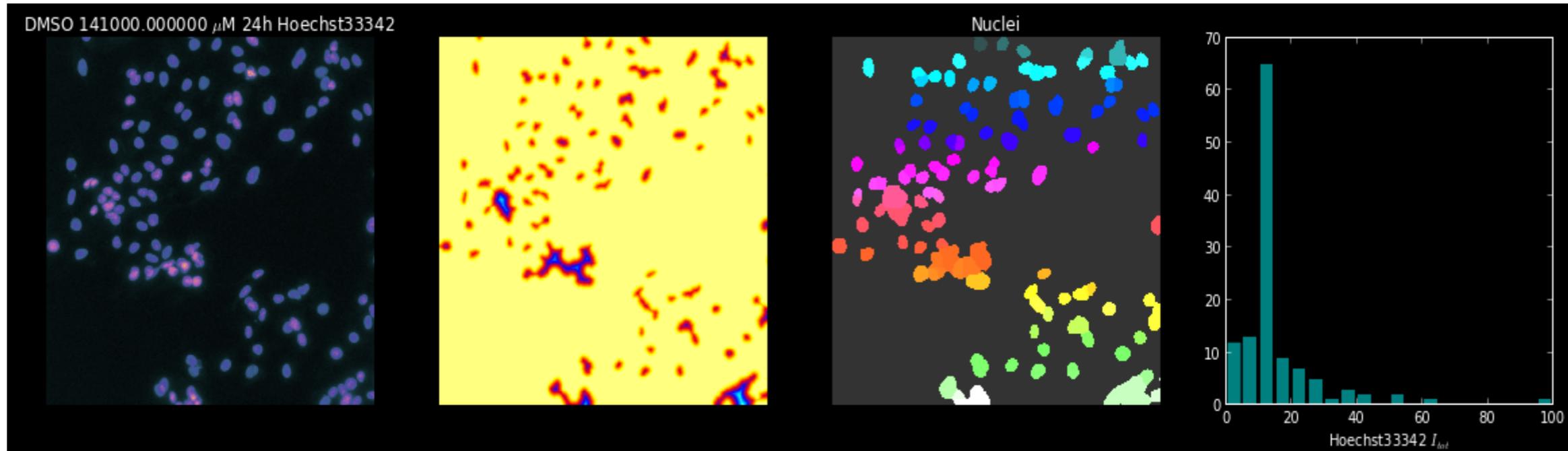
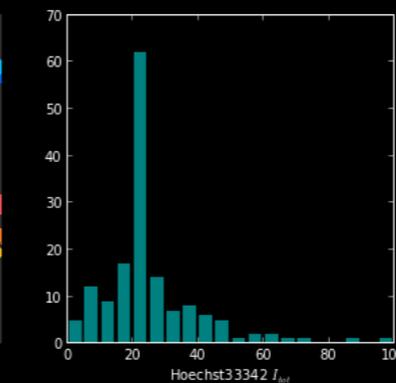
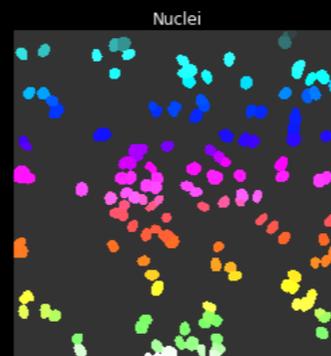
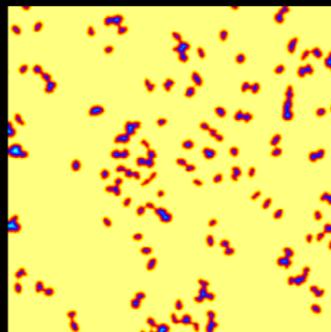
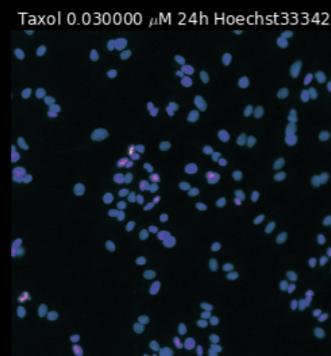


Image analysis and cell level feature feature extraction conducting by Cyprotex Inc. (proprietary software)

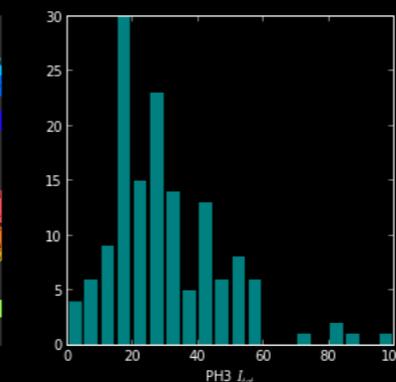
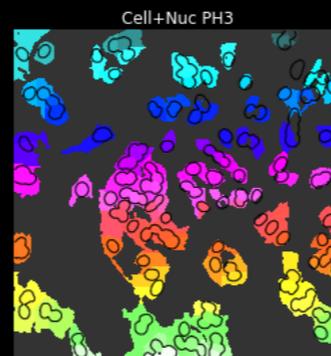
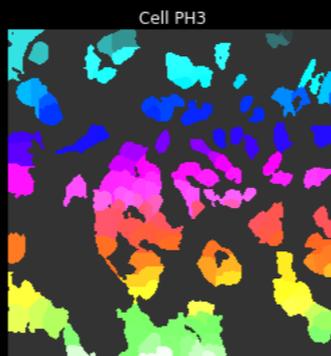
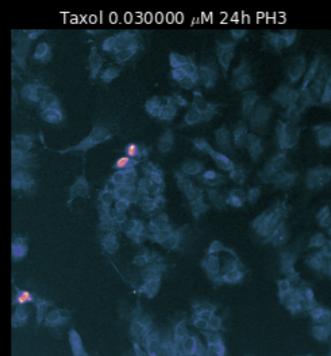
Taxol 0.03uM

Hoechst33342



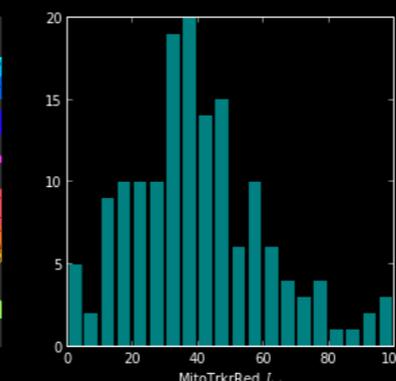
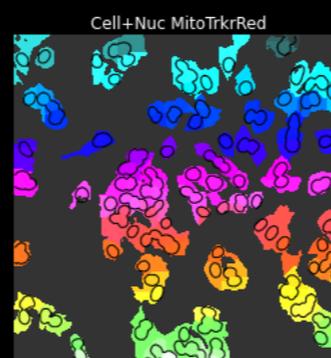
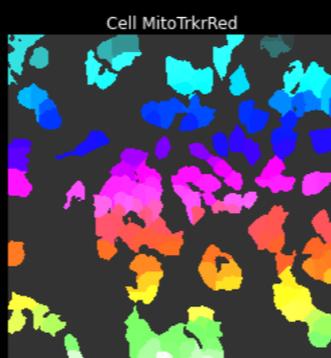
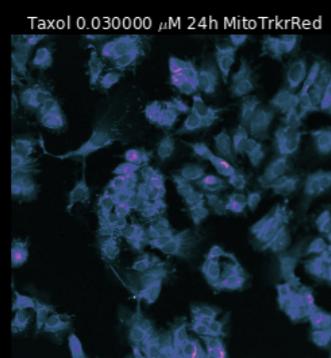
nuclear size (NS)
cell cycle arrest (CCA)
cell number (CN)

Phospho-Histone3



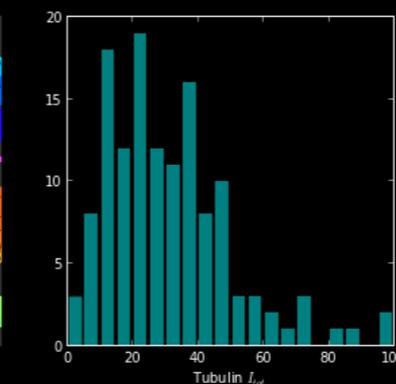
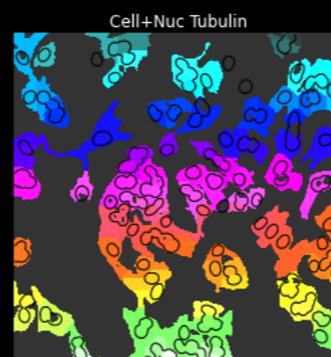
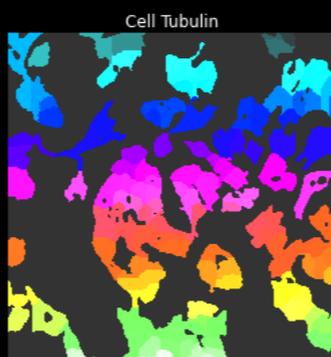
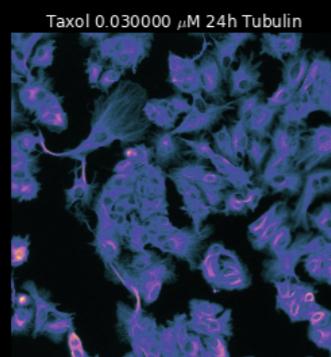
mitotic arrest (MA)

MitoTracker Red



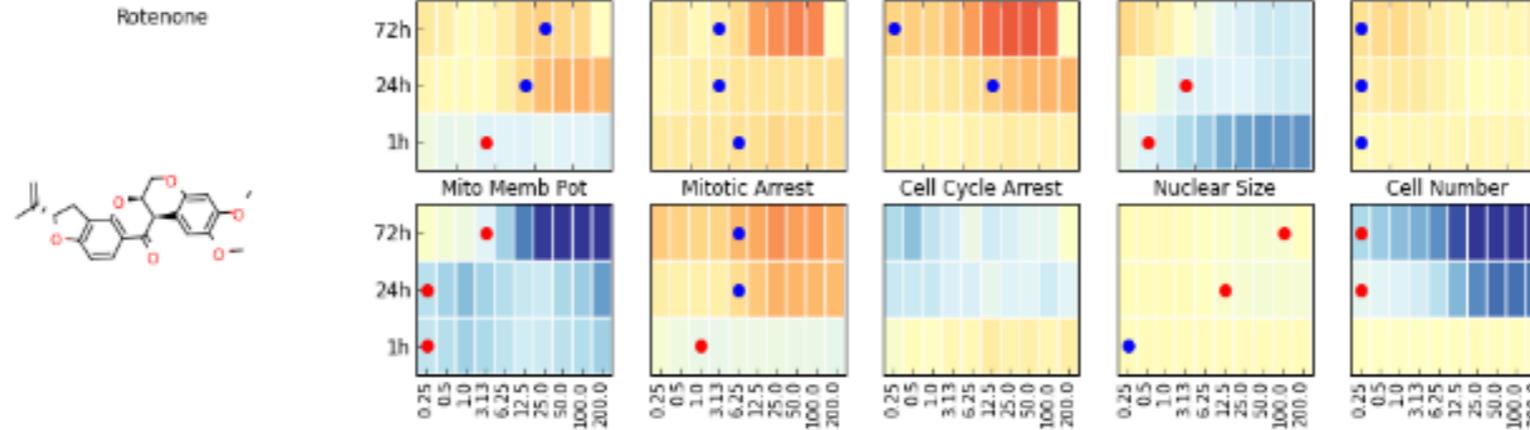
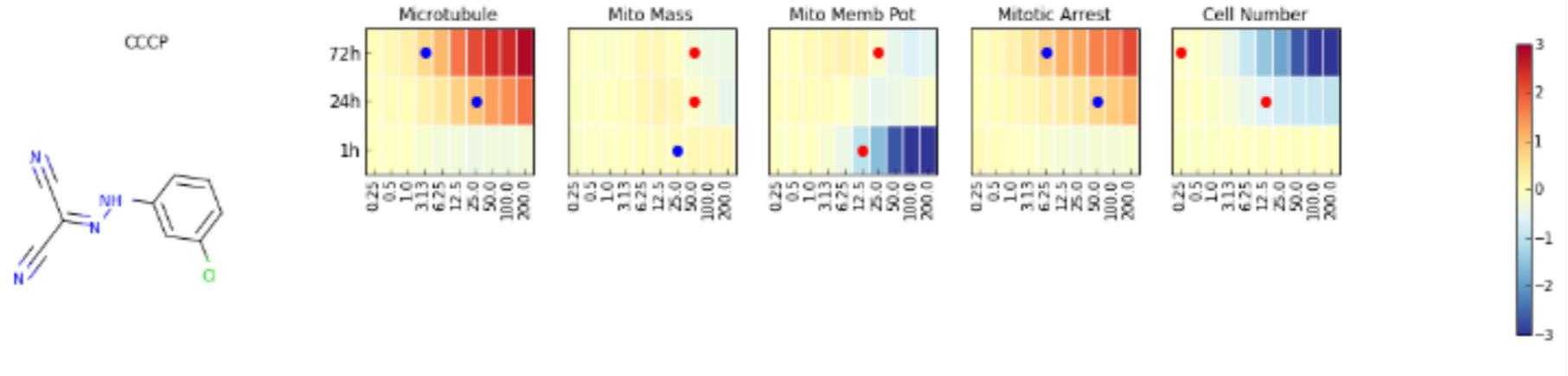
mitochondrial mass (MM)
mitochondrial membrane potential (MMP)

Phospho-Tubulin



microtubules (Mt)

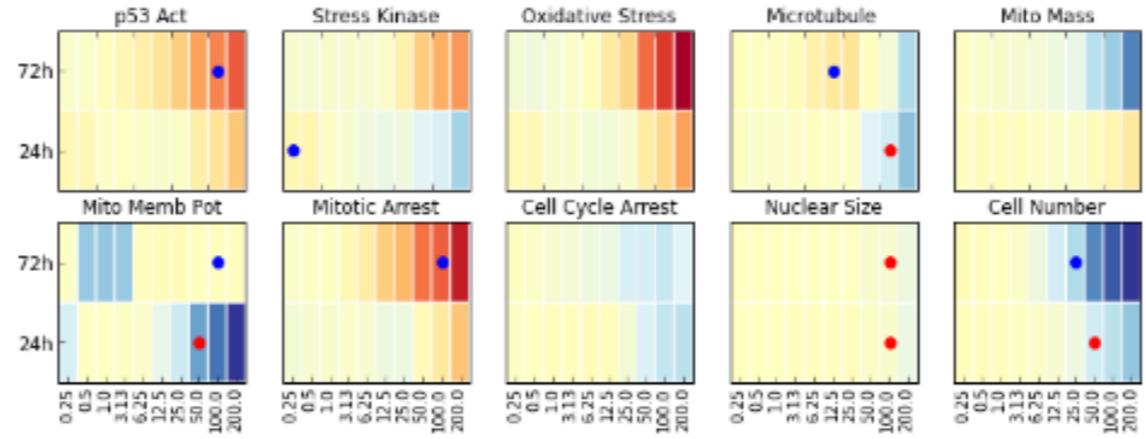
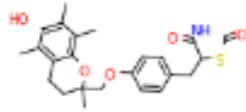
Mitochondrial disruptors



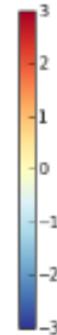
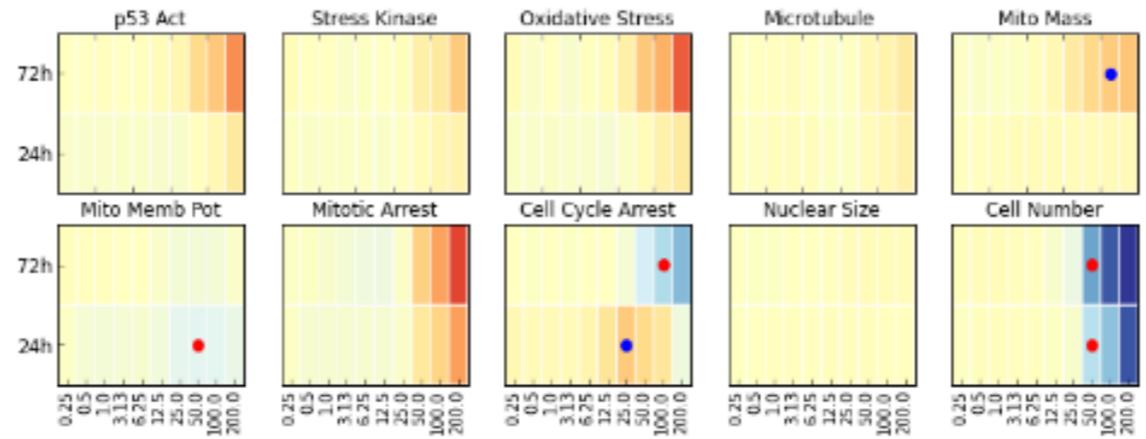
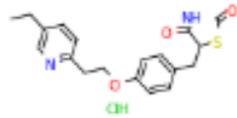
- log₂(fold change): decrease (BLUE), increase (RED) or no effect (YELLOW)
- Bioactivity profile: “deviation from normal state” of HepG2 cells

Thiazolidinediones (TZDs)

Troglitazone

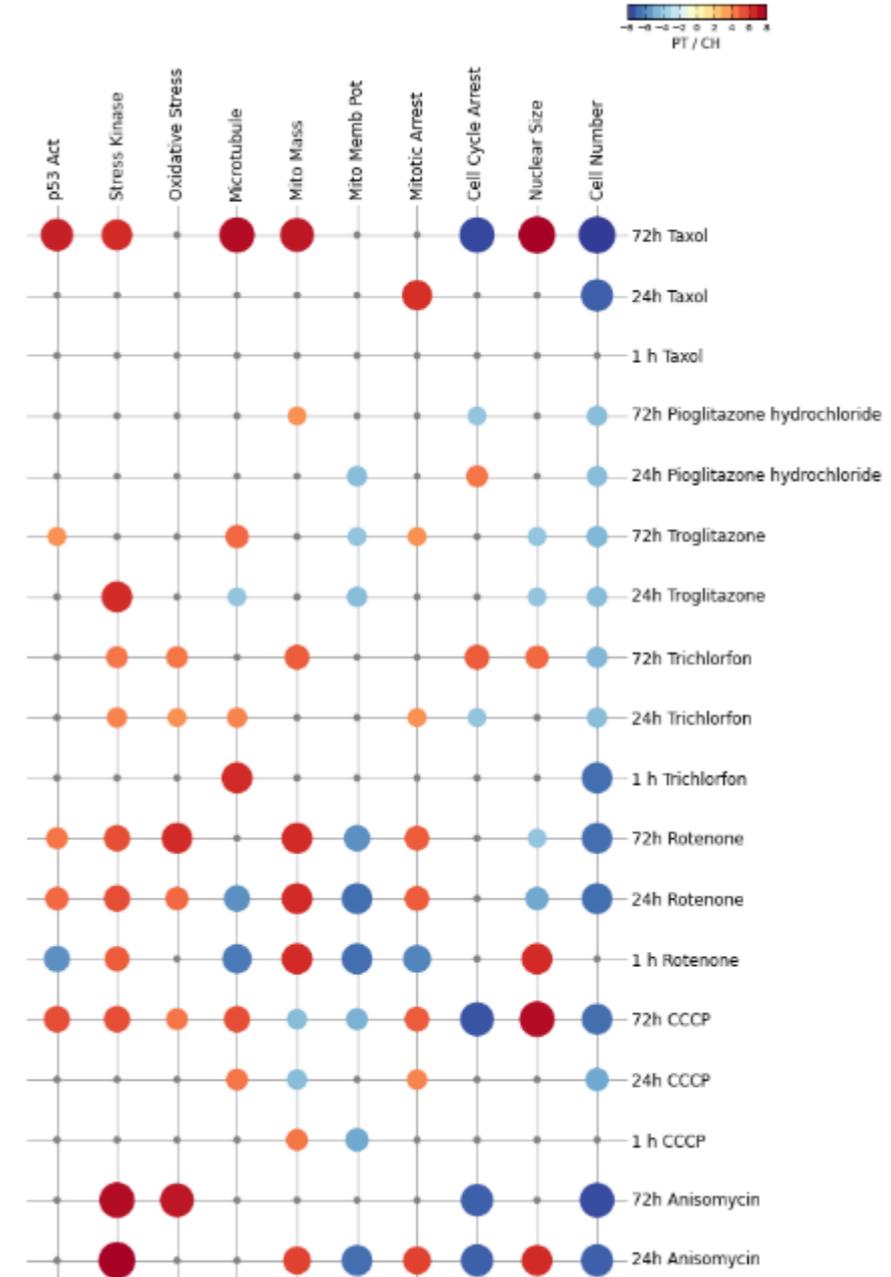


Pioglitazone hydrochloride



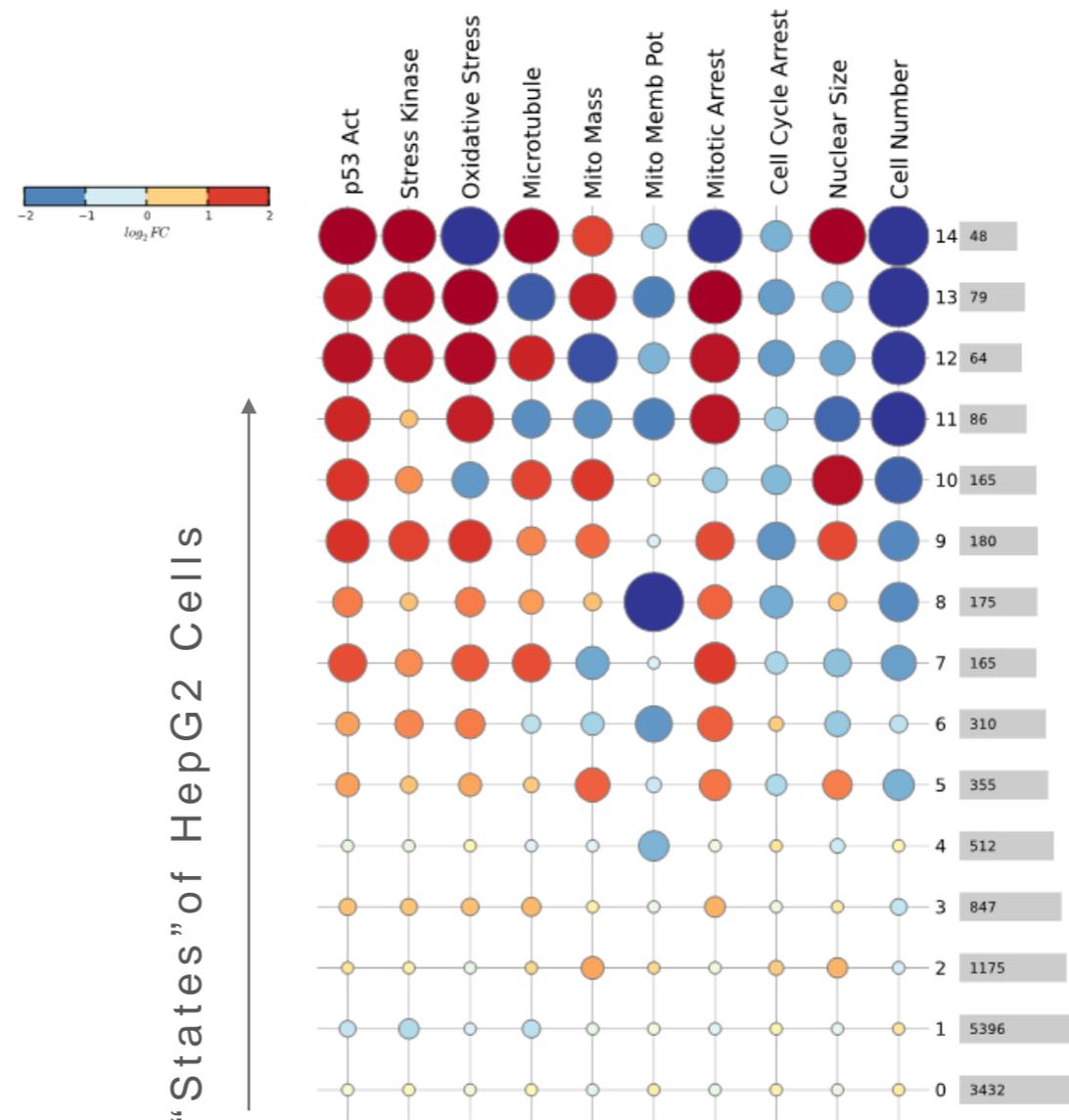
Summarizing Large-Scale HCI Data

- Each chemical produces a 10 dimensional HCI response for each treatment (concentration & time)
- Results in close to 10^5 data points or 10^4 vectors
- How do we summarize and interpret such data?
- **How do we predict tipping points using these data ?**



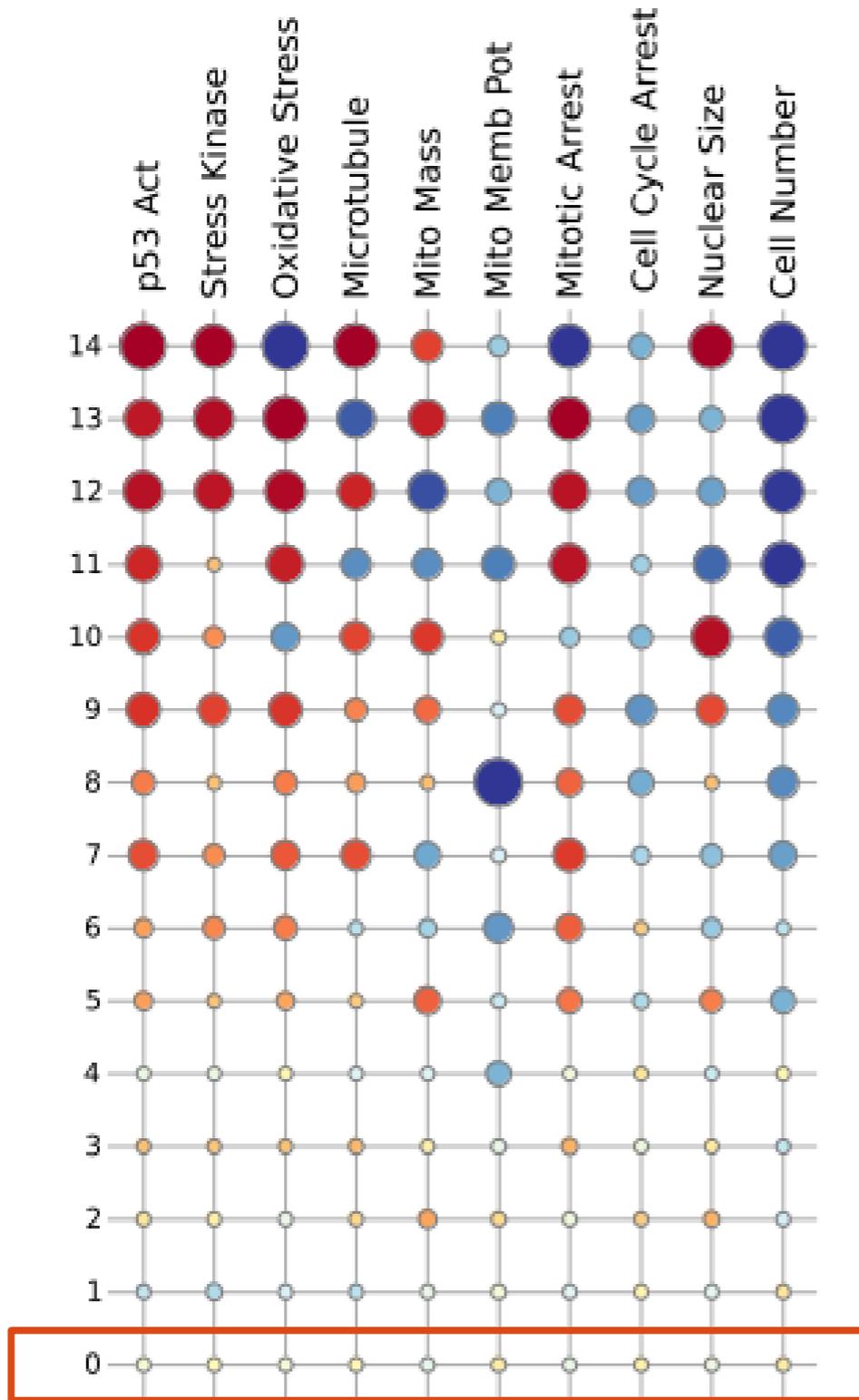
HCI to Phenotypic States

- We used unsupervised learning (clustering)
- Cluster all 10^4 treatment responses
- Derive phenotypic “states” of HepG2 cells
- Phenotypic states *could* represent canonical behaviours of cells
- We could use these phenotypic states to understand the dynamic response to chemicals



“Normal” State

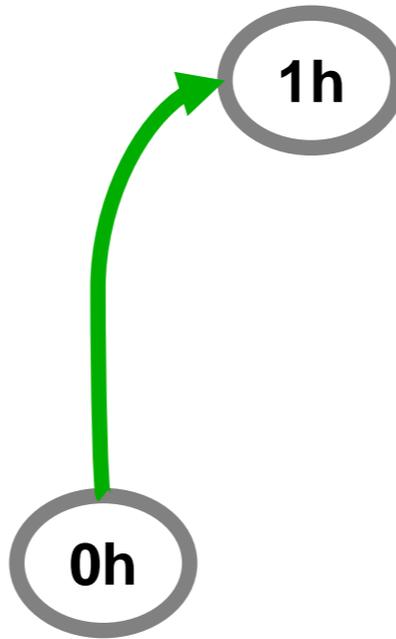
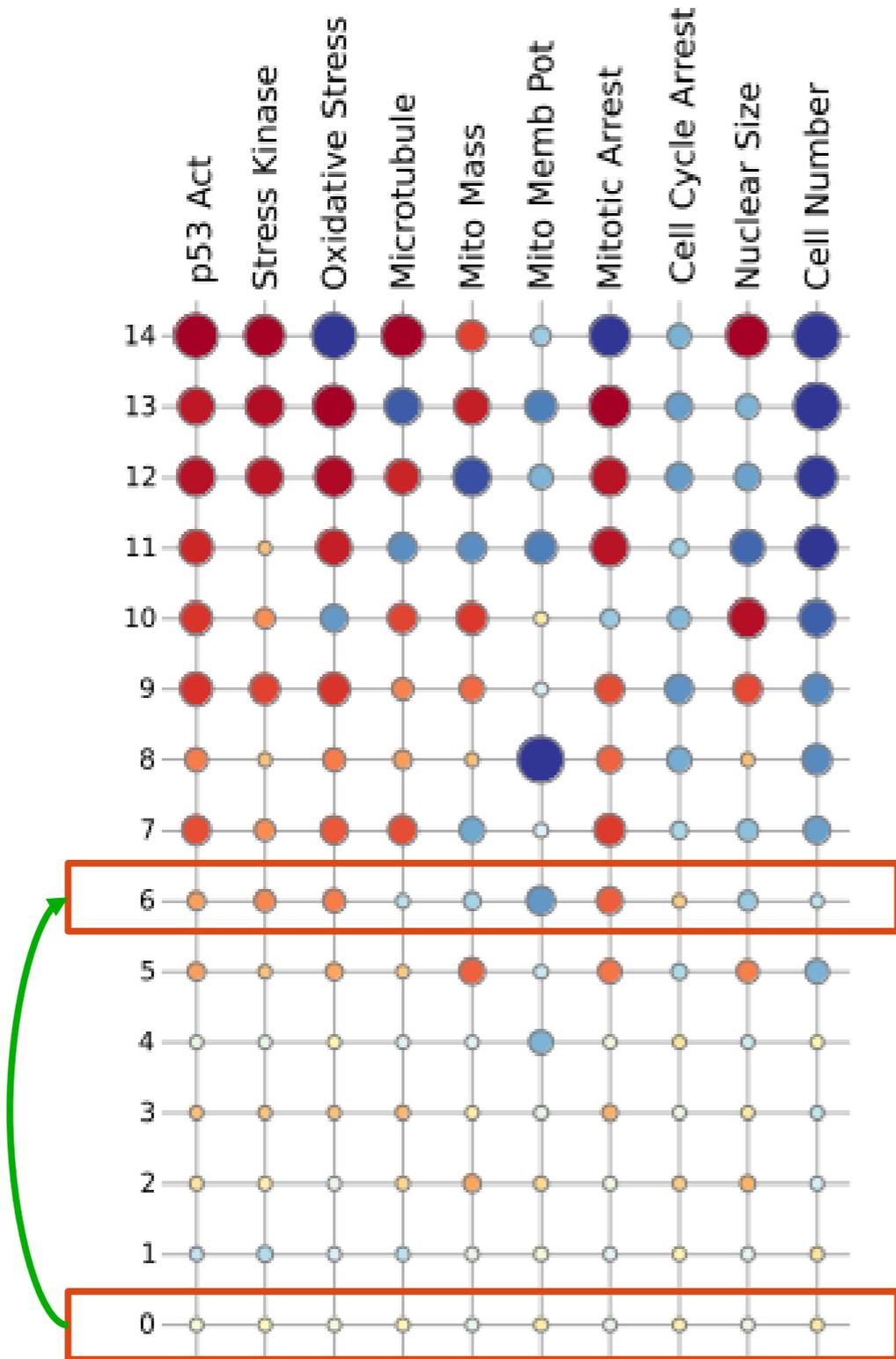
Fluazinam 0.78 uM



0h

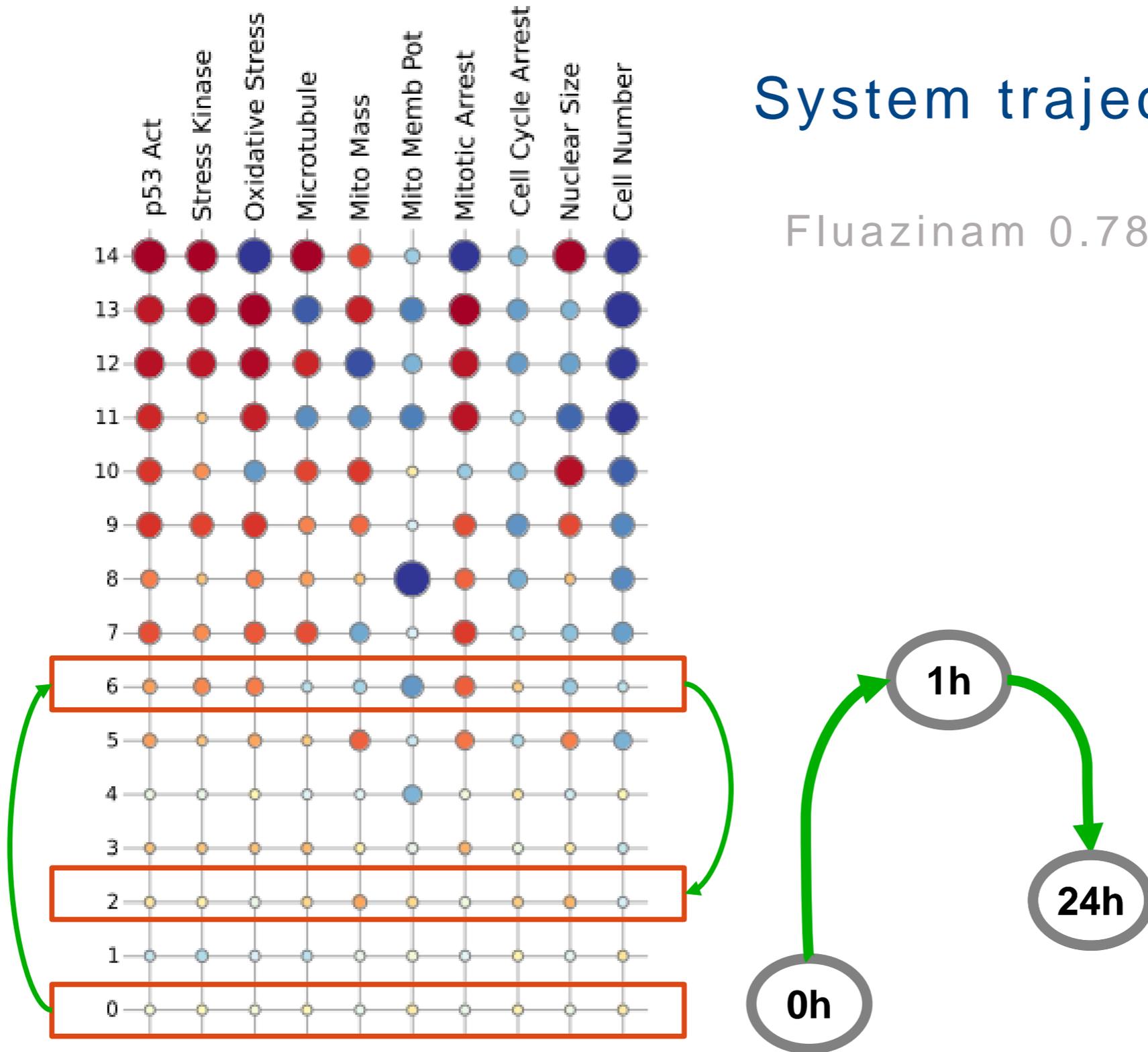
State Transition

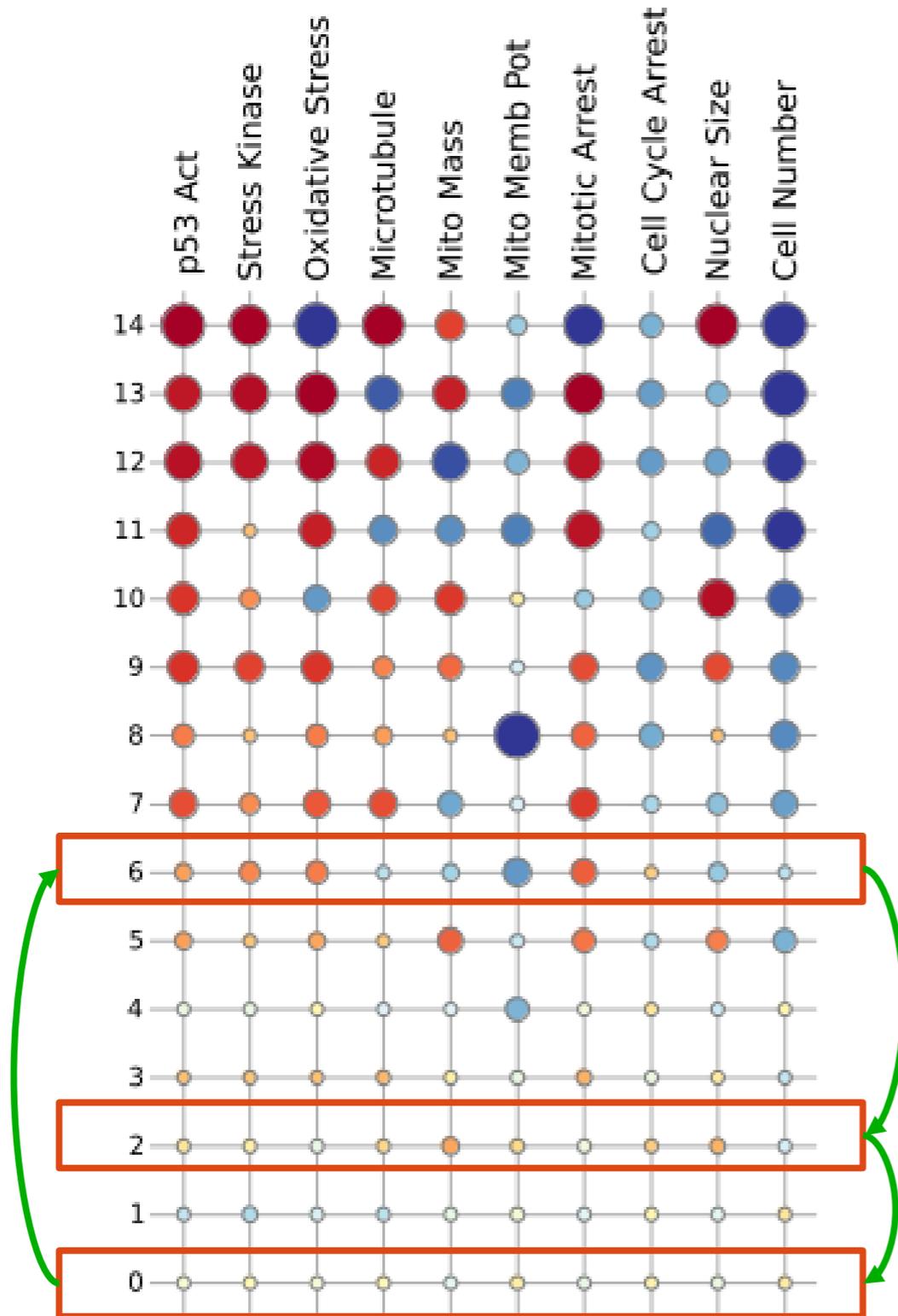
Fluazinam 0.78 uM



System trajectory

Fluazinam 0.78 uM

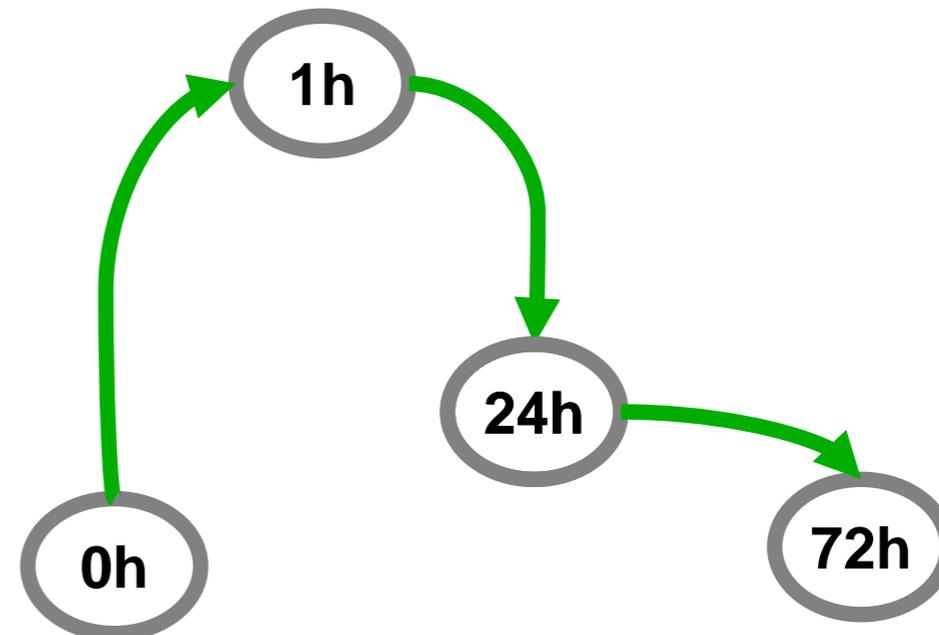




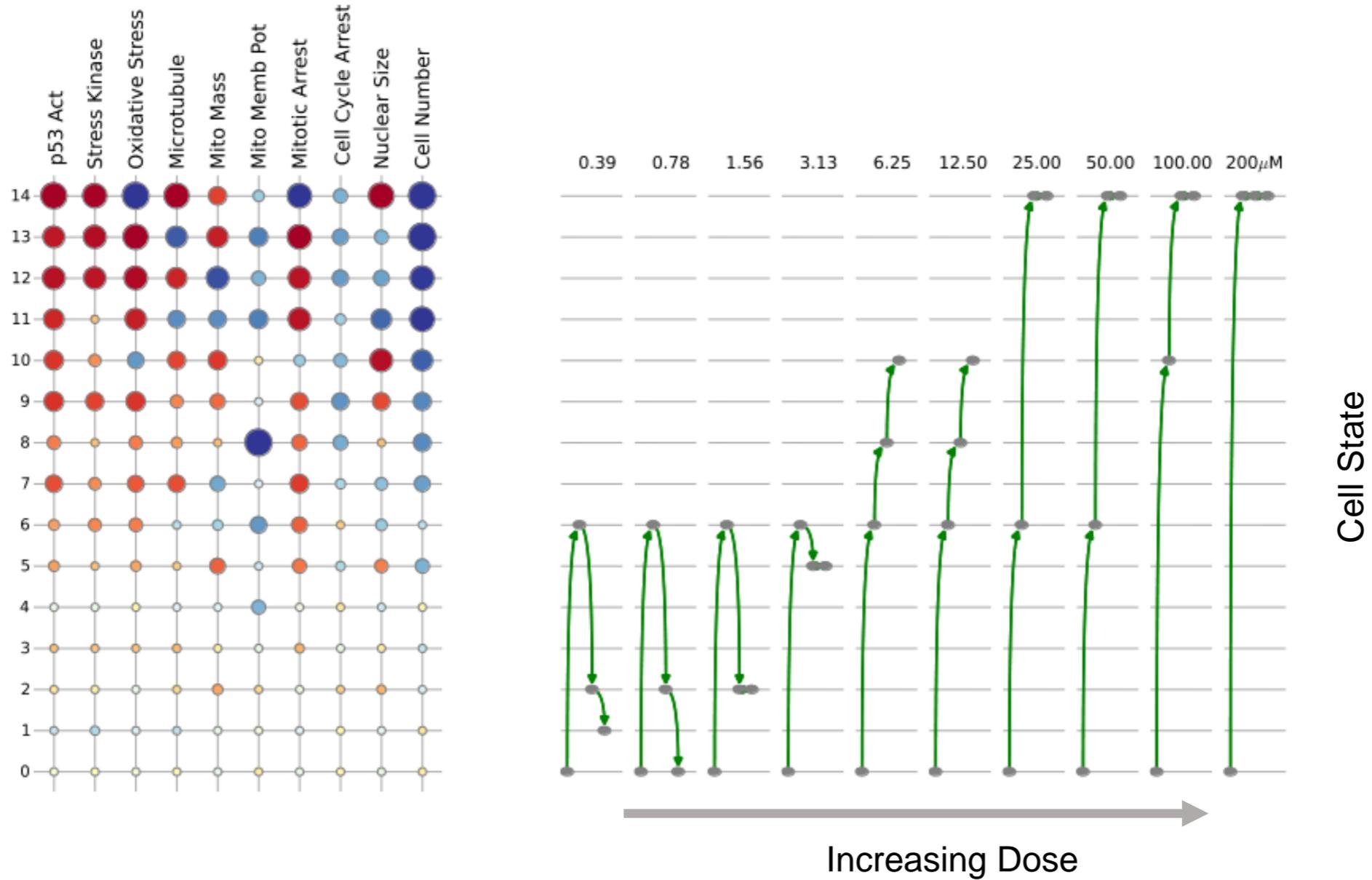
System trajectory

Fluazinam 0.78 uM

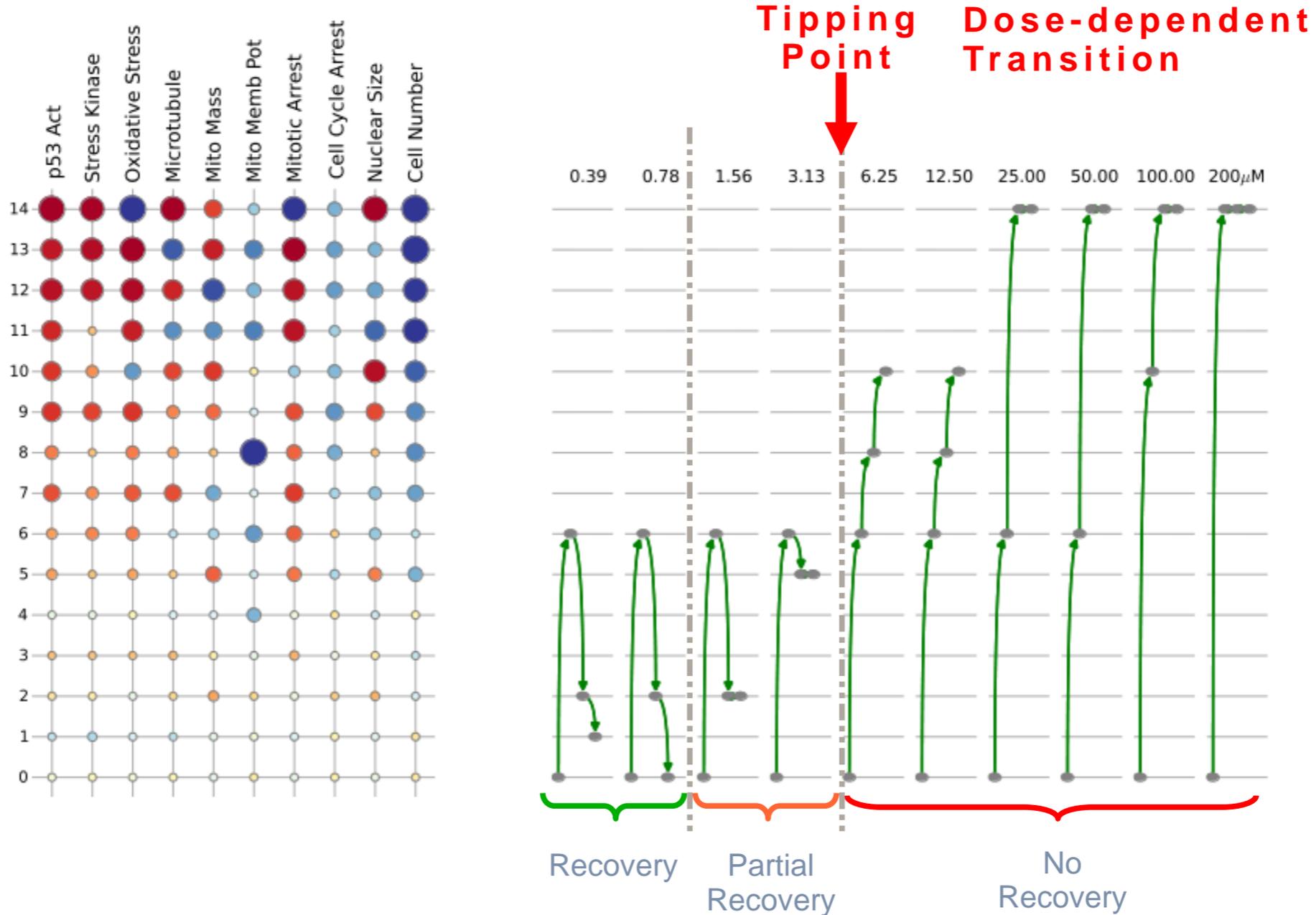
Trajectory = Sequence of states



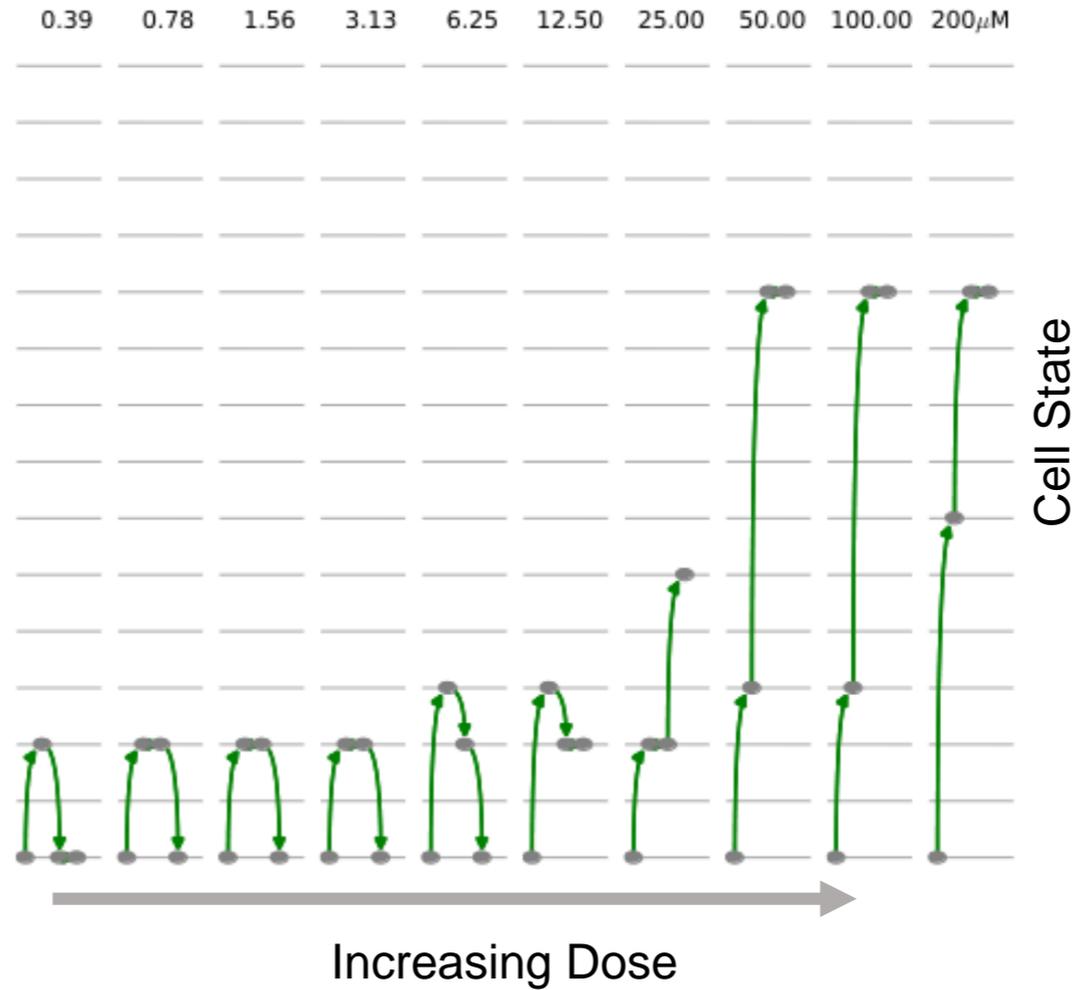
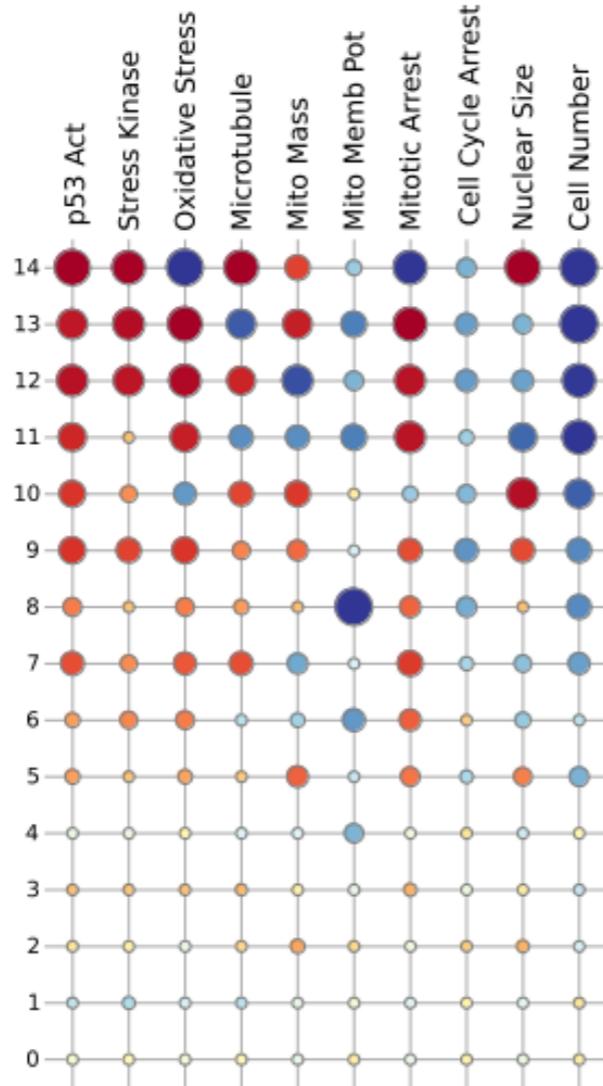
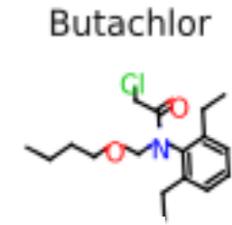
Fluazinam “Trajectories”



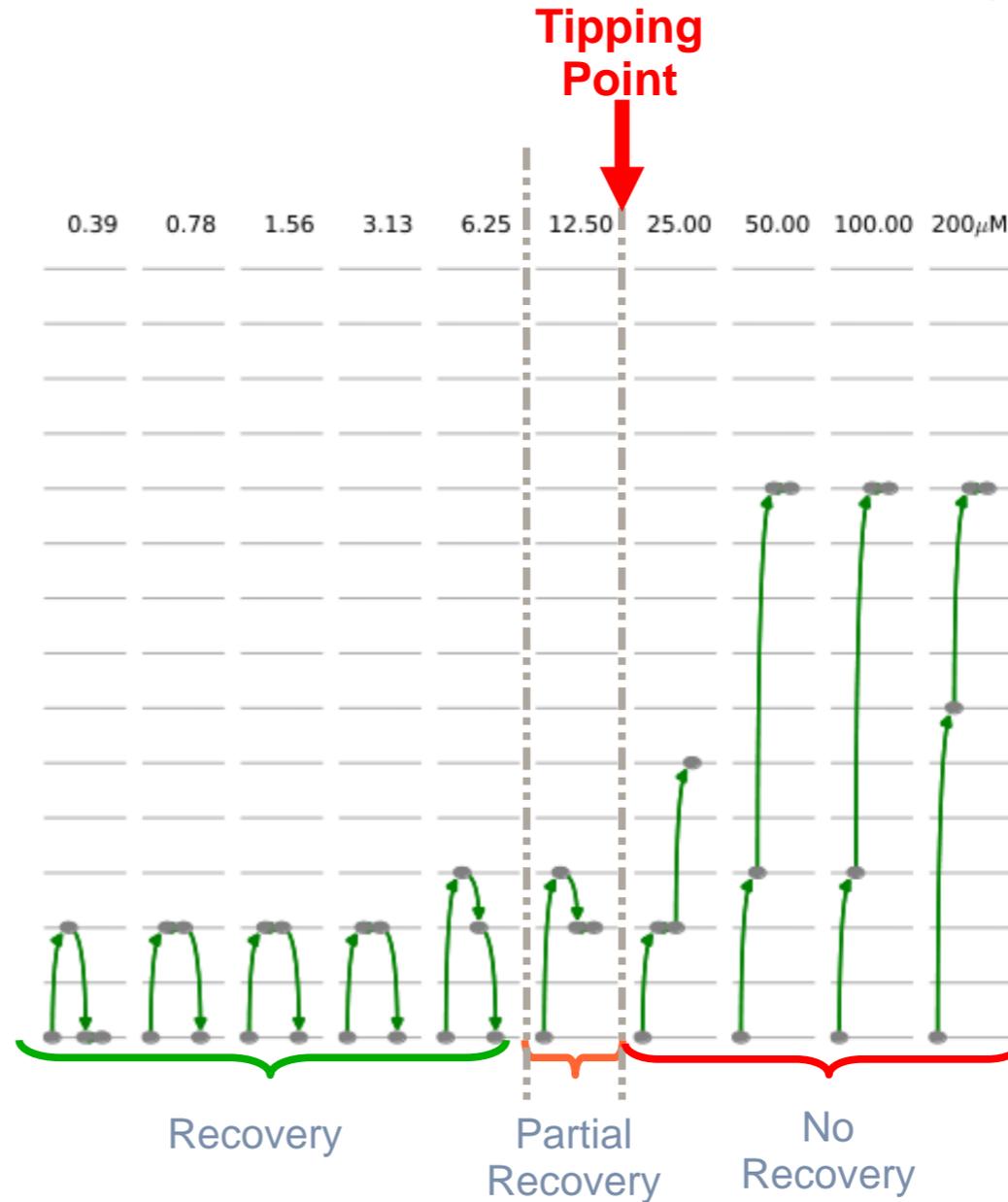
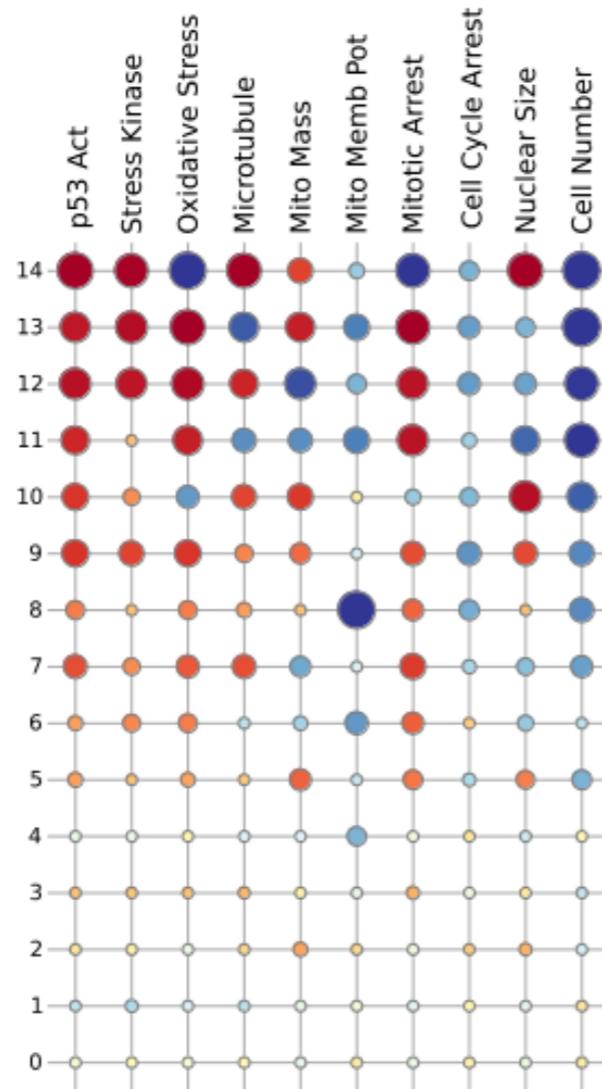
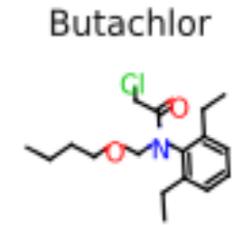
Fluazinam “Trajectories”



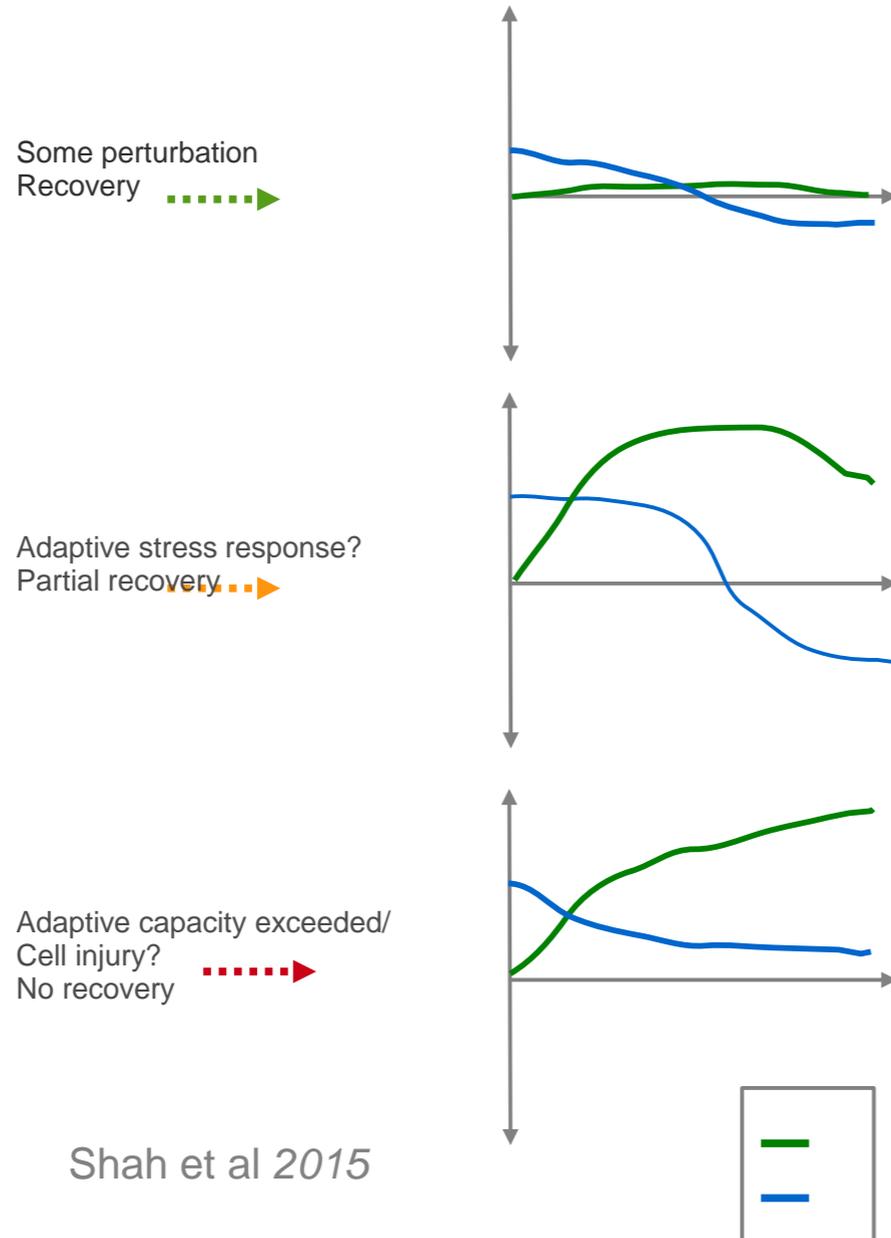
Butachlor Trajectories



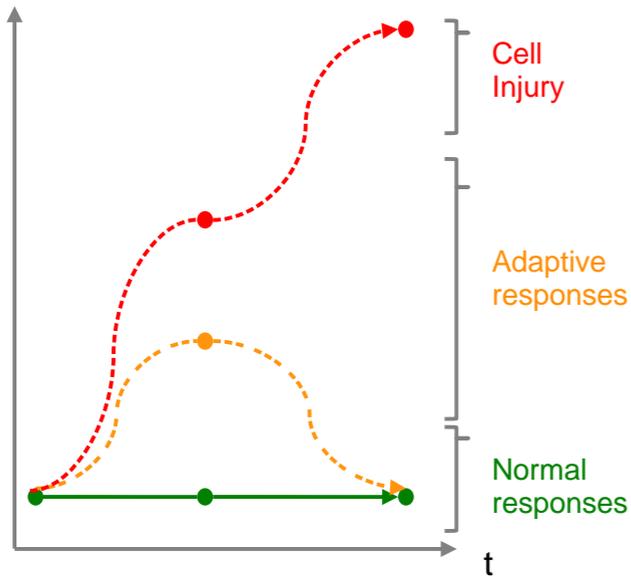
Butachlor Trajectories



Analyzing Trajectories Quantitatively

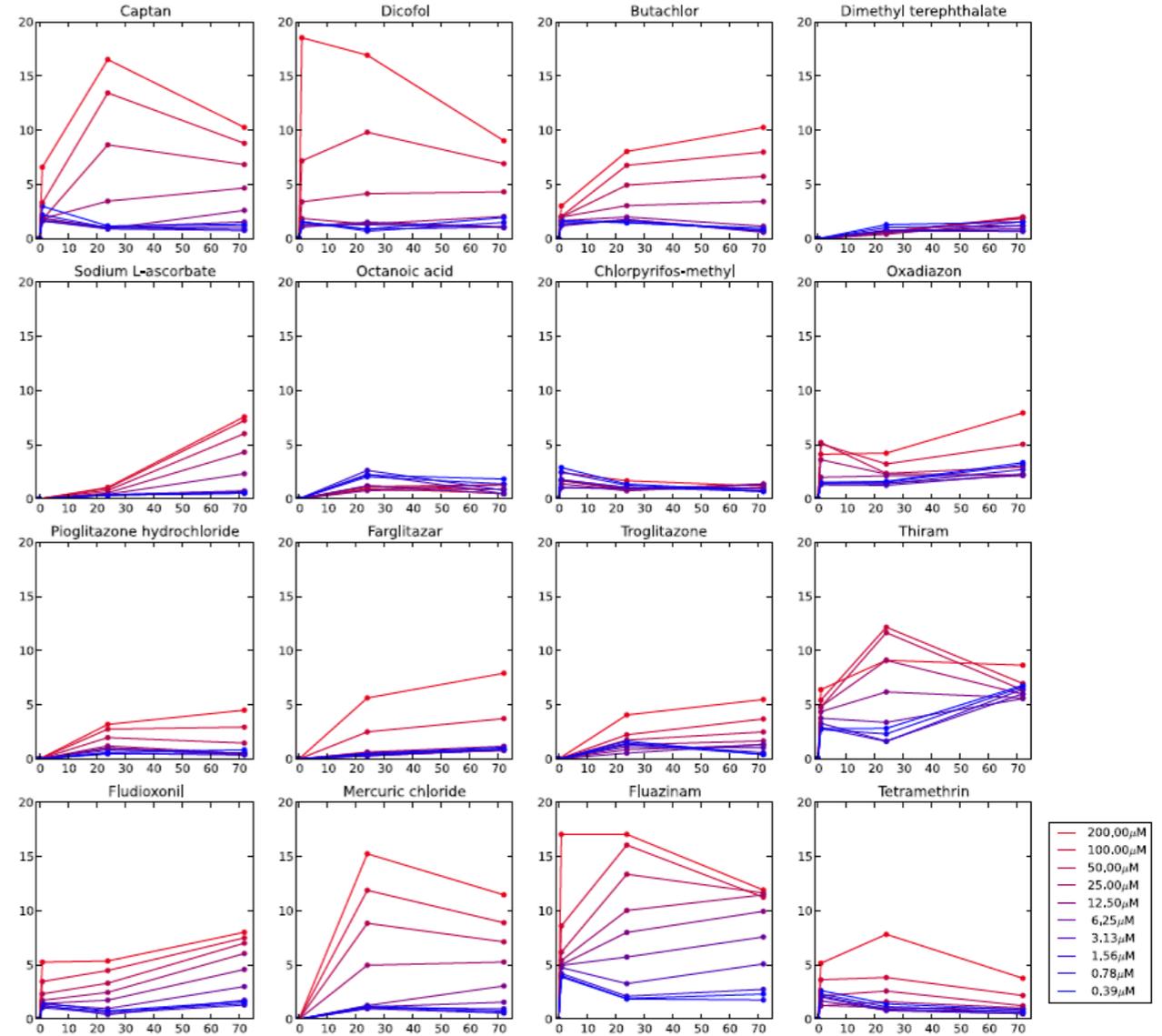


Quantitative Trajectories

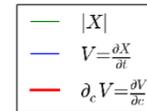
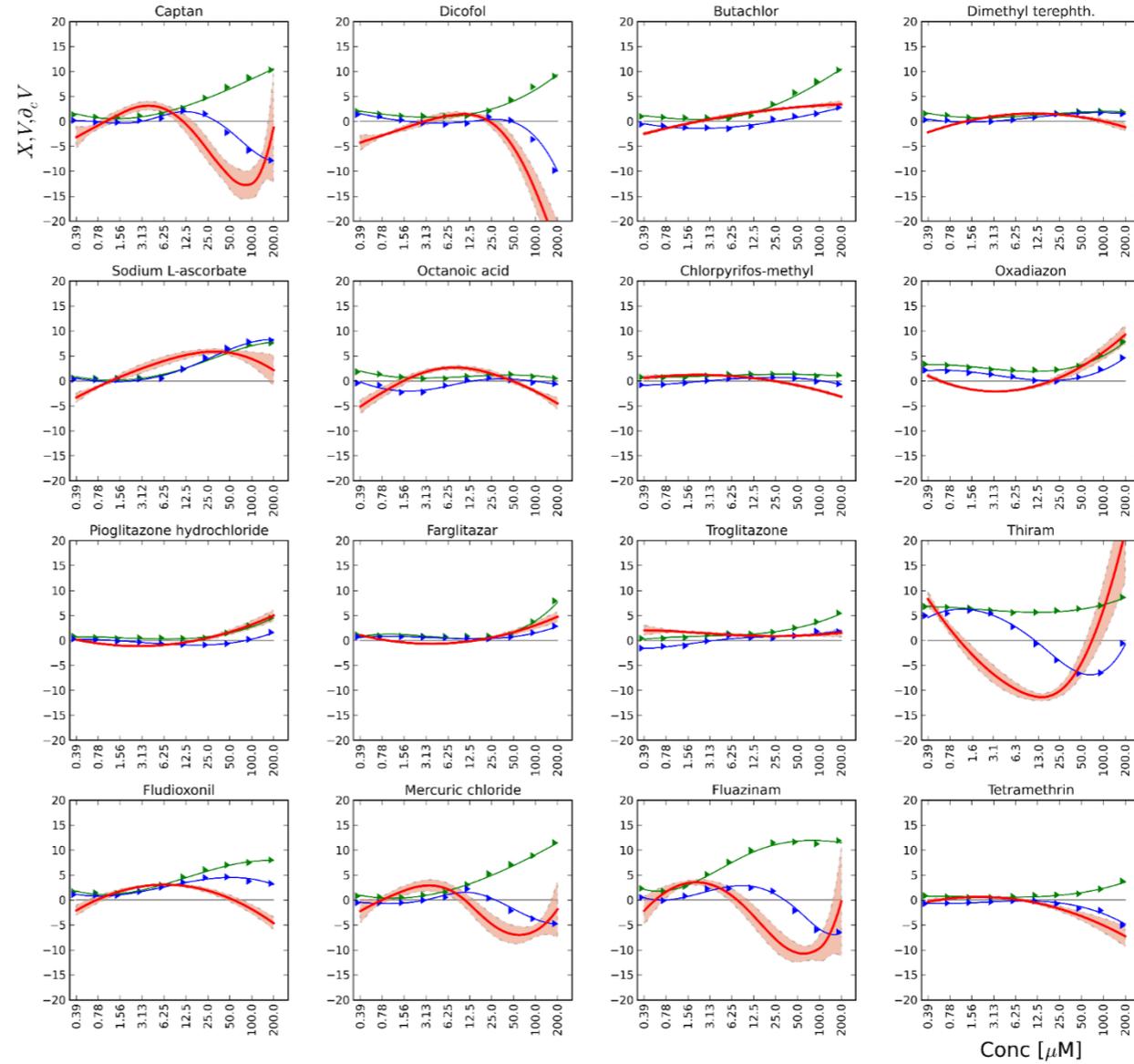
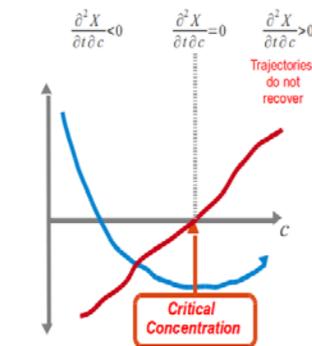
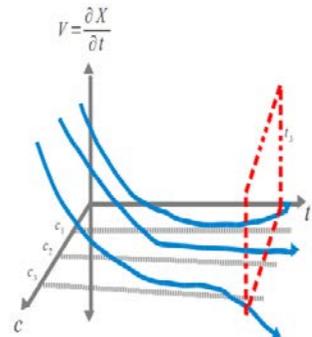
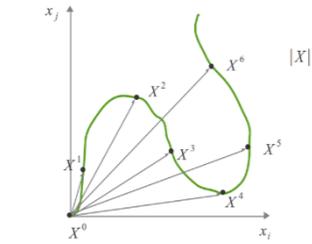


Trajectories

- - - - - Adverse
- - - - - Adaptive
- — — — — Normal

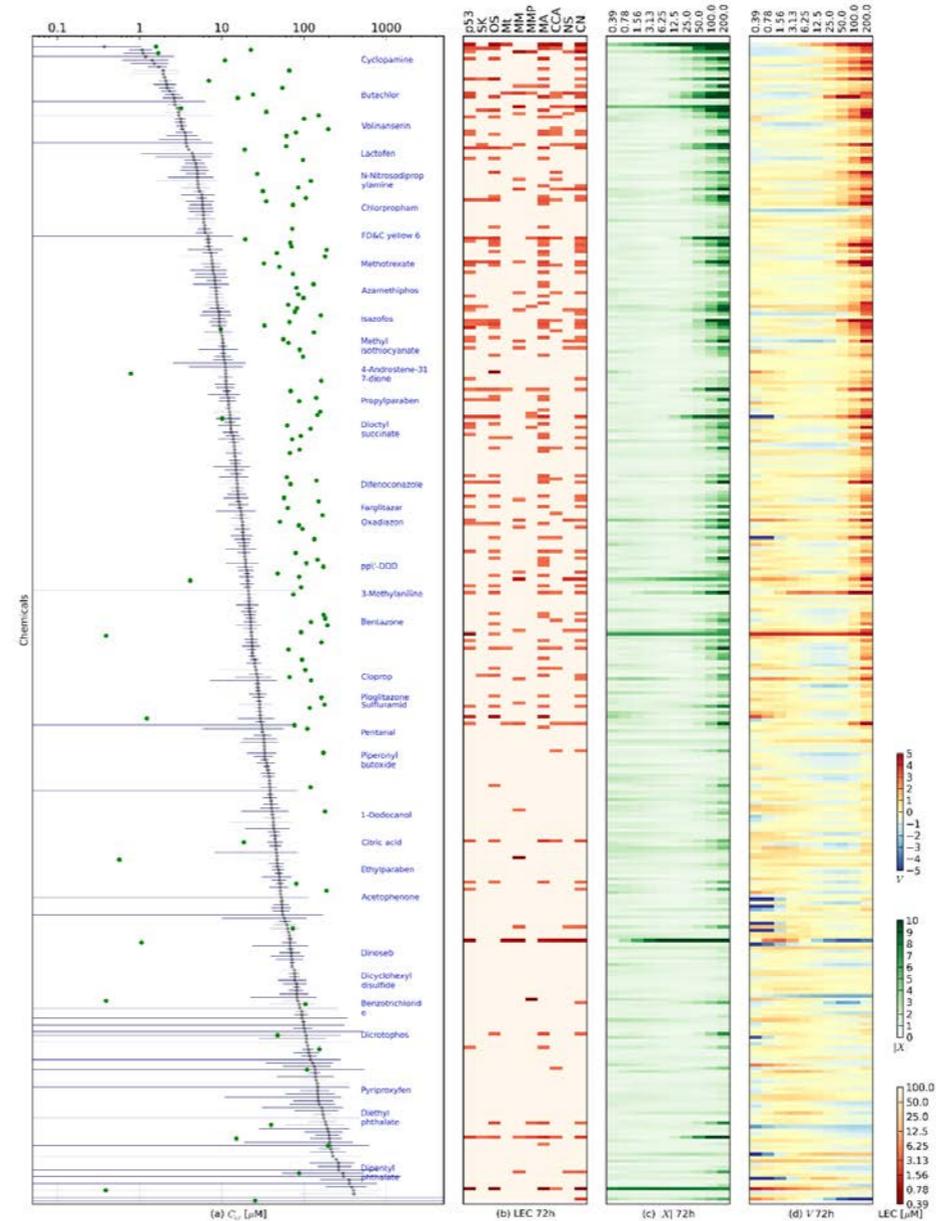


Dose-Dependent Transition



Critical Concentrations

- Can systematically identify critical concentrations- “tipping points”
- Tipping point precedes concentration that produces significant cell loss



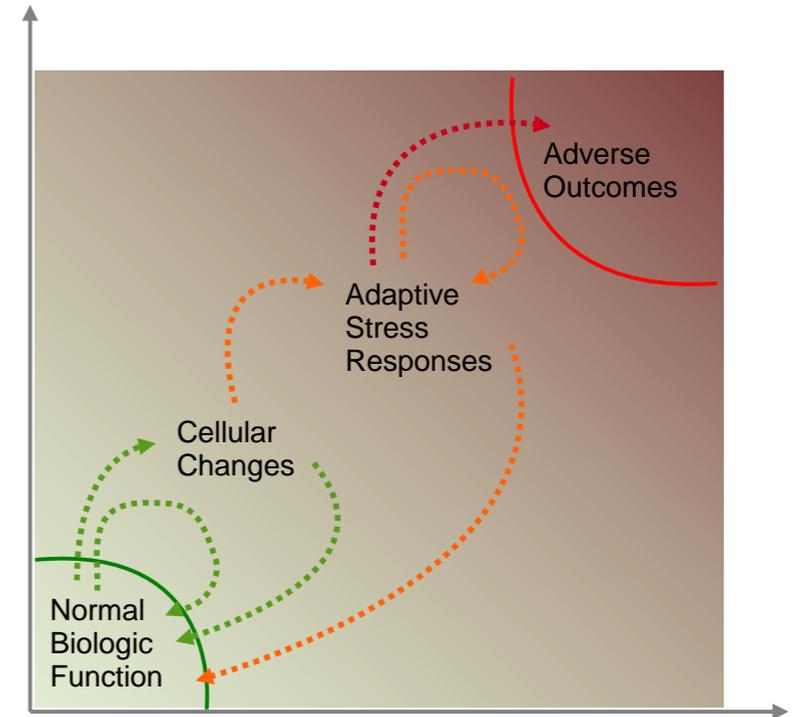
MANY CHALLENGES...

- ❑ Study design enhancements:
 - More physiologically-relevant cell model
 - More holistic cellular stress-response assays (e.g. *-omics*)
- ❑ Tipping point evaluation
 - Differentiating between PK and adaptation
 - Reproducibility
 - Biological relevance
 - *In vivo* Extrapolation

New study underway to address some of these challenges ...

Summary

- Complex biological data can offer new insights into cellular state
- Chemical-induced perturbations can be described by dynamic cellular trajectories
- Trajectory analysis can identify “tipping point” of cellular adaptation
- Additional research on linking tipping points with adversity
- Could be used as point of departure for risk assessment



Biologic Perturbations:

System Trajectories:

- ▶ Some perturbation/
Recovery
- ▶ Adaptive stress response/
Recovery
- ▶ Adaptive capacity exceeded/
Cell injury/
No recovery

Acknowledgements

- HCI Experiment

- Keith Houck
- David Dix
- Cyprotex

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- Matt Martin
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- Woodrow Setzer
- John Jack (NSCU)
- Jie Liu

Analysis

Woodrow Setzer
Kevin Crofton
Rusty Thomas
Richard Judson
Thomas Knudsen
Robert Kavlock