

Development and Use of High Content Tier 1 Screening Assays at the USEPA National Center for Computational Toxicology (NCCT)

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Disclaimer

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 - Applications
- **High Throughput Phenotypic Profiling (HTPP)**
 - Cell Painting Assay Description
 - Laboratory & Analysis Workflows
 - Concentration-Response Modeling
 - Applications



NCCT HTTr Project Team

National Center for Computational Toxicology



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*Computational
Systems Biologist*



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Statistician*



**Derik
Haggard**
ORISE Fellow



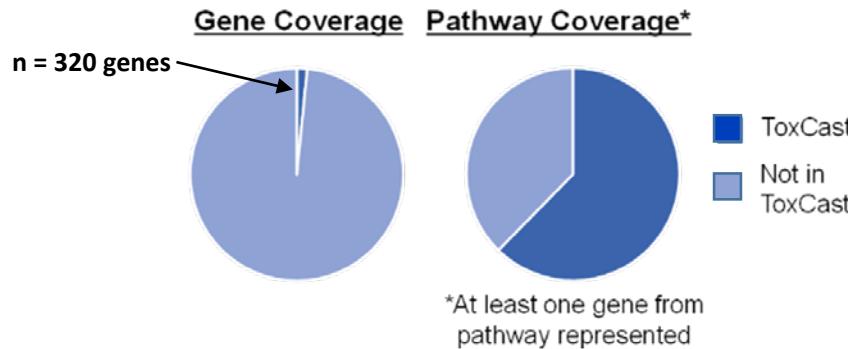
**Richard
Judson**
Bioinformatician



**Russell
Thomas**
Director

Background

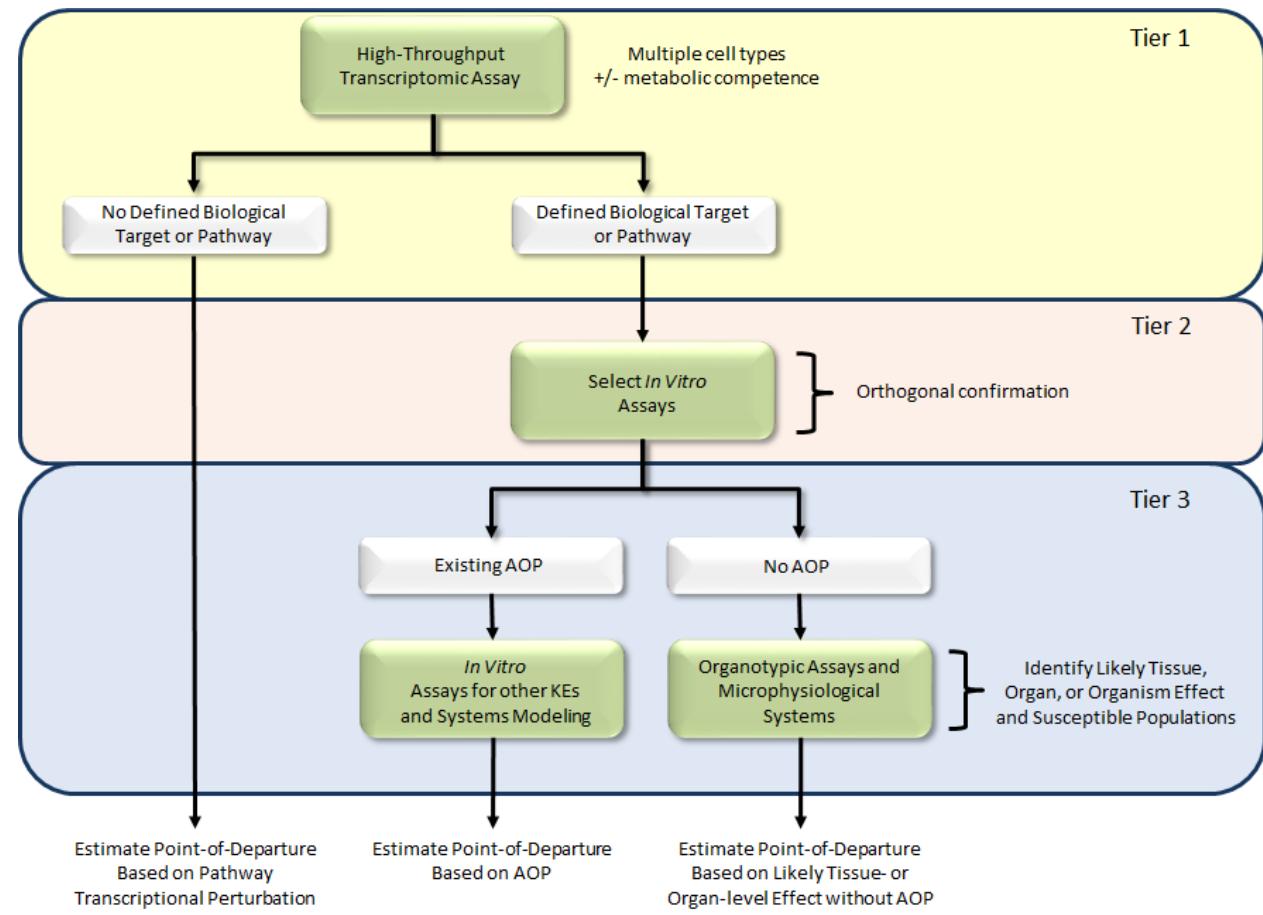
- ToxCast assays cover many genes and pathways, but do not provide complete coverage of biological space.



- USEPA Strategic Vision and Operational Roadmap:**

- Tier 1 strategy must cast the broadest net possible for capturing hazards associated with chemical exposure.
- Global gene expression provides a robust and comprehensive evaluation of chemically induced changes in biological processes.
- Increasing efficiency and declining cost of generating whole transcriptome profiles has made high-throughput transcriptomics (HTTr) a practical option for determining bioactivity thresholds in *in vitro* models.

A strategic vision and operational road map for computational toxicology at the U.S. Environmental Protection Agency

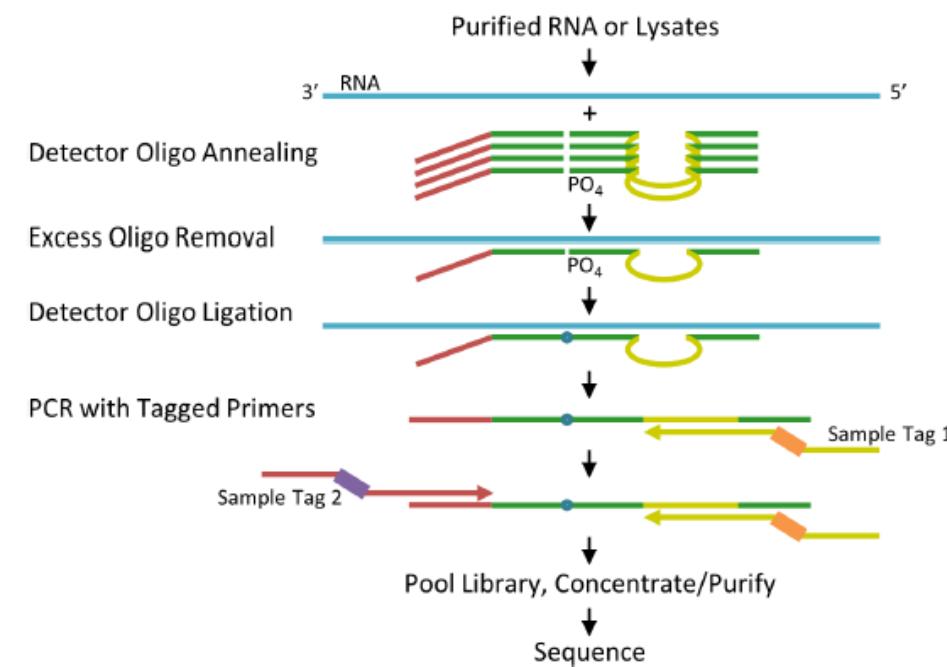


Background

Technology

- The **TempO-Seq** human whole transcriptome assay measures the expression of greater than 20,000 transcripts.
- Requires only picogram amounts of total RNA per sample.
- Compatible with purified RNA samples or **cell lysates**.
- Transcripts in cell lysates generated in 384-well format are barcoded according to well position and combined in a single library for sequencing using industry standard instrumentation.
- Scalable, targeted assay:
 - 1) specifically measures transcripts of interest
 - 2) ~50-bp reads for all genes
 - 3) requires less flow cell capacity than RNA-Seq
- Per sample fastq files are generated and aligned to BioSpyder sequence manifest to generate integer count tables.

TempO-Seq Assay Illustration



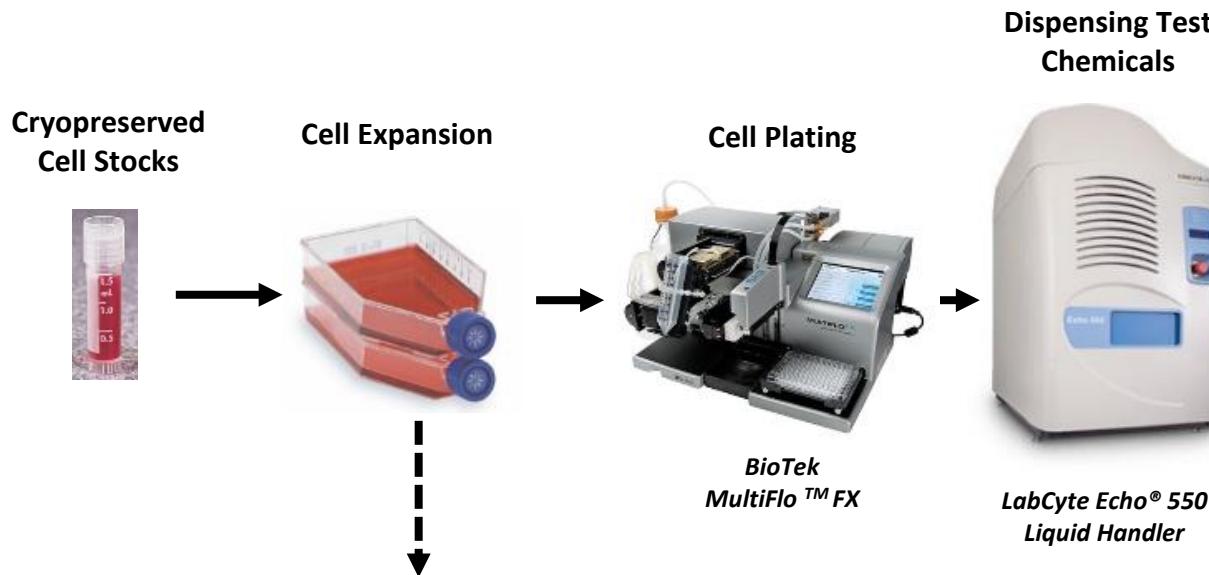
HTTr MCF Screen: Experimental Design

Parameter	Multiplier	Notes
Cell Type(s)	1	MCF7
Culture Condition	1	DMEM + 10% HI-FBS ^a
Chemicals	2,112	ToxCast ph1, ph2 Nominated chemicals from e1k / ph3
Time Points:	1	6 hours
Assay Formats:	2	TempO-Seq HCl Cell Viability & Apoptosis
Concentrations:	8	3.5 log ₁₀ units; semi log ₁₀ spacing
Biological Replicates:	3	--

- **Total number of samples:** 54,432
- **Total number of endpoint readouts:** 1.15x10⁹
- **Total size of fastq files:** 32.5 to 54.4 TB

^a MCF7 cells cultured in DMEM + 10% HI-FBS was selected as the test system to facilitate comparability to the Broad Institute Connectivity Map (CMAP) database (<http://portals.broadinstitute.org/cmap/>).

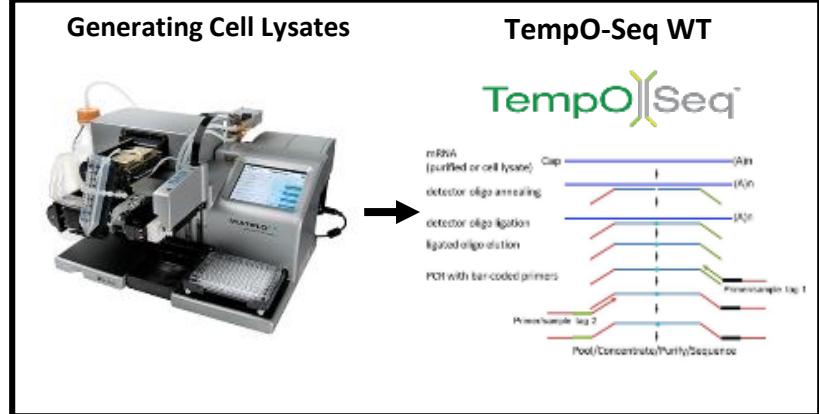
Experimental Workflow



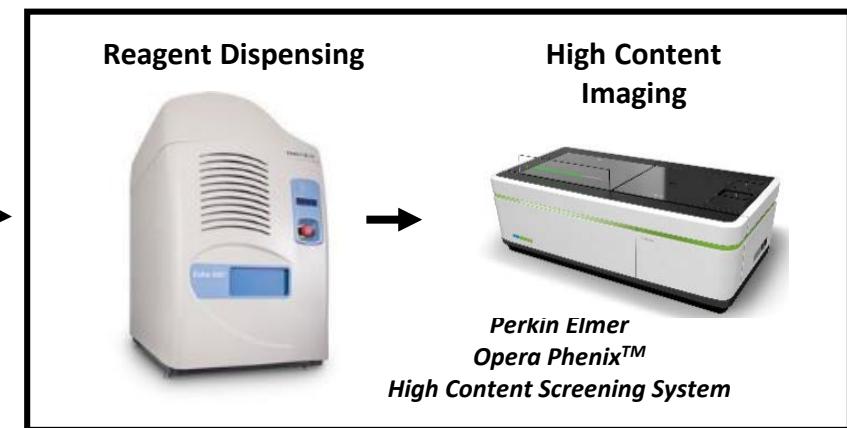
Standardized Expansion Protocol

Day In Vitro (DIV):	0	2	5	7	9	11	13	
Action:	Seed	MC	P	MC	P	MC	P	MC = Media Change P = Passage
Vessel:	T25		T75		T225		Test Plate(s)	Perform Experiment

Track 1: Targeted RNA-Seq

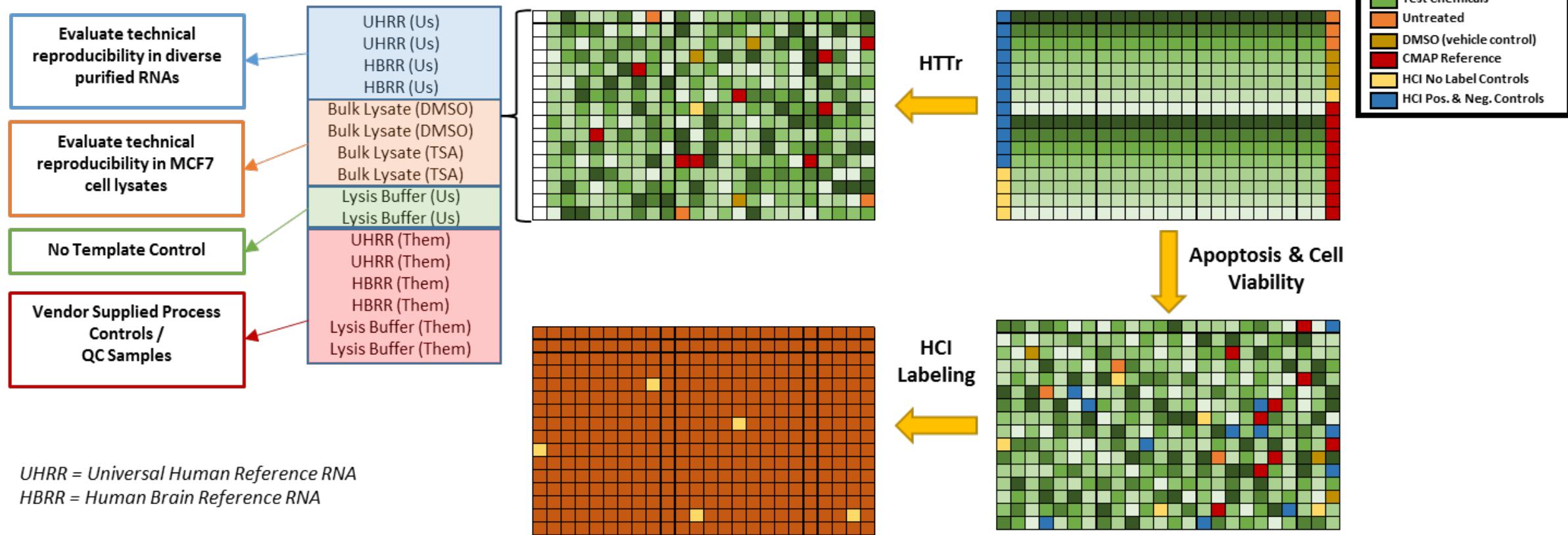


Track 2: Apoptosis / Cell Viability

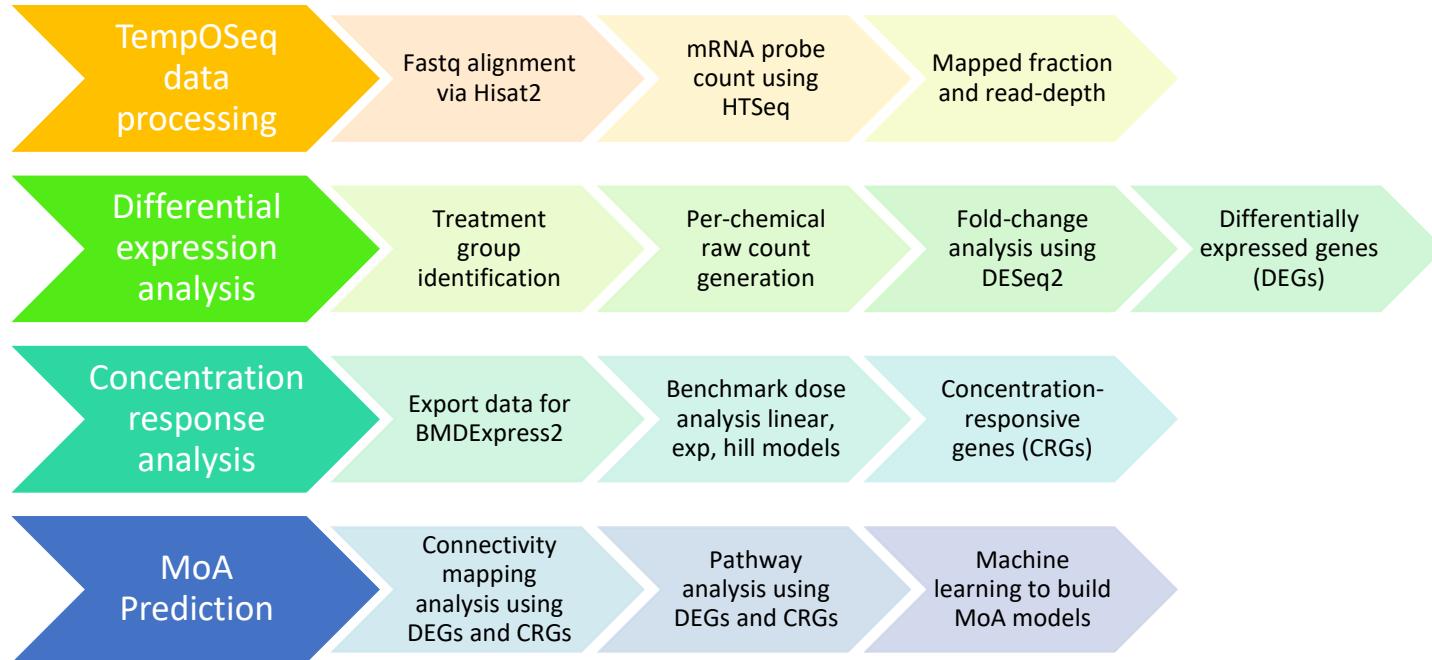


Treatment Randomization & Quality Control Samples

Treatment Randomization: *Each test plate uniquely randomized with respect to treatment.*
QC Samples: *Quality Control samples included on each plate*



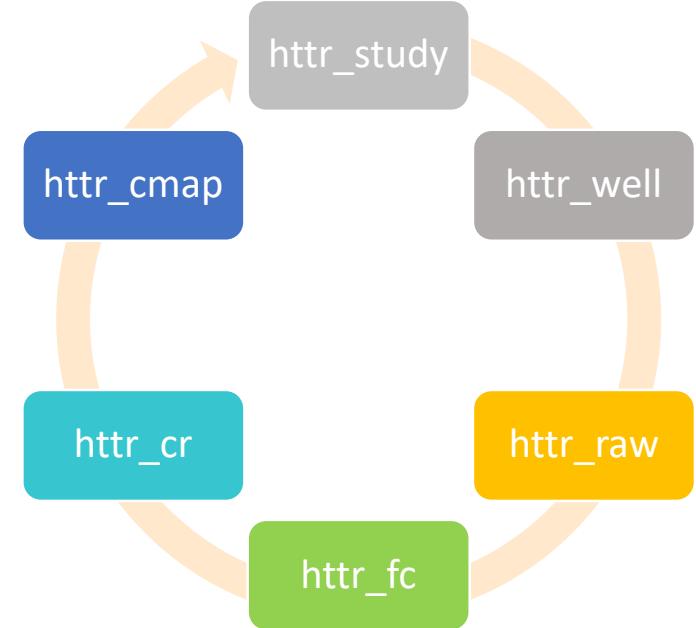
HTTr Analysis Pipeline & Infrastructure



Python & R analysis pipeline

<http://bitbucket.zn.epa.gov/projects/HTTR/repos/httr-wf-dev>

*Imran Shan
Josh Harrill
Woodrow Setzer
Richard Judson
Derik Haggard*

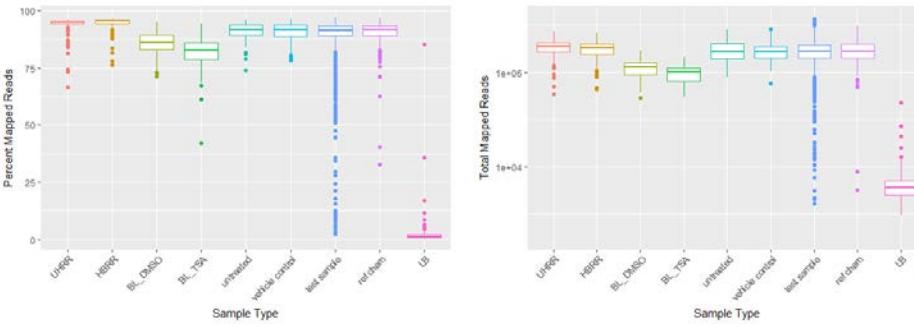
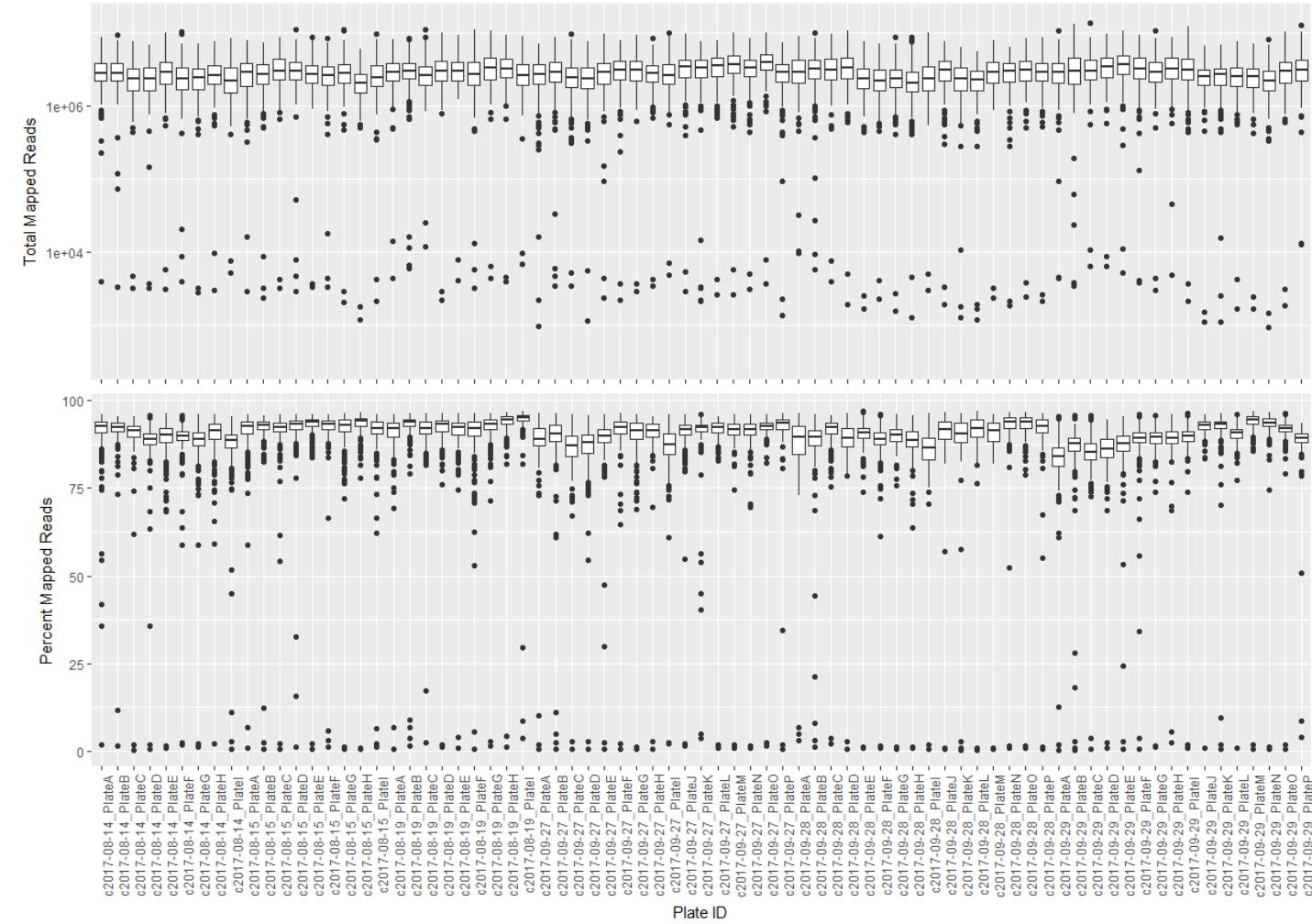
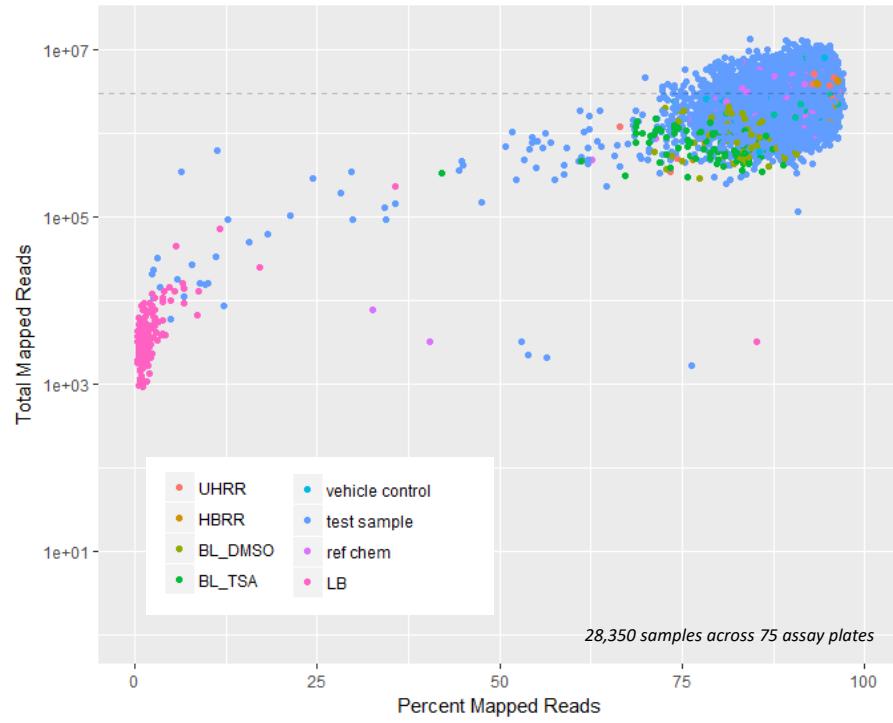


MongoDB

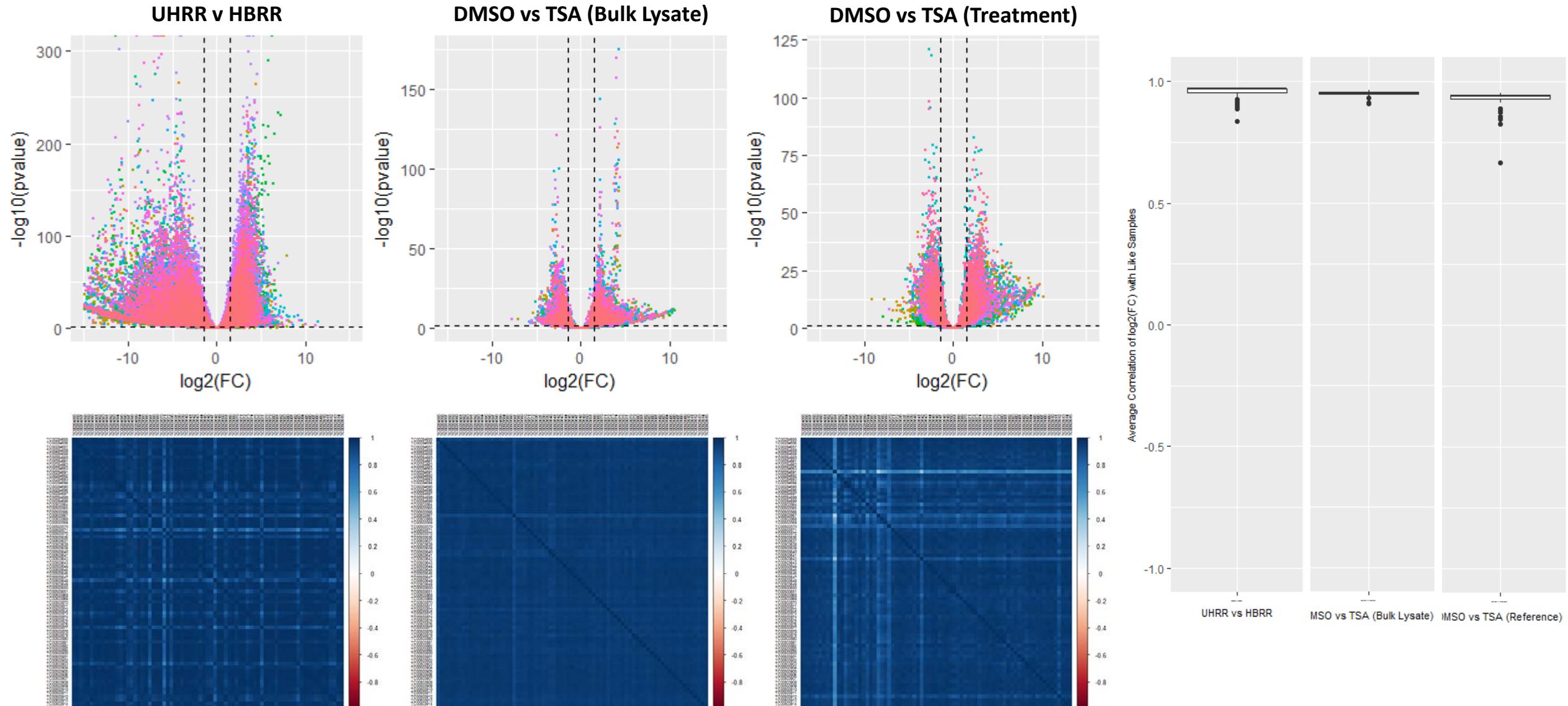
`mongodb://pb.epa.gov/httr_v1`
`mongodb://pb.epa.gov/cmap_v2`

Technical Reproducibility

Reproducibility of Read Depths and Mapping Rates



Reproducibility of $\log_2(\text{FC})$ Estimates



Concentration-Response Modeling / Bioactivity Thresholds

Benchmark Dose Modeling



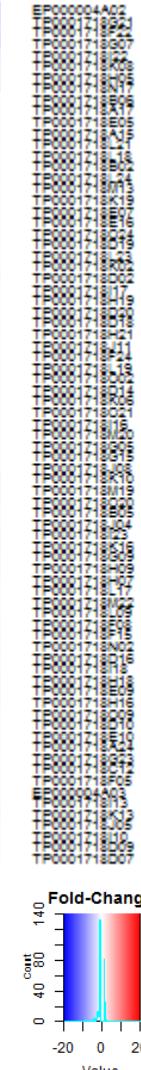
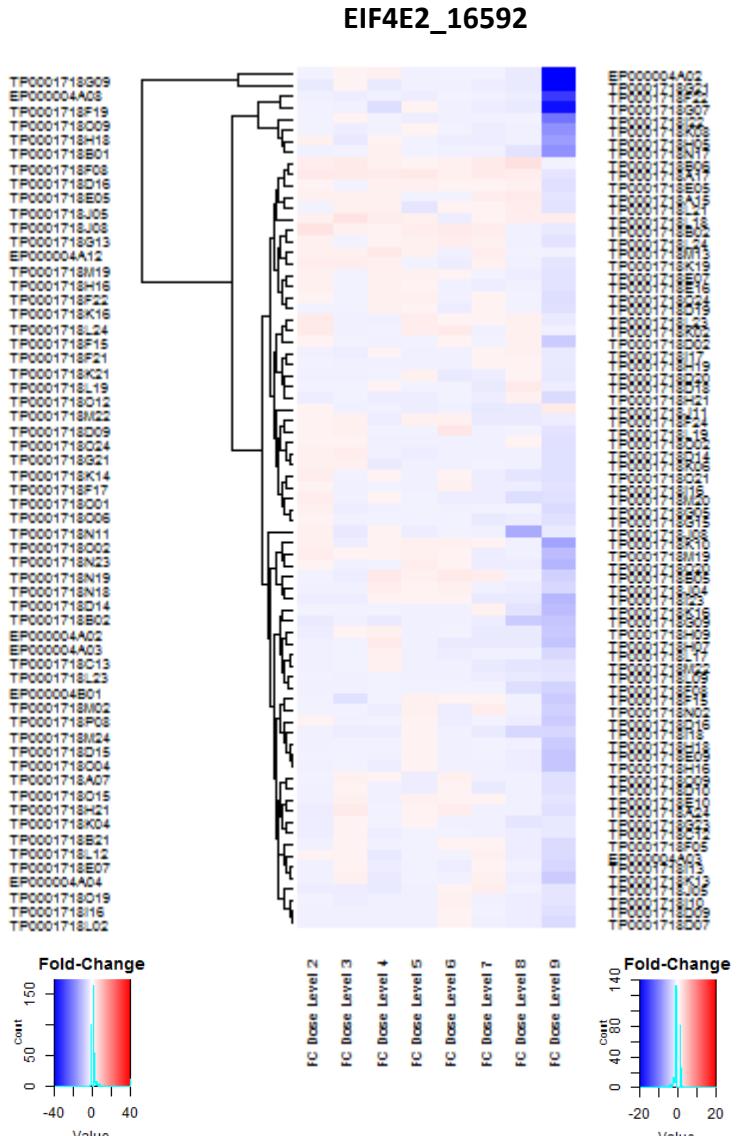
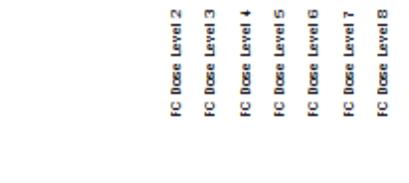
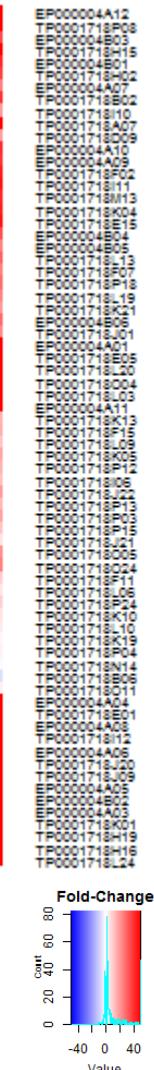
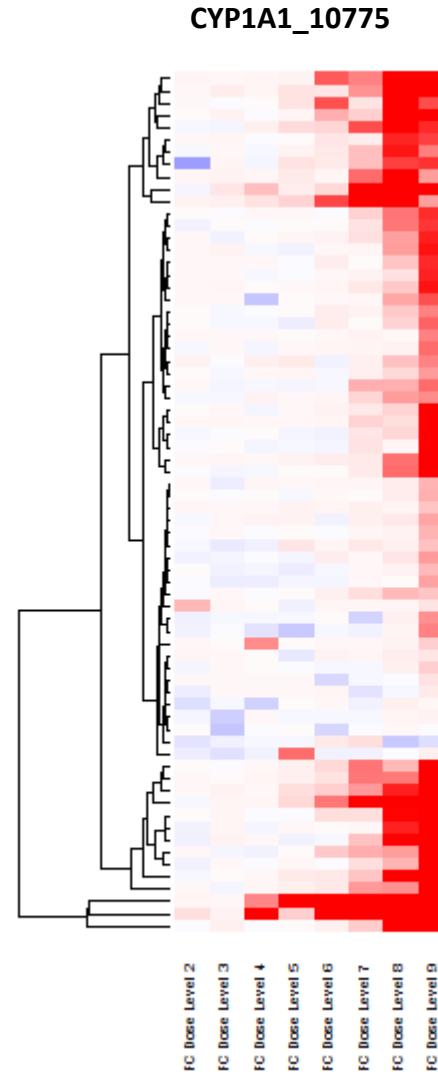
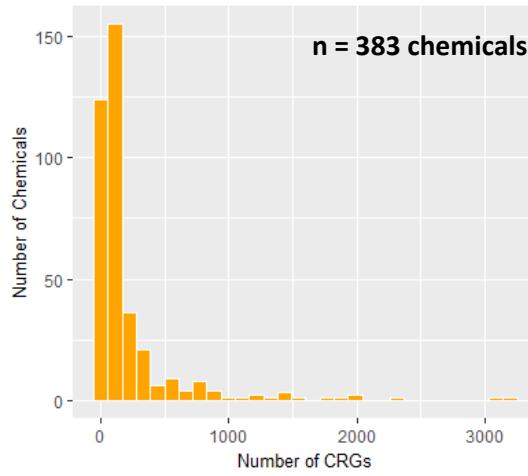
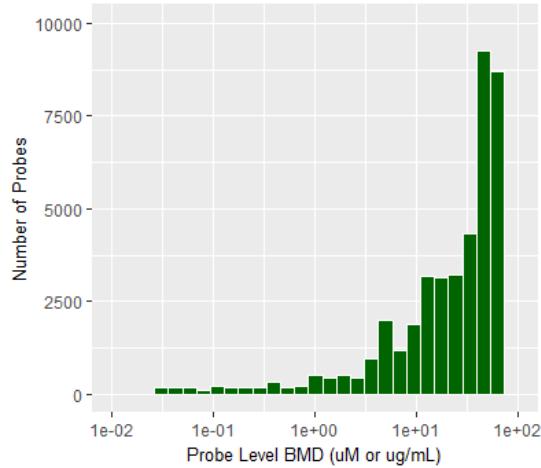
Parameter	Criteria ^a
Pre-filter:	ANOVA ($p_{\text{raw}} < 0.05$ & $ FC \geq 2$)
Models	Hill, Exponential 2, <i>poly2</i> , <i>power</i> , <i>linear</i>
BMR Factor:	1.349 (10 %)
Best Model Selection:	Lowest AIC
Hill Model Flagging ^b :	'k' < 1/3 Lowest Positive Dose Retain Flagged Models
Pathway Analysis:	Genes with $\text{BMD} \leq \text{Highest Dose} \geq 3$ $\geq 1\%$ Gene Set Coverage
Gene Set Collections ^c :	MSigDB_C2 MSigDB_H Reactome BioPlanet KEGG

^a Exploratory analysis – modeling criteria not finalized

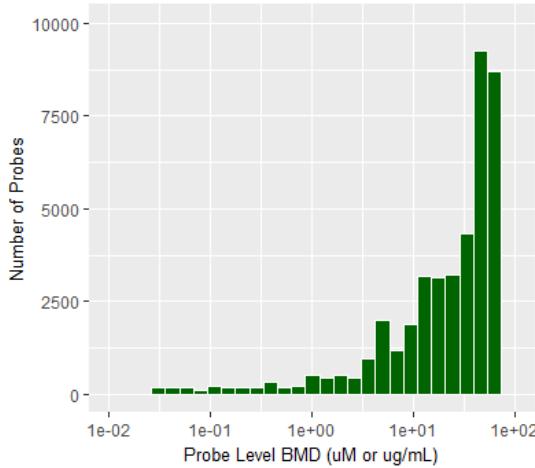
^c Gene Set Collections:

- **MSigDB_C2**: Curated gene sets from online pathway databases, publications and knowledge of domain experts (n = 4738).
- **MSigDB_H**: Coherently expressed signatures derived by aggregating many MSigDB gene sets to represent well-defined biological states or processes (n = 50).
- **Reactome**: Open-source, curated and peer reviewed pathway database with hierarchical pathway relationships in specific domains of biology. (n = 1764). Some pathways included in MSigDB_C2.
- **BioPlanet** (n = 1700): Curated pathway set developed by National Toxicology Program.

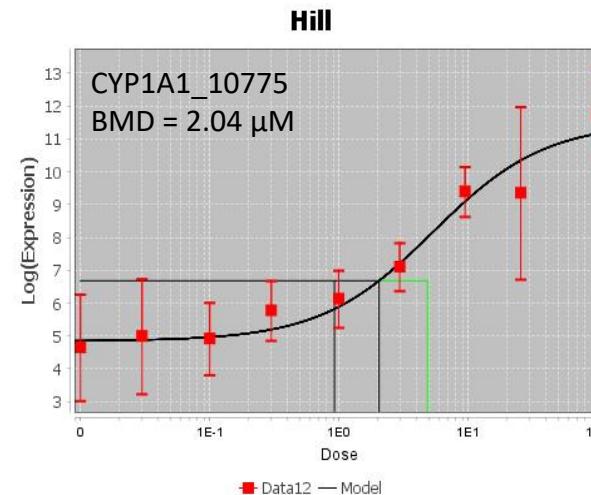
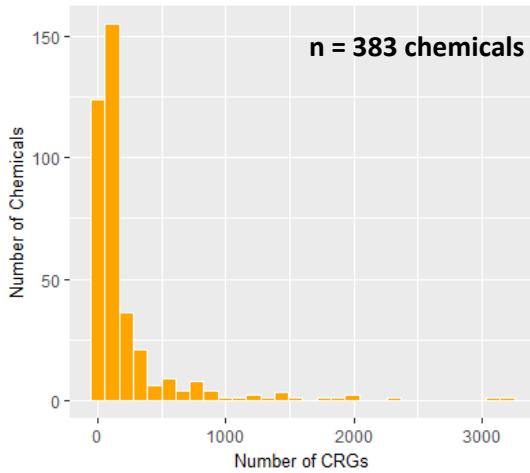
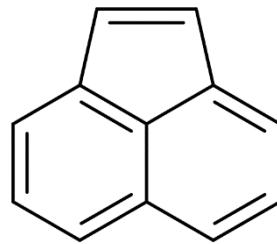
Benchmark Dose Modeling Summary



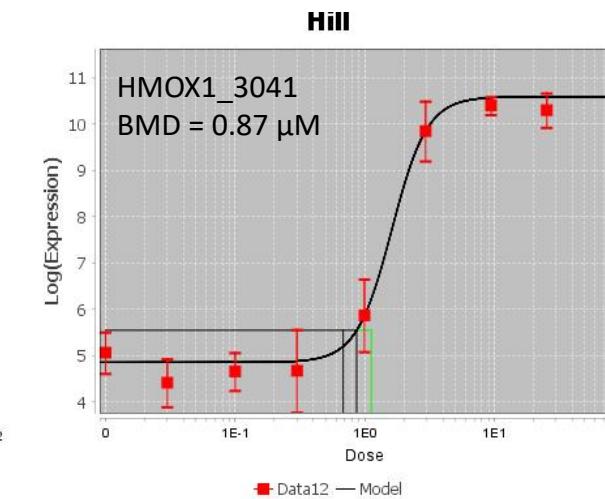
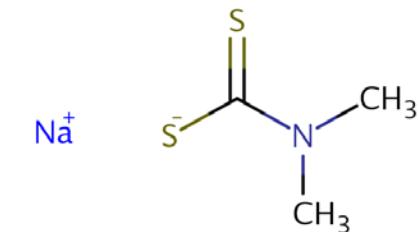
Benchmark Dose Modeling Summary



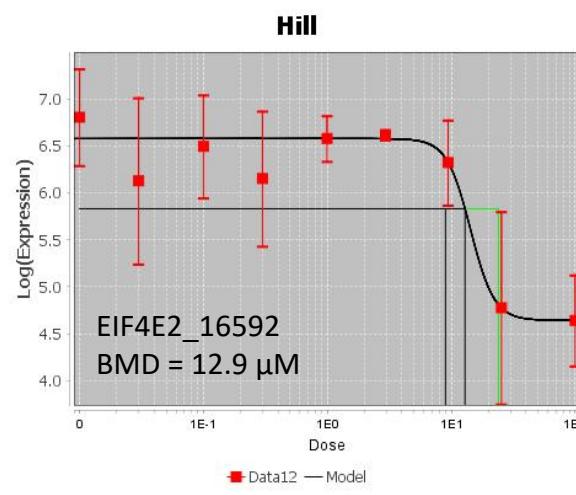
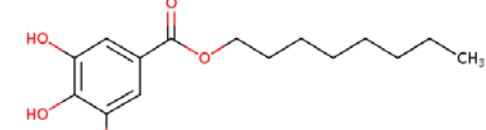
Acenaphthylene
208-96-8 | DTXSID3023845



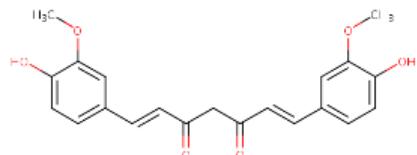
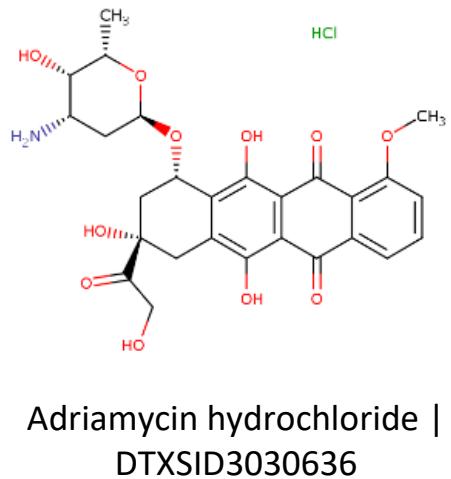
Sodium
dimethyldithiocarbamate
128-04-1 | DTXSID6027050



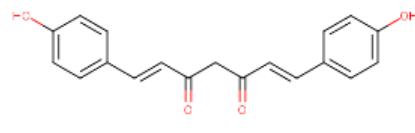
Octyl gallate
1034-01-1 | DTXSID4040713



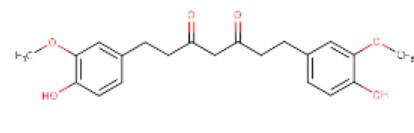
Case Study Chemicals



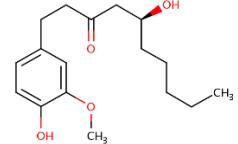
Curcumin |
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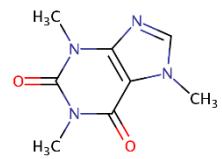
Bisdemethoxycurcumin |
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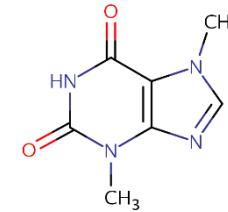
Tetrahydrocurcumin |
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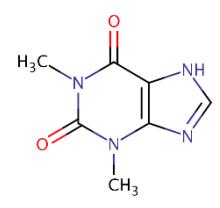
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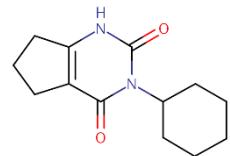
Caffeine |
DTXSID0020232



Theobromine |
DTXSID9026132

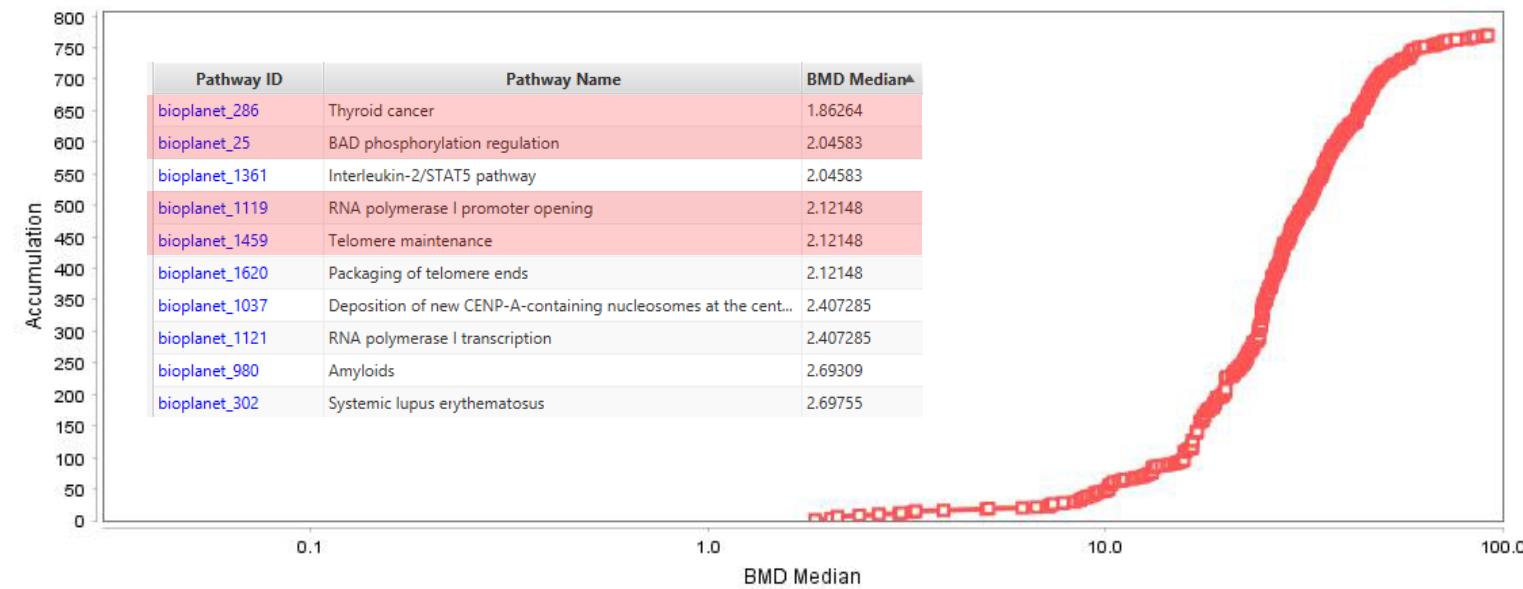
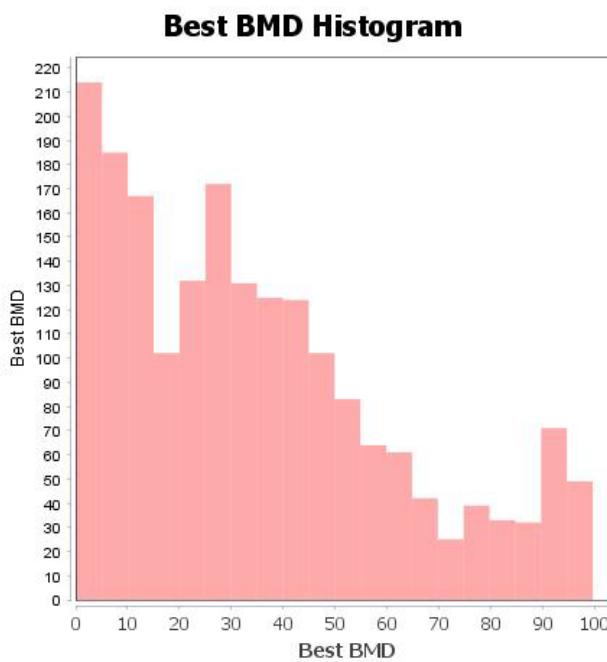
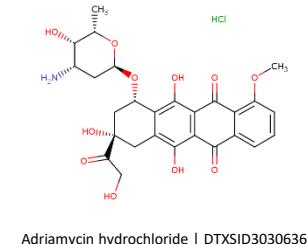
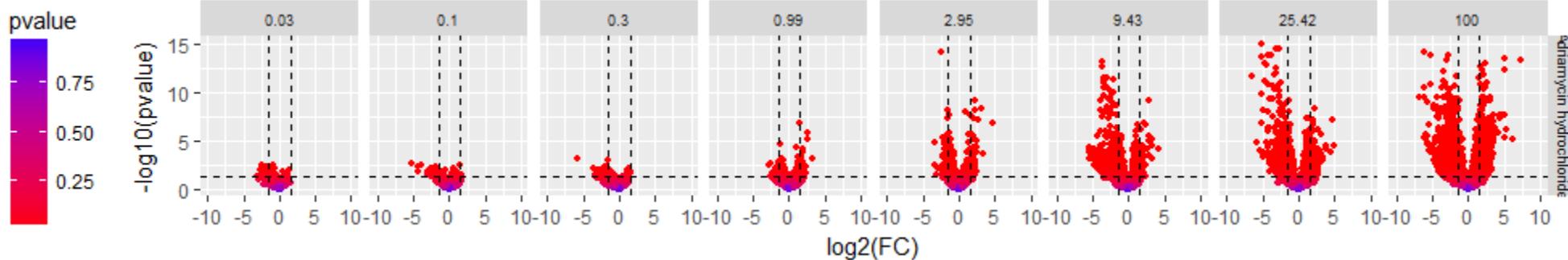


Theophylline |
DTXSID5021336



Lenacil |
DTXSID9042093

Doxorubicin (aka Adriamycin hydrochloride)

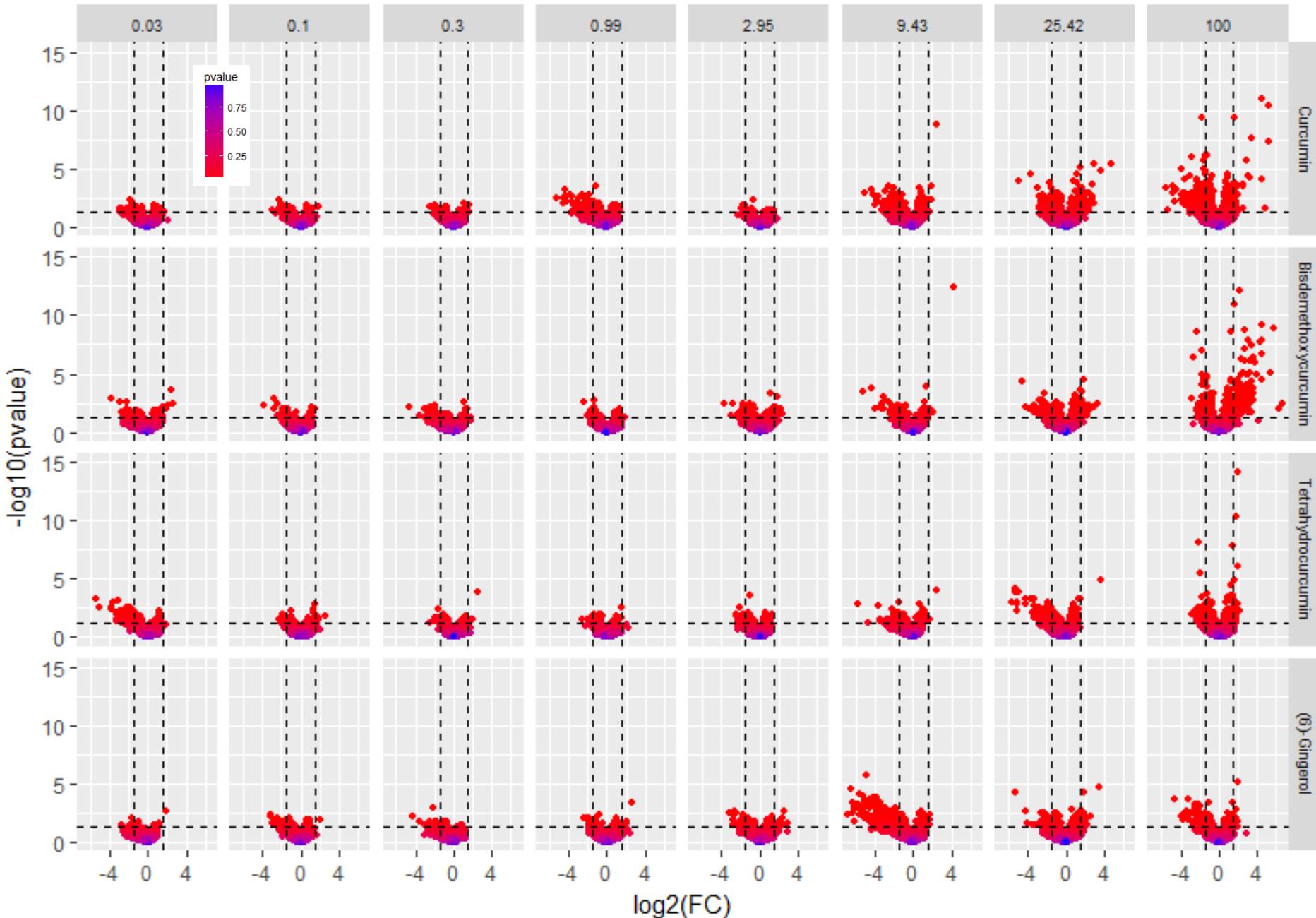


[Int J Mol Cell Med. 2015 Spring;4\(2\):94-102.](#)

Elevation of cAMP Levels Inhibits Doxorubicin-Induced Apoptosis in Pre-B ALL NALM-6 Cells Through Induction of BAD Phosphorylation and Inhibition of P53 Accumulation.

Fatemi A¹, Kazemi A¹, Kashiri M¹, Safa M².

Evaluating Structurally Related Chemicals


CC(O)c1ccc(cc1)C=CC2=C(C=C(C=C2)C(=O)c3ccc(O)c(O)c3)C(=O)c4ccc(cc4)O

Curcumin |
DTXSID8031077

CC1=CC=C(C=C1)C2=C(C=C(C=C2)C(=O)c3ccc(O)c(O)c3)C(=O)c4ccc(cc4)O

Bisdemethoxycurcumin |
DTXSID00872663

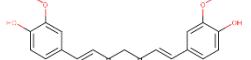
CC(O)c1ccc(cc1)C=CC2=C(C=C(C=C2)C(=O)C(=O)Cc3ccc(O)c(O)c3)C(=O)c4ccc(cc4)O

Tetrahydrocurcumin |
DTXSID30865801

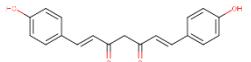
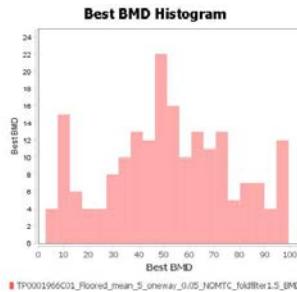
CC(C)CC[C@H]1CC[C@@H](CO1)C(=O)Cc2ccc(O)c(O)c2

(6)-Gingerol |
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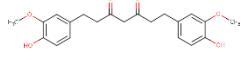
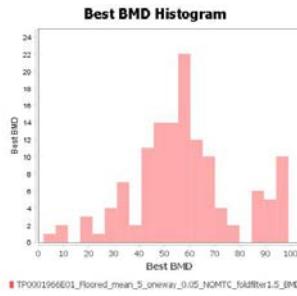
Gene Set Analysis Using BMD Modeling Results



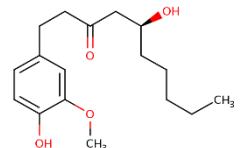
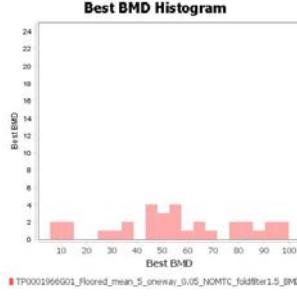
Curcumin | DTXSID8031077



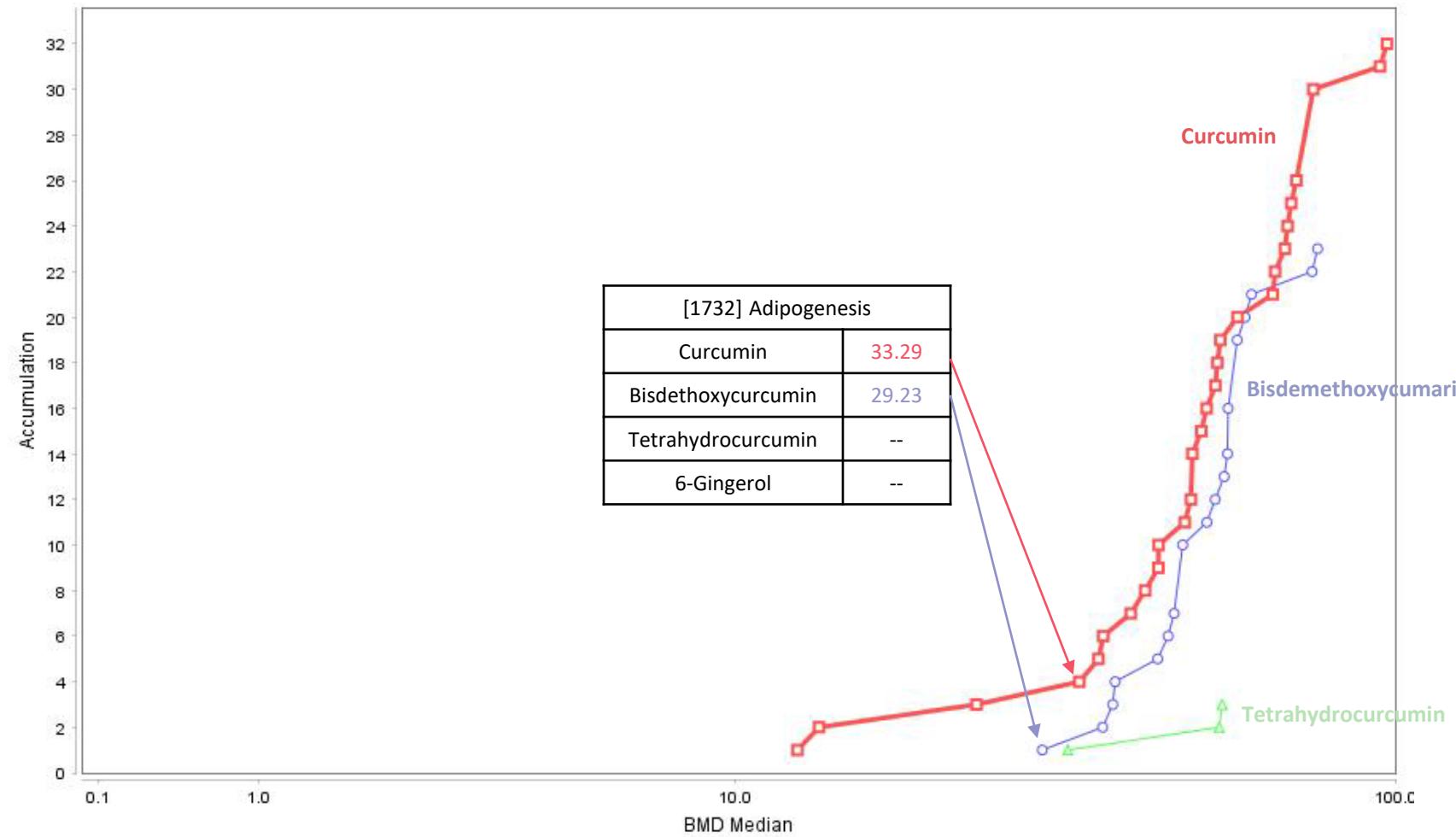
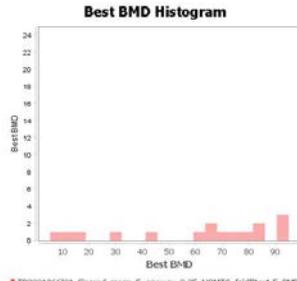
Bisdemethoxycurcumin | DTXSID00872663



Tetrahydrocurcumin | DTXSID30865801



(6)-Gingerol | DTXSID3041035



[Toxicol Appl Pharmacol.](#) 2017 Aug 15;329:158-164. doi: 10.1016/j.taap.2017.05.036.

Curcumin inhibits adipogenesis induced by benzyl butyl phthalate in 3T3-L1 cells.

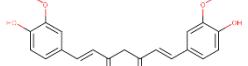
Sakuma S¹, Sumida M², Endoh Y², Kurita A², Yamaguchi A², Watanabe T², Kohda T², Tsukiyama Y², Fujimoto Y³.

[J Agric Food Chem.](#) 2016 Feb 3;64(4):821-30. doi: 10.1021/acs.jafc.5b05577. Epub 2016 Jan 25.

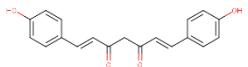
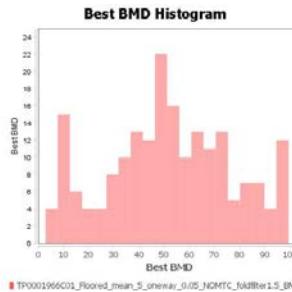
Bisdemethoxycurcumin Inhibits Adipogenesis in 3T3-L1 Preadipocytes and Suppresses Obesity in High-Fat Diet-Fed C57BL/6 Mice.

Lai CS^{1,2}, Chen YY¹, Lee PS¹, Kalyanam N³, Ho CT⁴, Liou WS⁵, Yu RC¹, Pan MH^{1,6,7,8}.

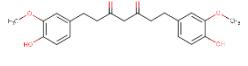
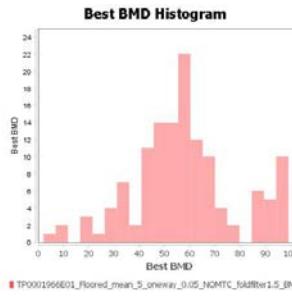
Gene Set Analysis Using BMD Modeling Results



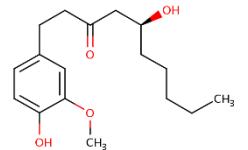
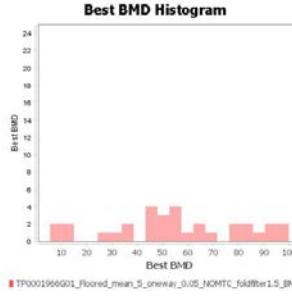
Curcumin | DTXSID8031077



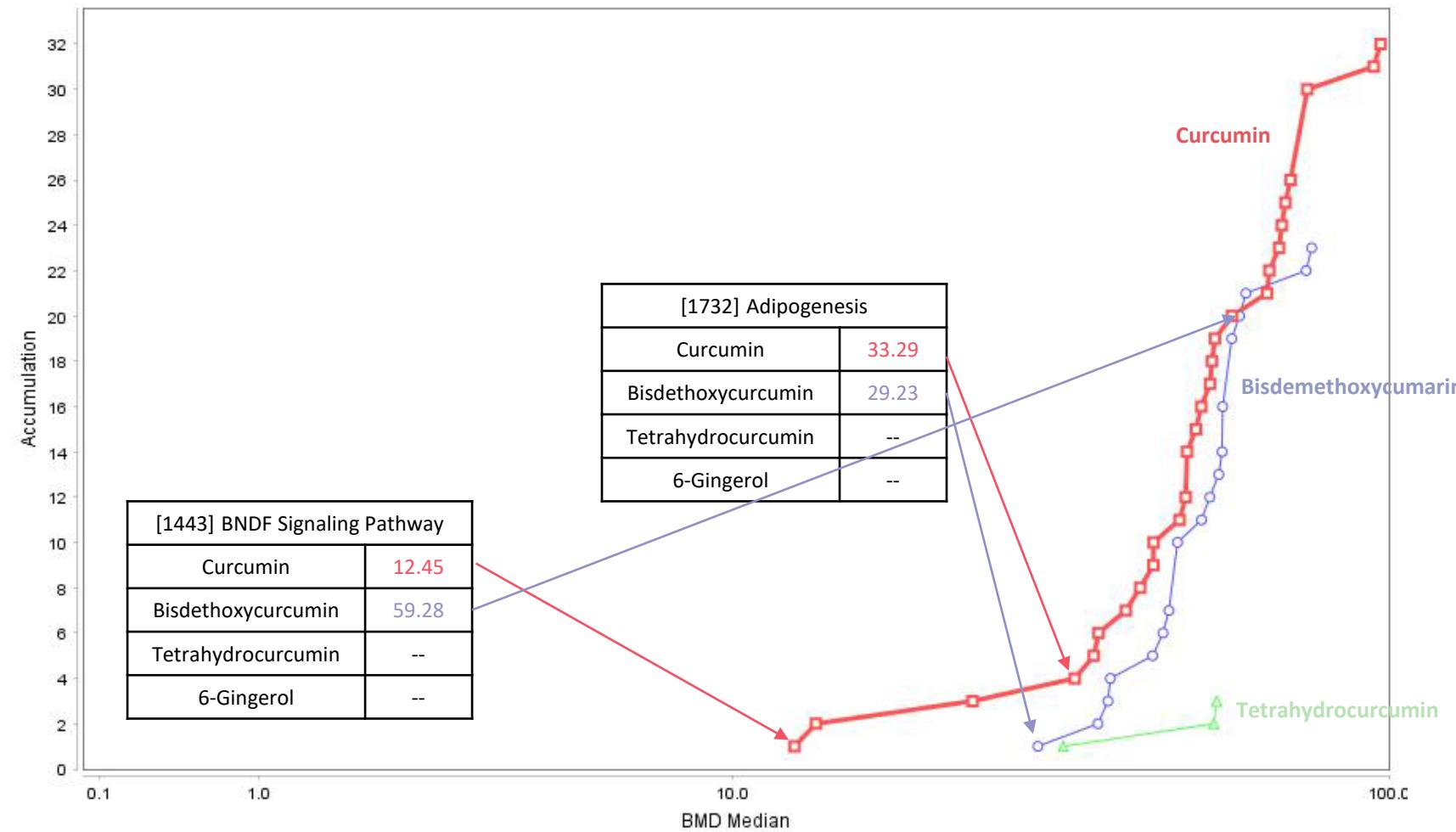
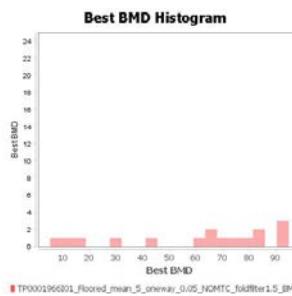
Bisdemethoxycurcumin | DTXSID00872663



Tetrahydrocurcumin | DTXSID30865801



(6)-Gingerol | DTXSID3041035



[Neuropeptides](#). 2016 Apr;56:25-31. doi: 10.1016/j.npep.2015.11.003. Epub 2015 Nov 11.

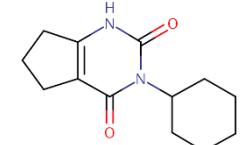
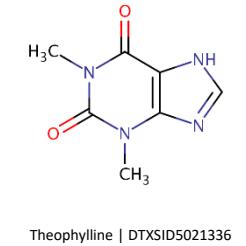
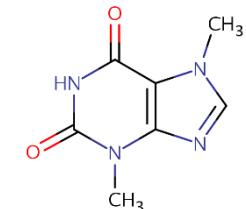
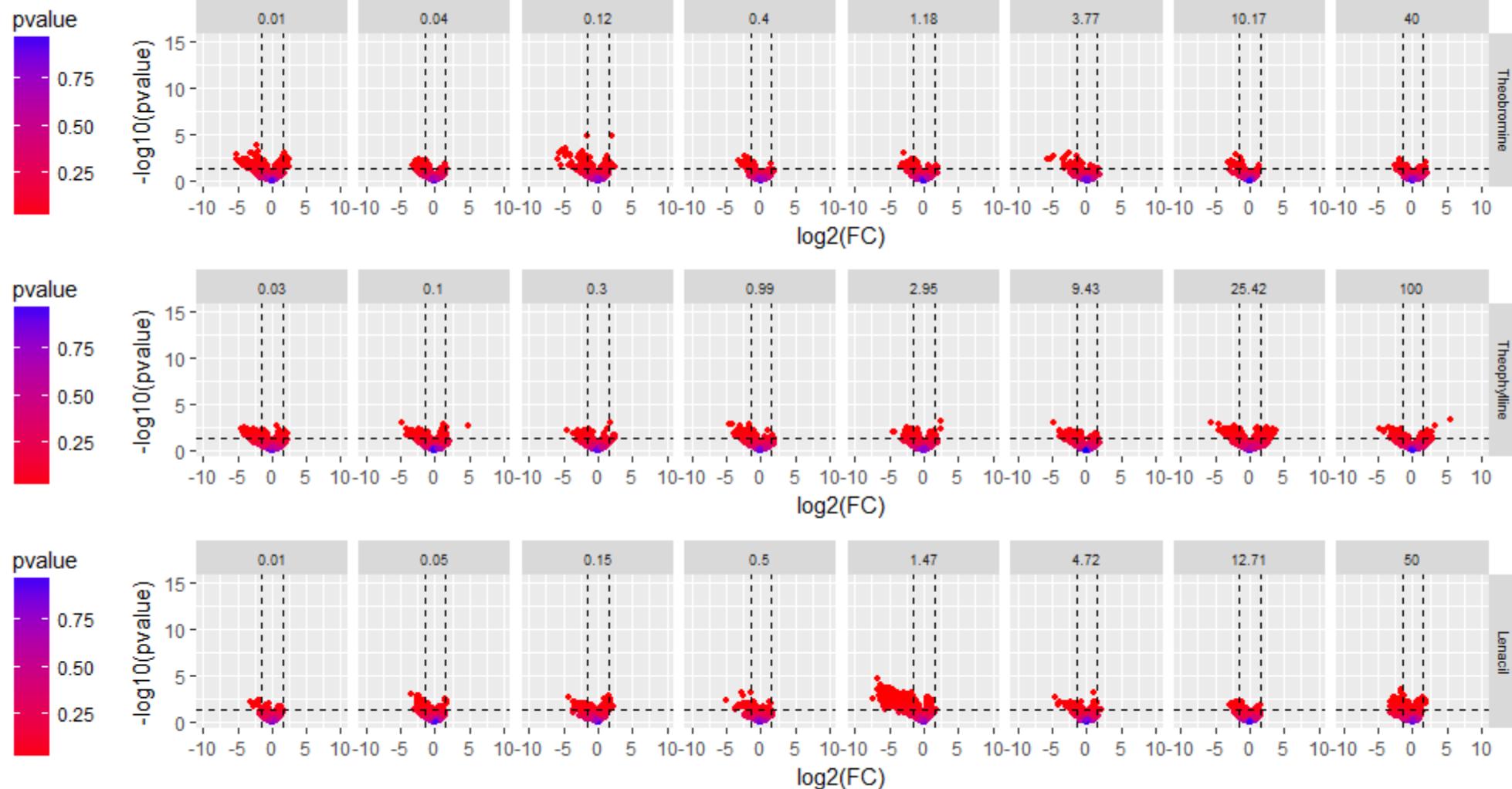
Effect of curcumin on serum brain-derived neurotrophic factor levels in women with premenstrual syndrome: A randomized, double-blind, placebo-controlled trial. [Fanaei H¹](#), [Khayat S²](#), [Kasaeian A³](#), [Javadimehr M⁴](#).

[Biomed Pharmacother](#). 2017 Mar;87:721-740. doi: 10.1016/j.biopha.2016.12.020. Epub 2017 Jan 14.

Curcumin confers neuroprotection against alcohol-induced hippocampal neurodegeneration via CREB-BDNF pathway in rats.

[Motaghinejad M¹](#), [Motevalian M²](#), [Fatima S³](#), [Hashemi H¹](#), [Gholami M⁴](#).

Caffeine Analogs



- Very few dose-responsive genes
- No significantly enriched pathways using BMDe standard workflow

Alternative Approach for Gene Set Analysis

Step 1: Calculate Response

- A gene set is a list / bag of genes
- Under one condition (chemical x dose) calculate “gene set response” separately for genes in the set and out of the set:

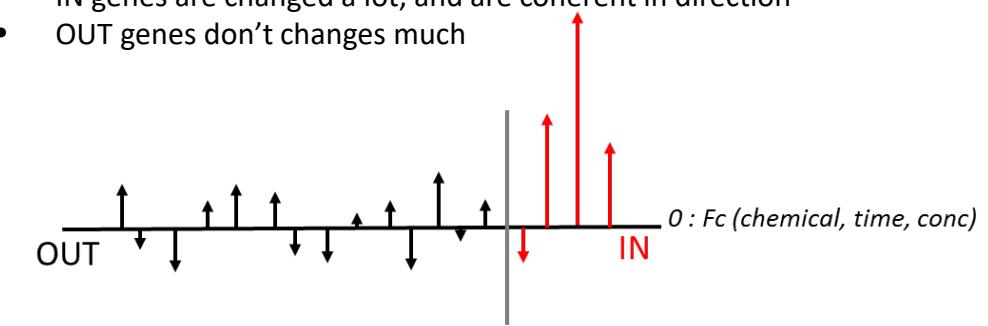
$$M = \sum_{i=1}^{ngene} \frac{fc_i}{sc_i^2} \sqrt{\sum_{i=1}^{ngene} \frac{1}{sc_i^2}}$$

$$R = M_{in} - M_{out}$$

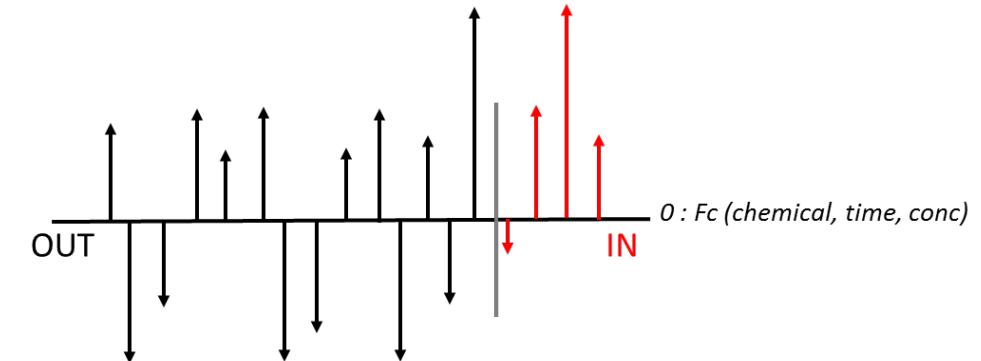
Step 2: CR Modeling

- For each chemical, fit using tcplFit
 - Constant, Hill , Gain-Loss methods
 - BMAD(pathway) = MAD of response for the pathway across the two lowest concentrations across all chemicals and times
- Hitcall:
 - tcplFit calls a hit
 - Top > 3*BMAD

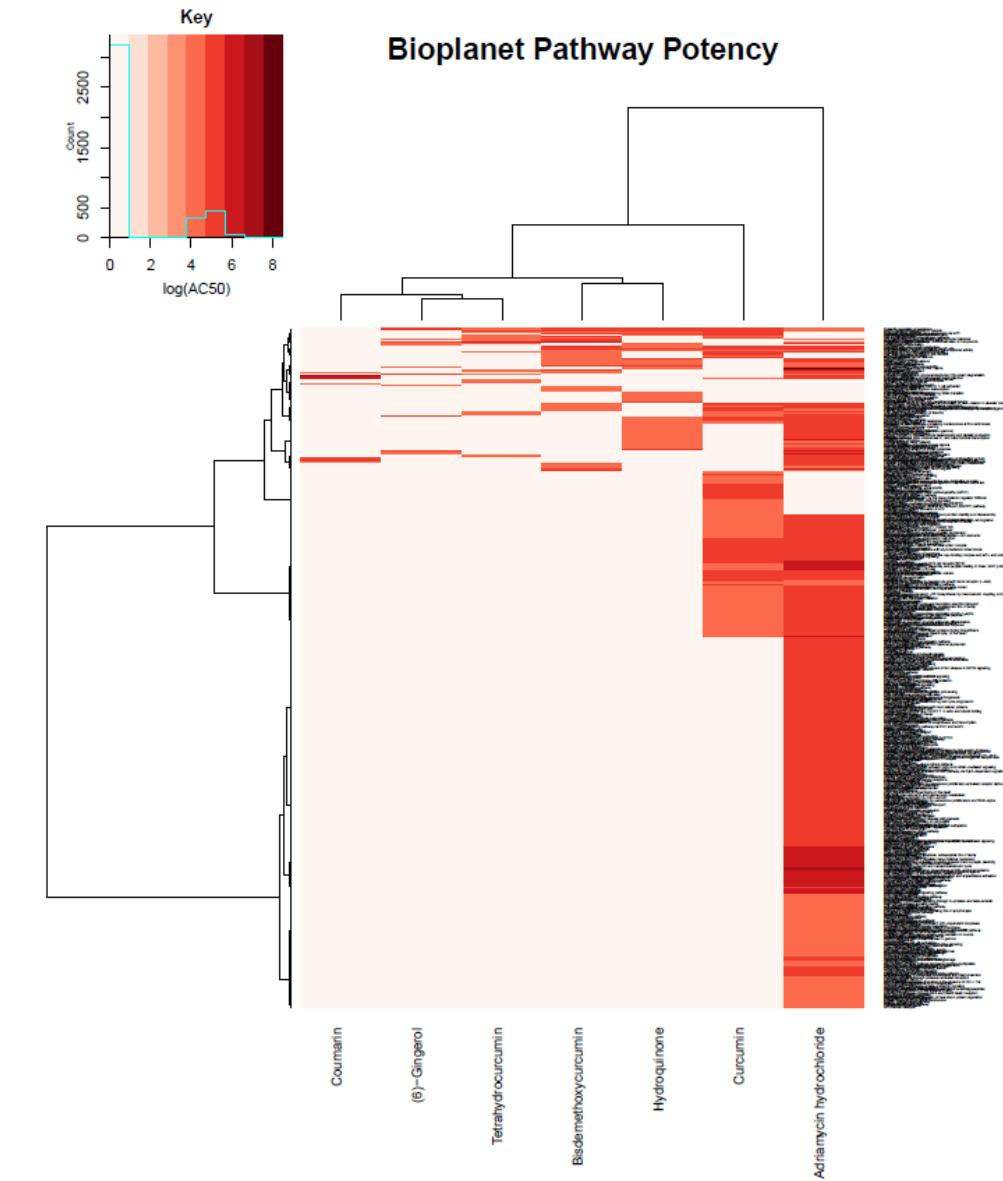
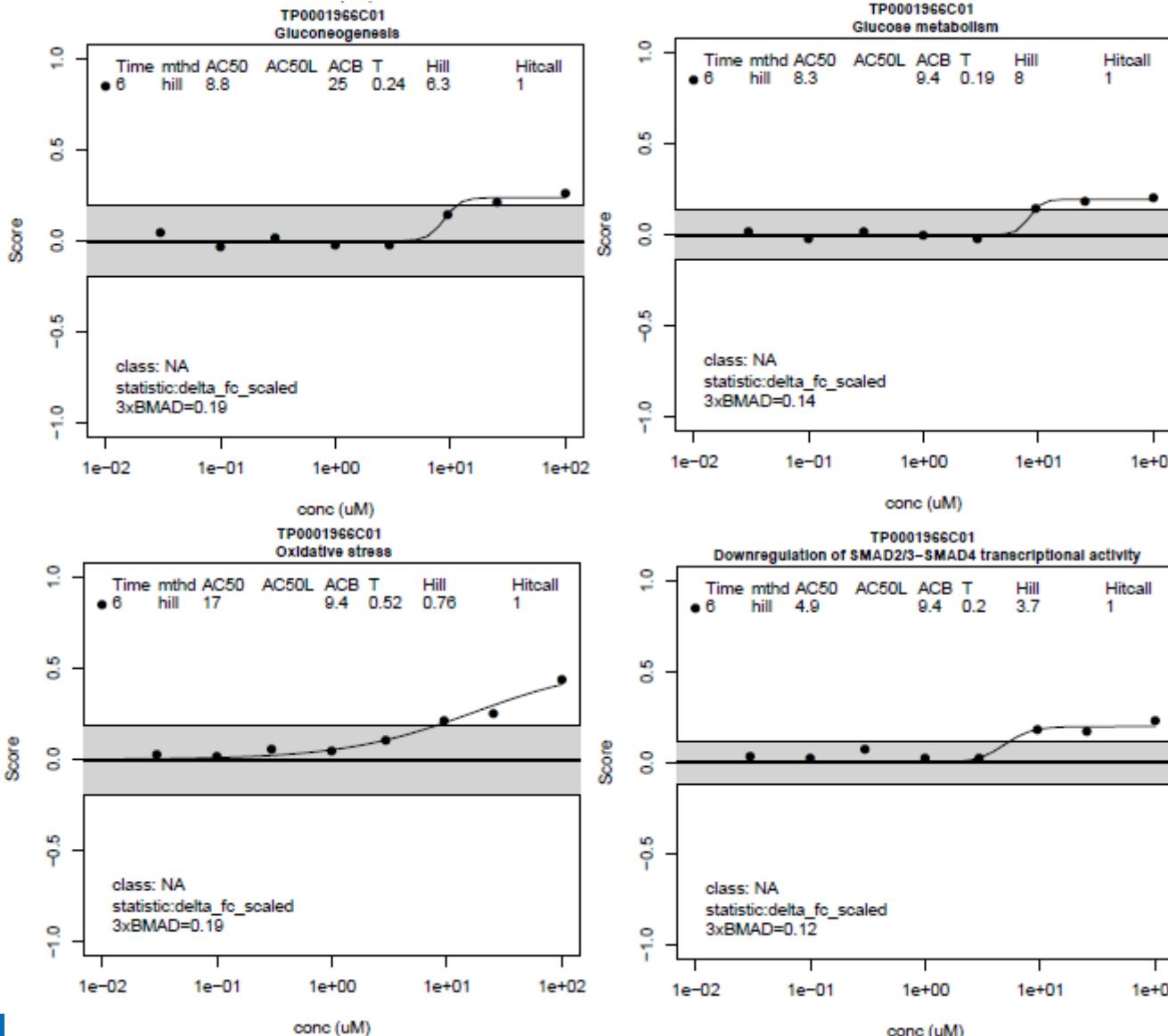
- IN genes are changed a lot, and are coherent in direction
- OUT genes don't changes much



- IN genes are changed a lot, and are coherent in direction
- OUT genes change a lot but are not coherent (mean ~ 0)



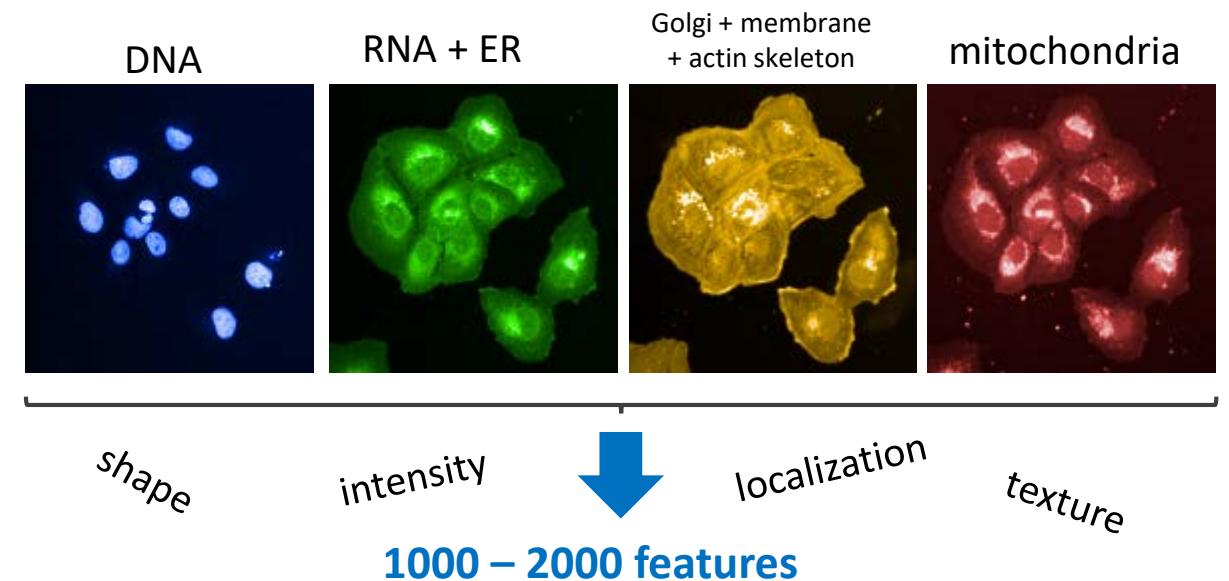
Comparing Activities Across Chemicals



High Throughput Phenotypic Profiling via High Content Image Analysis

Phenotypic Profiling

- Image-based phenotypic profiling is a chemical screening method that measures a large variety of morphological features of individual cells in *in vitro* cultures.
- Successfully used for functional genomic studies and in the pharmaceutical industry for compound efficacy and toxicity screening.
- No requirement for *a priori* knowledge of molecular targets.
- **May be used as an efficient and cost-effective method for evaluating the chemical bioactivity.**



- **Cell Painting (Bray et al., 2016, *Nature Protocols*):** A cell morphology-based phenotypic profiling assay multiplexing six fluorescent “non-antibody” labels, imaged in five channels, to evaluate multiple cellular compartments and organelles.

Experimental Workflow

Marker	Cellular Component	Labeling Chemistry	Labeling Phase	Opera Phenix	
				Excitation	Emission
Hoechst 33342	Nucleus	Bisbenzamide probe that binds to dsDNA	Fixed	405	480
Concanavalin A – AlexaFluor 488	Endoplasmic reticulum	Lectin that selectively binds to α -mannopyranosyl and α -glucopyranosyl residues enriched in rough endoplasmic reticulum		435	550
SYTO 14 nucleic acid stain	Nucleoli	Cyanine probe that binds to ssRNA		435	550
Wheat germ agglutinin (WGA) – AlexaFluor 555	Golgi Apparatus and Plasma Membrane	Lectin that selectively binds to sialic acid and N-acetylglucosaminyl residues enriched in the trans-Golgi network and plasma membrane		570	630
Phalloidin –AlexaFluor 568	F-actin (cytoskeleton)	Phallotoxin (bicyclic heptapeptide) that binds filamentous actin			
MitoTracker Deep Red	Mitochondria	Accumulates in active mitochondria	Live	650	760

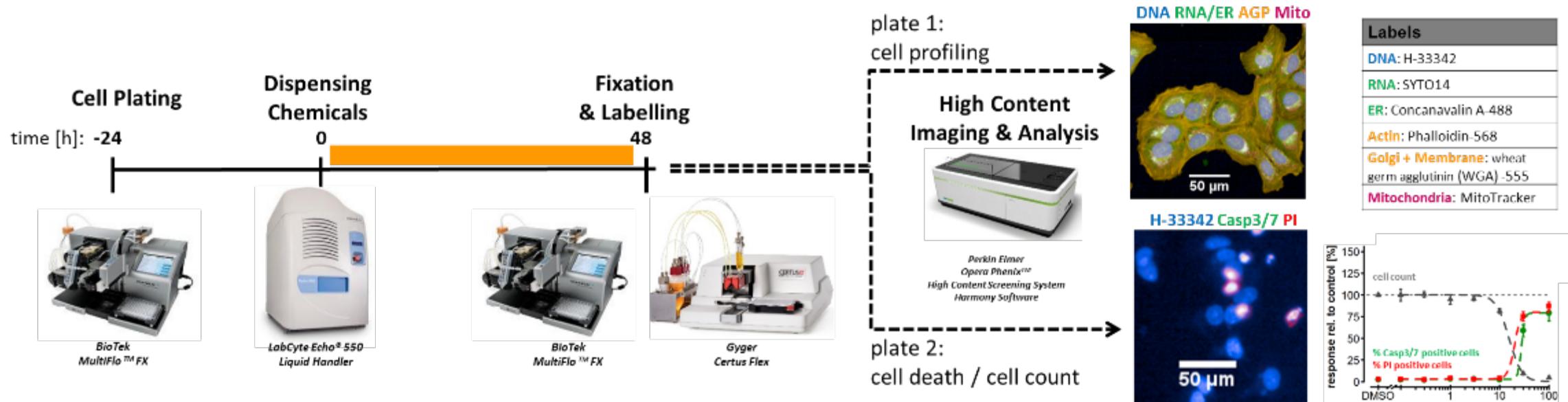


Image Analysis Workflow

Image Acquisition

Image Acquisition

- Perkin Elmer Opera Phenix
- 20x Water Immersion Objective
- Confocal Mode, Single Z
- CellCarrier-384 Ultra Microplates

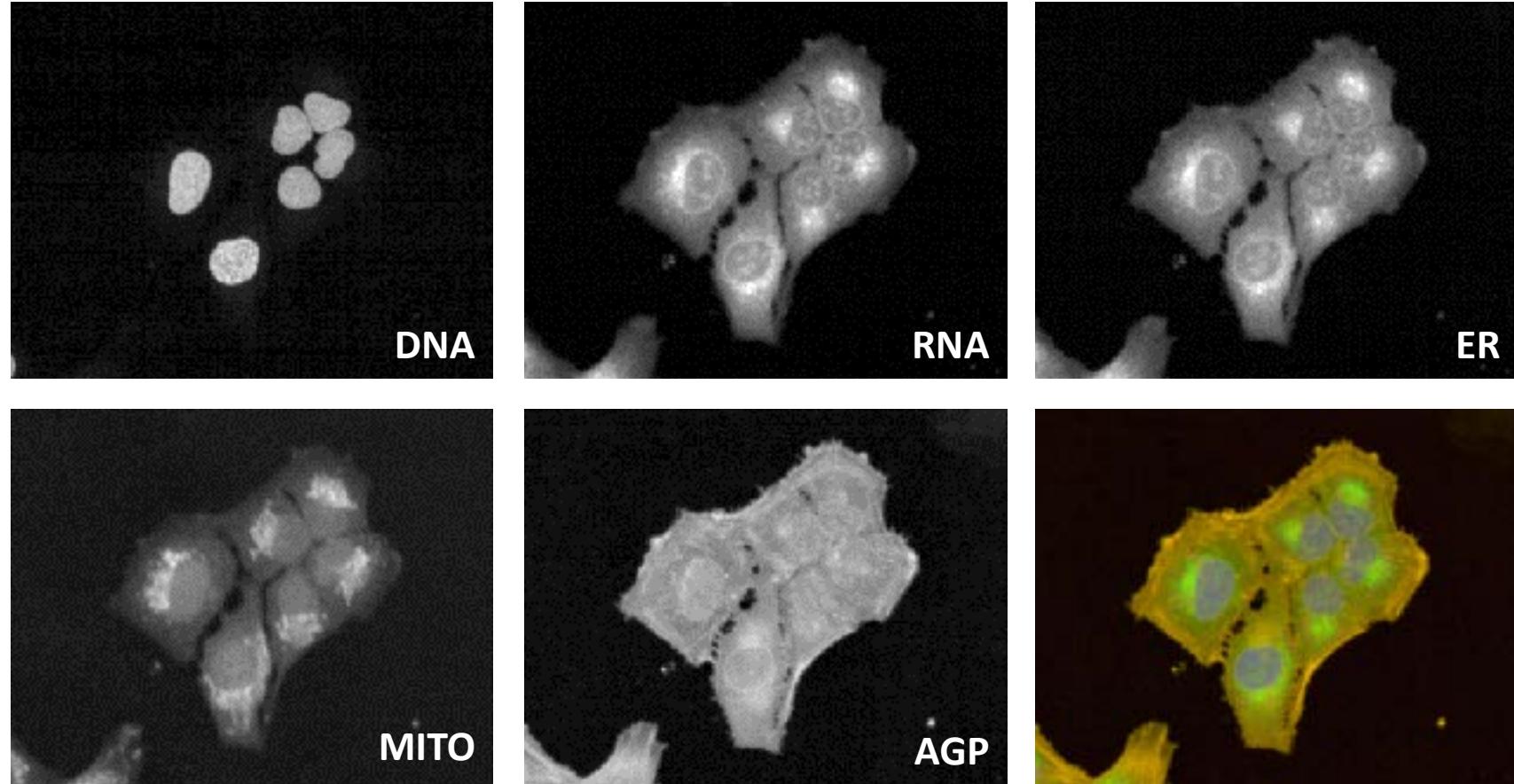
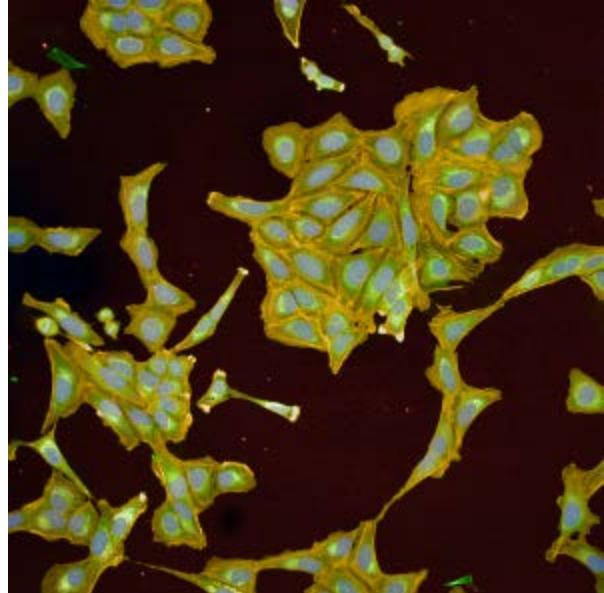
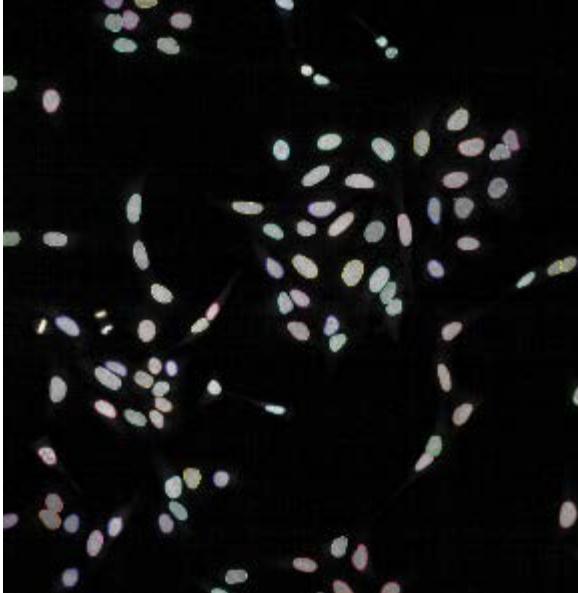


Image Analysis Workflow: *Nucleus and Cell Segmentation*

1. find nuclei



2. find cell outline



3. reject border objects

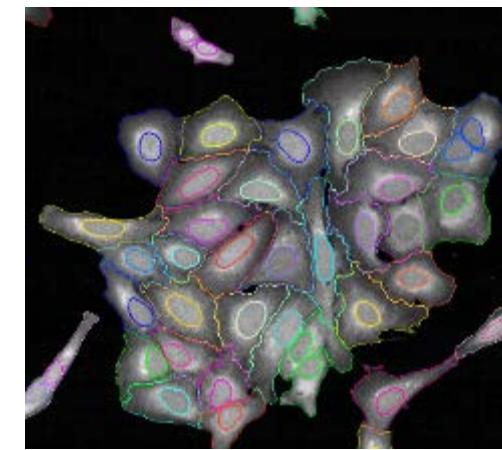
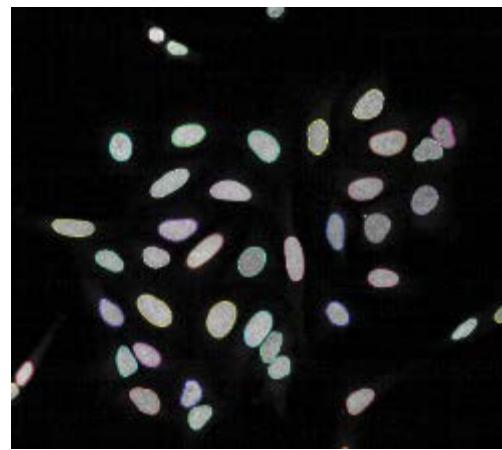
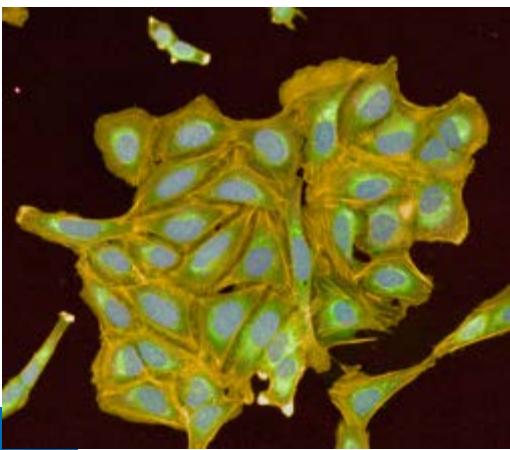
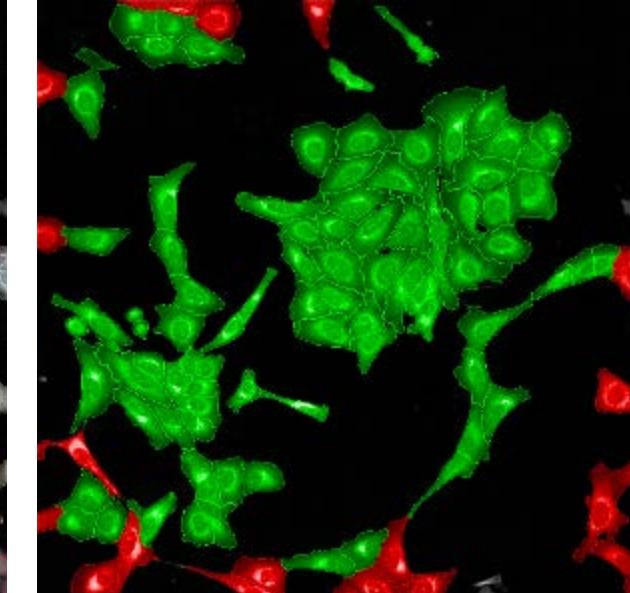
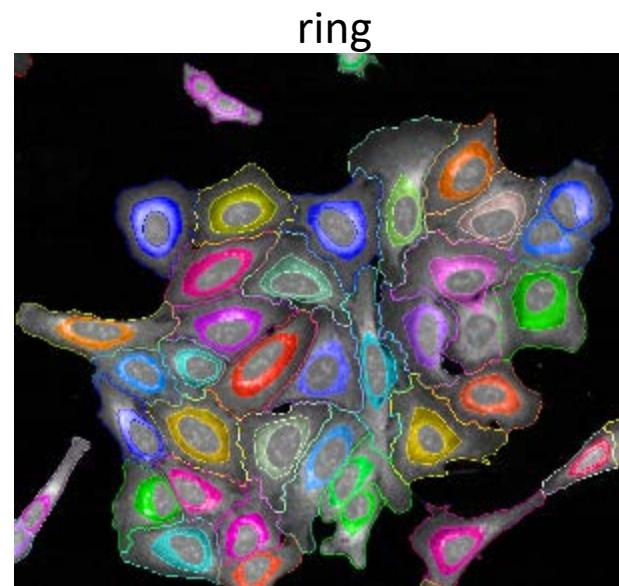
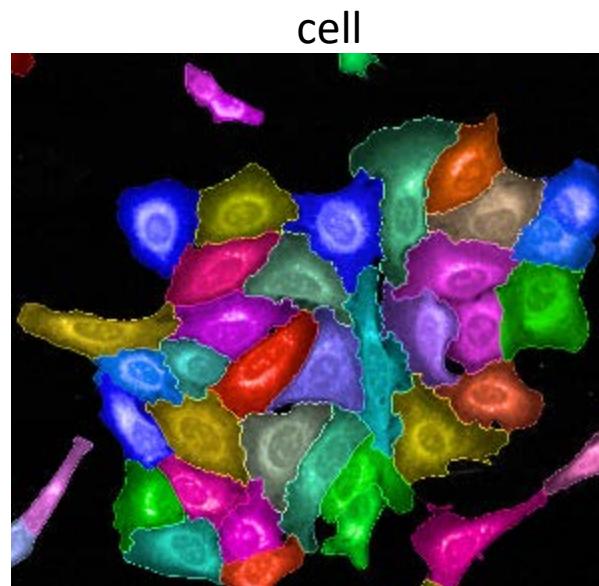
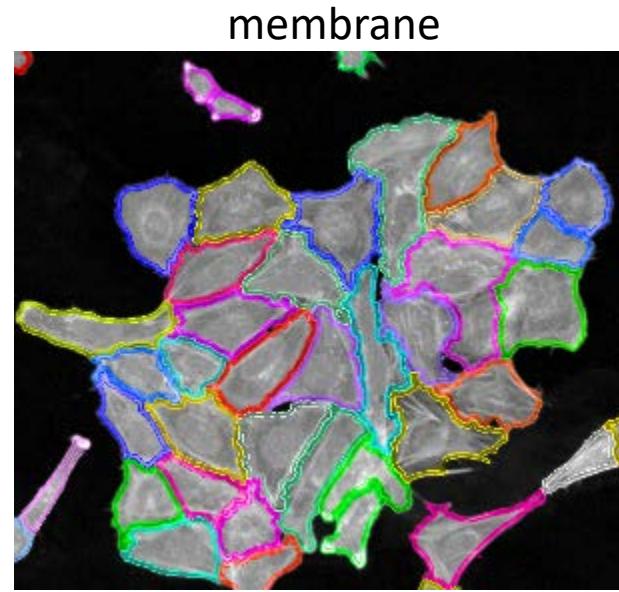
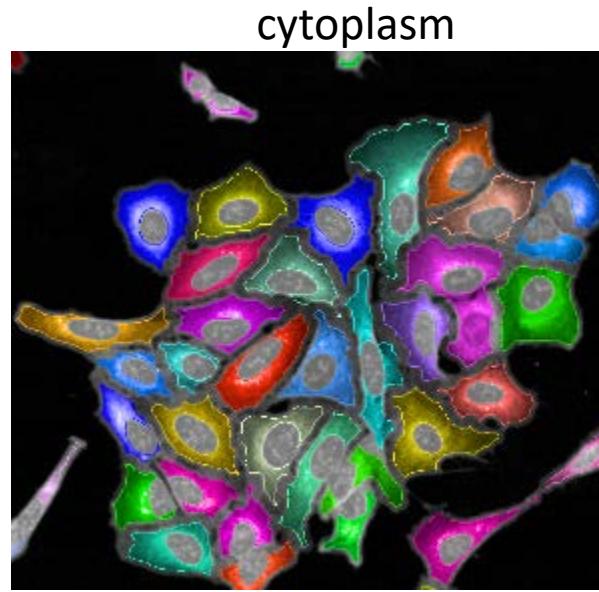
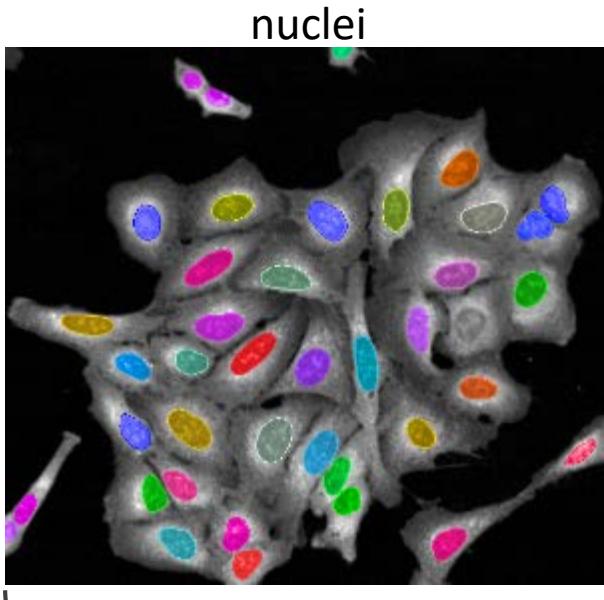
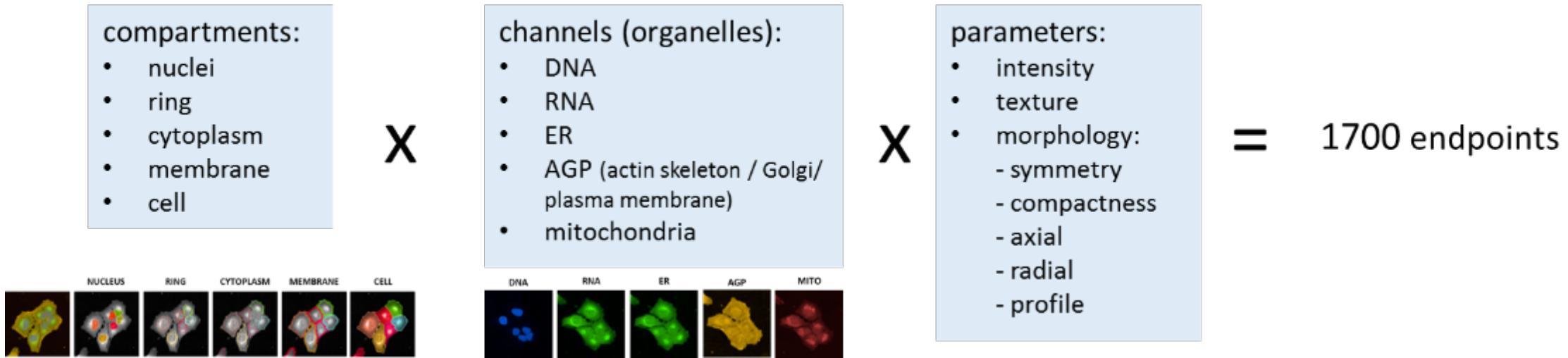


Image Analysis Workflow

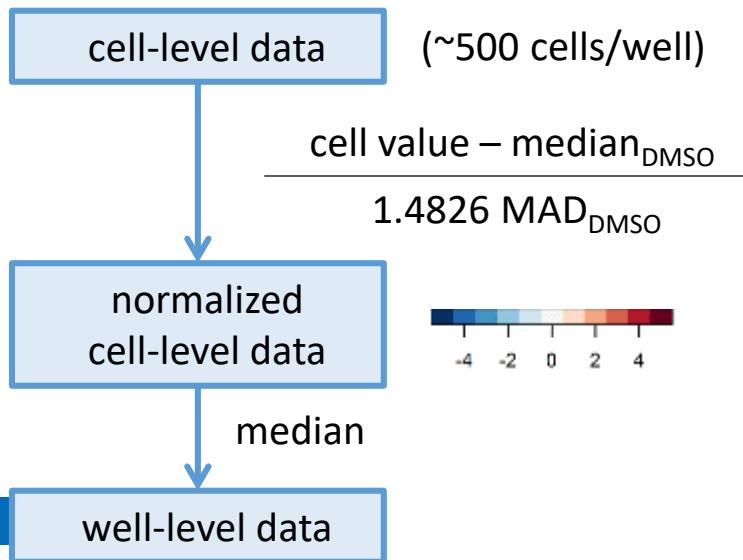
Define Cellular Compartments



Assay Outputs & Data Analysis

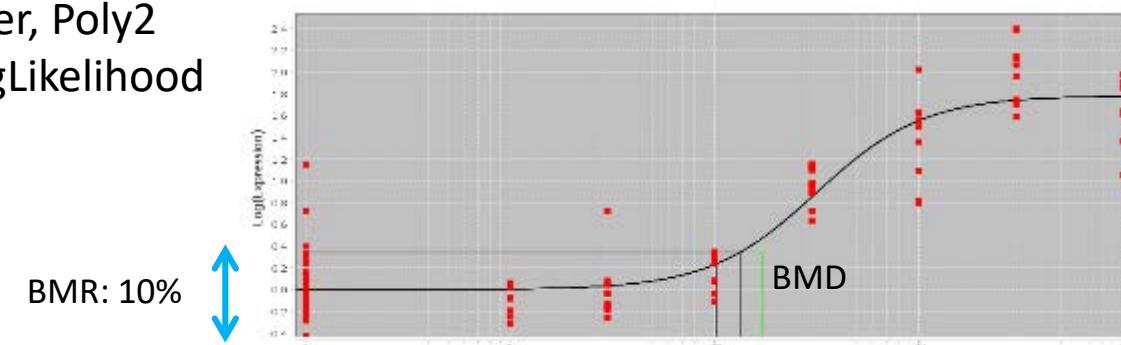


Data Reduction



BMD Modelling

- Well-level data x 3 technical replicates x 3 biological replicates = 9 values
- Filtered for affected parameters using ANOVA ($p \leq 0.01$, FDR adjusted)
- BMD modelling with BMDEXpress 2.0
 - 3 models: Hill, Power, Poly2
 - model with best logLikelihood selected



Objectives & Experimental Design

1. Miniaturize an existing assay (Bray et al. 2016) and establish a microfluidics-based laboratory workflow suitable for high-throughput screening purposes.
2. Test a set of 14 phenotypic reference and 2 negative compounds in seven cell lines.
3. Evaluate the applicability of the assay for:
 - a) grouping of chemicals with similar biological effects
 - b) derivation of *in vitro* point-of-departures (POD)
4. Identify chemicals & test concentrations for use as reference chemical controls in screening applications.

Parameter	Multiplier	Notes
Cell Type(s)	7	U2 OS, MCF7, HepG2, LNCap, A549, ARPE-19, HTB-9
Culture Condition	1	DMEM + 10% HI-FBS ^a
Chemicals	16	14 phenotypic reference chemicals, 2 negative controls
Time Points:	1	48 hours
Assay Formats:	2	Cell Painting HCl Cell Viability & Apoptosis
Concentrations:	8	$3.5 \log_{10}$ units; semi \log_{10} spacing
Biological Replicates:	3	Independent cultures

Reference Chemical Set

- Reference chemicals (n=14) with narrative descriptions of observed phenotypes were identified from Gustafsdottir et al. 2013.
- Candidate negative control chemicals (n=2) with no anticipated affect on cell phenotype were included in the reference set.

Compound Name	Chemical Use	Expected Phenotype
Amperozide	Atypical antipsychotic	Toroid nuclei
Berberine Chloride	Mitochondria complex I inhibitor	Redistribution of mitochondria
Ca-074-Me	Cathepsin B inhibitor	Bright, abundant golgi staining
Etoposide	Chemotherapeutic	Large, flat nucleoli
Fenbendazole	Anthelmintic	Giant, multi-nucleated cells
Fluphenazine	Typical antipsychotic	Enhanced golgi staining and some cells with fused nucleoli
Latrunculin B	Actin cytoskeleton disruptor	Actin breaks
Metoclopramide	D ₂ dompaine receptor antagonist	Enhanced golgi staining and some cells with fused nucleoli
NPPD	Chloride channel blocker	Redistribution of ER to one side of the nucleus
Oxibendazole	Anthelmintic	Large, multi-nucleated cells with fused nucleoli
Rapamycin	Macrolide antibiotic / antifungal	Reduced nucleolar size
Rotenone	Mitochondria complex I inhibitor	Mitochondrial stressor
Saccharin	Artificial Sweetener	Negative Control
Sorbitol	Artificial Sweetener	Negative Control
Taxol	Microtubule Stabilizer	Large, multi-nucleated cells with fused nucleoli
Tetrandrine	Calcium channel blocker	Abundant ER

Phenotypic Profiles in U-2 OS Cells

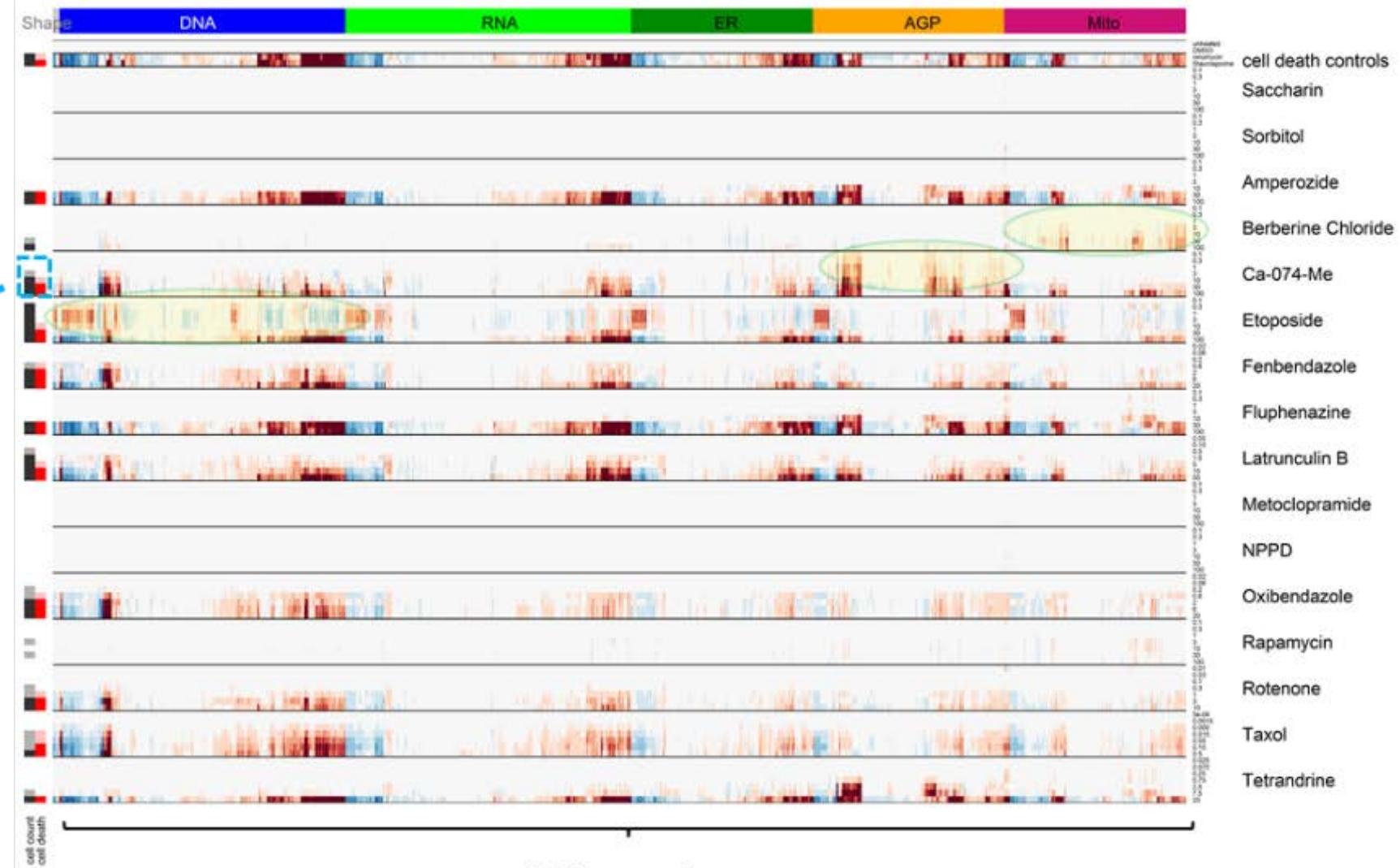
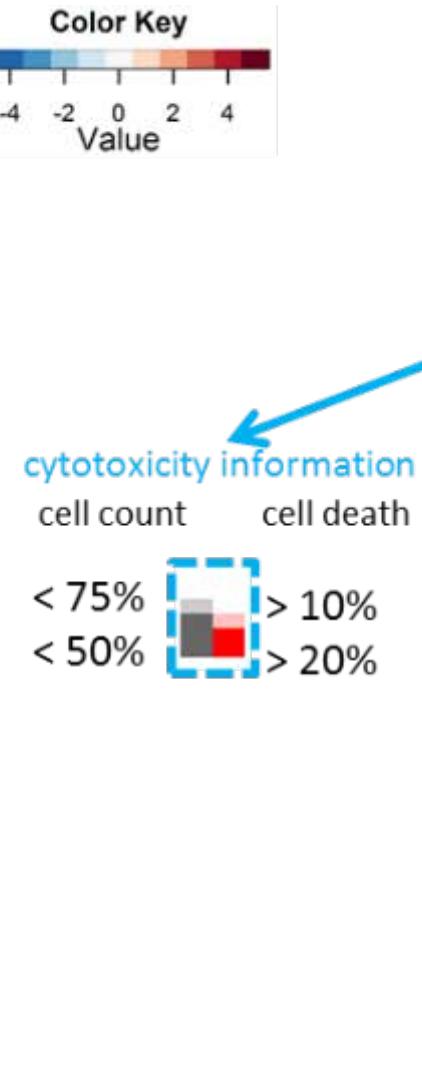


Fig 1. MAD normalized well-level data of U-2 OS cells were averaged across 3 technical and 3 biological replicates. Endpoints are ordered according to the corresponding channel/organelle. The color key on the left indicates reductions in cell count and increases in cell death. Treatment with different chemicals resulted in distinct profiles. Some effects observed at non-cytotoxic concentrations.

Phenotypic Profiles Are Consistent with Observed Effects

Parameters with marked effects:

Channel	Compartment	Domain
Mito	Cytoplasm	Texture
Mito	Cytoplasm + Ring	Intensity: Maximum
Mito	Entire Cell	Compactness (of the bright spots)

Literature: redistribution of mitochondria

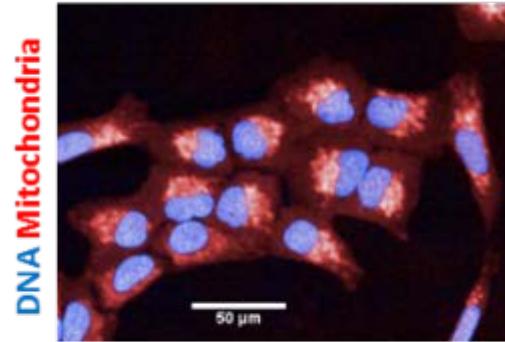
Channel	Compartment	Domain
AGP	Cytoplasm + Ring	Texture
AGP	Cytoplasm + Ring	Intensity: Maximum
AGP	Entire Cell	Profile (=distribution of intensity)

Literature: bright, abundant Golgi stain

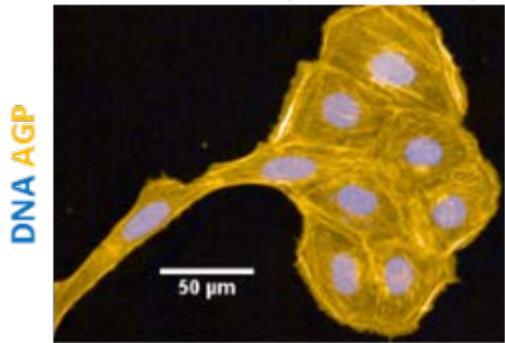
Channel	Compartment	Domain
"shape"	Entire Cell	Morphology: Area, Length, Width
DNA + RNA	Nuclei	Compactness (of the bright spots) Texture
ER + AGP	Cytoplasm + Ring	Intensity: Sum
all	Entire Cell	Morphology: intensity distribution

Literature: large, flat nucleoli

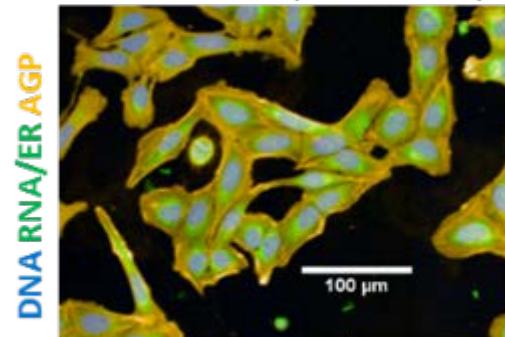
solvent control (0.5% DMSO)



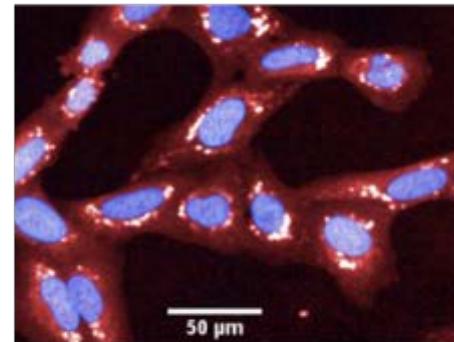
solvent control (0.5% DMSO)



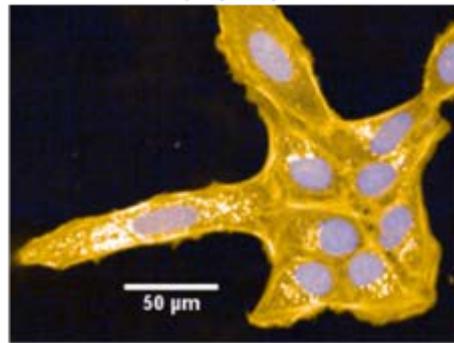
solvent control (0.5% DMSO)



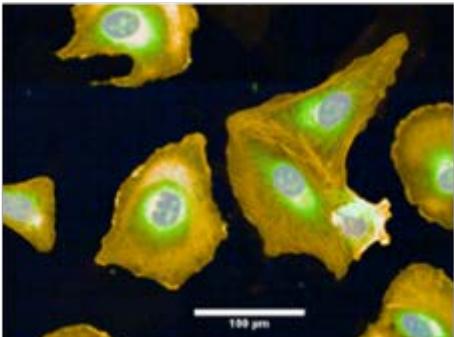
Berberine Chloride (10 μM)



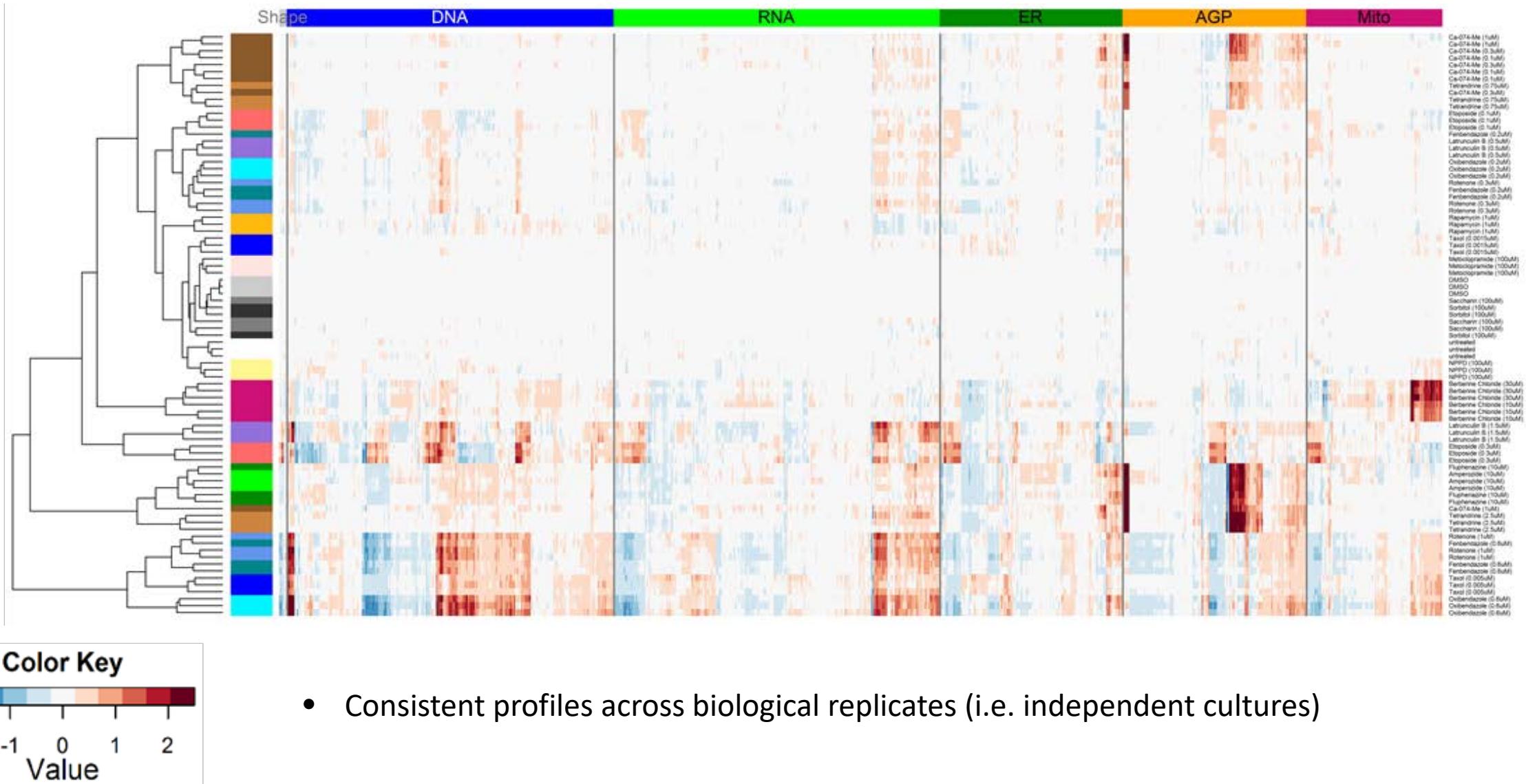
Ca-074-Me (1 μM)



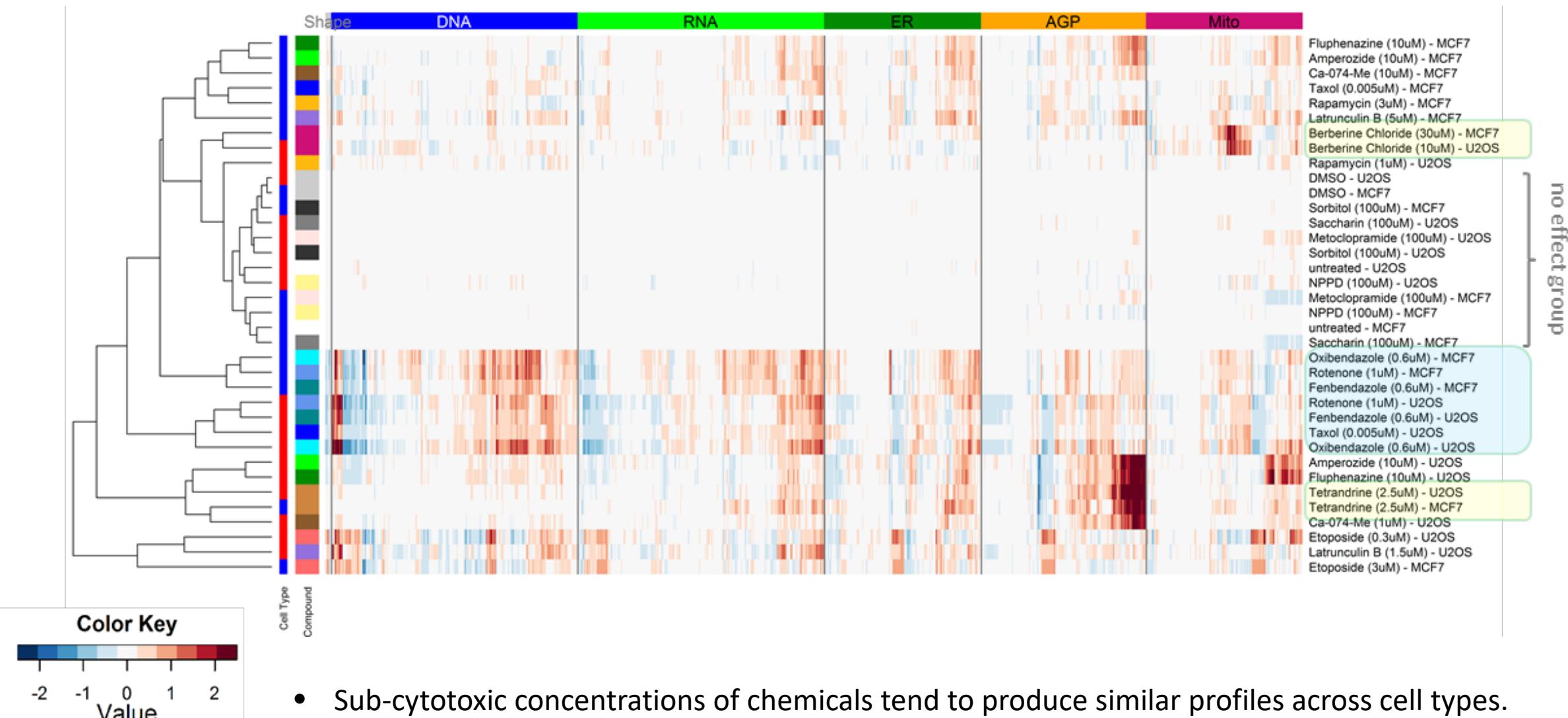
Etoposide (1 μM)



Reproducibility Across Biological Replicates

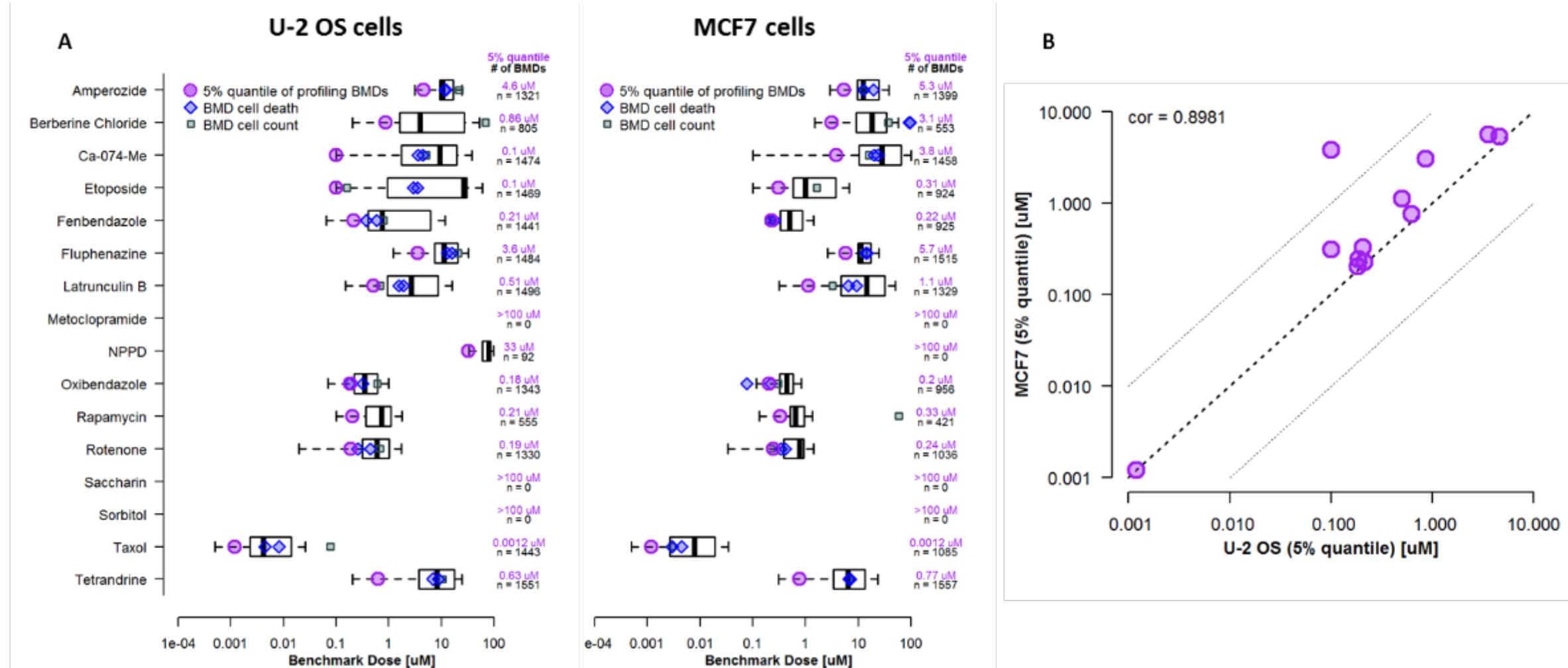


Chemical Profiles Across Two Cell Types



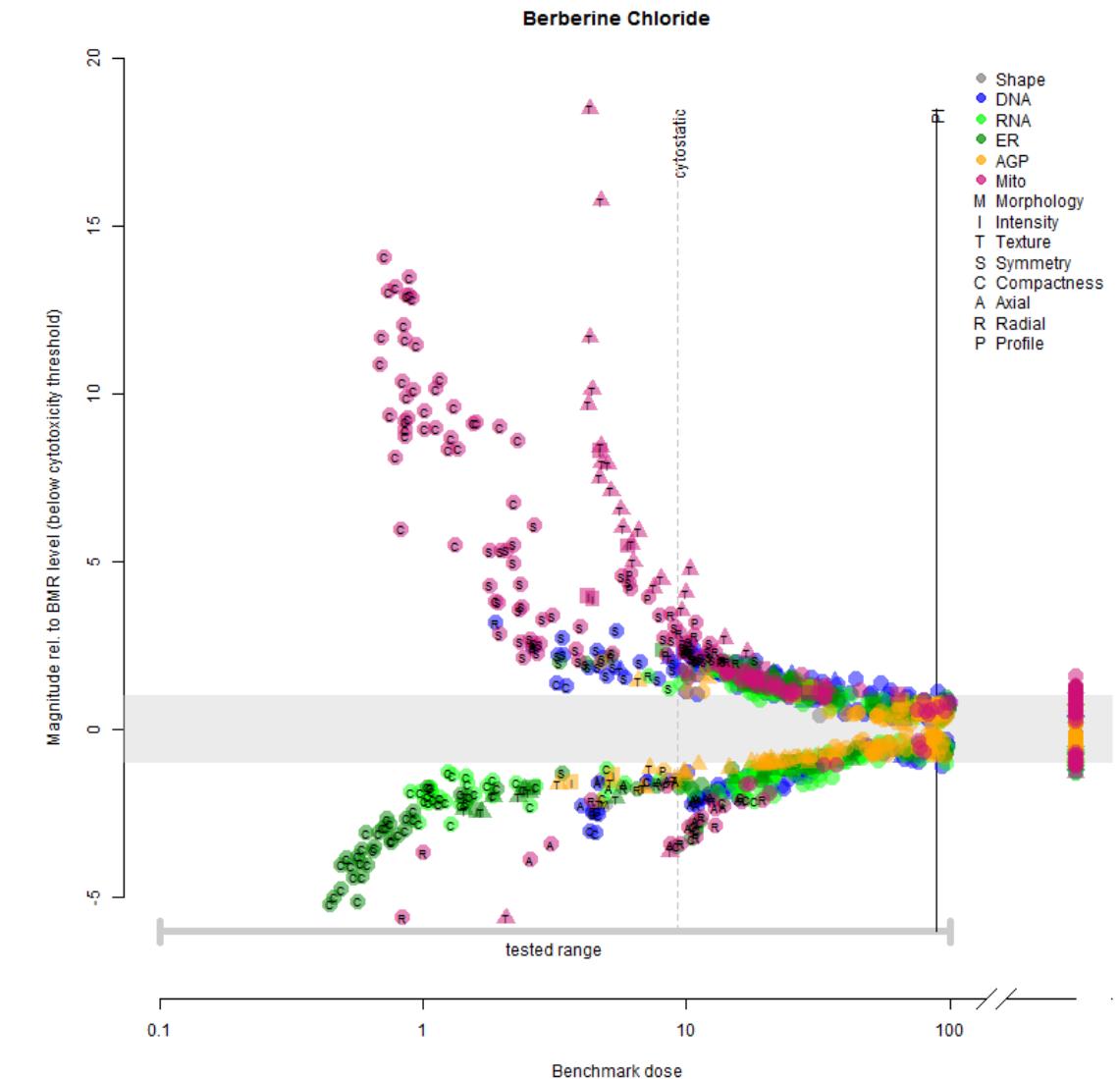
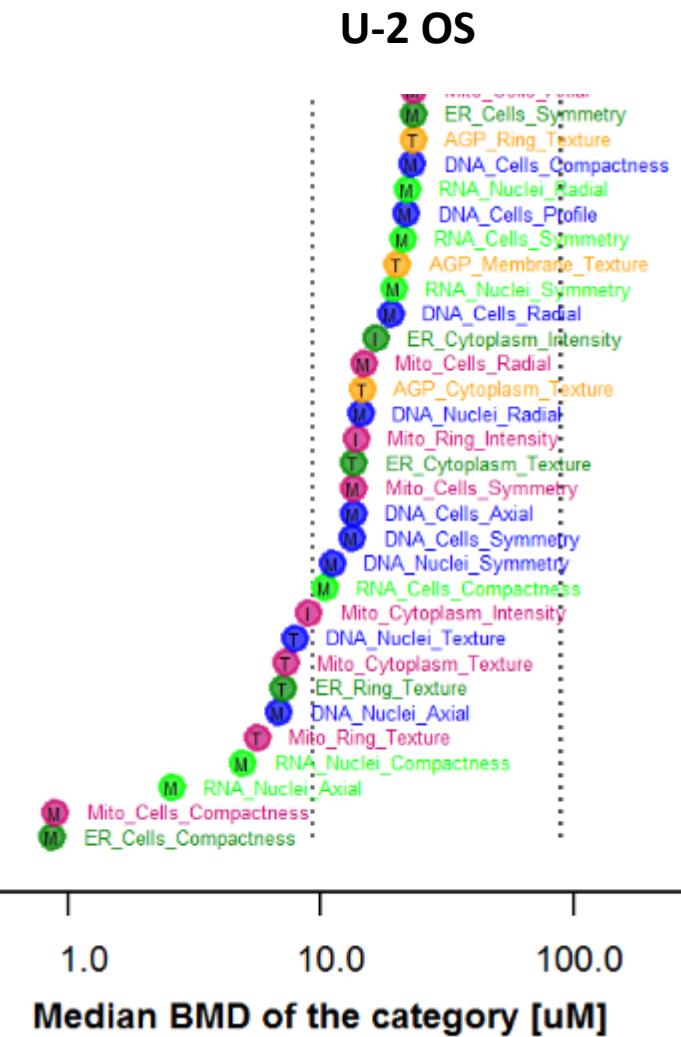
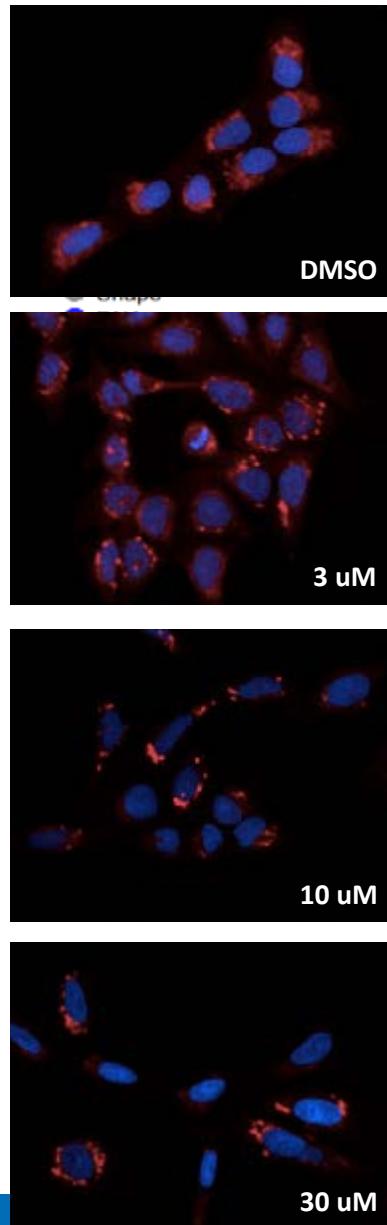
- Sub-cytotoxic concentrations of chemicals tend to produce similar profiles across cell types.

Determination of In Vitro Points of Departure (POD)



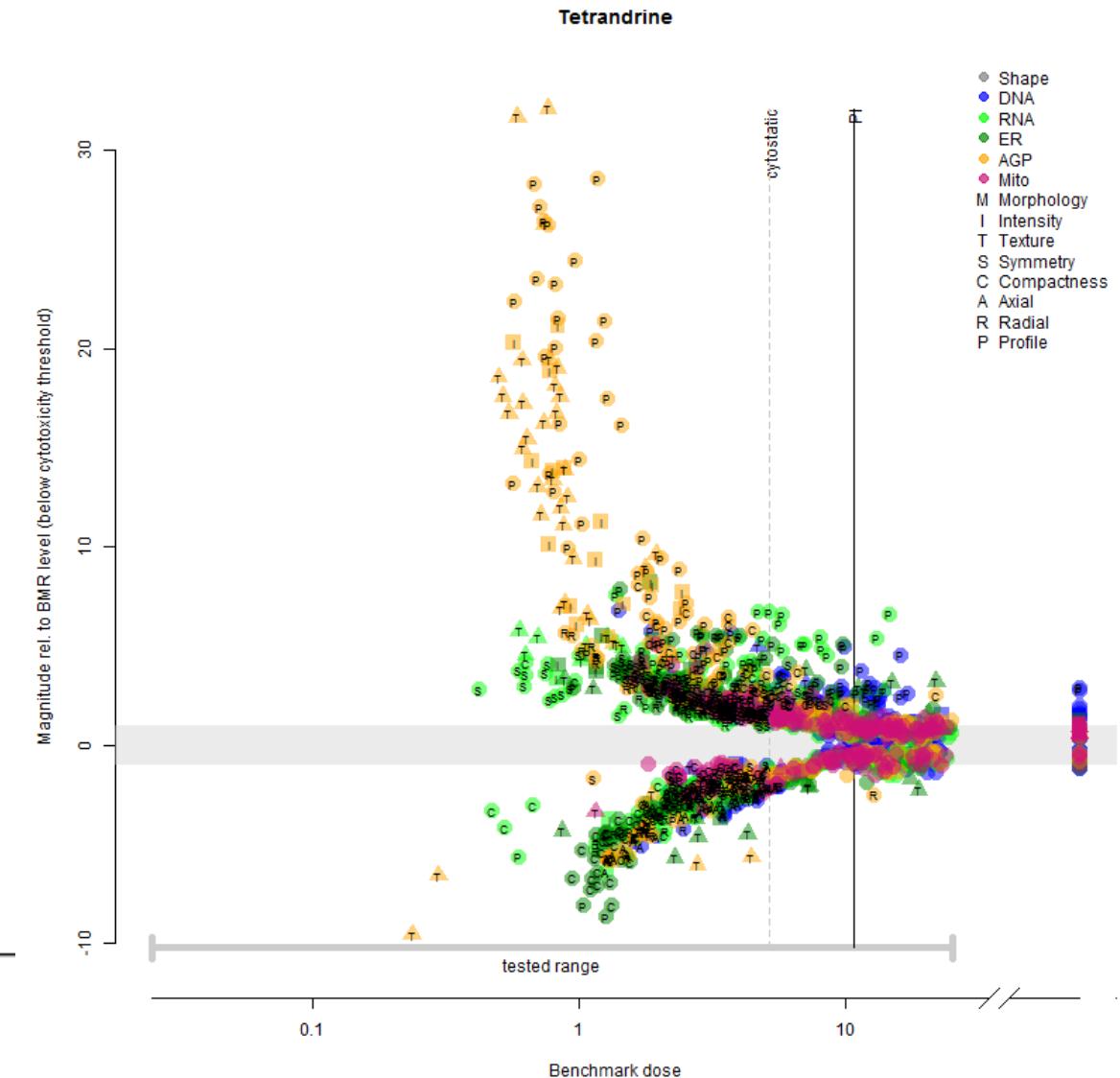
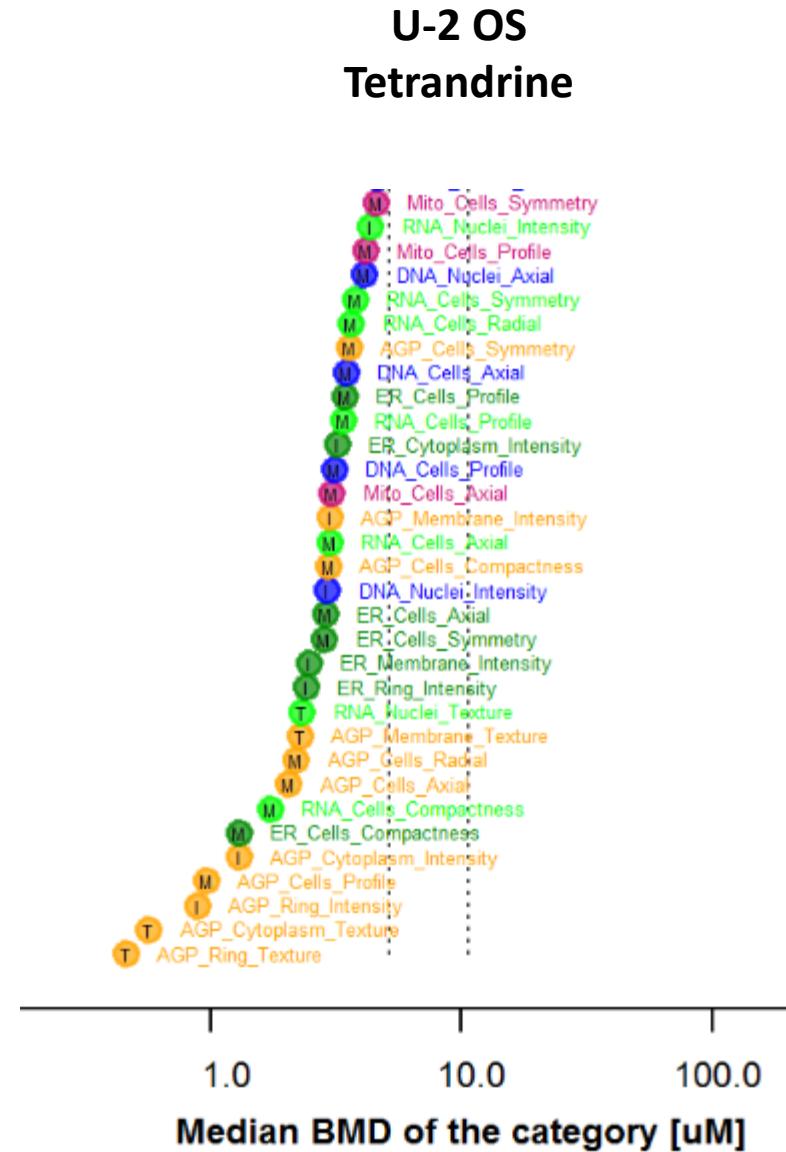
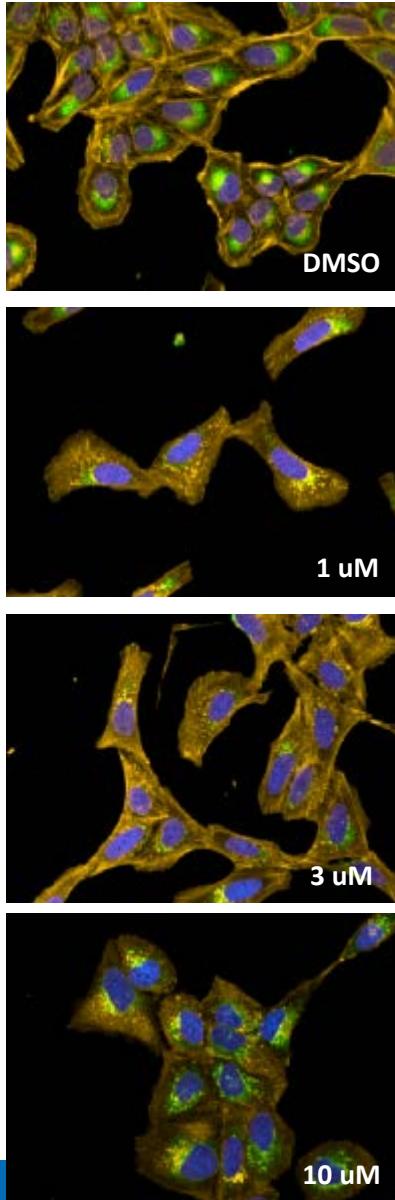
- Thresholds for effects on cell morphology are often below cytotoxicity thresholds, with separation of ≥ 1 order of magnitude in many cases.
- Potency estimates are largely consistent across cell types, with some exceptions.

Phenotype Ontogeny Analysis



- Phenotype ontology analysis illustrates differences in chemical response profiles.

Phenotype Ontogeny Analysis



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Pete Shepard
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Jason Downing

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Andy White
Sophie Malcomber
Richard Stark*

National Toxicology Program:

Scott Auerbach

Sciome:

Jason Phillips



National Center for Computational Toxicology

