A fluorescence microscopy image showing a dense network of cells. The cells are stained with green, red, and blue dyes. The green staining highlights the cell nuclei, while the red staining highlights the cell membranes or cytoplasm. The blue staining highlights the extracellular matrix or fibrotic matrix deposition. The overall image has a dark background with bright, colorful cell structures.

Imaged-Based High Content Phenotypic Screening

THERACAT Consortium

7th February 2020

John Dawson

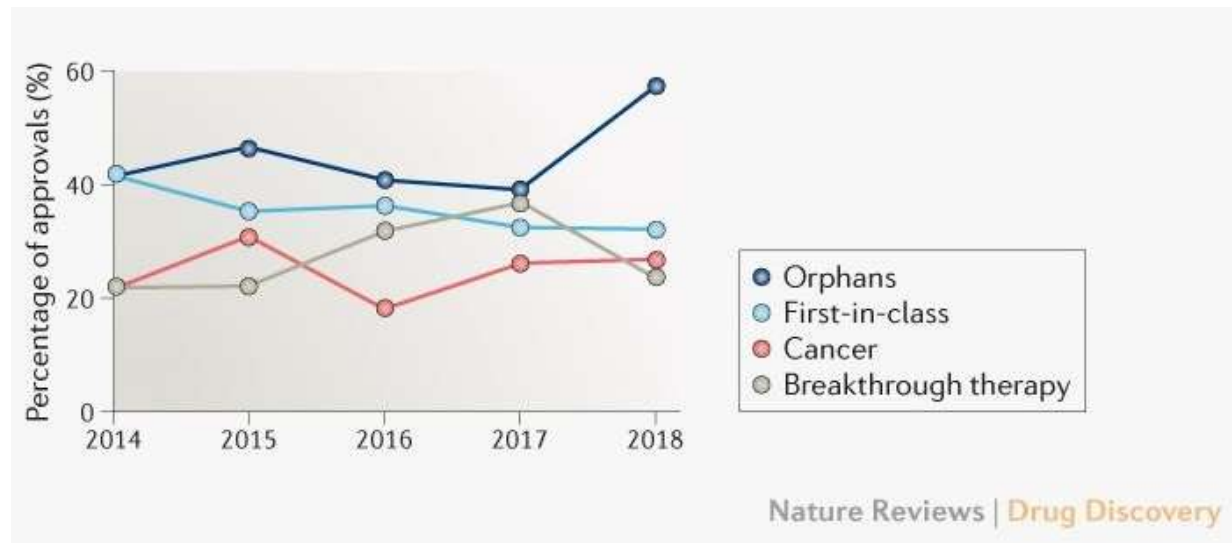
Lead Scientist, Phenotypic Screening, Edinburgh Cancer Discovery Unit

Fibrotic matrix deposition



Overview

1. Drug discovery challenges and why we use phenotypic assays
2. Imaging technologies advancing high-content analysis (HCA) and developments in model assays
3. Examples of phenotypic HCA assays.

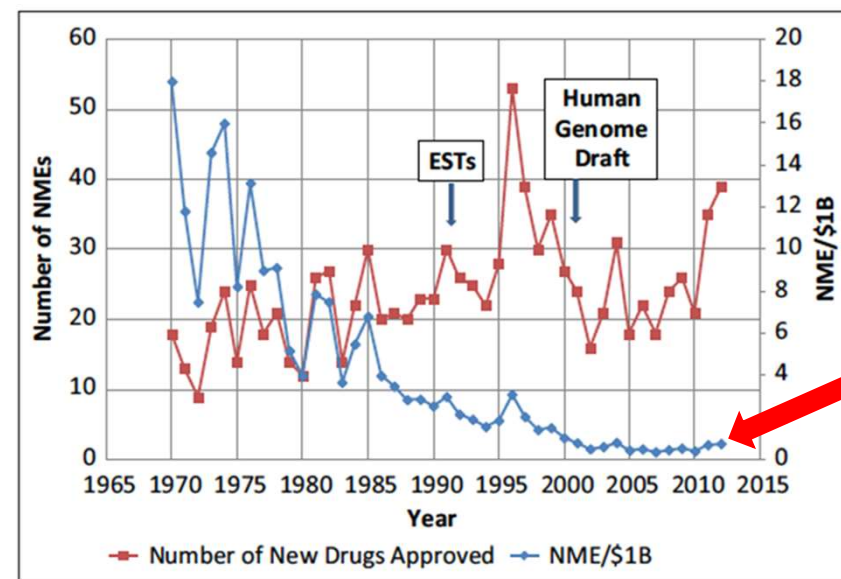
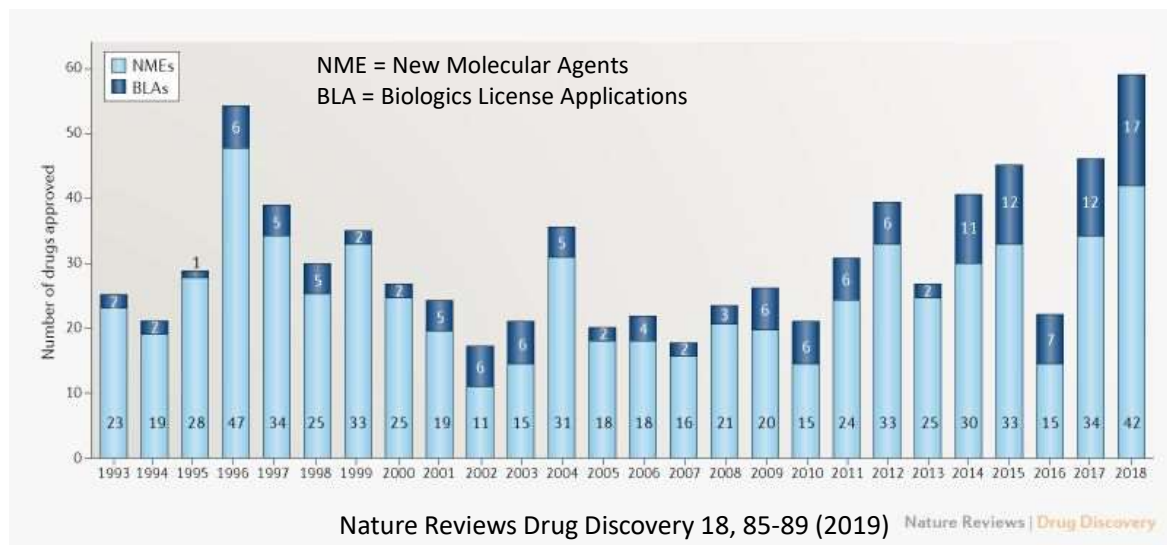


Nature Reviews Drug Discovery 18, 85-89 (2019)

The rising cost of drug discovery

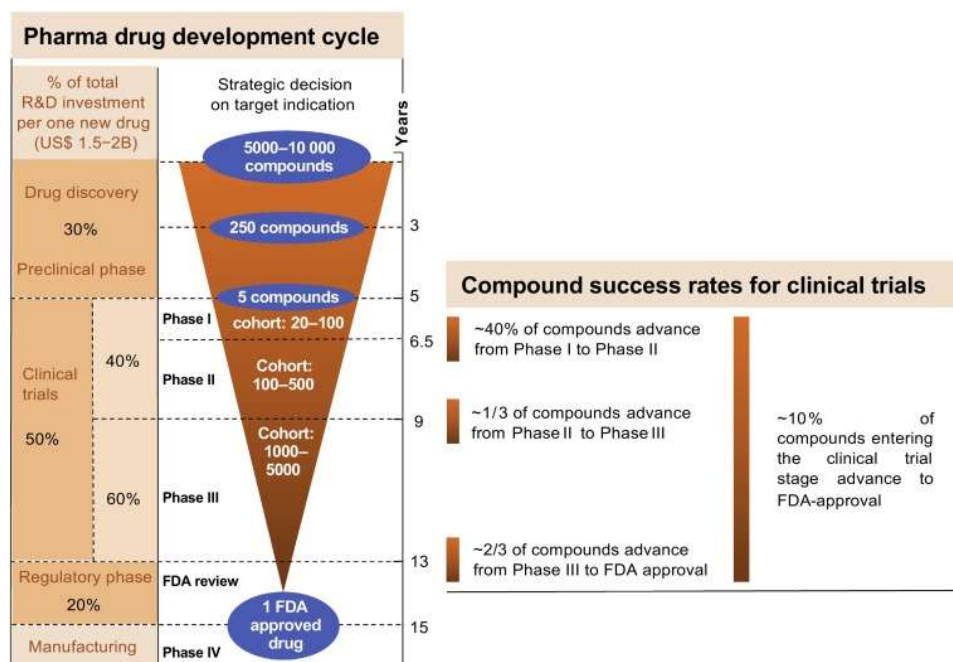
In 2016 a study calculated that it costs \$2.558 billion to produce a new drug (*Journal of Health Economics* Volume 47, May 2016, Pages 20-33)

In 2018 a retrospective study of clinical trials between 2000-2015 of 21,143 compounds revealed that the highest three success rates were 32.6% for clinical studies of ophthalmology drug candidates, 25.5% for cardiovascular drug candidates, and 25.2% for infectious disease products. The lowest percentage came from oncology trials, at just 3.4%. (*Biostatistics*, Volume 20, Issue 2, April 2019, Pages 273-286)



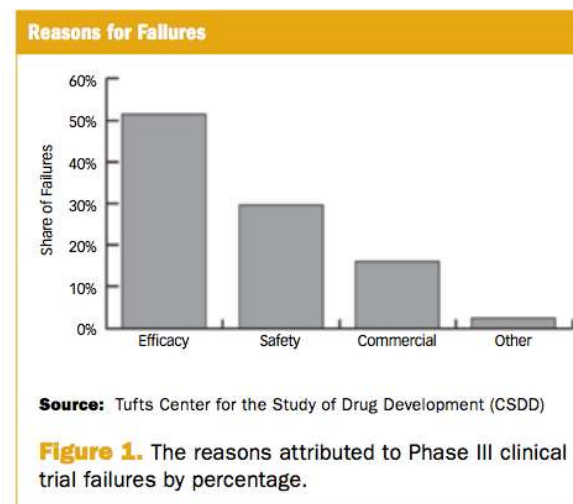
Adapted from: *J Biomol Screen.* 2013 18(10) 1143-1155

Reasons for clinical trial failure



Trends in Pharmacological Sciences

Volume 40, ISSUE 8, P577-591, August 01, 2019



<http://www.appliedclinicaltrialsonline.com/phase-iii-trial-failures-costly-preventable>



It takes a long time to fail!

DPOM: Target-directed Drug Discovery (TDD): High Throughput Screening in target based drug discovery



It takes a long time to bring a candidate drug to preclinical testing

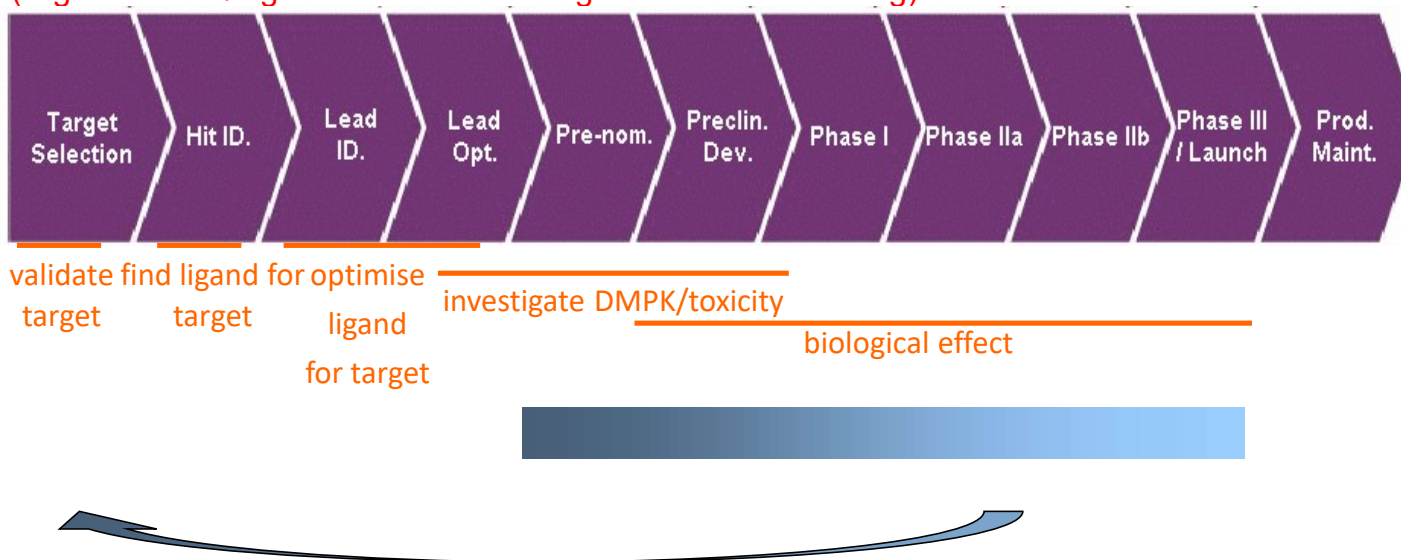
Phenotypic Drug screening: (drug discovery in reverse) -just like the old days!



Problem: Current preclinical models of disease do not fully recapitulate clinical disease and therefore do not predict clinical efficacy.

Standard DPOM: Drug Project Operating Model

(High numbers/high attrition – most drugs fail in clinical testing)



Answer: We need earlier testing of compounds in biologically relevant assays.

This can be achieved by frontloading the biology by screening for candidate compounds using a phenotypic approach.



What is a phenotype?

“a set of observable characteristics of an individual resulting from the interaction of its genotype with the environment.”

Why use phenotypes?

- Target agnostic; in contrast to target-based discovery.
 - *Useful for when diseases are poorly understood (no targets), are very heterogeneous (too many targets!) or targets are hard/complicated to drug.*
- Phenotypic screening has been successfully used for a long time and it can be better at finding “first-in-class” drugs (i.e. novel targets).
- Phenotypic screening is compatible with complicated, disease recapitulating models.
- Phenotypic screening can also work in tandem (and does in some companies) with current models of drug discovery.



Historical Drug Discovery Strategies: *Serendipitous Phenotypic Drug Discovery*

(screening natural or synthetic chemical libraries in physiological based assays)

Animal models



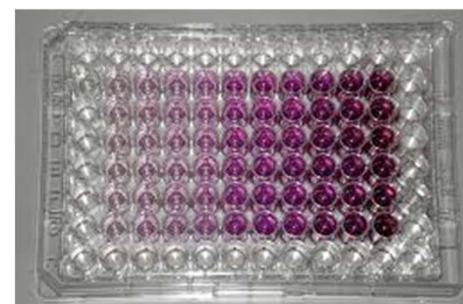
Lianne and Bill Russell - Oak Ridge National Labs

<https://www.ornl.gov/news/mammalian-genetics-pioneer-liane-russell-writes-mouse-house-history>

Eggs



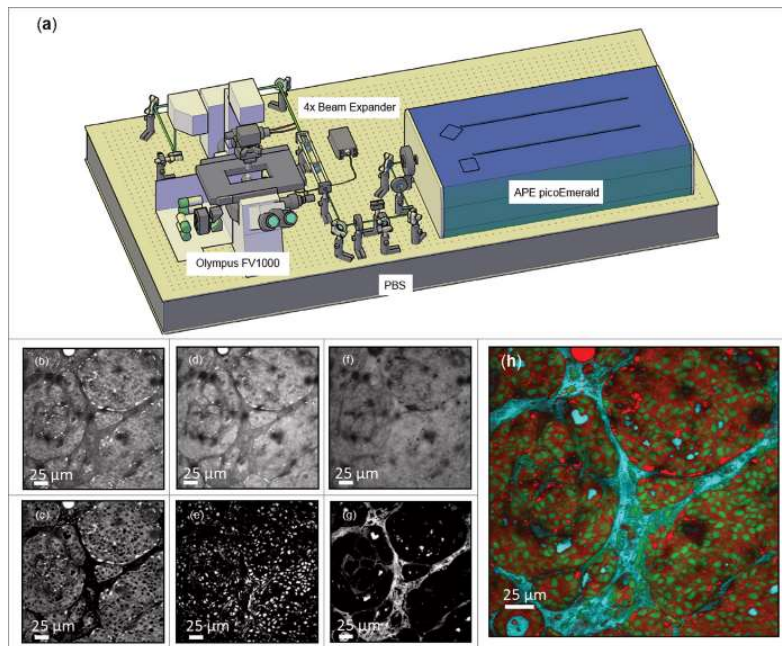
Cell Viability



Why Use Phenotypes? – Biology is complicated



In vivo imaging of squamous cell carcinoma cells (green), collagen (blue) and red blood cells (red).

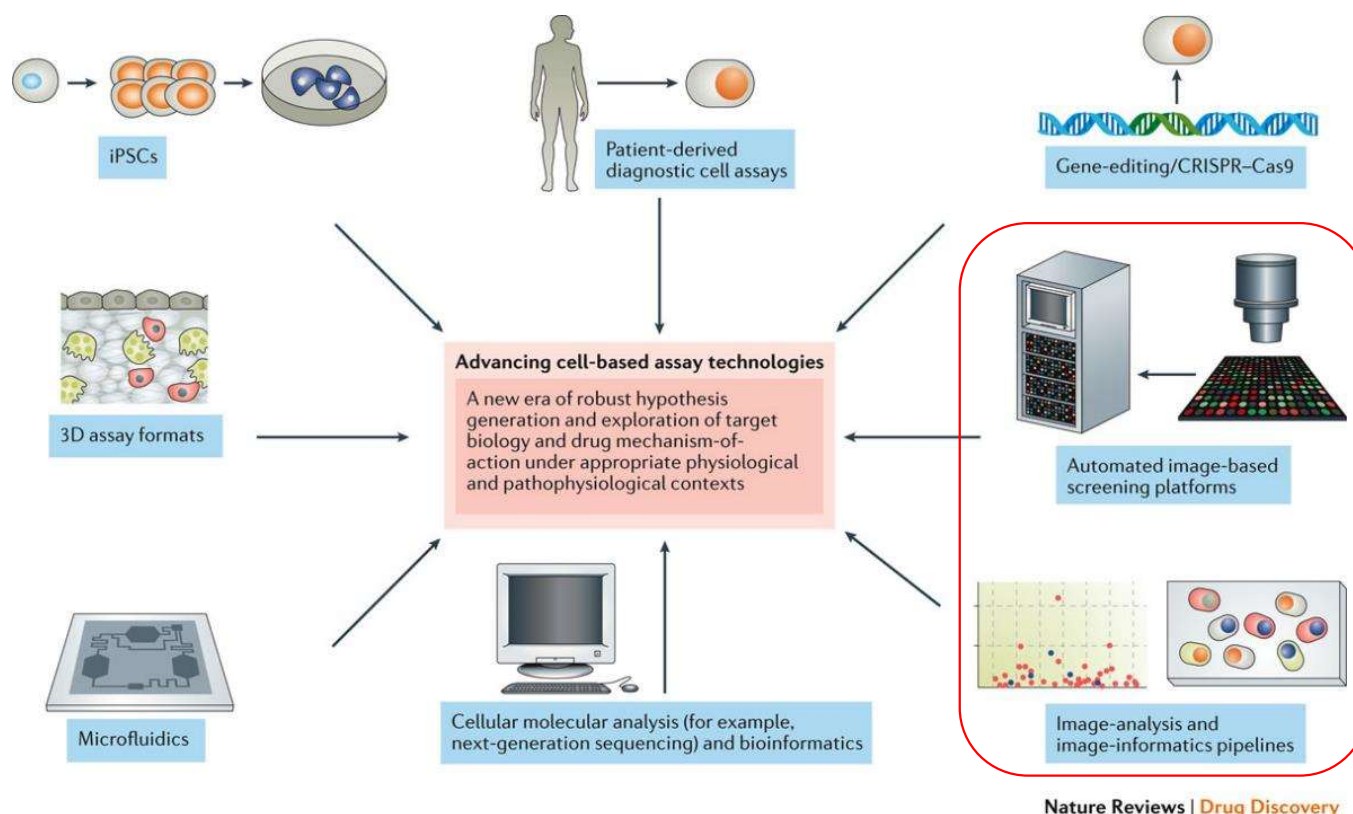


Multimodal imaging of cancer *in vivo*.

Lee et al., IntraVital Volume 4, 2015 - Issue 1

Are our disease models good enough?

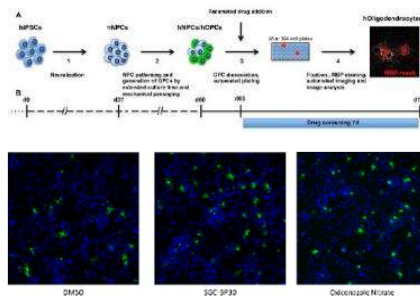
- Recent advances in patient-derived primary cell models



Why Use Phenotypes? – Biology is complicated

Neurological

Screening for compounds promoting Oligodendrocyte differentiation using hiPSC cultures

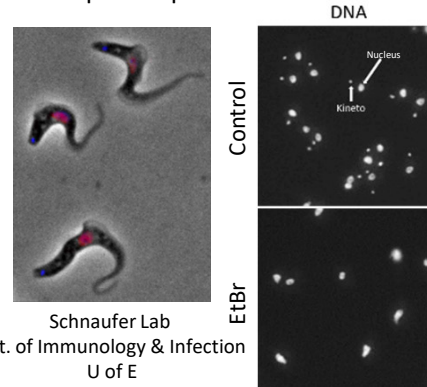


Dario Magnani/ Siddharthan Chandran
MRC Centre for Regen. Med. U of E

Outputs: O4⁺/MBP⁺ OLs, OL morphology

Infectious Disease

Inhibiting *Trypanosoma brucei* kinetoplast replication

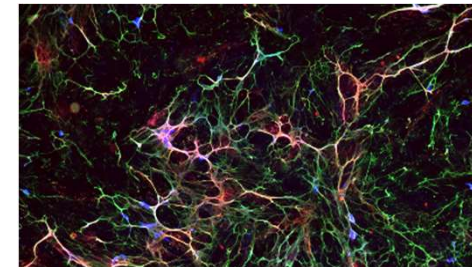


Schnauffer Lab
Inst. of Immunology & Infection
U of E

Outputs: Tryp viability, cell cycle stage and kinetoplast number

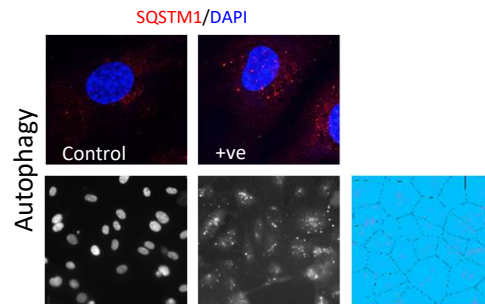
Respiratory

Fibrosis ECM deposition assay
(Collaboration with UCB Pharma)



Outputs: cell viability, fibronectin, collagen I, III and IV

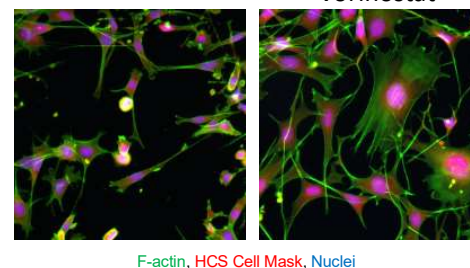
Cellular Processes



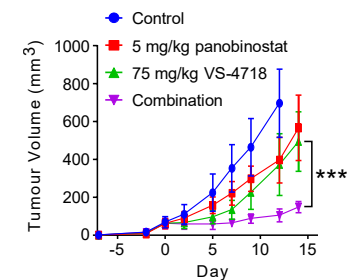
Andrea Martello Centre for Cardiovascular Science U of E

Outputs: Cell counts, autophagy puncta and localisation

Oncology

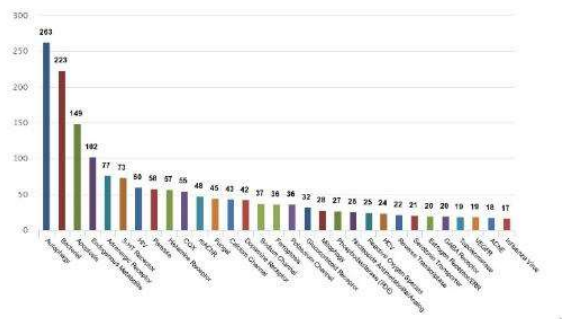
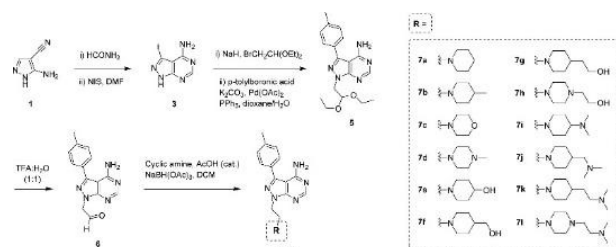


Outputs: Cell number, cell cycle and morphology



Edinburgh Cancer Discovery Unit Collaborations

What can be screened?

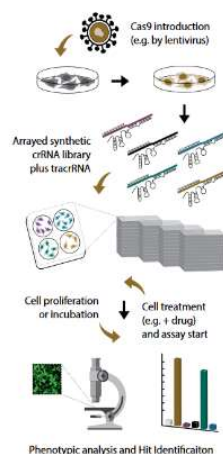


Small targeted chemical libraries (10s of compounds)

- Target can be known but not required for phenotypic screening.
- Can use very complicated phenotypes requiring difficult biological conditions
- Low throughput
- Very focused chemistry

Annotated compound libraries (10-1000s)

For example established compounds for repurposing or focused chemical probes sets



Genetic screens; CRISPR or RNAi (up to whole genome screens)

- No chemistry!
- Can search for novel targets
- Knockouts or knockdowns of genes is not equivalent to chemical inhibition.
- Can be difficult to introduce vectors into cells.

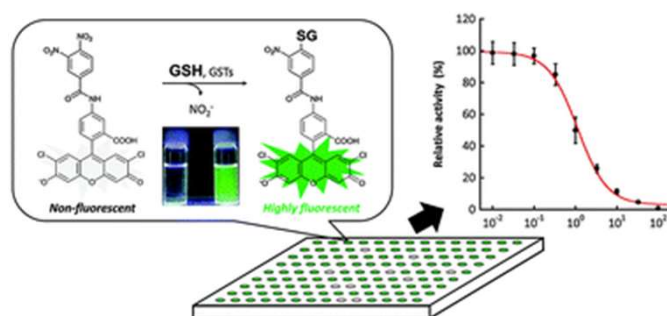
Large diverse chemical libraries (1000s, 10k+ compounds)

- Target can be known but not required for phenotypic screening.
- Harder to use very complicated biological conditions
- High-throughput
- Diverse chemistry

What do we mean by high-content phenotypic screening?

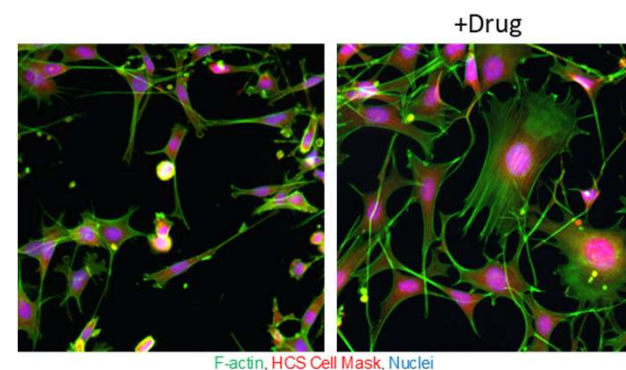
High-throughput screening

- Designed to assay thousands-millions of compounds rapidly in a (simple) **single** endpoint assay, e.g. inhibition of a target enzyme.



High-content screening

- Captures **multiple features** (high-content) per sample to quantify phenotypes.



Advances in technology enables - Edinburgh Phenomics Drug Discovery Capabilities



Edinburgh Cancer Discovery Unit

RPPA, Cytokine Arrays and NanoString
(antibody-based protein array and gene expression analysis)

RPPA and
Cytokine
arrays



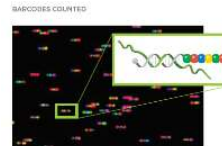
BioMek FX/NX



Nanoplotter 2.1E



nCounter Analysis System



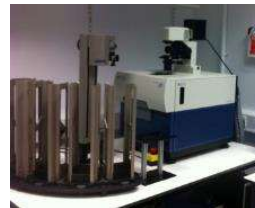
High-content Image Acquisition and Analysis



ImageXpress confocal



IncucyteZoom



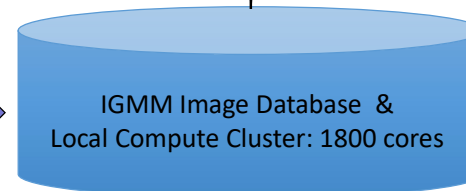
ImageXpress-XL -PAA



IncucyteZoom

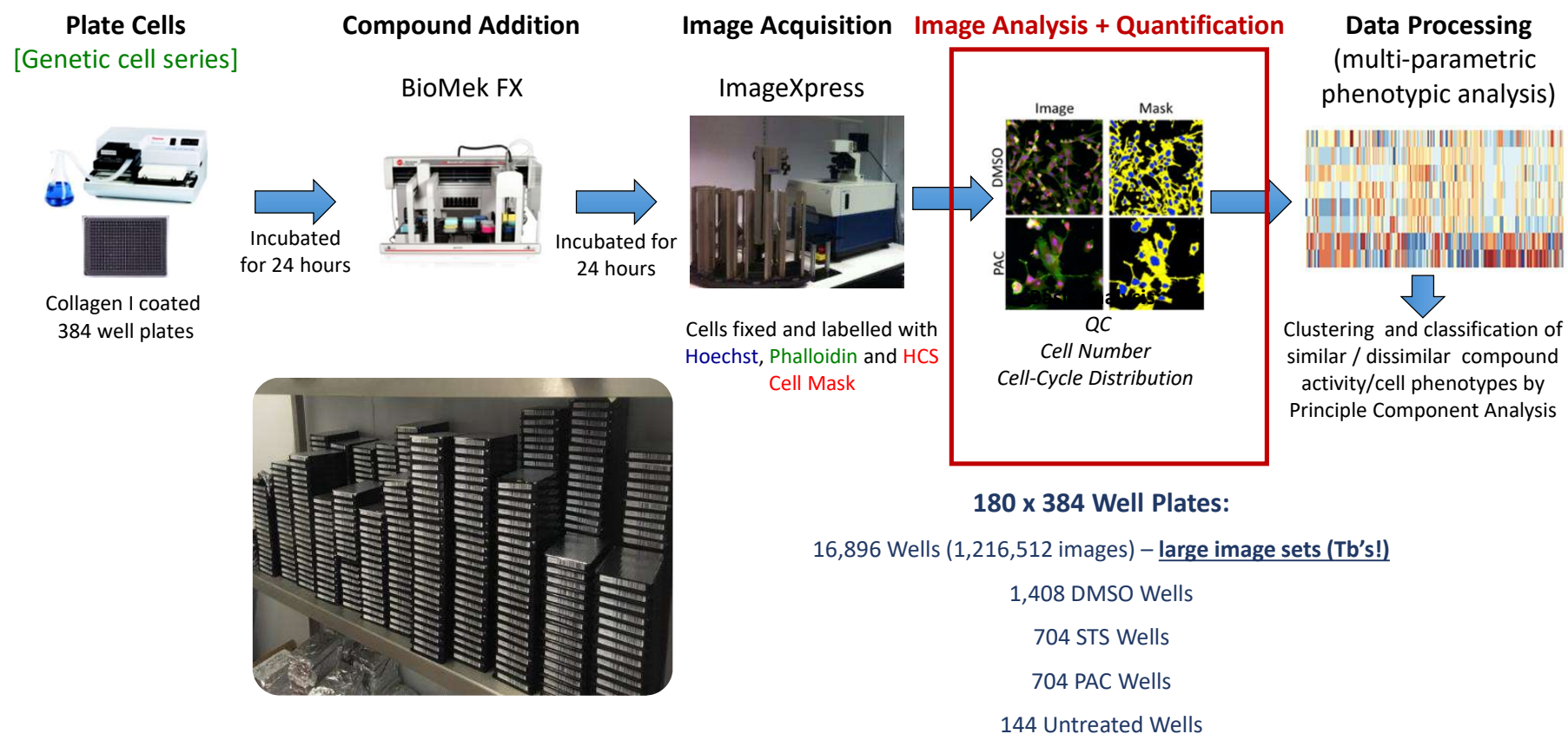


ImageXpress confocal



(12k)120,000
FDA (1,280)
Annotated (>200)
Sub-libraries
(kinase/protease/Epig
enetic/industry)

High-Content Screening Workflow





Quality Control

Cell QC

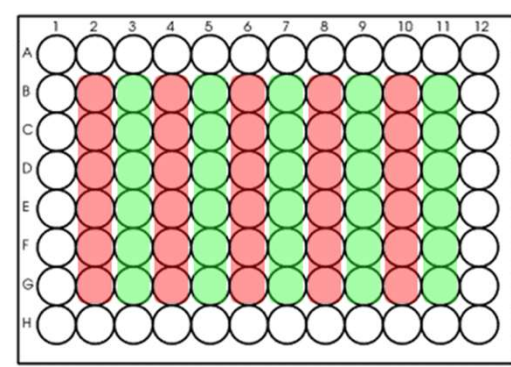
- Healthy cells free of mycoplasma
- Cells need to look and be growing normally
- Try to screen within a set number of passages

Image QC

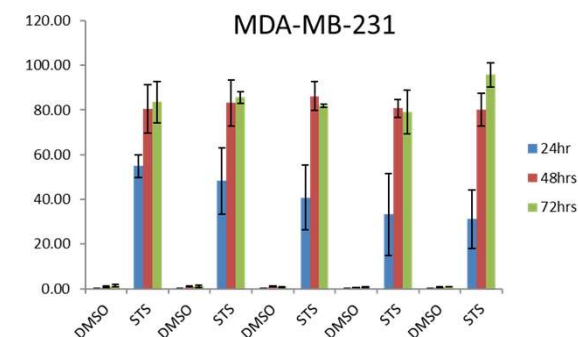
- Identify any images that are out of focus or contain debris
- During acquisition correct for uneven illumination (can be done on the images as well)

Assay QC

Assay robustness is measured with positive and negative controls.



■ DMSO (Negative)
 ■ STS (Positive)



Z-Factor	24Hrs	48Hrs	72Hrs
MDA-MB-231	0.14	0.72	0.694253
HCC1569	-0.57	0.35	0.774934

Note that if $\sigma_p = \sigma_n$, 0.5 is equivalent to a separation of 12 standard deviations between μ_p and μ_n

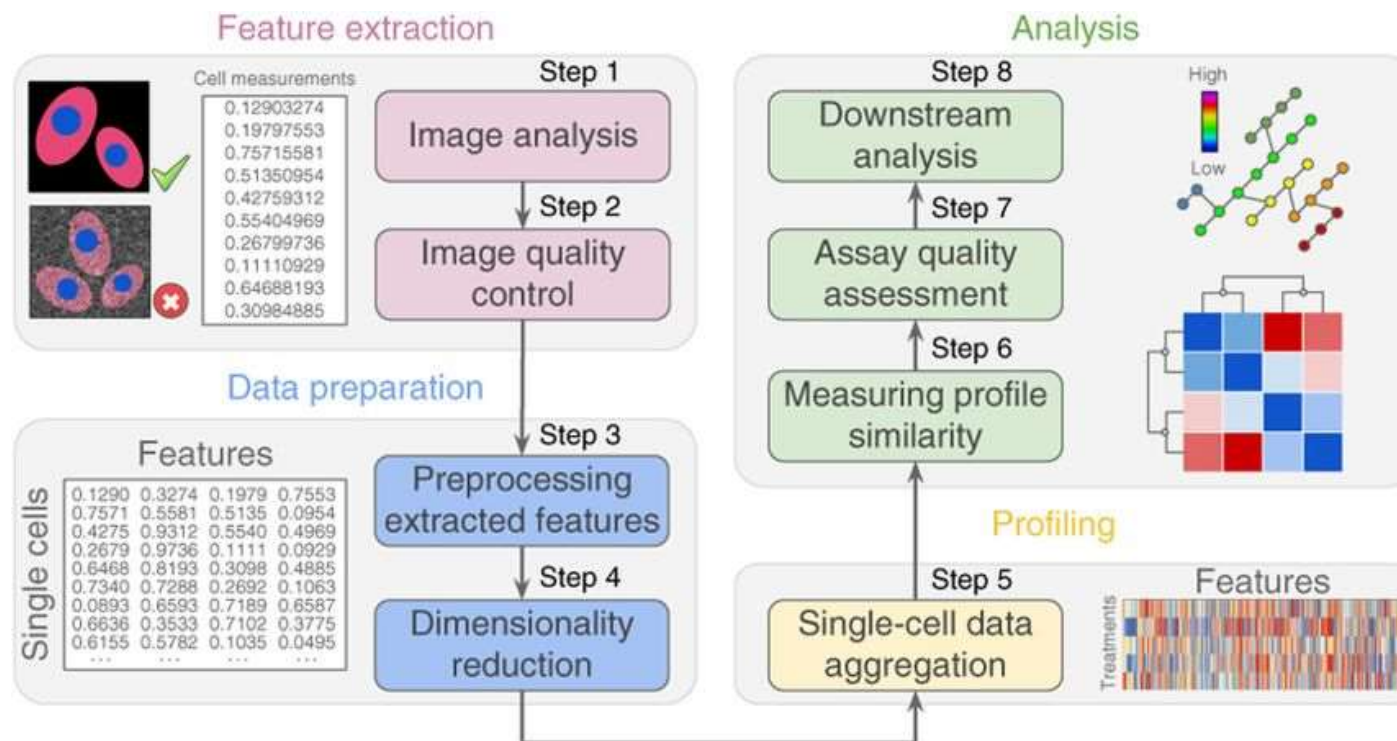
Z'-factor

1.0
 between 0.5 and 1.0
 between 0 and 0.5
 less than 0

Interpretation

Ideal. Z-factors can never exceed 1.
 An excellent assay.
 A marginal assay.
 There is too much overlap between the positive and negative controls for the assay to be useful.

Typical Analysis Work Flow – Data Analysis

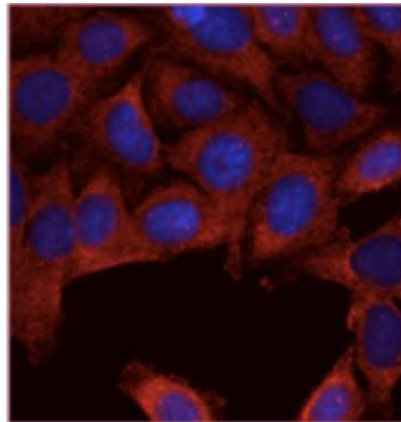


Nature Methods volume 14, pages 849–863 (2017)

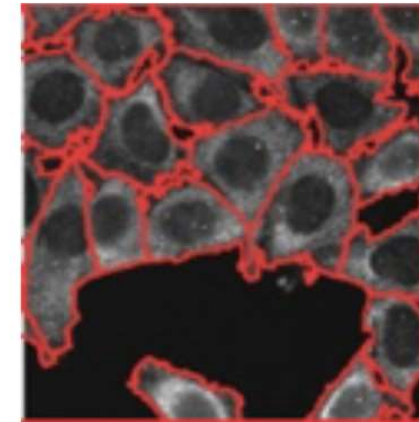
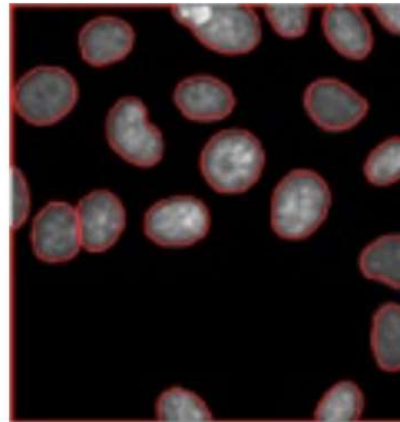
Describing the Phenotype – Image Analysis



Original image:



Processed images:

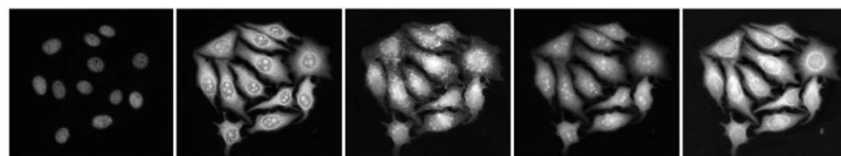
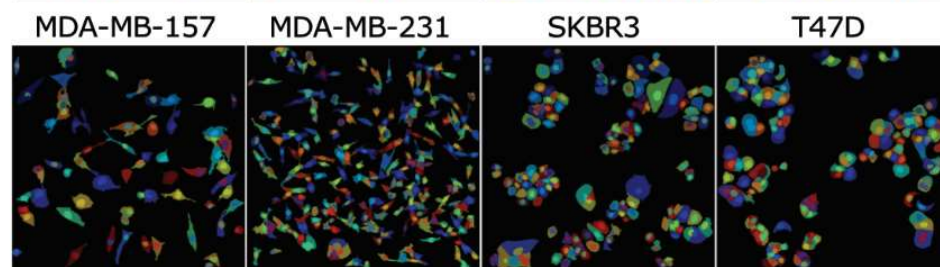
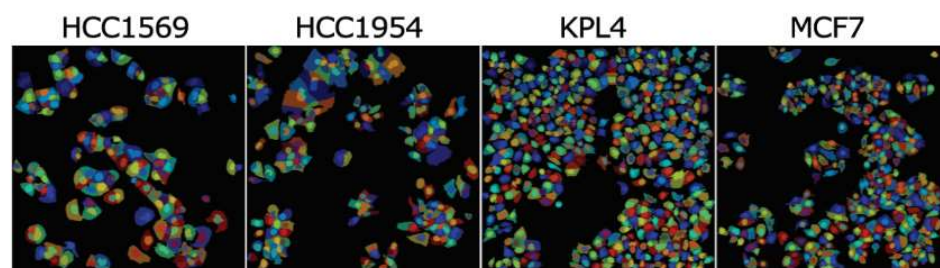


https://clue.io/connectopedia/cell_painting_features



Describing the Phenotype – Image Analysis

CellPainting - Unbiased phenotypic profiling



Hoechst

Nuclei

SYTO 14

Nucleoli

Wheat germ agglutinin + Phalloidin

Golgi, plasma membrane, actin

Concanavalin A

Endoplasmic reticulum + Nucleoli

MitoTracker

Mitochondria

Analysis:
CellProfiler
14,000 small molecules



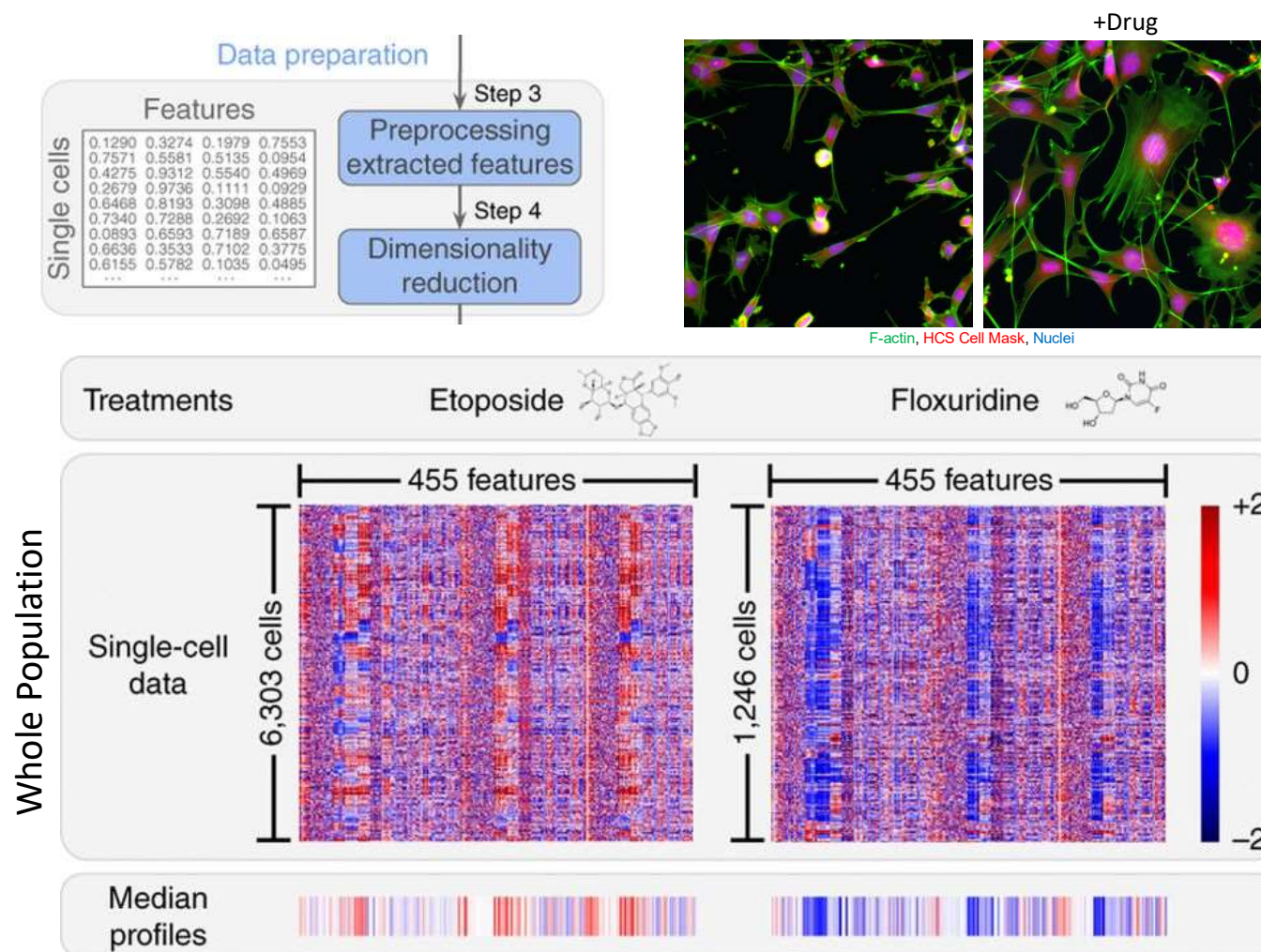
Multiparametric phenotypic profiling

Channel	n
DNA	355
AGP	387
ER	387
Mito	387
RNA	387

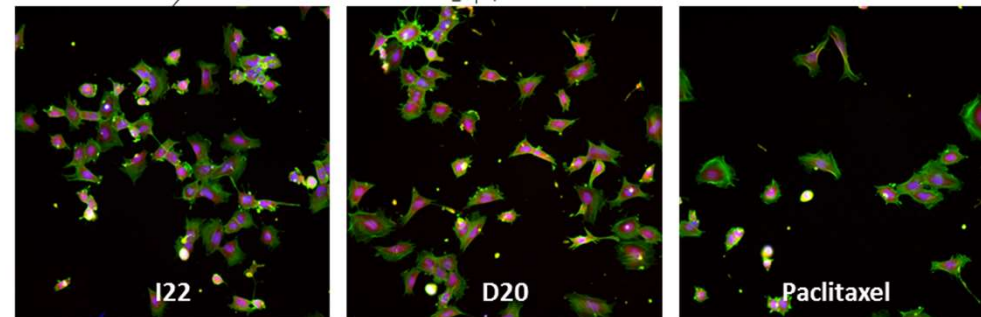
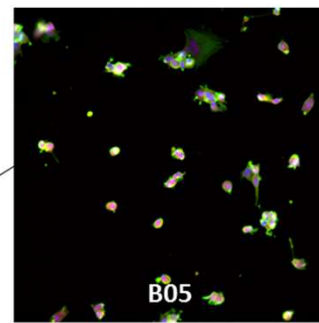
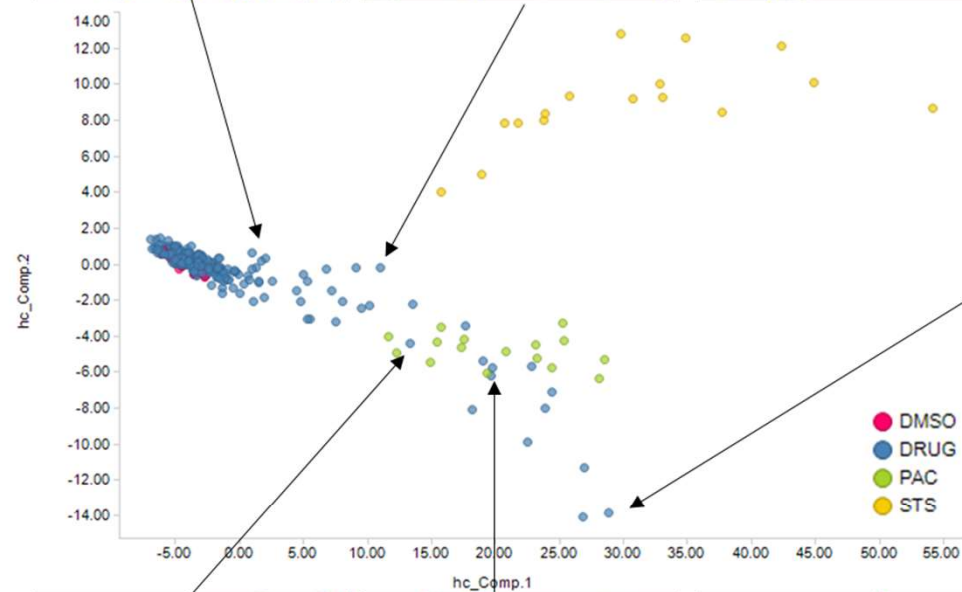
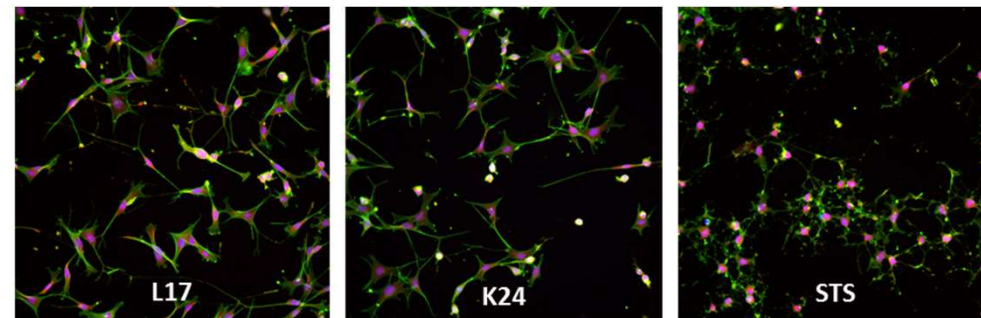
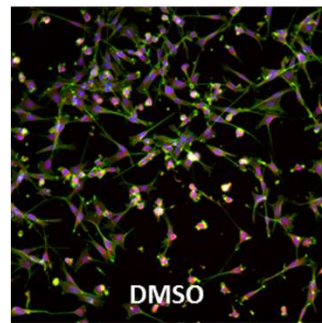
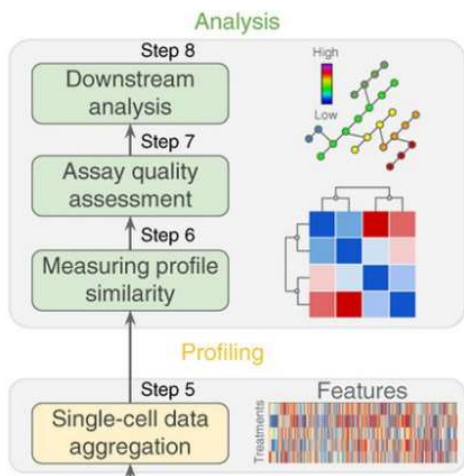
Compartment	n
Cells	596
Cytoplasm	582
Nuclei	605

FeatureGroup	n
AreaShape	144
Correlation	300
Granularity	208
Intensity	225
Location	66
Neighbors	21
RadialDistribution	180
Texture	630

Describing the Phenotype – Data Processing



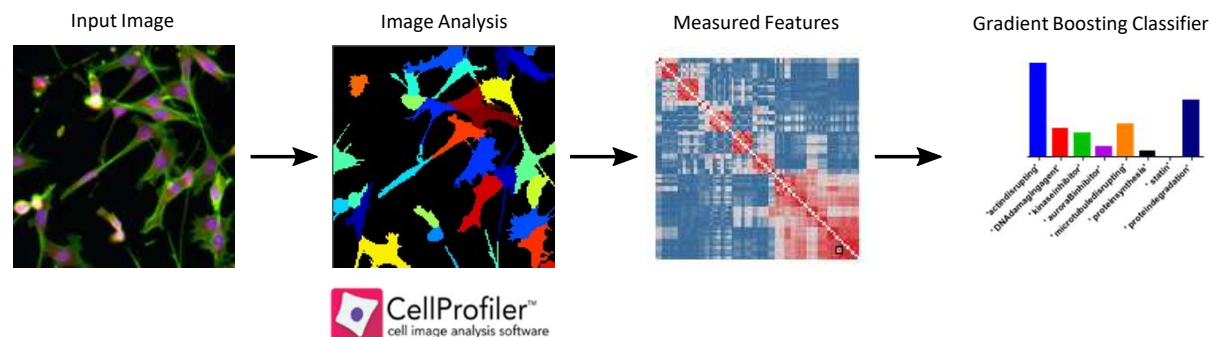
Describing the Phenotype – Data Profiling and Analysis



Describing the Phenotype – Data Analysis

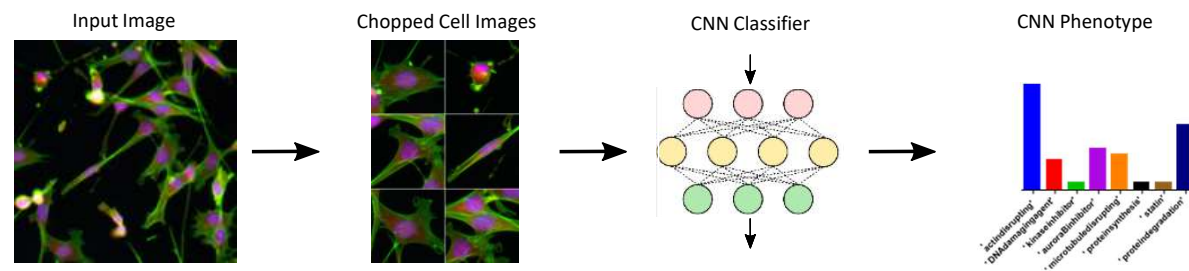
i Image analysis algorithm segmentation and feature extraction; ensemble based tree classifier

User defined set of features to describe a phenotype.



ii AI: Deep learning on raw image (300x 300 pixels) data; convolution neural network classifier (cNN)

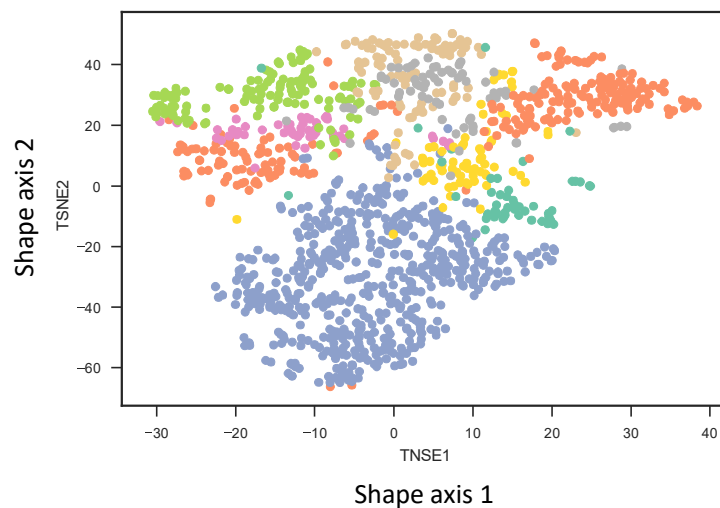
AI learns features that describe phenotype.



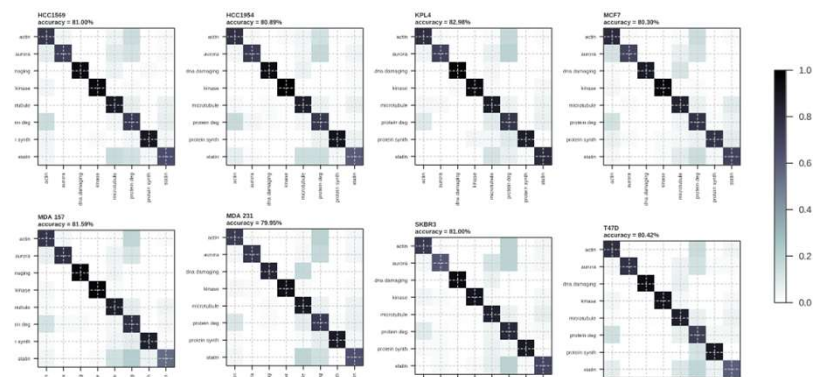
Describing the Phenotype – Data Analysis



Compound Clustering

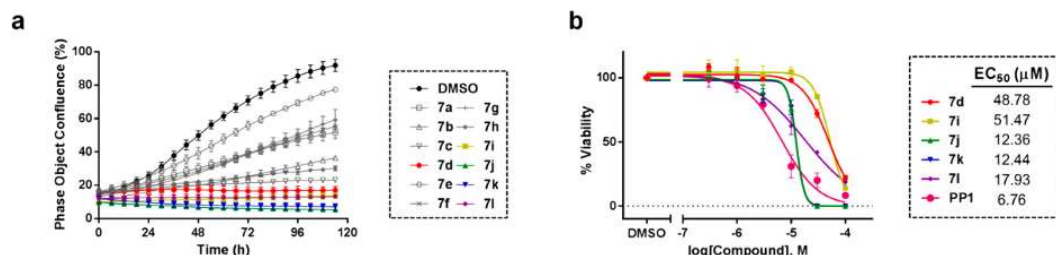
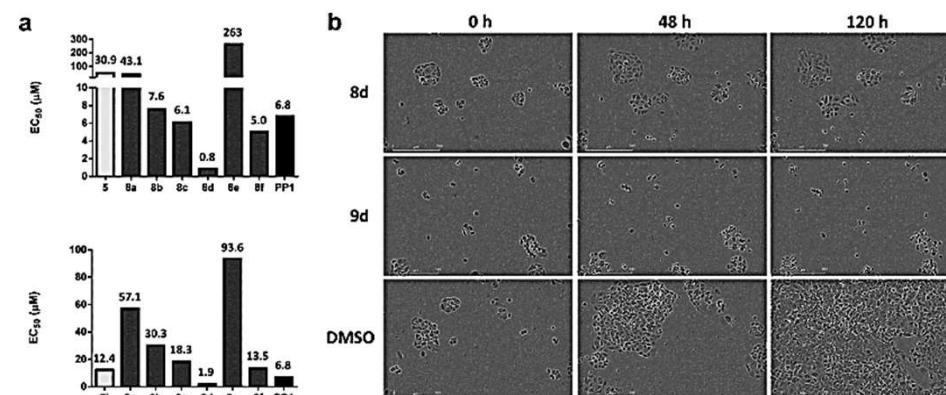
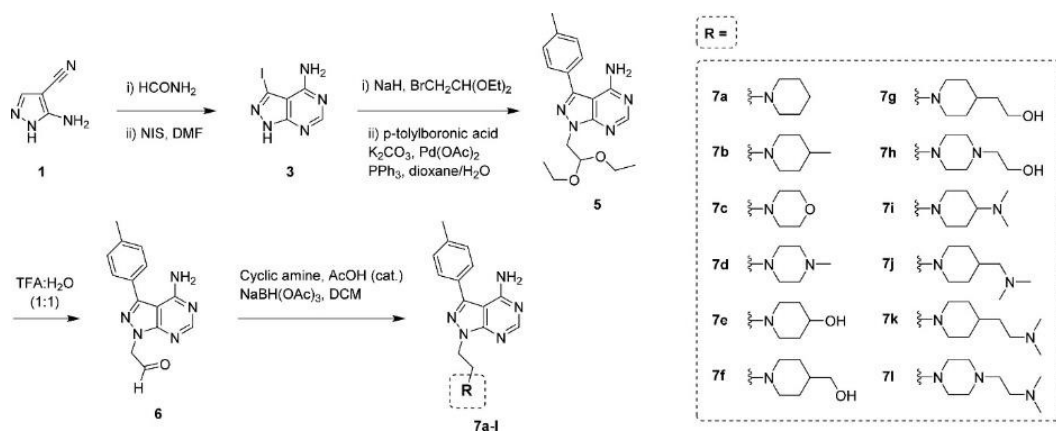


Compound MOA Prediction



Take novel compounds and compare their fingerprints to those of known drugs

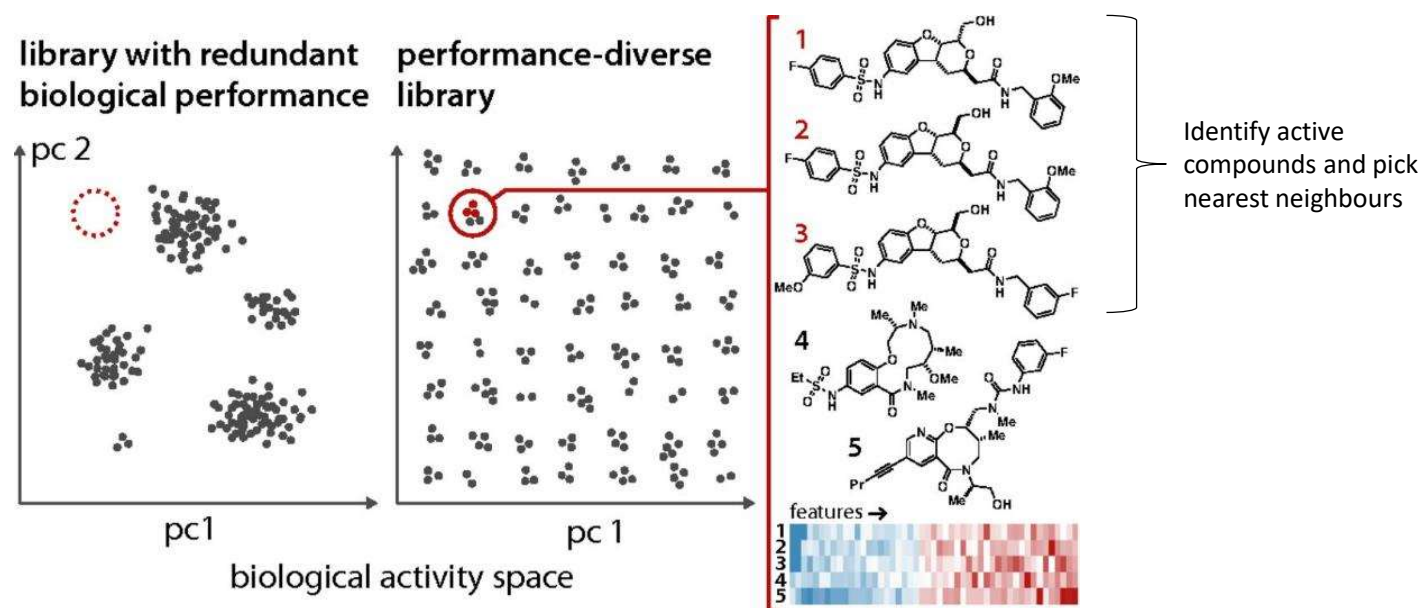
1. Screening of small targeted-compound libraries – Src kinase inhibitors in breast cancer



Simple phenotypic readouts to progress active compounds

- Kinetic growth (confluence)
- Cell Viability

1. Using chemical diversity libraries to identify novel inhibitor starting points.

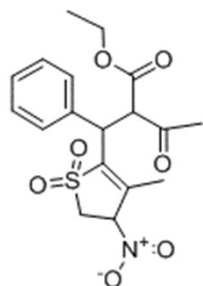
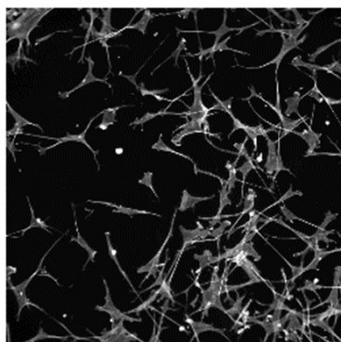
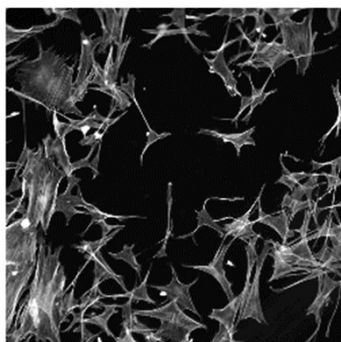


PNAS July 29, 2014 111 (30) 10911-10916

Chemical diversity libraries covers a wider range of chemistry and, potentially, more biology

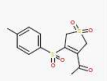
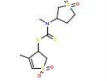



1. Chemical diversity library screening: Chemi-informatics



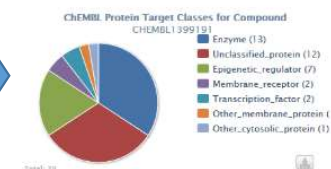
Structure
similarity
search on
ChEMBL



Compound	Synonyms	Similarity	Max Phase	Parent Mol Weight
 CHEMBL1399191		73.9	0	314.38
 CHEMBL1701193		73.77	0	355.52
		72.43	0	510.52



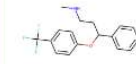
Compound Target Summary

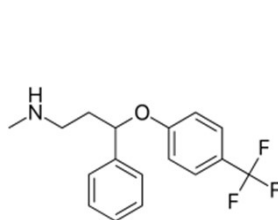


Published Screening Data

Compound	Target	Assay	Assay Type	Assay ID	Assay Name
CHEMBL1399191	ACE	IC50	Enzyme	1	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	2	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	3	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	4	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	5	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	6	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	7	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	8	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	9	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	10	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	11	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	12	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	13	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	14	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	15	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	16	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	17	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	18	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	19	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	20	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	21	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	22	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	23	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	24	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	25	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	26	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	27	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	28	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	29	Angiotensin-converting enzyme (ACE) inhibition
CHEMBL1399191	ACE	IC50	Enzyme	30	Angiotensin-converting enzyme (ACE) inhibition

Predict targets

Query	Target Key	Target Name	Description	P-Value	MaxTC
 fluoxetine	QK3886_RAT	SLC6A4	Transporter	1.844e-25	1.00
	QK0A4_HUMAN	SLC6A4	Sodium-dependent serotonin transporter	2.149e-17	1.00
	QK72C_RAT	HR23C	5-hydroxytryptamine receptor 2C	2.226e-15	1.00
	NK0A4_RAT	SLC6A4	Sodium-dependent serotonin transporter	7.777e-16	1.00
	QK0A2_HUMAN	SLC6A4	Sodium-dependent noradrenaline transporter	9.092e-16	1.00
	SC6A2_MOUSE	SLC6A2	Sodium-dependent noradrenaline transporter	9.215e-15	1.00
	NK0A3_MOUSE	SLC6A3	Sodium-dependent dopamine transporter	1.133e-08	1.00
	CAC1C_HUMAN	CACNA1C	Voltage-dependent L-type calcium channel subunit alpha-1C	3.025e-09	1.00
	CAC1C_RAT	CACNA1C	Voltage-dependent L-type calcium channel subunit alpha-1C	6.132e-06	1.00
	NK0A3_RAT	SLC6A3	Sodium-dependent dopamine transporter	3.288e-05	1.00
	QK0YTR4_RAT	SLC6A2	Transporter	0.0000893	1.00
	HR03_HUMAN	HR23C	Histamine H3 receptor	0.001212	1.00
	CP02B1_HUMAN	CYP2D6	Cytochrome P450 2D6	0.00157	1.00
	KCNH2_HUMAN	KCNH2	Potassium voltage-gated channel subfamily H member 2	0.02309	1.00
	AD0A08_HUMAN	AD0A08	Adenosine deaminase 2	0.05176	1.00



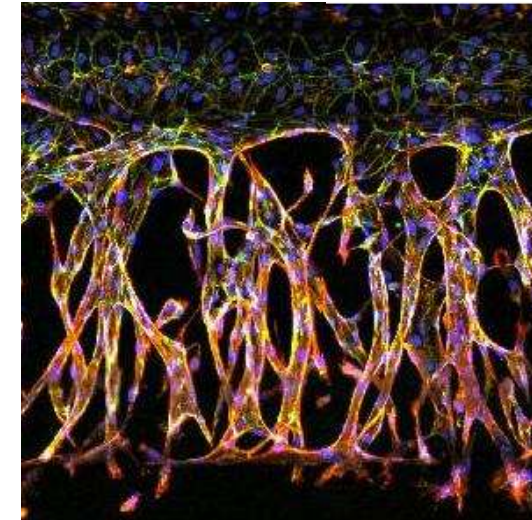
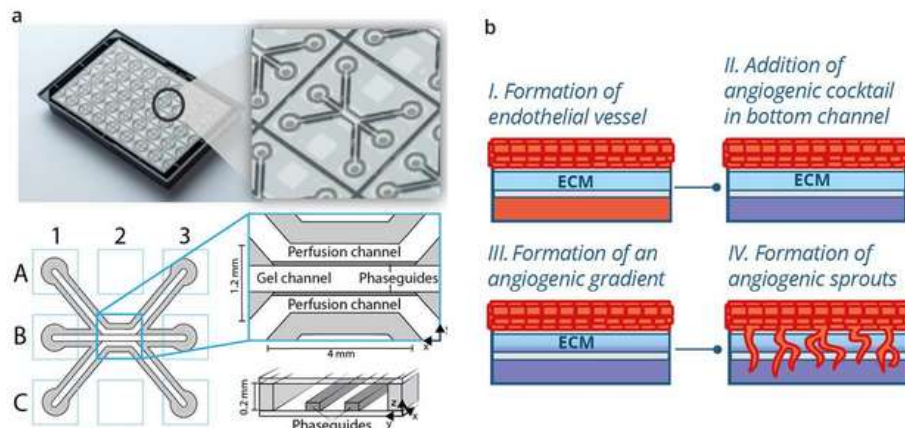
SEA relates proteins based on the set-wise chemical similarity among their ligands. It can be used to rapidly search large compound databases and to build cross-target similarity maps.



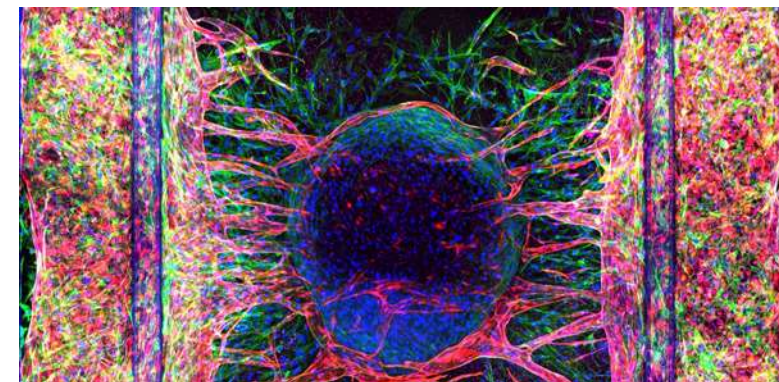
Keiser MJ, Roth BL, Armbruster BN, Ernsberger P, Irwin JJ, Shoichet BK. Relating protein pharmacology by ligand chemistry. Nat Biotech 25 (2), 197-206 (2007).

**other chemical similarity tools are available*

5. Miniaturised Complex 3D Assay Formats



Angiogenesis

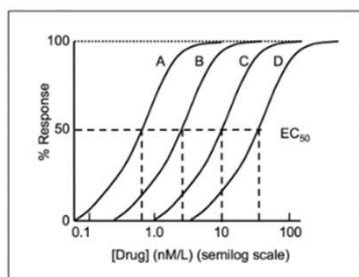


Vascularized
tumour spheroids

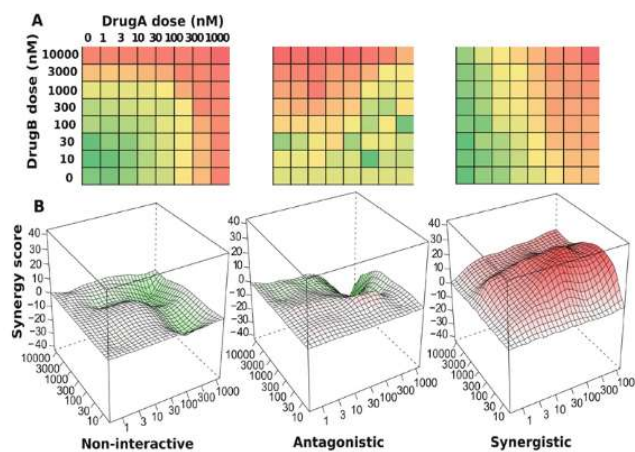
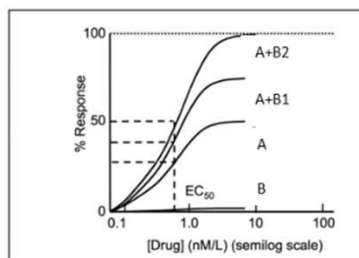
6. Combination drug screening

Chemical-chemical screening strategy

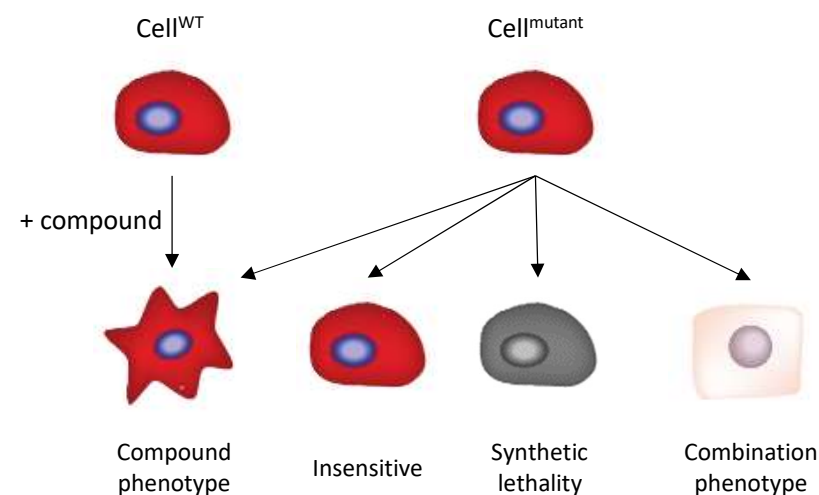
Potency



Potentiation

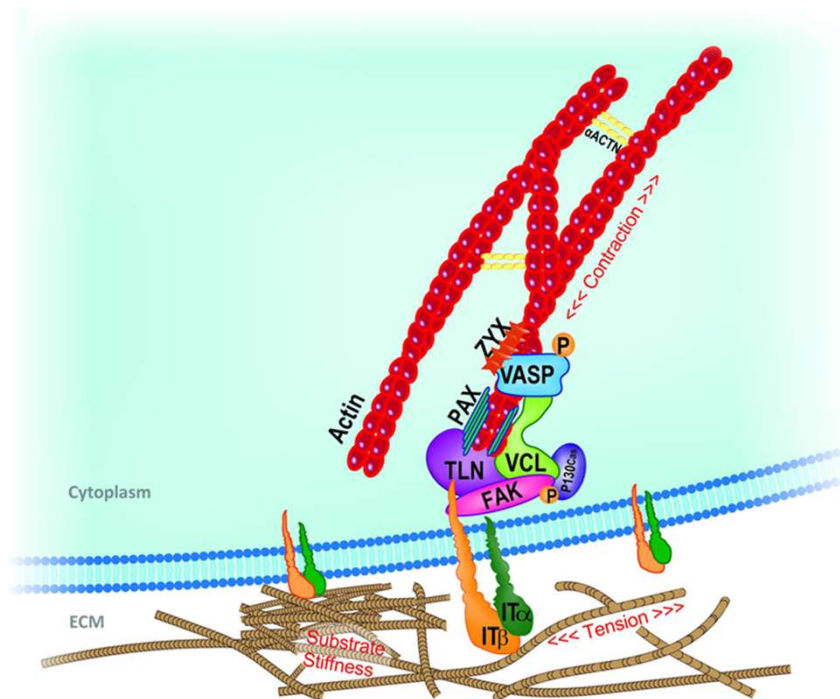


Chemical-genetic screening strategy



Multiple combinations becomes technically challenging especially with large dose matrix setups.

Focal Adhesion Kinase (FAK)



SCC FAK-Wild type

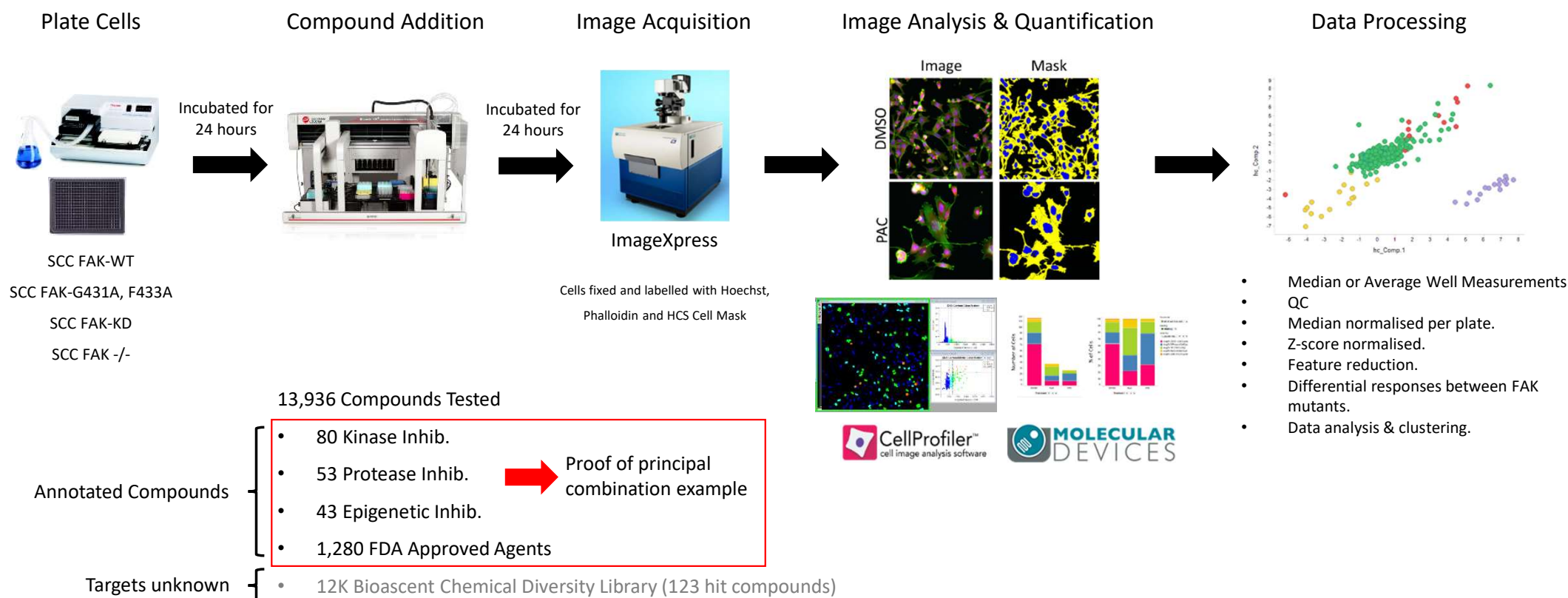
SCC FAK-G431A, F433A (CDC37 chaperone mutant)

SCC FAK-Kinase dead

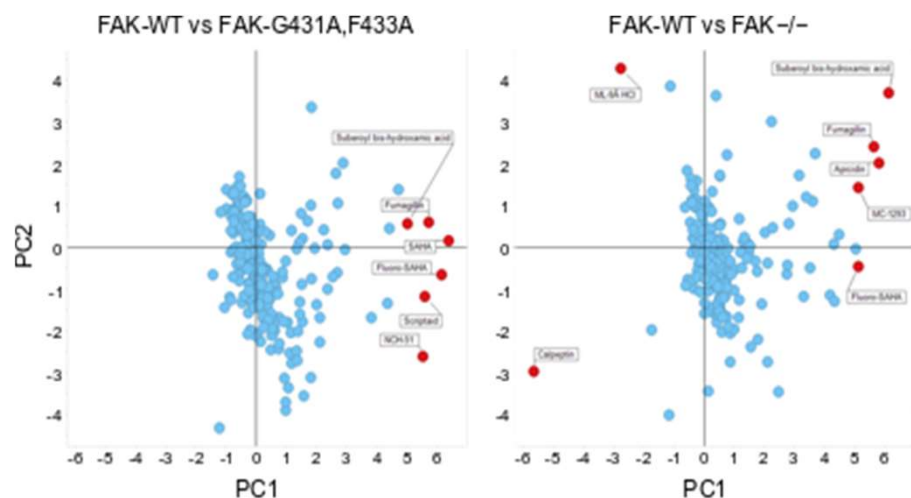
SCC FAK-deleted

FAK Combination Phenotypic Screen Summary

Aim – To identify compounds that synergise with a FAK kinase inhibitor using a genetic kinase dead.

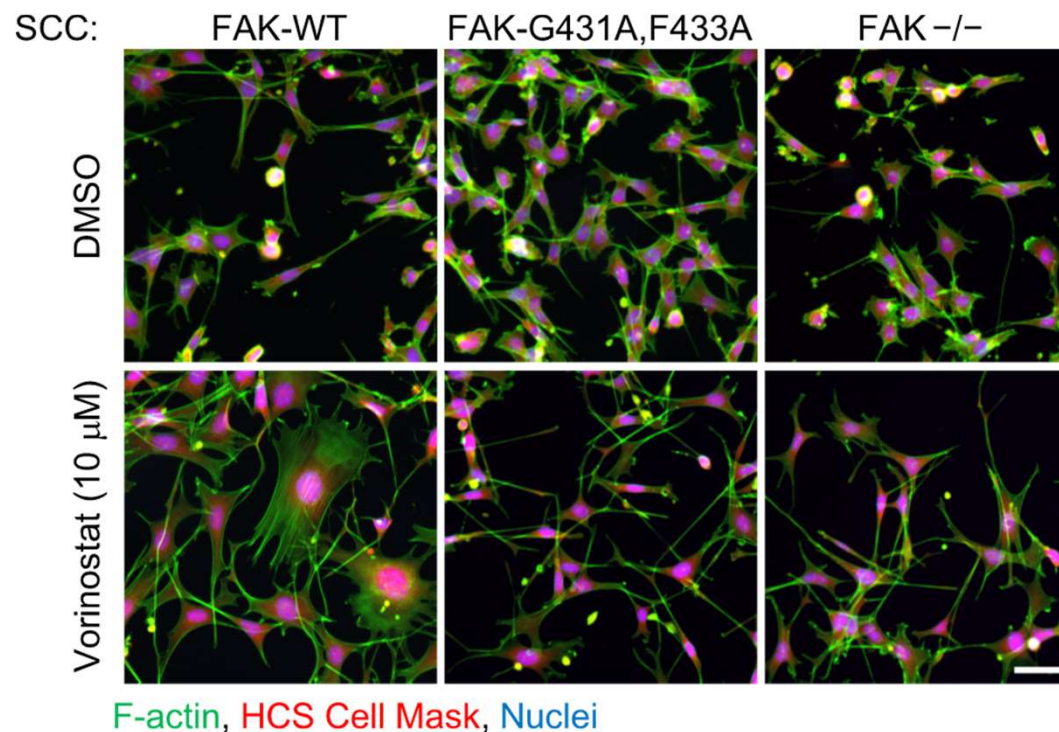


Protease, Kinase and Epigenetic (PKE) annotated tool compound library (176 in total).

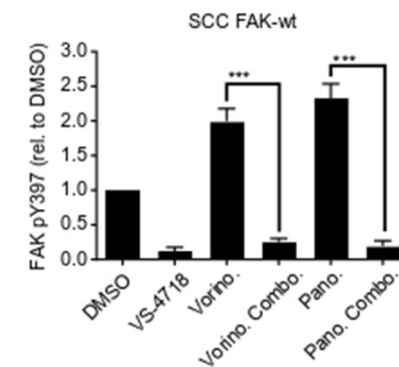
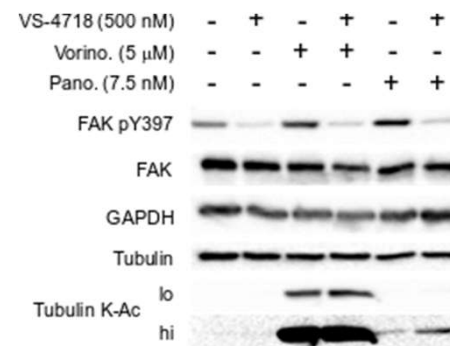
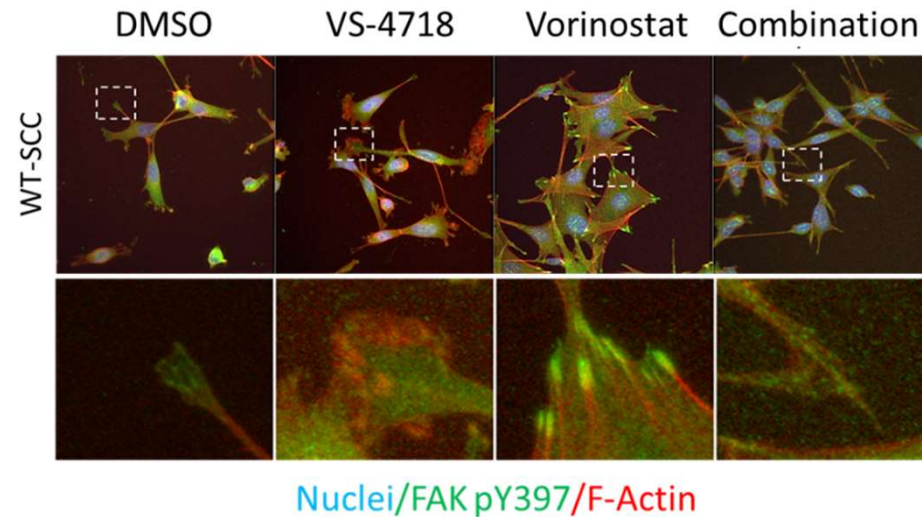


Chemical Name	Hit Score	Target	Cell Line
Suberoyl bis-hydroxamic acid	3.5	HDAC	-/-
Calpeptin	3.5	Calpain; Cathepsin L	-/-
SAHA	2.8	HDAC	G431A
Fumagillin	2.8	Met AP2	-/-
Apicidin	2.7	HDAC	-/-
ML-9A-HCl	2.7	MLCK	-/-
Fluoro-SAHA	2.7	HDAC	G431A
NCH-51	2.6	HDAC	G431A
Fumagillin	2.4	Met AP2	G431A
Scriptaid	2.4	HDAC	G431A
MC-1293	2.2	HDAC	-/-
Fluoro-SAHA	2.0	HDAC	-/-
Suberoyl bis-hydroxamic acid	2.0	HDAC	G431A

Proof of principle example – Histone deacetylase inhibitors



SCC model – HDAC combination with the FAK kinase inhibitor VS4718

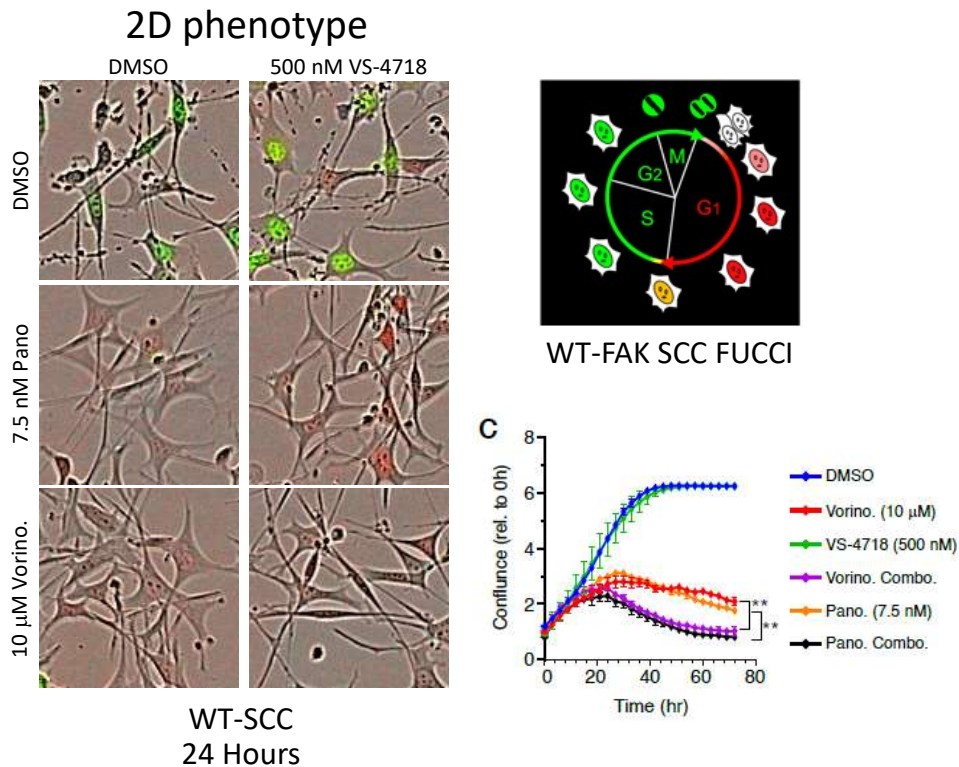


SCC-FAK model

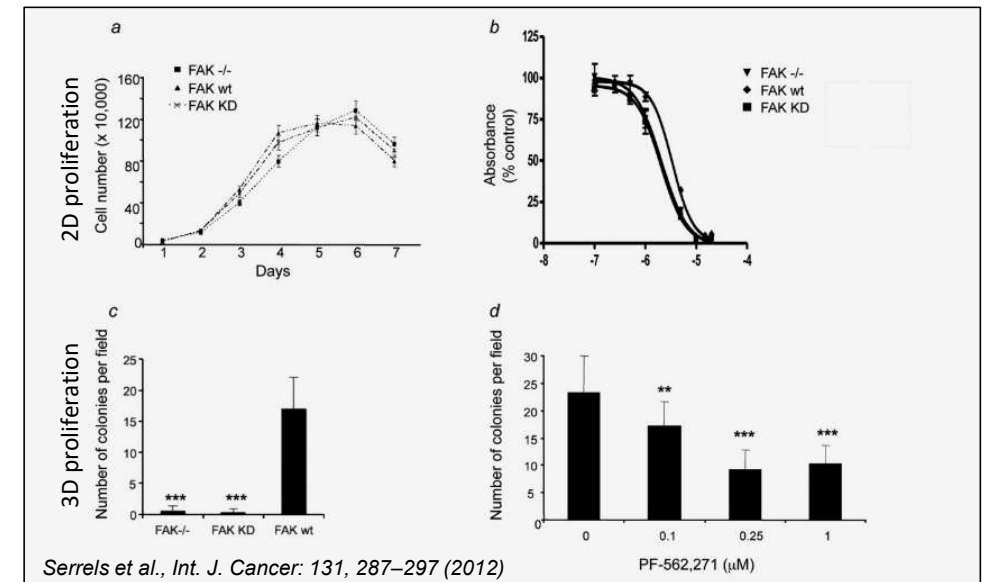


Vorinostat and **panobinostat** were selected to take forward for subsequent validation with a FAK kinase inhibitor (**VS-4718**).

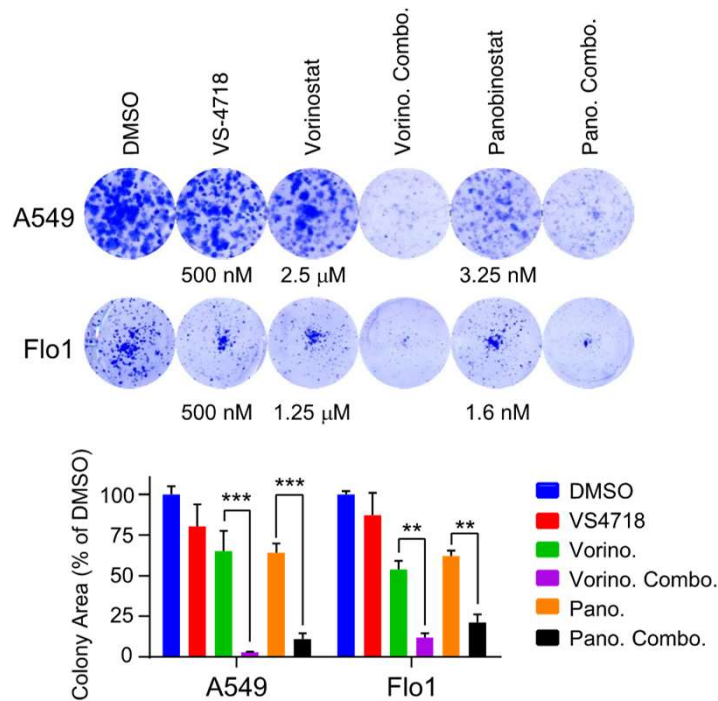
Combination does not synergistically inhibit 2D proliferation of SCC cells.



FAK is required for 3D, but not 2D proliferation

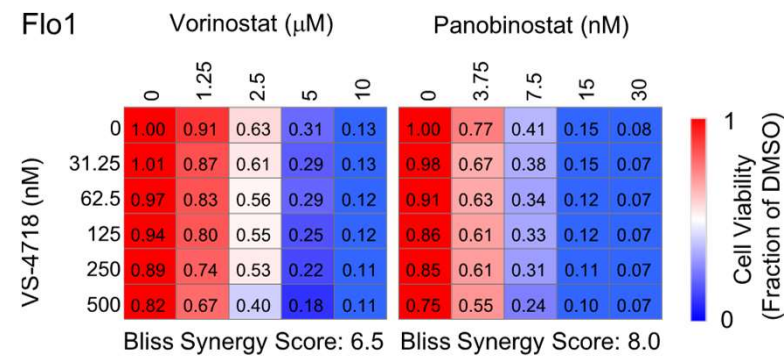
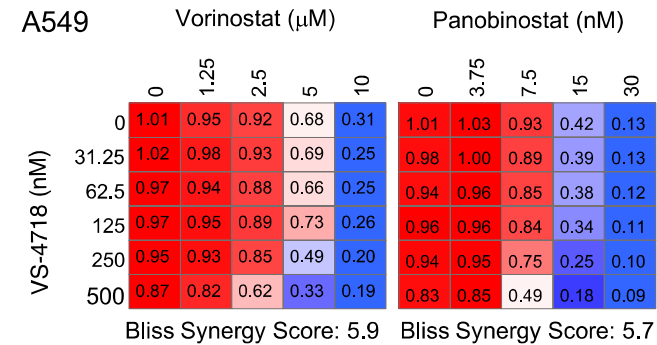


Combination of HDAC and FAK inhibitors blocks growth of A549 and Flo1 cell lines

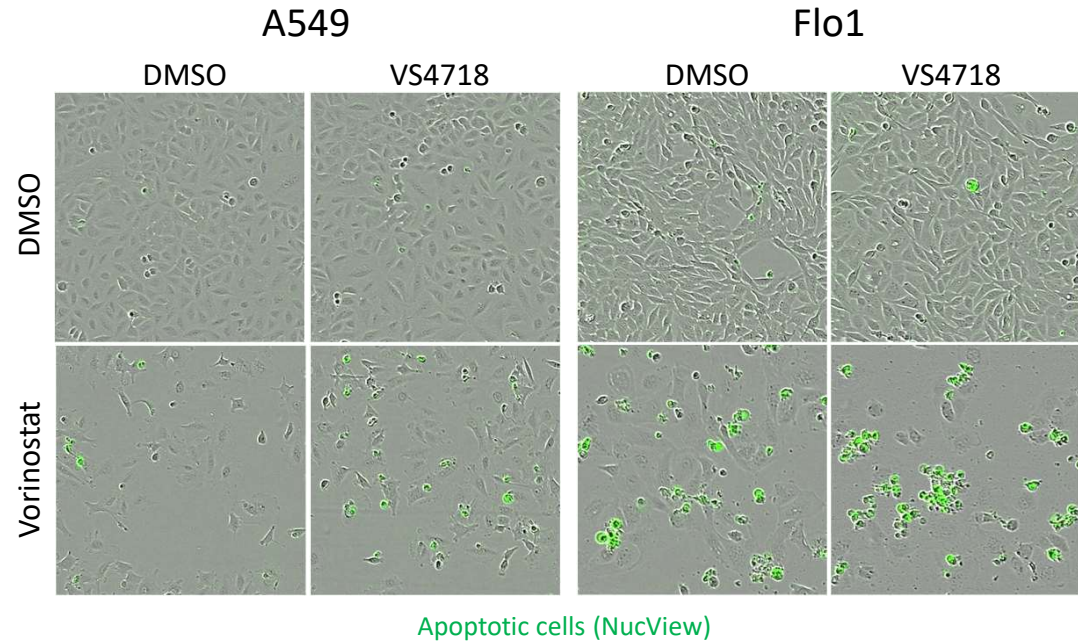
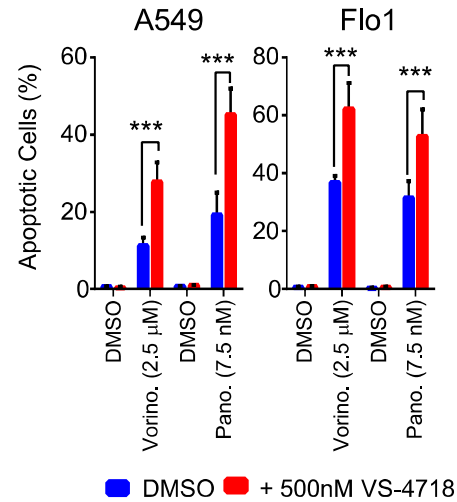
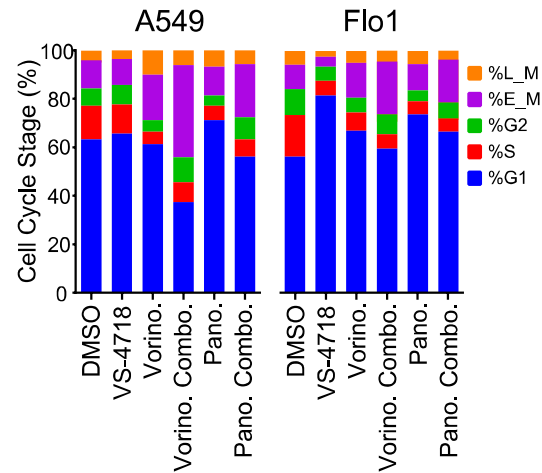


A549 cells are a lung adenocarcinoma

Flo1 cells are a oesophageal adenocarcinoma



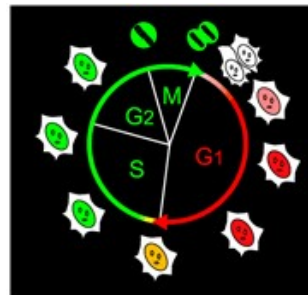
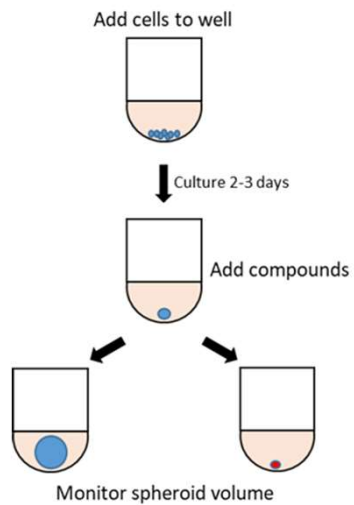
Combination of HDAC and FAK inhibitors induce cell cycle arrest and apoptosis.



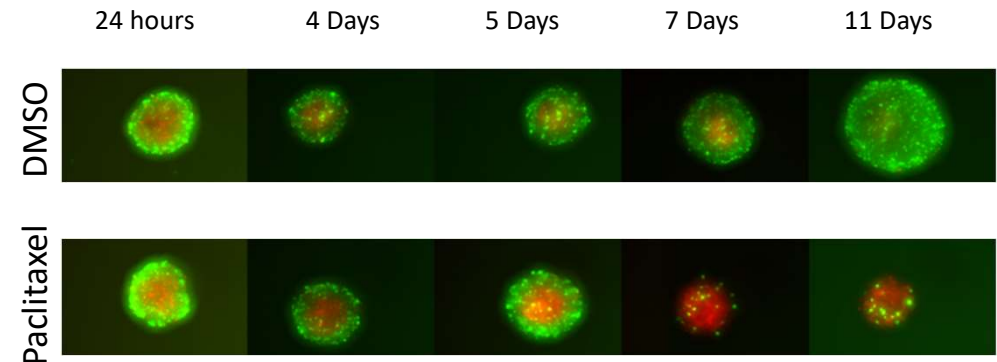
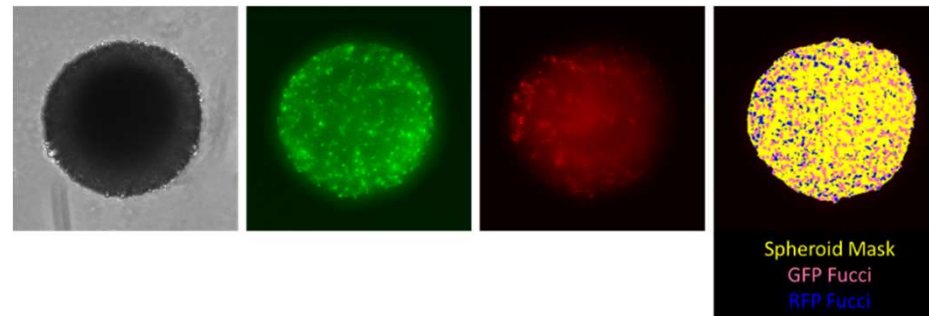
Phenotypic assays - 3D Spheroid Cultures

SCC cells expressing FUCCI (Fluorescent Ubiquitination-based Cell Cycle Indicator)

3D spheroid cell culture



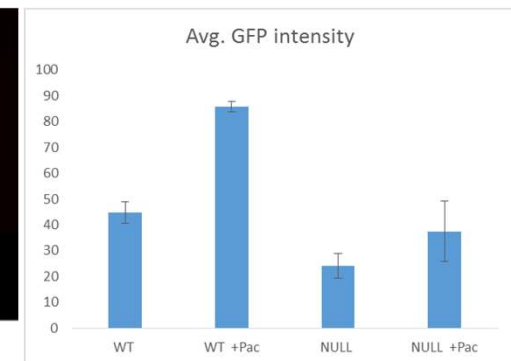
FUCCI Cell Cycle



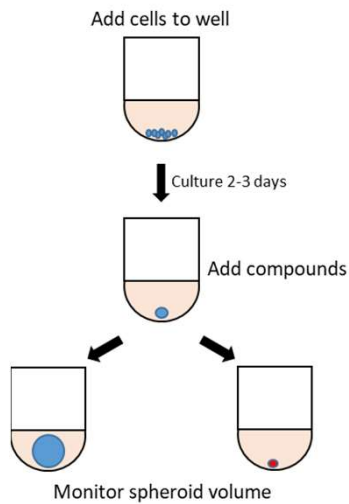
Drug addition

16 hrs of Pac increases GFP signal suggesting cell cycle arrest in S/G2/M phase

Spheroid dies after 48 hours (S/G2/M phase preferentially)

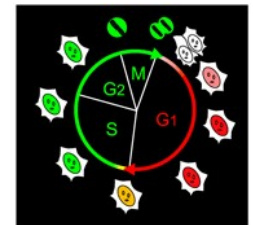
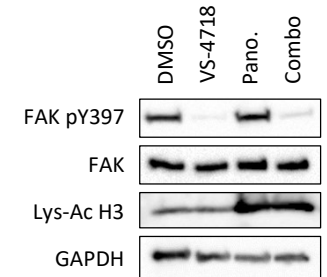
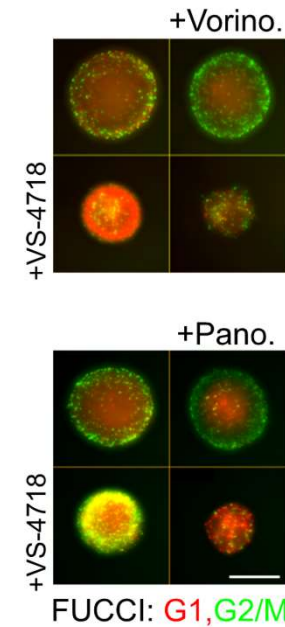
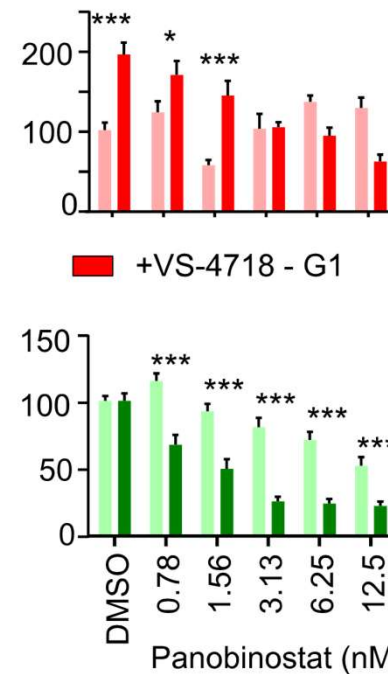
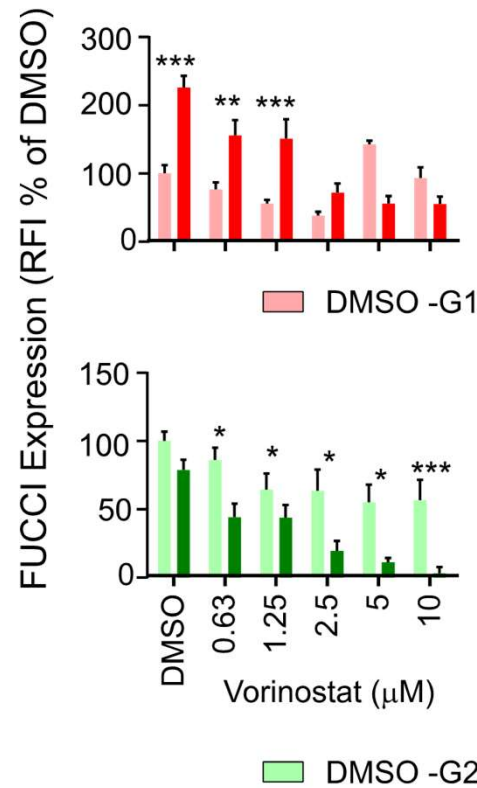


Combination of HDAC and FAK inhibitors blocks growth of SCC cells in a 3D spheroid model of growth.

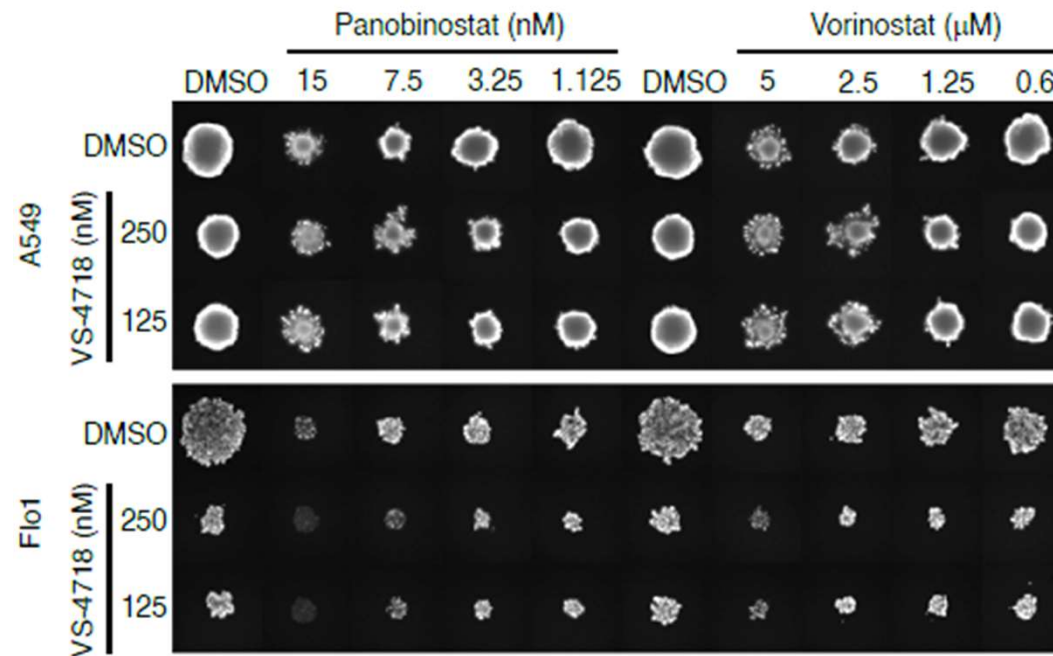


Day 7

WT-FAK SCC FUCCI

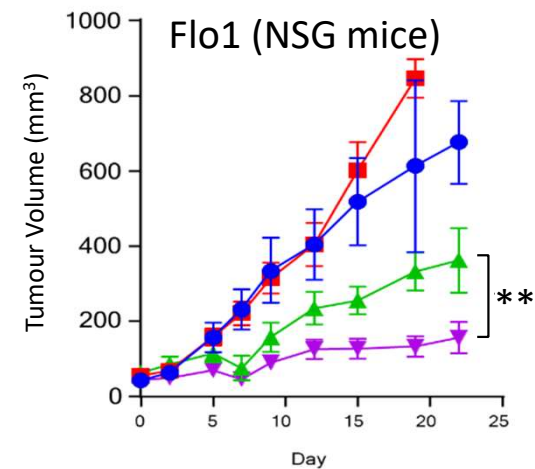
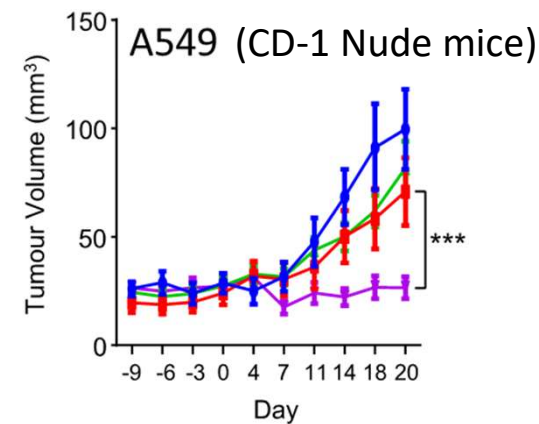
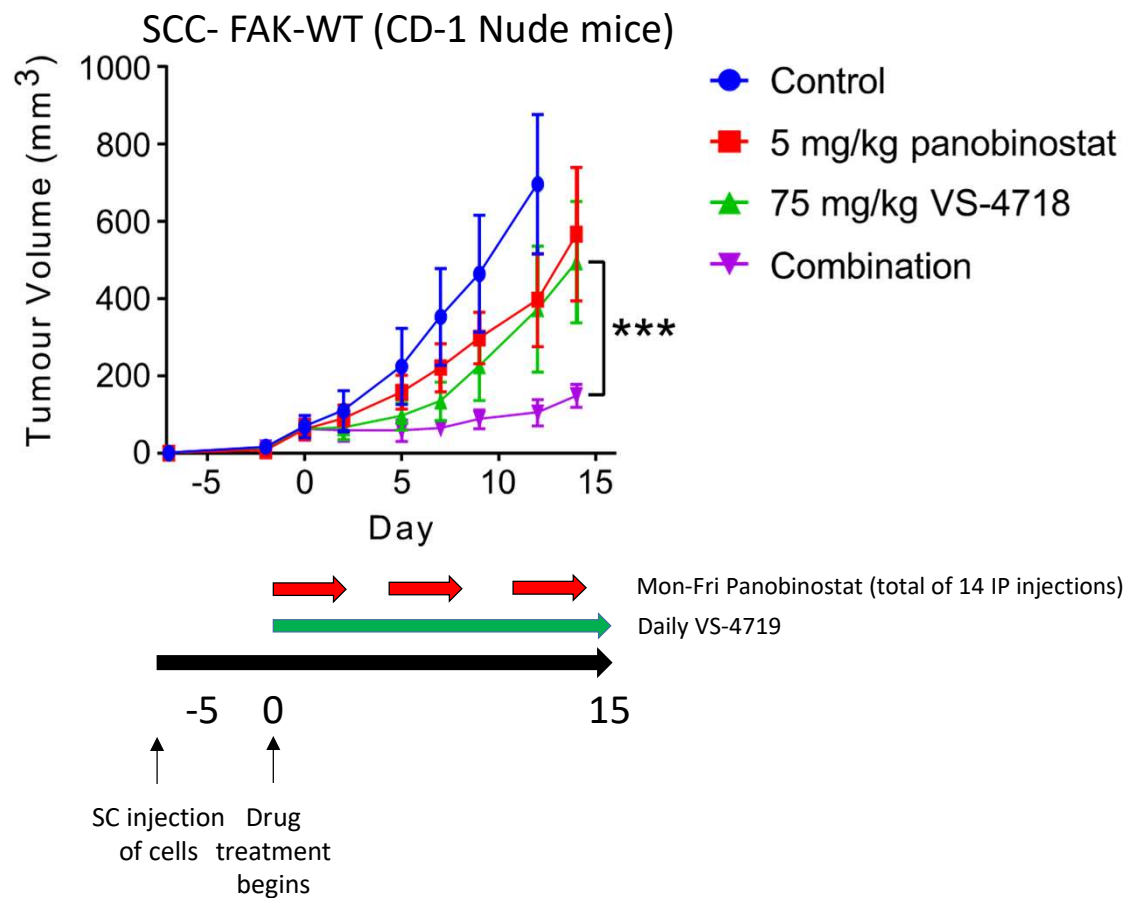


Combination of HDAC and FAK inhibitors blocks growth of A549 and Flo1 cells in a 3D spheroid model of growth.

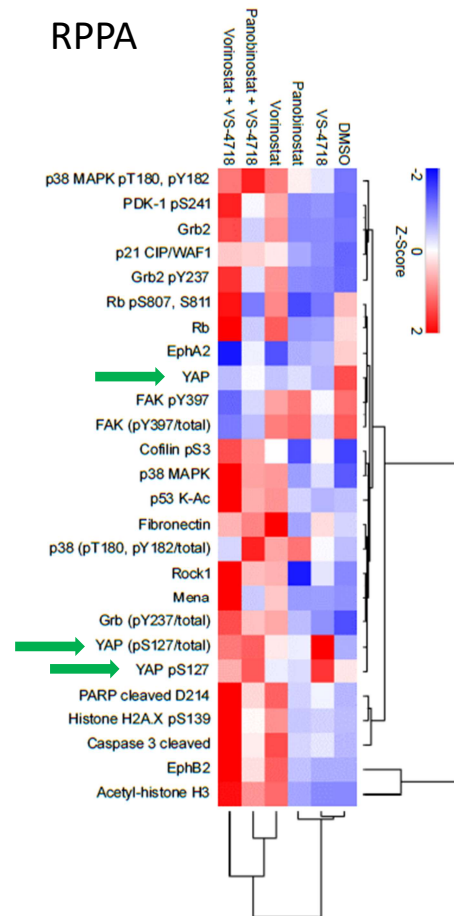


Spheroids labelled with Calcein AM viability dye on day 7

Combination of HDAC and FAK inhibitors blocks growth of tumours.

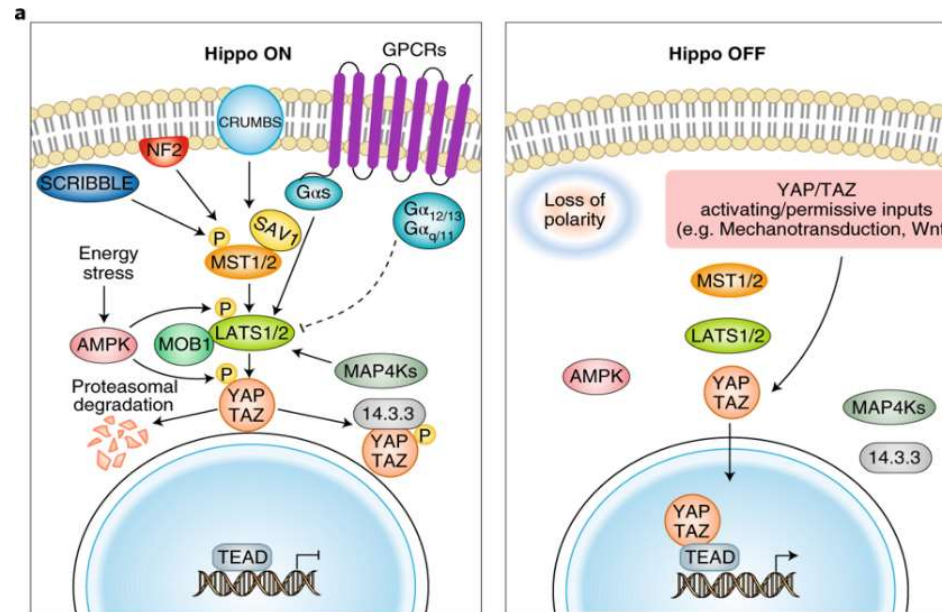


A FAK and HDAC inhibitor combination targets YAP signalling



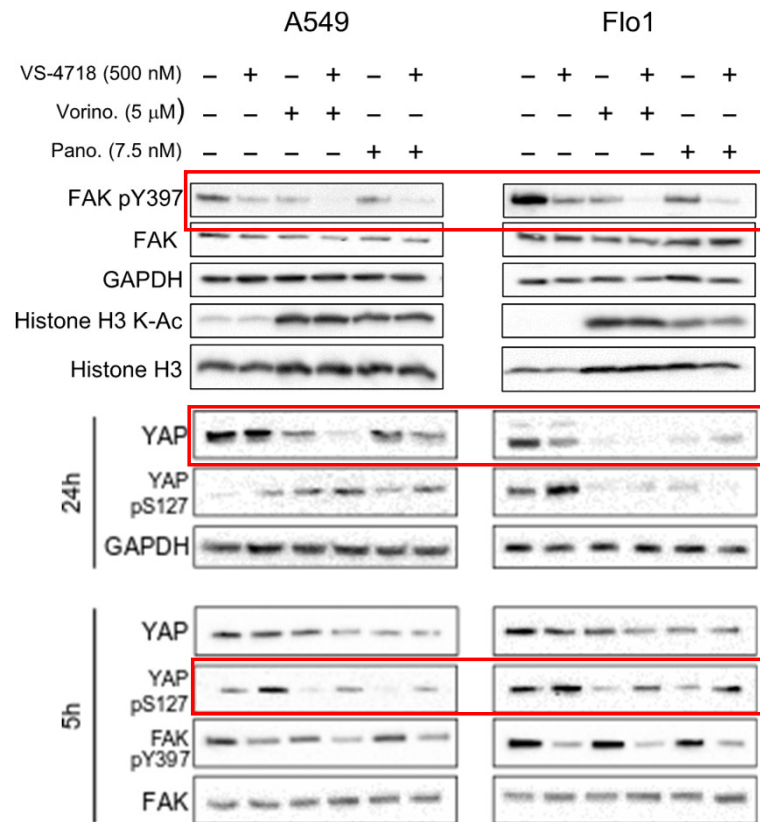
Profiled 120 antibodies covering a range of signalling pathways

Hippo signalling

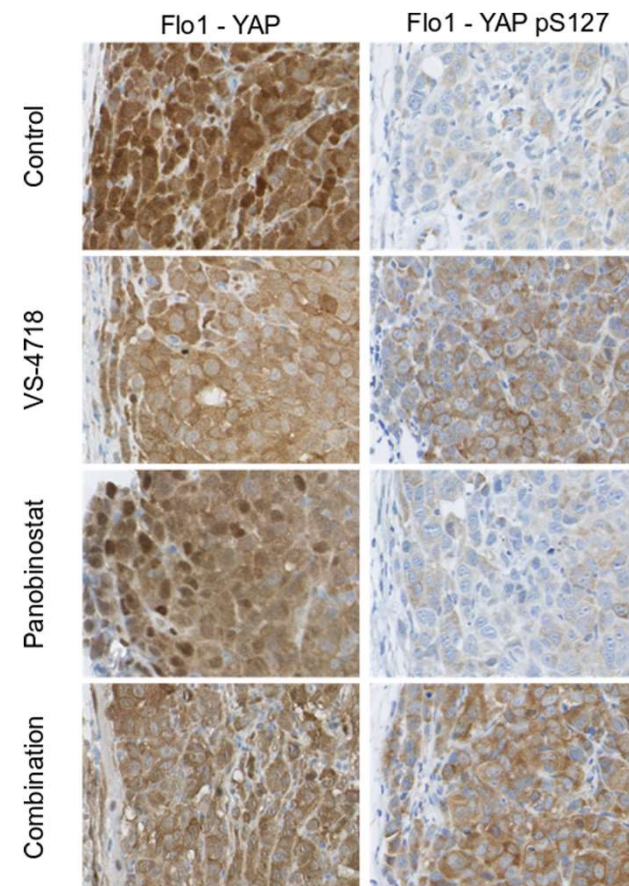


Combination of HDAC and FAK inhibitors abolishes FAK activity, and cooperatively inhibits YAP nuclear translocation and expression

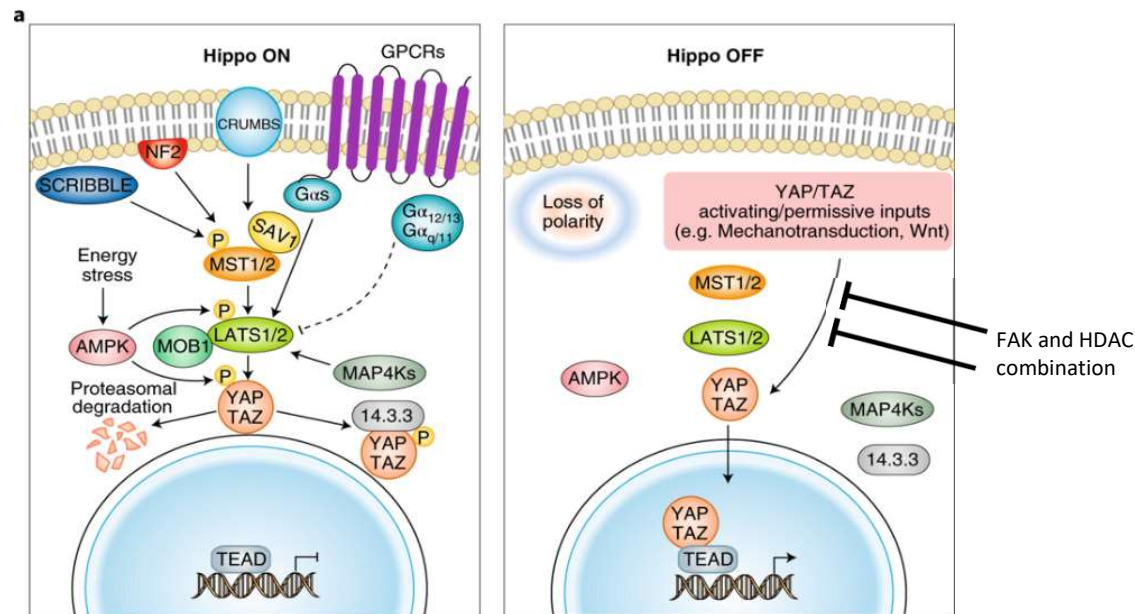
Validation



YAP expression in vivo



A FAK and HDAC inhibitor combination targets YAP signalling



Molecular Cancer Therapeutics

A Synergistic Anti-Cancer FAK and HDAC Inhibitor Combination Discovered by a Novel Chemical-Genetic High-Content Phenotypic Screen

DOI: 10.1158/1535-7163.MCT-19-0330



Conclusions

1. Drug discovery challenges and why we use phenotypic assays
2. Imaging technologies and developments in model assays
3. Examples of phenotypic high-content analysis (HCA) assays



Collaborators

Cancer Research UK Edinburgh Centre

Margaret Frame

Neil Carragher

Val Brunton

Asier Unciti-Broceta

Morwenna Muir

John Marwick (Fibrosis model with UCB)

Richard Elliott (Oesophageal screen)

Becka Hughes (Oesophageal screen & CellPainting)

Scott Warchal (CellPainting)

Alison Munro (Nanostring)

Kenneth Macleod (RPPA & cytokine arrays)

Ashraff Makda (Liquid handling and automation)

Leolie Telford-Cooke (iPSC oligodendrocyte model)

Other Collaborators

Daniel Lietha (FAK structural advice)

Siddharthan Chandran (iPSC oligodendrocyte model)

Dario Magnani (iPSC oligodendrocyte model)

Migla Miskinyte Reis (Trypanosome kinetoplast assay)

Tamara Sirey (miRNA mimetics mitochondrial function)

Claire Smillie (miRNA mimetics mitochondrial function)

Andrea Caporali (Autophagy screen)