



Future of Reproductive and Developmental Toxicity Testing: computational and organoids

Thomas B. Knudsen, PhD

National Center for Computational Toxicology

US Environmental Protection Agency

Research Triangle Park, NC 27711

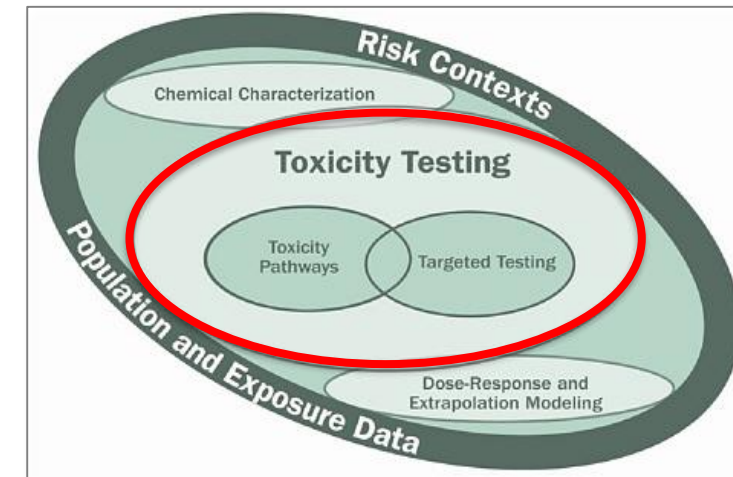
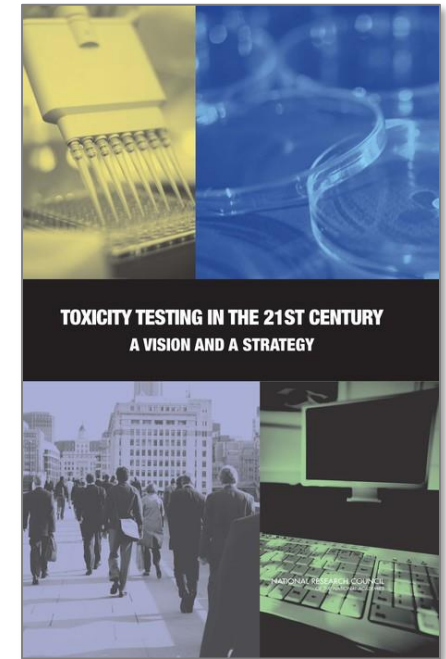
ORCID 0000-0002-5036-596x

American College of Toxicology and Teratology Society

DISCLAIMER: The views expressed in this presentation are those of the presenter and do not necessarily reflect the views or policies of the US EPA

Paradigm for 'predictive toxicology'

- Mechanistic understanding of biology is becoming increasingly dependent on 'big data': by 2025 the volume of genomics data is projected to exceed that from astronomy, YouTube and Twitter combined.
- *Toxicity Testing in the Twenty-first Century* [National Academy of Sciences, 2007] flips testing from data-poor observation in animal studies (*in vivo*) to data-rich evaluation associated with pathway-level profiling (*in vitro*, *in silico*).
- Emphasis on new approach methods (NAMs): HTS/HCS data, human cells and cell lines, chemical-biological interaction(s), computational and organotypic models, concentration-response and extrapolation based on exposure models.
- An integrated approach to toxicity assessment (eg, IATAs) brings it all together in the 'animal-free zone' where possible and targeted testing where necessary, assimilating hazard-exposure information into pathway-based risk assessment.



<https://www.nap.edu/catalog/11970/toxicity-testing-in-the-21st-century-a-vision-and-a-strategy>

Key Points

*"It's tough to make predictions,
especially about the future"*

-Yogi Berra

- Automated HTS assays enable rapid chemical screening to help '*decode the toxicological blueprint of active substances that interact with living systems*' [Sturla et al. 2014].
- Reducing a self-organizing biological system to simpler assays for chemical profiling disrupts the spatial and temporal dynamics that render it adaptive in the first place.
- Vast HTS data now in hand, the need arises for organotypic culture models (*in vitro*) and computer (*in silico*) systems that can rebuild this complexity.
- Focus of this lecture is on predicting the potential for human developmental and reproductive toxicity (DART) testing with less reliance on vertebrate animal testing.

*“Molecular biology took Humpty Dumpty apart ...
mathematical modeling is required to put him back together again.”*

– Schnell et al. (2007) Amer Scientist

Outline: computational and organoid approaches

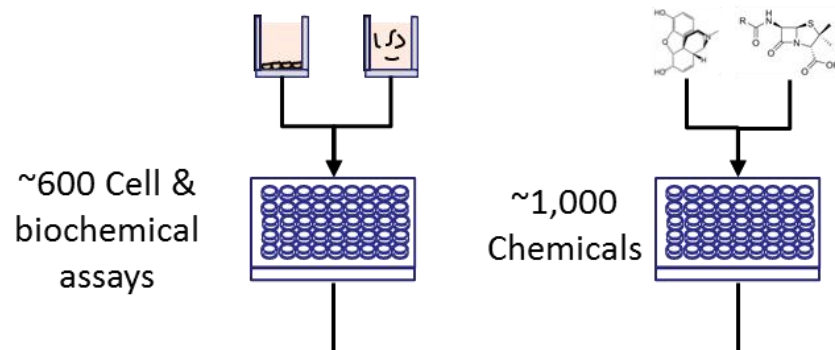
1. Profiling the ToxCast library with a pluripotent human (H9) embryonic stem cell assay.
2. AOP-based ontologies for developmental toxicity: case study on developmental vascular toxicity.
3. Virtual Tissue Models (VTM): computer simulation and biomimetic systems.



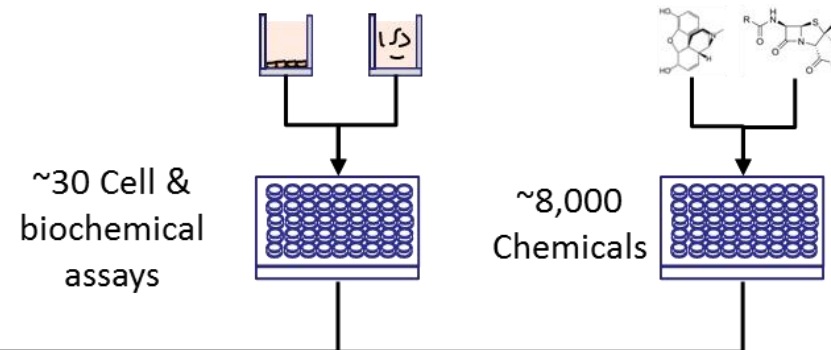
January 23, 2006

Shifting toxicology to pathway-based approaches

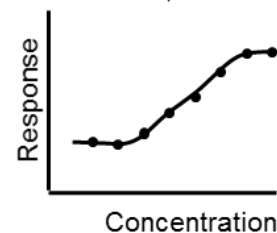
ToxCast



Tox21

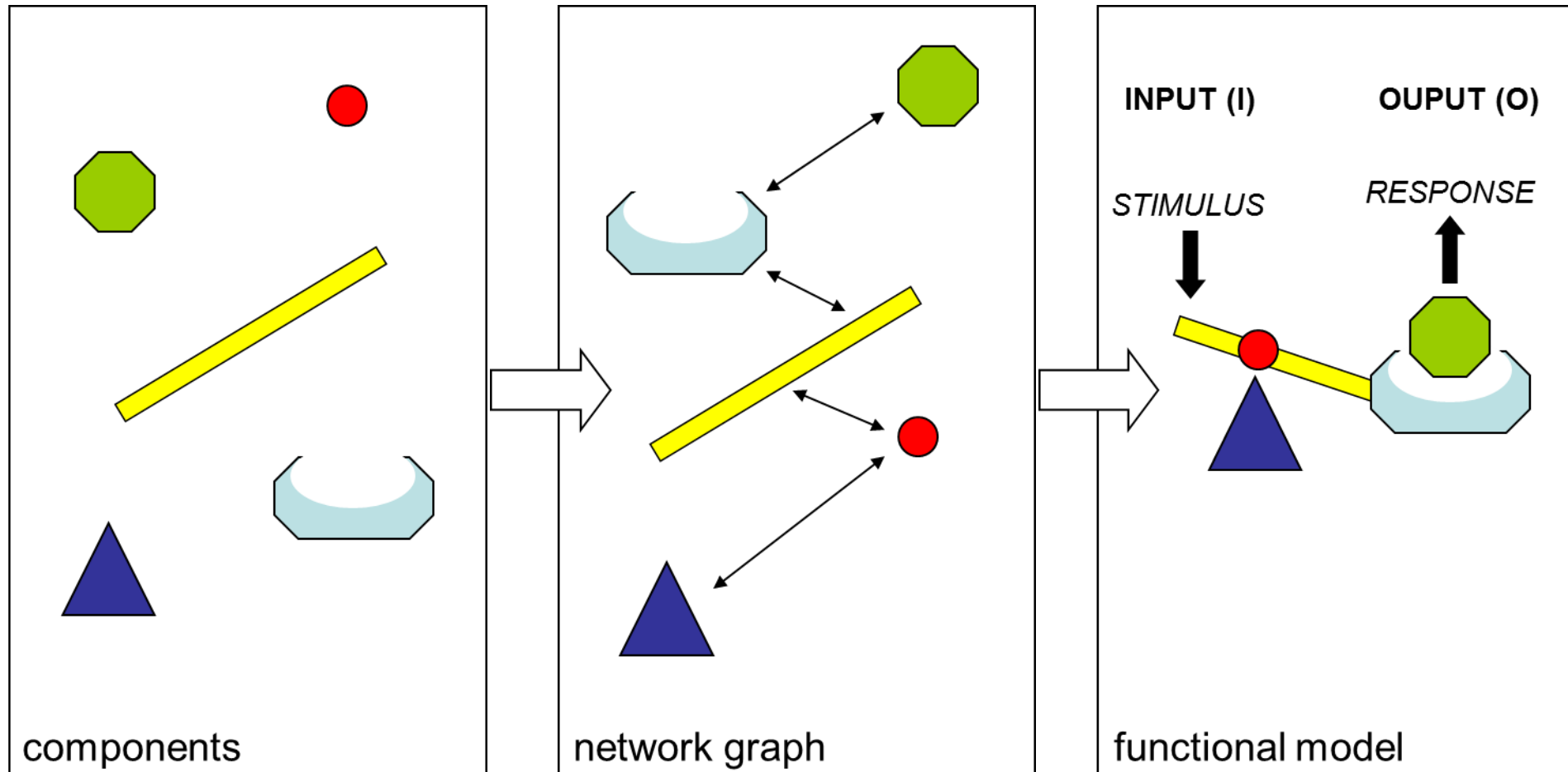


Set	Chemicals	Assays	Completion
ToxCast Phase I	293	~600	2011
ToxCast Phase II	767	~600	2013
ToxCast Phase III	1001	~100	Ongoing
E1K (endocrine)	880	~50	2013



<https://www.epa.gov/chemical-research/toxicology-testing-21st-century-tox21>

Why systems models are needed ...



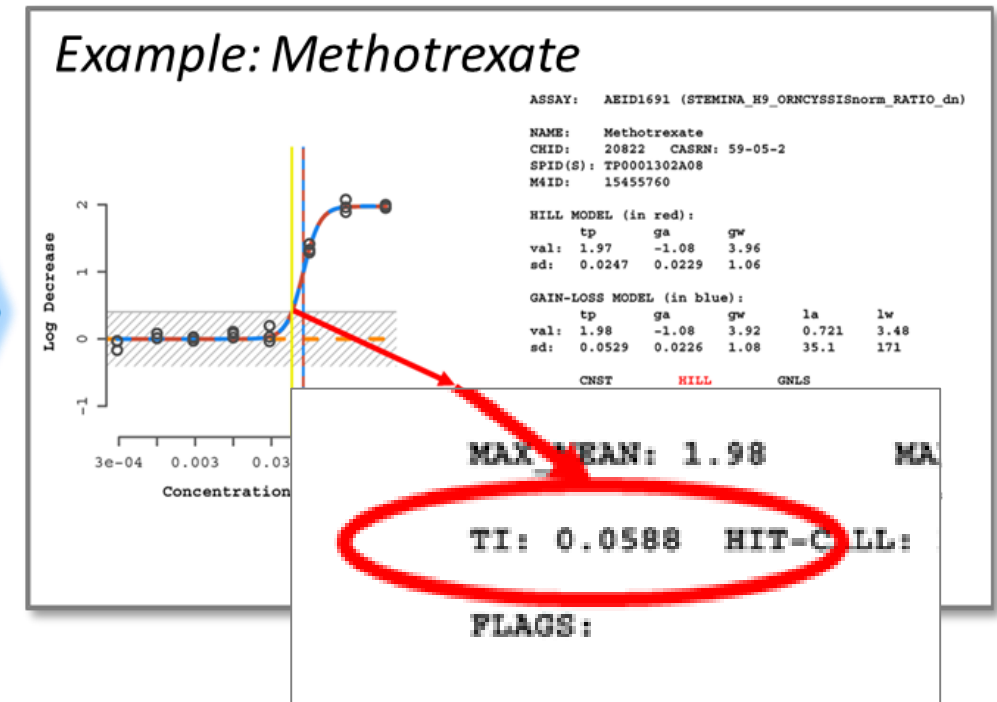
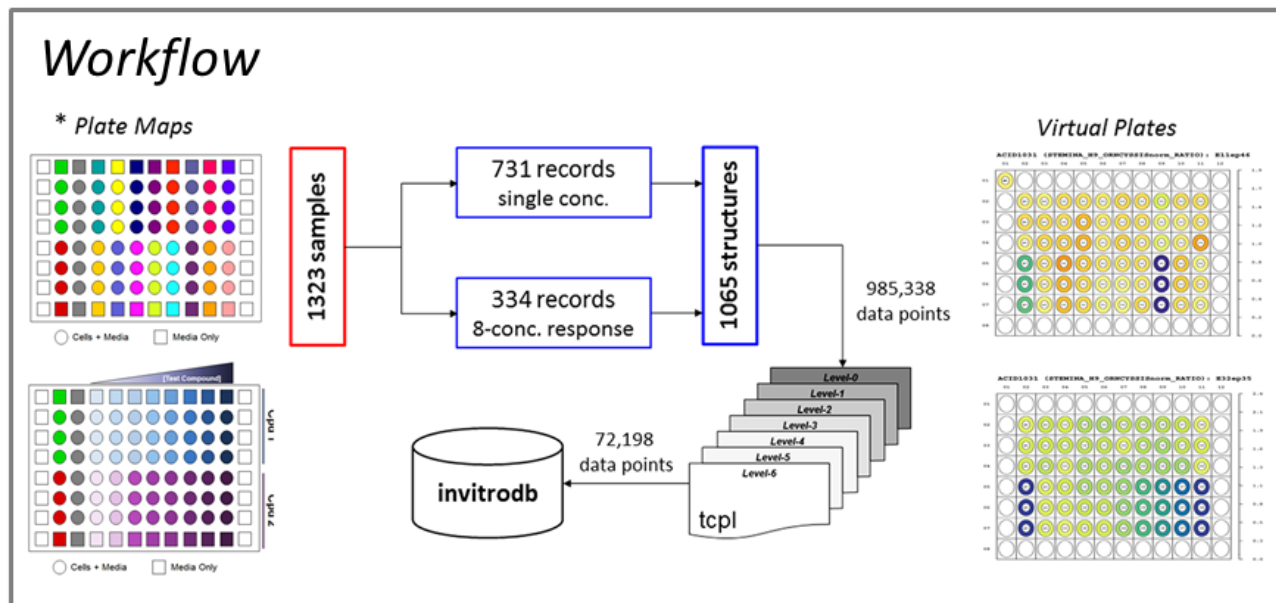


Profiling the ToxCast library with a pluripotent human (H9) embryonic stem cell assay

Objective: increase the diversity and relevance of assays in ToxCast that can be used to profile chemicals for potential adverse effects on human embryonic development.

ToxCast_STM assay

- devTOX^{qP} assay from Stemina Biomarker Discovery
- pluripotent H9 stem cells exposed → secretome of 3rd day analyzed by metabolomics
- critical drop of ornithine:cystine ratio is the targeted biomarker
- pharma test set yields 77% accuracy (0.57 sensitivity, 1.00 specificity) [Palmer et al. 2013]
- **Key point:** 183 of 1065 (17%) ToxCast chemicals tested positive in this screen



SOURCE: Zurlinden et al. (NCCT manuscript in clearance)

Performance anchored to ToxRefDB

Key point: balanced accuracy improves with evidence for DevTox

		Stringency Filter Applied to DevTox Anchor			
		Base	Low	Medium	High
in vitro	in vivo				
	TP	85	60	35	19
	FP	14	37	23	9
	FN	217	127	51	11
	TN	116	208	176	88
	n	432	432	285	127
	sensitivity	0.281	0.321	0.407	0.633
	specificity	0.892	0.849	0.884	0.907
	PPV	0.859	0.619	0.603	0.679
	NPV	0.348	0.621	0.775	0.889
	ACC	46.5%	62.0%	74.0%	84.3%
	MCC	0.190	0.202	0.332	0.554
		any dLEL rat OR rabbit	SOME evidence rat OR rabbit	CLEAR evidence rat OR rabbit	CLEAR evidence rat AND rabbit

STM versus rat WEC

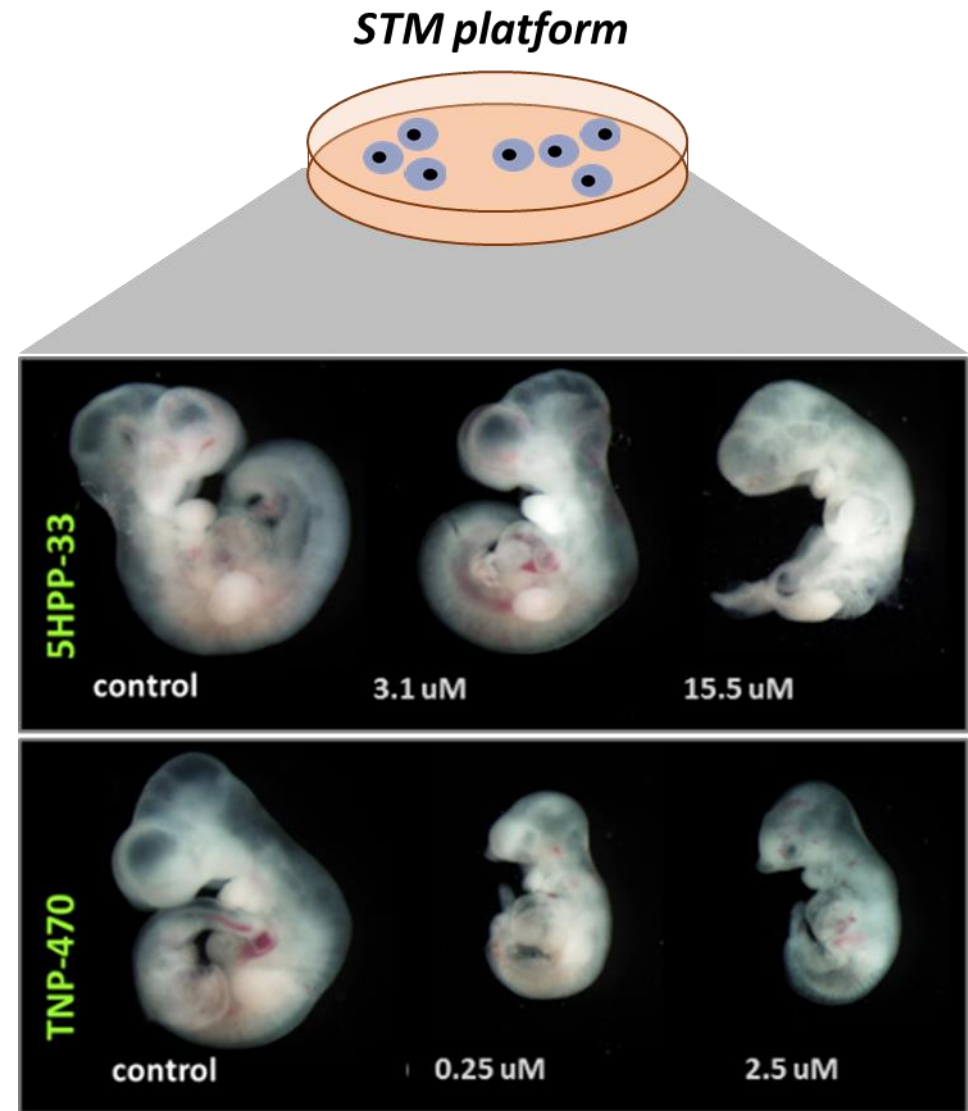
5HPP-33: *synthetic thalidomide analog*

- T.I. predicted 9.5 μM
- AC50 observed 21.2 μM (embryo viability)

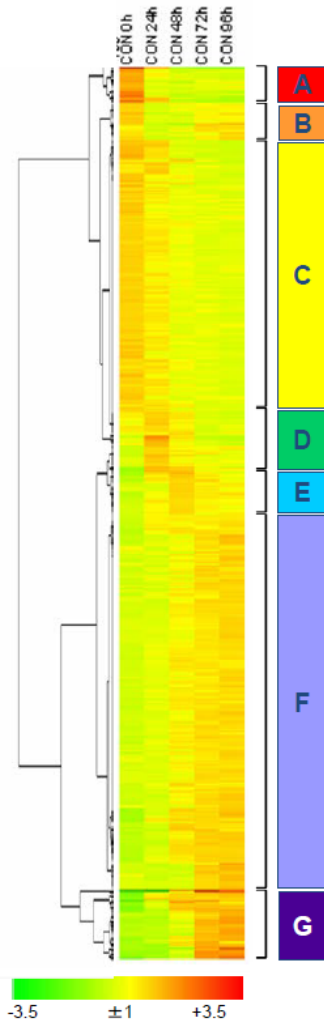
TNP-470: *synthetic fumagillin analog*

- T.I. predicted 0.01 μM
- AC50 observed 0.04 μM (dysmorphogenesis)

Key point: exposure-based potential for DevTox predicted by STM assay (quantitative prediction).

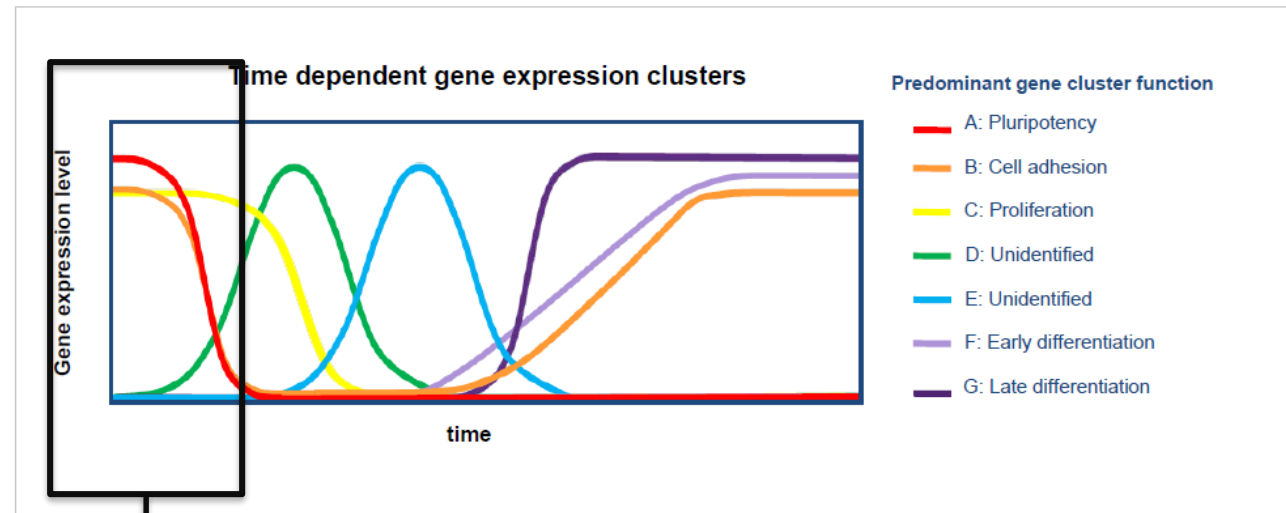


SOURCE: Ellis-Hutchings et al. (2017) *Reprod Toxicol*



EST differentiation – related gene expression

THE
TERATOLOGY
SOCIETY
BIRTH DEFECTS RESEARCH • EDUCATION • PREVENTION
EST. 1960



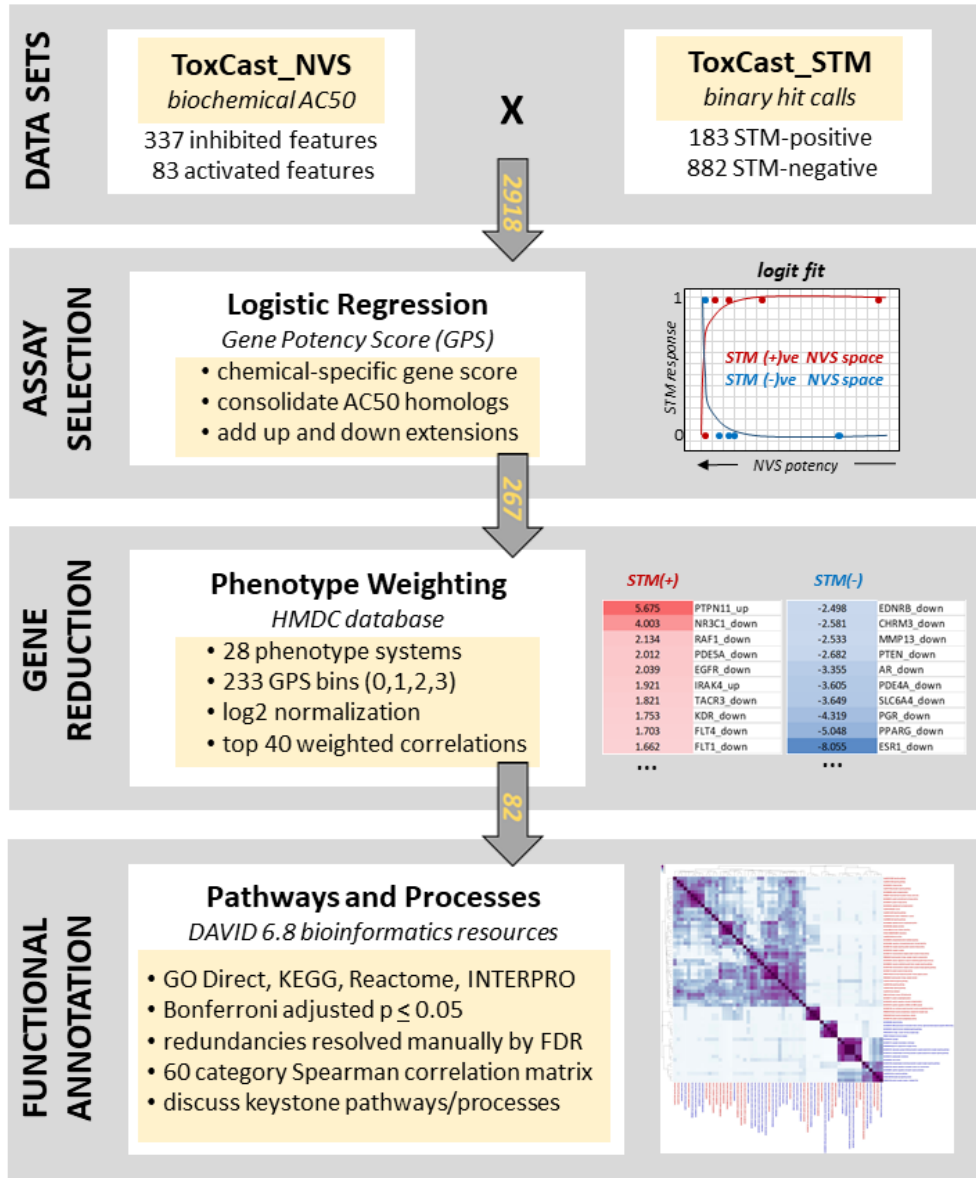
Van Dartel et al., 2010

SLIDE SOURCE: Aldert Piersma, RIVM

phase of the differentiation trajectory addressed by ToxCast_STM assay

Keystone Pathways (predicted)

- Mining STM response against biochemical pathways constructed from ToxCast_NVS.
- What we can and cannot say about the applicability domain of the STM response:
 - **sensitive domain:** regulation of PI3K signaling, FoxO signaling pathway, and focal adhesion pathway.
 - **insensitive domain:** GPCR signaling through G(q) and steroid hormone mediated signaling pathways.



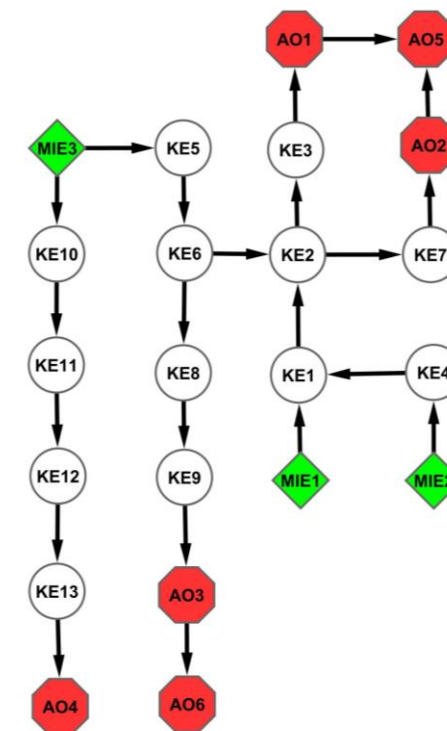
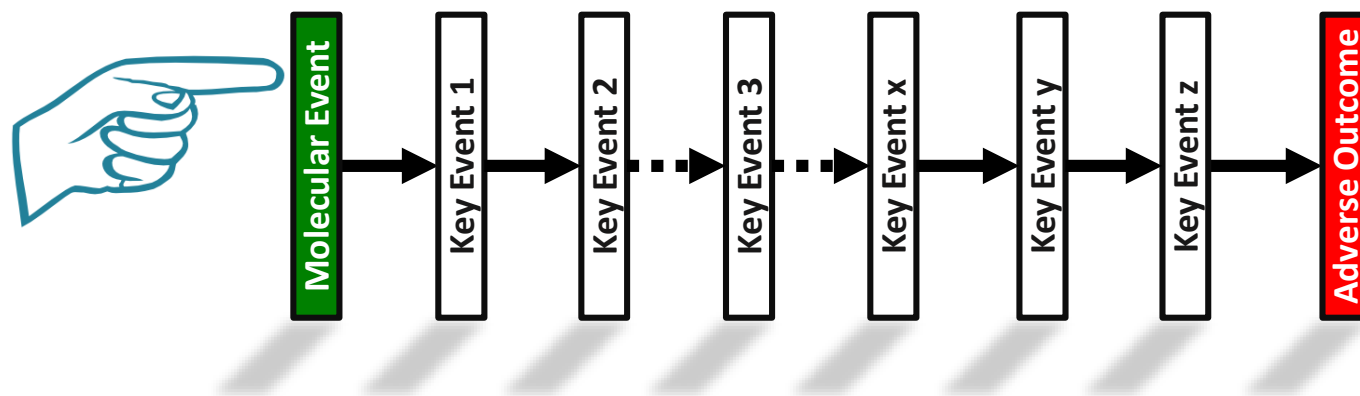
SOURCE: Zurlinden et al. (NCCT manuscript in clearance)



AOP-based ontologies for developmental toxicity: *case study on developmental vascular toxicity*

Objective: formalize a mechanistic framework for developmental toxicity that can be used to quantitatively link adverse outcomes with MIEs and KERs in the angiogenic cycle.

AOP Core Principles



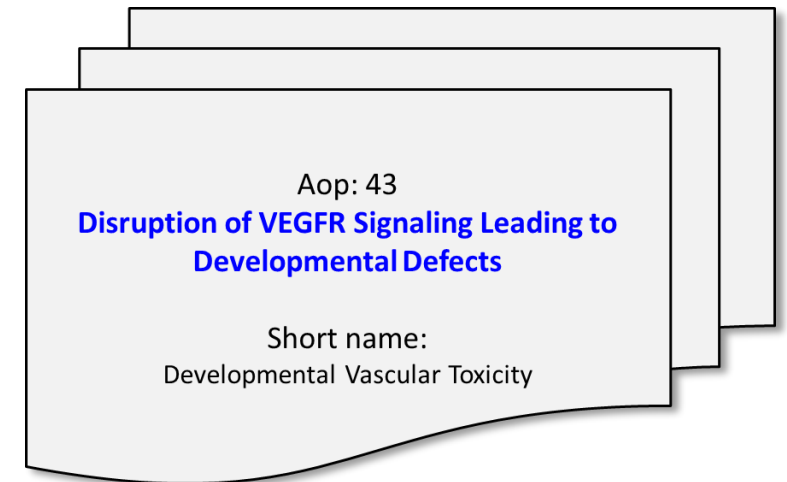
1. **AOPs are not chemical-specific** (based on biological motifs of failure)
2. **AOPs are modular** (individual relationships based on weight of evidence)
3. **Individual AOPs are a pragmatic simplification** (linearized sequence of biology)
4. **AOP networks are the functional unit of prediction** (in most cases)
5. **AOPs are living documents** (evolve as knowledge grows)

SOURCE: Villeneuve et al. (2014) Toxicol Sci

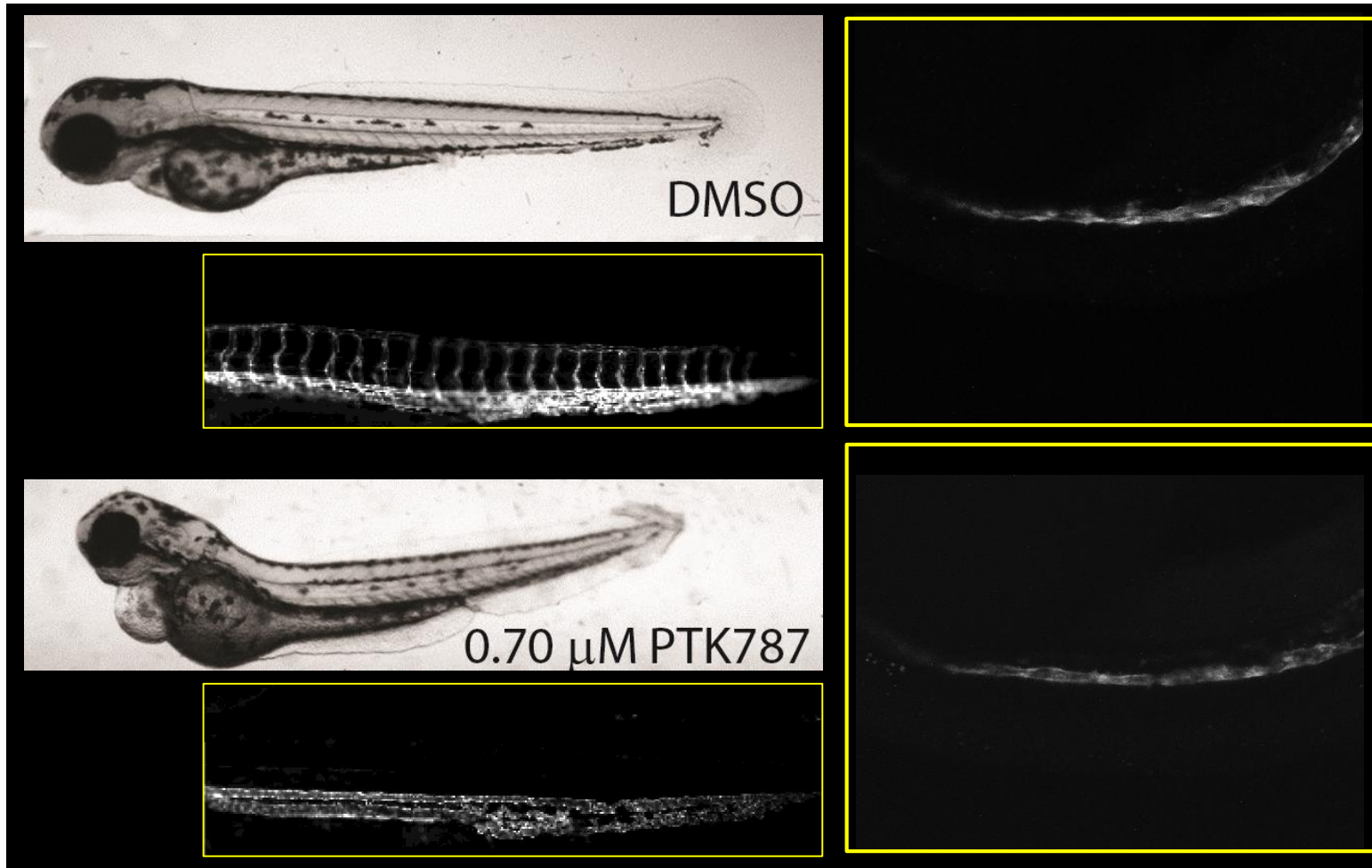


Vascular Development

- Blood vessel development is essential to embryogenesis (cardiovascular is first functioning organ system across *Vertebrate* species).
- Vascular insufficiency is tied to many disease processes (stroke, diabetes, preeclampsia, neonatal respiratory distress, osteoporosis, teratogenesis, ...).
- Aop43: one of 28 AOPs included in the OECD work plan with status 'open for citation & comment' [<https://aopwiki.org/aops/43>].

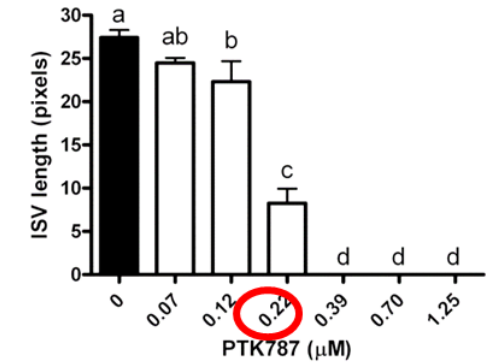


VEGFR2 inhibition (PTK787)

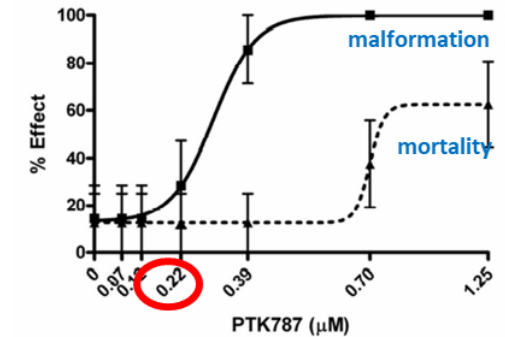


SOURCE: Tal et al. (2014) *Reprod Toxicol*

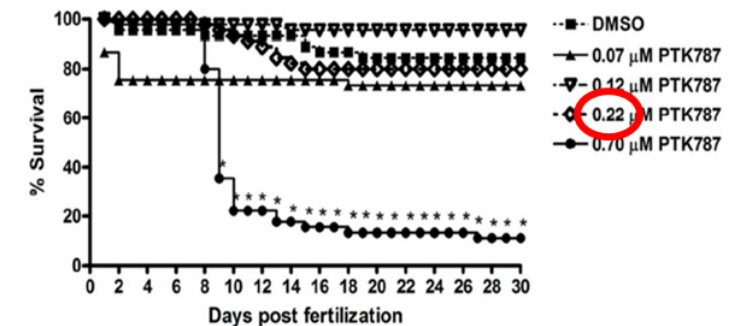
ISV length
(72 hpf)



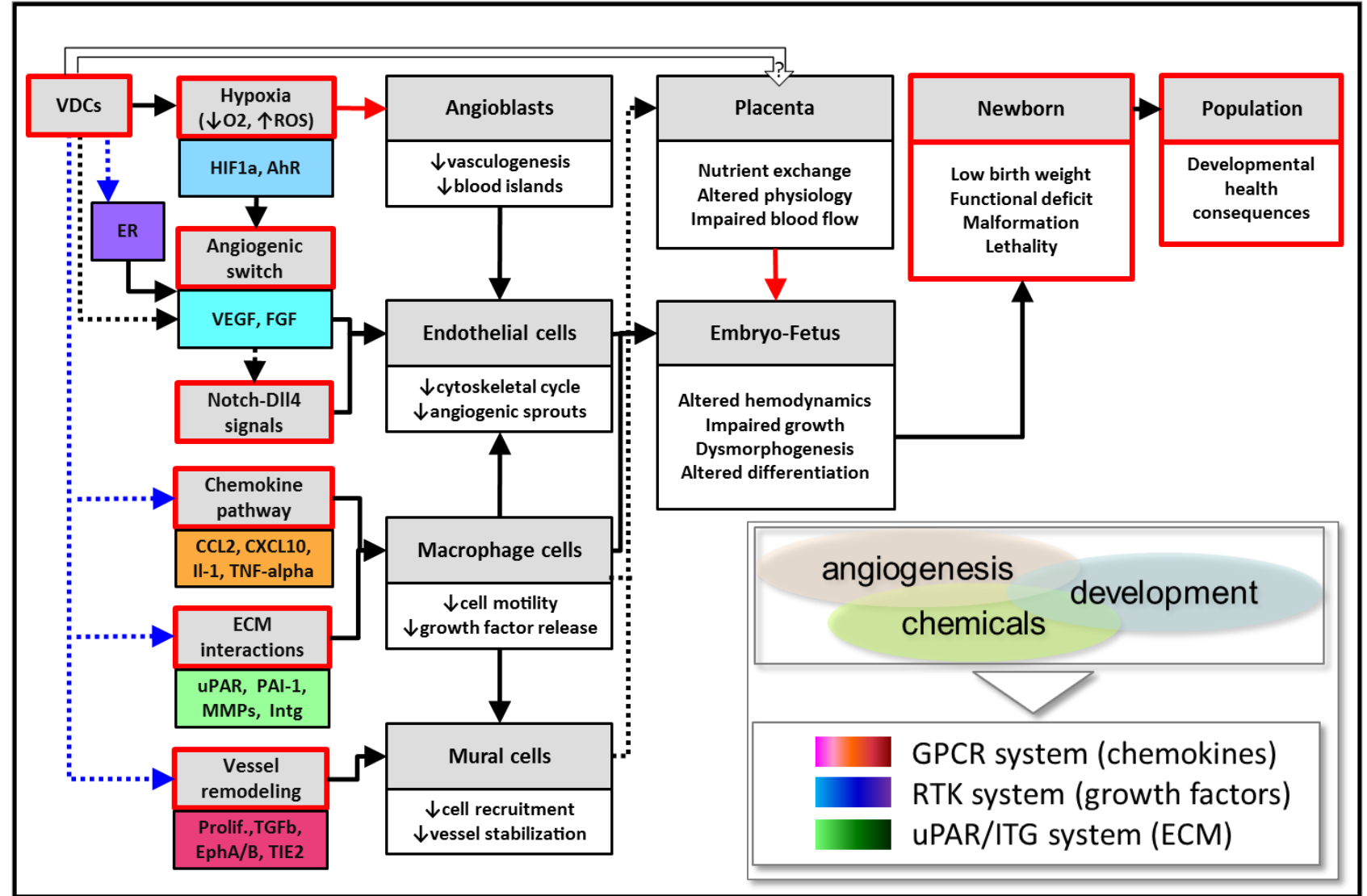
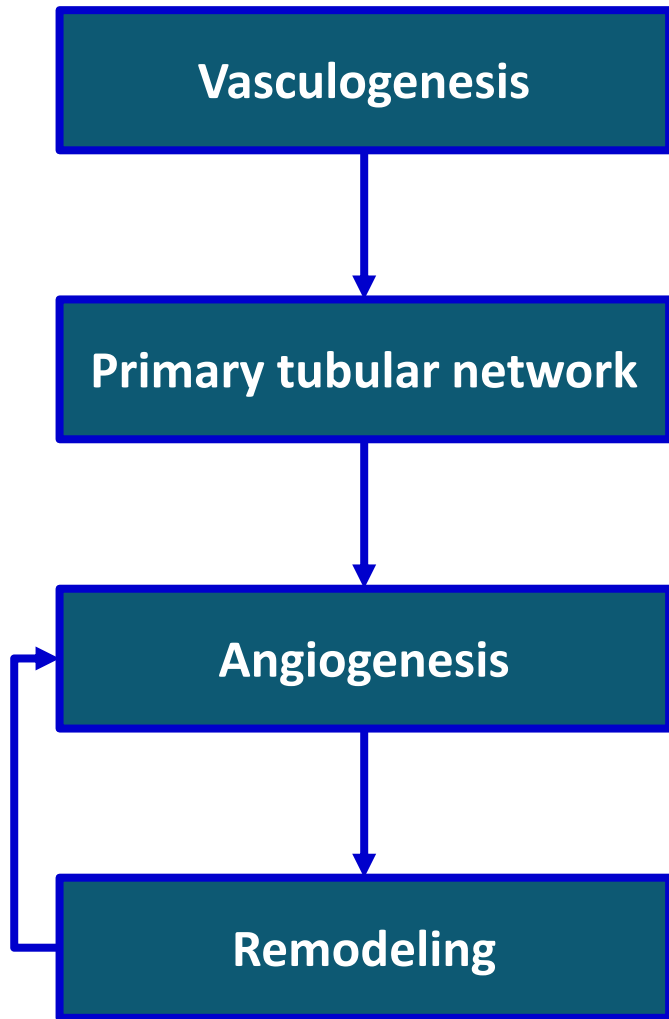
Terata
(120 hpf)



Lifespan
(10 dpf)



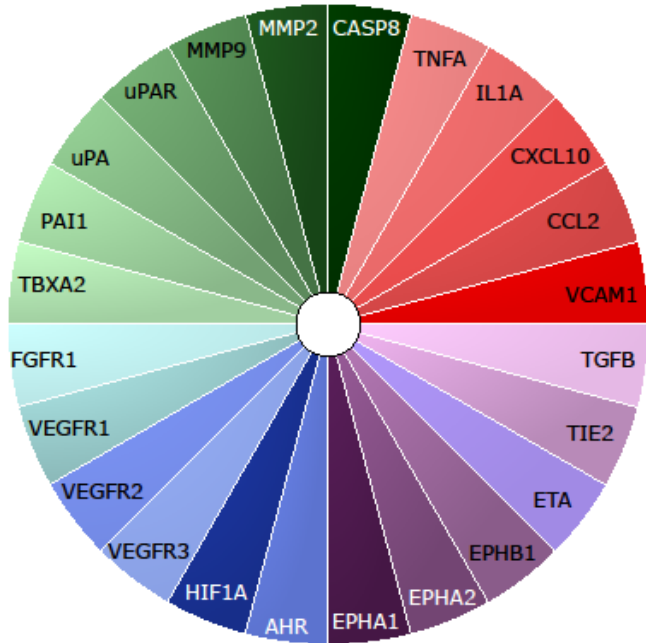
Aop43 framework



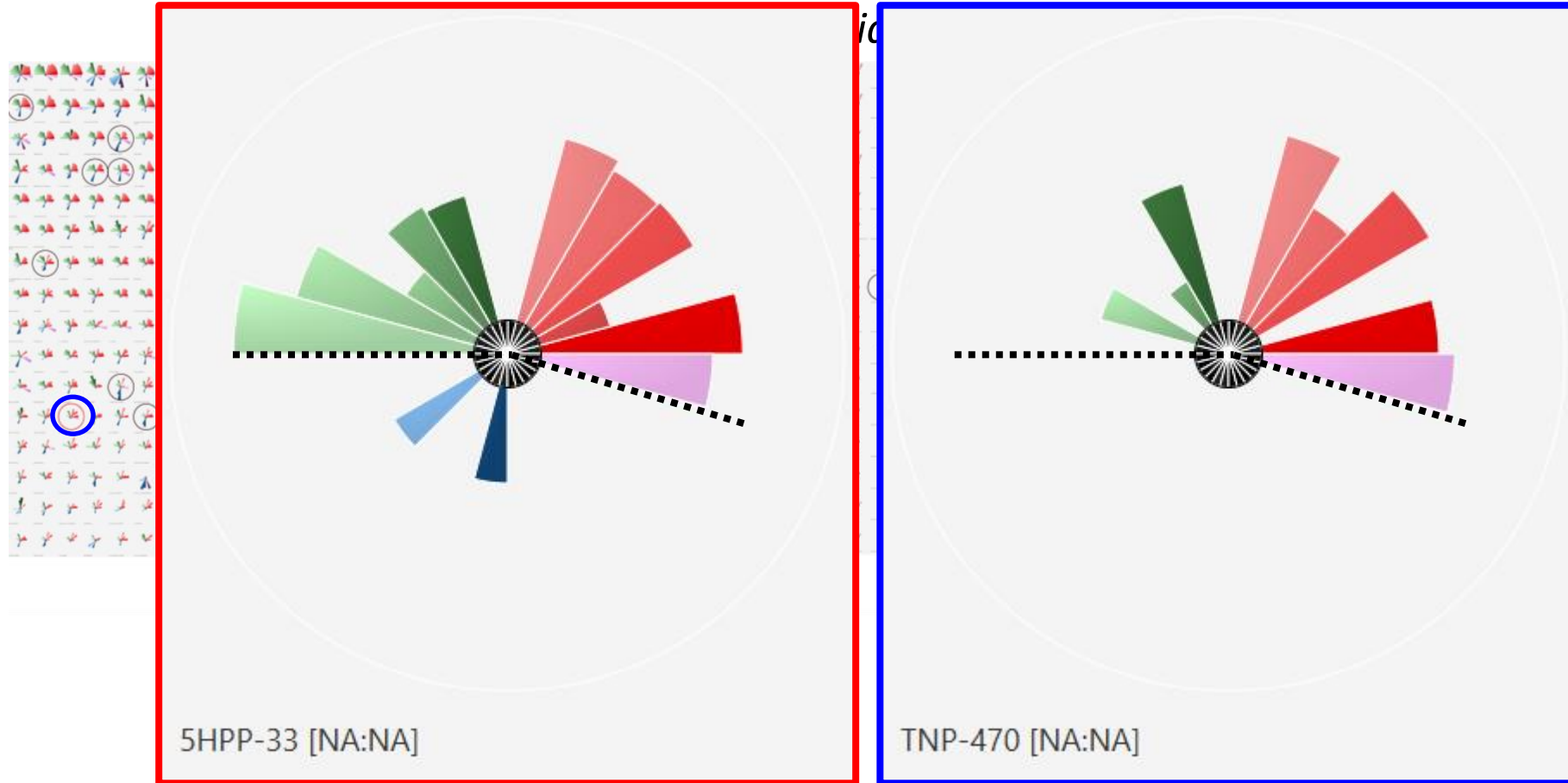
SOURCE: Knudsen and Kleinstreuer (2011) Birth Defects Res

AOP-based ranking: predicted vascular disrupting chemicals (pVDCs)

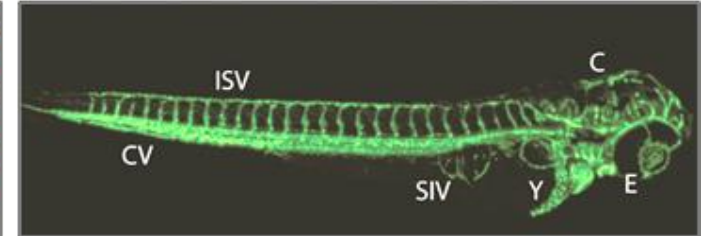
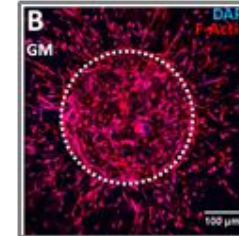
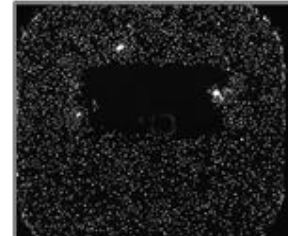
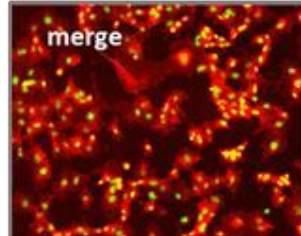
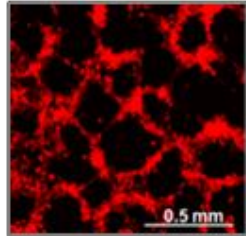
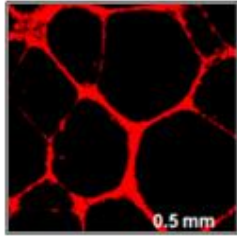
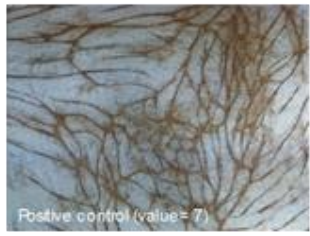
24 ToxCast target assays
(pVDC ToxPi)



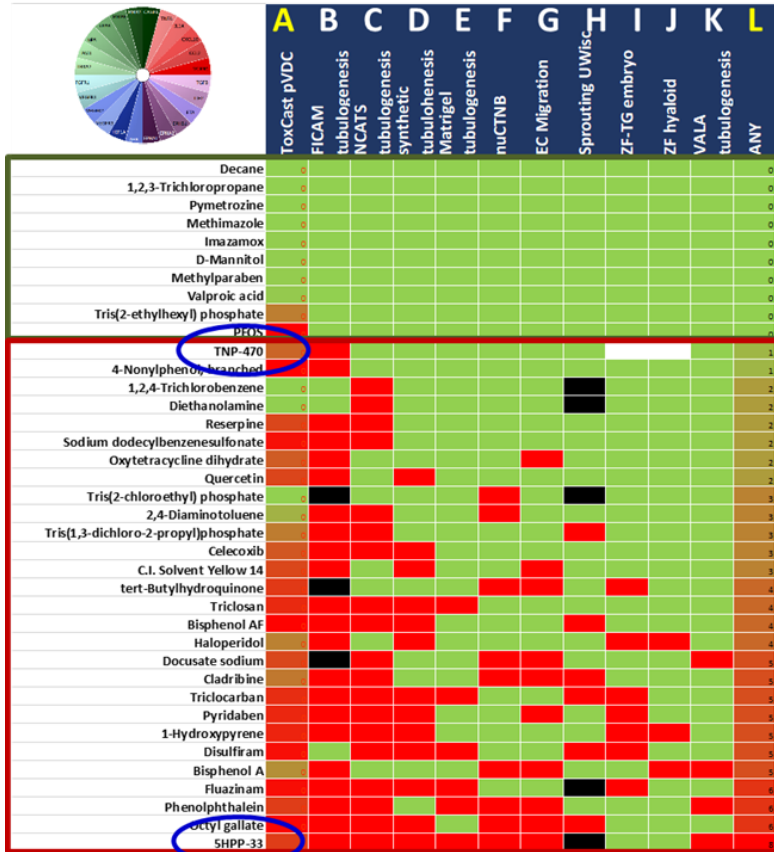
1058 ToxCast chemicals ranked by pVDC ToxPi



SOURCE: Kate Saili, NCCT



- inactive
- active
- cytotoxic
- no data



A pVDC ToxPi

B HUVEC tubulogenesis (FICAM)

C HUVEC tubulogenesis (NCATS)

D tubulogenesis in synthetic matrices (HMAPS)

E tubulogenesis in Matrigel (HMAPS)

F nuCTNB biomarker (VALA)

G endothelial cell migration (VALA)

H iPSC endothelial sprouting (HMAPS)

I ISV reporter zebrafish (NHEERL)

J reporter zebrafish (UDUBLIN)

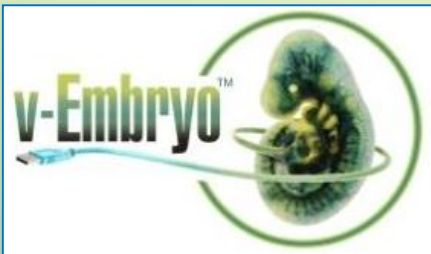
K HUVEC tubulogenesis (VALA)

L ANY (B to K)

sensitivity 0.89, specificity 0.80
balanced accuracy 87% (PPV 93%, NPV 73%)

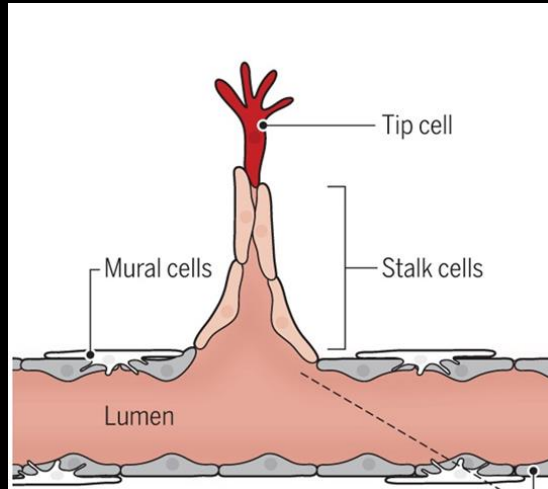
SOURCE: Sali et al. (submitted)

Virtual Tissue Models (VTM): computer simulation and biomimetic systems



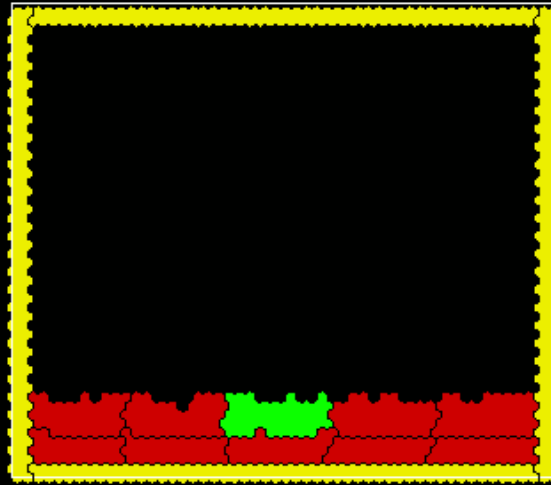
Objective: build and test computer models of complex tissues that advance critical phenomena (specificity, canalization, plasticity) for quantitative prediction for virtual screening and *in silico* testing.

Computer simulation: cell agent-based models (cABMs)



Li and Carmeliet (2018) Science

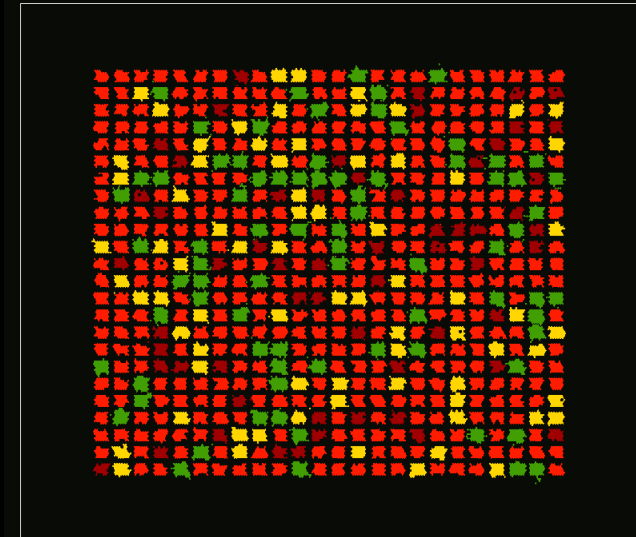
VEGF corridors



Nicole Kleinstreuer



VEGF165
MMPs
VEGF121
sFlit1
TIE2
CXCL10
CCL2

Network assembly

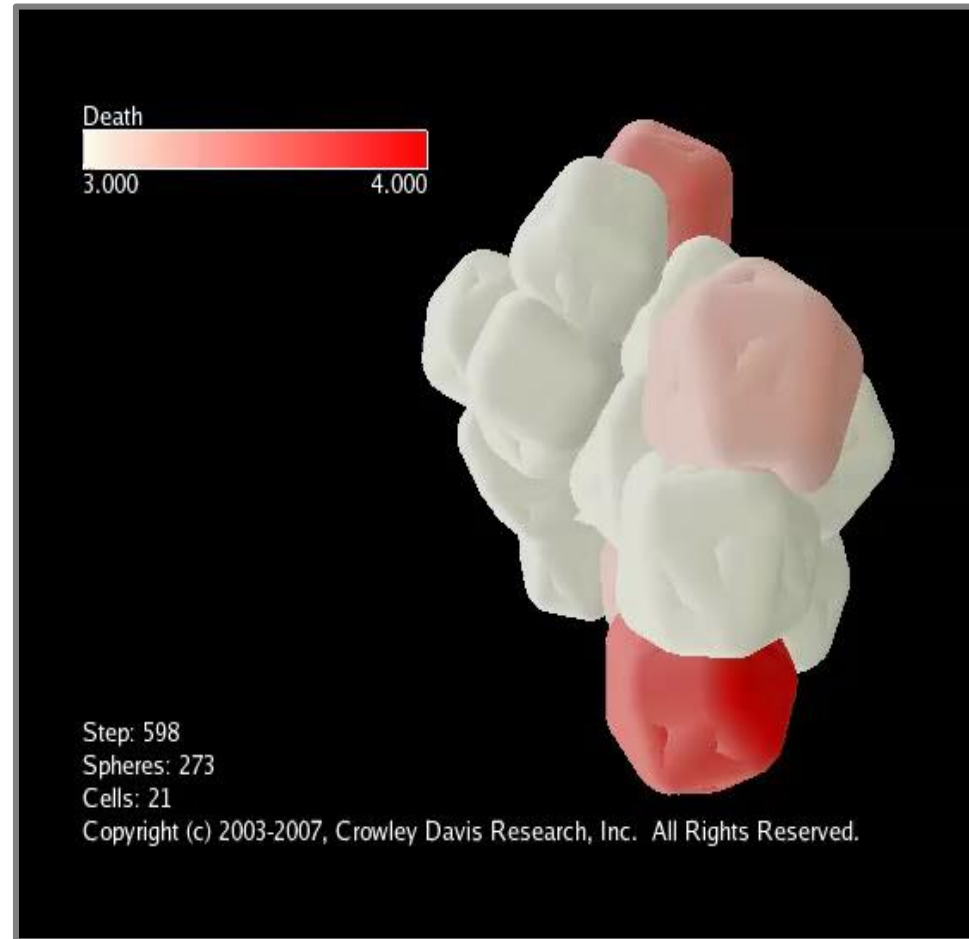


Kleinstreuer et al. (2013) PLoS Comp Biol

SOFTWARE: www.compuCell3d.org
BioComplexity Institute, Indiana U

-  **Endothelial Stalk**
-  **Endothelial Tip**
-  **Mural Cell**
-  **Inflammatory Cell**

Anatomical homeostasis in a self-regulating 'Virtual Embryo'



*SOURCE: Andersen, Newman and Otter
(2006) Am. Assoc. Artif. Intel.*

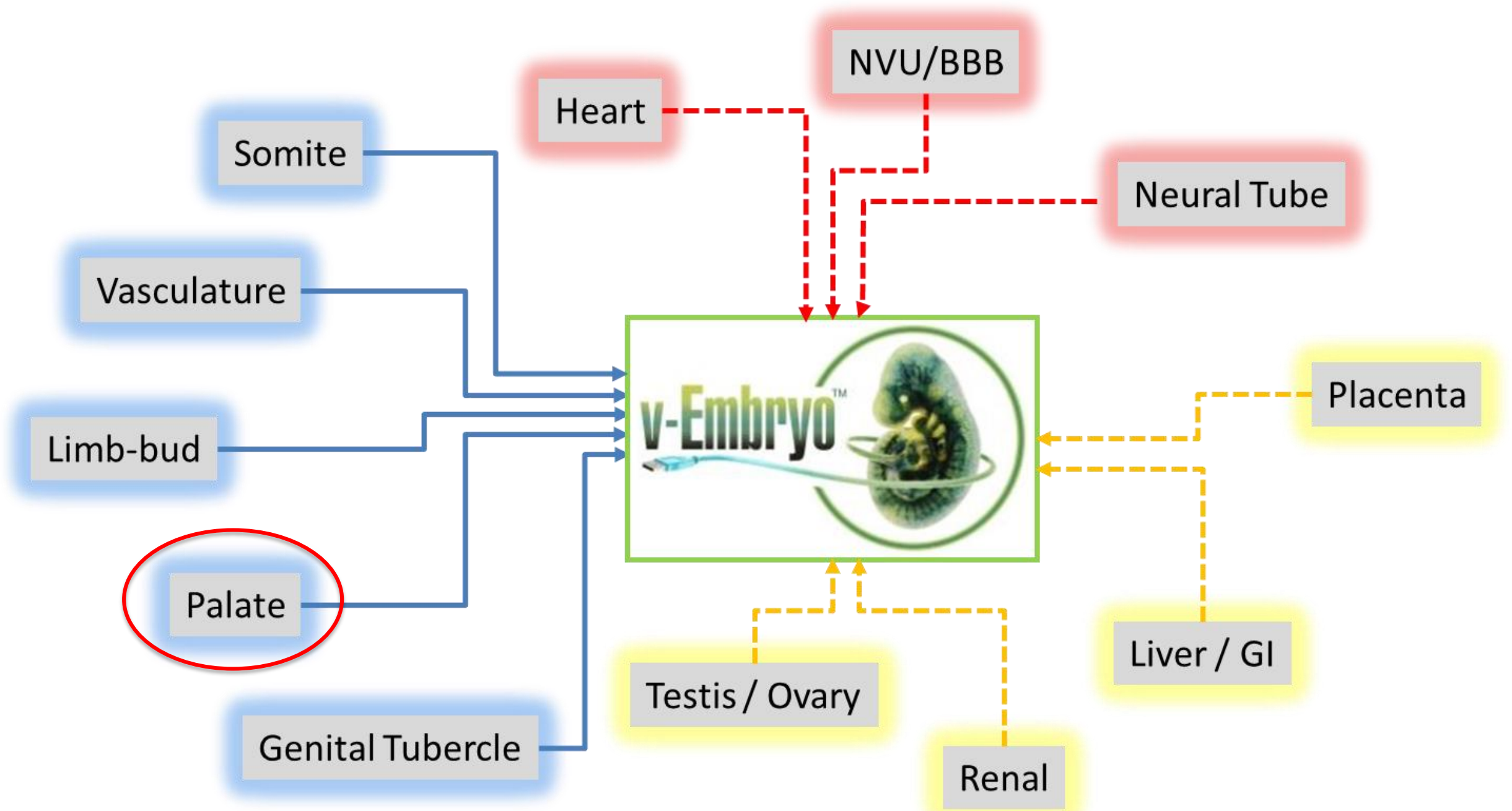
cABMs in predictive DART

Approach: build and test self-organizing morphogenetic systems *in silico* using an open-source modeling environment ([CompuCell3d.org](https://compuCell3d.org)).

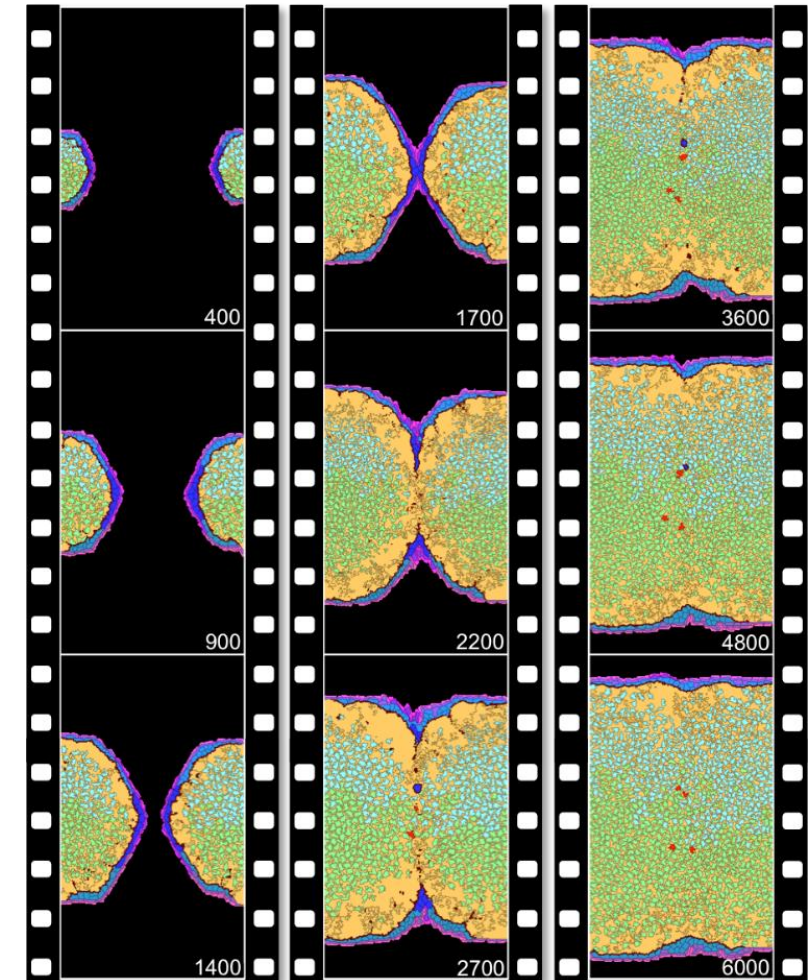
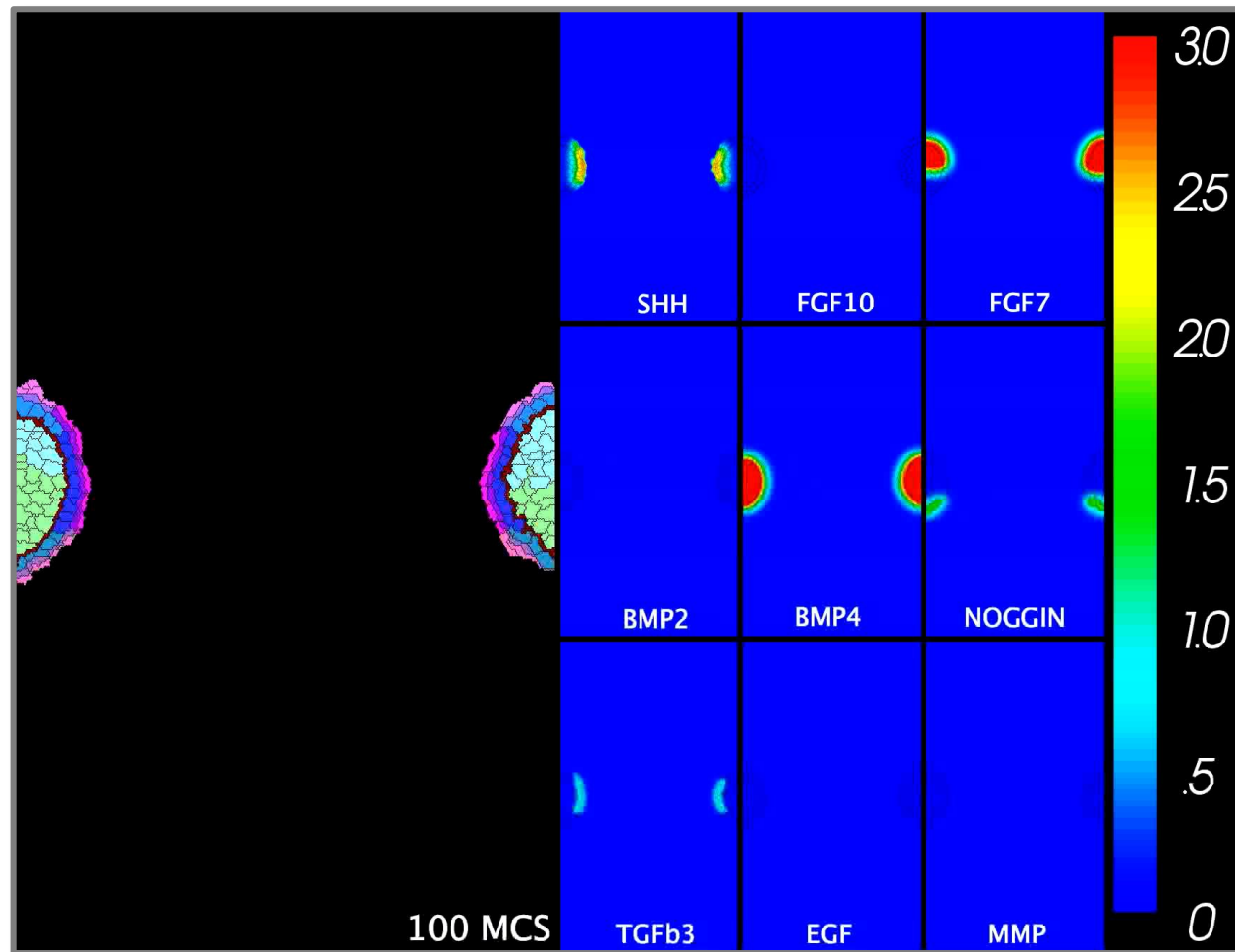
Input: A.I. cast into mathematically-defined cells (agents), synthetic gene circuits, and viscoelastic properties to emulate developmental progression ([embryogeny](#)).

Emergence: simulation resolves into normal or perturbed phenotypes reading *in vitro* data input from specific ToxCast assays ([cybermorphs](#)).

Output: probabilistic rendering of where, when and how a developmental defect might occur ([critical phenomena](#)).

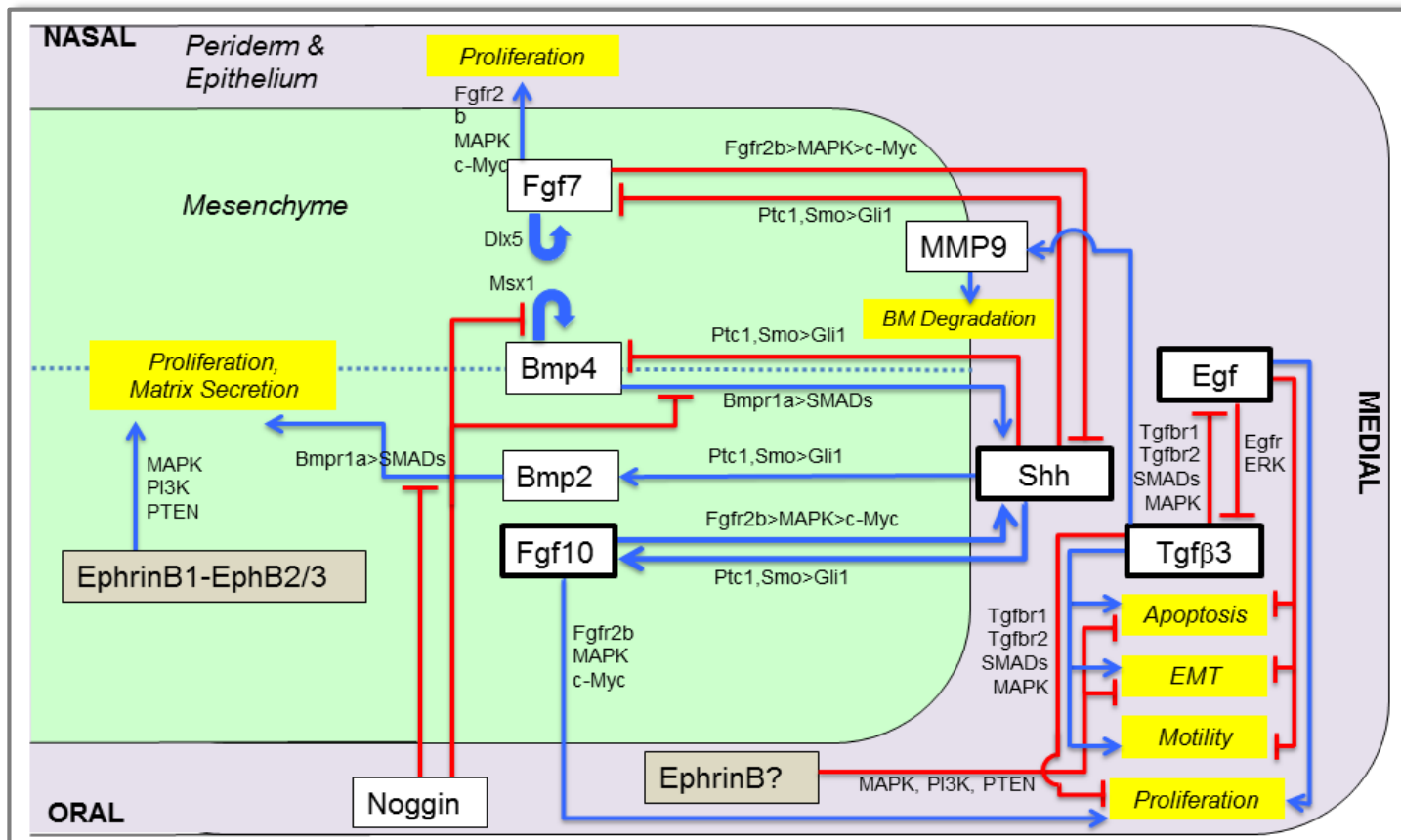


Palatal fusion: epithelial seam breakdown and mesenchymal confluence



SOURCE: Hutson et al. (2017) Chem Res Toxicol

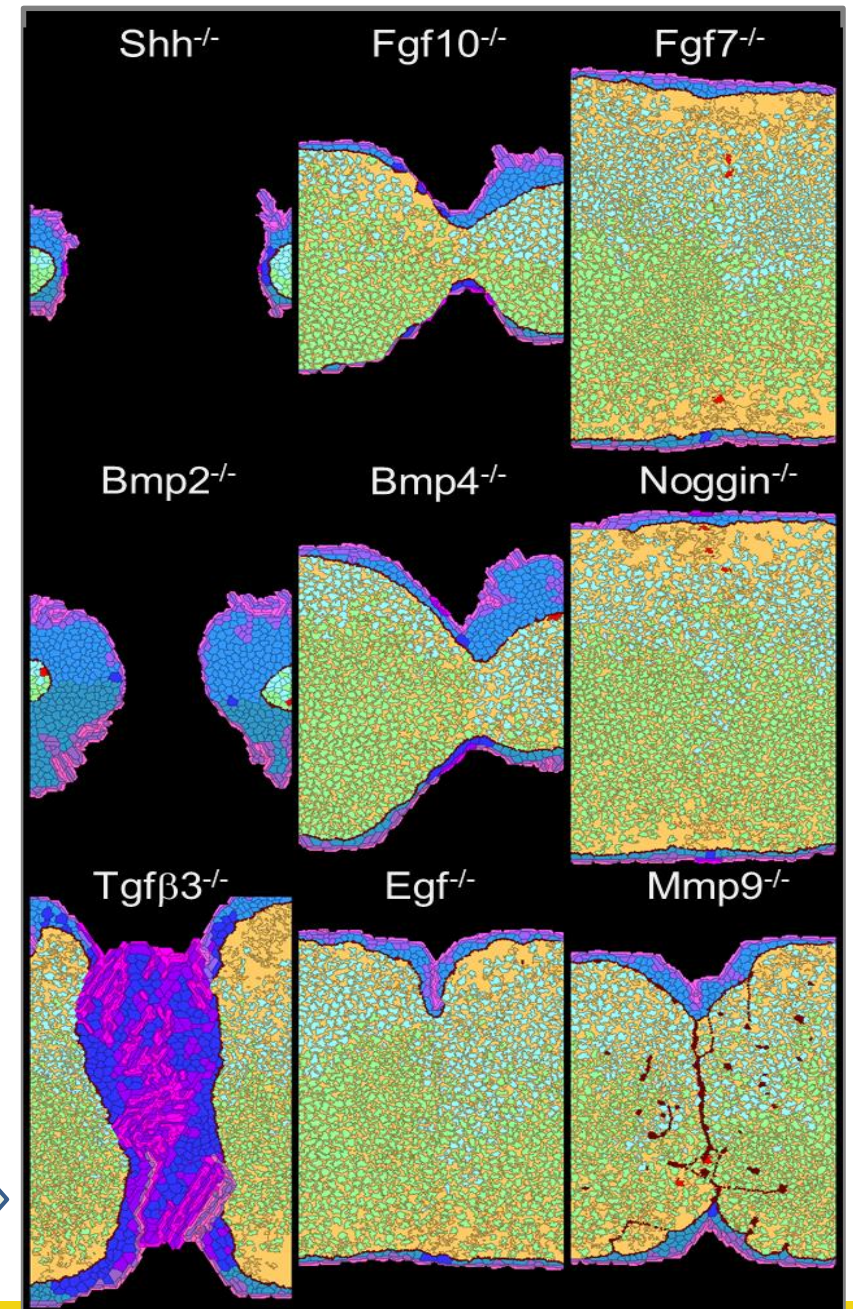
Hacking the control network



A.I. = synthetic cell signaling networks

Cybermorphs = simulated loss of function

SOURCE: Hutson et al. (2017) Chem Res Toxicol



Practical Reproductive and Developmental Toxicology

Computational Model of Secondary Palate Fusion and Disruption

M. Shane Hutson,^{*,†,‡} Maxwell C. K. Leung,[‡] Nancy C. Baker,[§] Richard M. Spencer,[§]
and Thomas B. Knudsen^{*,||,Ⓢ}

[†]Department of Physics & Astronomy, Department of Biological Sciences and Vanderbilt Institute for Integrative Biosystem Research & Education, Vanderbilt University, Nashville, Tennessee 37235, United States

*Oak Ridge Institute for Science & Education, Oak Ridge, Tennessee 37832, United States

⁵Leidos, Research Triangle Park, Durham, North Carolina 27711 United States

¹National Center for Computational Toxicology, Office of Research & Development, U.S. Environmental Protection Agency, Research Triangle Park, Durham, North Carolina 27711, United States

S Supporting Information

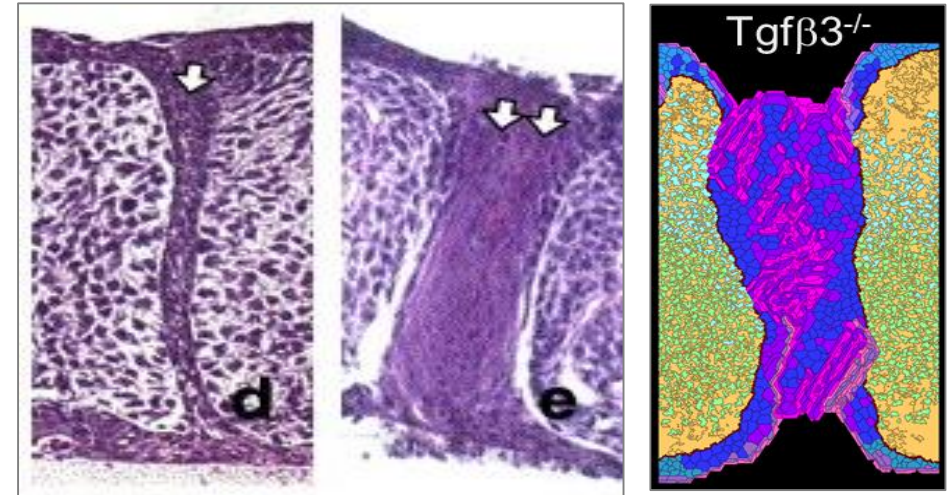
ABSTRACT: Morphogenetic events are driven by cell-generated physical forces and complex cellular dynamics. To improve our capacity to predict developmental effects from chemical-induced cellular alterations, we built a multidisciplinary agent-based model in CompuCell3D that recapitulates the cellular networks and collective cell behavior underlying growth and fusion of the mammalian secondary palate. The model incorporated multiple signaling pathways (TGF β , BMP, FGF, EGF, and SHH) in a biological framework to recapitulate morphogenetic events from palatal outgrowth through midline fusion. It effectively simulated high-level phenotypes (e.g., midline contact, medial edge seam (MES) breakdown, mesenchymal confluence, and fusion defects) in response to genetic or environmental perturbations. Perturbation analysis

of various contact features revealed model functionality with respect to cell signaling systems and feedback loops for growth and fusion, dense individual cell behaviors and collective cellular behavior leading to physical contact and midline fusion, and quantitative analysis of the TGF/EGF switch that controls MBS breakdown—a key event in morphogenetic fusion. The virtual palate model was then constructed with theoretical chemical perturbation scenarios to simulate switch behavior leading to a disruption of the TGF/EGF chronic (e.g., desin) and acute (e.g., retinoic acid) chemical exposures. This computer model adds to existing systems models of palate development and provides a platform for simulation and quantitative prediction of adverse effects of chemical exposures on palate development. The model was used to predict the effects of chemical exposures on palate development and to identify potential mechanisms of action for adverse effects of chemical exposures on palate development. The model was used to predict the effects of chemical exposures on palate development and to identify potential mechanisms of action for adverse effects of chemical exposures on palate development.

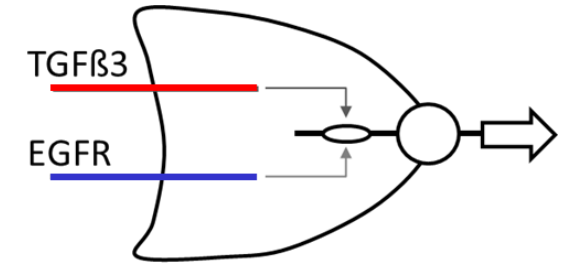
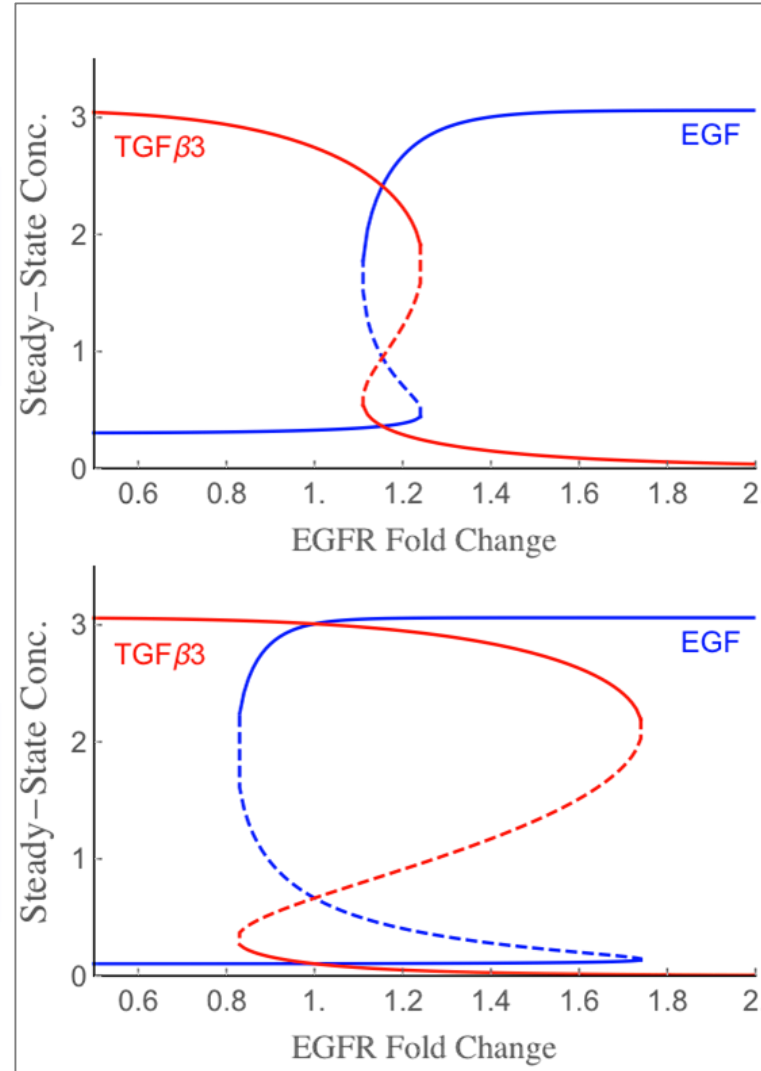
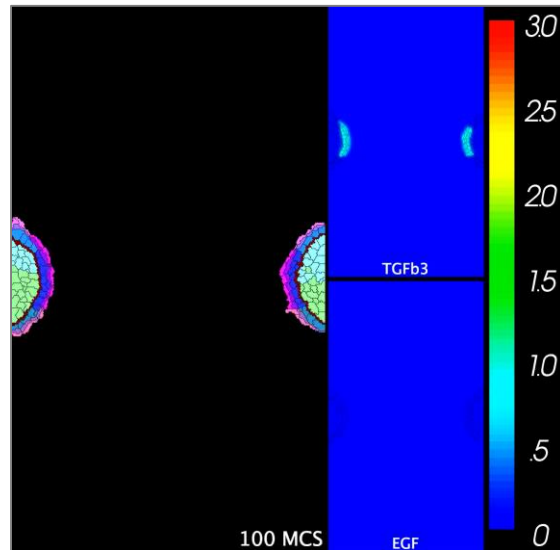
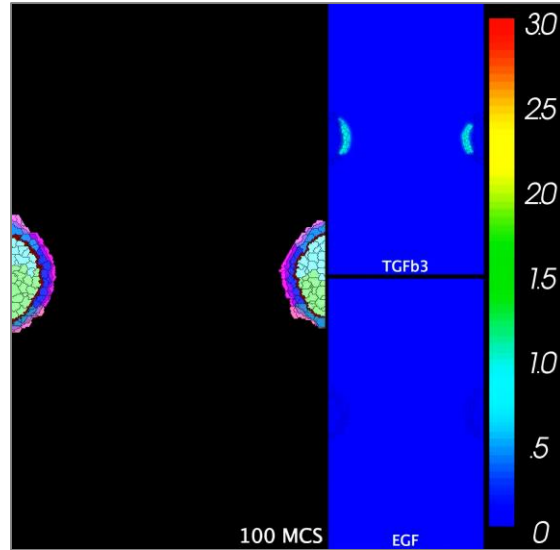
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Reviewer Comment: “Crucial mechanisms occurring during palate fusion, especially opposing palatal shelf adhesion, are not considered in the model. In fact, the main reason why Tgf-b3 KO mice have cleft palate is a failure of opposing MEE adhesion, leading to separation of palatal shelves after their initial contact. Even in those strains in which palatal shelves adhere partially, I have never seen a MES as the one shown in Fig. 5.”

Our Response: TGF- β 3 knockout mouse palates transduced with ALK vectors *in vitro*. (from Dudas et al. 2004).



Messin' with the switch: *two scenarios for bistable switch dynamics*



1. Narrow hysteresis:
less resilient but reversible

2. Broad hysteresis:
more resilient but irreversible

ToxCast dataset

ChemicalName	FR_up	FR_down	1_down	b1_down	ToxRefDB
Methylene bis(thiocyanate)	1.14	2.13	5.93	4.26	NEG
Zoxamide	14.22	1.85	17.37	9.69	NEG
2-(Thiocyanomethylthio)benzothiazole	2.28	1.54	6.48	7.21	NEG
Diphenylamine	32.71	1.49	5.95	1.63	NEG
Azamethiphos	0.89	1.81	1000.00	1000.00	NEG
Bromacil	20.50	1.57	1000.00	1000.00	NEG
Forchlorfenuron	0.02	1.53	1000.00	1000.00	NEG
Methyl isothiocyanate	4.60	1.44	1000.00	1000.00	NEG
Diuron	16.51	1.44	1000.00	1000.00	NEG
Rotenone	0.82	1.42	1000.00	1000.00	NEG
Captan	4.59	2.57	7.15	7.25	POS
Triflumizole	32.71	2.48	19.88	19.88	POS
Butachlor	32.71	2.47	17.85	17.85	POS
Captafol	1.02	2.20	3.76	3.25	POS
Thiram	4.45	1.96	6.95	5.38	POS
Raloxifene hydrochloride	12.40	1.91	15.94	10.94	POS
Fluazinam	2.39	1.61	2.48	4.84	POS
Carbaryl	0.07	1.55	1000.00	1000.00	POS
Linuron	10.91	1.46	1000.00	1000.00	POS
Maneb	0.01	1.46	1000.00	1000.00	POS
Bendiocarb	8.75	1.43	1000.00	1000.00	POS
Fipronil	1.18	1.43	1000.00	1000.00	POS
Propoxur	1.67	1.43	1000.00	1000.00	POS
TNP-470	7.78	1.57	3.97	3.61	x
1-(2,3,8,8-Tetramethyl-1,2,3,4,5,6,7,8-octal	8.33	2.10	9.74	1.88	x
Trimethylolpropane triacrylate	2.02	1.80	5.17	1.41	x
Dilodomethyl 4-methylphenyl sulfone	3.15	1.77	3.74	17.68	x
1,2-Benzisothiazolin-3-one	8.22	1.74	11.91	14.70	x
Tralopyril	18.30	1.68	0.87	1.08	x
Bis(trichloromethyl)sulfone	1.95	1.61	4.49	5.74	x
N,N,N-Trimethyloctadecan-1-aminium chl	2.22	1.56	1.77	1.45	x
beta-Nitrostyrene	7.12	1.52	2.01	2.34	x
4,5-Dichloro-3H-1,2-dithiol-3-one	2.71	1.47	6.42	6.56	x
Tri-o-cresyl phosphate	8.95	1.45	9.54	1.56	x
Isobornyl methacrylate	13.66	1.44	21.86	1.97	x
SAR102779	0.05	1.43	12.95	14.97	x
PharmaGSID_48511	12.19	1.37	11.22	17.33	x
Perfluoroundecanoic acid	6.81	1.35	4.76	5.04	x
FR167356	17.65	2.06	1000.00	1000.00	x
Monobutyl phthalate	0.01	1.35	1000.00	1000.00	x
Niclosamide	0.58	2.14	1000.00	1000.00	x
Tripropylene glycol diacrylate	26.52	2.09	1000.00	1000.00	x
CP-457920	3.50	1.92	1000.00	1000.00	x
Trimethylolpropane trimethacrylate	32.85	1.81	1000.00	1000.00	x
alpha-Terpinyol acetate	39.18	1.64	1000.00	1000.00	x
3-(4-tert-Butylphenyl)-2-methylpropanal	35.26	1.62	1000.00	1000.00	x
1,4-Dinitrobenzene	2.95	1.54	1000.00	1000.00	x
S8281832	34.72	1.54	1000.00	1000.00	x
2-(Morpholin-4-ylidithio)-1,3-benzothiazol	5.61	1.52	1000.00	1000.00	x
Tolclofos-methyl	7.71	1.49	1000.00	1000.00	x
1,1':3',1''-Terphenyl	11.98	1.38	1000.00	1000.00	x
Estrone	0.03	1.35	1000.00	1000.00	x

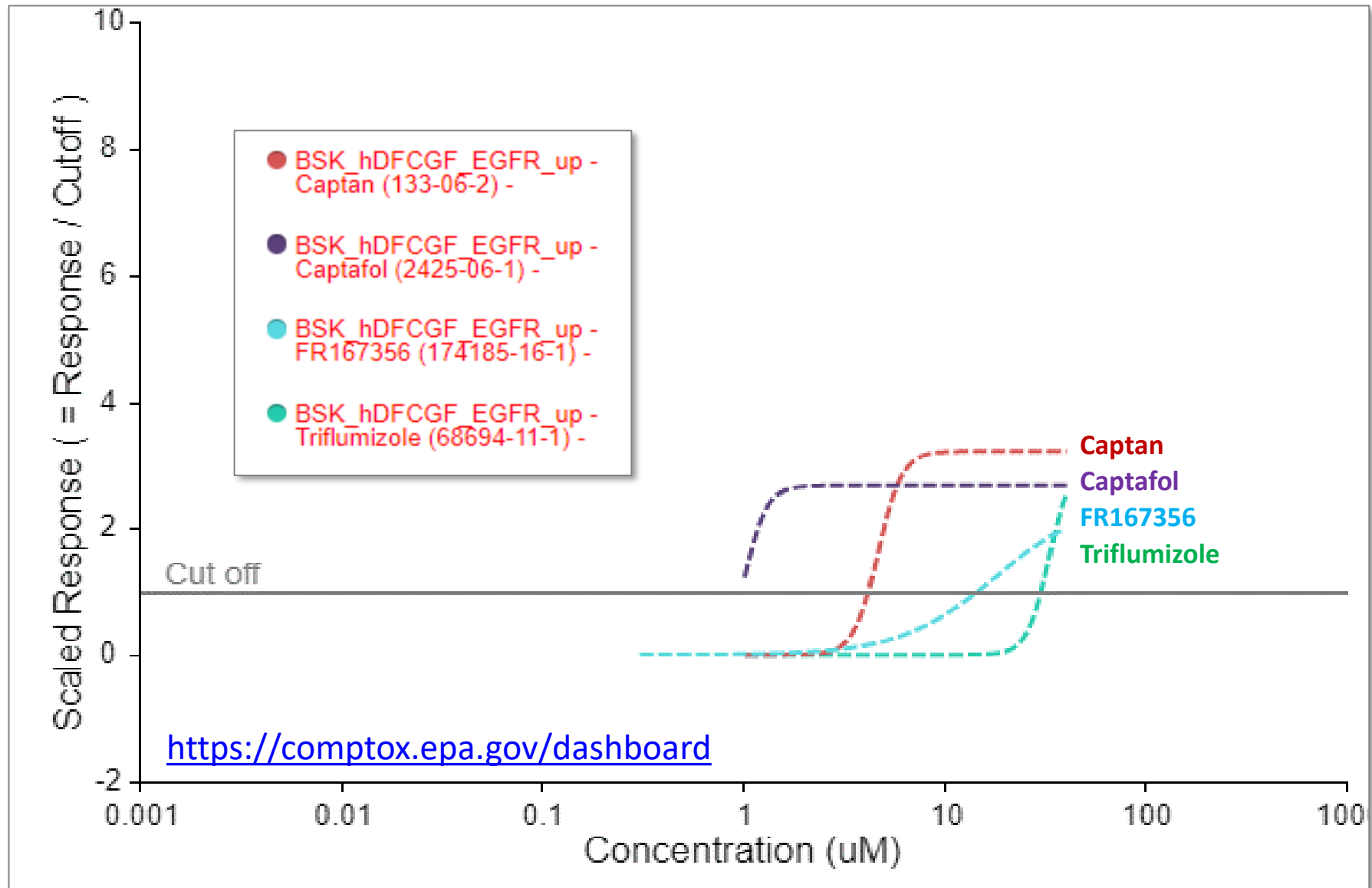
\uparrow EGFR
 μ M effect in vitro
 \downarrow TGF β 1
AC50 top AC50 top DevTox

Captan	4.59	2.57	7.15	7.25	POS
Triflumizole	32.71	2.48	19.88	19.88	POS
Butachlor	32.71	2.47	17.85	17.85	POS
Captafol	1.02	2.20	3.76	3.25	POS
Thiram	4.45	1.96	6.95	5.38	POS
Raloxifene hydrochloride	12.40	1.91	15.94	10.94	POS
Fluazinam	2.39	1.61	2.48	4.84	POS

- 54 chemicals \uparrow EGFR density
- some also \downarrow TGF-beta signaling

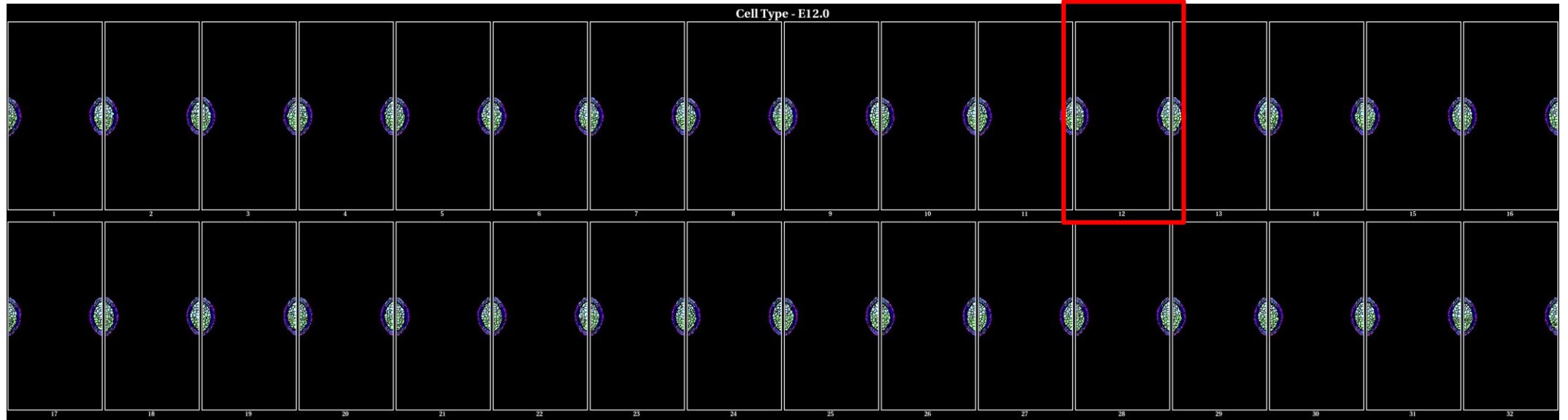
- negative for developmental toxicity in ToxRefDB
- positive for developmental toxicity in ToxRefDB
- no developmental toxicity data in ToxRefDB

EGFR signaling: ↑ immunoreactivity relative to DMSO

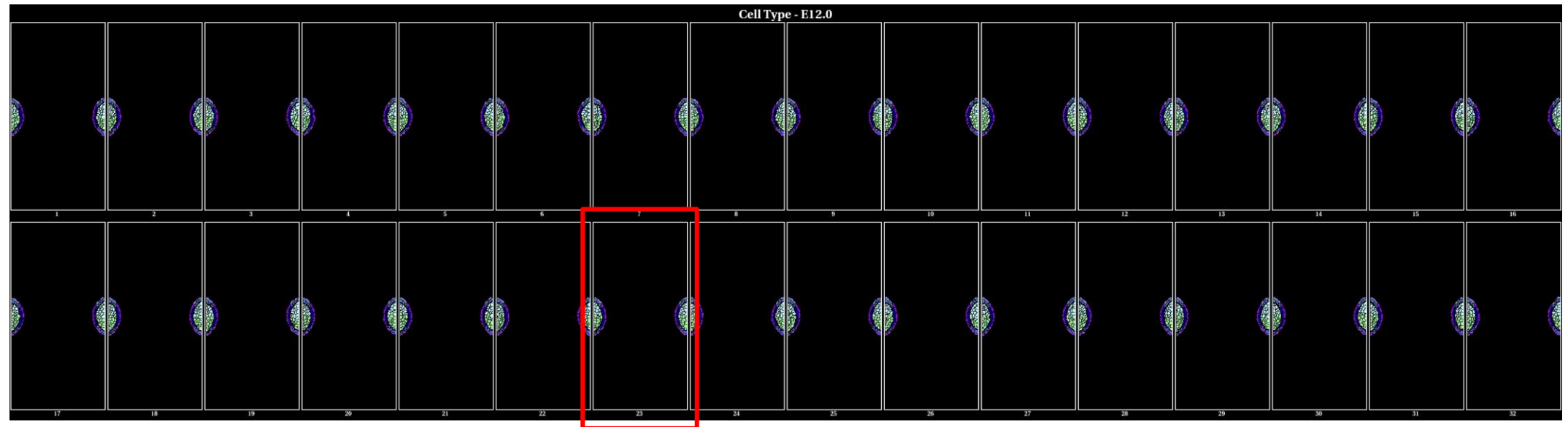


***In silico* dose-response:** \uparrow EGFR conc. response in topological context

Captan

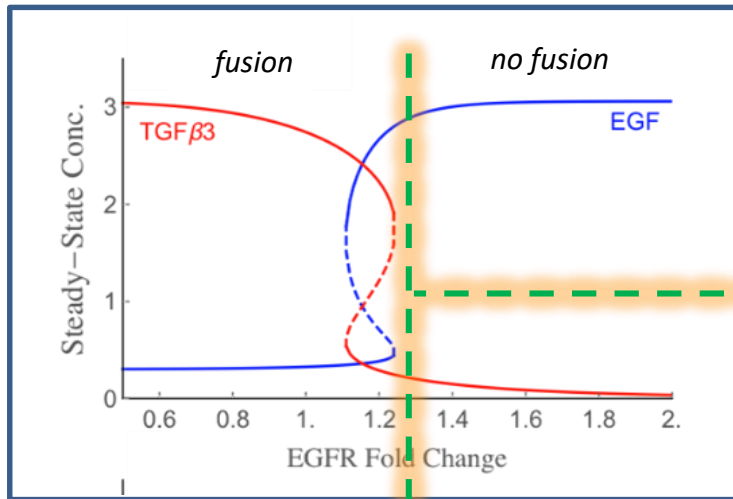


FR167356



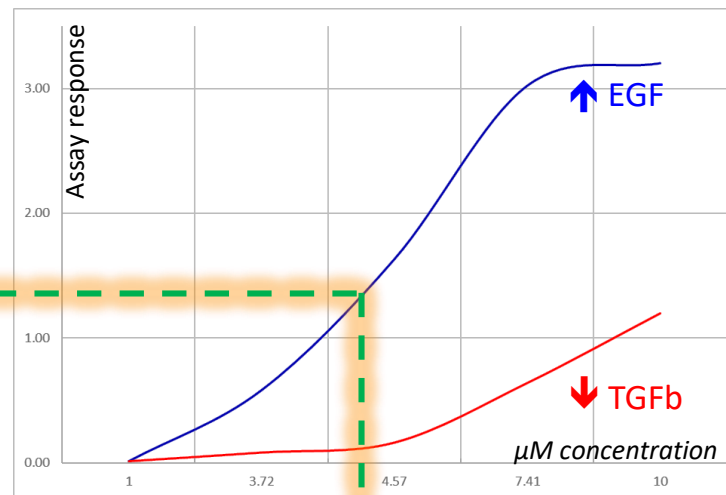
Predictive model: critical phenomenon

INPUT: switch dynamics



tipping point predicted by
computational dynamics
(hysteresis switch)

Captan in ToxCast



OUTPUT: tipping point
mapped to concentration
response (4 μM)

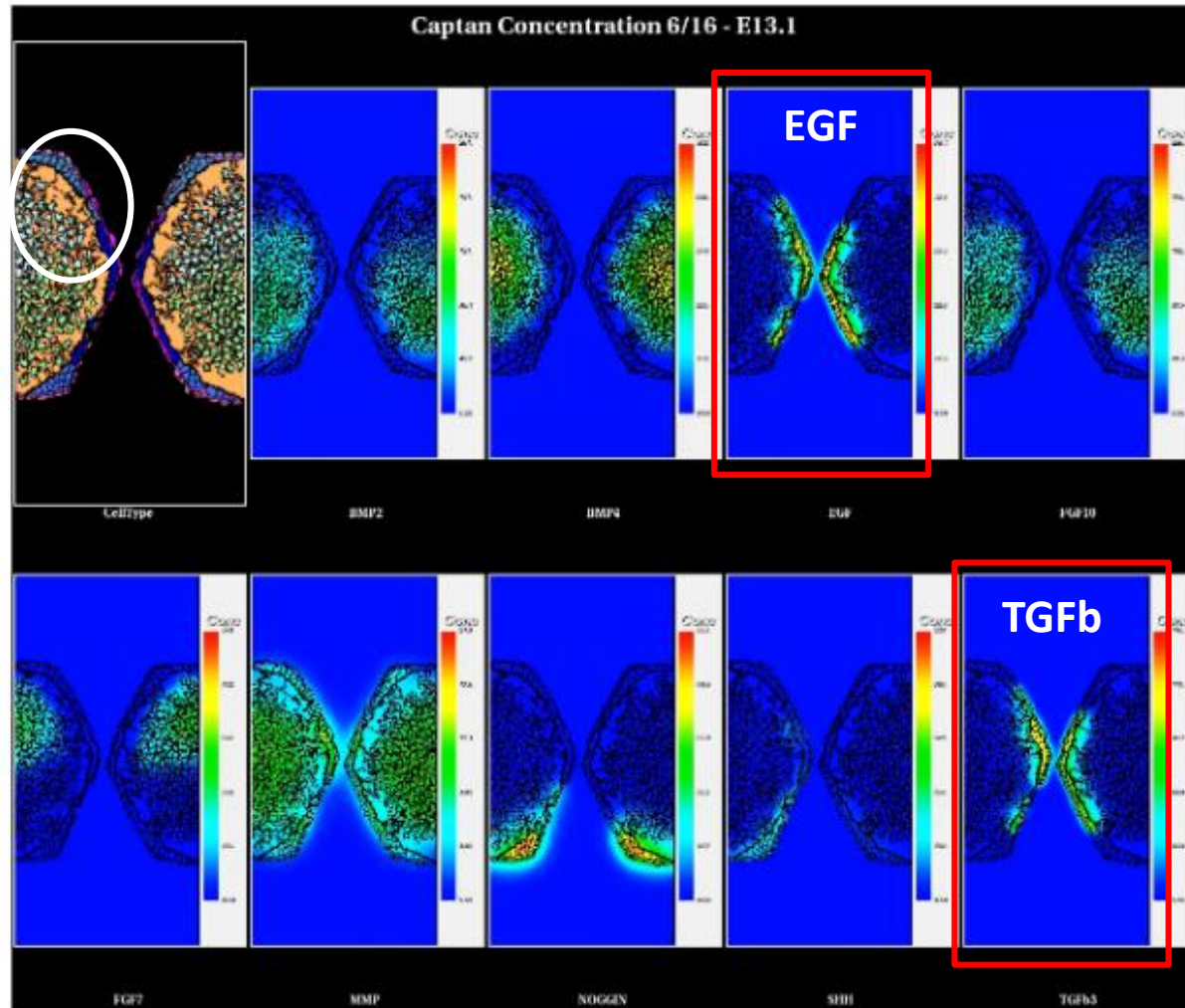
Captan in ToxRefDB
NOAEL = 10 mg/kg/day
LOAEL = 30 mg/kg/day

human HTTK model
2.39 mg/kg/day would
achieve a steady state of
4 μM in fetal plasma

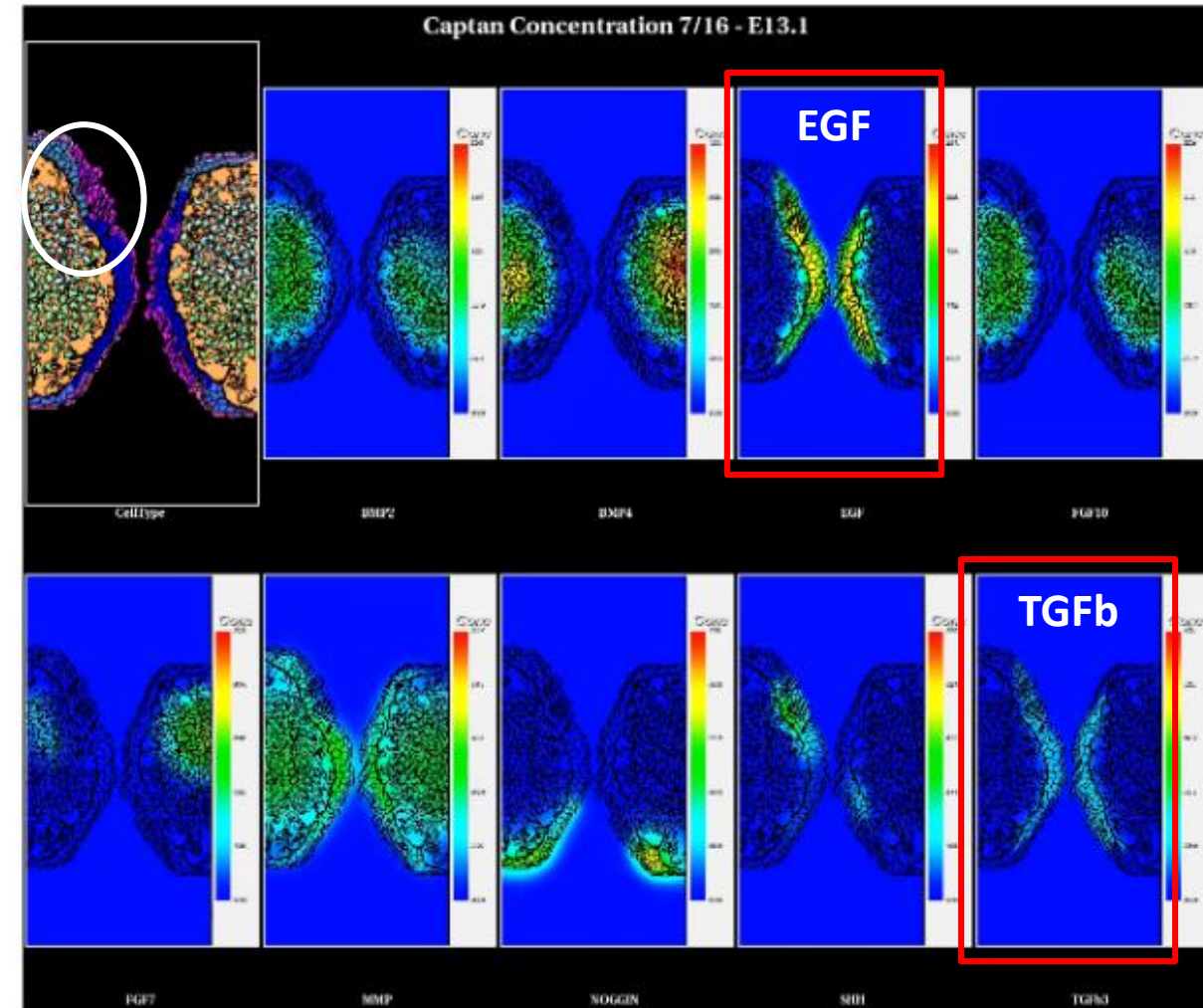
CompTox exposure prediction
 0.88×10^{-7} mg/kg/day

Pathogenesis: simulating the perfusion alterations

pre-critical dose



post-critical dose



Cleft palate: multiple mechanisms inferred from ToxCast



ToxCast Chemicals

summarized by ToxCast gene score and chemotype for machine-learning

Animal studies

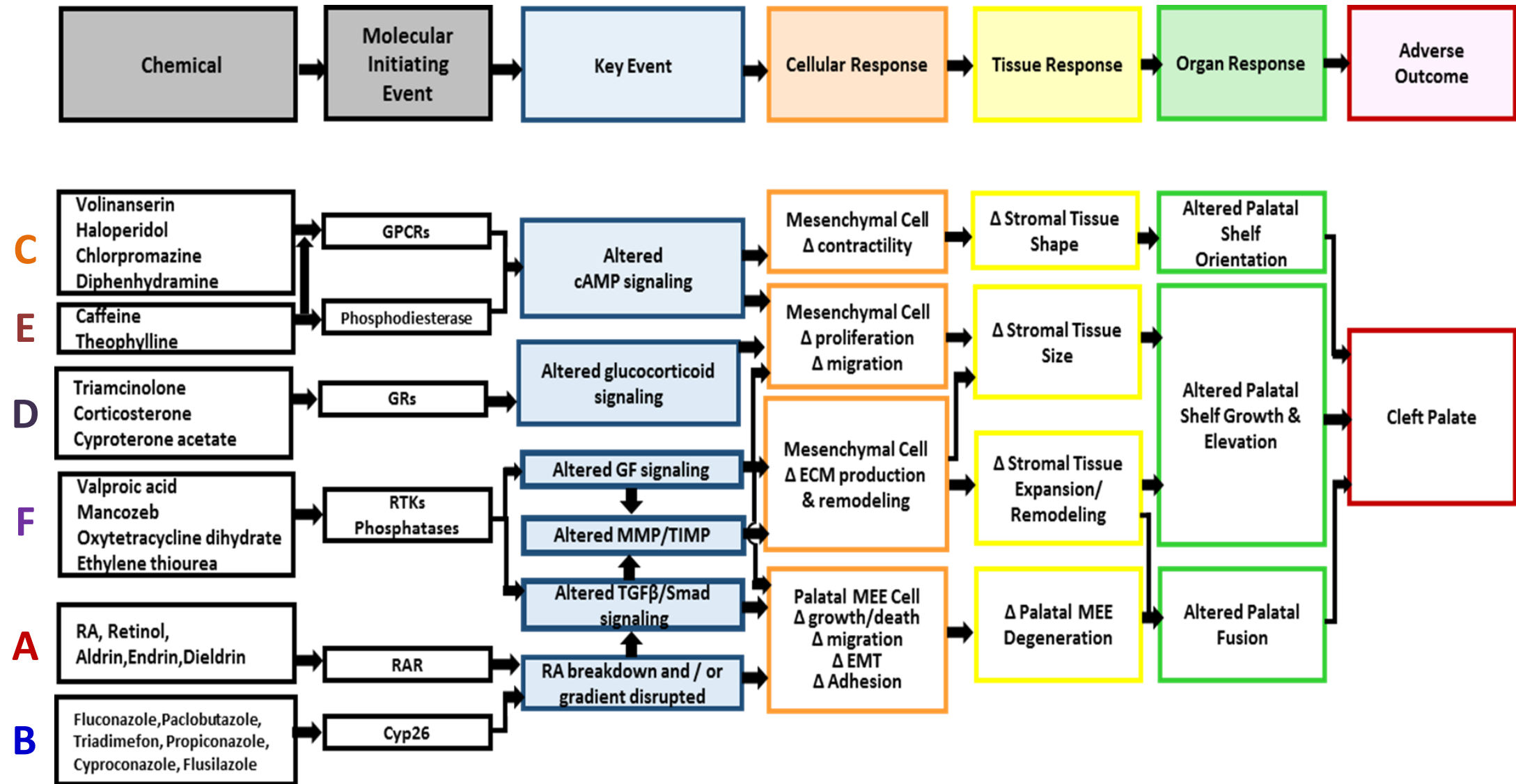
63 of 500 chemicals associated with cleft palate in ToxRefDB or biomedical literature

AOP clusters

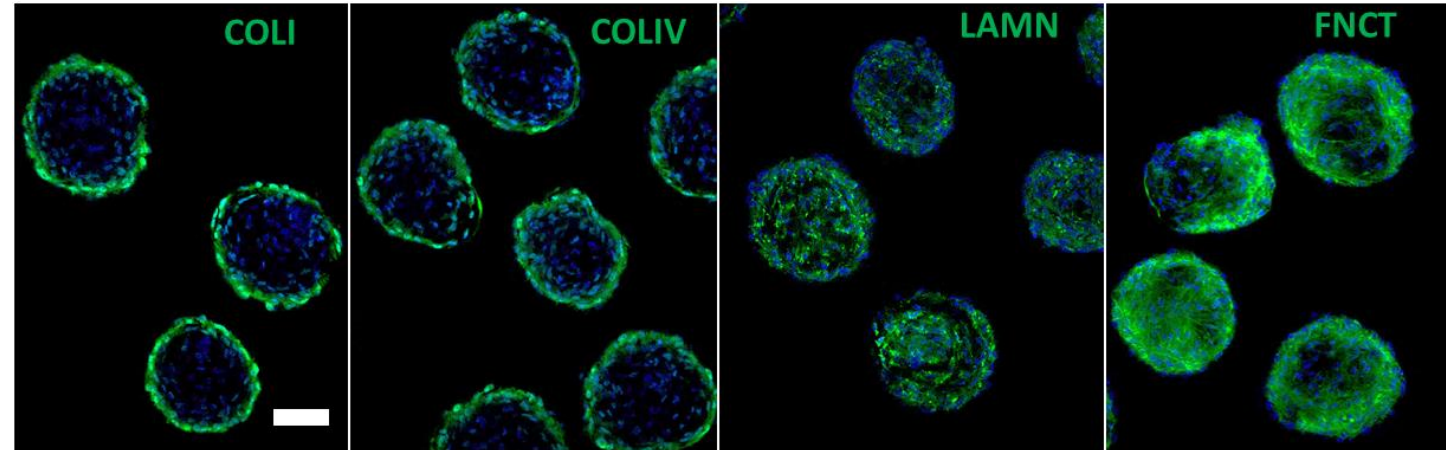
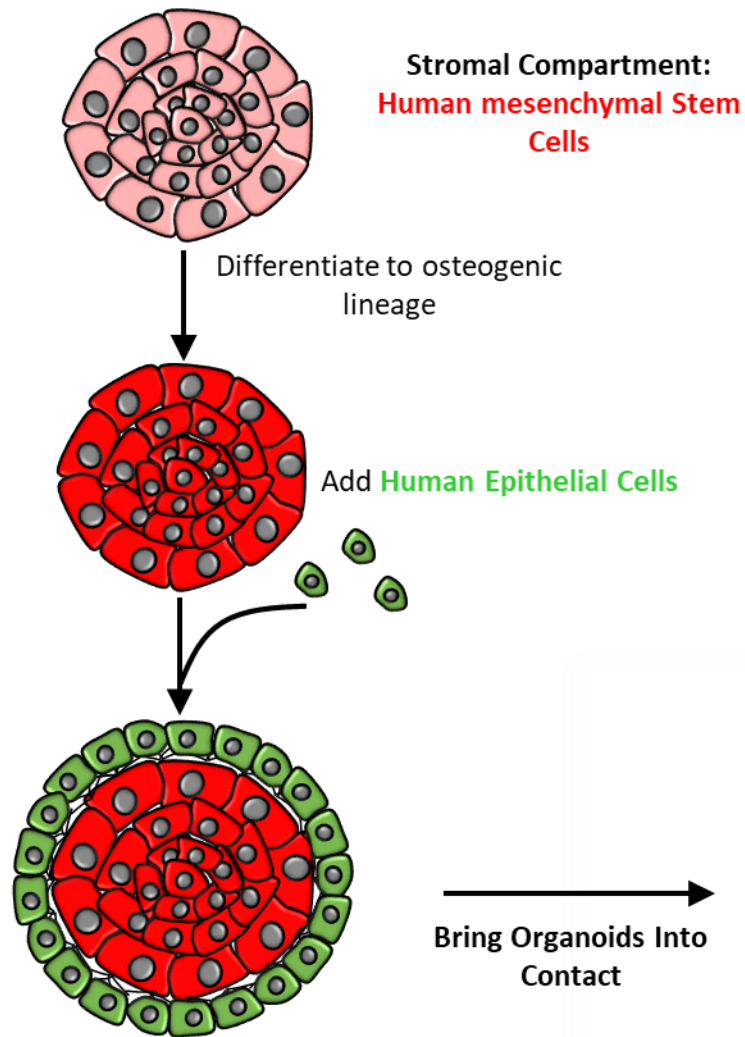
6 mechanistic pathways inferred from integration of HTS data with chemical structure.

SOURCE: Baker et al. (manuscript)

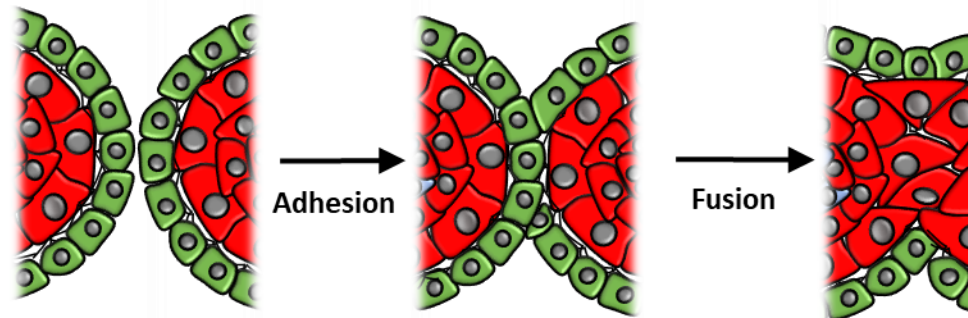
AOP clusters: inferred from chemical structure-bioactivity profiles



Fusion-competent organoids



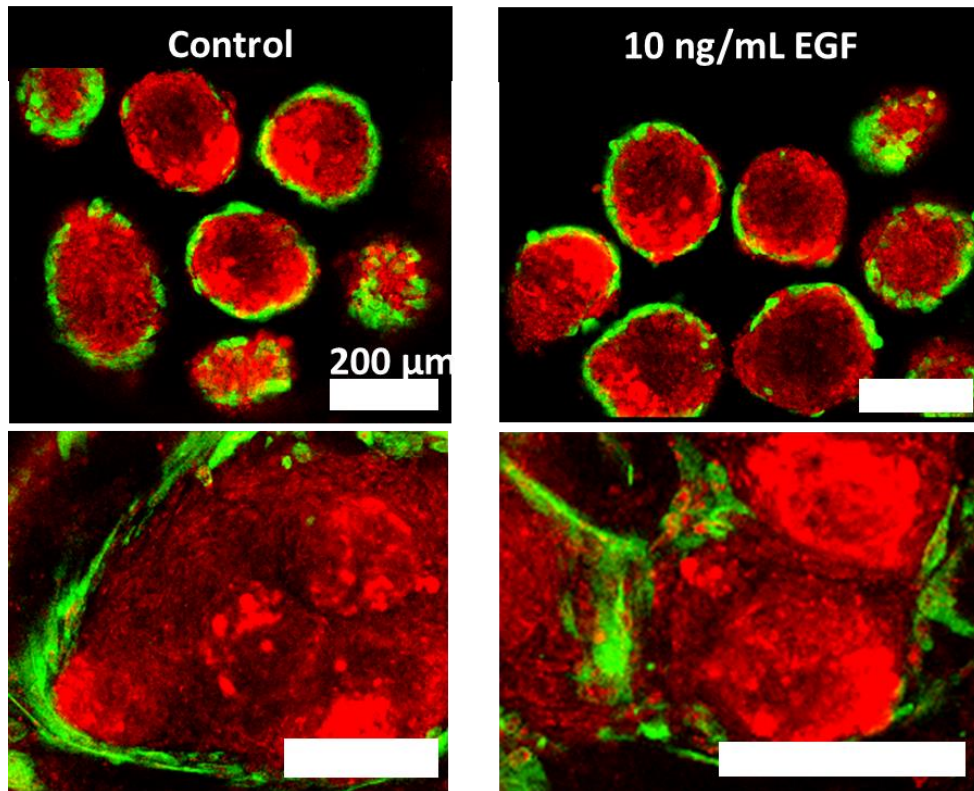
In Vitro Fusion



Monitor Adhesion and Fusion of
Mesenchymal/**Epithelial** Organoids

SOURCE: Belair et al. (2018) *Toxicol Sci*

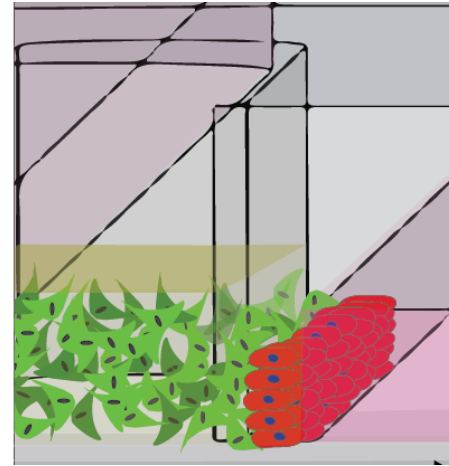
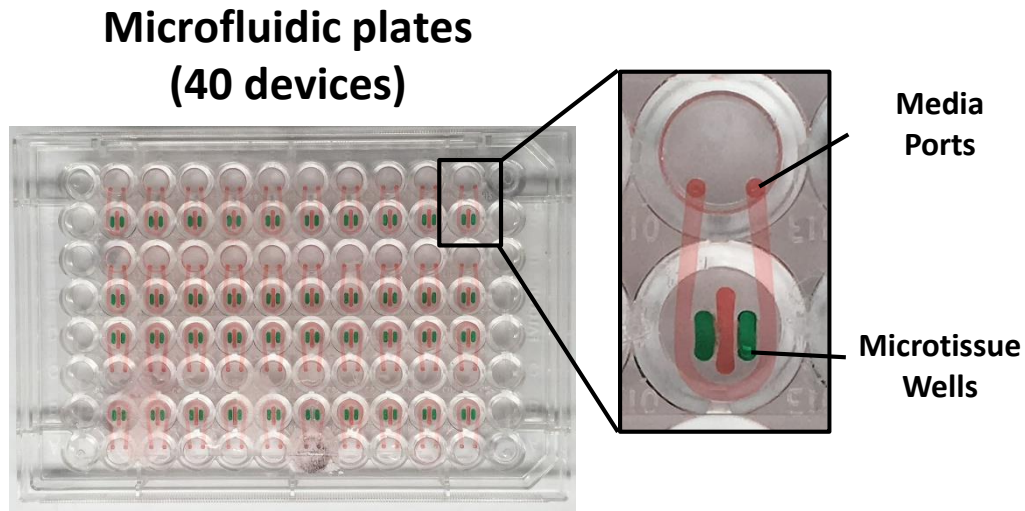
Fusion is delayed by excessive EGF Signaling



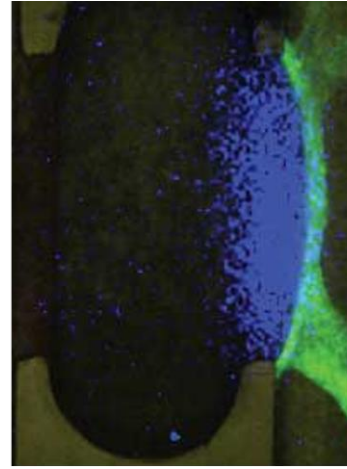
Chemical	Perturbation Days 0-2	Perturbation Days 0-4	Cytotoxicity
TCDD			
All-Trans Retinoic Acid (ATRA)		✓	✓
Dexamethasone			
Corticosterone			
Triamcinolone		✓	
Valproic Acid	✓		
Fluconazole			
Caffeine			
Nicotine			
Tributyltin	✓	✓	✓
Triadimefon			
Theophylline	✓		

- 2,400 spheroids per batch (120 wells per week) to assess tissue fusion in a human cell-based system.
- Process is sensitive to pharma compounds acting on various pathways (EGF, IGF, FGF, HGF, BMP);
- Sensitive to chemicals (ATRA, TBT, VPA, Theophylline, Triamcinolone) via viability or epithelial migration.

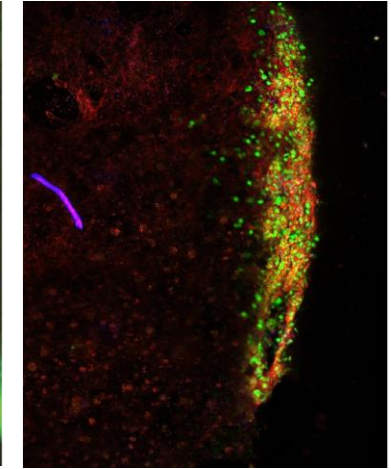
Microphysiological system: reverse-engineering E/M interactions during outgrowth



Gli-luciferase

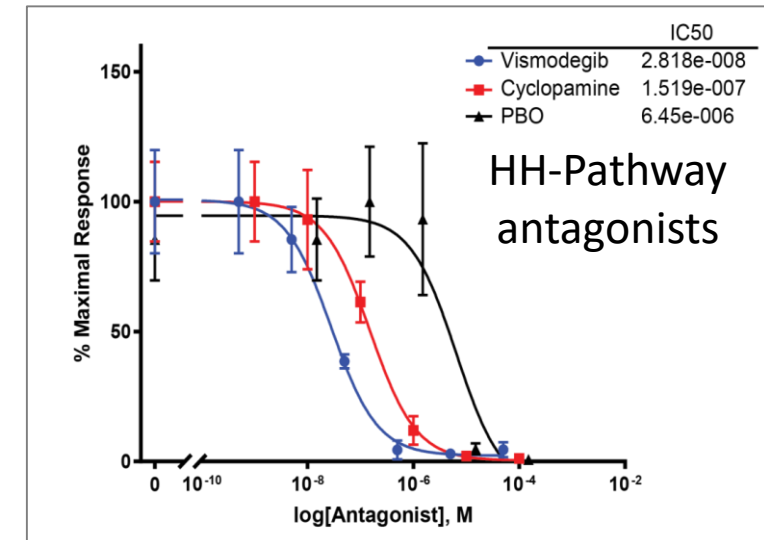


Ki67 proliferation

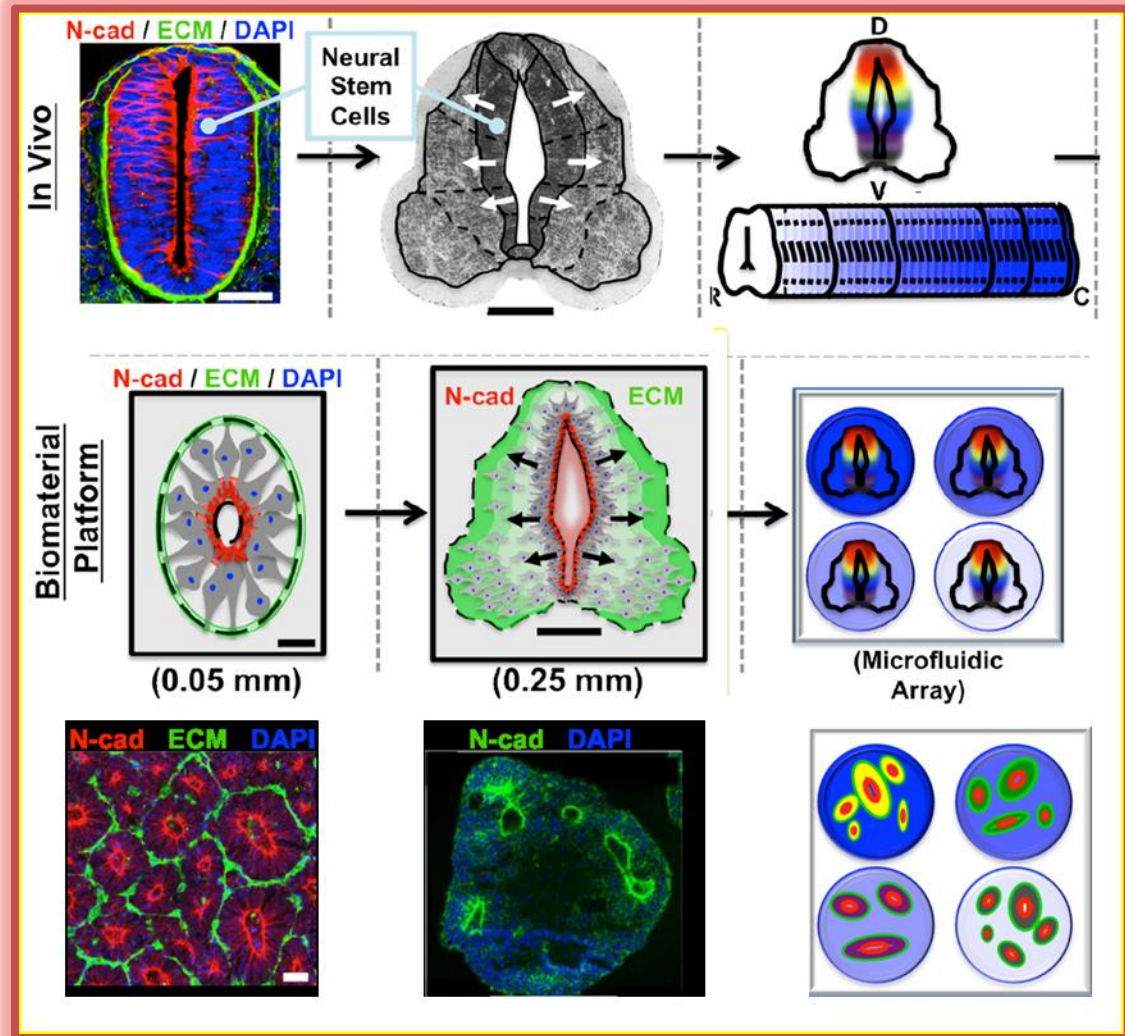
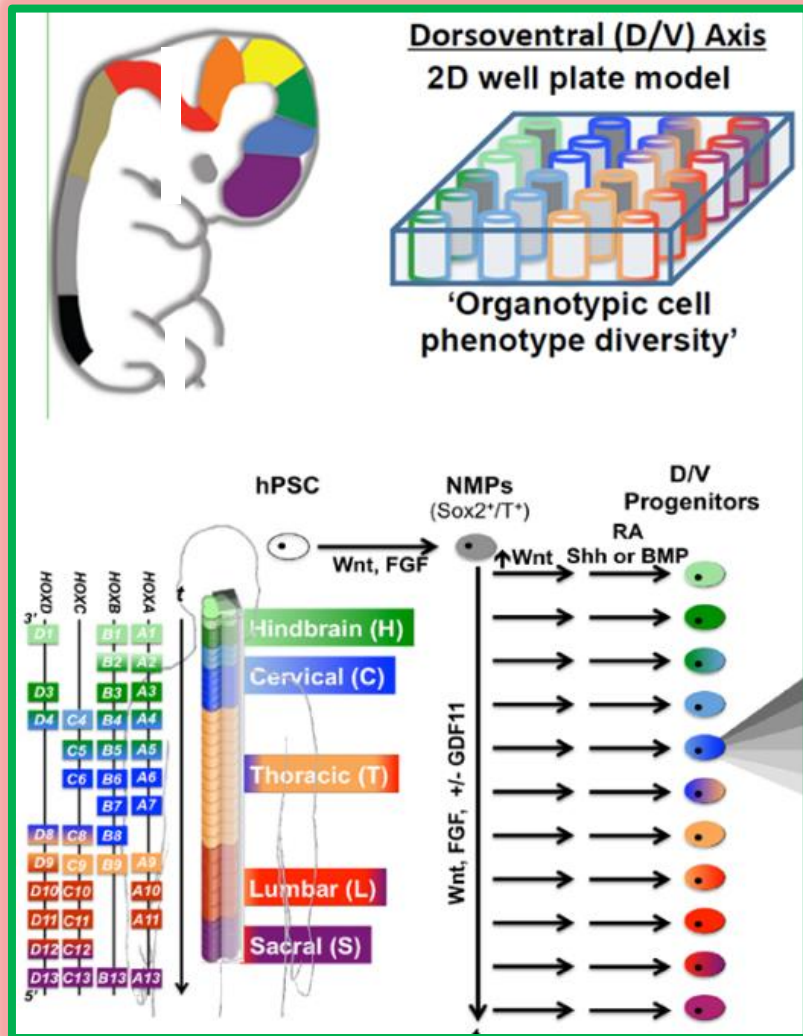


- 3D epithelial / mesenchymal organization
- SHH gradient directs Gli1-outgrowth
- HTS and HCI amenable
- fluorescent and luminescent readouts

SOURCE: Brian Johnson, U Wisconsin (HMAPS)



Micropatterning: regionally-diverse stem cell arrays for the human neural tube



SOURCE: Randolph Ashton, U Wisconsin H-MAPS Center [Lippman et al. 2015; Knight and Ashton 2015]

In a nutshell ...

- Advances in biomedical, engineering, and computational sciences enable high-throughput screening (HTS) to profile the toxicological landscape.
- Surfeit of HTS data now in hand, a practical need arises to formally translate this information into actionable biological understanding.
- Information must be collected, organized, and assimilated across multiple levels of biological organization to meet these requirements.
- Computational systems and human organoids models are uniquely positioned to help shift decision-making to mechanistic prediction.

*Computer modeling
is 3R's compliant!*



<https://www.pinterest.com/courtney1882/disney-ratatouille/>

Pondering the way forward ...

Translational: what do synthetic models of human development - both computational and organoids - bring to future of DART testing?

Investigational: how smart must these models be (A.I.) to support decision-making in the animal-free (3Rs) zone?

Operational: what best practices are needed to implement synthetic models into an integrative decision framework (eg, AOP-based IATAs)?

Communication: what are the practical considerations for science, engineering, and stakeholder engagement (academics, government, industry, NGOs, policy, ...)?

National Center for Computational Toxicology

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- Brian Johnson – U Wisconsin



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