

Mechanistic modeling of the cancer-immunity cycle: a platform approach in I-O

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ASCPT

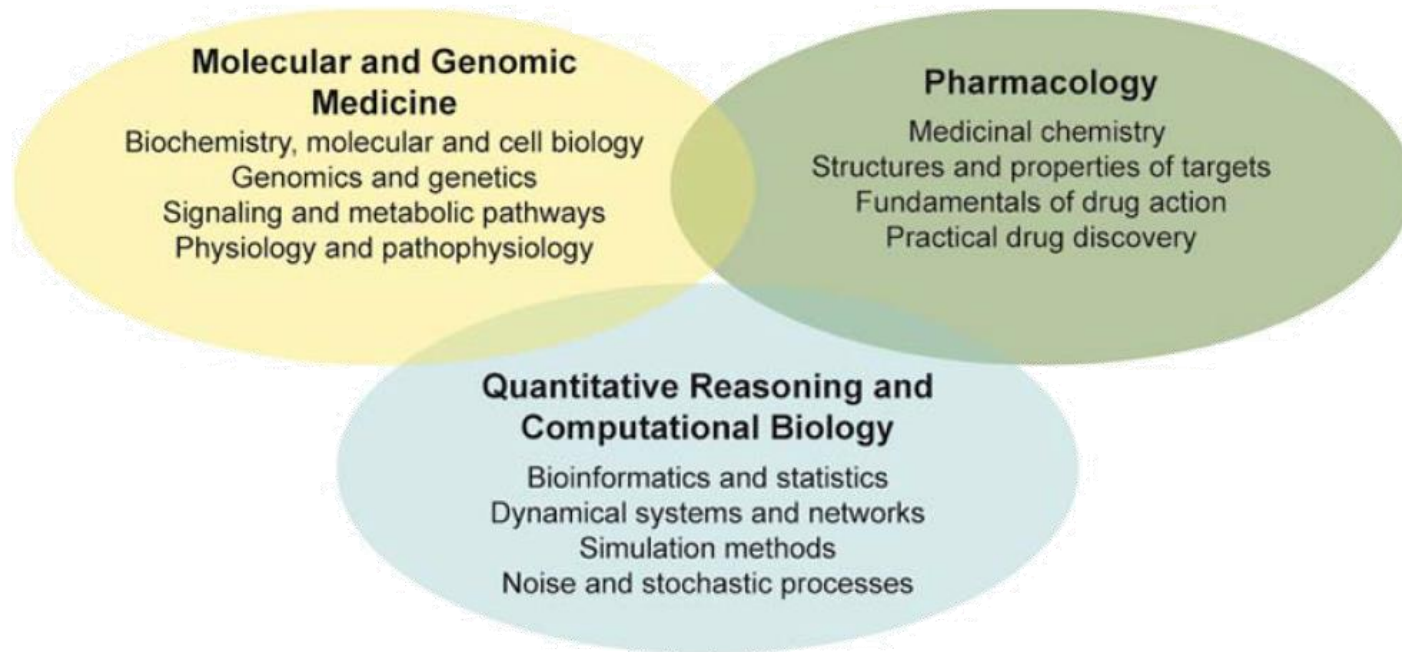
March 11, 2016

Agenda

- **Discussion of quantitative systems pharmacology (QSP) and mechanistic QSP platform models**
- **QSP at Bristol-Myers Squibb**
- **Melanoma immuno-oncology QSP platform**
 - **Melanoma I-O QSP platform biological scope**
 - **Pathway-level results in a virtual patient (VP)**
- **Example with virtual populations (VPops)**
- **Software & infrastructure considerations**

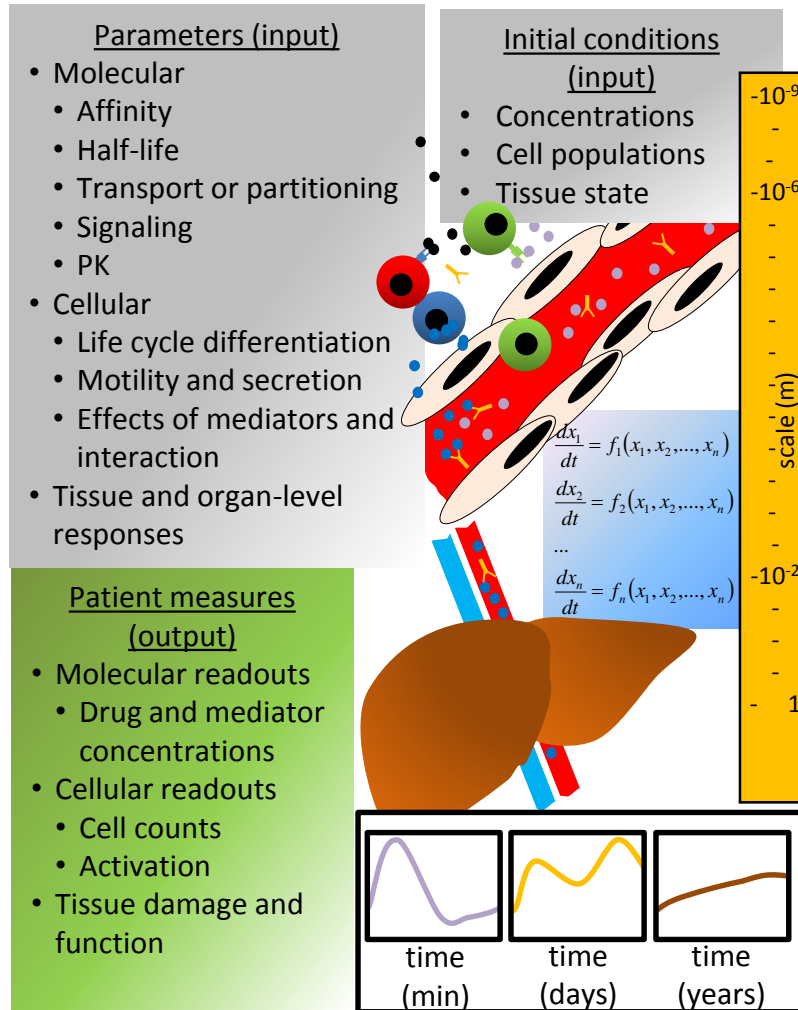
Quantitative (and) Systems Pharmacology

A multidisciplinary science that takes a mathematical approach to pharmaceutical R&D by integrating methodologies from pharmaceutical sciences, engineering, and systems biology.



Sorger, P.K., et al. (2011) "Quantitative and systems pharmacology in the post-genomic era: new approaches to discovering drugs and understanding therapeutic mechanisms." An NIH White Paper by the QSP Workshop Group,

QSP platform model scope



- QSP platform models mechanistically link target modulation to disease outcome
- System focus: can create the link before trial data are available for a new intervention/therapy
- Mechanistic (biomarker) and outcome data are used to calibrate the model for related therapies or to evaluate model performance
- Models are refined as additional data are available
- Potentially resource-intensive but broad application

Schmidt, B. J., et al. (2013). "Mechanistic systems modeling to guide drug discovery and development." *Drug Discov Today* 18(3-4): 116-127

QSP at BMS

- **6 Dedicated QSP modelers in Quantitative Clinical Pharmacology group (we're hiring!)**
- **Substantial & continued investment in platform development and approaches**

Oncology & Immuno-Oncology

- ◆ **Melanoma I-O Platform**
- ◆ **Antibody-Drug Conjugate Platform**
- ◆ **Physiologically-Based Tumor Receptor Occupancy**

Immunoscience

- ◆ **Rheumatoid Arthritis**
- ◆ **Immunogenicity**

Cardiovascular Disease

- ◆ **Heart Failure**
- ◆ **Coagulation/Thrombosis**

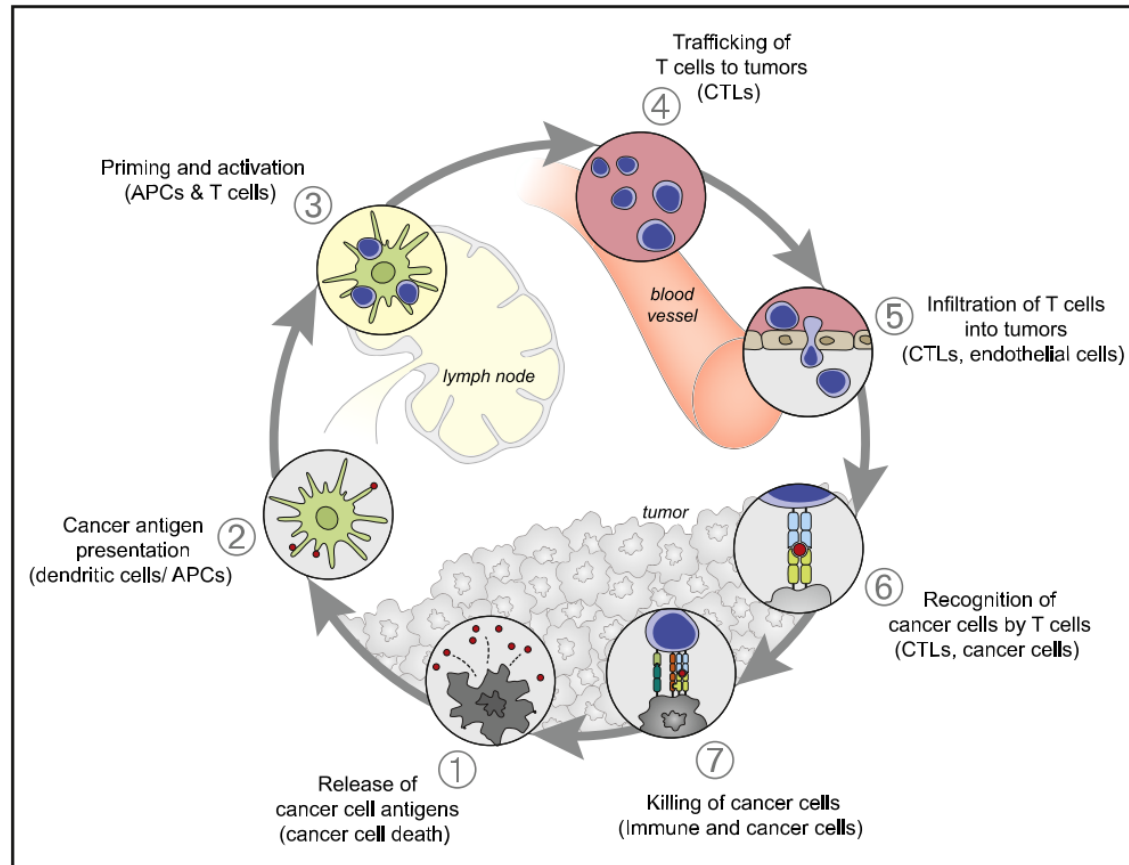
Fibrosis

- ◆ **Nonalcoholic Steatohepatitis**

Additional Platform Resources

- ◆ **Diabetes/Metabolic Diseases**

Melanoma immuno-oncology platform biological scope: cancer-immunity cycle



Chen, D. S. and I. Mellman (2013). "Oncology meets immunology: the cancer-immunity cycle." *Immunity* 39(1): 1-10.
RightsLink License 3814541352883.

Melanoma immuno-oncology platform: staged development

Pilot (Stage 1)

1. Map development
 - Lesion
 - Blood
 - Cells
 - Mediators
 - Interactions
 - Therapies
2. Equations
3. Parameterize, calibrate one VP

5 months

Complete cancer-immunity cycle (Stage 2)

1. Map development
 - Lymph node
 - Tumor lymphoid structures
 - Angiogenesis
 - Metastatic potential
 - Cytokine regulation expansion
 - Additional cell types
 - Additional therapeutic target pathway modulation
2. Equations
3. Parameterize
4. Calibrate a set of VPs

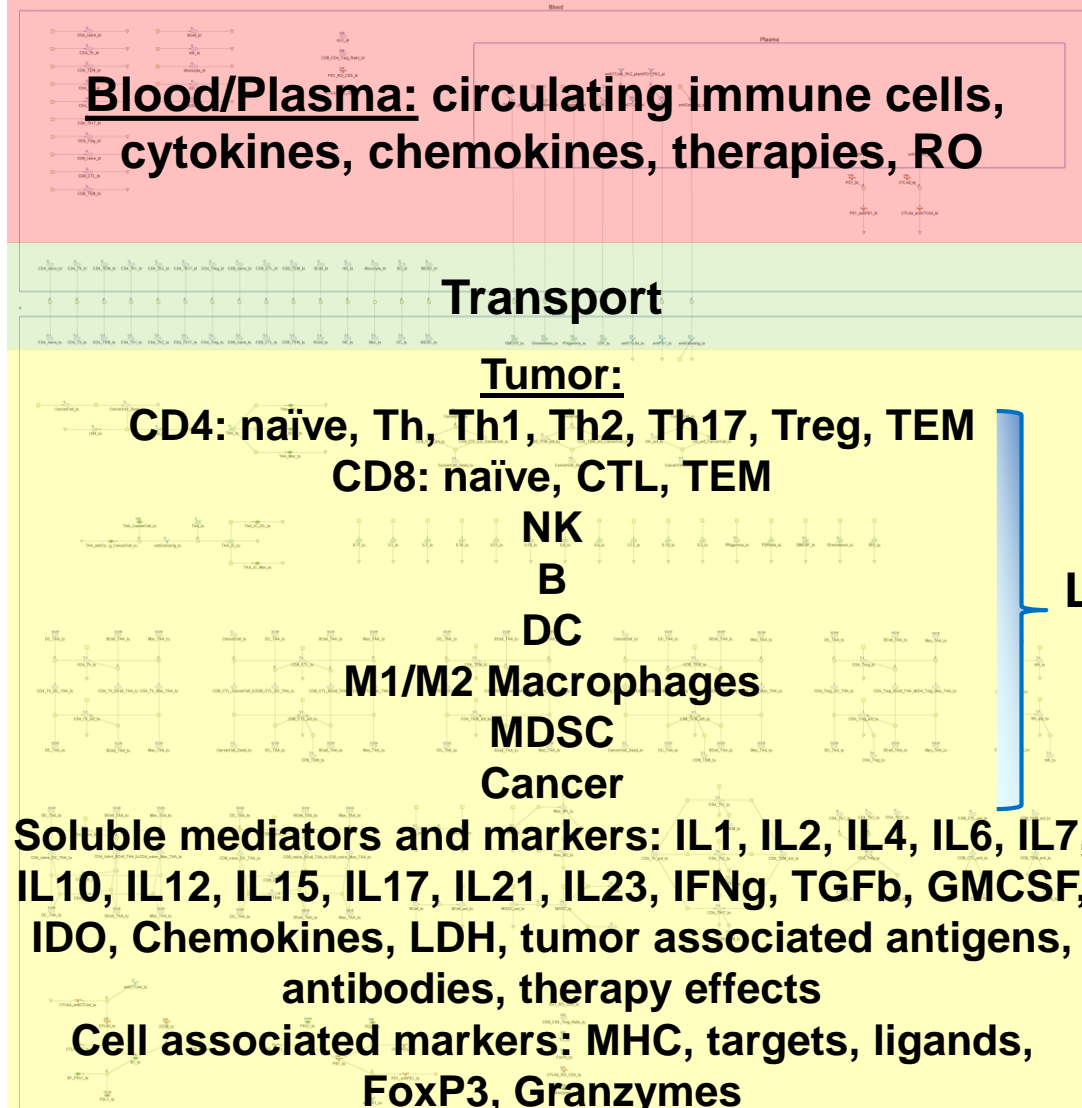
18 months

- Develop mechanistic hypotheses
- Starting point for virtual populations
- Compare options for combination therapies



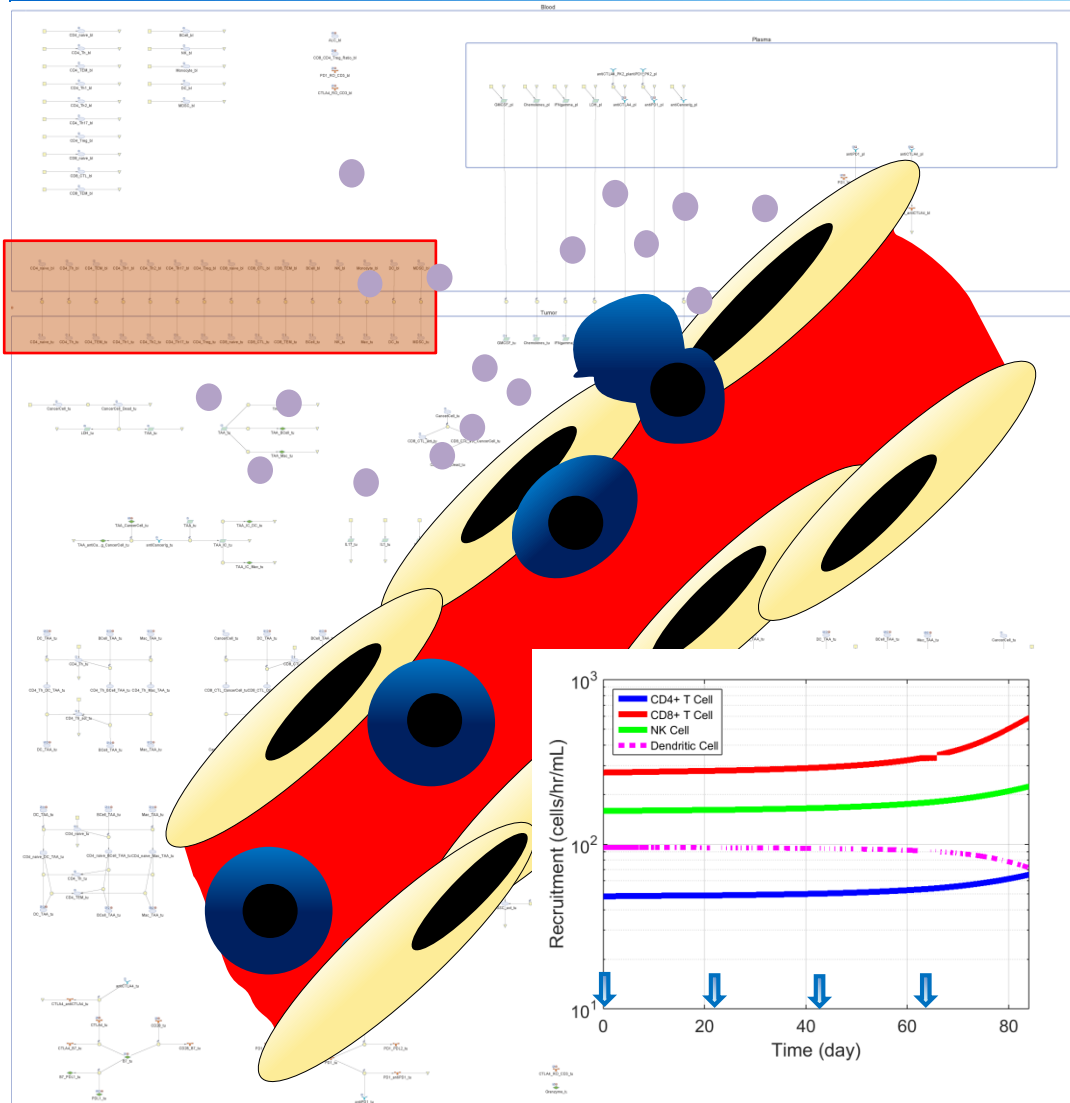
Melanoma immuno-oncology pilot project: cells, cytokines, and biomarkers

149 species
249 reactions
1014 parameters



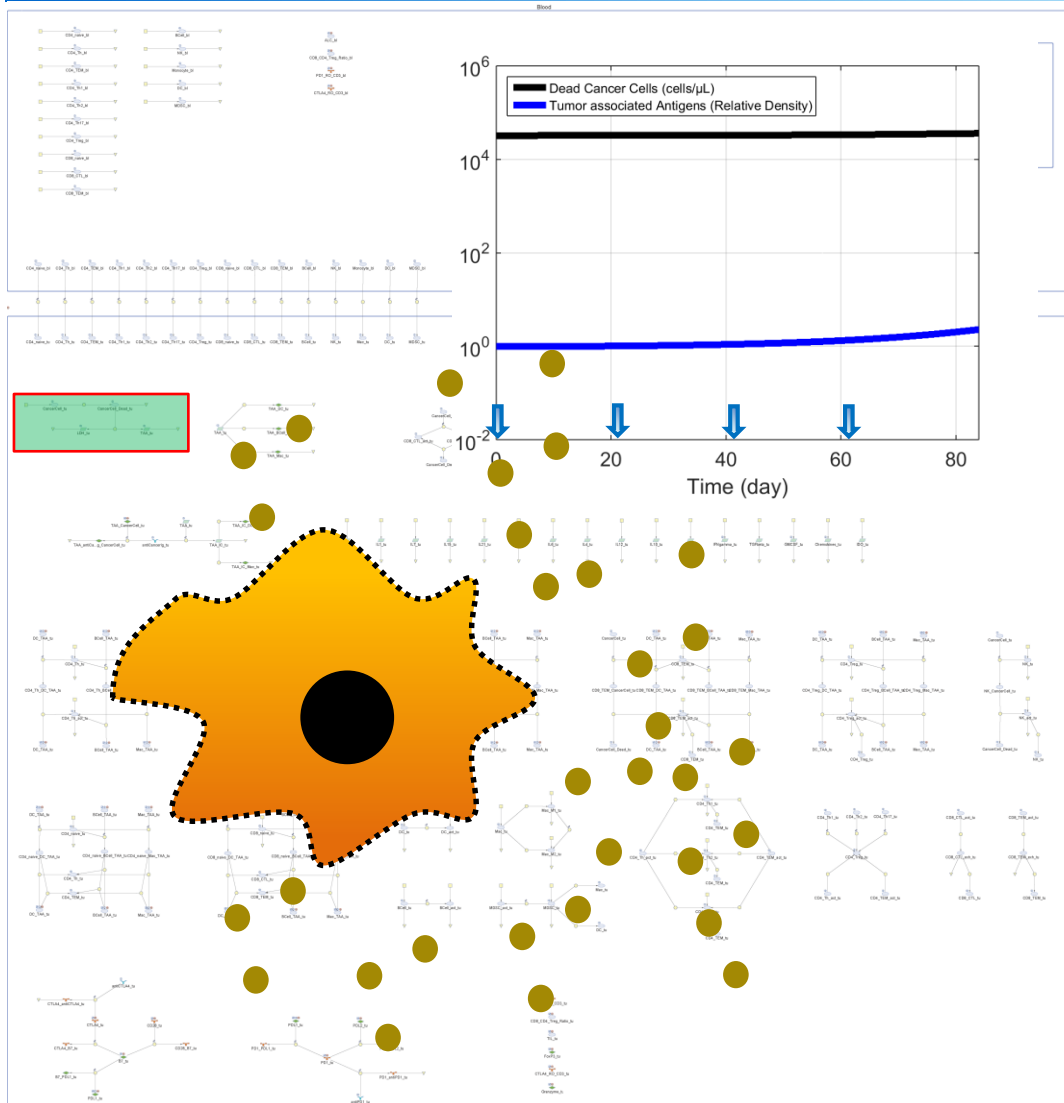
Development tool:
MATLAB SimBiology

Representation of the cancer-immunity cycle: immune cell trafficking and tumor infiltration



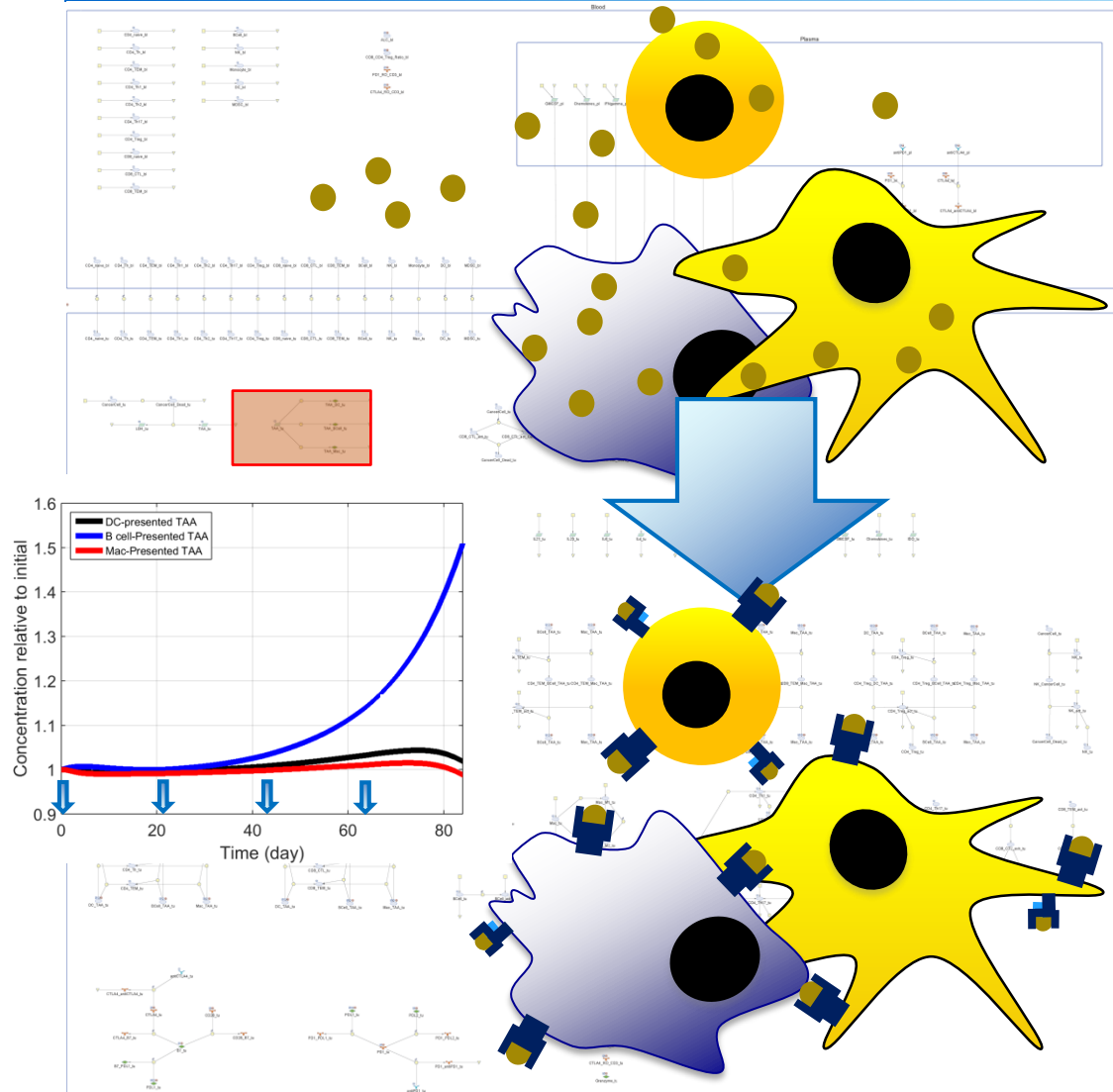
- I-O therapy administered in example simulation to enable an effective immune response
- Pool of immune cells in blood represents production of immune cells throughout the body (e.g., lymph nodes, bone marrow)
- Tumor infiltration is regulated by chemokines released within the tumor microenvironment

Representation of the cancer-immunity cycle: release of cancer antigens



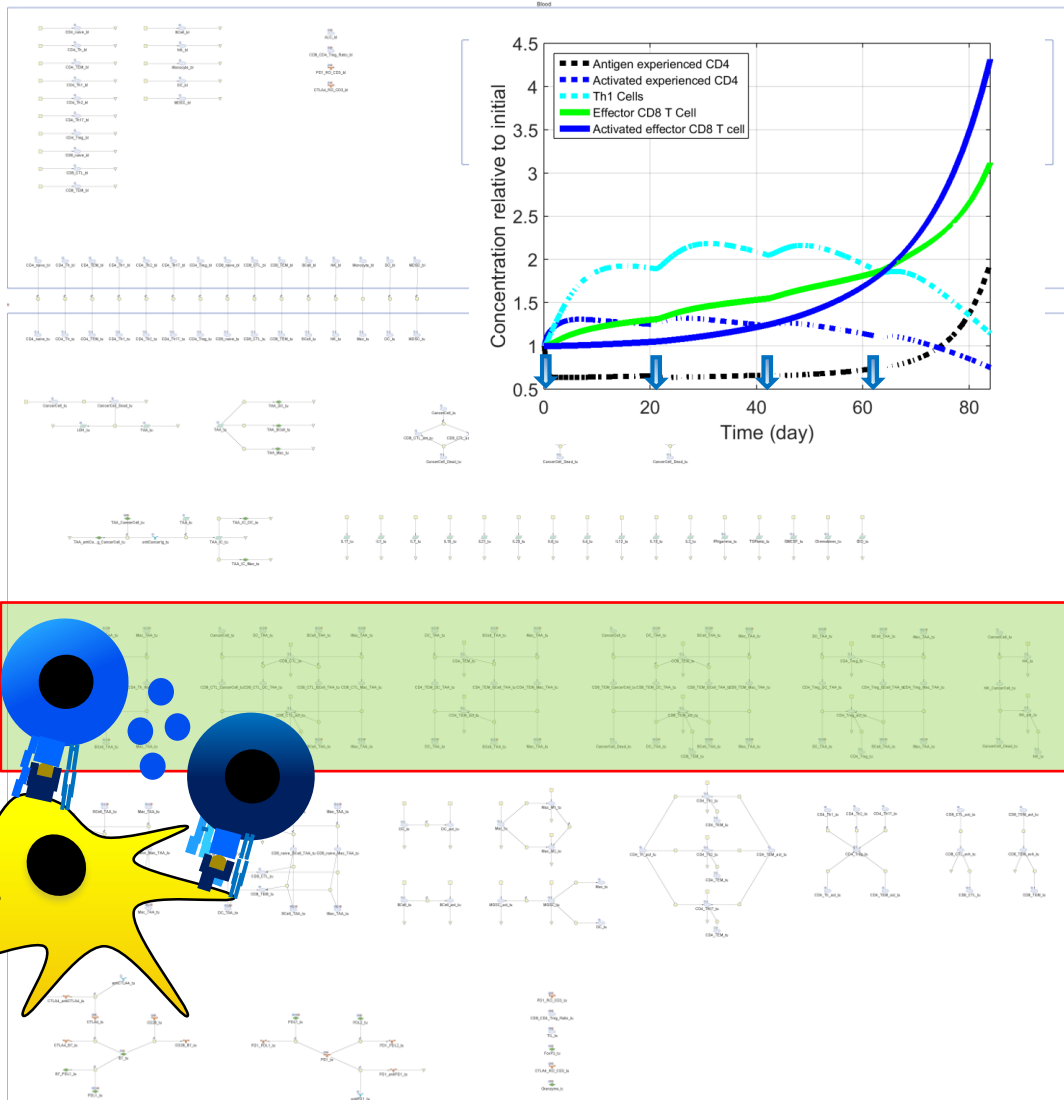
- Dead cancer cells release components, that can serve as tumor-associated antigens (TAA)

Representation of the cancer-immunity cycle: cancer antigen presentation



- Released TAA in tumor can be internalized, processed, and presented by dendritic cells, macrophages, and B cells within the tumor or lymph node (stage 2)
- The level of TAA presented per APC contributes to the degree of T cell activation

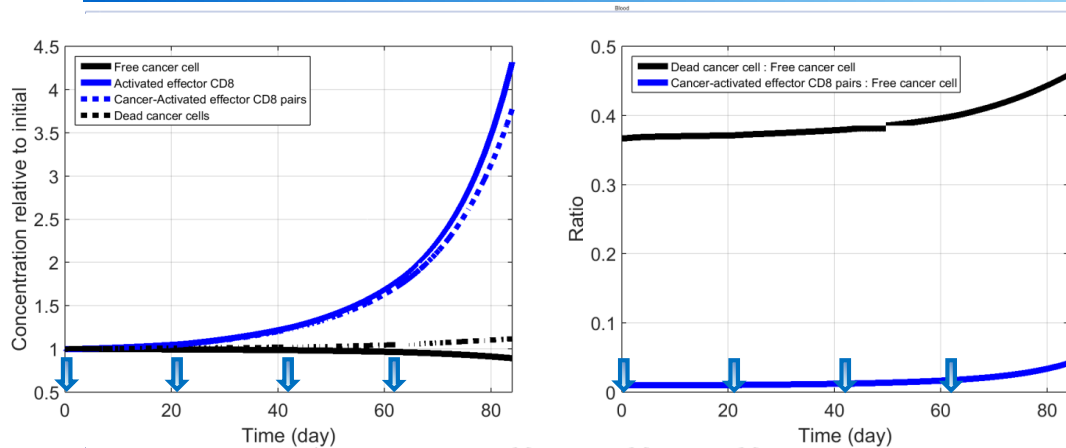
Representation of the cancer-immunity cycle: cancer cell recognition (1 of 3)



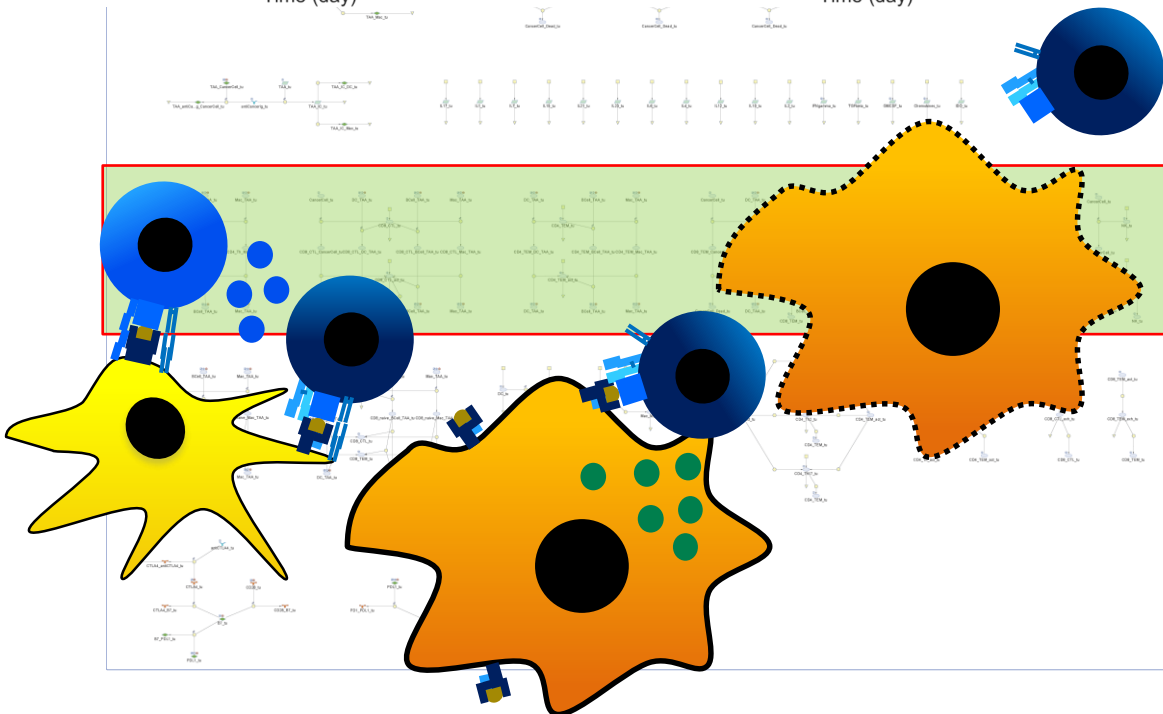
- Presentation of TAA can activate CD4+ and CD8+ T cells



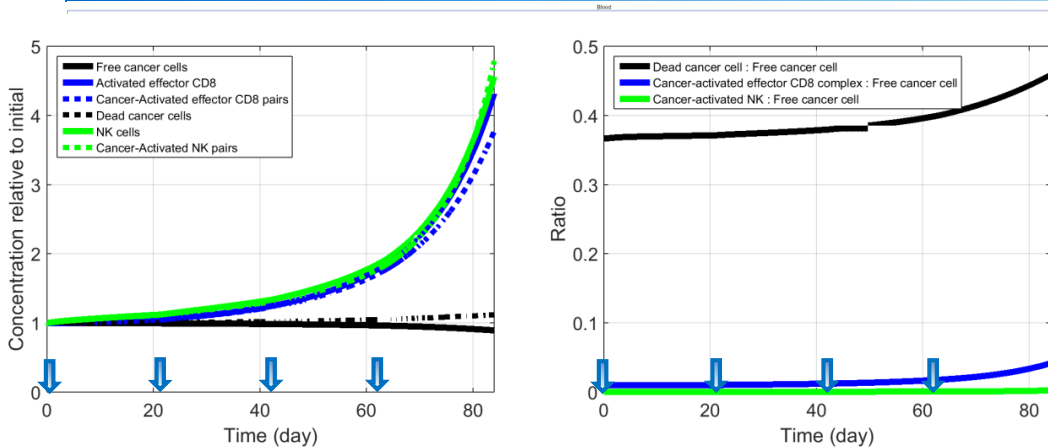
Representation of the cancer-immunity cycle: cancer cell recognition (2 of 3)



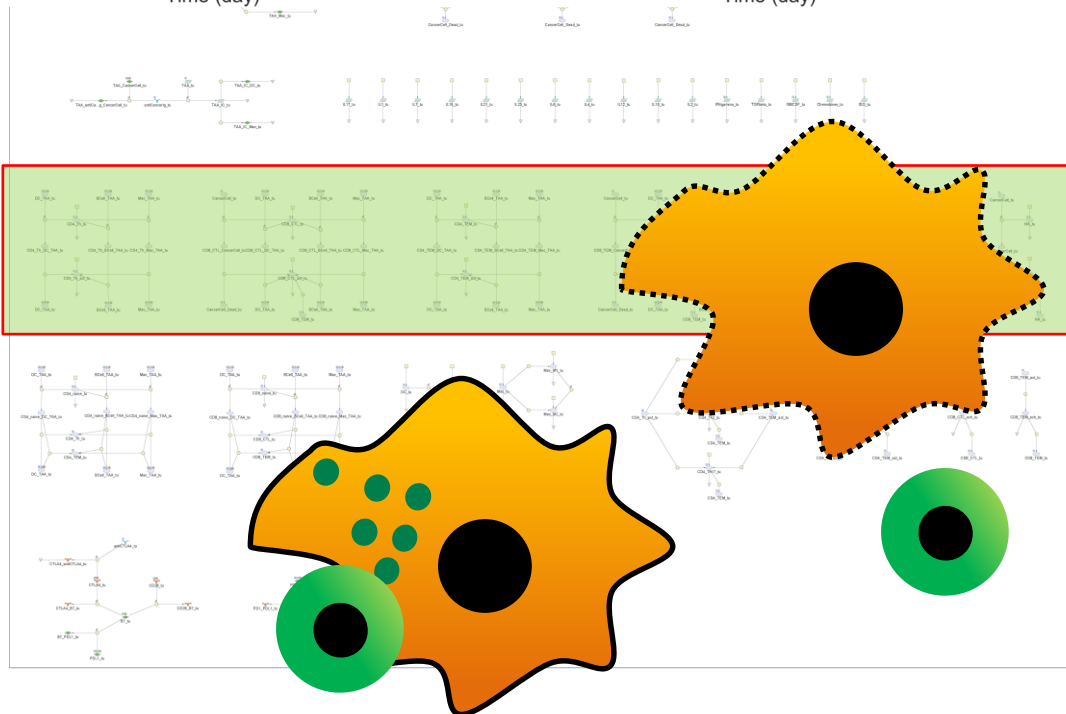
- Presentation of TAA can activate CD4+ and CD8+ T cells
- CD8+ T cells can directly bind to cancer cells presenting MHC-TAA complexes
- APC are protected from CD8+ CTL-mediated killing
- Cancer cells are killed by activated CD8+ CTL



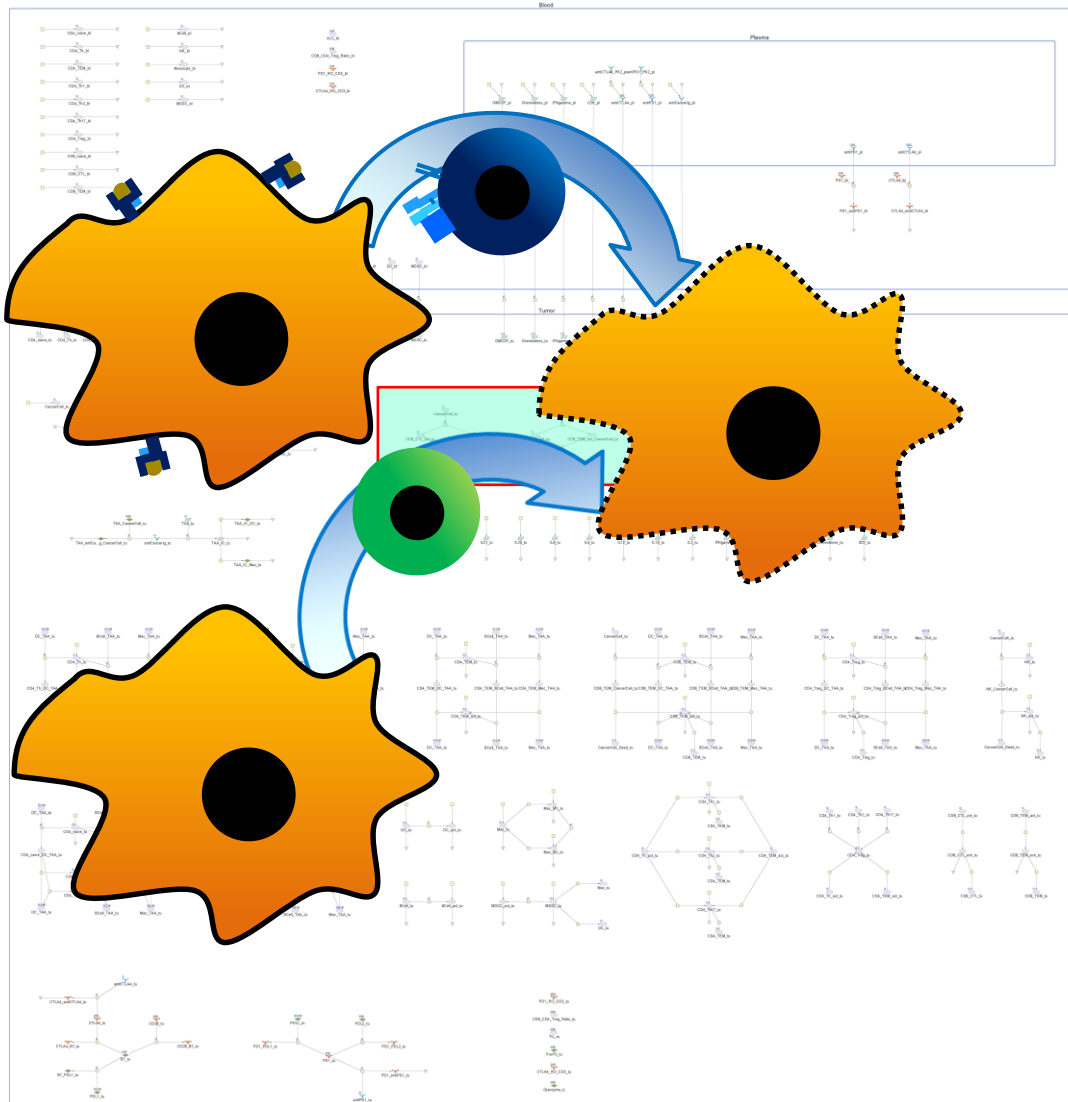
Representation of the cancer-immunity cycle: cancer cell recognition (3 of 3)



- Presentation of TAA can activate CD4+ and CD8+ T cells
- CD8+ T cells can directly bind to cancer cells presenting MHC-TAA complexes
- APC are protected from CD8+ CTL-mediated killing
- Cancer cells are killed by activated CD8+ CTL
- **Natural killer (NK) cells detect downregulated MHC I expression on the cancer cells**
- **This leads to NK cell activation and direct killing of the cancer cells**

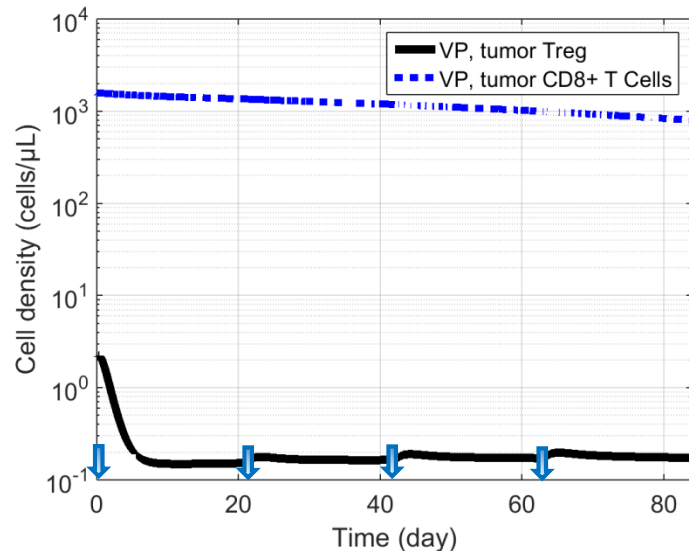
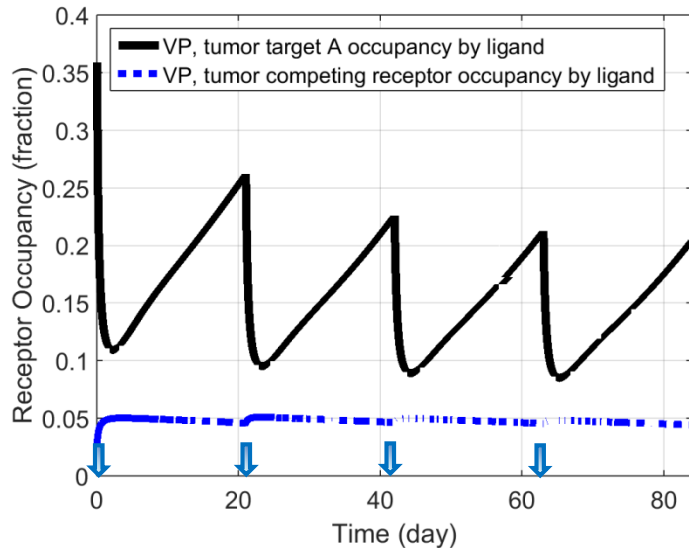


Representation of the cancer-immunity cycle: cancer cell killing



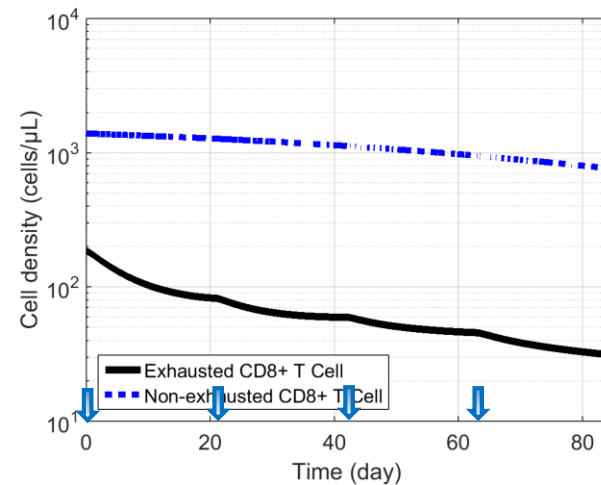
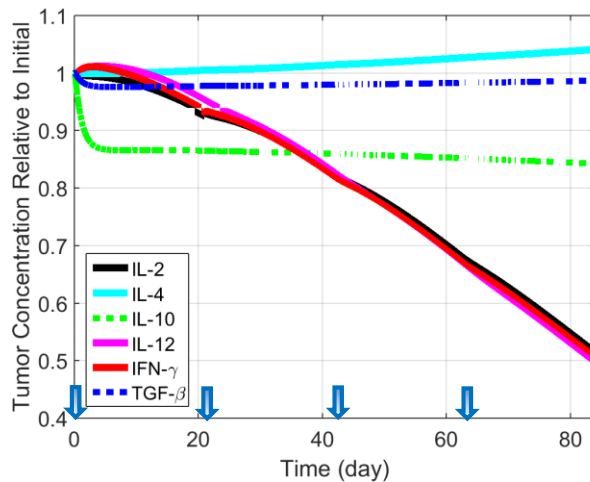
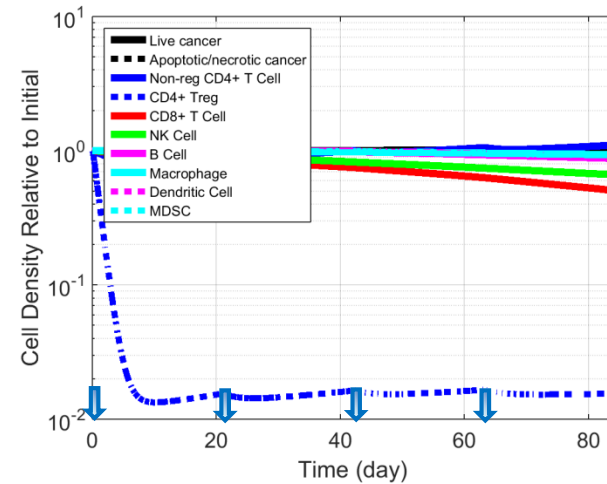
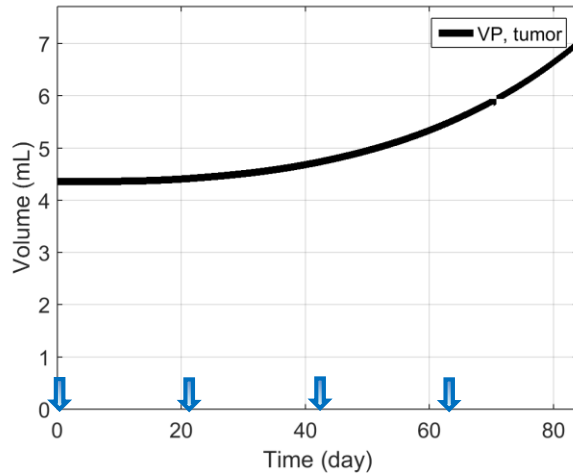
- Activated CD8+ T cells and NK cells carry out additional killing of the cancer cells
- Activation and cytokines contribute to exhaustion of CD8 T-cells and upregulation of exhaustion markers

Therapy A proximal PD

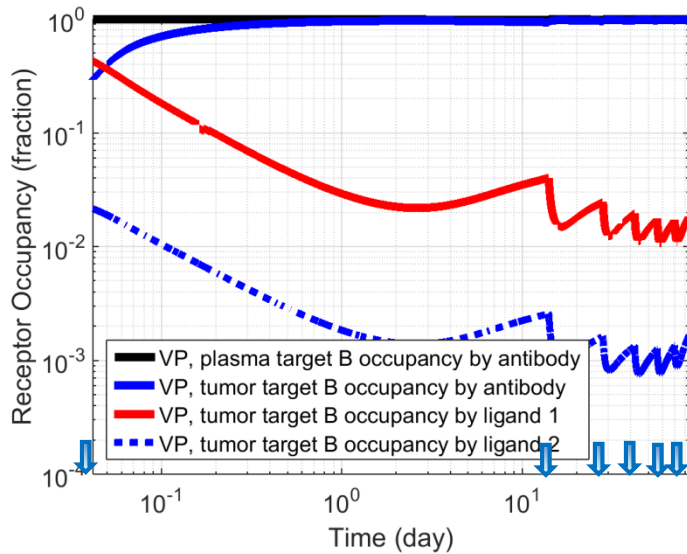


- **Two therapies implemented**
- **Typical values used for PK**
- **Multiple effects of engagement of target A**
 - **Free target A ligand to bind to a competing receptor**
 - **Target A is expressed on T regs: antibody-dependent cell-mediated cytotoxicity**

Pilot VP: response to therapy A

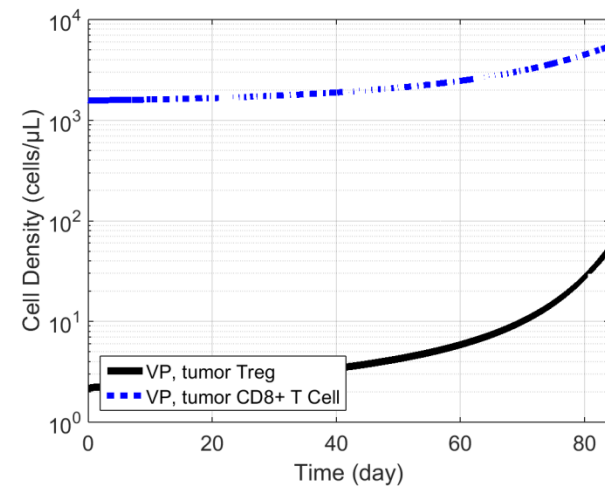
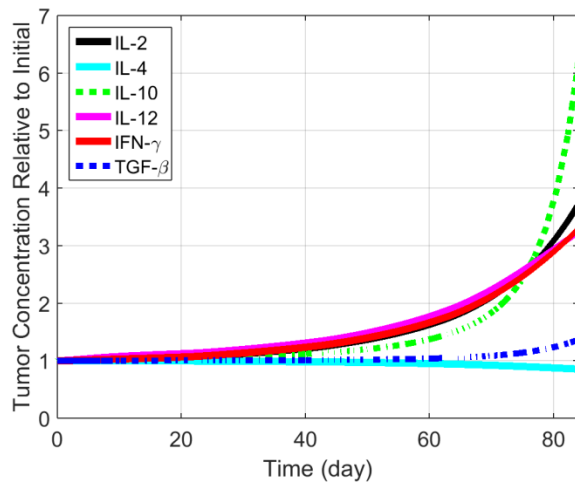
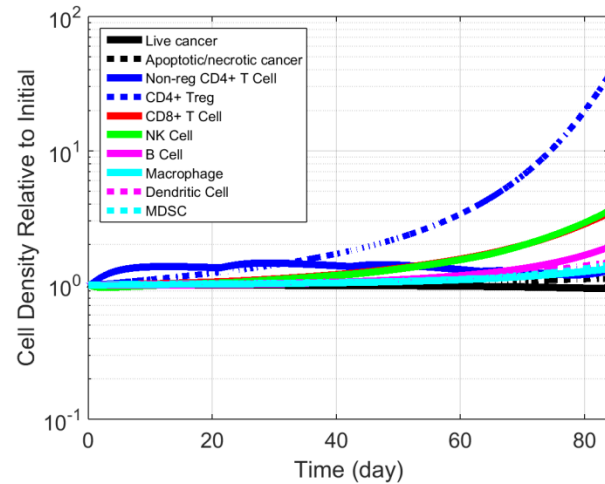
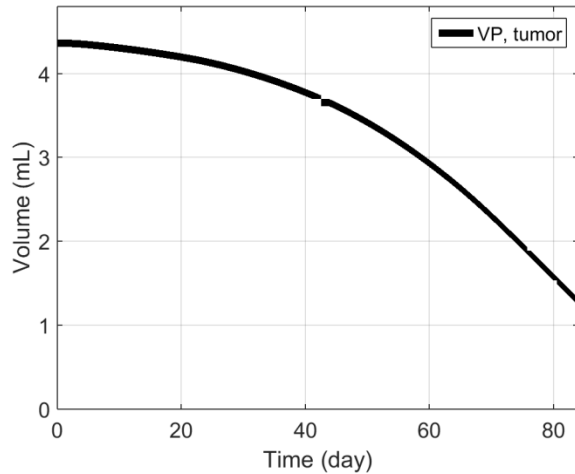


Therapy B proximal PD

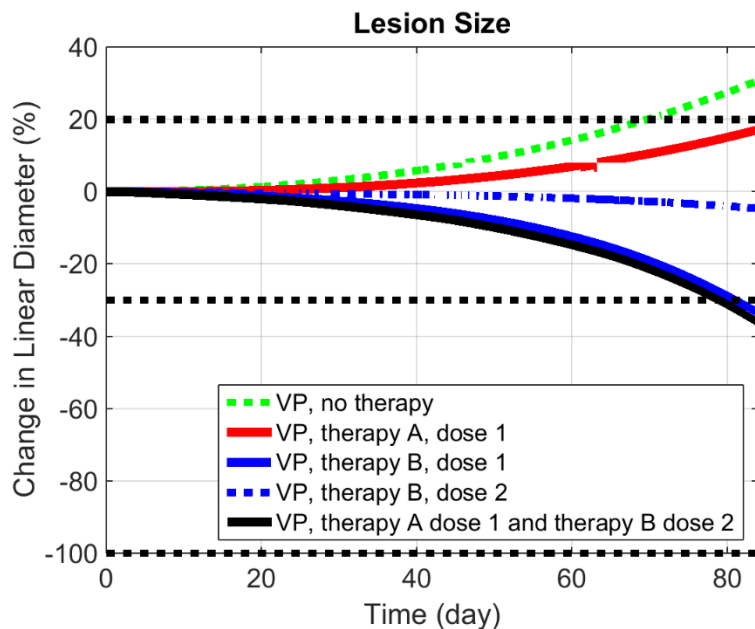
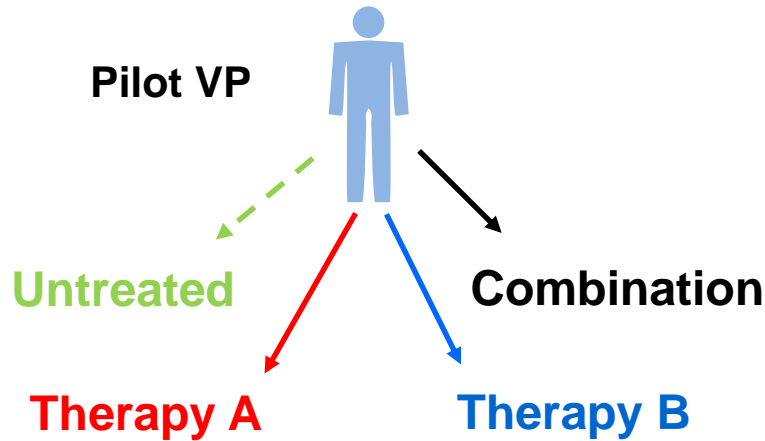


- Target B receptor occupancy is shown following infusion
- Therapy B
- Target B ligand 1
- Target B ligand 2
- Simulations account for affinity as well as expression

Pilot VP: response to therapy B



Pilot VP: lesion response to combination therapies



- We have taken the same VP and tested different immuno-oncology therapies
- Note the simulated increased response for the combination relative to monotherapies at the same concentrations
- Will add additional feedback mechanisms in stage 2
- Alternate VPs will facilitate exploring phenotypes that may have greater benefit from the combination
- Develop virtual populations: increase confidence in distribution of response phenotypes

Stage 2 expansion: cells, cytokines, and other biomarkers

Blood/Plasma

Pilot: circulating immune cells, cytokines, chemokines, RO, therapy A and B
Stage 2: expand immune cells, 3 more therapies (checkpoint inhibitors, agonists)

Transport

Tumor & lymph node

Pilot cell types: CD4: Naïve, Th, Th1, Th2, Th17, Treg, TEM; CD8: Naïve, CTL, TEM; NK, B, DC, M1/M2 Macrophages, MDSC, Cancer

Stage 2 cell types: CD4: TFH, TCM; CD8: TCM; B: Naïve, Plasma (short & long lived), Memory; VEC, LEC, CAF, pDC, N1/N2 Neutrophils, TIE2-Expressing Monocytes, Lymph node fibroblasts

Pilot mediators and markers (21): IL1, IL2, IL4, IL6, IL7, IL10, IL12, IL15, IL17, IL21, IL23, IFN γ , TGF β , GM-CSF, IDO, Chemokines, LDH, tumor associated antigens, therapy A and B

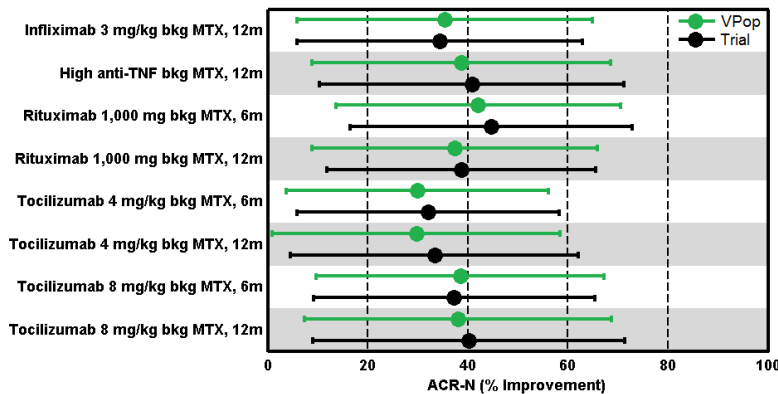
Stage 2 mediators and markers (39): IL18, IFN1, TNF α , CXCL8, CXCL9, CXCL12, CCL4, CCL2, CCL5, CCL20, CCL21, CCL22, MCSF, PGE2, ICAM1, VEGFA, VEGFC, Ang2, ECM, MMP, new therapies

Pilot cell associated markers: MHC, target-associated markers, FoxP3, granzymes

Stage 2 target-associated cell markers

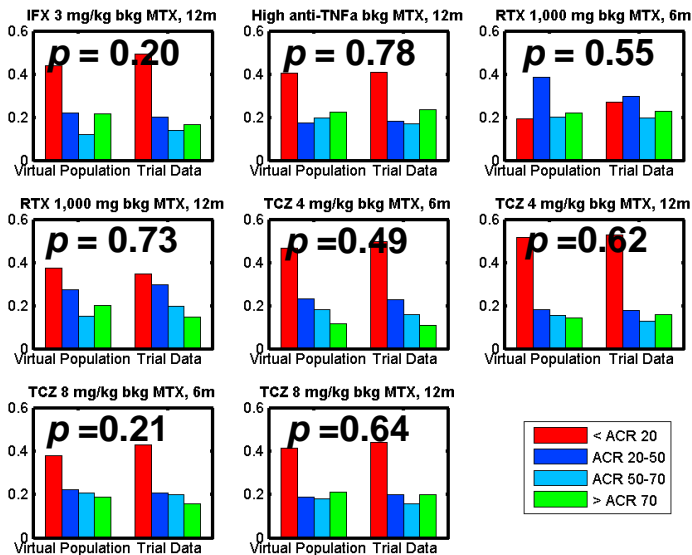
Some of the new processes in Stage 2: hypoxia, vessel and ECM density (metastatic potential), cancer and immune cell migration to the lymph node, adaptive immune response in the lymph node

Trial results for a virtual population: an example in rheumatoid arthritis



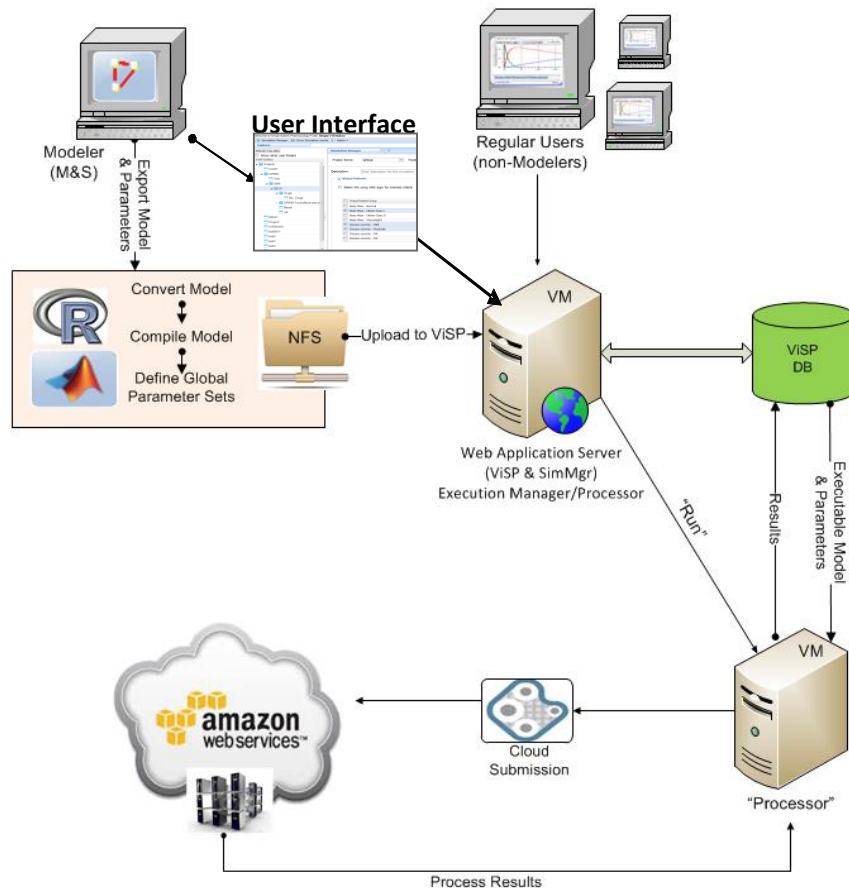
$p=0.65(0.54)$
 $p=0.28(0.68)$
 $p=0.56(0.99)$
 $p=0.75(0.66)$
 $p=0.10(0.99)$
 $p=0.03(0.99)$
 $p=0.40(0.56)$
 $p=0.24(0.69)$

- A cohort of 1,206 VPs was developed algorithmically
- Cohort VPs all exhibit feasible baseline biomarkers and therapeutic responses
- Many virtual populations (768) were created
- Composite goodness-of-fit criterion was acceptable for each virtual population
- Agreement for one virtual population across multiple trials is illustrated
- Virtual population calibration gives a basis for population response extrapolation with new therapies



Schmidt, B. J. et al. (2013). "Alternate virtual populations elucidate the type I interferon signature predictive of the response to rituximab in rheumatoid arthritis." *BMC Bioinformatics* 14: 221. Originally published by Biomed Central.

Virtual Systems Pharmacology (ViSP) HPC platform



- QSP software and infrastructure development are 2-fold:

- Provide tools and interfaces for non-modelers to access simulations (left)
- Provide computing resources for computationally-intensive models and algorithms

Ermakov, S., et al. (2014). "Virtual Systems Pharmacology (ViSP) software for mechanistic system-level model simulations." *Front Pharmacol.* 5: p. 232.

Take home

- **Mechanistic quantitative systems pharmacology (QSP) modeling platforms can address a variety of questions**
 - **Elucidate and predict efficacy and biomarker trends**
 - **Evaluate combinations**
 - **Dosing strategy**
- **Modeling platforms are non-trivial**
 - **Require foresight and planning**
 - **Continual development, re-use**
- **Software & infrastructure considerations**
 - **May require customized development**
 - **Virtual populations can be resource hungry**
 - **Cloud computing resources**

Acknowledgements

Rosa & Co.:

- Derek W. Bartlett*
- Mike Reed
- Katherine Kudrycki
- Christina Friedrich
- Douglas Chung
- Ananth Kadambi

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Quantitative Clinical Pharmacology

- Tarek A. Leil*
- Craig Thalhauser (QSP)
- Sergey Ermakov (former BMS QSP)

Clinical Pharmacology & Pharmacometrics

- Shruti Agrawal
- Amit Roy
- Satyendra Suryawanshi

Genomics

- Patricia B. Ross-MacDonald
- Nathan Siemers

Discovery Medicine:

- Bruce S. Fischer
- Andres A. Gutierrez (former BMS)
- Raphael A. Clynes
- Praveen Aanur
- Suba Krishnan

Oncology Discovery

- Maria Jure-Kunkel
- Joe Fagnoli
- Henry Kao

Preclinical Candidate Optimization

- Zheng Yang
- Huadong Sun
- Haiqing Wang

Translational R&D Analytics

- Kaushal Desai

Translational R&D IT

- Marko Miladinov

Clinical Biomarkers

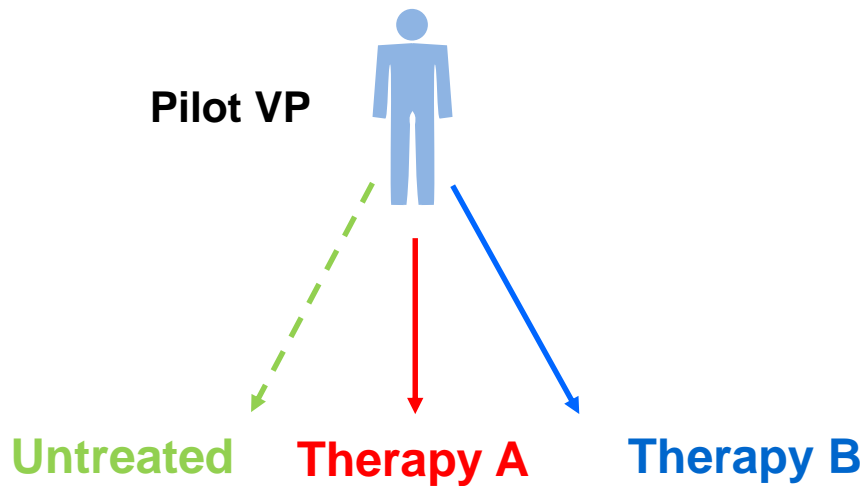
- Jaclyn Neely

ASCPT and Session Chairs

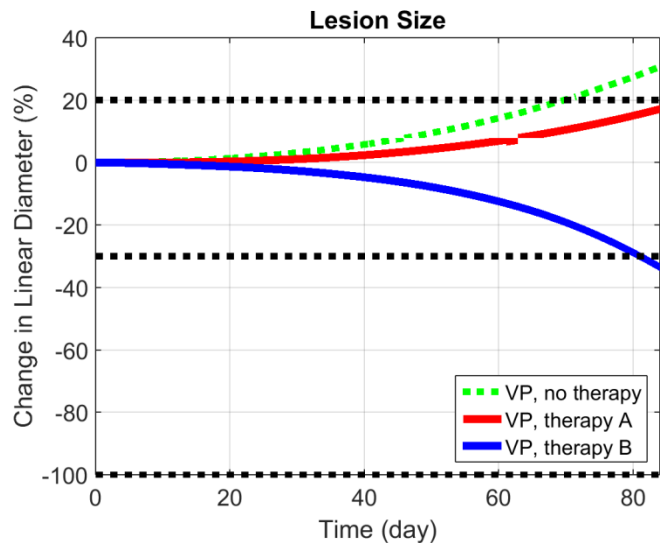


Backup

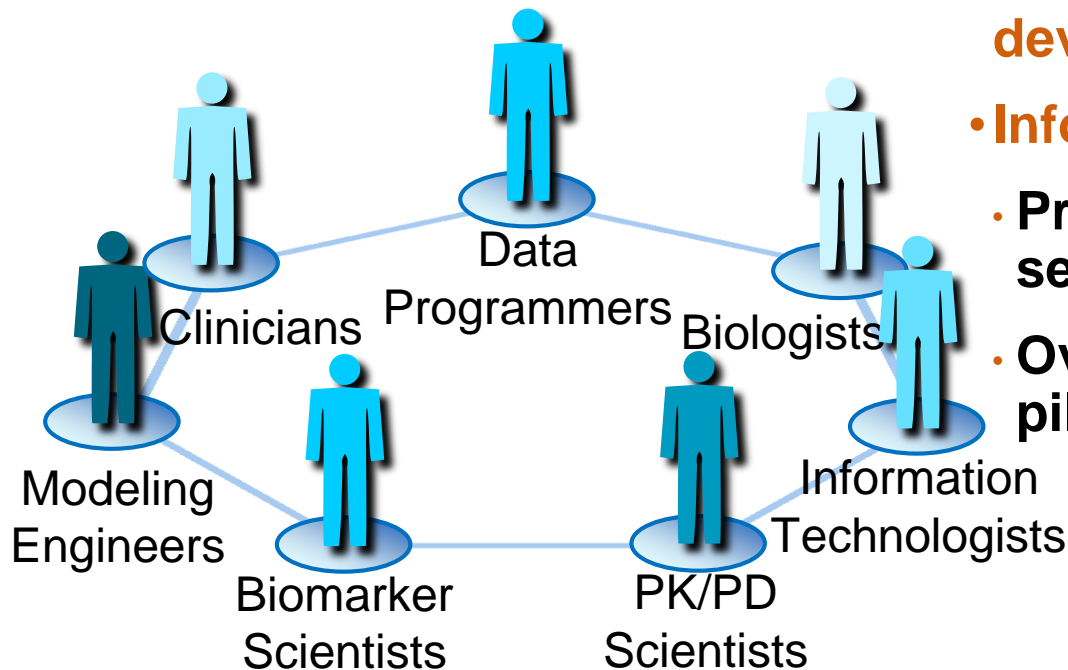
Therapy implementation with the VP



- We have taken the same VP and tested different immuno-oncology therapies
- Lesion size is calculated based on number of cancer and immune cells in the simulated lesion

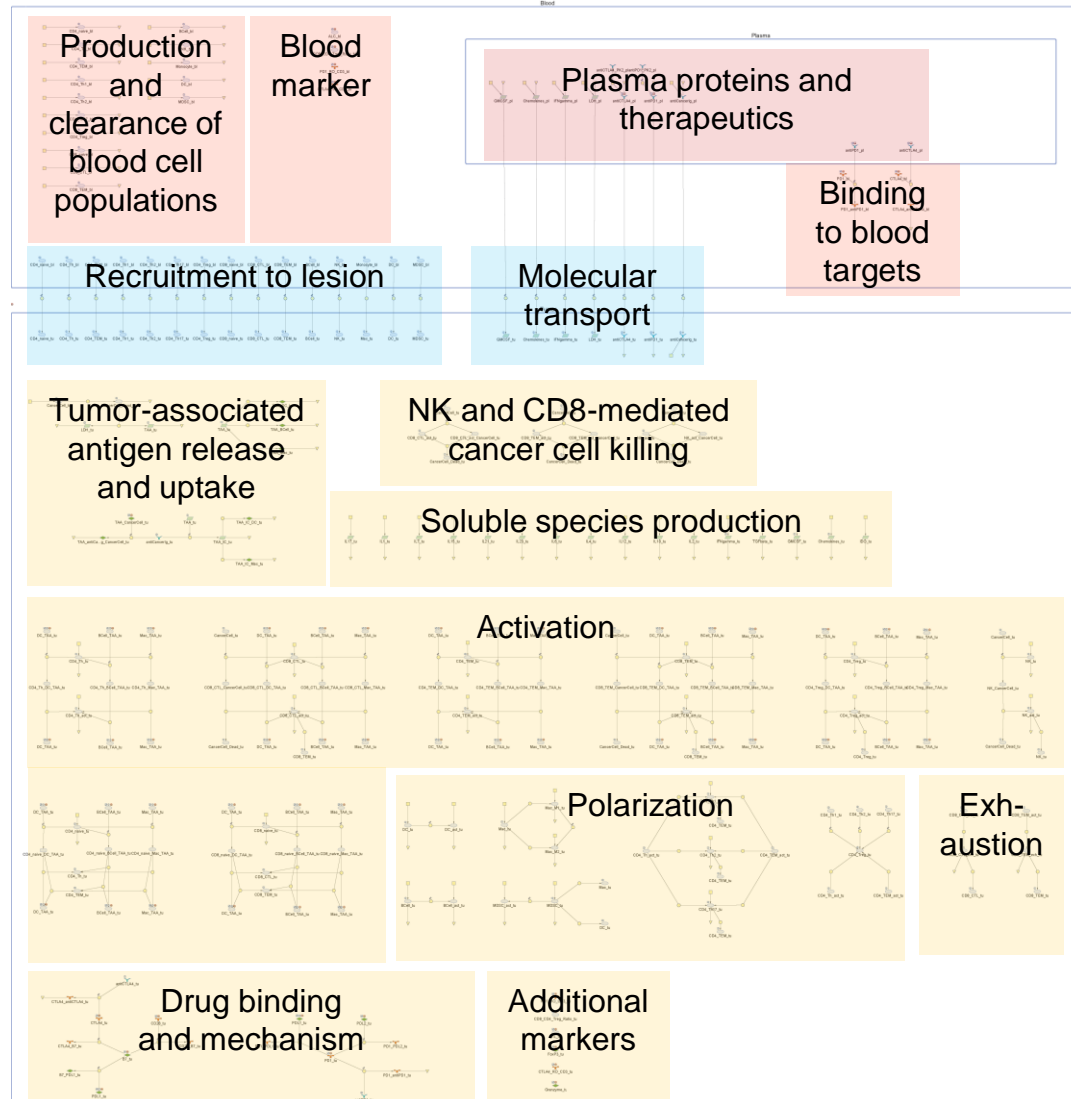


Melanoma immuno-oncology platform: development team



- **Cross-function team of drug development scientists**
- **Leverage external resources to accelerate model development**
- **Information-intensive**
 - **Preclinical and clinical data sets**
 - **Over 500 publications for pilot**

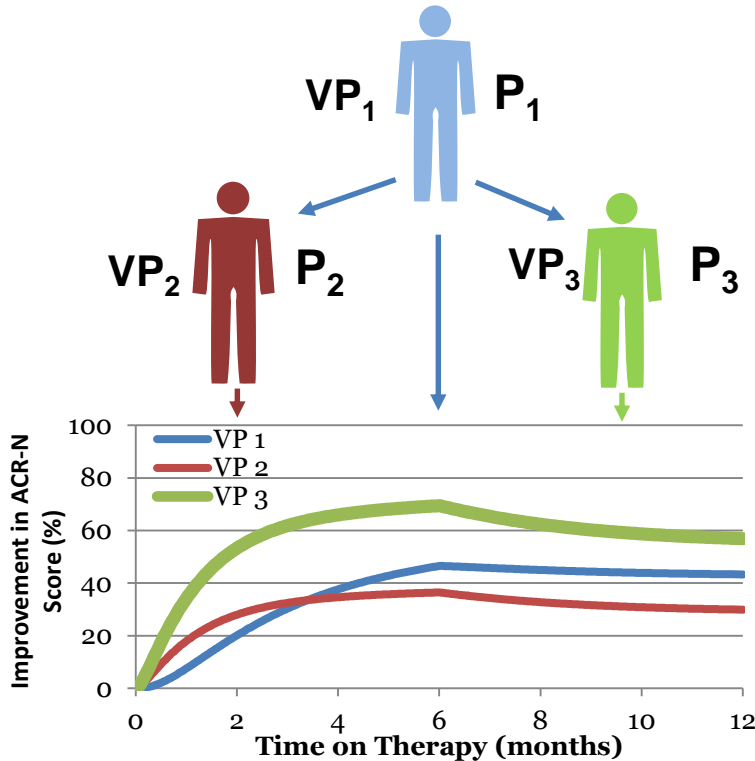
Melanoma immuno-oncology pilot project: processes



Treatment/Simulation	Measure	Feasible Range for VP
Untreated (Baseline RA)	Plasma C-Reactive Protein	<255 mg/L
	Synovial Tissue Volume Occupied by Cells	<0.95 (Fraction)
	Synovial Sublining B Cell Density	0.48 - 37.92 (x10 ⁶ cells/mL)
	Synovial Sublining T Cell Density	0.32 - 408.48 (x10 ⁶ cells/mL)
	CD4: CD8 T Cells	1-3 (ratio)
	Circulating CD28 ⁺ /CD4 ⁺ T Cells	<0.61 (fraction of CD4 ⁺ T Cells)
	Circulating Th17 Cells	<0.85 (fraction of CD4 ⁺ T Cells)
	Average Synovial NK Cell Density	<6 (x10 ⁶ cells/mL)
	Synovial Sublining Plasma Cell Density	9.28 - 119 (x10 ⁶ cells/mL)
	Synovial Macrophage Density	18.16 - 189.36 (x10 ⁶ cells/mL)
	Synovial Lining FLS Density	18 - 104.1 (x10 ⁶ cells/mL)
	Cartilage Degradation Rate	0.1 - 1.5 (mm/yr)
	Bone Metabolism Rate	<-1 - 1 (x10 ⁻⁶ mL/hr)
	Serum TNFa Level	<3.6 (ng/mL)
	Serum IL-1Ra	0.1 - 5.2 (ng/mL)
	Serum COMP	2.6 - 32 (μg/mL)
	Serum VEGF	0.025 - 5.5 (ng/mL)
	Serum IL-1	<1.03 (ng/mL)
	Serum Free and Complexed IL-6	<52 (ng/mL)
	Serum Total IL-6R	<0.0185 - 218 (ng/mL)
	Serum Total SGP-130	50 - 1068 (ng/mL)
NSAID, 27.5 ng/ml, 1 year	Improvement in JSN Progression Rate	-25% to 50%
	Improvement in BES Progression Rate	-25% to 50%
	Improvement in ACR-N Score	>-10%
Methotrexate, 14.2mg/wk, 1 year	Plasma C-Reactive Protein	<255 mg/L
	Synovial Tissue Volume Occupied by Cells	<0.95 (Fraction)
	Improvement in JSN Progression Rate	>-25%
	Improvement in BES Progression Rate	>-25%
	Improvement in ACR-N Score	>-25%
Methotrexate, 16.5mg/wk, 1 year	Same feasibility constraints as MTX 14.2	
Adalimumab, 40 mg s.c., and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	
Rituximab, 1000 mg, and MTX, 6 months, following 1 year on MTX	Same feasibility constraints	
Rituximab, 1000 mg, and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	
Tocilizumab, 4 mg/kg, and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	
Tocilizumab, 8 mg/kg, and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	
Anakinra, 100 mg s.c., and MTX, following 1 year on MTX	Same feasibility constraints	
Infliximab, 3 mg/kg, and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	
Infliximab, 10 mg/kg, and MTX, 1 year, following 1 year on MTX	Same feasibility constraints	

- 21 baseline measures of pathology
- 53 response measures on 10 therapeutic interventions

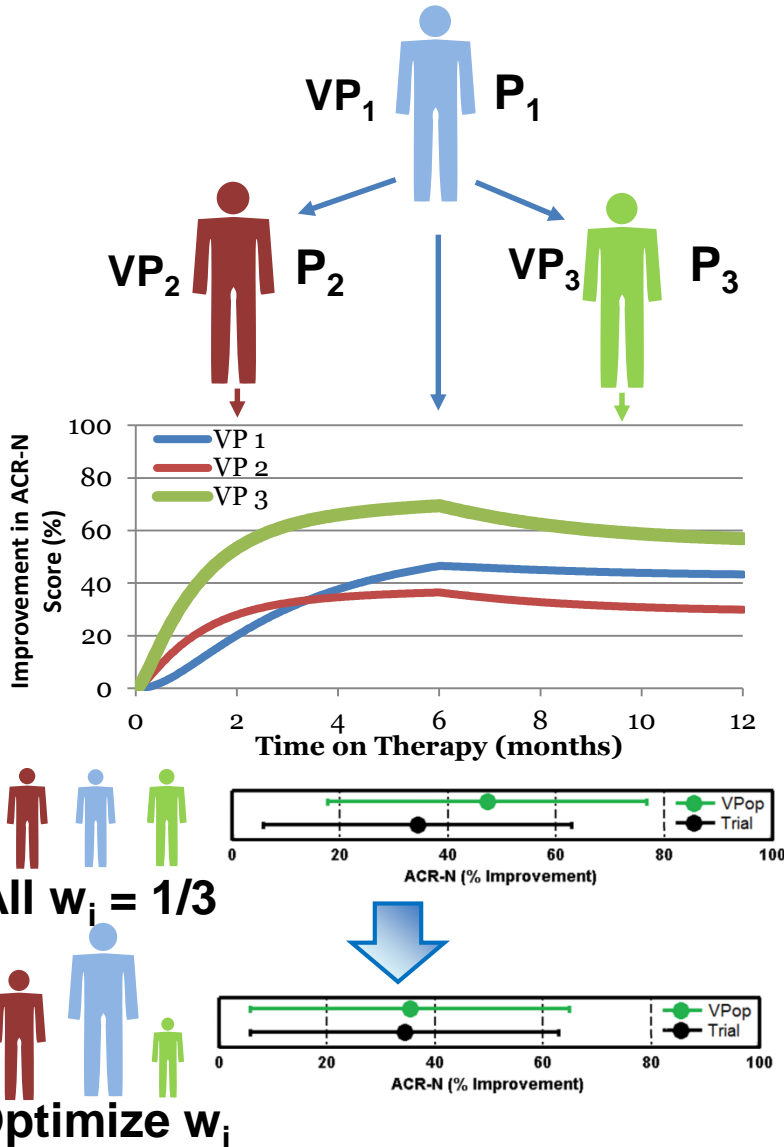
Alternate VPs simulate variability: example from a rheumatoid arthritis study (1 of 2)



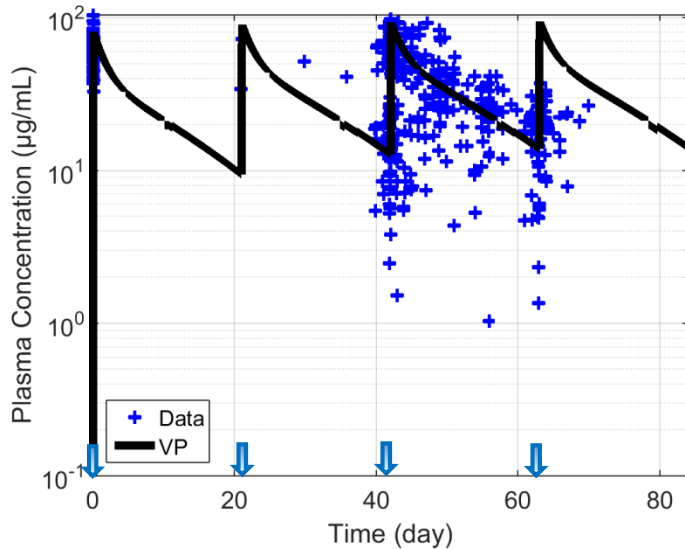
- Alternate VPs can be created to form a VP cohort
- All VPs must meet feasibility criteria
- Responses to therapies are generally consistent with patient class
- Pathophysiology (cell counts, concentrations) feasible and in agreement with literature

Alternate VPs simulate variability: example from a rheumatoid arthritis study (2 of 2)

- Alternate VPs can be created to form a VP cohort
- All VPs must meet feasibility criteria
- Responses to therapies are generally consistent with patient class
- Pathophysiology (cell counts, concentrations) feasible and in agreement with literature
- **Once a cohort of VPs is created, they may not match trial statistics**
- **“Prevalence” weights can be optimized to improve the match, giving a virtual population**
- **Algorithms have been developed optimizing prevalence weights**

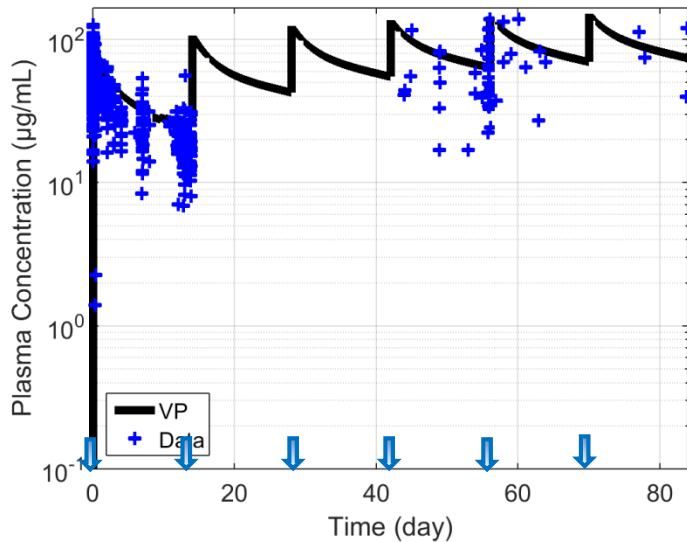


Therapy A PK



- Patient data are shown for comparison
- Previously reported pharmacokinetic parameters were used for the VP

Therapy B PK



- Patient data are shown for comparison
- Previously reported PK parameters were used for the VP