

Mathematical Modelling of Cancer Stem Cells

Thomas Hillen

University of Alberta

June 21, 2024

Review article:

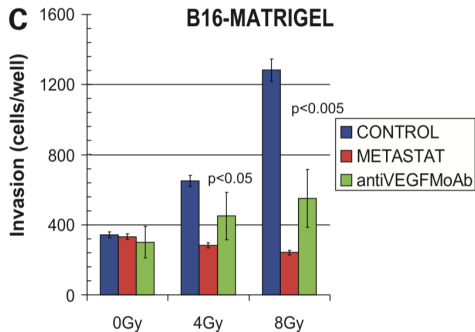
TH, A. Shyntar, Modelling of Cancer Stem Cell Driven Solid Tumors, book chapter, Springer 2024.

Article

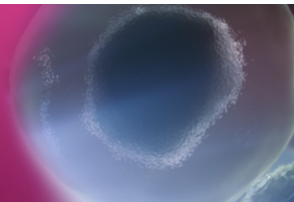
Angiogenesis and tumor growth inhibition by a matrix metalloproteinase inhibitor targeting radiation-induced invasion

Alexandre Kaliski, Laurence Maggiorella, Keith A. Cengel, Denis Mathe, Valerie Rouffiac, Paule Opolon, Nathalie Lassau, Jean Bourhis, and Eric Deutsch

DOI: 10.1158/1535-7163.MCT-05-0179 Published November 2005



International Journal of Oncology



Journal Home

Current Issue

Forthcoming Issue

Special Issues

Most Read

Most Cited
(Dimensions)

Most Cited
(CrossRef)

uPA/uPAR downregulation inhibits radiation-induced migration, invasion and angiogenesis in IOMM-Lee meningioma cells and decreases tumor growth in vivo

Authors: Odysseas Kargiotis, Chandramu Chetty, Venkateswara Gogineni, Christopher S. Gondi, Sai Muralikrishna Pulukuri, Athanassios P. Kyritsis, Meena Gujrati, Jeffrey D. Klopfenstein, Dzung H. Dinh, Jasti S. Rao

- “ Recently, ionizing radiation has been shown to enhance invasiveness of surviving tumor cells ...”



Article

The STAT3/Slug Axis Enhances Radiation-Induced Tumor Invasion and Cancer Stem-like Properties in Radioresistant Glioblastoma

Jang-Chun Lin ^{1,2,3}, Jo-Ting Tsai ^{2,3}, Tsu-Yi Chao ^{1,4}, Hsin-I Ma ^{5,6} and Wei-Hsiu Liu ^{5,6,*} 

- “Accumulating research indicates that GBM contains cancer stem-like cells (CSCs), which are radioresistant and result in therapeutic failure.”
- “Transwell and microarray assay demonstrated that radioresistant GBM cells (GBM-R2I2) exhibit increased invasion and self-renewal abilities compared with parental GBM cells. ”

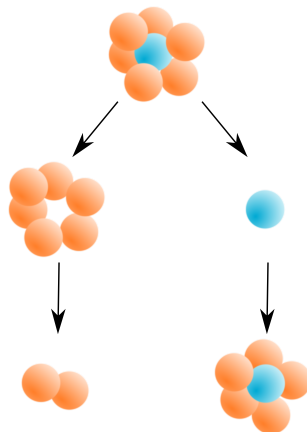
Cancer Stem Cells

Cancer stem cells (**CSCs**)

- self-renewing
- able to repopulate a heterogeneous tumor
- less sensitive to treatment
- **Main drivers behind tumor growth!**

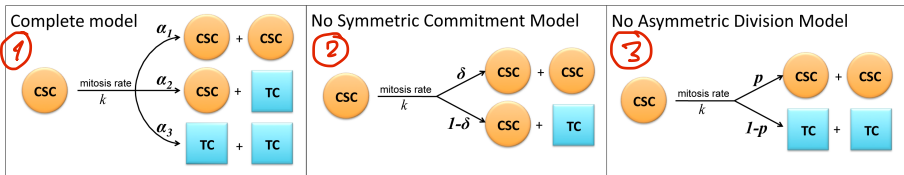
Non-stem Cancer cells (**TCs**)

- unable to repopulate the heterogeneous tumor
- relatively sensitive to treatment



* Figure from A. Rhodes

Basic CSC models



$$\begin{cases} \text{CSC} & \dot{u} = -ku + 2k\alpha_1 u + k\alpha_2 u \\ \text{TC} & \dot{v} = +2k\alpha_3 u + k\alpha_2 u \end{cases}$$

$$\begin{cases} \dot{u} = k(-1 + 2\alpha_1 + \alpha_2)u \\ \dot{v} = k(2\alpha_3 + \alpha_2)u \end{cases}$$

know: $\alpha_1 + \alpha_2 + \alpha_3 = 1$

$$\alpha_2 = 1 - \alpha_1 - \alpha_3$$

$$\begin{aligned}\dot{u} &= k(-1 + 2\alpha_1 + 1 - \alpha_1 - \alpha_3)u \\ &= k(\alpha_1 - \alpha_3)u\end{aligned}$$

$$\begin{aligned}\dot{v} &= k(2\alpha_3 + 1 - \alpha_1 - \alpha_3)u \\ &= k(\alpha_3 + 1 - \alpha_1)u\end{aligned}$$

$$\left. \begin{aligned}\dot{u} &= (\alpha_1 - \alpha_3)ku \\ \dot{v} &= (1 - \alpha_1 + \alpha_3)ku\end{aligned} \right\} \textcircled{1}$$

\updownarrow Same!

$\textcircled{2}$:
Hilfen

$$\left. \begin{aligned}\dot{u} &= \delta ku \\ \dot{v} &= (1 - \delta)ku\end{aligned} \right\} \textcircled{2}$$

$$\delta = \alpha_1 - \alpha_3$$

$$1 - \delta = 1 - \alpha_1 + \alpha_3$$

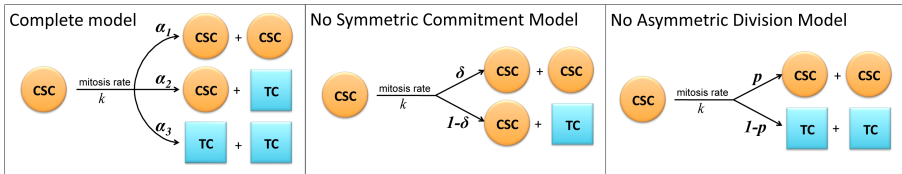
$$\delta = 2p - 1$$

$\textcircled{3}$:
Natalia

$$\left. \begin{aligned}\dot{u} &= (2p - 1)ku \\ \dot{v} &= \underline{2(1 - p)ku}\end{aligned} \right\} \textcircled{3}$$

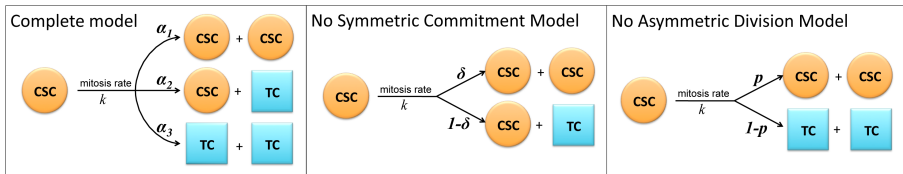
$$\begin{aligned}1 - \delta &= 1 - 2p + 1 \\ &= 2(1 - p)\end{aligned}$$

Basic CSC models



- All models are mathematically equivalent!

Basic CSC models



- All models are mathematically equivalent!

For stem cells $u(t)$ and non-stem cells $v(t)$ we use the basic model

$$u_t = \delta \gamma u$$

$$v_t = (1 - \delta) \gamma v$$

Mathematical Models for Cancer Stem Cells

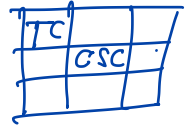
- Ganguli, Puri, *Cell Prolif.*, 2006
Sole et al., *J. Theor. Biol.* 2006
Carcinogenesis through mutations of normal stem cells
- Dingli, Michor, *Stem Cell*, 2006
"Successful Therapy Must Eradicate Cancer Stem Cells"
- Marciniak-Czochra, et al, *Stem Cells and Development*, 2009 *Kononova*
Stem cell dynamics plus feedback control
- Lowengrub, Christini, Wise, et al, 2008-11
Detailed cancer growth model in tissue, including spatial dynamics, tissue stiffness, force balances, growth factors and inhibitors, and cancer stem cells plus feedback control
- • Enderling, et al 2009, TH et al 2012, Fasano et al 2016, Shyntar et al 2022
The tumor growth paradox and tumor invasion paradox

Outline

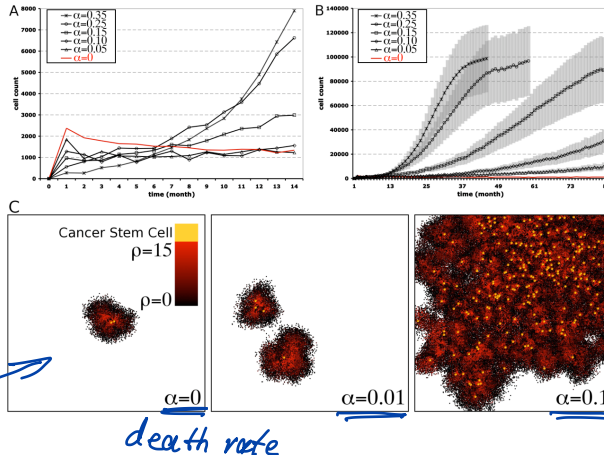
- Model 1: An agent-based model: Simulations
- Model 2: A birth-jump model: Existence, uniqueness.
- Model 3: A reaction-diffusion model: The tumor invasion paradox
- Model 4: An ODE model: The tumor growth paradox

germ. sing. pert.

Model 1: Agent based modelling (ABM)

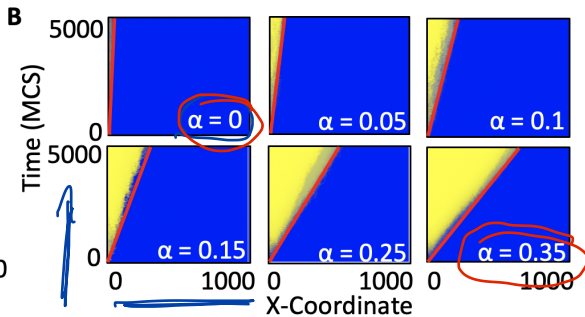
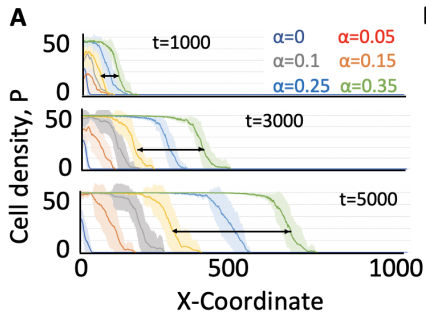


- Enderling et al. *Cancer Research* 2009.
- CSC: yellow, Tumor cells (TC) red-black. α death rate of TC.



Individual Based Model

Ashna Patel and H. Enderling



Model 2: Birth-jump model for cancer stem cells

CSC

$$\frac{\partial u}{\partial t} = \underbrace{D_u \Delta u}_{\text{diffusion}} + \delta \int_{\Omega} \underbrace{K(x, y, p(x, t))}_{\rho = u + v} \underbrace{\gamma u(y, t)}_{\rho} dy \quad \text{--- } \cancel{\alpha u} \quad (1)$$

TC

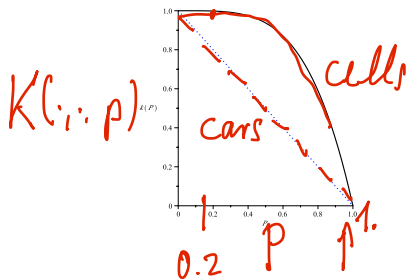
$$\frac{\partial v}{\partial t} = \underbrace{D_v \Delta v}_{\text{diffusion}} + \underbrace{(1 - \delta) \int_{\Omega} K(x, y, p(x, t)) \gamma u(y, t) dy}_{\text{birth}} + \underbrace{(-\alpha v)}_{\text{death}} + \underbrace{\int_{\Omega} K(x, y, p(x, t)) \rho v(y, t) dy}_{\text{birth}} \quad (2)$$

- $u(x, t)$ cancer stem cells, $v(x, t)$ differentiated cancer cells
 $\rho(x, t) = u(x, t) + v(x, t)$: total tumor population
- D_u, D_v : diffusion rates
- δ : rate of symmetric mitosis of CSC
- γ, ρ : mitosis rates for SC and NSCC, respectively
- $K(x, y, p(x, t))$: volume constraint

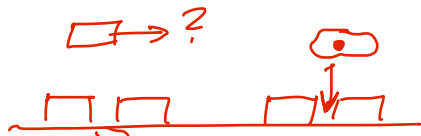
Volume constraint

$K(x, y, p(x, t))$:

- probability density of a cell at location y to give rise to a daughter cell at location x .
- The dependence on p expresses the volume effect (crowding effect), and proliferation is only possible if space is available, i.e. $p < p^*$.



car parking problem:



Global existence

- (Maddalena 2014) Global existence and uniqueness of (1),(2).
- (Borsi, Fasano, Primicerio, TH, 2015) Global existence and uniqueness for model (1),(2) with no diffusion.
- (Delgado, Duarte, Suarez, 2016): Global existence and uniqueness for

$$\frac{\partial u}{\partial t} = D\Delta u + \delta \int_{\Omega} K(x, y, u(x, t)) \gamma u(y, t) dy + \underline{\underline{f(u)}}$$

Reduction 1

Expand integration kernel as

$$\underline{K(x, y, p)} = \underline{q(x, y)} \underline{k(p)}$$

$$\int \underline{K(x, y, p(x, t))} u(y, t) dy \approx \underline{k(p)} (u + \underline{Bu_{xx}})$$

where

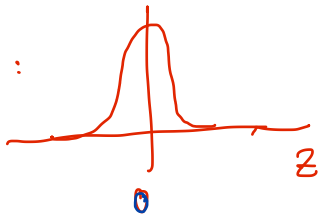
$$\underline{\int q dy} = 1, \quad \underline{B = \frac{1}{2} \int (x - y)^2 q dy}.$$

Moment expansion: $q(x-y)$

$$\int_{\Omega} q(x-y) u(y) dy = q * u(x)$$

$$= \int_{\Omega} q(z) u(x-z) dz$$

assume:



likely to move small steps z .

Use Taylor expansion

$$\int_{-\Omega} \underbrace{q(z) u(x-z)}_{=} dz = \int_{-\Omega} q(z) \left(u(x) - z u'(x) + \frac{z^2}{2} u''(x) - \frac{z^3}{6} u'''(x) + \dots \right) dz$$

$$= u(x) \underbrace{\int q(z) dz}_{=1} - u'(x) \underbrace{\int z q(z) dz}_{=0 \text{ if } q \text{ symmetric}} + \frac{u''(x)}{2} \underbrace{\int z^2 q(z) dz}_{\text{2nd moment}} - \frac{u'''(x)}{6} \underbrace{\int z^3 q(z) dz}_{=0 \text{ symmetry}} + \dots$$

$$\approx \underline{\underline{u(x) + \mathbb{B} u''(x)}}$$

Model 3: A reaction-diffusion model

$$u_t = Du_{xx} + \delta\gamma k(p)(u + Bu_{xx})$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)(u + Bu_{xx}) + \rho k(p)(v + Bv_{xx}) - \alpha v.$$

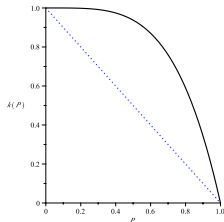
Model 3: A reaction-diffusion model

$$\begin{aligned}
 u_t &= \cancel{D}u_{xx} + \delta\gamma k(p)(u + \cancel{B}u_{xx}) \\
 v_t &= \cancel{D}v_{xx} + (1 - \delta)\gamma k(p)(u + \cancel{B}u_{xx}) + \rho k(p)(v + \cancel{B}v_{xx}) - \alpha v.
 \end{aligned}$$

Model 4: Focus on the kinetic part and remove all spatial derivatives.

$$\begin{aligned}
 U_t &= \underline{\delta\gamma k(P)U} \\
 V_t &= \underline{(1 - \delta)\gamma k(P)U} - \underline{\alpha V} + \underline{\rho k(P)V}.
 \end{aligned}
 \left. \vphantom{\begin{aligned} U_t \\ V_t \end{aligned}} \right\}$$

- $U(t)$: Cancer stem cells, mitosis rate γ
- $V(t)$: non-stem tumor cells, mitosis rate ρ
- δ : fraction of symmetric mitosis events
- Volume constraint, $P = U + V$,
 $k(P) = \max\{1 - P^\sigma, 0\}$, $\sigma \geq 1$.



The Tumor Growth Paradox

Definition

Let $P_\alpha(t)$ denote the total tumor population at time t , with a non stem cell death rate of α . The population exhibits a **tumor growth paradox** if there exists parameter values $\alpha_1 > \alpha_2$ and an open interval (t_1, t_2) such that $P_{\alpha_1}(0) = P_{\alpha_2}(0)$ and

$$\underline{P_{\alpha_1}(t)} > \underline{P_{\alpha_2}(t)}, \quad \text{for } t \in \underline{(t_1, t_2)}.$$

The Tumor Growth Paradox

Definition

Let $P_\alpha(t)$ denote the total tumor population at time t , with a non stem cell death rate of α . The population exhibits a **tumor growth paradox** if there exists parameter values $\alpha_1 > \alpha_2$ and an open interval (t_1, t_2) such that $P_{\alpha_1}(0) = P_{\alpha_2}(0)$ and

$$P_{\alpha_1}(t) > P_{\alpha_2}(t), \quad \text{for } t \in (t_1, t_2).$$

Theorem (TH, Enderling, Hahnfeldt, 2013).

Model 4 shows a tumor growth paradox.

Singular perturbation theory

Model 4:



$$U_t = \delta \gamma k(P)U$$

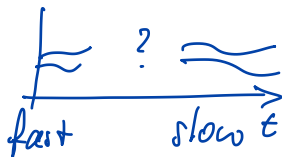
$$V_t = (1 - \delta) \gamma k(P)U - \alpha V + \rho k(P)V.$$

Small parameter: $\delta = 0.1 - 0.001$.

Fast and slow systems

Fast system

$$\begin{aligned}U_t &= 0 && U \text{ const.} \\V_t &= \gamma k(P)U - \alpha V + \rho k(P)V.\end{aligned}$$



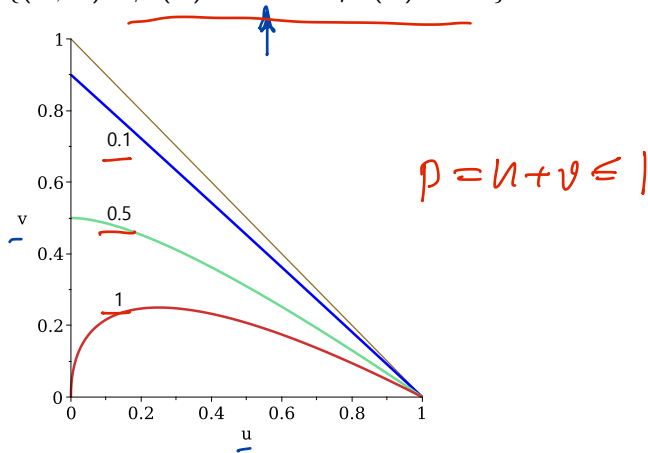
Slow system, $(\tau = \delta t)$

$$\left\{ \begin{array}{l} U_\tau = \gamma k(P)U \leftarrow \\ 0 = \gamma k(P)U - \alpha V + \rho k(P)V \end{array} \right\} \leftarrow$$

slow manifold

Slow manifold

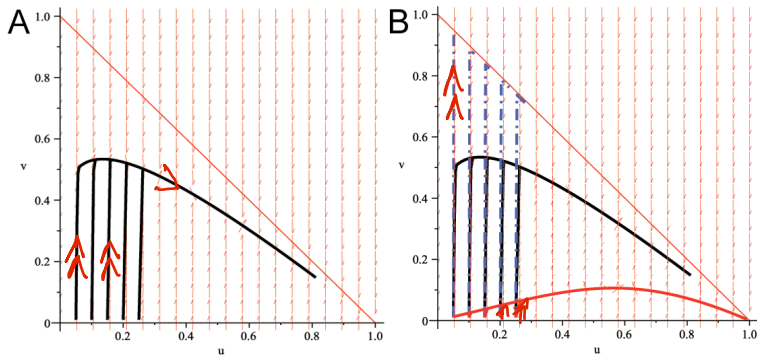
$$\mathcal{M} = \{(U, V) : \gamma k(P)U - \alpha V + \rho k(P)V = 0\}$$



Fast dynamics

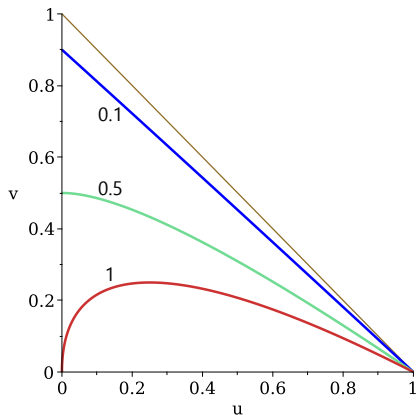
The fast dynamics relaxes quickly onto the **slow manifold**

$$\mathcal{M} = \{(U, V) : \gamma k(P)U - \alpha V + \rho k(P)V = 0\}$$



$\alpha = 0.05$ (blue), $\alpha = 1$ (black), $\alpha = 5$ (red).

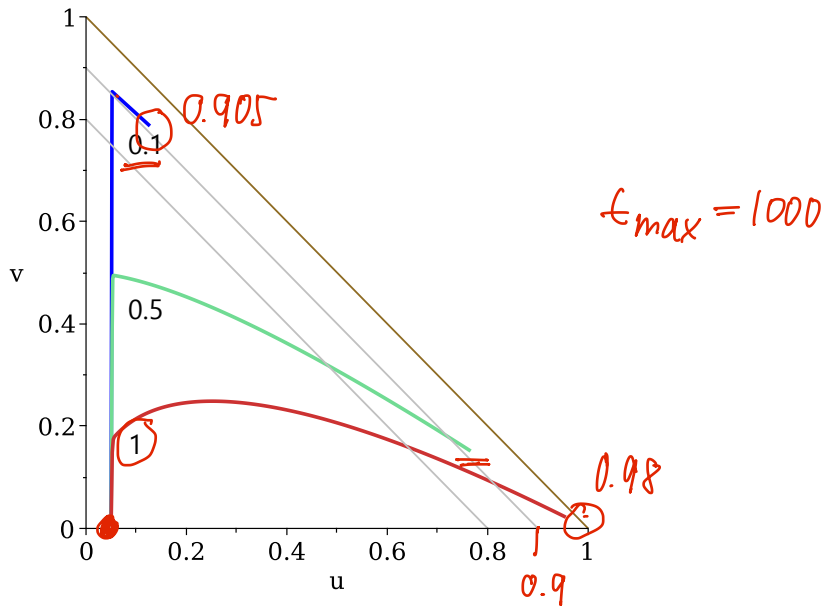
Slow dynamics



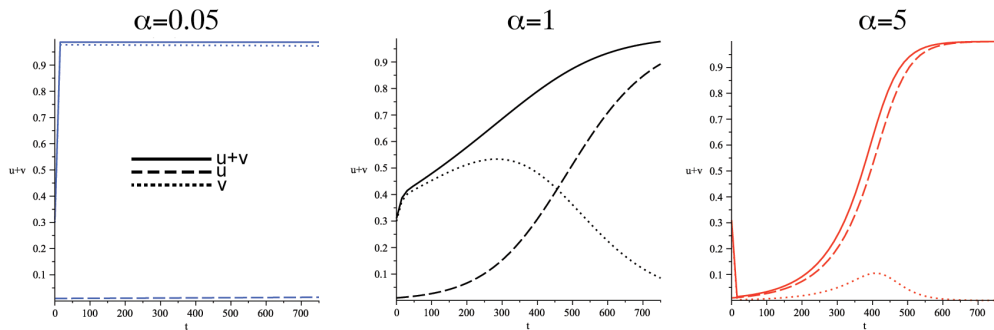
Lemma

Consider two clonogenic death rates $\alpha_1 > \alpha_2 > 0$. Then, on the slow manifold, the stem cell growth rate is larger for the population with the larger death rate α_1 .

Tumor Growth Paradox



Stem cells versus differentiated cancer cells



Cell populations as functions of time

- stem cells (dashed), differentiated cells (dotted), total population (solid)

Inclusion of treatments



$$u_t = \delta k(p)u - \underline{R_u(t)}u$$

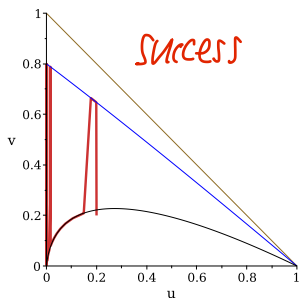
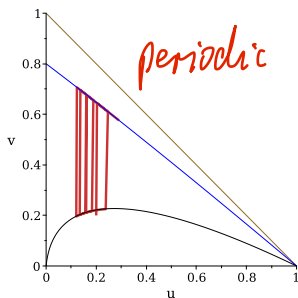
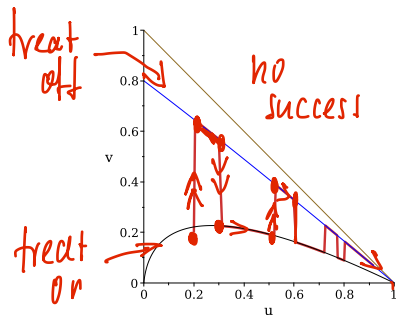
$$v_t = (1 - \delta)k(p)u + \rho k(p)v - \alpha v - \underline{R_v(t)}v.$$



Inclusion of treatments

$$u_t = \delta k(p)u - R_u(t)u$$

$$v_t = (1 - \delta)k(p)u + \rho k(p)v - \alpha v - R_v(t)v.$$



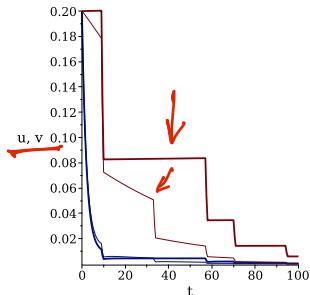
(A) insufficient treatment, (B) treatment oscillations, (C) successful treatment

Differentiation promoters

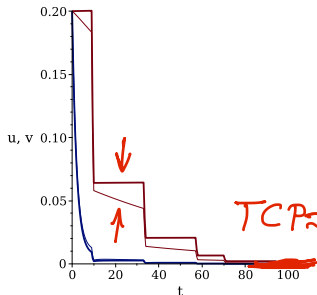
- CSC are less sensitive to treatments.
- Differentiation promoters can be used to push CSC into differentiation and make them more sensitive.
- In (Bachman et al 2012), we included differentiation promoters into the model and calibrated it on cancer data.

Differentiation promoters

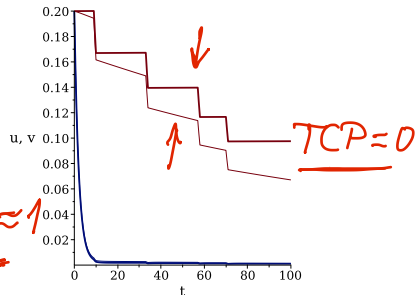
- CSC are less sensitive to treatments.
- Differentiation promoters can be used to push CSC into differentiation and make them more sensitive.
- In (Bachman et al 2012), we included differentiation promoters into the model and calibrated it on cancer data.
- **CSC, TC**, **thick: no diff. promoter**, **thin: with diff. promoter**



head and neck



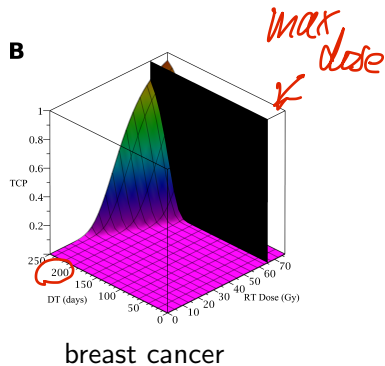
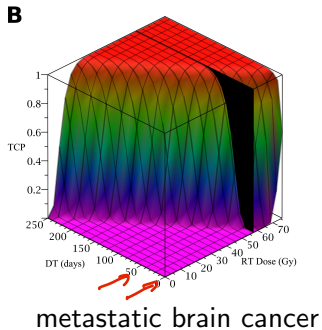
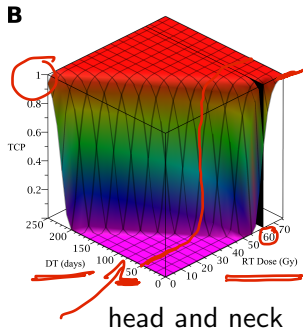
metastatic brain cancer



breast cancer

Tumor Control Probability (w. Bachman)

TCP = probability that the cancer is cured.



More on treatments

- In (Konstorum et al 2016) we included various feedback mechanisms and found an Allee effect.

More on treatments

- In (Konstorum et al 2016) we included various feedback mechanisms and found an Allee effect.
- In (Jilkine, Gutenkunst 2014, Rhodes, TH, 2016) study of de-differentiation. We include a de-differentiation promoter survivin and a survivin inhibitor YM155 and fitted the model to mouse data. Inhibition of survivin leads to better treatment.

Back to the reaction-diffusion model (Model 3)

$$u_t = \underline{Du_{xx}} + \delta\gamma k(p)(u + \underline{Bu_{xx}})$$

$$v_t = \underline{Dv_{xx}} + (1 - \delta)\gamma k(p)(u + \underline{Bu_{xx}}) + \rho k(p)(v + \underline{Bv_{xx}}) - \alpha v.$$

Back to the reaction-diffusion model (Model 3)

$$u_t = Du_{xx} + \delta\gamma k(p)(u + Bu_{xx})$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)(u + Bu_{xx}) + \rho k(p)(v + Bv_{xx}) - \alpha v.$$

Theorem: ([Fasano et al 2016](#)): Local and global existence of classical solutions.

Back to the reaction-diffusion model (Model 3)

$$u_t = Du_{xx} + \delta\gamma k(p)(u + Bu_{xx})$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)(u + Bu_{xx}) + \rho k(p)(v + Bv_{xx}) - \alpha v.$$

Theorem: (Fasano et al 2016): Local and global existence of classical solutions.

Simplify with $\gamma = \rho = 1$ and $B \approx 0$.

Back to the reaction-diffusion model (Model 3)

$$u_t = Du_{xx} + \delta\gamma k(p)(u + Bu_{xx})$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)(u + Bu_{xx}) + \rho k(p)(v + Bv_{xx}) - \alpha v.$$

Theorem: (Fasano et al 2016): Local and global existence of classical solutions.

Simplify with $\gamma = \rho = 1$ and $B \approx 0$.

Model 3a:

$$u_t = Du_{xx} + \delta k(p)u$$

$$v_t = Dv_{xx} + (1 - \delta)k(p)u + \rho k(p)v - \alpha v.$$

The Tumor Invasion Paradox

$$u_t = Du_{xx} + \delta k(p)u$$

$$v_t = Dv_{xx} + (1 - \delta)k(p)u + \rho k(p)v - \alpha v.$$

Theorem: (A. Shyntar et al. 2022)

Assume $k(p)$ is decreasing and $k(0) = 1$.

The Tumor Invasion Paradox

$$\begin{aligned}u_t &= Du_{xx} + \delta k(p)u \\v_t &= Dv_{xx} + (1 - \delta)k(p)u + \rho k(p)v - \alpha v.\end{aligned}$$

Theorem: (A. Shyntar et al. 2022)

Assume $k(p)$ is decreasing and $k(0) = 1$.

1. If $\alpha \geq 1$, then each front-like initial condition converges to a travelling wave with minimal wave speed

$$c^* = 2\sqrt{D}.$$

The Tumor Invasion Paradox

$$\begin{aligned}u_t &= Du_{xx} + \delta k(p)u \\v_t &= Dv_{xx} + (1 - \delta)k(p)u + \rho k(p)v - \alpha v.\end{aligned}$$

Theorem: (A. Shyntar et al. 2022)

Assume $k(p)$ is decreasing and $k(0) = 1$.

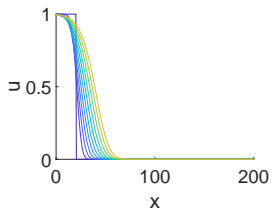
1. If $\alpha \geq 1$, then each front-like initial condition converges to a travelling wave with minimal wave speed

$$c^* = 2\sqrt{D}.$$

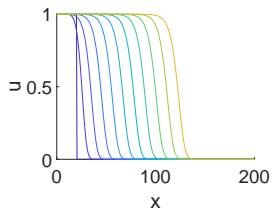
2. If $\alpha < 1$, then each front-like initial condition converges to a travelling wave with minimal wave speed

$$c^* = 2\sqrt{D\alpha}.$$

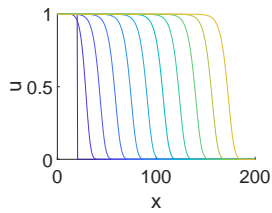
Simulations (A. Shyntar)



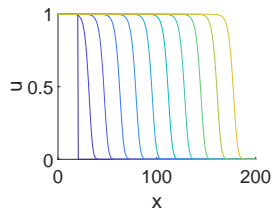
$\alpha = 0.05$



$\alpha = 0.5$

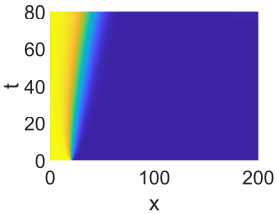


$\alpha = 1$

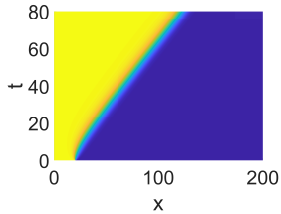


$\alpha = 5$

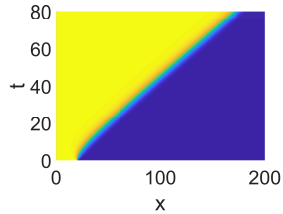
Simulations (A. Shyntar)



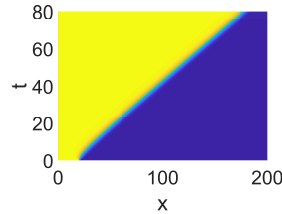
$\alpha = 0.05$



$\alpha = 0.5$



$\alpha = 1$



$\alpha = 5$

Proof of the invasion paradox

- We consider the PDE on the slow manifold \mathcal{M} from before.

Proof of the invasion paradox

- We consider the PDE on the slow manifold \mathcal{M} from before.
- On \mathcal{M} we can write v as a graph on u : $v_\alpha(u)$

Proof of the invasion paradox

- We consider the PDE on the slow manifold \mathcal{M} from before.
- On \mathcal{M} we can write v as a graph on u : $v_\alpha(u)$
- Then the reaction diffusion system reduces to one equation on \mathcal{M} :

$$u_t = Du_{xx} + k(u + v_\alpha(u))u$$

Proof of the invasion paradox

- We consider the PDE on the slow manifold \mathcal{M} from before.
- On \mathcal{M} we can write v as a graph on u : $v_\alpha(u)$
- Then the reaction diffusion system reduces to one equation on \mathcal{M} :

$$u_t = Du_{xx} + k(u + v_\alpha(u))u$$

- We show that this is of Fisher-KPP type and use the known results.

Treatments (A. Shyntar)

$$u_t = Du_{xx} + \delta\gamma k(p)u - \varepsilon h(t)u$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)u + \rho k(p)v - \alpha v - h(t)v.$$

The hazard function is computed from the linear-quadratic model

$$h(t) = (\alpha_p + \beta_p d_{eff}(t))d(t).$$

Treatments (A. Shyntar)

$$u_t = Du_{xx} + \delta\gamma k(p)u - \varepsilon h(t)u$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)u + \rho k(p)v - \alpha v - h(t)v.$$

The hazard function is computed from the linear-quadratic model

$$h(t) = (\alpha_p + \beta_p d_{\text{eff}}(t))d(t).$$

We start with brachytherapy and typical prostate cancer values:

$$\alpha_p = 0.15 \text{Gy}^{-1}, \quad \beta_p = 0.0048 \text{Gy}^{-2}$$

Treatments (A. Shyntar)

$$u_t = Du_{xx} + \delta\gamma k(p)u - \varepsilon h(t)u$$

$$v_t = Dv_{xx} + (1 - \delta)\gamma k(p)u + \rho k(p)v - \alpha v - h(t)v.$$

The hazard function is computed from the linear-quadratic model

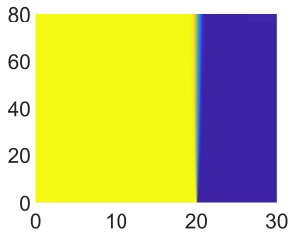
$$h(t) = (\alpha_p + \beta_p d_{eff}(t))d(t).$$

We start with brachytherapy and typical prostate cancer values:

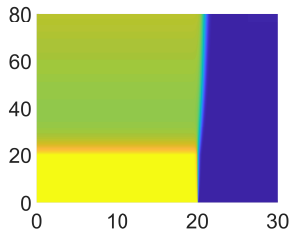
$$\alpha_p = 0.15 \text{Gy}^{-1}, \quad \beta_p = 0.0048 \text{Gy}^{-2}$$

and two radiation dose rates $R_0 = 5.71 \text{ Gy/day}$ (realistic) and $R_0 = 50.0 \text{ Gy/day}$ (unrealistic).

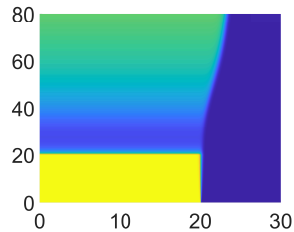
Brachytherapy



no treatment

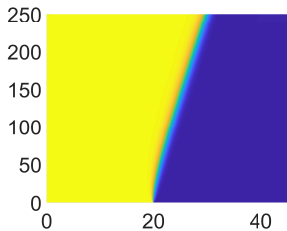


R_0 low

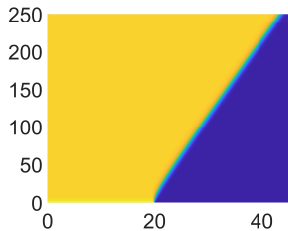


R_0 high

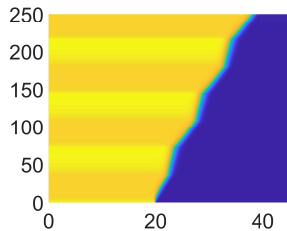
Intermittent therapy



no treatment

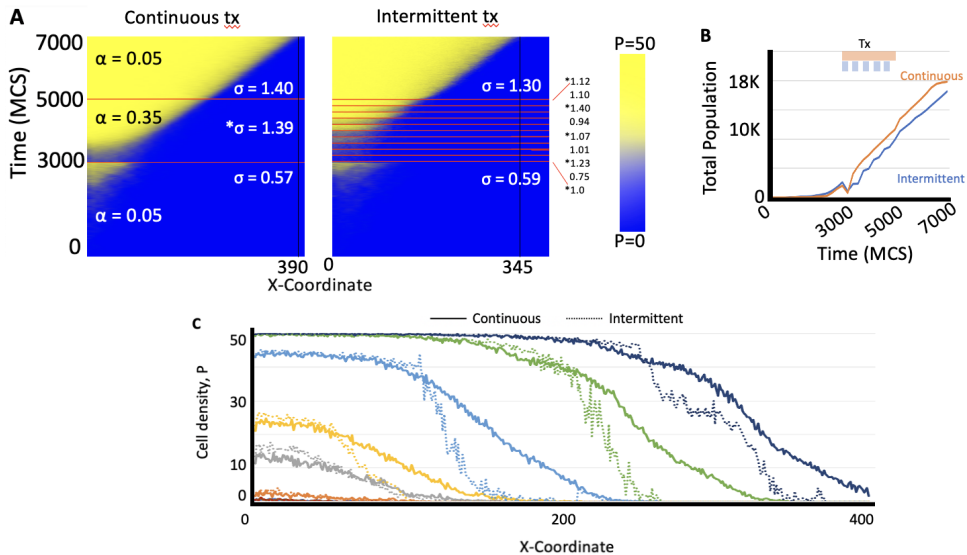


continuous

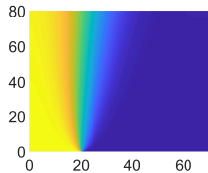


intermittent

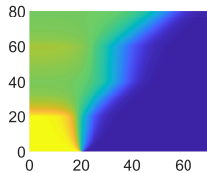
Intermittent therapy (ABM)



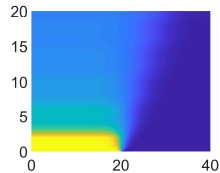
Fractionation therapy (glioma parameters)



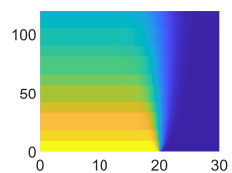
no treatment



20 days



2 days



10 min

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.
- Our ODE analysis is based on Fenichel's theorems of [geometric singular perturbation theory](#). An equivalent for PDEs is not available yet ...

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.
- Our ODE analysis is based on Fenichel's theorems of [geometric singular perturbation theory](#). An equivalent for PDEs is not available yet ...
- [Birth-jump models](#) are a useful modelling tools, but hard to analyse. Moments expansions help.
- Apply to [tumor spheroids](#), where CSC are found on the outer rim.

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.
- Our ODE analysis is based on Fenichel's theorems of [geometric singular perturbation theory](#). An equivalent for PDEs is not available yet ...
- [Birth-jump models](#) are a useful modelling tools, but hard to analyse. Moments expansions help.
- Apply to [tumor spheroids](#), where CSC are found on the outer rim.
- Inclusion of [stochastic effects](#). For example for low cell numbers during treatment one could compute the [tumor control probability](#).

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.
- Our ODE analysis is based on Fenichel's theorems of [geometric singular perturbation theory](#). An equivalent for PDEs is not available yet ...
- [Birth-jump models](#) are a useful modelling tools, but hard to analyse. Moments expansions help.
- Apply to [tumor spheroids](#), where CSC are found on the outer rim.
- Inclusion of [stochastic effects](#). For example for low cell numbers during treatment one could compute the [tumor control probability](#).

Thank you

Conclusions

- CSC are related to many [Hallmarks of Cancer](#), such as sustained growth, immortality, treatment resistance. They are likely to play an important role in other hallmarks as well such as metastasis and immune evasion, for example.
- Our ODE analysis is based on Fenichel's theorems of [geometric singular perturbation theory](#). An equivalent for PDEs is not available yet ...
- [Birth-jump models](#) are a useful modelling tools, but hard to analyse. Moments expansions help.
- Apply to [tumor spheroids](#), where CSC are found on the outer rim.
- Inclusion of [stochastic effects](#). For example for low cell numbers during treatment one could compute the [tumor control probability](#).

Thank you

Special thanks to:

A. Shyntar, M. Rhodes, A. Patel, H. Enderling, P. Hahnfeldt, I. Borsi, A. Fasano, M. Primicerio