Mathematical Modelling of Cancer from Cell to Tissue Level

Mark Chaplain



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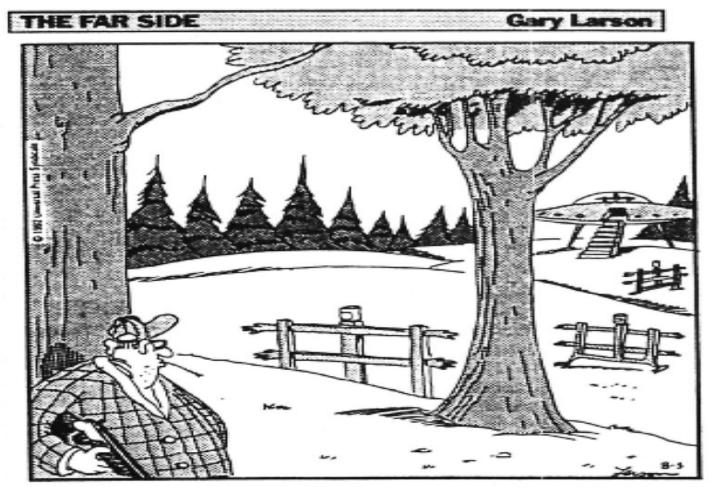
IMPAKT 2014 Brussels, 9 May 2014

Talk Overview

- Intracellular modelling
 - gene regulatory networks
- Cell-scale modelling
 - in vitro cell migration and retinal angiogenesis
- Tissue-scale modelling
 - cancer invasion
- Future perspectives

Mathematical Modelling

"The Zeonians came with the answers to many secrets of the universe. Vern, regrettably, came with thick glasses and his deer rifle."

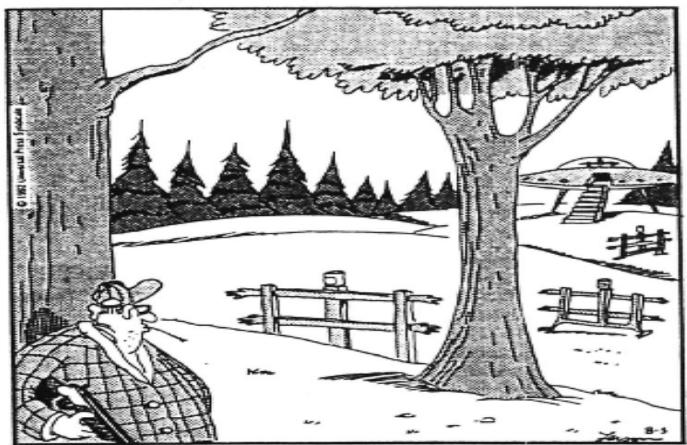


The Zeonions came with the answers to many secrets of the universe. Vern, regrettably, came with thick glasses and his deer rifle.

Mathematical Modelling

"The Zeonians came with the answers to many secrets of the universe. Vern, regrettably, came with thick glasses and his deer rifle."

THE FAR SIDE Gary Larson



The Zeonions came with the answers to many secrets of the universe. Vern, regrettably, came with thick glasses and his deer rifle.

Mathematical Modelling at IMPAKT 2014

"The participants came with the answers to many secrets of Breast Cancer. M. Chaplain, regrettably, came with some mathematics and his equations."



The Zeonions came with the answers to many secrets of the universe. Vern, regrettably, came with thick glasses and his deer rifle.

The Art of Mathematical Modelling

Definition: Mathematical Model

A mathematical model is a description of a system using mathematical terminology

The process of developing or creating a mathematical model is known as mathematical modelling

Applications of Mathematical Modelling: Weather Forecasting



The Hallmarks of Cancer

Cell, Vol. 100, 57-70, January 7, 2000, Copyright @2000 by Cell Press

The Hallmarks of Cancer

Review

Douglas Hanahan* and Robert A. Weinberg†

*Department of Biochemistry and Biophysics and Hormone Research Institute University of California at San Francisco San Francisco, California 94143 †Whitehead Institute for Biomedical Research and Department of Biology Massachusetts Institute of Technology Cambridge, Massachusetts 02142 evolve progressively from normalcy via a series of premalignant states into invasive cancers (Foulds, 1954).

These observations have been rendered more concrete by a large body of work indicating that the genomes of tumor cells are invariably altered at multiple sites, having suffered disruption through lesions as subtle as point mutations and as obvious as changes in chromosome complement (e.g., Kinzler and Vogelstein, 1996). Transformation of cultured cells is itself a





Hallmarks of Cancer: The Next Generation

Douglas Hanahan^{1,2,*} and Robert A. Weinberg^{3,*}

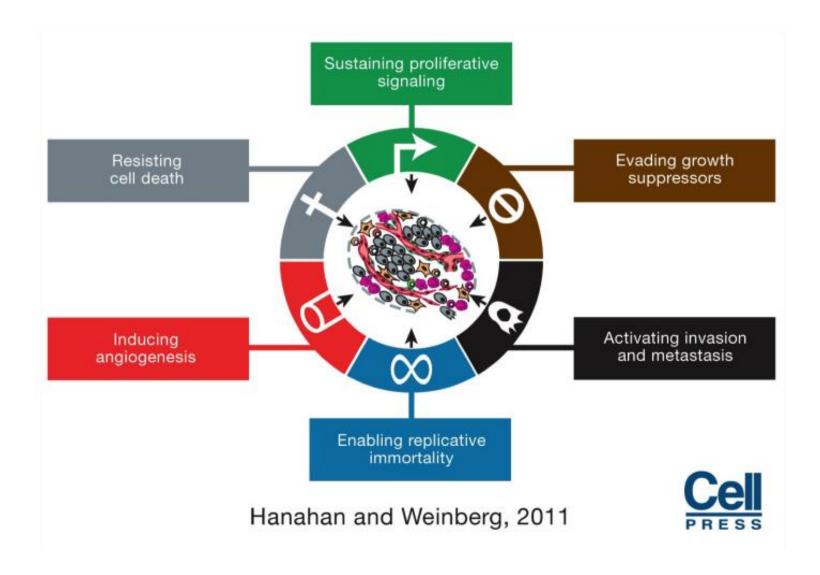
¹The Swiss Institute for Experimental Cancer Research (ISREC), School of Life Sciences, EPFL, Lausanne CH-1015, Switzerland

²The Department of Biochemistry & Biophysics, UCSF, San Francisco, CA 94158, USA

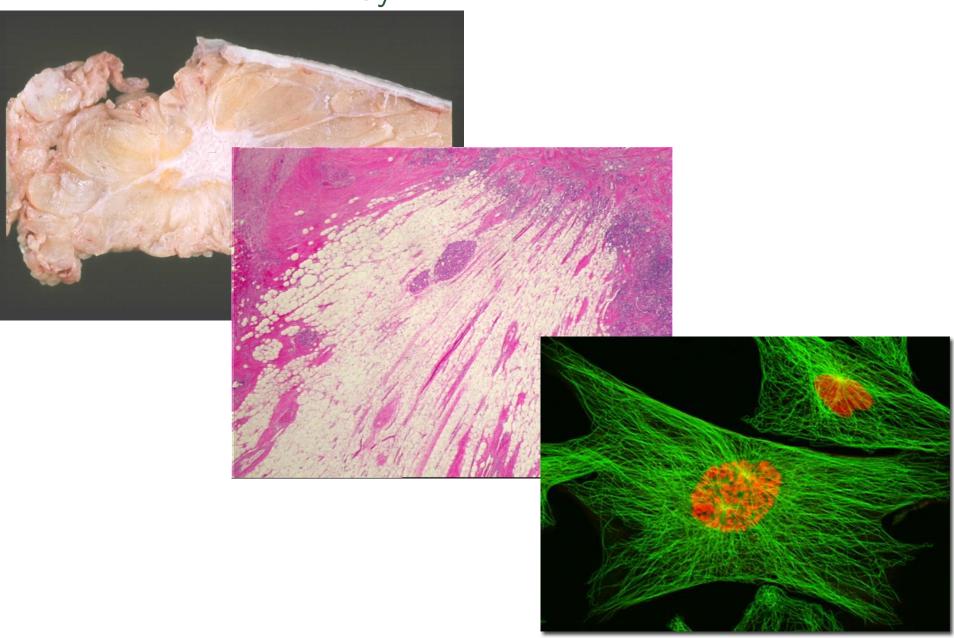
Whitehead Institute for Biomedical Research, Ludwig/MIT Center for Molecular Oncology, and MIT Department of Biology, Cambridge, MA 02142, USA

*Correspondence: dh@epfl.ch (D.H.), weinberg@wi.mit.edu (R.A.W.) DOI 10.1016/j.cell.2011.02.013

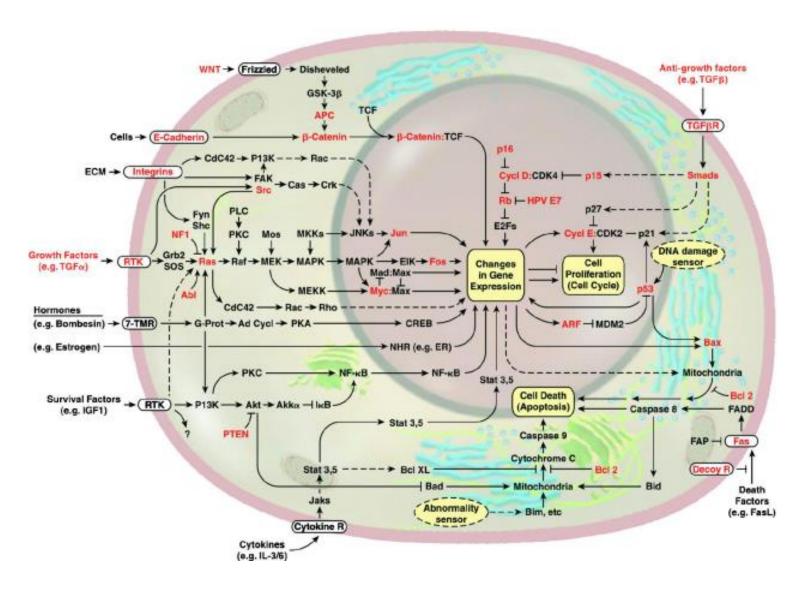
The Hallmarks of Cancer



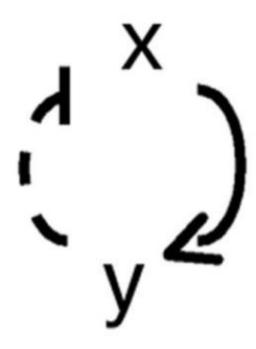
Cancer: A Multiscale System



Intracellular modelling: Gene regulatory networks

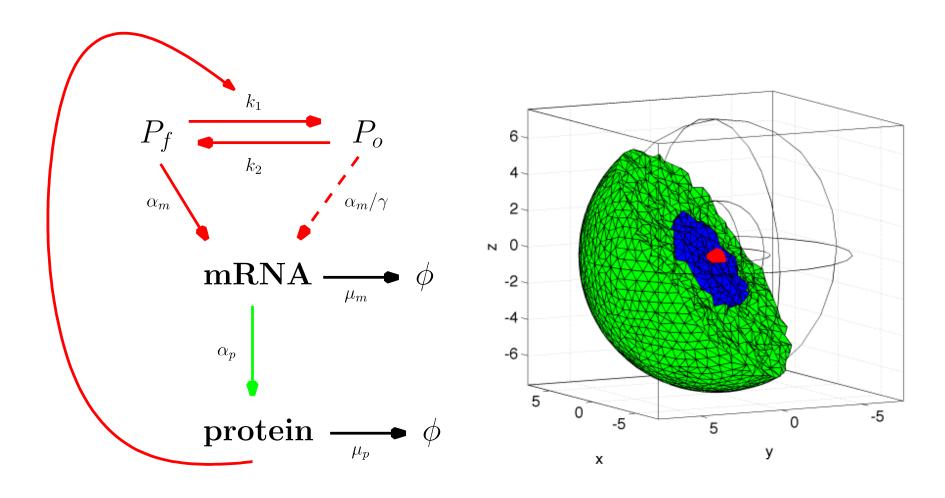


Gene regulatory networks: Negative feedback loops



A generic negative feedback loop: species x produces y which then inhibits x, in turn reducing levels of y...

Hes1 Spatial Stochastic Model



Hes1 Spatial Stochastic Model

$$P_f + protein \qquad \frac{k_1}{k_2} \qquad P_o, \quad (\text{promoter}, x_m, \text{nucleus})$$

$$P_f \qquad \frac{\alpha_m}{m} \qquad mRNA, \quad (\text{promoter}, x_m, \text{nucleus})$$

$$P_o \qquad \frac{\alpha_m/\gamma}{m} \qquad mRNA, \quad (\text{promoter}, x_m, \text{nucleus})$$

$$mRNA \qquad \frac{\alpha_p}{m} \qquad mRNA + protein, \quad (\text{cytoplasm}, \Omega_c)$$

$$mRNA \qquad \frac{\mu_m}{m} \qquad \phi, \quad (\text{entire cell}, \Omega)$$

$$protein \qquad \frac{\mu_p}{m} \qquad \phi, \quad (\text{entire cell}, \Omega)$$

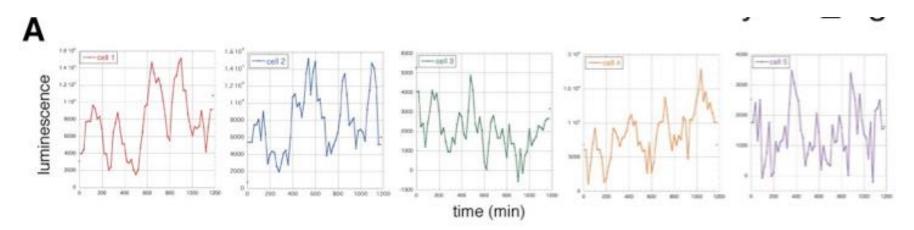
$$protein_i \qquad \frac{D/h^2}{m} \qquad protein_{i+1}, \quad (\text{entire cell}, \Omega)$$

$$protein_i \qquad \frac{D/h^2}{m} \qquad mRNA_{i+1}, \quad (\text{entire cell}, \Omega)$$

$$protein_i \qquad \frac{D/h^2}{m} \qquad protein_{i-1}, \quad (\text{entire cell}, \Omega)$$

$$mRNA_i \qquad \frac{D/h^2}{m} \qquad mRNA_{i-1}, \quad (\text{entire cell}, \Omega)$$

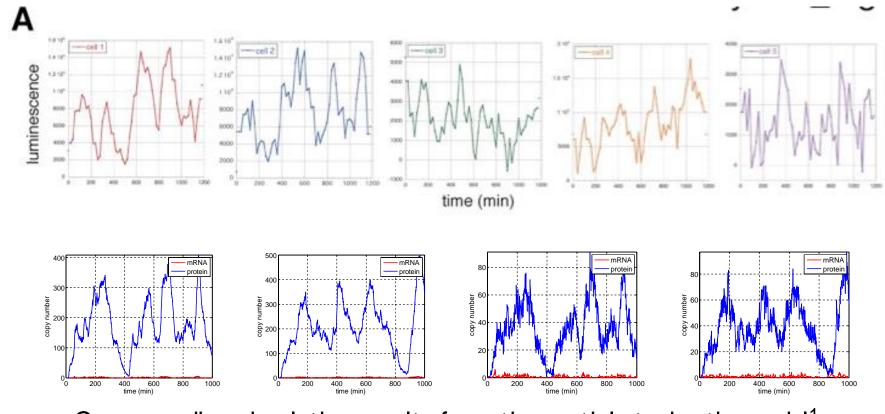
Hes1: Experimental Data/Simulation Results



Experimental data from Kobayashi et al. showing Hes1 protein levels in murine embryonic stem cells.

¹Kobayashi et al. (2009) The cyclic gene Hes1 contributes to diverse di∉erentiation responses of embryonic stem cells *Genes Dev.* 23, 1870 - 1875

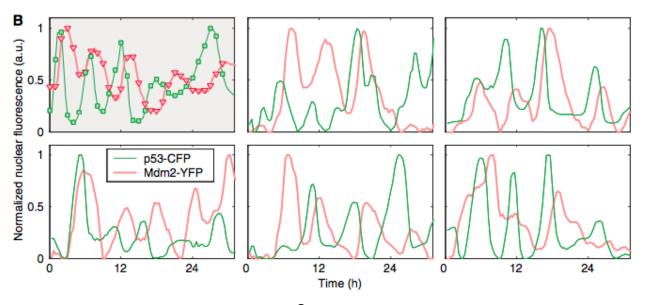
Hes1: Experimental Data/Simulation Results



Corresponding simulation results from the spatial stochastic model¹.

¹Sturrock, Hellander, Matzavinos, Chaplain (2013) Spatial stochastic modelling of the Hes1 gene regulatory network: intrinsic noise can explain heterogeneity in embryonic stem cell di erentiation. *J. R. Soc. Interface* 10, 20120988

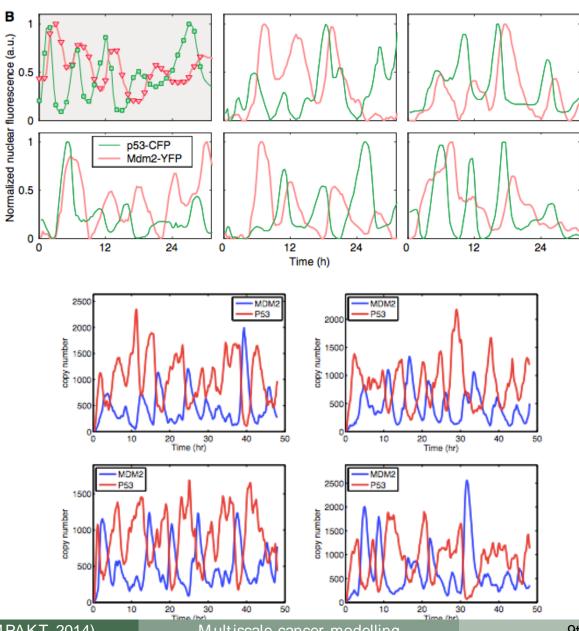
Intracellular modelling: p53-Mdm2 System



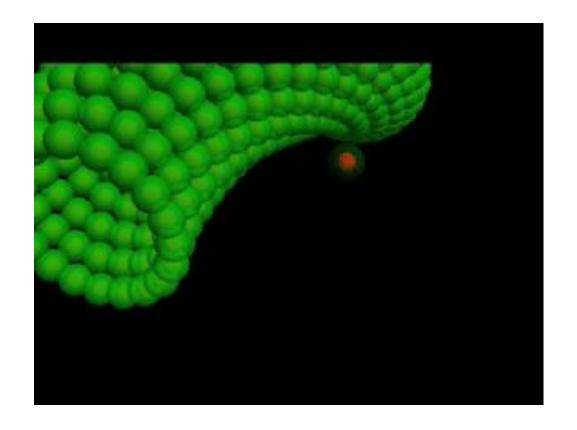
Experimental data from Lahav et al.² showing p53 and Mdm2 protein levels in individual cells.

²Lahav et al. (2004) Dynamics of the p53-Mdm2 feedback loop in individual cells. *Nature Genetics* 36, 147 - 150

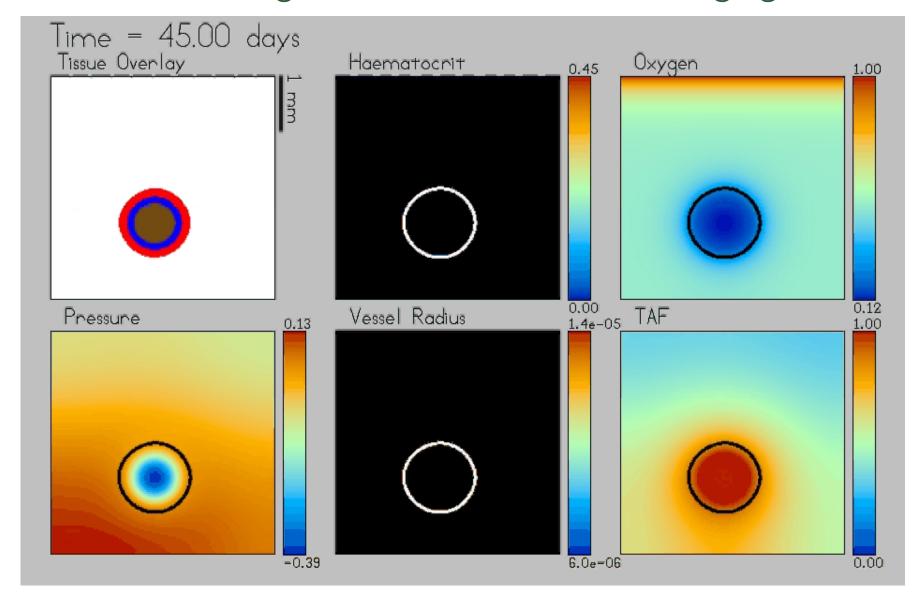
Intracellular modelling: p53-Mdm2 System



Single Cell Migration: Intravasation and Metastatic Spread



Individual Cell Migration: Tumour-induced Angiogenesis



cancer cells
$$\rightarrow$$
 MDE² \rightarrow ECM³ \leftrightarrow cancer cells \uparrow \leftarrow \leftarrow

Cancer cells, $c(\mathbf{x},t)$: secrete MDE, invade ECM, proliferate

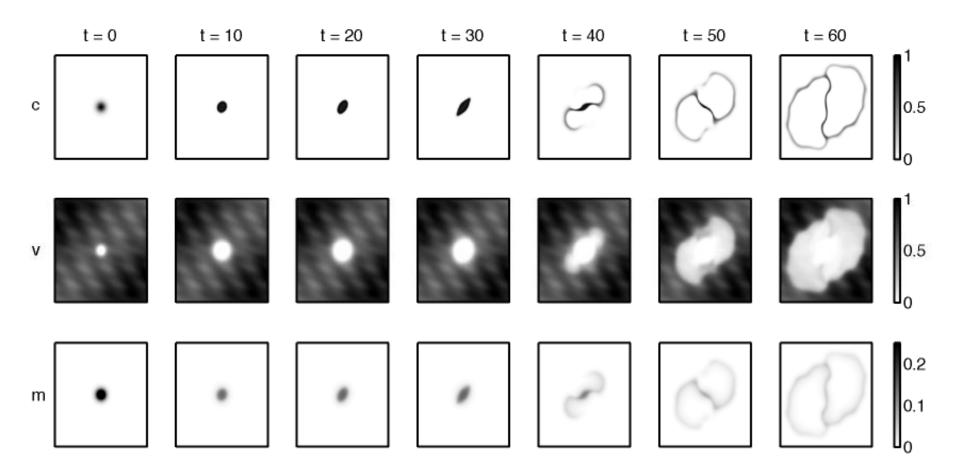
ECM, $v(\mathbf{x},t)$: degraded by MDE, re-modelling

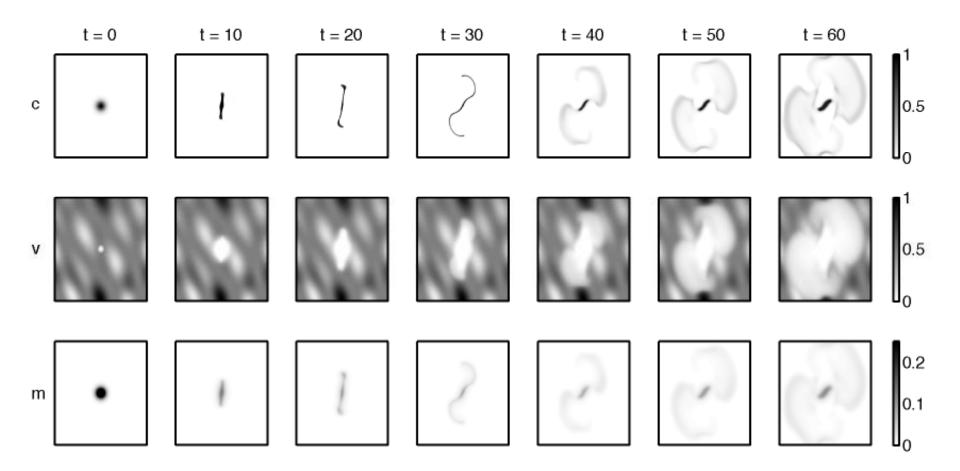
MDE, $m(\mathbf{x},t)$: secreted by cancer cells, diffuse, degrade ECM, decay

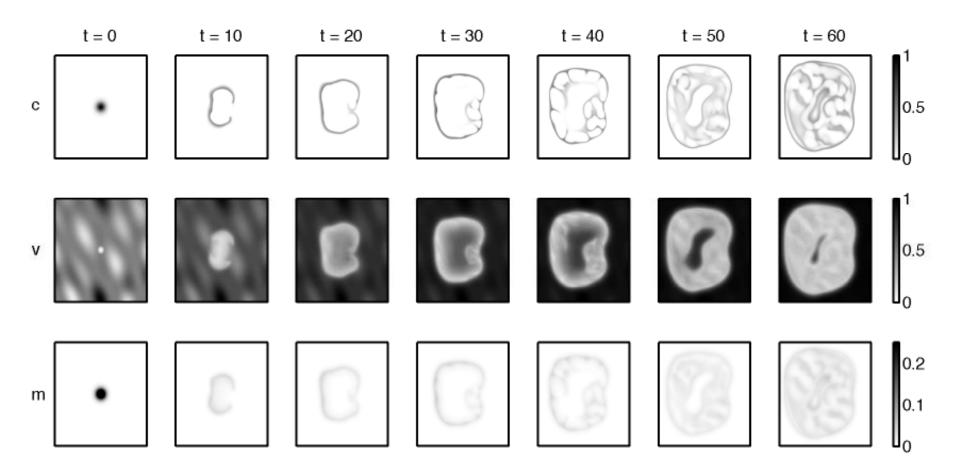
²matrix degrading enzymes

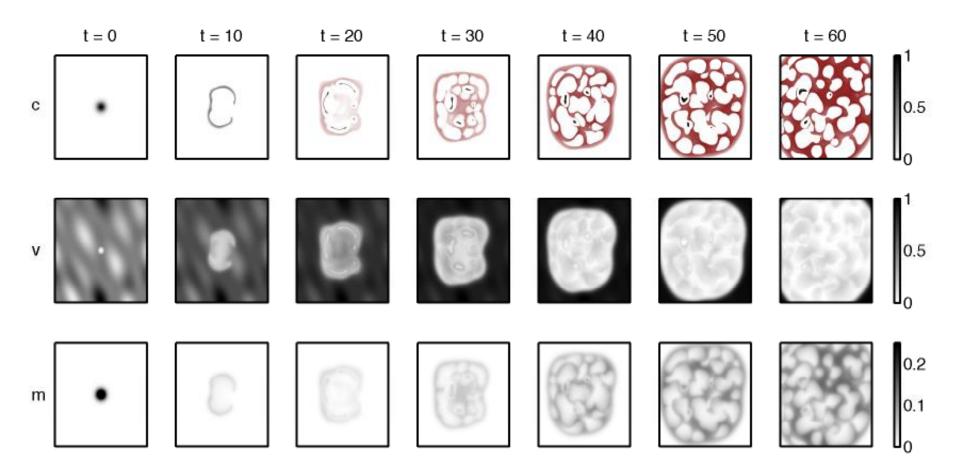
³extracellular matrix

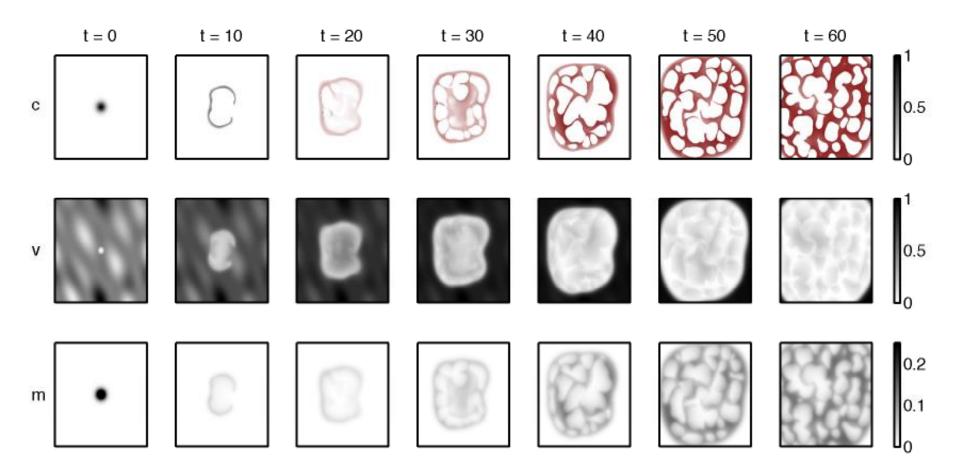
2D simulation results, time-dependent adhesion parameters:











Tissue scale modelling: Experimental Data Infiltrative growth pattern (INF) classification⁴:

J Gastroenterol (2012) 47:1279-1289

1281

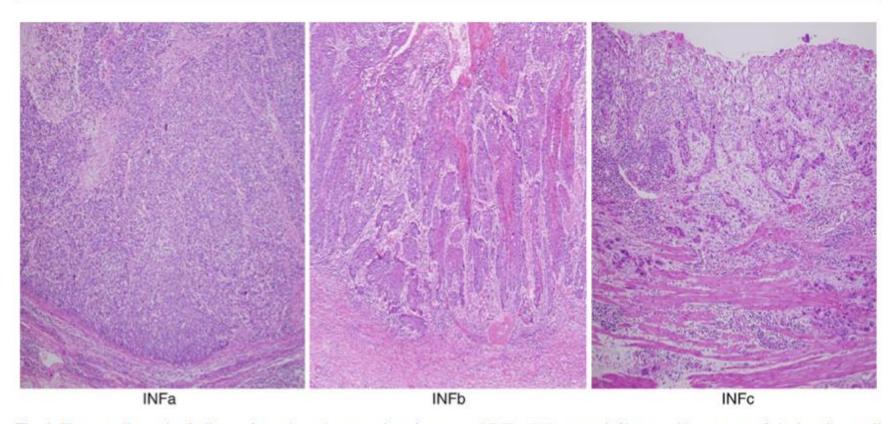
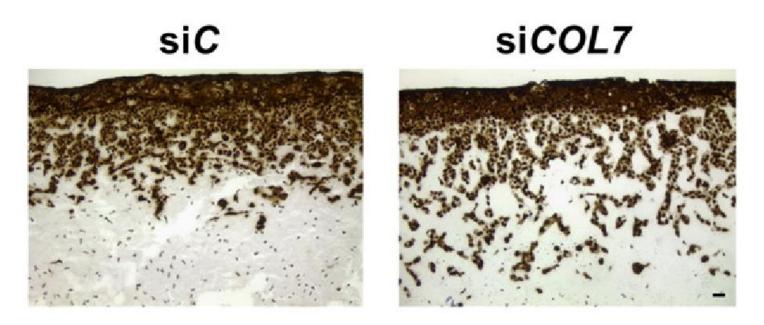


Fig. 1 Hematoxylin-eosin findings of esophageal cancer invasive patterns. *INFa* tumor extends downward continuously and expansively from the epithelium, *INFb* intermediate pattern between INFa

and INFc, *INFc* tumor infiltrates with a pattern of single cells, small and large tumor nests, or a trabecular arrangement of tumor cells in the lamina propria mucosa or submucosa (×40)

⁴Ito et al. (2012) New invasive patterns as a prognostic factor for superficial esophageal cancer. *J. Gastroenterol.* 47, 1279 - 1289

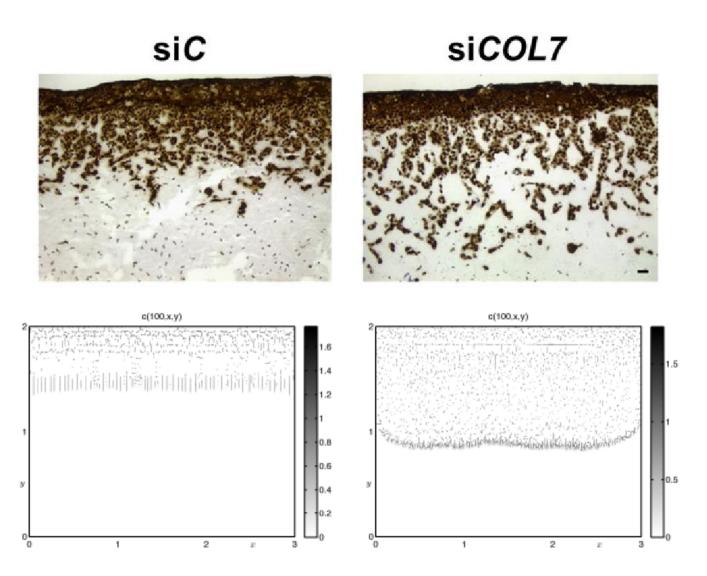
Tissue scale modelling: Organotypic Invasion Assay Organotypic assay results:



Cancer cell invasion in an organotypic invasion assay. Image on the left shows reduced invasion in a gel with collagen VII. Image on the right shows an increased invasion into a gel without collagen VII. Collagen VII is a key ECM component involved in anchoring cells⁵.

⁵Martins et al. (2009) Increased invasive behaviour in cutaneous squamous cell carcinoma with loss of basement-membrane type VII collagen. *J. Cell Sci.* **122**, 1788-1799

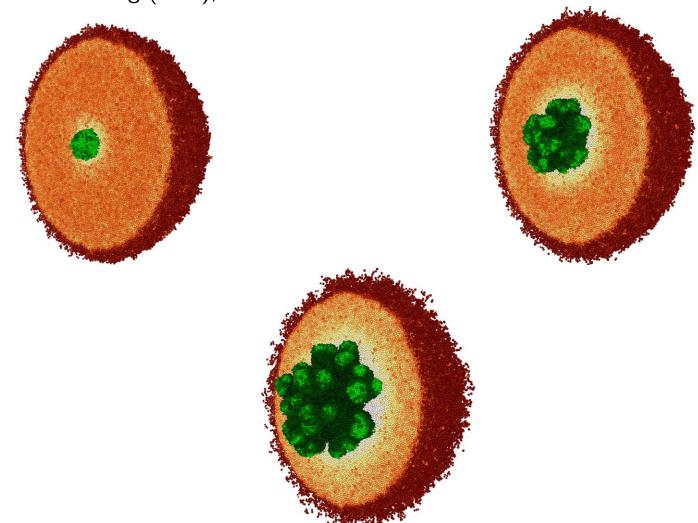
Tissue scale modelling: Organotypic Invasion Assay



Corresponding simulation results with baseline cell-cell adhesion on the left and reduced cell-cell adhesion on the right.

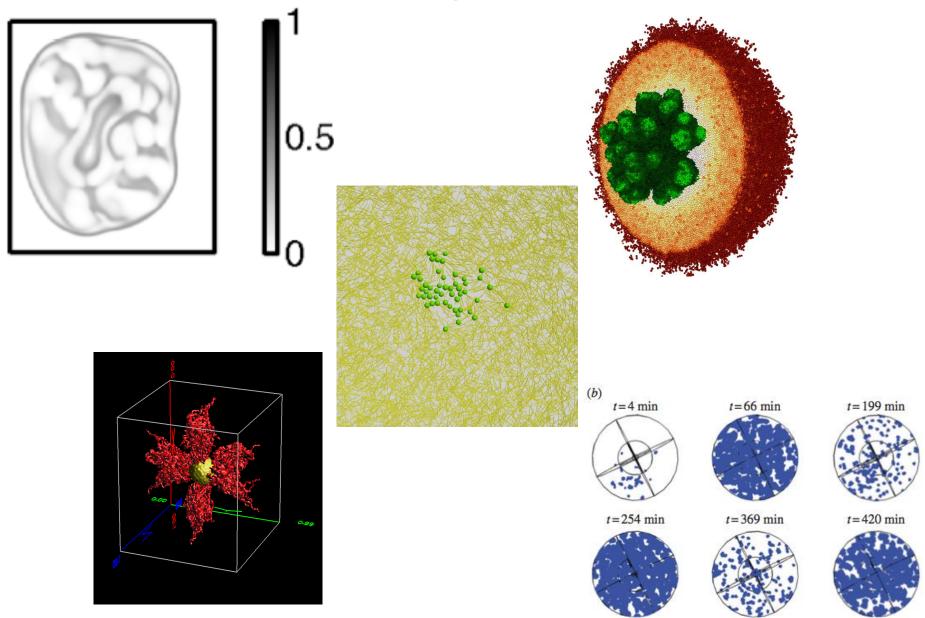
Future Perspectives

IBM Blue Gene/Q Supercomputer: Interdisciplinary Centre for Mathematical and Computational Modelling (ICM), Warsaw

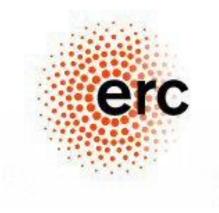


 10^9 individual cells...

Future Perspectives: Creating a Virtual Solid Tumour



Thank You



European Research Council