

# A Nonlocal Model for Cancer Invasion

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*This talk can be downloaded from my web site*

`www.ma.hw.ac.uk/~jas`

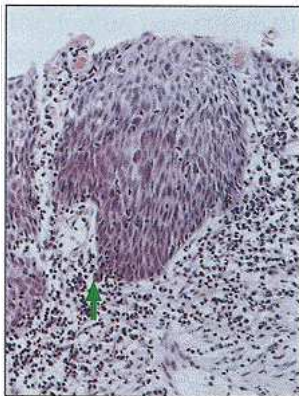
## Collaborators

Kevin Painter Heriot-Watt University

Nicola Armstrong Formerly Heriot-Watt University

Stephen Gourley University of Surrey

# Introduction to Cancer Invasion

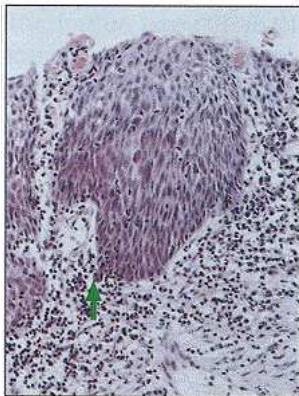


Cells in a solid tumour invade surrounding tissue due to changes in:

- migration
- protease/anti-protease production
- adhesion

Carcinoma of the uterine cervix

# Introduction to Cancer Invasion



Cells in a solid tumour invade surrounding tissue due to changes in:

- migration
- protease/anti-protease production
- **adhesion**: decreased cell-cell adhesion and increased cell-matrix adhesion

Carcinoma of the uterine cervix

## Modelling Adhesion in Cancer

Variables:  $n(x, t)$  tumour cell density,  $m(x, t)$  matrix density

$$\frac{\partial n}{\partial t} = - \overbrace{\frac{\partial}{\partial x} [n \cdot K_{nn}]}^{\text{cell-cell adhesion}} - \overbrace{\frac{\partial}{\partial x} [n \cdot K_{nm}]}^{\text{cell-matrix adhesion}} + \overbrace{n(1-n)}^{\text{cell proliferation}}$$

$$\frac{\partial m}{\partial t} = - \underbrace{\lambda \cdot n \cdot m^2}_{\text{matrix degradation}}$$

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$K_{nn} =$  cell flux due to cell-cell adhesion

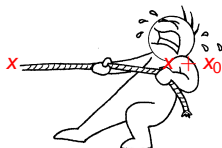
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## Modelling Cell-Cell Adhesion

- Adhesive flux  $K_{nn}$  is proportional to the force due to breaking and forming adhesive bonds (Stokes' Law: low Reynolds number)
- The force on a cell at  $x$  exerted by cells and matrix a distance  $x_0$  away depends on:
  - 1 cell and matrix densities at  $x + x_0$
  - 2 distance  $|x_0|$
  - 3 sign of  $x_0$  ( $\Rightarrow$  direction of force)

$$f(x, x_0) = g(n(x + x_0, t), m(x + x_0, t)) \cdot \omega(x_0)$$



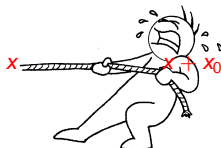
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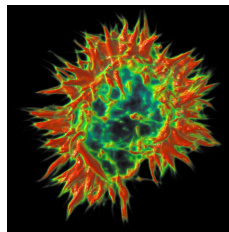
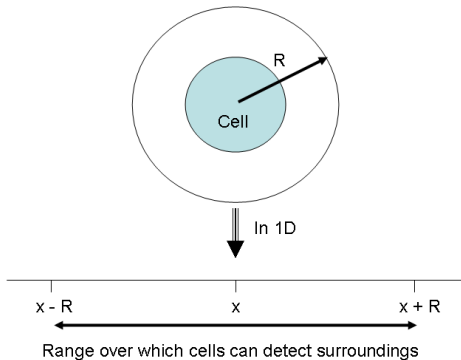
$$f(x, x_0) = g(n(x + x_0, t), m(x + x_0, t)) \cdot \omega(x_0)$$

- Total force = sum of all forces acting on cells at  $x$

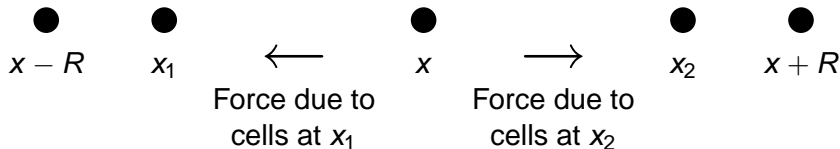
$$F(x) = \int_{-R}^{+R} f(x, x_0) dx_0$$



## Model Details: The Sensing Radius, $R$



## Model Details: The Function $\omega(x_0)$

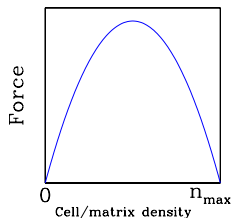


$\omega(x_0)$  is an odd function. For simplicity we take

$$\omega(x_0) = \begin{cases} -1 & \text{if } -R < x_0 < 0 \\ +1 & \text{if } 0 < x_0 < +R \end{cases}$$

## Model Details: The Function $g(n)$

- At low cell densities, the force  $f(x, x_0)$  will increase with cell density at  $x + x_0$  when this is small.
- However, there will be a density limit beyond which cells will no longer aggregate.
- We account for this via a nonlinear  $g(\cdot)$ ; we take  $g(n, m) = n(n_{max} - n - m)$ . Here  $n_{max}$  corresponds to no empty space.
- We rescale to give  $n_{max} = 2$ .



## Modelling Adhesion in Cancer

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$$K_{nn} = \alpha \int_{-1}^1 n(x + x_0, t) \cdot (2 - n(x + x_0, t) - m(x + x_0, t)) \cdot \omega(x_0) dx_0$$

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$$K_{nm} = \beta \int_{-1}^1 m(\mathbf{x} + \mathbf{x}_0, t) \cdot (2 - n(\mathbf{x} + \mathbf{x}_0, t) - m(\mathbf{x} + \mathbf{x}_0, t)) \cdot \omega(\mathbf{x}_0) d\mathbf{x}_0$$

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Extension to 2-D is straightforward

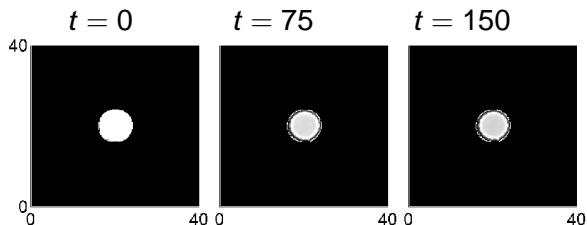


## Simulation of a Non-Invasive Tumour

For cell-cell adhesion ( $\alpha$ ) relatively large and cell-matrix adhesion ( $\beta$ ) relatively small, the model predicts a non-invasive tumour

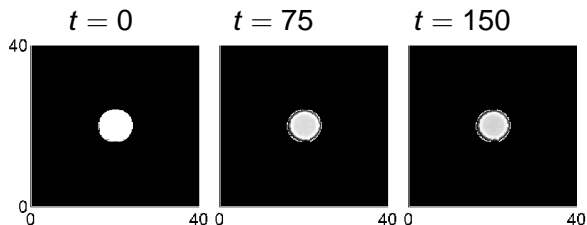
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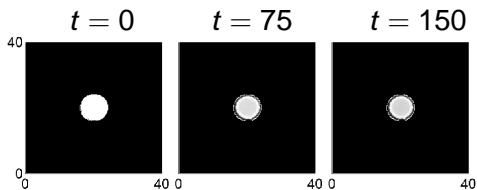
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Invasion can be initiated either by decreasing cell-cell adhesion ( $\alpha$ ) or by increasing cell-matrix adhesion ( $\beta$ )

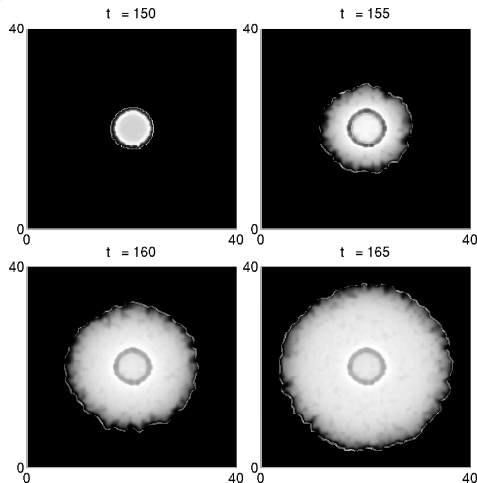
# The Sequential Development of an Invasive Tumour

Stage 1:  
non-invasive  
tumour growth



# The Sequential Development of an Invasive Tumour

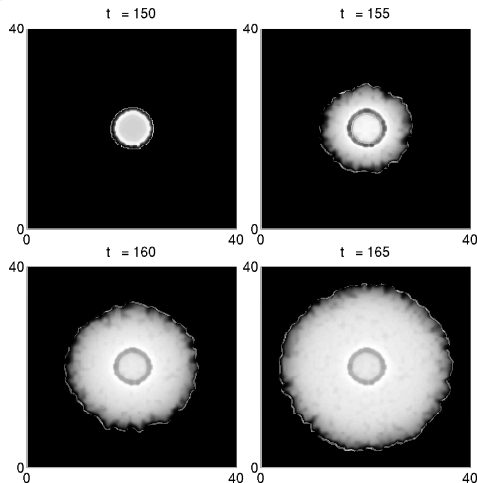
Stage 2:  
mutation,  
followed by  
tumour invasion



# The Sequential Development of an Invasive Tumour

## Tumour morphology:

Detailed studies of tumour pathology reveal a correlation between the invasive potential of tumours and their shape. (Tumour shape is often quantified via fractal dimension.)

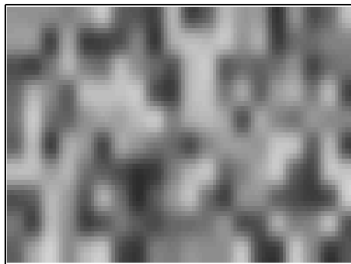


## Explanation of Tumour Fingering

Model solns predict: invasion of uniform matrix  $\Rightarrow$  flat boundary  
invasion of non-uniform matrix  $\Rightarrow$  fingering



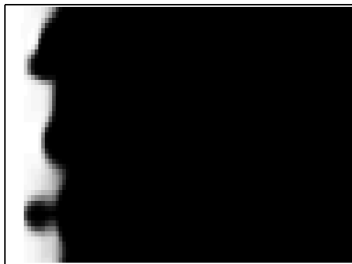
Cells



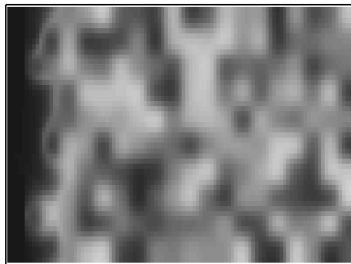
Matrix

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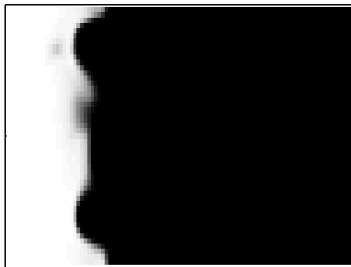


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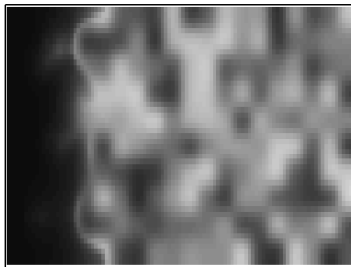


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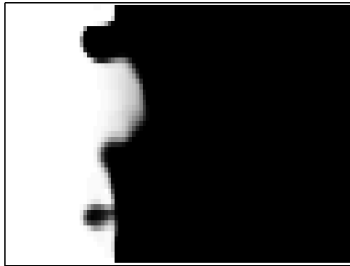
Cells



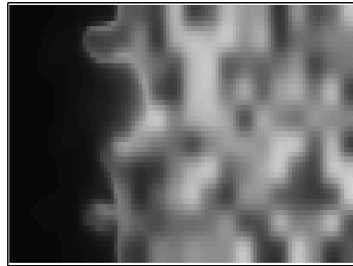
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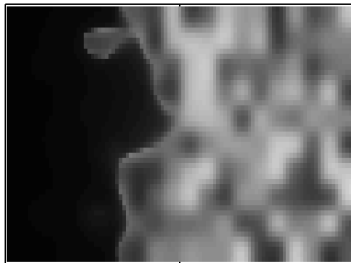
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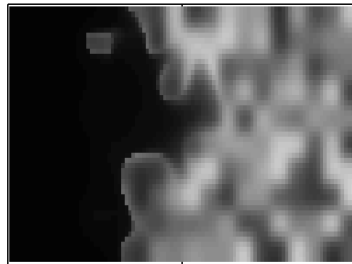
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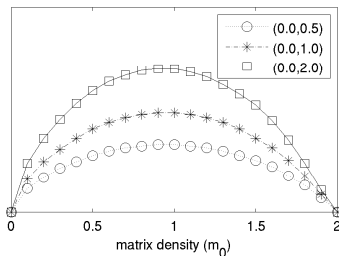
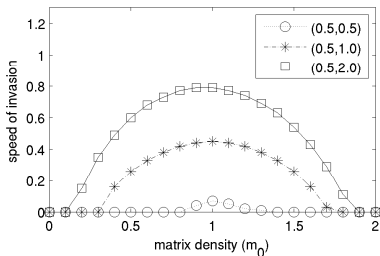
Cells



Matrix

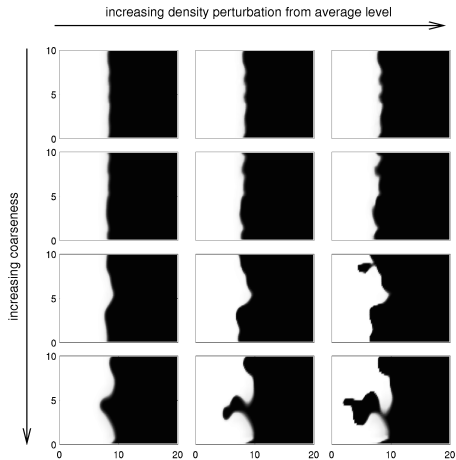
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Basic explanation: invasion speed varies with matrix density.

# Explanation of Tumour Fingering



# Conclusions and Challenges

- Our model results are consistent with traditional thinking on cancer invasion.
- The model makes quantitative predictions on how invasion speed depends on adhesion strengths and matrix density, which are experimentally testable.
- The model makes detailed predictions on how tumour fingering depends on matrix heterogeneity; these are also experimentally testable.
- The model raises many computational challenges, in particular concerning extension to 3-D.

## References

[N.J. Armstrong, K.J. Painter, J.A. Sherratt](#): A continuum approach to modelling cell adhesion. *J. Theor. Biol.* **243**, 98-113 (2006).

[J.A. Sherratt, S.A. Gourley, N.J. Armstrong, K.J. Painter](#): Boundedness of solutions of a nonlocal reaction-diffusion model for adhesion in cell aggregation and cancer invasion. *Eur. J. Appl. Math.* **20**, 123-144 (2009).

[K.J. Painter, N.J. Armstrong, J.A. Sherratt](#): The impact of adhesion on cellular invasion processes in cancer and development. *J. Theor. Biol.* in press.



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  - Introduction to Cancer Invasion
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  - Model Details: The Function  $\omega(x_0)$
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