



Multi-scale mathematical modelling of epithelial tissues to uncover the mechanisms of onset, progression, prevention and reversion of complex diseases

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On the menue today:

Systems biology for the analysis of Complex epitheilal tissue diseases:

What? Why? How?

Complex epithelial tissue diseases: challenges



(3) Slow pathological progression

(4) Negative side effects of treatments that are often ineffective

How can we understand, diagnose, prevent and revert)?

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What is systems biology?

Model construction, calibration and validation: data integration and analysis

Clinical and experimental data Mathematical computational predictions

Experimental design

Systems biology pipeline



Model to agree with experimental data



(What?)

Why?

(How?)

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Our working example:



System of interacting pathogens, immune cells and epithelial tissue.

Figure adapted from: Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Key clinically relevant quesitons



- What is the (clinical) outcome of this system?
- How is it affected by genetic or environmental **risk factors**?
- How can systemic infection be prevented?
- How could the risk of antibiotics resistance be **minimized**?

What are the challenges?



Complex and non-linear

- Synergy between risk factors (network-as-buffer)
- Negative side effects of treatments (propagation of disturbances)

Dynamical

- Multiple processes co-ocurring at different (temporal) scales
- Disease progression

Quantitative:

- Dose-dependency of qualitative transitions
- Need for opimization of treatments

How can systems biology help?





- Perturbation analysis (of risk factors)
- Optimization of treatments
- Predicting the infectious dynamics
- Identify vulnerable patient cohorts



What?

Why?

How?

Step 1: Formalization



Non-linear network of feedback interactions: **A dynamical system**

$$\begin{split} \frac{dS_{a}(t)}{dt} &= \frac{\kappa_{S}}{\mu_{S}} S_{a}(t)(1 - S_{a}(t)) - \frac{\theta_{S}}{1 + \epsilon_{SB}B(t)} S_{a}(t) \\ &- \phi_{NS}N(t)S_{a}(t) - \phi_{MS}M(t)S_{a}(t), \\ \frac{dS_{v}(t)}{dt} &= \kappa_{S}S_{v}(t) + \frac{\theta_{S}}{1 + \epsilon_{SB}B(t)} S_{a}(t) - \frac{\delta_{S}}{K + S_{v}(t)} S_{v}(t), \\ \frac{dN(t)}{dt} &= \alpha \frac{R(S_{a}(t))}{(1 + \epsilon_{NB}B(t))(1 + \epsilon_{NM}M(t))} N_{v} - \delta_{N}N(t), \\ \frac{dM(t)}{dt} &= \beta \frac{N(t)}{1 + \epsilon_{MB}B(t)} M_{v} - \delta_{M}M(t), \\ \frac{dB(t)}{dt} &= \frac{\kappa_{B}}{1 + \epsilon_{BS}R(S_{a}(t))} B(t)(\tilde{B} - B(t)) \\ &- \phi_{SB}R(S_{a}(t))B(t) - \phi_{NB}N(t)B(t). \end{split}$$

$$R(S_{a}(t)) = \begin{cases} R_{\text{off}} & \text{if } S_{a}(t) < S^{-} \text{ or } \{S^{-} \leq S_{a}(t) < S^{+} \text{ and} \\ & R(S_{a}(t^{-})) = R_{\text{off}}\}, \\ R_{\text{on}} & \text{if } S_{a}(t) \geq S^{+} \text{ or } \{S^{-} \leq S_{a}(t) < S^{+} \text{ and} \\ & R(S_{a}(t^{-})) = R_{\text{on}}\}, \end{cases}$$

Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Integration of experimental data



Step 2: Parametrization and validation



(cont. Parametrization and validation)



(model agrees with 13 independent datasets)

Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Step 3: Model analysis (a) Perturbation analysis

Question: How robust is the system?

- How much do we have to hit the system until the functionality is lost?
- Quantification of the fragility of the system.



(a) Perturbation analysis



Figure adapted from Mayo, A.E. et al., 2006. *LoS Biology*, 4(4), pp.555–561.

Homeostasis: a robust property of the system



2017. Front. Physiol. 8:115.

Step 3: Model analysis (b) Sensitivity analysis

Question: What causes the loss of homeostasis?

 Computational tolos to identify the changes in parameters that are most likely to result in disease



Mechanisms of dysbiosis



Most sensitive parameters:

- rate of bacterial transmigration through the barrier (θS),
- bacterial carrying capacity (µS),
- killing rate of bacteria by macrophages (φMS)

Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Less sensitive:

- propensity to develop sepsis (Sv)
- unresolved host responses (R)

Step 3: Model analysis (c) Bifurcation analysis

Question:

How do the the risk factors affect the infectious dynamics?



Step 3: Model analysis (c) Bifurcation analysis



Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Step 4: Checking consistency of predicitons with experimental data





Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115.

Consistent with experimental data: Andonegui et al, Shock 2009

Using the model for treatment optimization

(A) Optimal treatments for reversion of immune scarring (Patient cohort 1) - apically applied antibiotics



(B) Optimal antibiotics dose for prevention of sepsis (Patient cohort 2) - antibiotics in the blood vessel



Domínguez-Hüttinger, E. et al., 2017. Front. Physiol. 8:115. Tackling antibiotics resistance!

From description to prediction









Design of optimal treamtents

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Conclusions

Black box (a bit more) illuminated



Systems biology to understand, prevent and optimally treat complex epithelial tissue diseases 31



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Mathematical Modeling of Streptococcus pneumoniae Colonization, Invasive Infection and Treatment

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Complex epithelial tissue diseases – a systems biology perspective

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Imperial College London



Clinical and

experimental

data



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Mathematical computational predictions



Instituto de

Matemáticas



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Thank you for your attention.



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