Model evaluation and comparison

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MMED 2019

Goals

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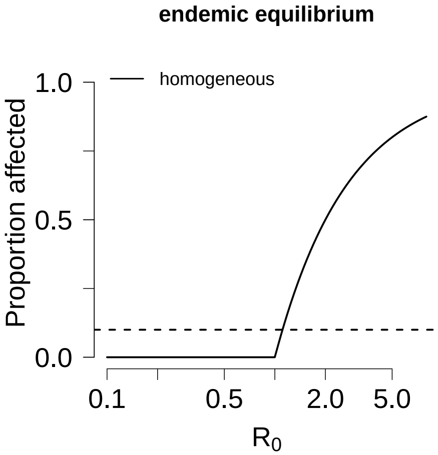
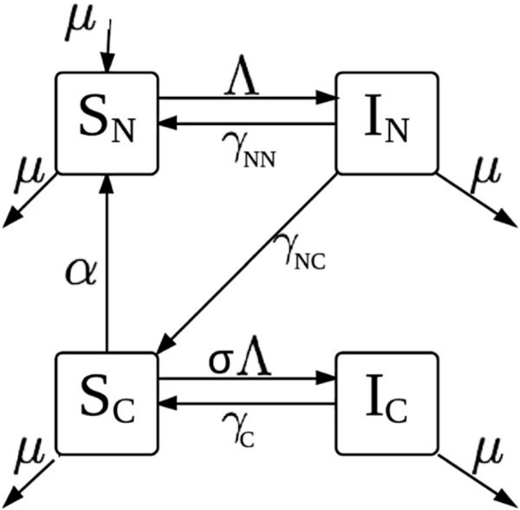
Outline

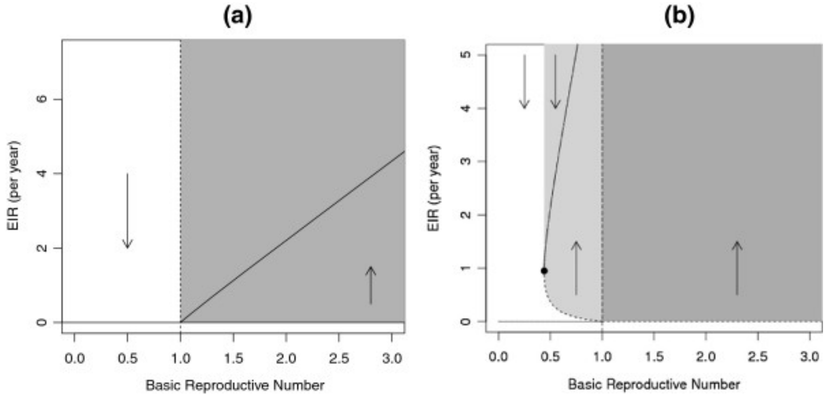
Disease thresholds



Effects of clinical immunity

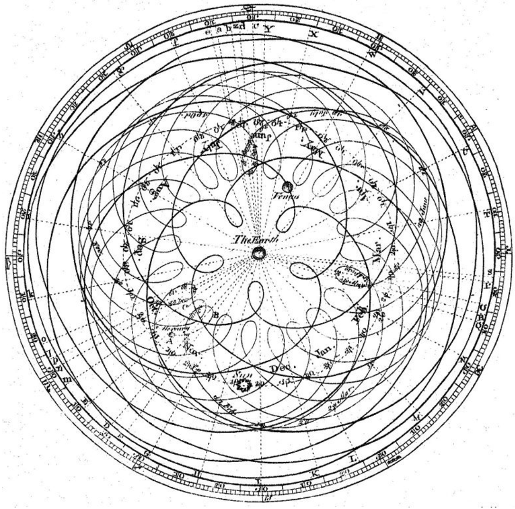


Bistability



Outline

Ptolemy v. Copernicus



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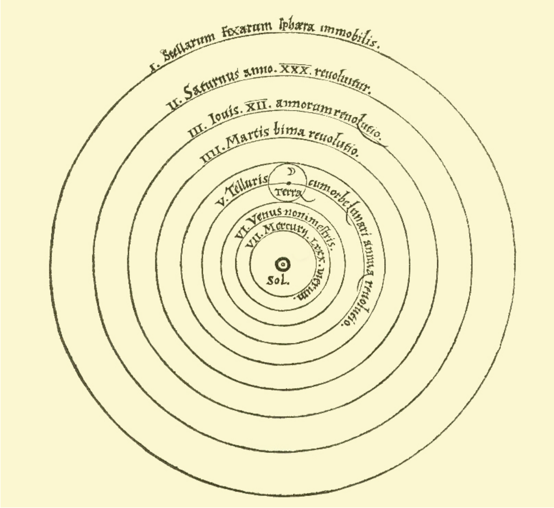

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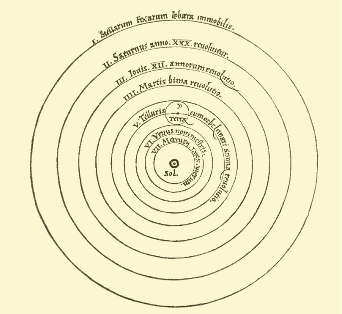

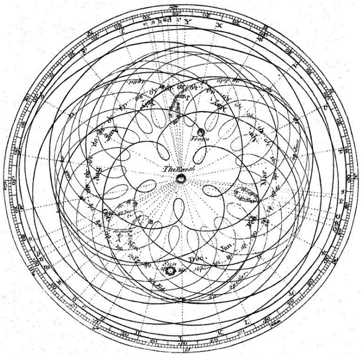

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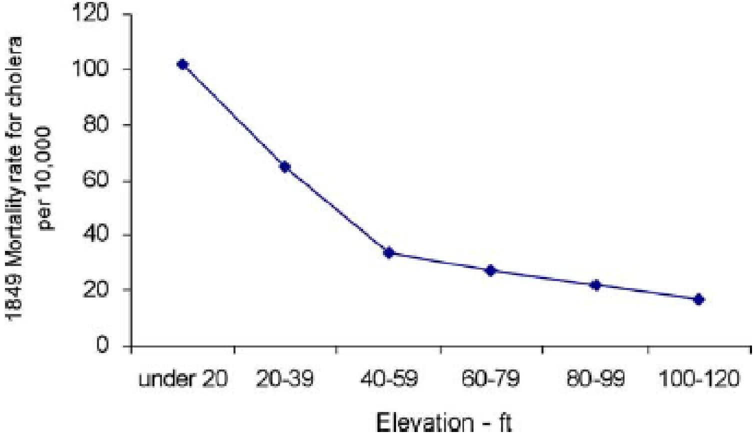

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Model Validation

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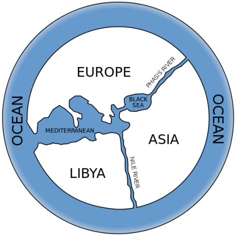

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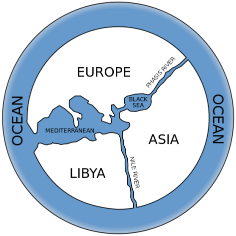

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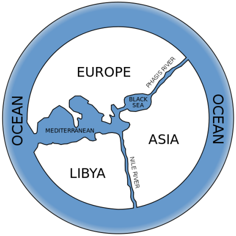

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Validation measures

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- Precision

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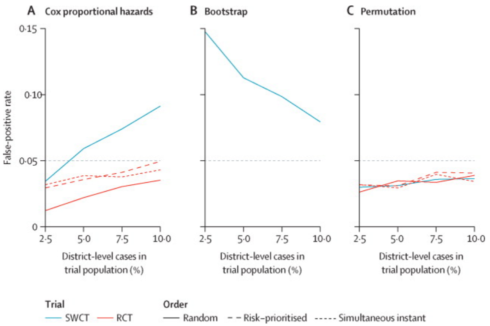

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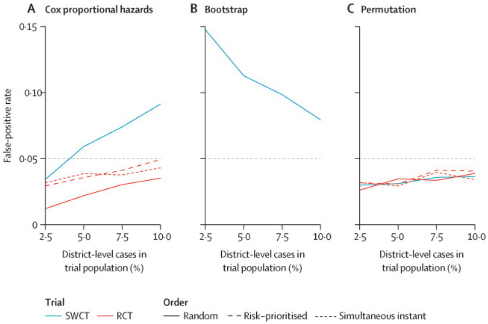

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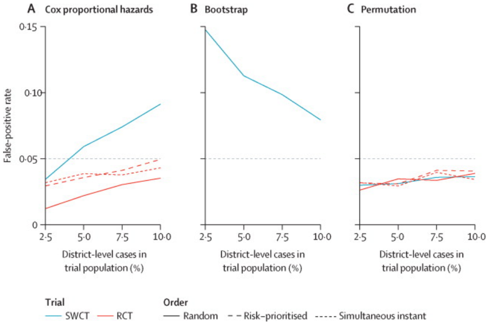

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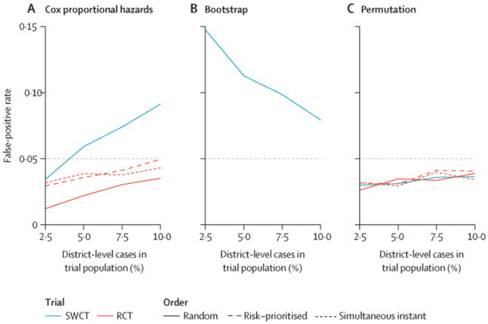

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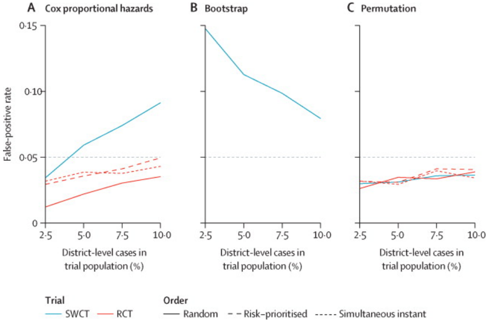

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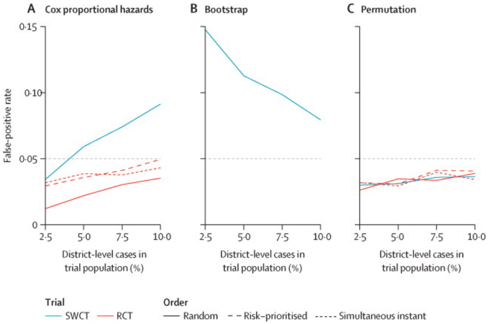

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Outline

Conceptual models

Prediction

Model Validation

Model Evaluation
- Goodness of fit
- Capturing patterns
- Going beyond

Conclusion

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ICI3D

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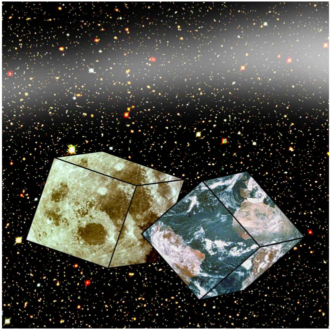

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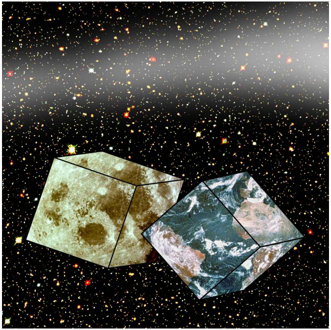

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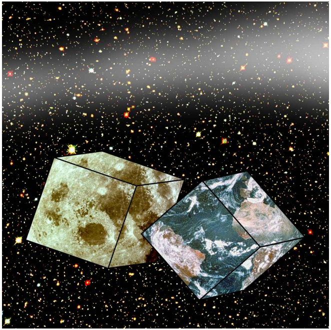
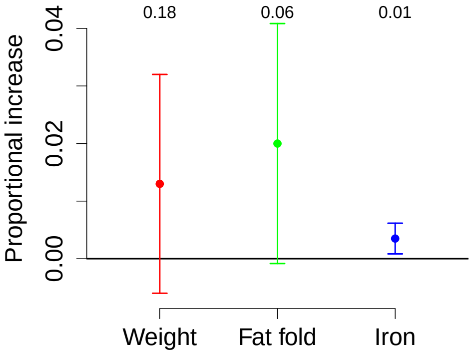
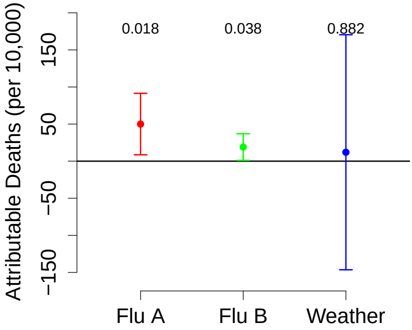


Vitamin study



... with confidence intervals



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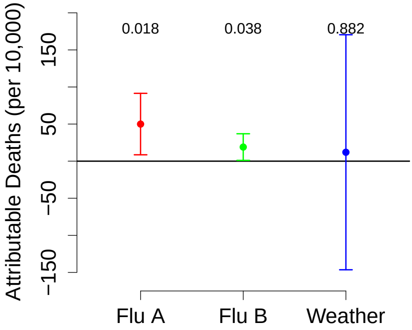

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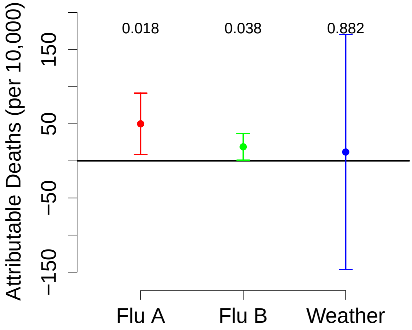

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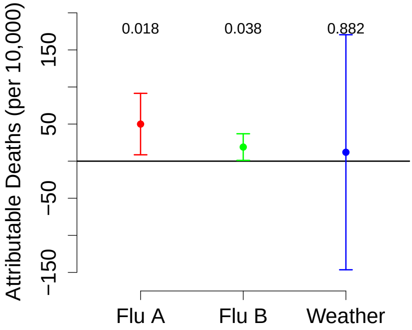

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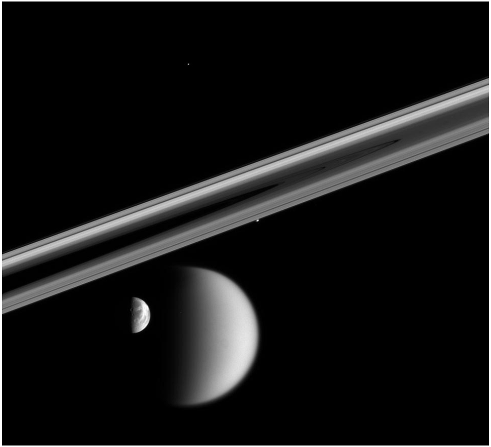
Predicting way out of sample



Essentially, all models are wrong, but some are useful.
– Box and Draper (1987), *Empirical Model Building . . .*

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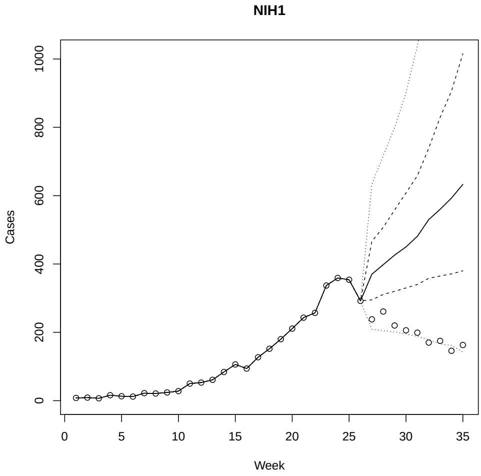

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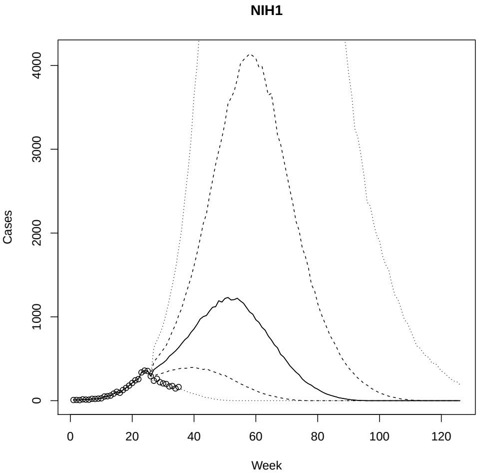

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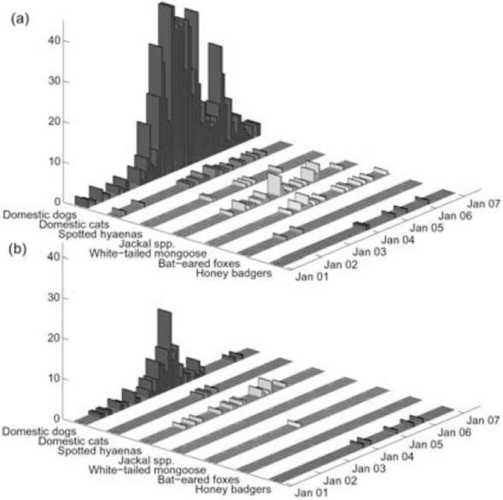
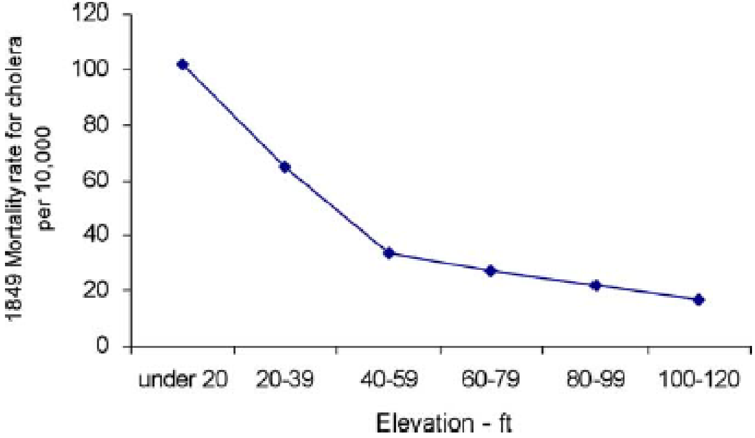


Testing hypotheses



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Hard questions

Answers are not always easy

Outline

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- Clarify thinking

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Title: Model evaluation and comparison
Attribution: Jonathan Dushoff, McMaster University, MMED 2019

Source URL: https://figshare.com/collections/International_Clinics_on_Infectious_Disease_Dynamics_and_Data/3788224
For further information please contact admin@ici3d.org.