



Agent-based modelling for landscape ecology

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Outline

- Introduction to Agent-Based Modelling (ABM)
- Example ABM
- Coupling ABM with other models
- Issues with ABM





Agent-Based Modelling

- Various origins, including
 - **Complex systems:** Heterogeneity and Interactions matter
 - **Economics:** Dissatisfaction with *Homo economicus* model
 - **Social Science:** More formal exploration of theory
 - **DAI:** Exploitation of social and psychological theory in artificial systems
- Agent-based modelling is **computer simulation** that explicitly represents **individual heterogeneity** and **interactions**



Agent-Based Modelling

- What is an agent?
 - An explicit **representation** of an individual (person / animal / plant / household / company / government) in a simulation
- Interactions are any effect that one individual may have on another
 - Interpersonal: Negotiation, Markets, Norms, Imitation
 - Stigmergic (indirect – mediated through physical persistence): Ant Trails, Signs, Writing, Traps, Recordings
 - Landscapes
- Interactions form a multi-layered social network
 - Each layer is a relationship



Balinese Water Temples

- Rice farmers in Bali belong to subaks
 - Average size 42 hectares
 - Plan cropping patterns and irrigation
 - Coordinate with other subaks via water temples
- Water temple coordination highly ritualised

([Lansing, 1991](#); [Lansing & Kremer, 1993](#))



The rice farming dilemma in Bali: 1

■ Water

- Limited availability
 - Upstream subaks restrict supply downstream
 - Rainy season Nov-Apr
- Lack of water reduces rice yield



**Need to plant at
different times**

■ Pests

- Occur naturally in rice paddies
- Dispersed from neighbouring fields
- Controlled using fallow periods



**Need to plant at
the same time**

The rice farming dilemma in Bali: 2

- Traditional method

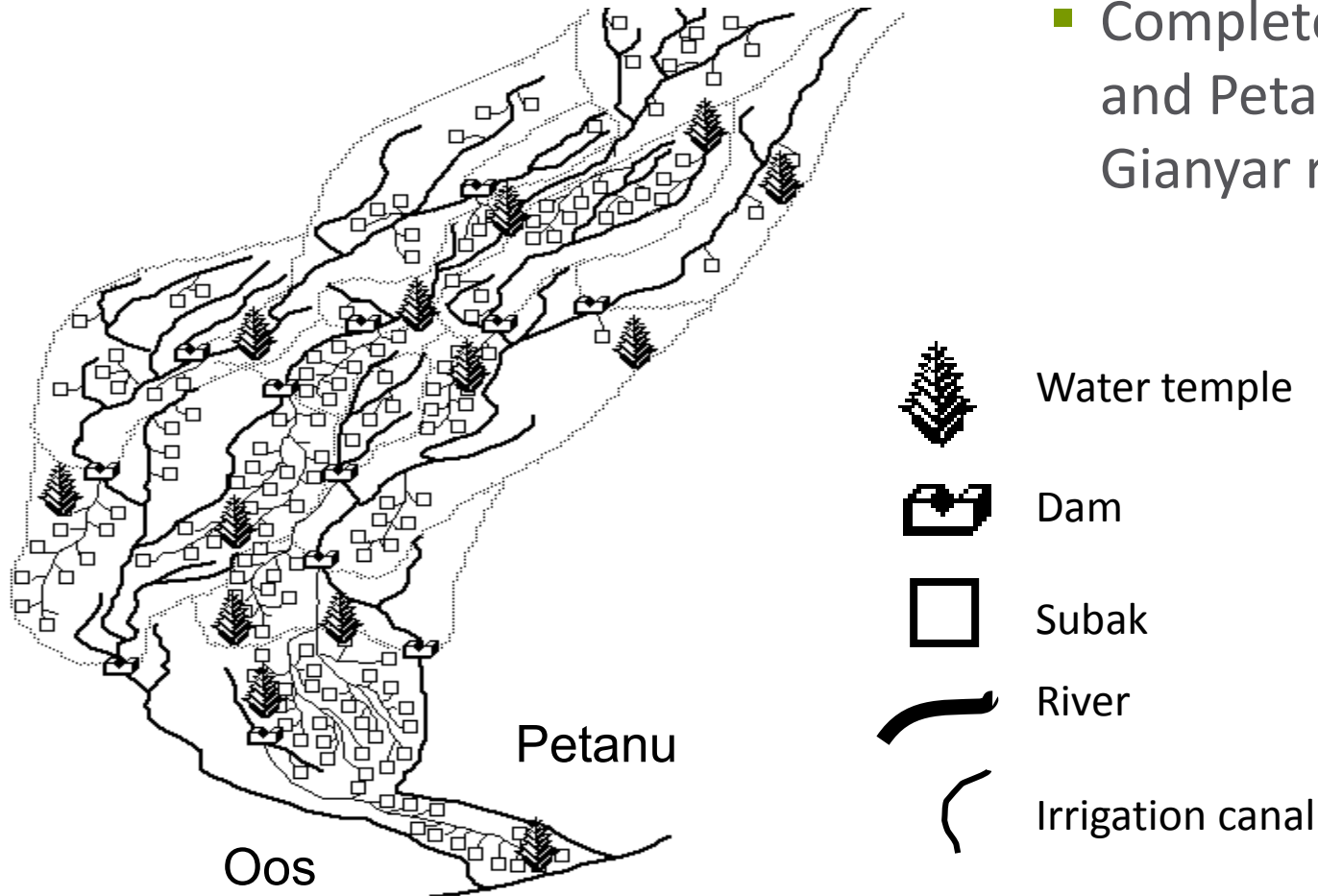
- No fertilisers
- No pesticides
- Recovers quickly from drought and plague
- Lasted hundreds of years

- Modern method

- Financial cost of fertilisers and pesticides
- Fertilisers impact coastal ecology
- Fewer fallow periods
- Higher expected yields...

Lansing and Kremer's models

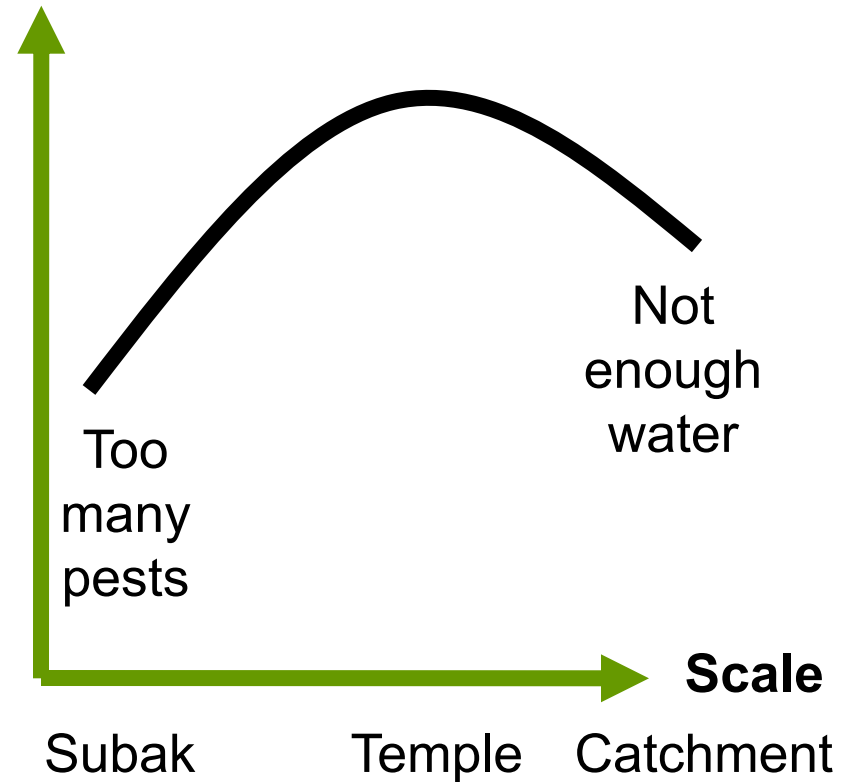
- Complete model of Oos and Petanu rivers in Gianyar region



One-year model

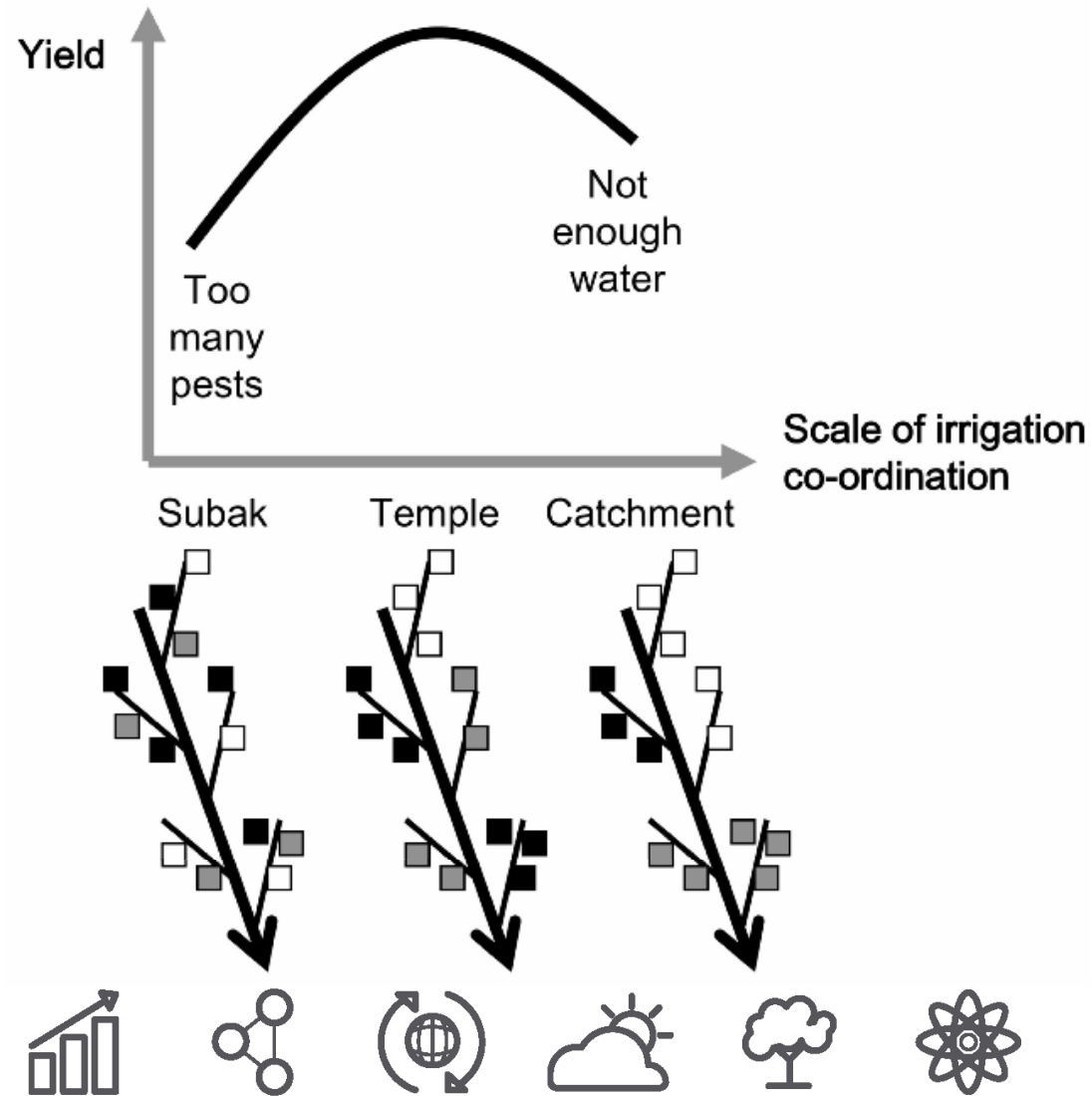
- Include hydrology, rice growth and pest dynamics
- Vary scale of cropping pattern co-ordination
- Maximum yield at temple scale

Yield



Dynamic model

- Simple agent based model
- Agents copy the planting schedule of the most successful neighbour
- Temple scale co-ordination emerges



Issues with coupling models

- Various levels of coupling ([Antle et al., 2001](#)):
 - Loose coupling: exchange of variables
 - Issue: Mars Climate Orbiter
 - Close coupling: +linked common subprocesses
 - Issue: Components still not specifically designed to work together
 - Full integration: *one* model with appropriate spatial and temporal scales
 - Issue: Less reuse, more expensive

The coupled-
model approach
to shed building...

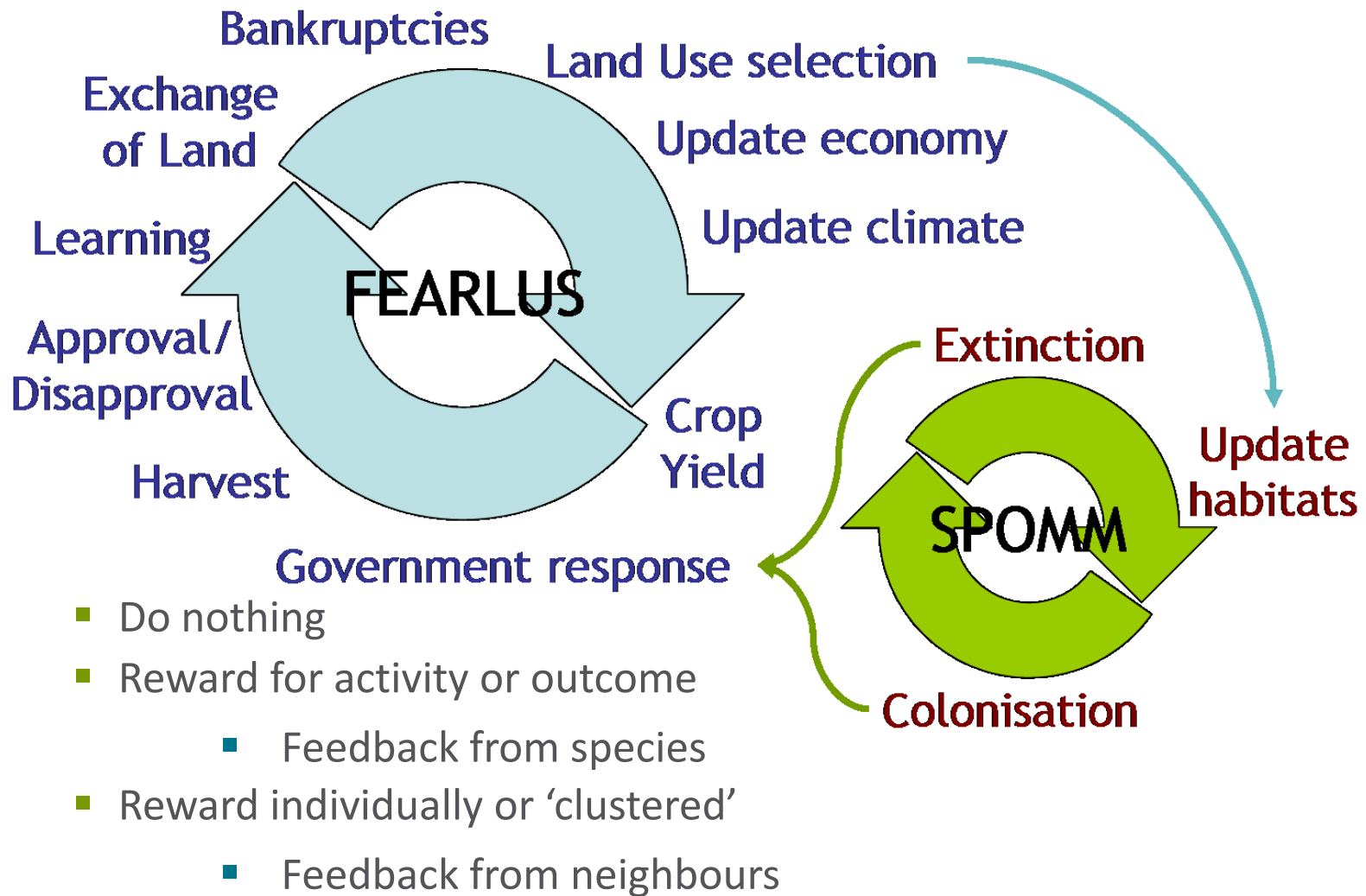


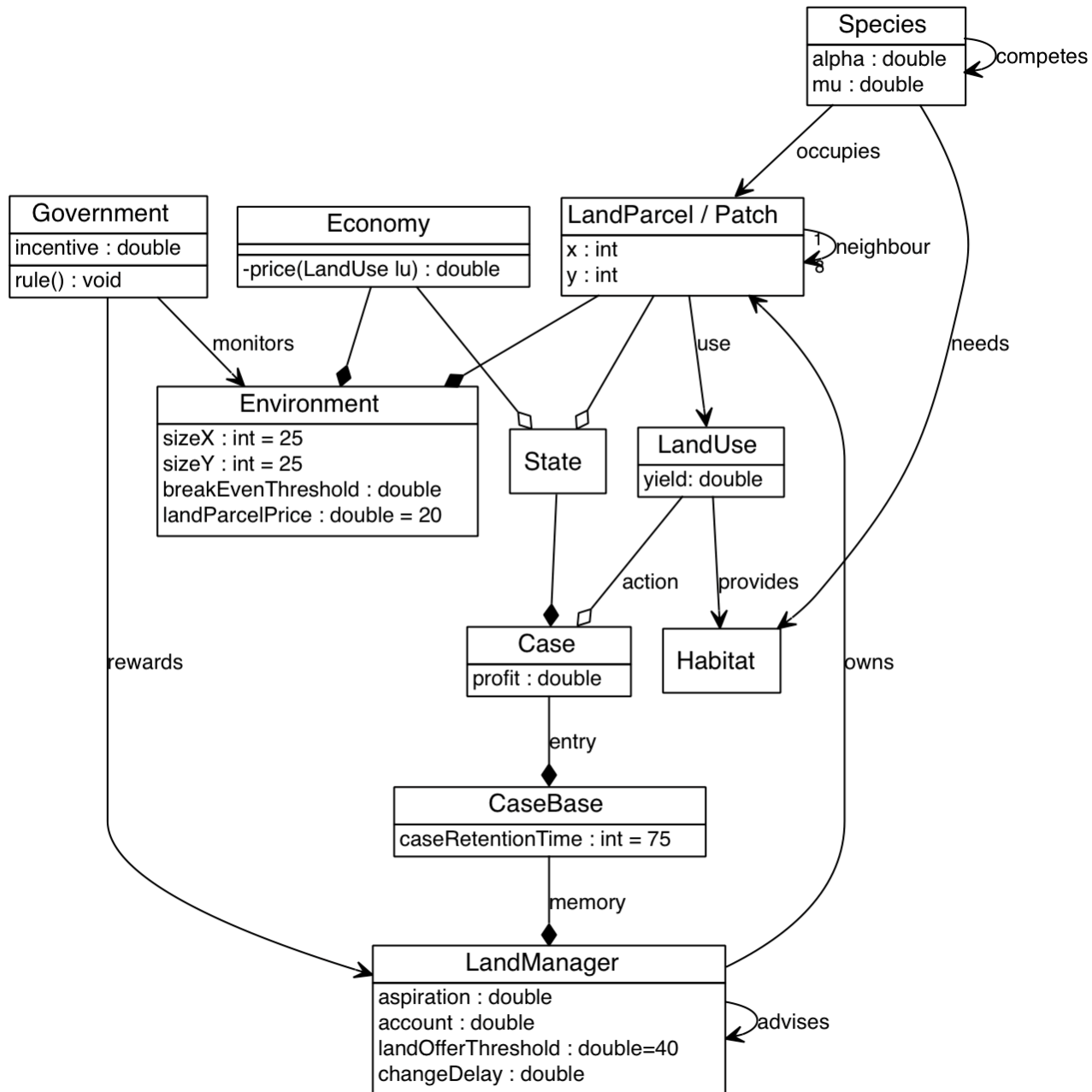
Coupling FEARLUS-SPOMM

- Key points for coupling models
 - Similar levels of abstraction/detail
 - No duplication of subprocesses
 - Compatible spatial and temporal scales
 - Compatible underlying assumptions
- Further requirements for this work
 - SPOMM to be a credible biodiversity model in its own right
 - Suggests coupling rather than integration
 - FEARLUS-SPOMM to be a credible model
 - Suggests integration rather than coupling
- Approach
 - Design SPOMM for integration with FEARLUS
 - Maintain separate (coupled) and integrated versions



FEARLUS SPOMM

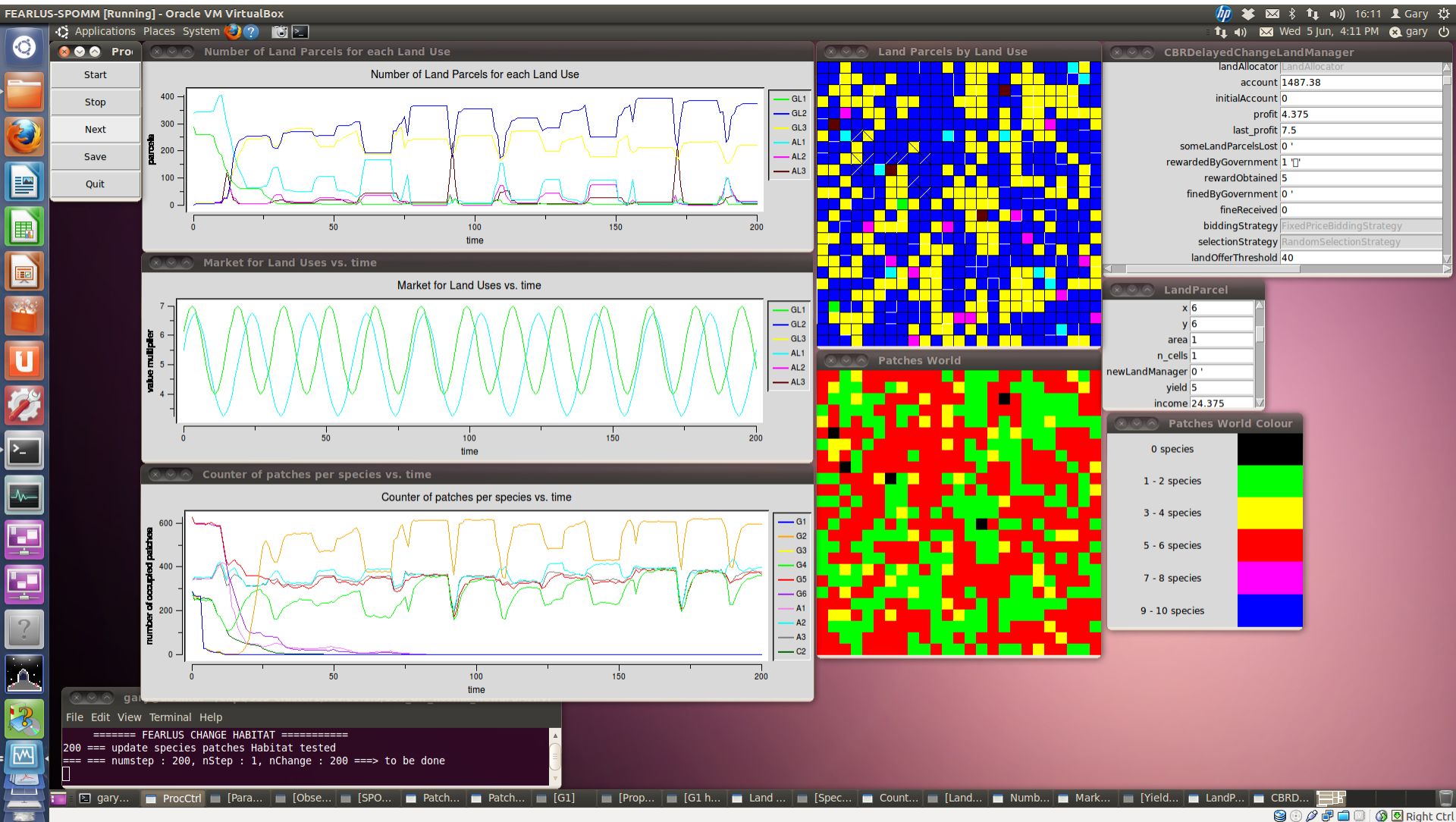




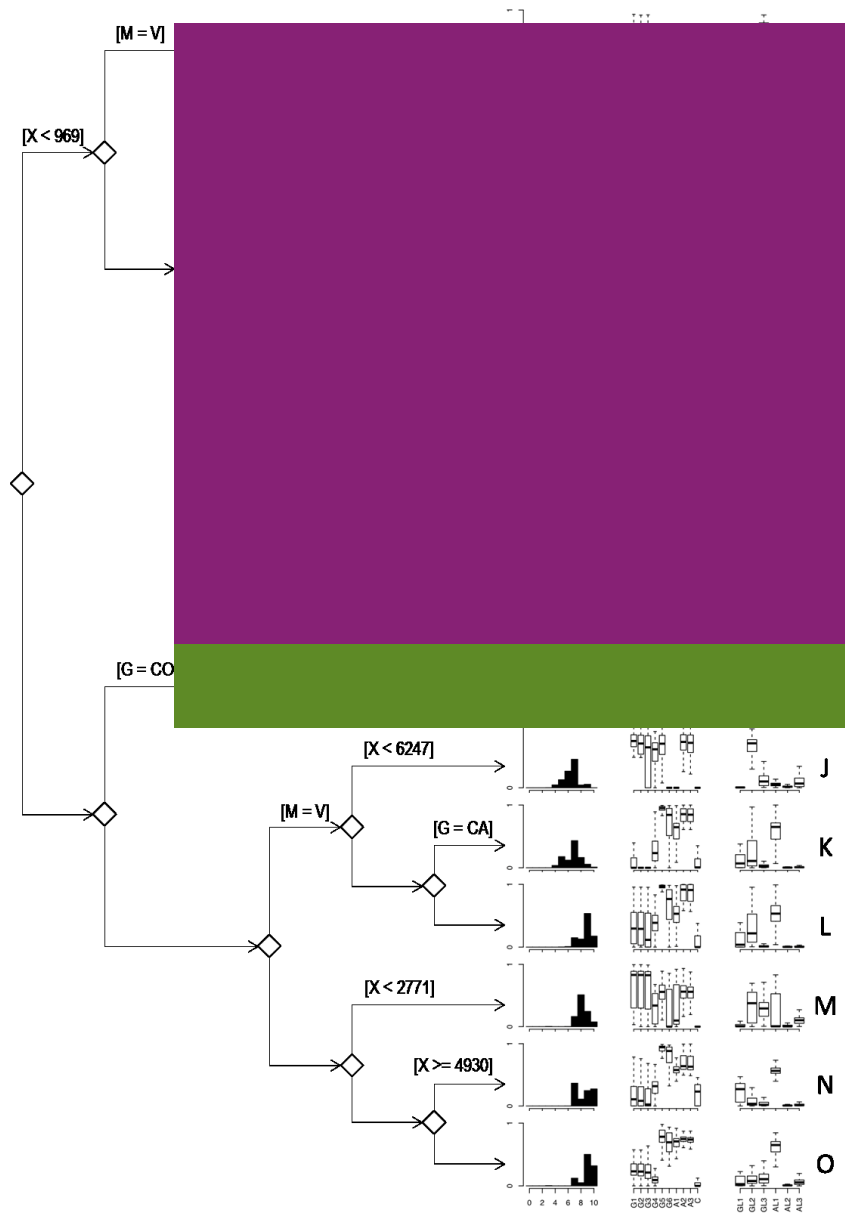
Screenshot



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Decision tree analysis



- Below a threshold of government expenditure, the market drives outcomes, and species richness is lower
- Above the threshold, policy is the main driver
 - Outcome based incentives seem more robust to other influences (market, input costs, aspirations)

[Polhill, Gimona and Gotts, 2013,
[Environmental Modelling and Software](#)]

Participatory ABM

- Various researchers working at various levels of the participation ladder
 - Exploring policy scenarios a common ABM ‘use case’ in empirical contexts
- “[Companion Modelling](#)” school of ABM
 - Mostly French researchers
 - Focus on solving social/environmental issues
 - Not on “the right way” to model a case study
 - Use role-playing games
 - Regular training courses available



Issues

- How to simulate human decision-making
- Lack of theoretical underpinning / too *ad hoc*

“But you should see some of the artificial society models hallucinated by the engineers. They don't even know the social science clichés, never mind the, say, three or four findings that the field has actually produced.”

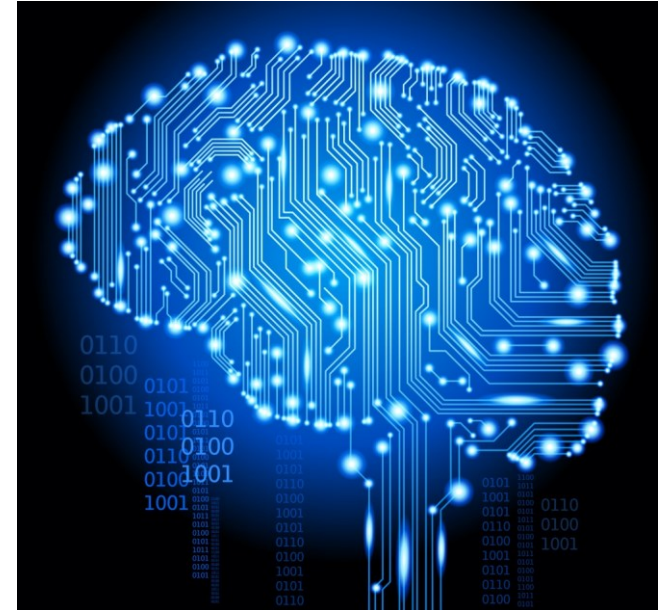
([Agar, 2003, JASSS](#))

- Need too much data in empirical contexts
- Validation
- Too difficult to learn



Decision-making

- Diversity of practice in ABM
 - *H. economicus*, GAs, heuristics, Linear Programming, formalisations of theory, decision trees, algorithms from AI (e.g. case-based reasoning, neural nets), interview / experiment / game data, ...
- Suppose MIT built an AI server
 - Guarantees human-like decision-making
 - Would you use it?



Economics and ABM

- The ABM community exist on a spectrum in their attitude towards economics:
 - “**Economics**, as developed over the past half-century and more, **is not useful** for the analysis and support of formal policy; **it should simply be ignored** by serious social scientists” [[Moss, 1999](#)]
 - ABM as a branch of computational economics allowing the study of non-rational agents [[Axtell, 2000](#)]
- Most, however, would see ABM as distinct from neoclassical economics in:
 - Emphasising the importance of agent heterogeneity
 - Emphasising the significance of agent interactions
 - Emphasising heuristic, cognitively plausible or boundedly rational modes of human decision making
 - Less concern with equilibria



Farm decisions aren't all economic

The Guardian, UK, Tuesday 24 April 2007

In 1995, producers got 24.5p a litre for their milk; the average today is 18p a litre, which represents a loss of more than 3p on every litre. Kemble Farms has been getting 19p a litre.

...

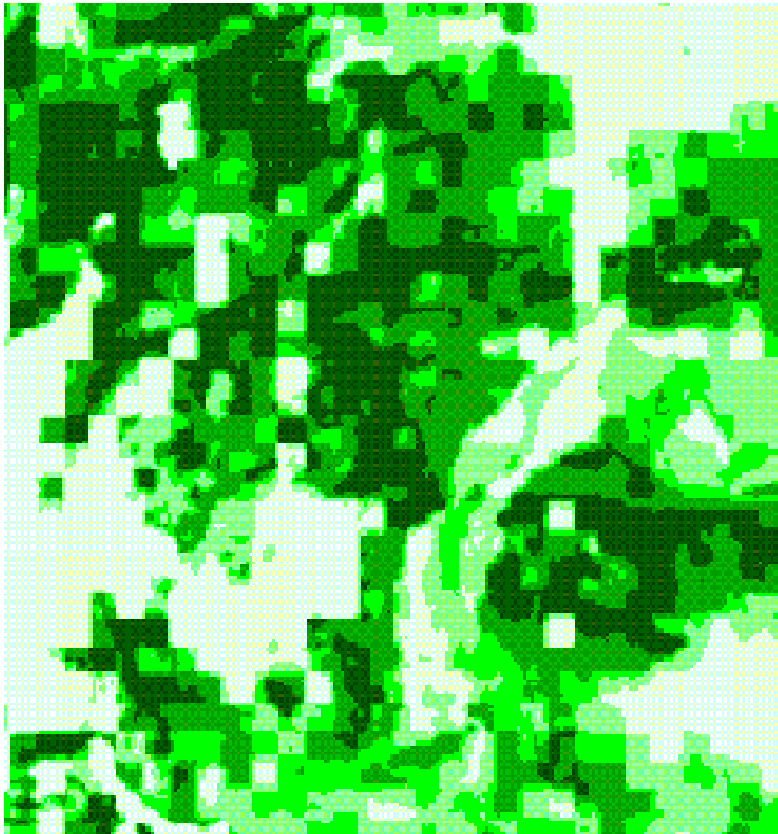
The irony for Colin Rank, one of the family that owns Kemble Farms, is that his cows drink water from a Cotswold spring that he could bottle and sell for 80p a litre. **“We're giving it to cows and devaluing it by turning it into milk.** Like all dairy farmers we could pack up tomorrow and do something better with our capital, but **we do it because we have an emotional investment in the land and the animals.** And we know there's a market for our product, if only the market worked.”

[Felicity Lawrence]



Predicting forestry in Scotland

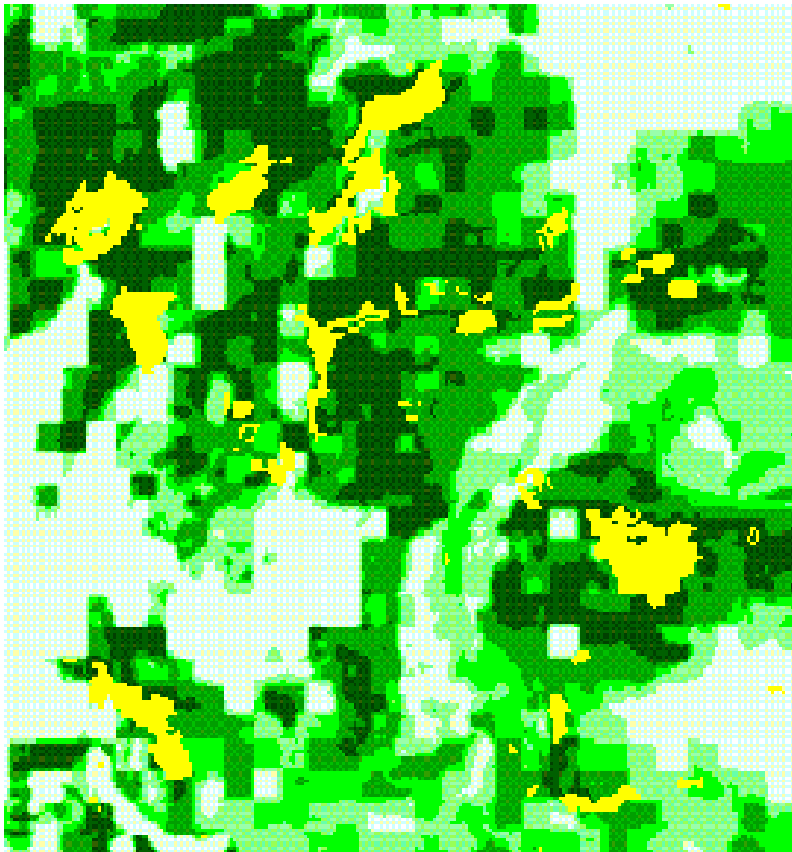
(Aspinall & Birnie,
unpub.)



- Forestry is profitable
- Probability of forestry
 - Dark green = higher P
- Based on suitability
 - Climate
 - Gradient
 - Soil type



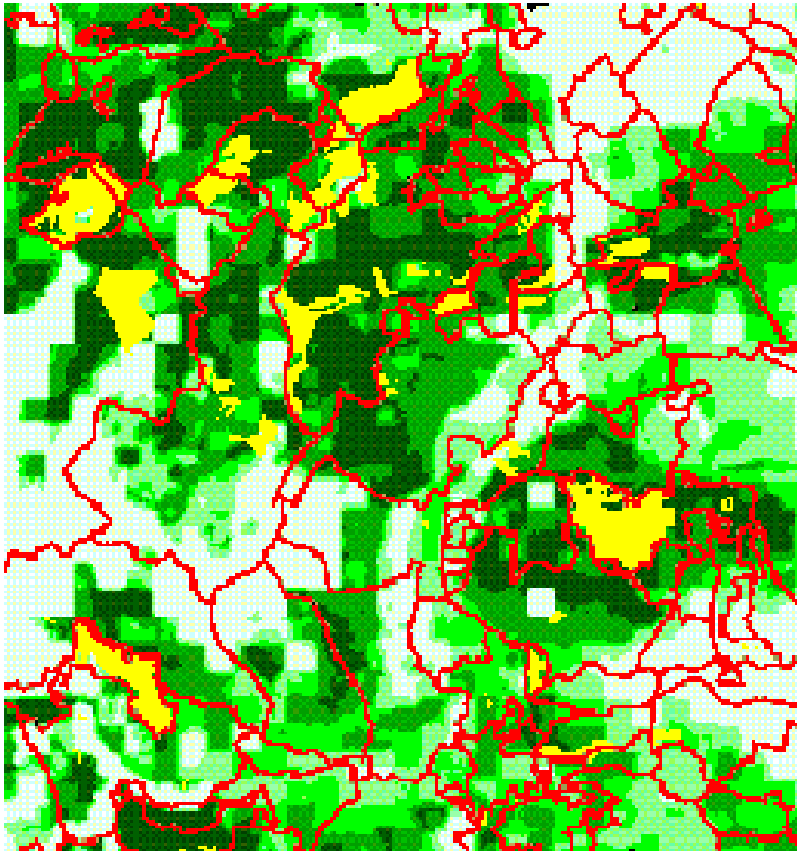
Predicted versus actual forestry



- Yellow shows actual forestry
- Green shows predictions
- Large areas of high suitability but no forestry



Influence of land ownership

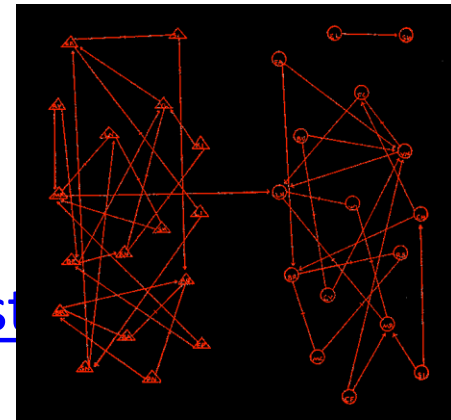


- Red lines show ownership boundaries
- Land use is based on more than suitability and (simple) economics
- Sociological factors
 - e.g. Grouse shooting
- Landscape pattern at the regional scale is a function of local interactions and individual preferences



Theory: Social science and interactions

- Moreno [[1934](#)] thought to be one of the first to attempt to visualise social networks
 - (Friendships in 4th graders on right – copied from Freeman 2000)
- Granovetter [[1973](#)] – strong and weak ties; latter spread innovation
 - Overlap of friendship networks
- Bourdieu [[1983](#)] – social capital
- Social Network Analysis [[Wasserman & Faust 1994](#)]
 - Focus on relatively stable interactions
 - Techniques include interviews, questionnaires, experiments, observations, using existing records of transactions and ‘snowballing’

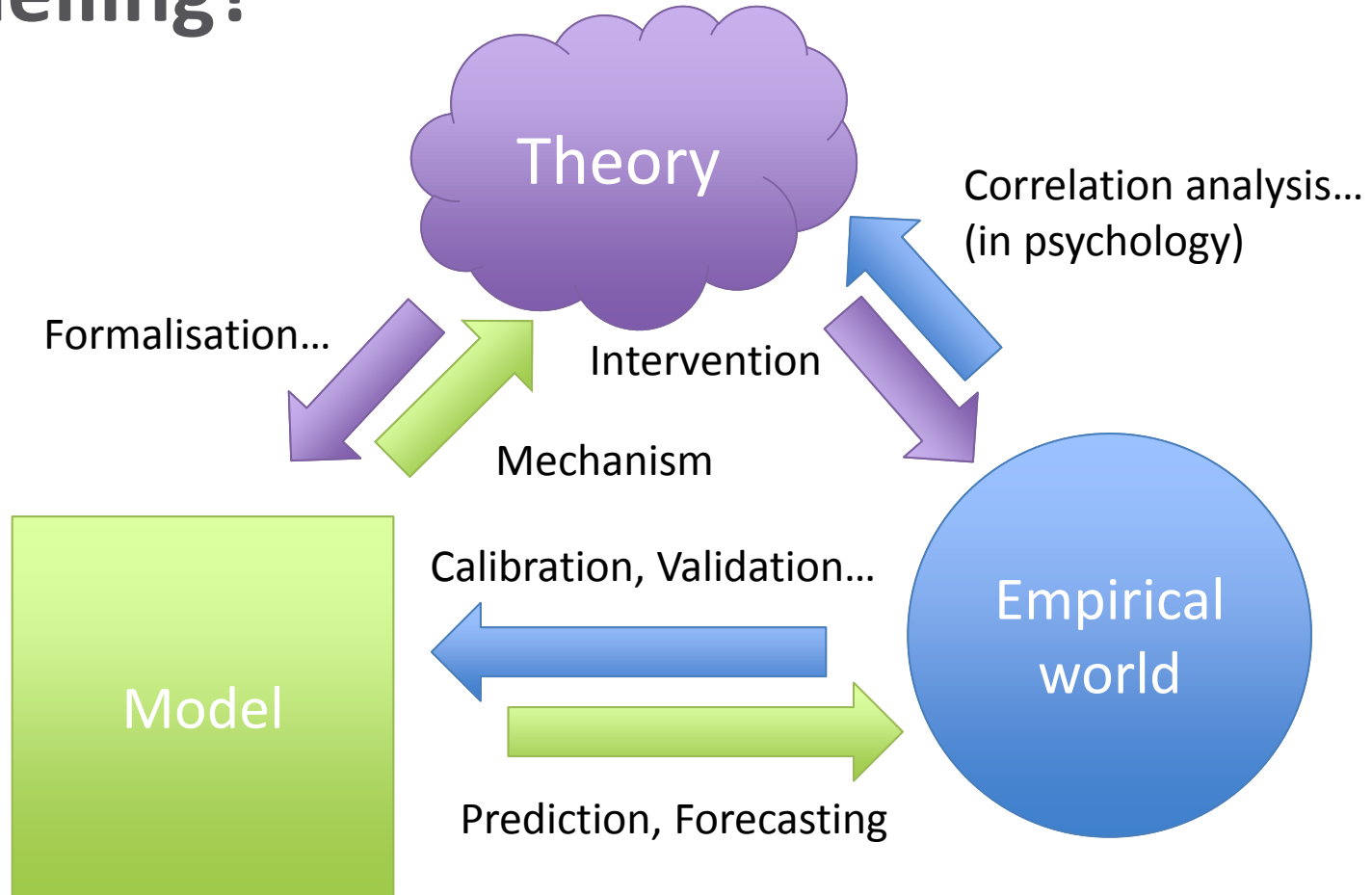


Social science and interactions

- Actor Network Theory [[Latour 2005](#)]
 - A sociology of associations; not currently 'fashionable'
 - Often what social scientists think agent-based modelling is
 - The relationship is probably more complex, e.g.
 - Latour argues that groups are processes – i.e. they don't exist without people doing things to maintain them;
 - also, vocabulary should be that used by those being studied, not imposed by the researcher
 - In ABMs group structure and nomenclature may be fixed

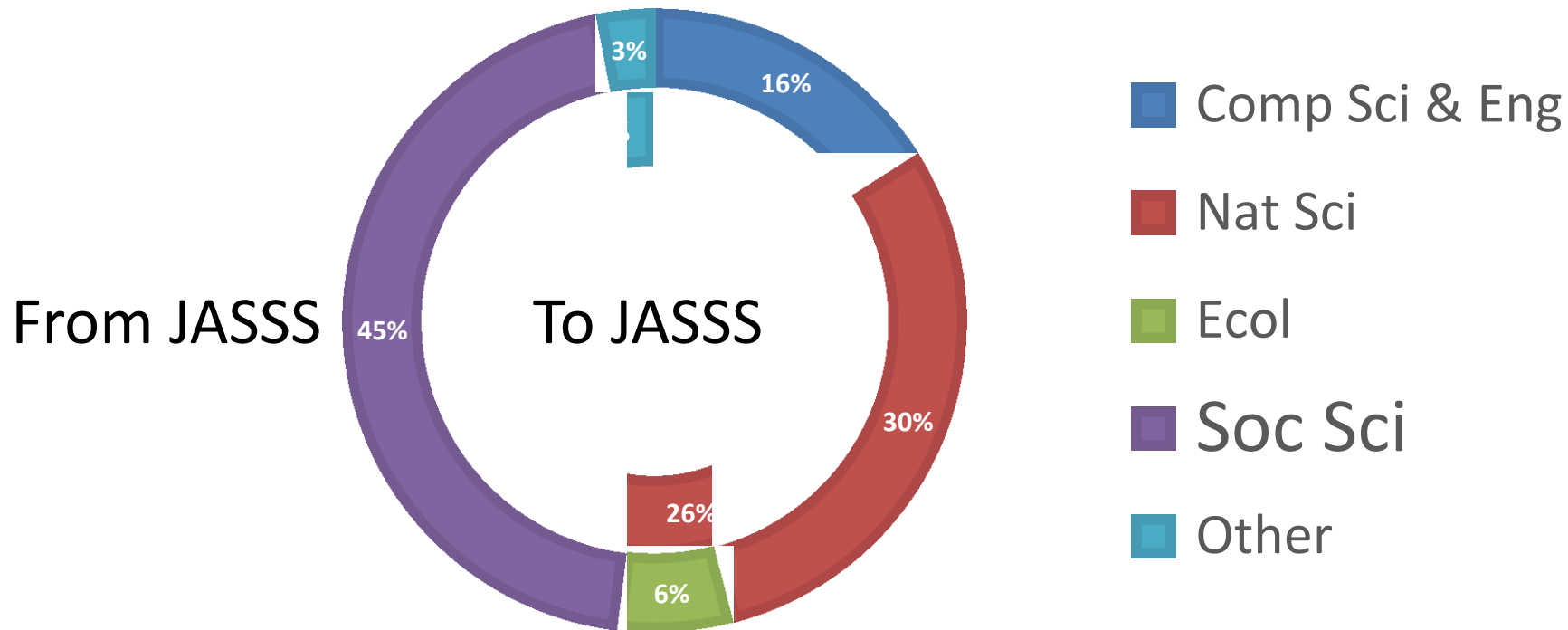


Relationship between theory and modelling?



Social sciences and ABM

- [Squazzoni & Casnici \(2013\) JASSS](#)
 - Citations of JASSS 2002-2012
 - ABM not recognised in 'mainstream' social science



Obtaining data for empirical ABM

- Empirical ABM usually conducted as part of large interdisciplinary projects
 - Data not just collected for the ABM...
 - ... and usually not collected by ABMers
- Existing datasets may be useful for data not collected as part of the project
 - Don't always know in advance what data you'll need
 - Can be ambiguity about who will be responsible for getting it
- Easy to get data on heterogeneity and attributes
- Difficult to get data on interactions and influence
 - Odd, since this should be what *social* science is all about!
- Really difficult to get data on interactions with and influences of the environment / landscape
 - But check environmental psychology and actor network theory



Qualitative and quantitative data

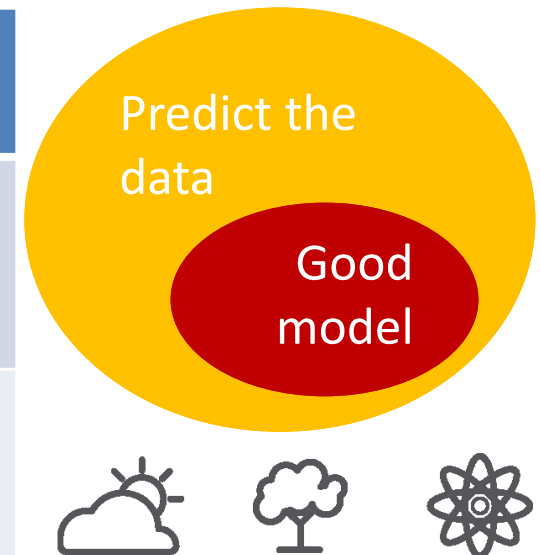
- Qualitative data
 - Interviews, focus groups, workshops
 - Determining model structure and boundary
 - Determining general rules in the model
 - Where these cannot be fitted from quantitative data
- Quantitative data
 - Tables, formulas
 - Determining model structure and boundary
 - Configuring algorithms implementing processes
 - Initialisation and input data



Validation: Oreskes et al. (1994)

- What we are calling validation, [Oreskes et al.](#) call verification
- In complex, open systems, it is difficult to know where to draw the system boundary
 - Everything is connected to everything else
 - Verification (i.e. that a model is a (permanent) statement of truth) is impossible
 - Something from outside the system could change it
- Even if verification were possible, consider the argument:
 - All good models predict the validation data
 - My model predicts the validation data
 - Therefore my model is a good model
- This commits the logical fallacy of affirming the consequent

	My model is a good model	My model is a bad model
My model predicts the data	Consistent with 'all good models predict the data'	Consistent with 'all good models predict the data'
My model does not predict the data	Inconsistent with 'all good models predict the data'	Consistent with 'all good models predict the data'



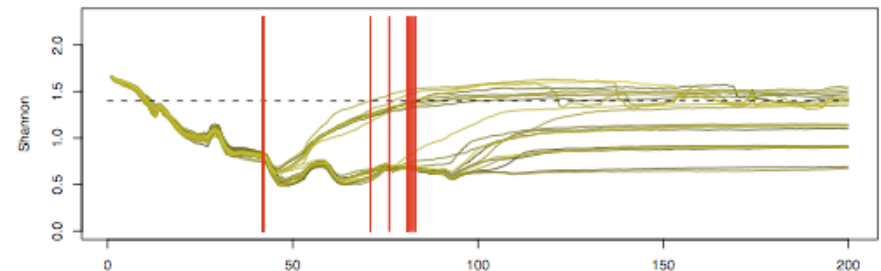
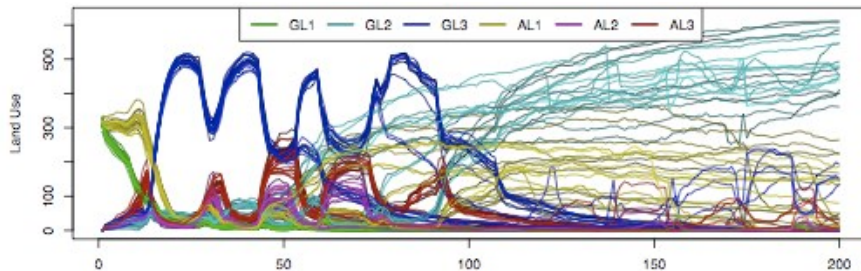
Complex systems and validation

- Complex systems consist of partially connected hierarchies of heterogeneous interacting components
- Their dynamics switch among multiple ‘metastable’ states
- Their trajectories are path-dependent
 - Sensitivity to initial conditions: like chaotic systems, small changes can have large long-term impacts
 - Non-ergodicity: the history of states visited by the system can preclude the possibility of some other states in future
- Partial predictability
 - No underlying function as such



Ockham's razor

- Given a model with fewer parameters that fit the data and a model with more parameters that also fit the data, we should prefer the model with fewer parameters
- In complex systems, history can follow multiple trajectories

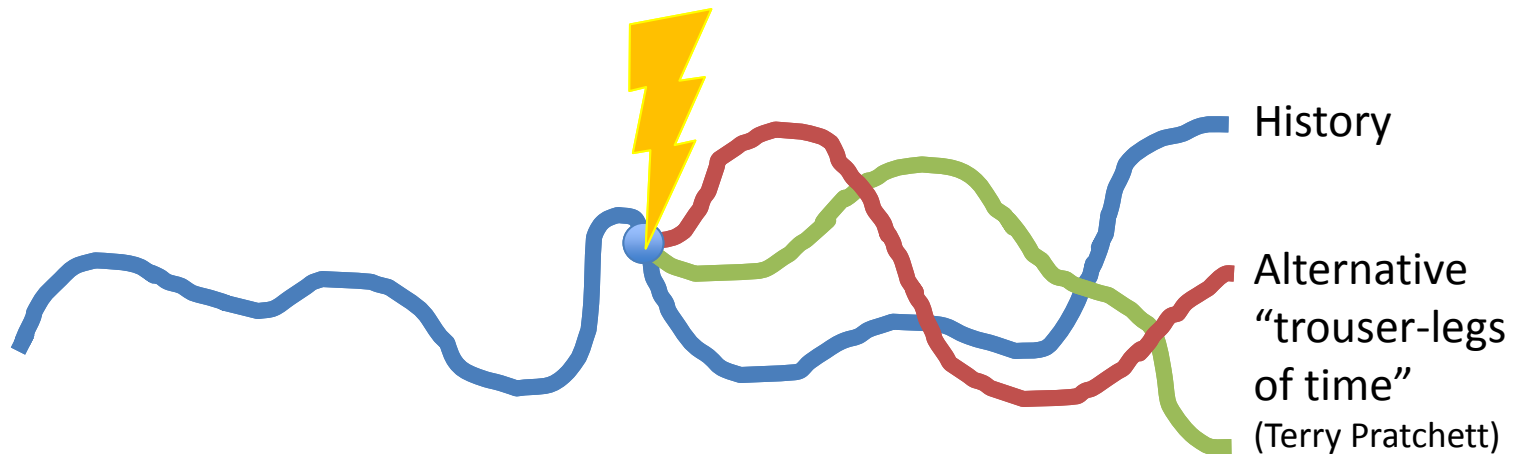


- So do you want a model that follows history?
 - Or one that can simulate what might have happened?



Models and history

- Which model's predictions would you prefer?
 - Model A, few parameters, only follows the blue line
 - Model B, many parameters, can follow all three lines
- Ockham's razor says Model A...
 - But this could have been a one-in-a-million chance!



What does fit to data tell us?

	My model is a good model	My model is a bad model
My model predicts the data	We have fit the data and the model is expected to predict well in future	Oversimplified, unrealistic assumptions, doesn't explain anything, and doesn't allow for the possibility things could have turned out differently
My model does not predict the data	There is a possible world in which the model would have been right; we fit patterns in the data	We must reject the model and ignore its predictions



What else is there besides fit-to-data?

- Fit-to-data need not be the only measure
- We can also evaluate models by their descriptiveness
 - ‘Ontology’ (in computer science sense)
 - Formal, explicit representations of shared conceptualisations ([Gruber 1993](#))
 - Not so much an issue for traditional modelling
 - Just the number of parameters



How can we evaluate ontologies?

- Logical consistency checking
 - Trivial
- Populating it with instances
 - An ABM's ontology will be populated as soon as it is run
 - Ease of population of an ABM from data?
 - But then just comparing database ontology with ABM's
- Stakeholder / expert evaluation
 - Most popular / common method
 - But just comparing expert's ontology with ABM's
- (More general) comparison with existing ontologies



How can we compare ontologies?

- Still an active area of research
 - ‘Interoperability’
- Ontologies are to some extent qualitative and subjective
 - Ignored in traditional modelling
 - Analytical tractability, ‘elegance’, Ockham’s razor assumed by default
 - Tangential provocation: elegance is creationism?
 - Philosophical debate over whether ontologies are observed or created (Klein & Hirschheim 1987)
- Four main methods:
 - Token matching, graph analysis, machine learning and semantic information content
 - First two most prevalent



Fit-to-data vs. ontology

- Fit-to-data is still important for predictive empirical modelling
- What weight should we give to fit-to-data as opposed to ontology?
 - Most likely it is context-sensitive

Methods in Ecology and Evolution



Methods in Ecology and Evolution 2016, 7, 679–692

doi: 10.1111/2041-210X.12541

SPECIAL FEATURE: 5TH ANNIVERSARY OF *METHODS IN ECOLOGY AND EVOLUTION*

The relative performance of AIC, AIC_C and BIC in the presence of unobserved heterogeneity

Mark J. Brewer^{1,*}, Adam Butler² and Susan L. Cooksley³



AIC, AIC_C and BIC

- AIC: Akaike Information Criterion

- $AIC = -2 \log l(\hat{\theta}) + 2p$

- BIC: Bayes Information Criterion

- $BIC = -2 \log l(\hat{\theta}) + p \log n$

- AIC_C: Corrected AIC for small sample size

- $AIC_C = AIC + \frac{2p(p+1)}{n-p-1}$

Parameter /
Data set size
penalty

- Notation

- p number of parameters; n data set size

- $l(\hat{\theta})$ likelihood of maximum likelihood model

- Fit-to-data measure



Fit-to-data vs. ontology

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The relative performance of AIC, AIC_C and BIC in the presence of unobserved heterogeneity

“We find that the relative performance of model selection by different information criteria is heavily dependent on the degree of unobserved heterogeneity between data sets ... Relying on a single form of information criterion is unlikely to be universally successful.”

- Unobserved heterogeneity
 - Only sampled from one site at one time, but model is supposed to be more general



Learning ABM

■ Societies

- European Social Simulation Association
 - Annual conference (Dublin in September 2017)
 - www.essa.eu.org
 - Regular summer school (Wageningen in June 2017)
 - ESSA@Work



■ Journals

- Journal of Artificial Societies and Social Simulation
 - Online, open-access, jasss.soc.surrey.ac.uk
- Various others, but not specialising in ABM
 - Landscape Ecology, Environment & Planning, Ecological Economics, Environmental Modelling & Software, Computers, Environment & Urban Systems, Ecological Modelling, Computational & Mathematical Organization Theory, ...



Learning ABM

- Standards

- ODD protocol (Grimm et al. [2006](#); [2010](#))
 - Documentation protocol for describing ABMs in journal articles
 - Readable and comprehensive

- Tools (lots of others...)

- Netlogo (ccl.northwestern.edu/netlogo/)
- Repast Symphony (repast.github.io)

- Norms

- Publish your source code! www.openabm.org



Summary

- There are very few, if any, landscapes untouched by human activity
 - Complex social-environmental dynamics can be simulated using ABM
 - Coupling ABM with other models needs to be done carefully
- ABM is the computer simulation of heterogeneous interacting agents
 - Whatever an ‘agent’ is
- Algorithms for human decision-making not necessarily specified
 - But ABM less constrained than other approaches
- More needs to be done to connect ABM with theory
 - Some of that needs to be done by social scientists!
- Validation not just about fit-to-data
 - Richer ontological ‘expressivity’ one of ABM’s key benefits
- Lots of tools, journals, training and events out there



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