Introduction

Social-ecological memory (SEM) is believed to be a fundamental component of a social-ecological system's resilience to change (Folke ref!). This SEM is dynamic, and is reshaped in positive and negative ways both internally (e.g. as social norms within a group change) and externally (e.g., as knowledge) from beyond a group is transferred into it).

Methods

Here we provide a high-level description of the agent-based model we used to explore the conditions under which biocultural hysteresis might arise; a full description using the ODD protocol (Grimm ref!) is provided as Supplementary Material. Our ABM is implemented in NetLogo 6.4 [ref!].

Model description

Landscape The model comprises a grid with two types of patches (labelled 'a' and 'b') representing sources of different knowledge - this is intended to represent places where specific species or geographic features are present. The grid comprises 50 x 50 square grid cells (patches). We assume that a patch can not contain both types. The types are not inherently positive or negative, just different. The initial amount of type 'a' in the landscape is controlled by the `n-p-a` parameter, with patches allocated to each type at random.

Agents Agents belong to units (i.e., a social network), with the number of agents and units controlled by the `n-agents` and `n-unit` parameters, respectively. The units are not antagonistic but are social groupings that internally share knowledge. They move through the landscape, and as they do so, their understanding of how to 'use' each of the two resource types changes; this knowledge is represented as a value from 0-100. This updating happens in three ways; the encounter method always occurs: the encounter method always occurs, and the other two can be turned off or on:

1. Encounter - at each time step, each agent updates its knowledge based on the current patch following a logistic curve. At each time step, there is a slight loss of knowledge of the use of the resource type different to the one the agent is in; the rate of this loss is controlled by `k-erosion`.
2. Spatial learning - if there are other agents in the patch, then each agent will gain a fraction (`transfer-fraction`) of the difference between its knowledge and that of either: (i) a random, (ii) the most knowledgeable agent, or (iii) the median knowledge across all other agents on the patch for both resource types.
3. Social learning - each agent will gain a fraction (`transfer-fraction`) of the difference between it and that of either: (i) a random, (ii) the most knowledgeable agent, or (iii) the median knowledge across all agents in its social network (unit) for both resource types; this transfer occurs irrespective of location.

The first represents individual learning via direct encou8nter with a resource, whereas the other two are forms of social learning.

At each time-step, agents move to one of the neighbouring patches (eight-cell neighbourhood). This movement follows these rules:

1. agents can not move to a patch that is in their memory (the most recently visited `memory-length` patches)

2. movement can be at random, or agents can preferentially move to one of the neighbours with the type they are most knowledgeable about

Agents live around ten ticks before dying (each time-step after they have reached an age of ten, there is a 10% chance of mortality). On an agent's death, their offspring inherit some fraction of their knowledge (based on a uniform distribution, U[`parent-transfer` , 1) and their location, social network, etc., but not their patch visit memory. There is a chance (`defect-unit`) that the offspring will be a member of another unit.

Scenarios

No change scenarios

1. Baseline conditions

First, we explored the dynamics of the model under the different learning conditions and movement without any change in the availability of the resources over time. Thus, we ran each combination of spatial learning, network learning, and random vs. preferential patch movement. For each of the six combinations, we ran 30 replicates for 50 generations with 60 agents in three social units. [SM for SA on this?]

2. Effects of transfer-fraction etc.

Change scenarios

, we explored the dynamics of the model under the different learning conditions without any change in the availability

Analysis

We analysed the data visually and did not use frequentist statstics (following White et al. (2014, ref!). We used R version X for the analyses with packages XYZ.

Results