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Development of a spatially explicit Agent-Based Model of human- resource interaction on Easter Island

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Abstract

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Contents

1	Introduction	1
1.1	The dispute about pre-historic Easter Island	1
1.2	Agent Based Modelling of human resource interactions	2
2	Methods and Model Description	3
2.1	Overview of the Model	3
2.2	Creating a 2D discretised Map of Easter Island	6
2.3	Agents and Agent-Environment Interaction	11
2.4	Agent's reaction to the harvest	19
2.5	Standard Run and Sensitivity Analysis	35
3	Results	38
3.1	Standard Run	38
3.2	Different theories	38
3.3	Different Tree Preference Functions, i.e. Agent Adaption	38
3.4	A less resilient society	39
3.5	Sensitivity Analysis of some uncertain parameters	39
3.6	Three different decision making processes	39
3.7	Perhaps, if I have time: Regional Dynamics	39
3.8	Fires	39
4	Discussion and Conclusion	40
4.1	Conclusion	40
	Bibliography	41
A	Details of the Model	44

Chapter 1

Introduction

1.1 The dispute about pre-historic Easter Island

- Easter Island's Pre-history is a fiercely debated topic
- Different theories exist on the population dynamics Hunt (2007) and Diamond (2011)/Bahn and Flenley (2017).
- The differences occur because archaeological data is connected to large uncertainties (e.g. tree patterns Rull (2020))
- Mathematical modelling has helped to explain possible scenarios of the dynamics and give interpretations of the historical developments.
- So far, all mathematical models focus on differential equation based approaches for the aggregate population of Easter Island.
- Brander and Taylor (1998)
- Variations of Brander and Taylor (1998): Summarise the reviews in Reuveny (2012), Merico (2017).
- Social institution Extension of Brander and Taylor (1998): Good and Reuveny (2006).
- Spatial Diffusion and Rats extension of Brander and Taylor (1998): Basener et al. (2008).

- The problem of these models is that with little variation in the parameters, any population dynamics can be achieved (Brandt and Merico, 2015).

1.2 Agent Based Modelling of human resource interactions

- What is Agent Based Modelling
- The basic structure of an ABM in human resource interactions: Agents in environment, Update all agents asynchronously, update environment. Within each update agents change their local environment and their behaviour/properties are in turn influenced by the local environment.
- It breaks with ODE-type of modeling because it enables:
 - spatially explicit modelling,
 - emergent global behaviour from local rules,
 - computational irreducibility of agent behaviour in terms of crisis.
 - Non-ergodic relation between agents and their environment.
 - Stochasticity is natural in the decision making process, due to an agent's imperfect knowledge of the global situation
- ABM in ancient historical population dynamics: Maya (Heckbert, 2013) and Anasazi (Axtell et al., 2002)
- Why ABM could help in Easter Island modelling: Merico (2017).
- Structure of this thesis.

Chapter 2

Methods and Model Description

2.1 Overview of the Model

I present an Agent-Based Model (ABM) that simulates the pre-historic temporal and spatial patterns of household agents on Easter Island and their interactions with the natural environment. The environment is encoded on a 2D discretised map with heterogeneous, geographic features. Agents rely both on a limited, non- or slowly renewable resource, the palm trees, and a limited, renewable resource, the arable land (in particular used for sweet potato cultivation). They obtain these resources by cutting trees and farming viable sites in their near surroundings, thereby changing their local environment. Consequently, the household's population growth or decline depends on the success of this resource acquisition. Furthermore, resource availability and other geographic indicators determine the settlement behaviour of the agents. The interaction with the natural environment, thus, constrains the settlement patterns as well as the population dynamics of the overall Easter Island society.

The model assumes yearly updates of the characteristic variables of each household agent and the environment throughout the simulated time period. The simulation starts with the arrival of the first settlers at Anakena Beach in

$$t_{\text{arrival}} = 800 \text{ A.D.} . \quad (2.1)$$

The initial population is assumed to be $\text{pop}_{\text{arrival}} = 40$ individuals (as in Good and Reuveny (2006), Brander and Taylor (1998), and similar to Brandt and Merico (2015)) spread on 2 households, that both settle close to Anakena Beach. Each time step, $\Delta t = 1 \text{ yr}$, all agents are updated and interact with their local environment sequentially in a randomised order. New household agents can appear throughout the simulation following reproduction and splitting of

existing agents. Following the alteration of the environment by all agents, the environment's state variables are updated once per year, denoted as natural update here (e.g. potential regeneration, or soil degradation). The simulation ends in 1800 A.D. with the arrival of European voyages marking the end of the isolated status of the pre-historic Easter Island society.

In Section 2.2, I describe the generation of the 2D discretised map comprising the environment of Easter Island as well as the yearly natural updates. In Section 2.3, I then focus on the household agents and the update procedure of a single agent: A single update comprises an adjustment of the agent specific properties, described in Section 2.3, the interaction between an agent and the environment, described in Section 2.3.2, and the consequent response of the agent's properties to the harvest, i.e. population growth or decline and potential re-settlement, described in Section 2.4. Figure 2.1 summarises all environmental variables, the agent variables, and their dependencies (except for re-settlement, which is described later in Figure 2.10).

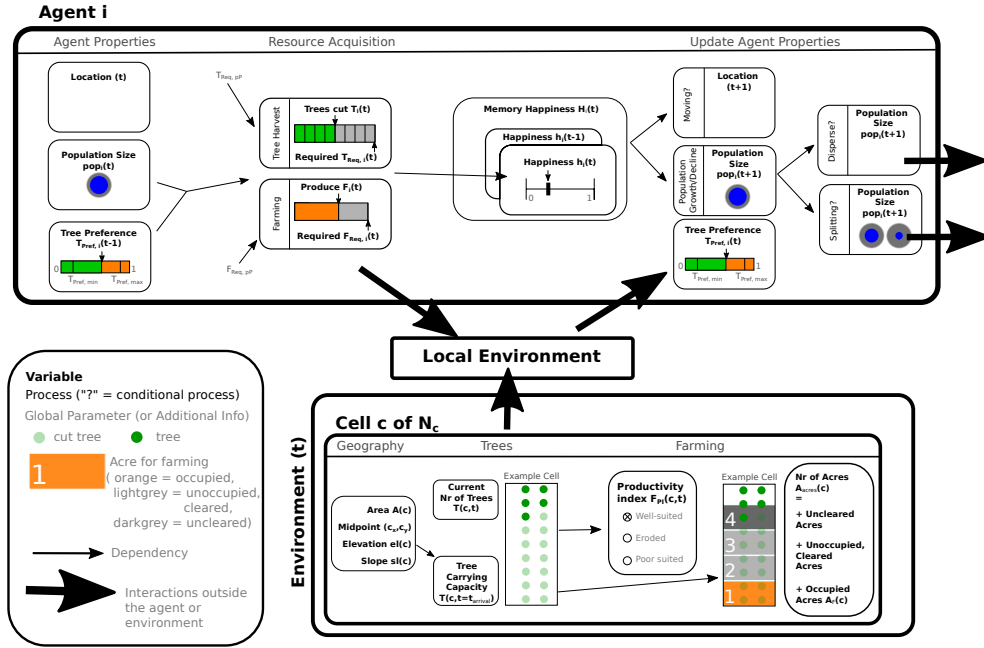


Figure 2.1: A sketch of an update step of agent i in this ABM, which is described in detail in Chapter 2. The environment consists of N_c discretised cells, c , with certain geographic properties: Area $A(c)$, midpoint \vec{c} , terrain elevation $el(c)$, and slope $sl(c)$. A cell has furthermore two ‘resource stocks’. The first resource stock is the number of trees $T(c, t)$, with a maximum of the cell’s carrying capacity (and initial state) $T(c, t = t_{arrival})$, which depends on $el(c)$ and $sl(c)$. The second resource stock is the number of arable (i.e. cells with a Farming Productivity Index $F_{PI}(c, t) > 0$) sites, $A_{acres}(c)$, with a basic unit of 1 acre, consisting of uncleared, cleared but unoccupied and occupied sites ($A_F(c, t)$ in acres). Agent i represents a household with a population size $pop_i(t)$, a settlement location $(x_i, y_i)(t)$ (corresponding cell $c_i(t)$), and a tree preference $T_{Pref, i}(t - 1)$, reflecting the state of the local environment in the previous year. From the population size and tree preference (and global, tunable per person resource requirement parameters, $T_{requ, pP}$ and $F_{requ, pP}$) the corresponding requirements for tree cutting, $T_{Req, i}(t)$ and farming, $F_{Req, i}(t)$, are calculated each year. The success of the resource acquisition from the local environment determines the current and memory happiness of the agent, $h_i(t)$ and $H_i(t)$. This latter then determines the agent’s population dynamics (including potential splitting or dispersion of the agent) and whether or not the agent relocates the settlement (according to a semi-rationale decision making process sketched in Figure 2.10 later). Finally, the tree preference, $T_{Pref, i}(t)$ is updated reflecting the state of the changed local environment.

2.2 Creating a 2D discretised Map of Easter Island

I create a discretised map dividing the island into a number of small 2D triangular cells with certain geographical features. I use a 2D equidistant grid ranging 18 km in latitudinal (from $-27.2050^\circ N$ to $-27.0437^\circ N$) and 24 km in longitudinal direction (from $-109.4650^\circ E$ to $-109.2227^\circ E$). The grid size is $\delta_x \approx 320$ m between points in x - (i.e. 75 points) and $\delta_y \approx 360$ m between points in y -direction (i.e. 50 points). In principle, the map can be created with any arbitrary resolution, constrained only by the resolution of the underlying geographical data. Also other grid types, e.g. with adaptive grid lengths to focus on regions of interest, are completely compatible with the model. While a higher resolution increases detailed geographical representation and reduces discretisation errors, computation time of the presented model scales highly non-linearly (see Section 2.4). Hence, a trade-off has to be found between detail or accuracy and computation time. I create 2D triangular cells from this grid using Hunter (2007)’s Delaunay triangulation package. A cell c is characterised by its midpoint $\vec{c} = (c_x, c_y)$. Since all cells are Delaunay triangles, their smallest angles are maximised and, hence, the midpoint, \vec{c} , provides a reasonable representation of the cell. The terrain features, elevation, $el(c)$, and slope, $sl(c)$, of Easter Island are obtained from a publicly available, high resolution elevation map (Jarvis et al., 2008) via Google Earth Engine (Gorelick et al., 2017) and evaluated at the corresponding midpoint \vec{c} . All cells located on the ocean (i.e. c with $el(c) = 0$) are masked out and discarded. The cells corresponding to the island’s three small crater lakes (in some periods reduced to two due to drought periods) are also identified. The remaining cells constitute the landmass of the discretised island, which can later be settled, deforested or farmed by the agents. With the resolution given above, $N_c = 2768$ cells remain with an area of roughly $A(c) = 0.06 \text{ km}^2 = 14.2 \text{ acre}$. The area of the discretised Easter Island is $A = 159.2 \text{ km}^2$, (163.6 km^2 in reality) providing a detailed, cellular representation of geographical features (location \vec{c} , area $A(c)$, elevation $el(c)$, and slope $sl(c)$).

Next to the geographical features described above, a cell has characteristic biological features. Each cell c has a tree number, denoted as $T(c, t)$ (or tree density $T(c, t)/A(c)$). While the assumption of constant climatic conditions throughout Easter Island’s history has been challenged recently (Rull, 2020), I only consider anthropogenic deforestation $T(c, t)$. Hence, the island’s forest system is assumed to be in equilibrium (c.f. Brander and Taylor (1998)) at the

time of the arrival of the first settlers, t_{arrival} and, thus, $T(c, t = t_{\text{arrival}})$ is the constant carrying capacity of palm trees for each cell c on the island. There is still some uncertainty about the total number and spatial patterns of palm trees at $t = t_{\text{arrival}}$. Mieth and Bork (2015) estimate a total of $16 \cdot 10^6$ trees covering 80% of the island from root casts in the soil, whereas e.g. Brandt and Merico (2015) initialise the model with a conservative estimate of $8 \cdot 10^6$ trees. Most studies assume an island wide, dense distribution of the palm trees. E.g. Bahn and Flenley (2017) state that soil sufficient for tree growth is present ‘almost everywhere on the island, apart from the steepest parts of the cliffs and the youngest lava surfaces’ (i.e. the highest elevations of Mount Terevaka). However, Rull (2020) also investigates the possibility of mosaic vegetation patterns with high densities of trees around the lakes and the coastal areas. The model presented here can incorporate any pattern of pre-arrival tree density. For the results in this thesis, I assume an equal density pattern excluding those cells with very high elevation or slope ($el(c) > 450$ m or $sl(c) > 10^\circ \Rightarrow T(c, t) = 0$). In this model, a total of

$$\mathbf{T}(t = t_{\text{arrival}}) = \sum_c T(c, t = t_{\text{arrival}}) = 16 \cdot 10^6 \quad (2.2)$$

trees¹ are distributed according to this density pattern. A resulting map of pre-arrival tree numbers $T(c, t_{\text{arrival}})$ in cells c extending on 86% of Easter Island is shown in Figure 2.2.

Through anthropogenic deforestation, the variable tree number in each cell, $T(c, t)$, declines. The importance of this human influence in degrading the environment compared to the impact made by a quickly increasing number of Polynesian rats is a strongly debated topic (e.g. Bahn and Flenley (2017) and Hunt (2007)) as described in the Introduction. However, there seems to be a consensus between both theories that rats effectively hindered tree regeneration by gnawing on the palm nuts. In line with these arguments, forest regeneration is not possible in the standard setting of this model. Thus, trees constitute an entirely non-renewable resource in this scenario. However, I further explore alternative experiments in which the forest can hypothetically regenerate following anthropogenic deforestation. Each year, tree numbers $T(c, t)$ in all cells c regrow logistically to their (local) carrying capacity $T(c, t = t_{\text{Arrival}})$ if there is no farming activity on the specific cells. The maximum growth rate of this localised logistic tree regeneration is believed to be rather slow and has even been made responsible for the ecological degradation of the island in earlier studies (e.g. Brander and Taylor (1998)). Brandt and Merico (2015) use

¹Bold symbols denote iterations over all cells (or agents) in the thesis.

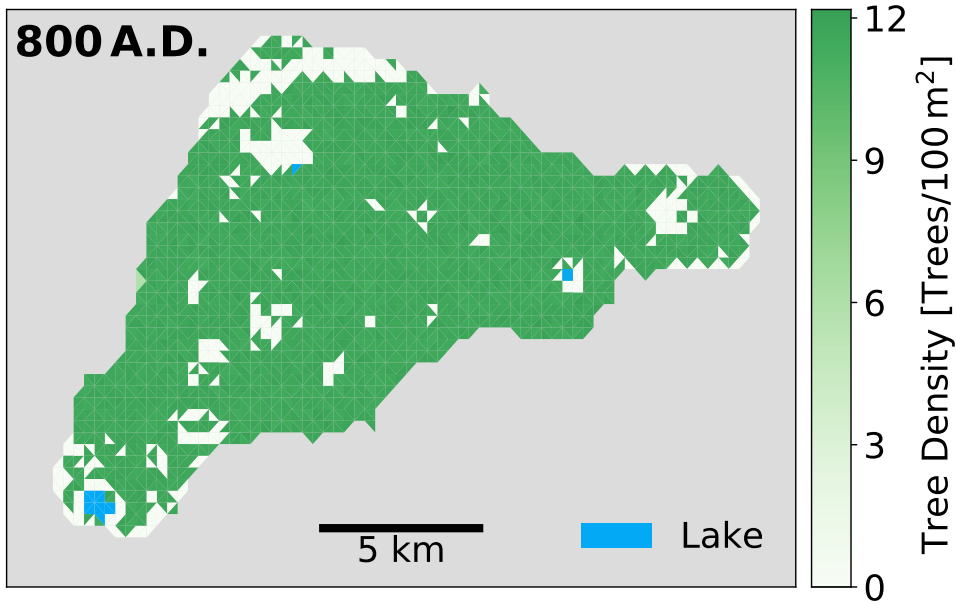


Figure 2.2: The carrying capacity density of trees in each cell $T(c, t_{\text{arrival}})/A(c)$.

a maximum tree regrowth rate between 0.02 and 0.07 1/yr for their model in the absence of rats. In experiments, in which tree regeneration is allowed in this model, the maximum logistic growth rate is

$$g_T = 0.05 \text{ 1/yr} . \quad (2.3)$$

Some cells are deforested entirely in a single update step, disabling their regeneration in the model. However, forest regrowth is also possible in such cells with seeds being transported to the empty cell e.g. through wind, birds or human activity. To incorporate this in the model, a small number of trees ‘pops up’ (0.5% of the cell’s carrying capacity) after a cell has been left barren, i.e. the cell has been without trees and any farming activity, for 10 consecutive years. In summary, in this model the tree number in a cell c either (standard setting) does not regenerate at all or (alternative setting) regenerates as

$$T(c, t+1) = \begin{cases} T(c, t) + T(c, t) \cdot g_T \cdot \left(1 - \frac{T(c, t)}{T(c, 0)}\right) & \forall c \text{ with } \mathbf{A}_F(c, t) = 0 \\ 0.005 \cdot T(c, 0) & \forall c \text{ with } T(c, t) = 0 \text{ and} \\ & \mathbf{A}_F(c, \hat{t}) = 0 \ \forall \hat{t} \in \{t-10, \dots, t\} \\ 0 & \text{else} \end{cases} \quad (2.4)$$

(neglecting anthropogenic deforestation). These two scenarios, without and with forest regeneration, allow for testing of the impact of the Polynesian rats, assuming that they effectively hindered tree regeneration.

The Easter Island society also cultivated renewable crops as an alternative to harvesting the non- or slowly renewable trees. Hence, agents in this model also farm on arable land in a two resource dependency similar to previous models (D'Alessandro, 2007). Farming produce in this model means in particular sweet potato cultivation, since this was the dominant staple crop (Louwagie, Stevenson, and Langohr, 2006) (at least in the later part of pre-historic times). As described in the Introduction, Easter Island's suitability for farming, especially w.r.t. climate and soil, has been subject to excessive debate. While the total potential of agricultural productivity remains uncertain, several studies identified arable sites by using data on rain, climate, temperature, elevation and soil quality in agricultural models (e.g. Louwagie, Stevenson, and Langohr (2006) and Puleston et al. (2017)). The quality of farming and soil suitability on Easter Island and its spatial dependency is an ongoing research field, with crucial implications for the peak population size (Puleston et al., 2017). The parametrisation of farming productivity shown in the remaining section, thus, is a strong limitation on the population dynamics.

In order to obtain a spatially explicit differentiation between arable and non-arable land, I use a map created by Puleston et al. (2017) (Figure 4) indicating regions meeting a certain viability criterion for sweet potato cultivation. This criterion is based on an agricultural model of climate data and soil quality and marked 19% of the island as agriculturally viable, mainly in the lowland, coastal region. However, widespread systems of gardens were also found in the upland regions classified as non-viable by Puleston et al. (2017)'s criterion. The authors state that these gardens added only a small fraction of actually farmed land to the viable region, though. Here, I use three levels of viability for cells of the discretised map: A cell is either 'well-suited' if located in the viable region, 'poorly suited' if located in the non-viable region which was nevertheless farmed, or 'non-viable' else (cp. with Puleston et al. (2017) (Figure 4)). The total resulting arable land area in this model (shown in Figure 2.3) is ca. 29 km² (i.e. 18%) for well-suited sites and, additionally, 50 km² (i.e. 31%) for poorly suited sites.

I distinguish well-suited from poorly suited cells by assigning different Farming Productivity Indices, $F_{PI}(c)$, for dryland farming to associated cells. Louwagie, Stevenson, and Langohr (2006) developed a classification for successful cultivation of several crops based on climate and soil property measurements at a few sites on the island and assigned classes of relative yields to them. One

of the studied sites (Vaitea), which coincides with the poorly suited region in Puleston et al. (2017) (compare Figure 1 of Louwagie, Stevenson, and Langohr (2006) with Figure 4 of Puleston et al. (2017)), was found not suitable for farming due to insufficient nutrition availability (with a relative yield of 0 – 20% compared to an optimal site) despite archaeological evidence of gardens in this area. To enhance yields, the islanders used techniques like labour intensive, large-scale lithic mulching, which mainly increased moisture availability, and efficient crop management, e.g. plant spacing and frequent fallowing (Louwagie, Stevenson, and Langohr, 2006). The per area productivity, however, remains low even with these techniques in place with nutrient availability being the main constraint as also implied by the analysis in Puleston et al. (2017). The other sites in Louwagie, Stevenson, and Langohr (2006) located at the foots of smaller craters along the arable coasts, were classified as mostly ‘marginally to moderately suitable’ for sweet potato cultivation for most climatic conditions with some locations showing ‘high suitability’ (relative yield > 80%) especially in wet years. These sites are mainly located in the well-suited or poorly suited regions of the map in Puleston et al. (2017). Hence, following roughly the classification by Louwagie, Stevenson, and Langohr (2006), a Farming Productivity Indices, $F_{PI}(c)$ is assigned to each cell (and its corresponding sites)

$$\begin{aligned} F_{PI}|_{\text{well}} &= 80\% && \text{for well-suited (highly to moderately suitable)} \\ F_{PI}|_{\text{poor}} &= 10\% && \text{for poorly suited (not suitable)} \\ F_{PI}|_{\text{non-viable}} &= 0\% && \text{for non-viable sites} \end{aligned}$$

depending on its classification by Puleston et al. (2017) into well-suited and poorly suited cells.

Soil erosion through radical deforestation and heavy rainfalls also constrain the farming productivity of the island especially in the later phase (e.g. Brander and Taylor (1998), Mieth and Bork (2005), Bahn and Flenley (2017), ...). As trees are removed from a region, rain can wash away nutrient-rich soil and reveal less fertile ground with reduced relative yield Mieth and Bork (2005). In the model, I assume that, as a well-suited cell is completely deforested, the land erodes and, thus, the cell’s $F_{PI}(c)$ reduces to

$$F_{PI}|_{\text{eroded}} = 50\% \quad \text{for well-suited cells with } T(c, t) = 0. \quad (2.5)$$

This soil degradation is reverted as soon as trees pop back up (i.e. if the cell has been kept barren (without farming) for the previous 10 years as described in equation 2.4).

Throughout the simulation, agents set up basic unit gardens of size 1 acre on arable (well-suited or poorly suited) cells. A cell on arable (i.e. well-suited or poorly suited) land has

$$A_{\text{acres}}(c) = \text{Rounded Down} (A(c)[\text{acres}]) \quad (2.6)$$

number of acres, which are denoted as sites and can each be occupied and farmed by an agent. Such a farming site yields a produce according to the (relative) Farming Productivity Index, $F_{\text{PI}}(c)$. The absolute productivity of an acre of arable land in units of people it can support is taken from calculations in Puleston et al. (2017) assuming two different Nitrogen fixation scenarios (see in detail later). The map of Farming Productivity Indices $F_{\text{PI}}(c)$ of all cells on Easter Island is shown in Figure 2.3, thus defining where agents have access to farming and how productive farming would have been in this location in the model.

2.3 Agents and Agent-Environment Interaction

2.3.1 Agent Properties

The ABM consists of a variable number of agents, $N_{\text{Agents}}(t)$, which represent households, situated on the discretised map derived in Section 2.2. An agent with index i has several varying properties describing its state at time t . The settlement is located at

$$\vec{x}_i(t) = (x_i, y_i)(t) \quad (2.7)$$

on the discretised map and, hence, associated with one specific cell $c_i(t)$. The agent's population size, i.e. the number of individuals in the household,

$$\text{pop}_i(t) \quad (2.8)$$

typically ranges from 12 (minimum 6) to ca. 42. While, all calculations and decisions on harvest and choosing a settlement location happen on the individual level, macroscopic aggregates are simply obtained by iterating over all agents, which I denote by bold symbols in the thesis (same as for iterating over cells). Agents rely on an intake of resources each year in order to sustain and potentially increase their population size. As mentioned before, I consider two major resources, trees and sweet potato farming, accessible through interaction with the environment. An agent i can harvest resources from cells with

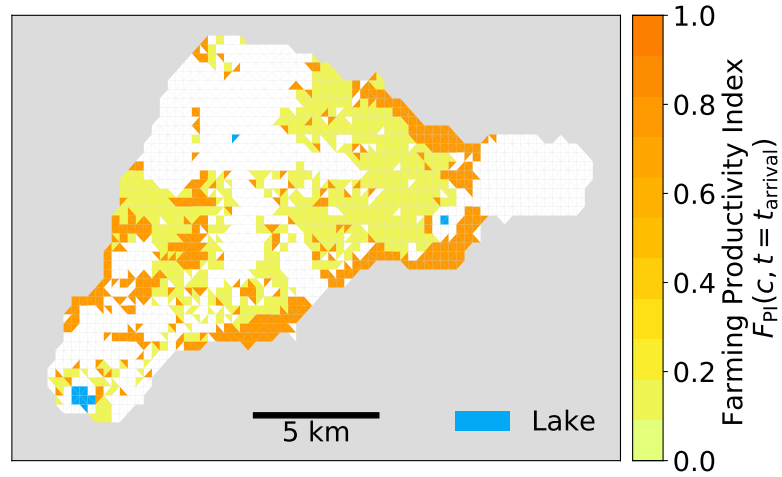


Figure 2.3: A map of the (sweet potato) Farming Productivity Indices, $F_{PI}(c)$, in each cell of the discretised map of Easter Island. The model makes use of the map of Puleston et al. (2017) classifying arable land into viable areas (here ‘well-suited sites’), non-viable but nevertheless partially farmed (here ‘poorly suited sites’), and non-viable sites derived from an agricultural model of climate and soil quality. This classification is combined with measurements of land suitability in several sites (Louwagie, Stevenson, and Langohr, 2006) giving rise to a simple, spatially explicit map of farming potential parametrised by the Farming Productivity Index $F_{PI}(c)$.

midpoints \vec{c} located within fixed radii of the agent's settlement:

$$C_T(c_i(t)) = \{\tilde{c} \mid \|\vec{c} - \vec{x}_i(t)\| \leq r_T\} \quad (2.9)$$

for the resource tree with tree search radius $r_T = 2$ km and

$$C_F(c_i(t)) = \{\tilde{c} \mid \|\vec{c} - \vec{x}_i(t)\| \leq r_F\} \quad (2.10)$$

for farming sites with farming radius $r_F = 1$ km.

The agent's total resource uptake is split between tree cutting and farming yield. The shares are given by a trait parameter, the tree preference $T_{\text{Pref}, i}(t)$ for agent i at time t , which adapts the agent's harvest behaviour to its local environment. In the first settlement phase, the islanders mainly lived off the abundant natural resources of the island, i.e. land birds, fish, and fruits from the trees Bahn and Flenley (2017) (which are all connected to the resource tree in this model). Over time, the economy 'switched from predominantly hunter-gatherer to a dryland farming society' (Louwagie, Stevenson, and Langohr, 2006). In the model, this behavioural shift results from a decrease in the variable tree preference parameter, $T_{\text{Pref}, i}(t)$ of each agent over time. The trait parameter is designed such that agent's adjust their resource requirements for next year given the current state of the local environment, in particular the level of deforestation. Hence, as the island's trees are removed and more arable land is cleared freeing space for agriculture, the agent's tree preference decreases and farming activity increases, accordingly. In this model, the tree preference, $T_{\text{Pref}, i}(t)$, depends on the local, relative change of tree density within the tree search radius r_T with respect to the initial state at $t = t_{\text{arrival}}$, i.e.:

$$T_{\text{Pref}, i}(t) = f_{\text{Tree Pref}} \left(\frac{\sum_{\tilde{c} \in C_T(c_i(t))} T(\tilde{c}, t)}{\sum_{\tilde{c} \in C_T(c_i(t))} T(\tilde{c}, t_{\text{arrival}})} \right) \quad (2.11)$$

The shape of the function $f_{\text{Tree Pref}}$ is an indicator of the responsiveness of the economy/society to environmental change. How fast do agents adapt their harvest behaviour, when the non-renewable resource, the trees, is depleted from the initial state? I consider four possibilities (shown in Figure 2.4): The tree preference $T_{\text{Pref}, i}(t)$ decreases

- linearly with the local, relative tree density decline (linear case).
- delayed with the local, relative tree density decline (delayed case).
- quicker than the local, relative tree density decline (careful case),

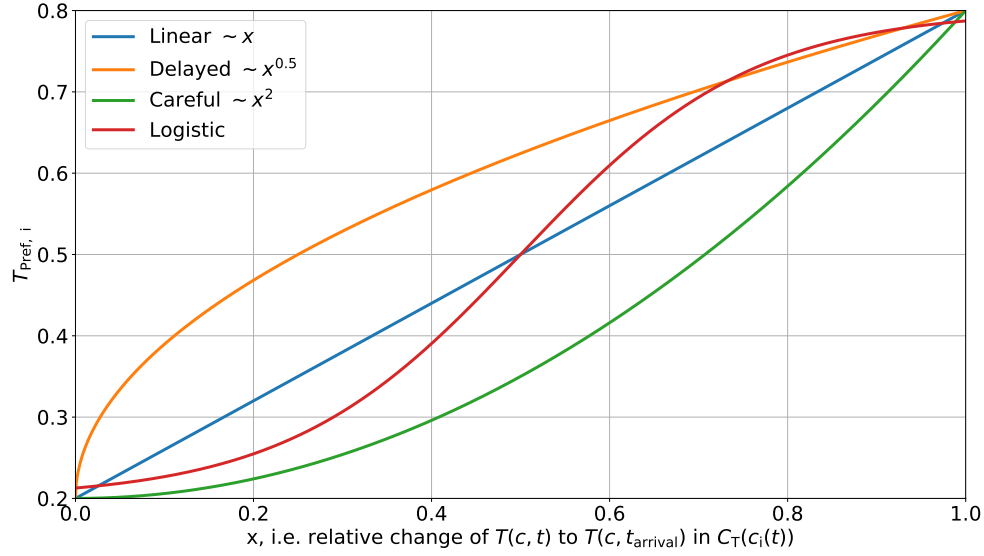


Figure 2.4: The relation of an agent's tree preference, $T_{\text{Pref}, i}(t)$, to relative changes in the local tree density for the four considered adaptive functions $f_{\text{Tree Pref}}$ with x given in equation 2.11.

- first delayed, and at some point quicker than the local, relative tree density decline (logistic case)

The tree preference is cut off at certain minimum and maximum thresholds, assuming an agent can not live purely off trees (and associated derivative products), but, at the same time, some tree cutting is always required even for maximum agricultural production (e.g. as cooking wood or for tools). Here, I choose:

$$T_{\text{Pref}, \min} = 0.2 \quad \text{and} \quad T_{\text{Pref}, \max} = 0.8 \quad (2.12)$$

In the standard setting in this model, I use the linear relation and, hence,

$$T_{\text{Pref}, i}(t) = \frac{\sum_{\tilde{c} \in C_T(c_i(t))} T(\tilde{c}, t)}{\sum_{\tilde{c} \in C_T(c_i(t))} T(\tilde{c}, t_{\text{arrival}})} \cdot (T_{\text{Pref}, \max} - T_{\text{Pref}, \min}) + T_{\text{Pref}, \min} \quad (2.13)$$

Since tree density is maximal at $t = t_{\text{arrival}}$, the initial agents start with maximal tree preference ($T_{\text{Pref}, i}(t = t_{\text{arrival}}) = 0.8 \quad \forall i$), which then (in general) decreases as the (local) deforestation intensifies.

An agent's required total resource uptake per year increases with the population size and the tree preference calculated after the harvest in the previous year. Hence, the resource requirements of tree harvest, $T_{\text{Req}, i}(t)$, and farming produce, $F_{\text{Req}, i}(t)$, are

$$T_{\text{Req}, i}(t) = T_{\text{Pref}, i}(t-1) \cdot \text{pop}_i(t) \cdot T_{\text{Req}, \text{pP}} \quad (2.14)$$

and, similarly,

$$F_{\text{Req}, i}(t) = (1 - T_{\text{Pref}, i}(t - 1)) \cdot \text{pop}_i(t) \cdot F_{\text{Req}, \text{pP}}, \quad (2.15)$$

where $T_{\text{Req}, \text{pP}}$ is the tree requirement per year per person in absence of agriculture and $F_{\text{Req}, \text{pP}}$ is the required agriculture production per year in the absence of tree cutting. These constant parameters determine the amount of tree harvesting and farmland occupation and, thus, are crucial for the temporal development of the island's environment.

The tree requirement per person, $T_{\text{Req}, \text{pP}}$, in principle depends on a multitude of factors and is presumably heterogeneous between agents. E.g. if sugary sap from cut tree trunks was used by some people as freshwater replacement as suggested by Mieth and Bork (2015), a much larger number of trees would have been needed to cut by those individuals. Here, I use a constant parameter of

$$T_{\text{Req}, \text{pP}} = 5 \frac{\text{Trees}}{\text{person} \cdot \text{yr}} \quad (2.16)$$

for all agents (for the standard model settings) based on the maximum harvest rate used in Brandt and Merico (2015), ca. 3 to 7 trees per year².

The agriculture requirement per person, $F_{\text{Req}, \text{pP}}$, is strongly connected to the definition of the farming productivity indices $F_{\text{PI}}(c)$ (Figure 2.3). Puleston et al. (2017) simulate the nutritional productivity of farming on well-suited land (as defined in Section 2.2) for two different environmental scenarios for the Nitrogen fixation in the soil, i.e. the rate at which Nitrogen is renewed, representing a major uncertainty in their model. This can be converted into the minimum land required to sustain one person using the nutrition content of sweet potato (1 t/yr roughly sustains 1 individual in the absence of other food sources):

$$F_{\text{Req}, i}(t) = \begin{cases} 0.5 \frac{\text{acre}}{\text{person}} & \text{for high N fixation} \\ 1.7 \frac{\text{acre}}{\text{person}} & \text{for low N fixation} \end{cases} \quad (2.17)$$

In this model, I do not consider fallowing as farming practice to increase productivity of arable land, as this, in general, reduces the productivity per total occupied area needed for each individual (see Table 1 in Puleston et al. (2017)). In fact, the only constrain for farming is availability of arable land in this model, not workforce or any social/political constraints (as included in Puleston et al. (2017)). I.e. I assume that, if enough land is available, the agent's

²Brandt and Merico (2015) use a only half of the initial trees before arrival of the first settlers, though)

occupy as many sites as necessary. Hence, the resource requirements for trees (in absolute numbers) and agricultural production (in acres of well-suited quality agriculture sites) are agent-specific, yearly varying features, which can be tuned through the global parameters $T_{\text{Req, pP}}$ and $F_{\text{Req, pP}}$.

The model, furthermore, allows for open-ocean fishing as a replacement for farming for some agents living near the Anakena coast. Instead of occupying arable land units and farming, these fishers gain sufficient agricultural resources by going out to sea on large canoes. In the initial phase of Easter Island settlement, excavations prove that shellfish, fish and even porpoise were a major part of the diet at the time (Bahn and Flenley, 2017). However, over time, these natural resources became increasingly scarce and many species even went extinct due to human predation, with open-ocean fish vanishing from the diet eventually (Diamond, 2011). As a resource management institution the Easter Island society installed taboos on the harvest of natural resources (Good and Reuveny, 2006). Fishing was mainly restricted to members of a specific chiefdom ('Miru') living at Anakena Beach (Bahn and Flenley, 2017) who would then presumably trade with others. Hence, in the model, every agent living within farming radius, r_F , distance of Anakena Beach (in cell c_{Anakena}) automatically becomes a fishing agent up to a maximum of $N_{\text{Fisher, Max}} = 10$ agents in total (i.e. no more than 500 people)

$$c_i \in C_F(c_{\text{Anakena}}) \cup N_{\text{Fishers}} < N_{\text{Fisher, Max}} \Rightarrow \text{Agent } i \text{ becomes a fisher} \quad (2.18)$$

While I assume that open-ocean fish supply is unlimited for those living at Anakena Beach, another constraint for the fishers is the requirement for trees. Since fishing presumably requires a quite extensive amount of wood (e.g. for canoes or firewood), the fishers minimum tree preference is increased to

$$T_{\text{Pref, min}}|_{\text{fisher}} = 0.5 \quad (2.19)$$

rather than $T_{\text{Pref, min}} = 0.2$ for farming agents. While fishing agents near Anakena Beach do not have any farming requirements due to their access to an unlimited resource stock from the sea, the correspondingly higher requirement for trees and an externally introduced restriction on their number limit the total amount of this resource extraction.

2.3.2 Agent-Environment Interaction – Tree and Agriculture Harvest

After determining the required amount of trees, $T_{\text{Req, i}}(t)$, and agricultural production, $F_{\text{Req, i}}(t)$, as described in Section 2.3.1, in a given year t , an agent ac-

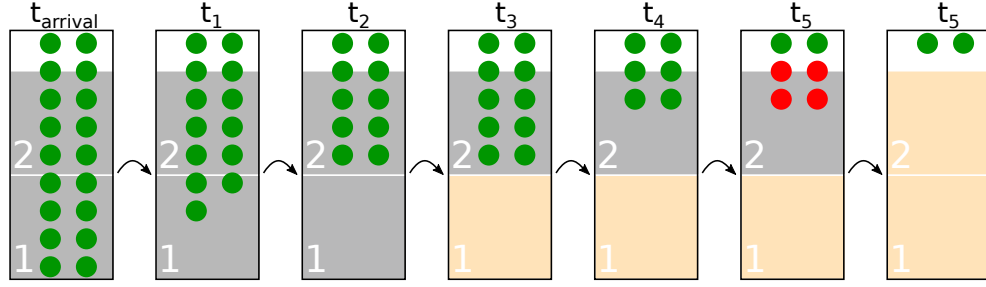


Figure 2.5: Sketch of an exemplary deforestation procedure (by arbitrary agents) in a cell c (black box) with an area of 2.3 acres. The cell is arable, with $F_{PI}(c) > 0$ and, thus, provides $A_{\text{acres}} = 2$ acres for potential farming (grey squares). Initially at t_{arrival} , the cell has 18 trees (carrying capacity). At some time t_1 , after deforestation 13 of these trees still exist. An Agent a removes 3 trees from the cell ($\rightarrow t_2$). Subsequently, Agent b then occupies the now cleared site (1 acre) on cell c for farming ($\rightarrow t_3$). Agent c cuts another 4 trees ($\rightarrow t_4$). And finally, at t_5 , an agent d , needs to occupy more sites to fill its farming requirement and cannot find any other arable, unoccupied site in $C_F(c_c)$ except for the second site in cell c . However the agent needs to burn 4 more trees (red) before being able to occupy the second acre on this cell ($\rightarrow t_5$).

quires sufficient resources (if available) from its local environment. This procedure is described in the remaining section. The sketch in Figure 2.5 shows an example of this process of deforestation and consequent replacement by farming in a cell.

Farming An agent occupies arable land unit sites, $A_{F,i}(t)$, with a fixed area of 1 acre associated to one cell and obtains a yearly harvest of

$$F_i(t) = \sum_{a \in A_{F,i}(t)} F_{PI}(c(a)) , \quad (2.20)$$

where a denotes a farmed acre and $c(a)$ is the corresponding cell of this acre. Note, for fishers $F_i(t) = F_{\text{Req},i}(t)$ holds immediately without farming and occupying sites. Agents keep all their currently occupied sites $A_{F,i}(t)$ until the next year. However, over time, the agents farming requirement, $F_{\text{Req},i}(t)$, can increase as the agent's population grows, its tree preference decreases or the soil quality of an agent's occupied sites degrades due to erosion. Hence, an agent i needs to acquire more arable sites only if the requirement for farming,

$F_{\text{Req},i}(t)$, exceeds the farming produce of the previous year, $F_i(t-1)$, i.e.

$$F_i(t-1) < F_{\text{Req},i}(t) \Rightarrow \text{Extend } A_{F,i}(t) \text{ and, thus, } F_i(t)! \quad (2.21)$$

In the search for new farming sites, an agent first considers only sites in well-suited cells, i.e. $c \in C_F(c_i(t))$ with $F_{\text{Pl}}(c) = F_{\text{Pl}}|_{\text{well}}$, in order to maximise farming efficiency. An acre in an arable cell can only be occupied (or added to $A_{F,i}(t)$) if at least this area of 1 acre is cleared off trees and not occupied. Assuming that the trees are evenly distributed on the cell's area, the condition can be calculated as

$$\left(1 - \frac{T(c,t)}{T(c,0)}\right) \cdot A(c) - \mathbf{A}_F(c,t) \geq 1 \quad (2.22)$$

where the first term is the treeless area in acres and the second term, $\mathbf{A}_F(c,t) = \sum_{j \in N_{\text{Agents}}(t)} \sum_{a \in A_{F,j}(t)} \delta(a=c)$, is the number of already farmed acres (by any agent) in cell c .

If there are no well-suited sites left that fulfil this condition, the agent uses the slash and burn method to reduce the number of trees $T(c,t)$ of a well-suited cell c (with at least one unoccupied acre). The agent starts burning trees on the cell that requires the least amount of trees removed (without leading to erosion of the cell) for the condition to hold. Burning trees and occupying sites continues until the farming requirement of the agent is satisfied or no more well-suited acres are available (even if this leads to erosion of the cell). The use of fires to clear space is supported by the extensive charcoal record starting with the period of intensified agriculture (Mieth and Bork, 2015). Here, I assume that if space is required for farming, trees were burned directly and independently of the continuous tree harvest. Of course, an agent could also use these trees first and (e.g. for extracting the sugary sap) then burn the remaining material to clear the land for next year as indicated by Mieth and Bork (2015), but this would require agents that plan ahead, which I do not consider in the harvesting process. If, all well-suited sites within $C_F(c_i(t))$ are occupied, but the agent's agricultural production does not yet meet the farming requirement ($F_i(t) < A_{\text{Req},i}(t)$), the agent also occupies sites on eroded cells and then on poorly suited cells in the same procedure.

Tree Harvest After filling the farming requirement, the agent then cuts trees according to its tree requirement $T_{\text{Req},i}(t)$. An agent i selects random cells $c \in C_T(c_i(t))$ with uniform probabilities and successively removes trees from these cells until the number of cut trees, $T_i(t)$ matches the requirement $T_{\text{Req},i}(t)$ or no further trees are present in $C_T(c_i(t))$. Unlike farming, where occupied

sites are kept and re-used (with the same productivity index) in the next update, the agent obviously needs to find new trees every year. While the agent's adapt their harvest behaviour via the tree preference as this non-renewable resource is depleted over time, a minimum amount of trees is always required and, hence, there's no equilibrium state without tree regrowth.

Happiness Agents have a variable happiness, $h_i(t)$, that reflects the success of the harvest of trees and farming produce each year. Here, an agent i 's happiness $h_i(t)$ depends on the ratio between the $T_i(t)$ cut trees and $F_i(t)$ agricultural produce in comparison to the requirements determined beforehand, $T_{\text{Req}, i}(t)$ and $F_{\text{Req}, i}(t)$, respectively. By assuming that both resources are equally indispensable for the agent, the happiness is equal to the smaller of the two fractions:

$$h_i(t) = \min \left(\frac{T_i(t)}{T_{\text{Req}, i}(t)}, \frac{F_i(t)}{F_{\text{Req}, i}(t)} \right) \quad (2.23)$$

If both requirements are filled for agent i , the happiness is maximal: $h_i(t) = 1$. However, if either $T_i(t) = 0$ or $F_i(t) = 0$, $h_i(t) = 0$ follows regardless of the success in harvesting the other resource. Since households have some resilience to a decline in harvest success (e.g. by storing food over more successful years), a memory happiness $H_i(t)$ is calculated in each year:

$$H_i(t) = \begin{cases} h_i(t) & \text{if } h_i(t) \geq h_i(t-1) \\ \frac{h_i(t) + h_i(t-1)}{2} & \text{if } h_i(t) < h_i(t-1) \end{cases} \quad (2.24)$$

If an agent's harvest success decreases (due to resource scarcity), its memory happiness $H_i(t)$ decreases monotonically. If e.g. all trees were to suddenly vanish within a year, an agent would have two years before its memory happiness plummets to its minimum $H_i(t) = 0$. However, if harvest success increases (e.g. due to moving the settlement to a better location), the memory happiness takes on the new happiness value immediately. As an indicator for successful resource acquisition, the memory happiness $H_i(t)$ determines the possible responses of agent i to the harvest, which I describe in the following Section 2.4.

2.4 Agent's reaction to the harvest

2.4.1 Population Dynamics

Following an agent's farming and tree cutting actions, its population size $pop_i(t)$ is adapted. The net (positive or negative) growth rate of the agent's population

at a specific time depends only on the memory happiness:

$$pop_i(t + 1) = g(H_i(t)) \cdot pop_i(t) \quad (2.25)$$

In fact, instead of assuming continuous growth or decline according to this growth rate, $g(H_i(t))$, the population dynamics is implemented as a discrete, stochastic process. Each individual member of the agent has a $\text{abs}(g(H_i(t)) - 1)$ probability to die if $g(H_i(t)) < 1$, or a $g(H_i(t)) - 1$ chance to reproduce (i.e. adding one individual to the household/agent) if $g(H_i(t)) > 1$. The population size stays constant if $g(H_i(t)) = 1$, denoted as H_{equ} . This results in a growth/decline of the population where each agent's population size trajectory is a single realisation of the stochastic process which on average matches the continuous dynamics in equation 2.25 (compare e.g. with Bungartz et al., 2009). Figure A.1 in Appendix A shows a few different realisations of a discrete, constant growth scenario with rate $g(H_i(t) = 1) = 1.007$ (i.e. with unconstrained resource availability) in comparison with the continuous growth. There is an excessive debate about the initial growth rate of the Easter Island population after the arrival of a small number of Polynesians (i.e. in a time period without resource constraints and, thus, $H_i(t) = 1$). Parameters used in the literature range from 0.7% per year (Bahn and Flenley, 2017) or 'always below 1%' (Brander and Taylor, 1998) to exceeding 3% (Hunt, 2007) for short periods of time or 2.3 – 4.5% (Brandt and Merico, 2015). It is clear that depending on the proposed chronology, researchers have to make very contrary assumptions on the population growth in order to fit the population dynamics to the few undisputed facts about the pre-historic society on Easter Island. If an arrival around 1200 A.D. is assumed (as in Hunt (2007) or Brandt and Merico (2015)), assuming a large population growth is unavoidable. It seems impossible that only a few hundred inhabitants in the 13th to 16th century could have created several hundred Moai statues (and caused a massive alteration of the island's environment). On the other hand, slower initial population growth needs to be assumed in studies proposing earlier arrival dates (around 800 A.D. (e.g. Bahn and Flenley (2017)) or even as early as 400 A.D. (Good and Reuveny (2006) and Brander and Taylor (1998))), since archaeological data indicates an intensification of human activity, which suggests a large population size, only starting after 1200 A.D. (e.g. Bahn and Flenley (2017)) and Hunt (2007)). Other theories, such as multiple, distinct periods of population growth and declines have been put forward (e.g. Cole and Flenley (2008)), but do not seem to be common in the context of Easter Island. Following Bahn and Flenley (2017), I choose an early arrival date here ($t_{\text{arrival}} = 800 \text{ A.D.}$), as described before, and, thus, a slow growth rate (in one year) in the case of

unlimited food supply and, therefore, continuously happy agents:

$$g(H_i(t) = 1) = 1.007 . \quad (2.26)$$

The specific dependency of the population growth or decline in the case of limited resources is a further uncertainty in modelling human-resource interactions in general. Lee and Tuljapurkar (2008) and Puleston and Tuljapurkar (2008) constructed a food-limited demography model applied to simulating the Easter Island society and farming constraints in Puleston et al. (2017). Here I use a strongly simplified assumption of this model to parametrise the impact of non-optimal harvests on the population dynamics. The authors derived age-dependent survival and fertility rates, which are both S-shaped curves w.r.t. the food availability (i.e. high in the case of unlimited food availability and low in the case of scarce food availability). Since, I do not consider (age-stratified) structures below the agent/household level, I simply assume a net growth rate with the same shape as the survival and fertility rates in Lee and Tuljapurkar (2008).

$$g(H_i(t)) \sim CDF(\Gamma_{\text{Dist}}(\text{shape}, \text{scale} = 0.1)) \quad (2.27)$$

where $CDF(\Gamma_{\text{Dist}})$ is the cumulative density function of the Gamma distribution (characterised by shape and scale parameter) with scale fixed as in Lee and Tuljapurkar (2008). I then tune the shape parameter of this function to obtain the same equilibrium point $g(H_i(t) = H_{\text{equ}}) = 1$, at which the population size remains constant, as in Puleston et al. (2017) (Supplementary Material):

$$H_{\text{equ}} = 0.6883 \quad \text{with } g(H_i(t) = H_{\text{equ}}) = 1 . \quad (2.28)$$

In order to test sensitivity of this parametrisation, I also investigate a larger shape parameter $\text{shape}^* = 3$, which leads to a less resilient population size when resource scarcity sets in. In this alternative, less resilient scenario, the growth rate declines faster if $H_i(t)$ decreases and the equilibrium point is reached for a higher happiness value $H_{\text{equ}}^* = 0.84$. The amplitude of the resulting function (for both scenarios) is scaled to give the chosen reproduction rate under unconstrained food supply from last paragraph $g(H_i(t) = 1) = 1.007$. Figure 2.6 shows the resulting two parametrisations of population dynamics (standard setting in blue and less resilient setting in red) with the happiness regime for net growth, $H_i(t) > H_{\text{equ}}$ (with a maximum of $g(H_i(t) = 1) = 1.007$) and the regime for net decline of the population size, $H_i(t) < H_{\text{equ}}$. It should be noted, that the use of the model in Puleston et al. (2017) is strongly simplified here. E.g. I am using a different notion of food/tree availability, which I express via the smoothed happiness $H_i(t)$, rather than Puleston et al.

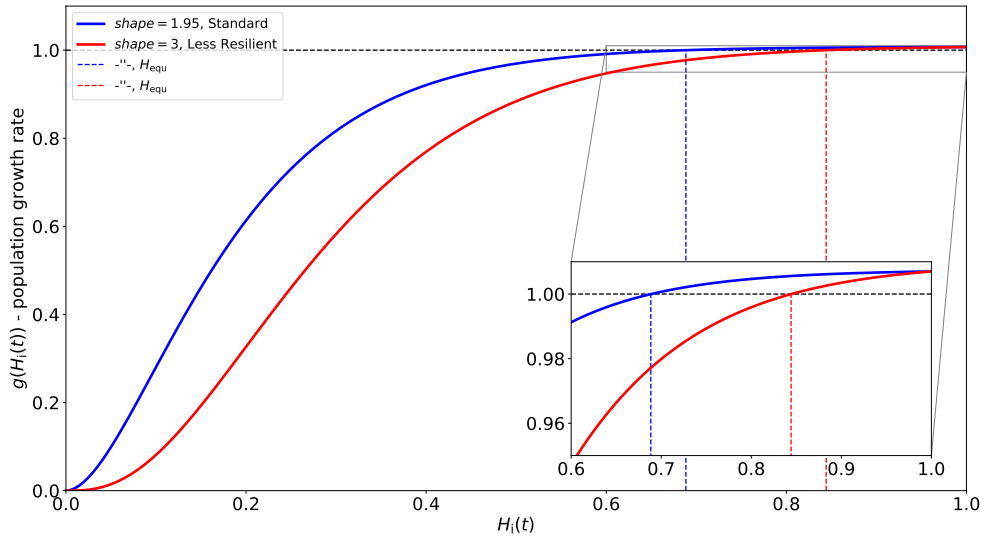


Figure 2.6: The growth rate of an agent's population size as a function of its memory happiness $H_i(t)$. Functional dependence follows simplified assumptions made in the food-limited demography model in Lee and Tuljapurkar (2008), Puleston and Tuljapurkar (2008), and Puleston et al. (2017). In the standard scenario (red) the agent's population size grows if $H_i(t) > H_{\text{equ}} = 0.6883$ and declines for smaller $H_i(t)$. An alternative, less resilient scenario is also tested, with a smaller population growth regime of $H_i(t) > 0.84$. The maximum growth rate in the case of maximum happiness (and thus unconstrained resource availability) is $g(H_i(t) = 1) = 1.007$.

(2017)’s food ratio. Also the distinction between survival and fertility rate especially given their age-dependency is entirely neglected. Nevertheless, the resulting dependency of the growth/decline rate on the agent’s happiness (and consequently its success in resource acquisition) given in Figure 2.6 seems to be a reasonable functional parametrisation.

There are upper and lower limits to the population size of an agent, causing it to split or disperse. If the household size pop_i of an agent i falls below a certain threshold $pop_min = 6$, the agent i is removed and the remaining individuals are adopted by other households chosen randomly within the moving radius distance, r_M ($C_M(c_i)$ defined later). If the household’s population becomes too large, a subgroup splits from it forming a new agent. According to Bahn and Flenley (2017), settlements found in archaeological excavations consisted of two to three dwellings, the basic domestic units (e.g. caves or stone houses). Assuming that roughly a dozen people can live in such a dwelling, which would include the larger family, a household has on average $2.5 \cdot 12 = 30$ individuals. In this model, if the population size increases to a value, such that roughly more than three dwellings would be needed, a group of twelve individuals splits and starts a new settlement on a different location of the island. It is clear that the social structure of the Easter Island population is much more complex than the independent, small households of a few dozen people assumed in this model. E.g. Diamond (2011) describes the existence of roughly a dozen clans or chiefdoms, or Puleston et al. (2017) consider an economic structure including an elite and working class. Also, there is clear evidence of exchange of goods between households, e.g. fish, stone tools or the Moai. All of these complex, cooperative structures are not considered here, but each agent farms and deforests individually. The splitting of a household after population growth occurs with a probability

$$Pr_{\text{splitting}} = \mathcal{N}(\mu = pop_{\text{max, mean}}, \sigma = pop_{\text{max, std}}) . \quad (2.29)$$

with $pop_{\text{max, mean}} = 3.5 \cdot 12 = 42$ and $pop_{\text{max, std}} = 3$. The remaining household abandons not required occupied farming sites. The splitting agent, immediately moves to a new location determined by the moving process described in Section 2.4.2. Hence, an agent typically represents a household of 12 (lower limit of 6) to 42 individuals that acts independent of other agents.

2.4.2 Moving the settlement

Agents relocate their settlement as an reaction to insufficient harvest success or after splitting from a large household to start a new settlement. If, after the

harvest, the agent's smoothed happiness is below the equilibrium point $H_{\text{equ}} = 0.6883$ (standard setting), i.e. population size has decreased with $g(H_i(t)) \leq 1$, the agent gives up the current location and searches a new location. The agent first chooses one cell among all cells within a certain radius according to probabilities that indicate how high the agent evaluates this location in several different categories. Within this new cell, the agent chooses a location with uniform probability and settles there.

In the initial phase of the simulation, agents can choose new locations from all cells on the island. However, if a certain total population size is exceeded (here $\text{pop}(t) \geq \text{pop}_{\text{restricted moving}} = 5000$ people), I externally enforce a restriction of the agents' ability to move around freely and, therefore, new settlements are only allowed within a certain radius of the agent's old location. When relocating the settlement, an agent i , thus, chooses from cells:

$$C_M(c_i, \text{pop}(t)) = \begin{cases} \{\tilde{c} \mid \tilde{c} \text{ on island}\} & \text{if } \text{pop}(t) < 5000 \\ \{\tilde{c} \mid \|\vec{c} - \vec{x}_i(t)\| \leq r_M\} & \text{else} \end{cases} \quad (2.30)$$

with radius $r_M = 5$ km.

In a semi-rational decision making process the agents decide on a new location by evaluating cells c within $C_M(c_i, \text{pop}(t))$ according to probabilities inferred from several different penalties: $P_{G(c)}$ for geographical constraints, $P_W(c)$ for freshwater proximity, $P_D(c)$ for population density, $P_T(c)$ for tree availability, $P_F(c)$ for farming land availability. High penalties represent unfavourable conditions (in the specific category) for settling in the specific cell. The choice of contributions and their functional dependency is described in the remaining Section. There is, of course, substantial freedom in modelling these evaluations and the decision making process. The framework is therefore kept flexible and other assumptions or new categories can easily be added or adjusted. There is no comparable approach for Easter Island society yet. In the ABM simulating the Anasazi people from Axtell et al. (2002) (and Janssen (2009)), agents that relocate their farms (and settlements) consider all eligible cells that fulfil certain nutrient production and water availability criteria and then chose the cell closest to the previous location. In general, I use a similar rationale but implement a more elaborate evaluation process that in particular introduces non-linear, continuous rather than binary evaluation criteria, more/different penalty categories and stochasticity in the decision making process.

Penalties for each category P_X ($X = \{G, W, D, T, F\}$) are calculated via logistic functions depending on a characteristic evaluation variable x ranging x_{\min} to x_{\max} . I determine the shape of the functional dependence of P_X on

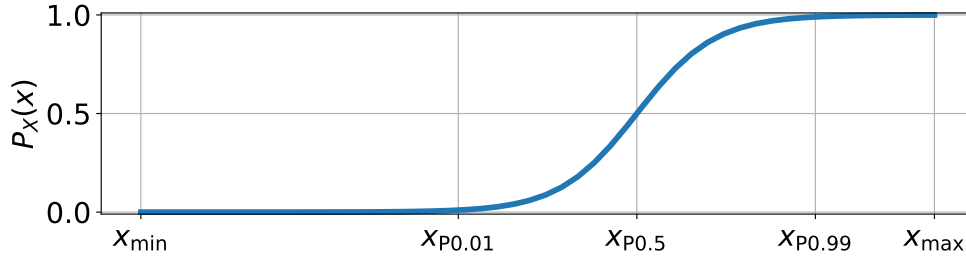


Figure 2.7: General shape of the logistic function $P_X(c)$ for a penalty for moving to a certain cell c in the category X ($\in \{W, G, D, T, F\}$). The penalty depends on a characteristic variable x , in combination with the thresholds, $x_{P0.01}$ and $x_{P0.99}$ (and x_{\min} and x_{\max}) and, thus, the steepness parameter k_X .

variable x through ‘thresholds’ $x_{P0.01}$ and $x_{P0.99}$ indicating the value of x at which the penalty P_X is smaller than 1% or larger than 99%, respectively, in this category X . The penalty P_X in a cell c with value $x(c)$ is then

$$P_X(c) = \frac{1}{1 + \exp\left(-k_X\left(x(c) - \frac{x_{P0.01} + x_{P0.99}}{2}\right)\right)} \quad (2.31)$$

where steepness k_X is

$$k_X = \left(\frac{x_{P0.99} - x_{P0.01}}{2}\right)^{-1} \cdot \log\left(\frac{0.99}{0.01}\right). \quad (2.32)$$

to fix the penalty to the respective values at thresholds $x_{P0.01}$ and $x_{P0.99}$. This function is shown for a general case in Figure 2.7. For each category X , this logistic function has the same (relative) shape between $x_{P0.01}$ and $x_{P0.99}$ given by k . Hence, by choosing $x_{P0.01}$ and $x_{P0.99}$, the sensitivity of penalty P_X to differences in variable x is chosen. If $x_{P0.01}$ and $x_{P0.99}$ are close together, the function converges to a sigmoid function. If they are far apart, the function resembles a more linear increase of penalty P_X with x . For $x = \frac{x_{P0.01} + x_{P0.99}}{2}$ the penalty is $P_X = 50\%$. Note, that if x is chosen such that large values are favourable (e.g. for the tree and agriculture penalty), choosing values $x_{P0.01} > x_{P0.99}$ simply mirrors the logistic function in equation 2.31 at $x = \frac{x_{P0.01} + x_{P0.99}}{2}$ and all $<$ or $>$ signs accordingly. This logistic dependence of penalties on a characteristic variable introduces non-linear evaluation of locations.

The parametrisation of evaluating new locations is, of course, strongly simplified. First, the decision making typically depends on more than one evaluation variable per penalty category, as assumed here. Secondly, the functional dependency of penalty w.r.t. the evaluation variable in general is more complex

than the simple logistic evaluation in equation 2.31. However, assuming that advantages and disadvantages of a potential location (summarised in a single variable) play a non-linear role in the agent's decision making, the use of a logistic function seems reasonable³. I determine the choice of the evaluation variable x and thresholds $x_{P0.01}$ and $x_{P0.99}$ by logical reasoning and rule-of-thumb estimates where necessary. The following paragraphs point out the motivation for the specific variables for the agent's evaluation process and the threshold choices in the standard settings of the model for each penalty category P_X ($X = \{G, W, D, T, F\}$). Table 2.1 summarises the variables and corresponding thresholds that together with equation 2.31 determine the penalties P_X w.r.t. x for all categories.

Water Penalty P_W There are very limited permanent sources of freshwater on the island, making it an important factor of settlement behaviour. Nearly all studies point out that the lakes inside the three volcano craters (Rano Kau in the South, Rano Raraku in the East, and Rano Aroi in the North) are a dominant factor in the population's freshwater supply. Other potential sources include pools in lava tubes and springs in the North Coast (all mentioned in Bahn and Flenley (2017)), an intermittent stream from Mount Terevaka, wells and water bubbles at low tide, and sugar cane juice (all mentioned in (Diamond, 2011)). Additionally, Mieth and Bork (2015) emphasizes the possibility to obtain a sugary sap from cut palm tree trunks, which could have replaced the need for freshwater for a large share of the population. However, the most reliable (and accessible) large freshwater supply are the volcano craters, which, thus, are 'obvious centres for human activity' (Bahn and Flenley, 2017). Consequently, I assume that potential locations close to (large) lakes are more likely settled. The evaluation variable w is radially increasing with the distance to the nearest lake weighted by the area of it:

$$w = \min_{\text{lake} \in [\text{Kau}, \text{Raraku}, \text{Aroi}]} \left(\frac{\|\vec{c} - \vec{\text{lake}}(t)\|^2}{r_{\text{lake}}^2 \pi} \right) \quad (2.33)$$

with $r_{\text{Kau}} = 506$ m, $r_{\text{Raraku}} = 170$ m, $r_{\text{Aroi}} = 75$ m and $\vec{\text{lake}}$ the position of the cells corresponding to the lakes. The thresholds are chosen as

$$w_{P0.01} = \frac{(0.5 \text{ km})^2}{r_{\text{Raraku}}^2 \pi} \quad w_{P0.99} = \frac{(5 \text{ km})^2}{r_{\text{Raraku}}^2 \pi} \quad (2.34)$$

³For example an agent might assign the same penalty to two locations 100 m and 500 m away from a large freshwater source. If instead the nearest lake is too far away from the agent to rely on it for everyday use, alternative sources have to be found, regardless of whether the distance is 5 or 10 km and therefore, the penalty is similarly high.

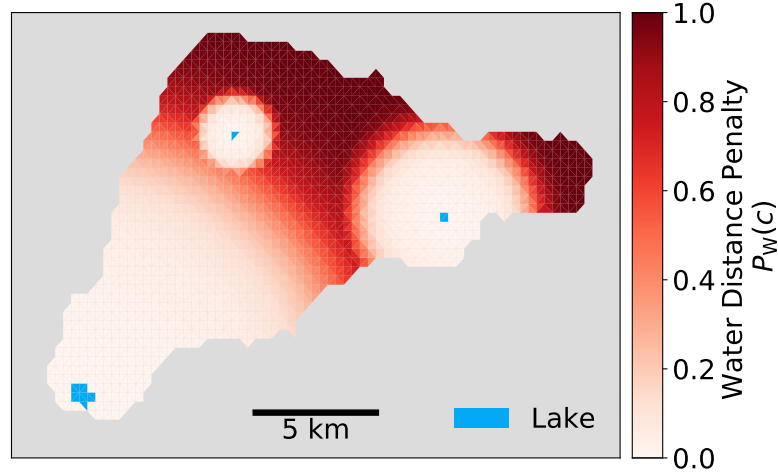


Figure 2.8: The water penalty $P_W(c)$ for all cells in times without drought, i.e. in which Rano Raraku (in the East) provides freshwater.

(0.5 and 5 km distance of a lake like Rano Raraku, respectively). Then, $P_W(c)$ is calculated from equation 2.31 with evaluation variable w , the corresponding thresholds and k_W as in equation 2.32:

$$P_W(c) = \frac{1}{1 + \exp\left(-k_W\left(w(c) - \frac{w_{P0.01} + w_{P0.99}}{2}\right)\right)} . \quad (2.35)$$

As described before drought periods during the Medieval Climate Anomaly and the Little Ice Age potentially lead a drying especially of Rano Raraku in the period before 1200 A.D. and between 1570 – 1720 A.D. (Rull, 2020). Except for these droughts, the water penalty is constant for all agents and times. A map of $P_W(c)$ (without drought) is shown in Figure 2.8.

Geographical Constraints (terrain elevation and slope) P_G High elevation and slope of Easter Island further penalise the settlement probabilities in this model. Archaeological evidence (e.g. the distribution of the Ahu and Moai) shows that the main settlements remained dominantly within the first 1 – 2 km of the coast, even if upland locations were farmed (Bahn and Flenley, 2017). There are several possible reasons for that including easier access to small-scale fishing, climatic conditions, or cultural reasons. Hence, I assume that the geographical penalty depends on the cell's elevation. While Easter Island is generally quite shallow, especially the North West coast and

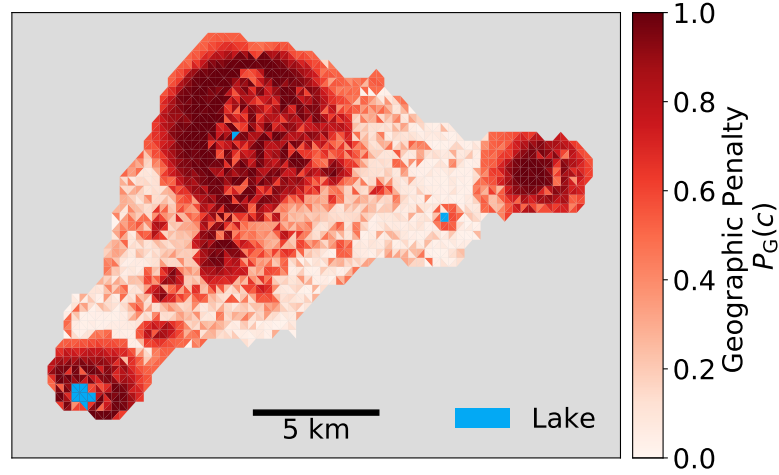


Figure 2.9: The constant geography penalty P_G for all cells.

the areas around the volcano craters are steep, making it difficult for large households to settle in these spots, e.g. due to the danger of soil erosion. Hence, locations with a large slope are also penalised. The location evaluation variables, $el(c)$ and $sl(c)$, and the corresponding chosen thresholds $el_{P0.01} = \min_c(el(c)) = 0$ m and $el_{P0.99} = \max_c(el(c)) = 300$ m (without any reference) for the elevation and $sl_{P0.01} = 0^\circ$ and $sl_{P0.99} = 7.5^\circ$ (without any reference) for the slope. Then, with corresponding k_{el} and k_{sl} from equation 2.32, the penalties for terrain elevation and slope are calculated as

$$P_{el}(c) = \frac{1}{1 + \exp\left(-k_{el}\left(el(c) - \frac{el_{P0.01} + el_{P0.99}}{2}\right)\right)} \quad (2.36)$$

$$P_{sl}(c) = \frac{1}{1 + \exp\left(-k_{sl}\left(sl(c) - \frac{sl_{P0.01} + sl_{P0.99}}{2}\right)\right)} \quad (2.37)$$

The (combined) geographical penalty P_G for a cell c is simply the average of P_{el} and P_{sl} :

$$P_G(c) = (P_{el}(c) + P_{sl}(c)) / 2 \quad (2.38)$$

Figure 2.9 shows the geographic penalty, P_G , which is constant for all agents and times.

Population density P_D Agents also avoid moving to locations with a large population density. While different agents share the same resources and, thus,

interact with the same environment, their actions and moving decisions are independent from each other. However, penalising potential new locations due to high population densities introduces a direct agent-agent interaction. To some degree, this is incorporated in the farming penalty as well, as regions with large population density, also have fewer available agriculture sites. I define the population density of a cell as the population size in all cells within the farming radius of cell \tilde{c} , i.e. $C_F(\tilde{c})$ divided by the corresponding area.

$$pd(\tilde{c}) = \frac{\text{pop}|_{\hat{c} \in C_F(\tilde{c})}}{r_F^2 \pi} \quad (2.39)$$

The thresholds are chosen as

$$pd_{P0.01} = 0 \frac{\text{ppl}}{\text{km}^2} \quad (2.40)$$

and

$$pd_{P0.99} = 300 \frac{\text{ppl}}{\text{km}^2} \quad (2.41)$$

with Vinton Kirch (2010) estimating values of 262 and 389 $\frac{\text{ppl}}{\text{km}^2}$ (according to Puleston et al. (2017)) on ‘prime agricultural land’ in Hawaii and Maui, which are likely overestimates of the maximum local densities on Easter Island (Puleston et al., 2017). The (time dependent) population density penalty for one cell is then

$$P_D(\tilde{c}) = \frac{1}{1 + \exp(-k_D(pd(\tilde{c}) - \frac{pd_{P0.01} + pd_{P0.99}}{2}))} \quad (2.42)$$

with the corresponding k_D from equation 2.32.

Tree Availability P_T Next, scarcity of trees in the surrounding of a specific location also decreases the probability to settle there. Hence, the tree penalty $P_T(\tilde{c})$ is determined via the evaluation variable $tr(c)$, the number of trees within $C_T(\tilde{c})$,

$$tr(\tilde{c}) = \sum_{\hat{c} \in C_T(\tilde{c})} T(\tilde{c}, t) . \quad (2.43)$$

A cell with large value of tr is assigned a lower penalty. The threshold for negligible tree penalty, $tr_{P0.01}$, is quite arbitrary. Here, I choose that an agent considers tree availability as ‘optimal’ if the tree number is sufficient to fill the tree requirement for a population at a very high population density of $pd =$

$pd_{P0.99}$ in the tree search radius, $C_T(c_i(t))$, with maximum tree preference $T_{Pref, \max}$ for roughly one generation (~ 45 yrs).

$$tr_{P0.01} = T_{Pref, \max} \cdot T_{Requ, pP} \cdot pd_{P0.99} \cdot \frac{r_T^2}{r_F^2} \text{ ppl} \cdot 45 \text{ yrs} = 216 \cdot 10^3 \text{ trees} . \quad (2.44)$$

The value of tr assigned to 99% penalty is the tree number required to keep the current agent's population at a happiness level of at least $h_i(t) = H_{equ}$ for the next year:

$$tr_{P0.99,i} = T_{Pref, i}(t) \cdot T_{Requ, pP} \cdot pop_i(t) \cdot H_{equ} , \quad (2.45)$$

which is typically 5 – 100 trees depending on the agent i and the time. On top of the logistic penalty dependency, I further enforce this limit, $tr_{P0.99}$, as a necessary condition for an agent to settle in the cell \tilde{c} (even if all other penalties are extremely favourable): $tr(\tilde{c}) \stackrel{!}{>} tr_{P0.99}$. In total,

$$P_T(\tilde{c}) = \begin{cases} \infty & \text{if } tr(\tilde{c}) < tr_{P0.99} \\ \frac{1}{1 + \exp\left(-k_{tr}\left(tr(\tilde{c}) - \frac{tr_{P0.01} + tr_{P0.99}}{2}\right)\right)} & \text{else} \end{cases} \quad (2.46)$$

Farming Land Availability P_F Finally, availability of farming sites influences the agent's moving decision. The penalty for farming, here, depends on two evaluation variables: The total available farming potential $F_{tot}(\tilde{c})$ and the available farming potential from non-eroded, well-suited cells only, $F_{well}(\tilde{c})$. The penalties for both variables are calculated and then averaged. The total available farming potential is simply a summation of all productivity indices of arable, unoccupied sites (i.e. acres within a cell) within $C_F(\tilde{c})$.

$$F_{tot}(\tilde{c}) = \left(\sum_{\hat{c} \in C_F(\tilde{c})} F_{PI}(\hat{c}) \cdot (A_{acres}(\hat{c}) - \mathbf{A}_F(\hat{c}, t)) \right) , \quad (2.47)$$

where $A_{acres}(c)$ is the number of acres and $\mathbf{A}_F(c, t)$ is again the number of occupied sites (and, therefore, unavailable to new agents) in cell c . Similarly, the farming potential for well-suited cells only is

$$F_{well}(\tilde{c}) = \left(\sum_{\hat{c} \in C_F(\tilde{c}) \cup F_{PI}(\hat{c})=1} F_{PI}(\hat{c}) \cdot (A_{acres}(\hat{c}) - \mathbf{A}_F(\hat{c}, t)) \right) . \quad (2.48)$$

This F_{well} is an important consideration for agents as it makes cells more favourable, if the farming produce can be obtained from a few well-suited

rather than a larger number of poorly suited sites, with a larger number of workers involved.

The threshold for an optimal location w.r.t. farming is the maximum possible land needed to be farmed by an agent with population 42.

$$\begin{aligned} F_{\text{well}, \text{P0.01}} &= F_{\text{tot}, \text{P0.01}} = (1 - T_{\text{pref}, \text{min}}) \cdot F_{\text{Req}, \text{pP}} \cdot 42 \text{ ppl} \\ &= \begin{cases} 16.8 \text{ acres (with } F_{\text{PI}}(c) = 1) \text{ for high N fixation scenario} \\ 57.1 \text{ acres (with } F_{\text{PI}}(c) = 1) \text{ for low N fixation scenario} \end{cases} \end{aligned} \quad (2.49)$$

The threshold for penalty $P_{\text{F}}(c) = 0.99$ is the agent's current farming requirement sufficient to obtain happiness $h_i(t) = H_{\text{equ}}$, i.e.

$$F_{\text{well}, \text{P0.99}, i} = F_{\text{tot}, \text{P0.99}} = (1 - T_{\text{pref}, i}(t)) \cdot F_{\text{Req}, \text{pP}} \cdot \text{pop}_i(t) \cdot H_{\text{equ}} \quad (2.50)$$

depending strongly on the tree preference and population. The parameter, k_{F} is the same for both evaluation variables F_{well} and F_{tot} .

As for trees, a necessary condition for moving to a cell is enforced: If the total⁴ farming potential $F_{\text{tot}}(\tilde{c})$ at a cell \tilde{c} is smaller than $F_{\text{tot}, \text{P0.99}}$, the farming penalty is set to $P_{\text{F}}(\tilde{c}) = \infty$ (and thus the cell is not considered regardless of other penalties). Then, the total penalty is

$$P_{\text{F}}(\tilde{c}) = \begin{cases} \infty & \text{if } F_{\text{tot}} < F_{\text{tot}, \text{P0.99}} \\ \frac{0.5}{1 + \exp(-k_{\text{F}}(F_{\text{well}}(c) - F_{\text{P0.5}}))} + \frac{0.5}{1 + \exp(-k_{\text{F}}(F_{\text{tot}}(c) - F_{\text{P0.5}}))} & \text{else} \end{cases} \quad (2.51)$$

with $F_{\text{P0.5}} = \frac{F_{\text{P0.01}} + F_{\text{P0.99}}}{2}$. In summary, the farming penalty is smallest for those cells surrounded by a lot of well-suited, available sites. The penalty is large for those cells surrounded by few available, arable sites in general and few available, well-suited sites in cells in particular.

In locations around Anakena Beach, where open-sea fishing is allowed, the agents do not farm. The farming penalty in these cells should not depend on availability arable land and instead encourage agents to move to this location. Hence, I decide to set the 'farming' penalty in these cells to

$$P_{\text{F}}(\hat{c}) = -1 \quad \forall \hat{c} \in C_{\text{F}}(c_{\text{Anakena}}) \quad (2.52)$$

From Penalties to Probability The resulting penalties for a cell \tilde{c} in $C_{\text{M}}(c_i(t))$ from all categories are linearly combined to obtain a total penalty, which is

⁴And, hence, also the well-suited

X	x	Description	$x_{P0.01}$	$x_{P0.99}$	Necessary Condition
W	w	Area weighted distance of cell to lake	$\frac{(0.5 \text{ km})^2}{r_{\text{Raraku}}^2 \pi}$	$\frac{(5 \text{ km})^2}{r_{\text{Raraku}}^2 \pi}$	
G	el	Elevation	0 m	300 m	
	sl	Slope	0°	7.5°	
D	pd	Population density within r_F	0	$300 \frac{\text{ppl}}{\text{km}^2}$	
T	tr	Number of trees within r_T	$216 \cdot 10^3$	$\sim 5 - 100^* \text{ Trees}$	at $x_{P0.99}$
F	F_{tot}	Total possible farming produce within r_F	16.8 acres	$\sim 1 - 13^* \text{ acres}$	at $x_{P0.99}$
	F_{well}	Possible farming produce of well-suited sites within r_F	- "- -	- "- -	- "- -

Table 2.1: The evaluation variable and chosen thresholds for each penalty category. Inserting these into the logistic function (equation 2.31) gives the penalties in each category: P_G for geography, P_W for freshwater proximity, P_D for population density, P_T for tree availability, P_F for farming land availability. Note, that $x_{P0.99}$ for category T and F , representing the minimum amount of resources required, depend on the specific agent's properties (denoted by *). This value is a further minimum condition for moving to the cell. For the farming penalty, the thresholds are calculated for the high Nitrogen fixation scenario here. For P_G and P_F , which have two elevation variables, the mean of the sub penalties gives the corresponding category penalty.

then converted to a discrete probability $Pr(\tilde{c})$ of moving to this cell. With (normed) weights $\vec{\alpha}$ (and the agent's tree preference $T_{\text{Pref}, i}(t)$):

$$\vec{\alpha} = \left(\alpha_G, \alpha_W, \alpha_D, \frac{T_{\text{Pref}, i}(t)}{\eta_i(t)} \cdot \alpha_T, \frac{(1 - T_{\text{Pref}, i}(t))}{\eta_i(t)} \alpha_F \right) \quad (2.53)$$

where $\eta_i(t) = \frac{\alpha_T T_{\text{Pref}, i}(t) + \alpha_F (1 - T_{\text{Pref}, i}(t))}{\alpha_T + \alpha_F}$ is a normalisation factor to ensure that, $\frac{T_{\text{Pref}, i}(t)}{\eta_i(t)} \cdot \alpha_T + \frac{(1 - T_{\text{Pref}, i}(t))}{\eta_i(t)} \cdot \alpha_F = \alpha_T + \alpha_F$ and, therefore, $\|\vec{\alpha}\| = 1$. The total penalty is:

$$P_{\text{tot}, i}(t) = \begin{cases} \infty & \text{if } \tilde{c} \notin C_M(c_i(t)) \\ \langle \vec{\alpha}, \vec{P} \rangle & \text{else} \end{cases} \quad (2.54)$$

with $\vec{P} = (P_G, P_W, P_D, P_T, P_F)$. Finally,

$$Pr(\tilde{c}) = \frac{1}{N} \cdot \exp(-\gamma \cdot P_{\text{tot}}(c)) \quad (2.55)$$

where N is a normalisation and γ is a dimensionless scaling factor, which represents the agent's tendency to actually follow the penalty evaluation. By increasing γ , the agent's move less likely to spaces with low probability (high total penalty). E.g. for $\gamma \rightarrow \infty$, agents have perfect knowledge of the island's properties and move to the optimal cell with minimal penalty, i.e. the decision making is an increasingly deterministic optimisation process⁵. On the other hand, $\gamma = 0$ implies that agent's just move to a any new location without consideration of the penalties associated with this new location. By choosing γ large, but finite, I set the agents up to make individualistic, semi-rational choices when moving, but include stochasticity (e.g. due to imperfect knowledge) in the decision. An agent moves to a site based on individual assessment. However, multiple agents share the same local environment and, thus, can quickly change the conditions of a location (e.g. by deforesting). Hence, when agents in this model decide on relocating their settlement, they do not calculate the society's optimal outcome as often assumed in mathematical models (Good and Reuveny (2006) or Bookstaber (2019)). They decide by avoiding locations that currently seem unfavourable based on their knowledge of the current situation.

Having selected a new cell, the agent chooses a location within this cell with uniform probability. Note, that the actual availability of arable, free land

⁵Proof: Let's consider the relation between $Pr(c_{\min})$, where c_{\min} denotes the cell with the minimal penalty, and $Pr(c)$ for all cells c . Then, $Pr(c_{\min})/Pr(c) = \exp(-\kappa P_{\text{tot}, \min}) / \exp(-\kappa P_{\text{tot}}(c)) = \exp(-\kappa(P_{\text{tot}, \min} - P_{\text{tot}}(c)))$. For $\gamma \rightarrow \infty$ this is $\delta_{c=c_{\min}}$.

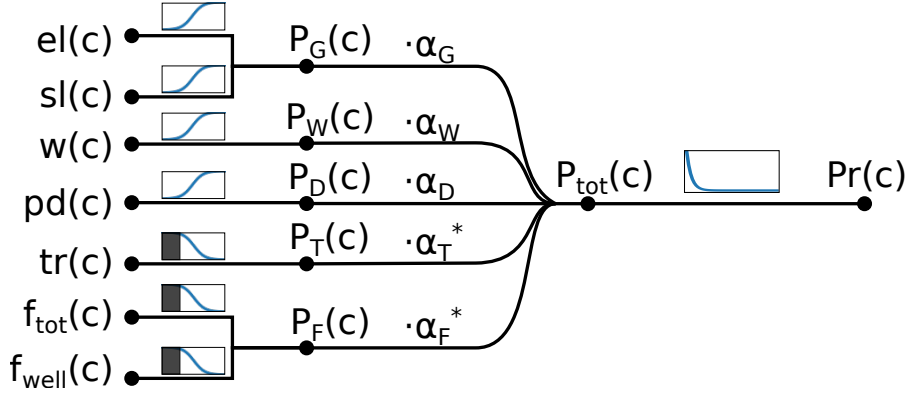


Figure 2.10: A sketch of the calculation of the probability for agent i to relocate its settlement to cell c : The category penalties (P_G for geography, P_W for freshwater proximity, P_D for population density, P_T for tree availability, P_F for farming land availability) are calculated via one or two characteristic evaluation variables described in the main text assuming a logistic functional dependence (blue curves). If two evaluation criteria are considered for one category, the resulting sub-penalties are averaged (crossings for P_G and P_F). For P_T and P_F , cells that do not have the minimum required resource availability are excluded (black boxes). The total penalty for cell c , $P_{tot}(c)$ is then a linear superposition of all category penalties (with the weights α_T^* and α_F^* adjusted according to the tree preference $T_{Pref,i}(t)$ (equation 2.53). The final probability for a cell c is derived as $Pr(c) \sim e^{-\gamma \cdot P_{tot}(c)}$ (blue line in the right part), with scaling factor γ .

and/or trees, might deviate slightly from the calculation of the cell's penalty (and corresponding probability), as the location of the settlement differs from the cell's midpoint, which was used for the penalty evaluation. This accuracy error decreases with higher discretisation resolution. The total procedure of calculating the probability is sketched in Figure 2.10.

With this procedure, agent's move (as resource availability becomes scarce or a subgroup splits from a large household) according to environmental features. The specific settings create spatial patterns of settlement behaviour which in turn non-linearly change the agent-environment interaction and, thus, environment dynamics overall.

This evaluation of potential sites when an agent moves is the bottleneck w.r.t. computation time in this model. The process scales quartic with the grid resolution $\delta_{x,y}$, i.e. $\mathcal{O}(\delta_{x,y}^4)$, the number of grid points per unit of length: The overall Number of cells N_c increases quadratic with $\delta_{x,y}$ and the evaluation

of penalties (e.g. summing up trees from cells in $C_T(\tilde{c})$) for a single cell also scales quadratic with the grid resolution. In order to increase efficiency, I use dot products and distance matrix computation from the python packages ‘numpy’ (Oliphant, 2006) and ‘scipy’ (Virtanen et al., 2020), both implemented in C++. An alternative implementation might adjust penalties immediately when the agent’s interact with the environment, which would scale as $\mathcal{O}(\delta^2 \cdot N_{\text{agents}}(t) \cdot N_{\text{timesteps}})$. However, since the resolution does not have to be too small for this study, and the number of moving actions is usually small compared to N_c and $N_{\text{timesteps}}$, the first implementation is still reasonably fast.

2.5 Standard Run and Sensitivity Analysis

The resulting model has a multitude of parameters, settings and parametrisations often associated with large uncertainties. There are in principle two different kinds of parameter choices described in the following paragraphs and summarised in Table 2.2.

The first category of parameters influences directly the island wide, aggregate population dynamics and peak population because they determine the amount of resource acquisition and availability per agent and the population growth with respect to harvest success (or agent’s happiness):

- the resource requirements calculated from the constant farming requirement per person $F_{\text{Req, pP}}$ in combination with the farming productivity indices $F_{\text{Pl, [well, eroded, poor]}}$, the tree harvest requirement per person $T_{\text{Req, pP}}$ as well as the values for $T_{\text{Pref, min}}$, and with a lower importance $T_{\text{Pref, max}}$, $T_{\text{Pref, min|fisher}}$ and $N_{\text{Fisher, Max}}$
- the initial number of trees $T(t_{\text{arrival}})$ and (if regeneration is enabled) the tree regeneration parameters, i.e. the logistic growth rate g_T , and pop up properties on barren land
- the demography model parameters, i.e. the shape and scale of the population size growth rate function depending on the harvest success $g(H_i(t))$ and the initial population growth rate $g(H_i(t) = 1)$.

Furthermore, the parameters t_{arrival} and $\text{pop}_{\text{arrival}}$ simply influence the timing of the dynamics. The uncertainties associated with these parameters are the main source for the discrepancies between contradictory theories about the history of Easter Island. This model presented here does not aim to dispute one theory or the other. In fact, the model can re-create the proposed population

Parameter	Std Run	Sensitivity Tests
t_{arrival}	800 A.D.	—
$\text{pop}_{\text{arrival}}$	40	—
$F_{\text{Req, pP}}$	$0.5 \frac{\text{acres}}{\text{person}}$	$1.7 \frac{\text{acres}}{\text{person}}$
$F_{\text{PI, [well, eroded, poor]}}$	[0.8, 0.5, 0.1]	—
$T_{\text{Req, pP}}$	$5 \frac{\text{Trees}}{\text{person}\cdot\text{yr}}$	$10 \frac{\text{Trees}}{\text{person}\cdot\text{yr}}$
$T_{\text{Pref, min}}$	0.2	—
$T_{\text{Pref, max}}$	0.8	—
$T_{\text{Pref, min}} _{\text{fisher}}$	0.5	—
$N_{\text{Fisher, Max}}$	10	—
$\mathbf{T}(t_{\text{arrival}})$	$16 \cdot 10^6$	—
g_{T}	0	5%/yr (with tree pop up of 0.5%/yr of carrying capacity on barren land for 10 yrs)
$g(H_i(t))$ (scale)	0.1	—
$g(H_i(t))$ (shape)	1.95	3
$g(H_i(t) = 1)$	1.007	—
Tree Pattern	uniform density for $el(c) < 450\text{m}, sl(c) < 10^\circ$	—
pop_{min}	6	—
$\text{pop}_{\text{max, mean}}$	42	—
$\text{pop}_{\text{max, std}}$	3	—
$\text{pop}_{\text{split}}$	12	—
r_{F}	1 km	—? TODO
r_{T}	2 km	—? TODO
$f_{\text{Tree Pref}}$	linear	delayed, careful, logistic
r_{M}	5 km (if $\text{pop}(t) > 5000$)	—? TODO
$x_{\text{P0.01}}$	Table 2.1	—
$x_{\text{P0.99}}$	Table 2.1	—
$\vec{\alpha}$	(0.2, 0.2, 0.2, 0.2, 0.2)	(0.0, 0.0, 0.0, 0.5, 0.5)
γ	20	0, 100 TODO
Droughts	800 – 1200, 1570 – 1720	—

Table 2.2: Choices of parameters for the standard run and sensitivity analysis. The upper half (separated by double line) mainly determines the aggregated population dynamics, the lower half determines the microscopic behaviour and thus influences mainly the spatial patterns.

dynamics by adjusting some of the parameters above. Hence, while choosing a standard set of parameters, I also investigate some alternative settings of these parameters (shown in Table 2.2) giving rise to different proposed theories of pre-history population dynamics on Easter Island.

The novel part of this study, however is the spatially explicit component and the stochastic, microscopic acting and decision making of the agents in the model. The values of parameters associated with this second category are even less known, but as described in the Introduction, reasonable assumptions on the values and functional dependences of the parameters can be made more naturally on the microscopic than the macroscopic level. The parameters in this category are related to the

- household size, i.e. the maximum and minimum population size of an agent (pop_{\min} , pop_{\max} , mean , $pop_{\max, \text{std}}$, pop_{split})
- resource search radii (r_F , r_T (in combination with the initial spatial distribution of trees, i.e. $T(c, t = t_{\text{arrival}})$ for cells c)
- shape of the response of the tree preference to the changing local environment
- decision making process when moving, i.e. the restricted moving radius r_M , penalty categories and their logistic dependency specified by the thresholds $x_{P0.01}$ and $x_{P0.99}$, the weights $\vec{\alpha}$, and the scale parameter γ .

Since multiple processes in the model are stochastic, each run is only a single realisation. While the aggregated results do not differ much between runs with the same setting, the spatial pattern of deforestation varies in general. I perform several ensemble runs, but there is no obvious way to obtain an aggregate spatial mean dynamics per se. Instead, variation in spatial patterns for the same experiment are described qualitatively.

Throughout the thesis, I have defined parameter setting for a standard run (details in Table 2.2). I perform several sensitivity simulations (also described in Table 2.2) and analyse the corresponding changes to this standard run in both categories of parameters related to the aggregate population dynamics and to the spatial patterns.

Chapter 3

Results

3.1 Standard Run

- Fig 1: Aggregate Dynamics (population, trees, mean penalties and happiness, fires, excess mortality/fertility). The plot that Esteban sketched during last Zoom Meeting [called statistics plot from now on]. All statistics plots are mean ensemble runs of 10 different seeds.
- Comparison of the spatial deforestation pattern with Rull (2020)'s Figure, which we sent to Valenti.

3.2 Different theories

Statistics Plots for a

- Run with low N fixation (instead of high)
- Run with tree regeneration and high N fixation
- Run with tree regeneration and low N fixation

3.3 Different Tree Preference Functions, i.e. Agent Adaption

- Runs with $f_{\text{Tree Pref}}$ delayed, careful, logistic.

I don't know yet if this makes any difference to the standard run and what difference. So we'll see.

3.4 A less resilient society

Run with a larger shape parameter of $g(H_i)(t)$. I don't know yet if this makes any difference to the standard run and what difference. So we'll see. I assume that the turning point of growing population to decreasing population size happens earlier. Maybe I'll just show the statistics plot.

3.5 Sensitivity Analysis of some uncertain parameters

$r_T, r_F, T_{\text{Req,pP}}$

3.6 Three different decision making processes

- Standard setting, $\gamma = 20$, $\alpha = (0.2, 0.2, 0.2, 0.2, 0.2)$.
- 'Only resource availability matters for moving decision' setting, $\gamma = 20$, $\alpha = (0, 0, 0, 0.5, 0.5)$.
- Hopping agents, that move to a random spot with uniform probability over the island, $\gamma = 0$, $\alpha =$ doesn't matter.

Results not yet known. I guess I'll describe qualitatively what happens to the spatial patterns. If the aggregate dynamics change, this would of course be a big, big result and I would focus on that.

3.7 Perhaps, if I have time: Regional Dynamics

Adjust the statistics plot of total population dynamics to looking at a few hand-defined regions and the plot the aggregate dynamics of them separately.

3.8 Fires

Plot the distribution of fires on the map over time. I imagine a map in which the color determines the timing of fires in each cell. I'm not sure yet how to do this exactly since fires in any cell occur at multiple times. Maybe I'll take the first occurrence. We'll see.

Chapter 4

Discussion and Conclusion

4.1 Conclusion

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Appendix A

Details of the Model

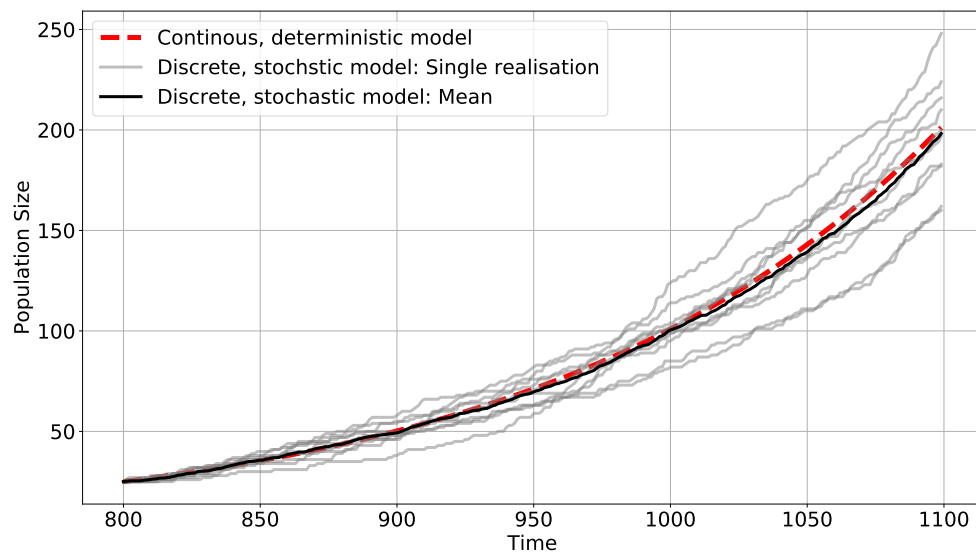


Figure A.1: Realisations (and the mean) of the discrete, stochastic population growth model (assuming $H_i(t) = 1$ for all t here. In comparison, the continuous exponential growth. The growth rate is $g(H_i(t) = 1) = 1.007$, as in the standard setting of the model.

