Why might climate change not cause conflict? an agent-based computational response

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Abstract

In this paper, we first briefly review the recent literature on climate change, resource scarcity and conflict. This is then followed by introducing an agent based computational model based on the theory of production and conflict which is capable of simulating the dynamics of micro-level resource conflicts. The model considers differences in resource attributes, differentiates between conflict subjects, takes into account bounded rationality, nonlinearity and feedback loops, and is enriched by a set of scenarios ranging between mild to severe resource shocks. Our results show that agents tend not to get engage in conflict during mild resource scarcity scenarios as they adapt to the changes and since the decreases in returns to resource predation and increases in their protective practices act as negative feedback loops, discouraging resource predators from allocating further effort to predation. The model results also show that scarcity is more likely to encourage product predation rather than resource predation among the agents.

JEL: Q54, D74, Q34, C61, C63

Keywords: Climate Change, Resource Scarcity, Conflict, Security, Agent-based Model

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1. Introduction

On December 8, 2009, a day after United Nations Climate Change Conference started in Copenhagen, *the Proceedings of the National Academy of Sciences* (PNAS) published a paper by Marshall Burke and his colleagues claiming that the risk of civil war increases in Africa when the temperature is higher (Burke, *et al.,* 2009). Almost a year later, the same journal published a paper by Halvard Buhaug (2010a) titled “Climate not to blame for African civil wars”, rejecting the results of Burke, *et al.* (2009). Few months later Burke and his colleagues responded to Buhaug’s paper (Burke, *et al.,* 2010b) which in turn received a response from Buhaug (Buhaug, 2010b). Sutton *et al.* (2010) also published a letter in PNAS titled “Does warming increase the risk of civil war in Africa?”, raising concerns with the findings of Burke *et al.* (2009) which received a response later in the same year in an another letter to PNAS (Burke *et al*., 2010c).

This is not an isolated or unusual exchange since academic debate continues on whether climate change might initiate new or intensify current conflicts (Salehyan, 2008; Scheffran, *et al*., 2012). Several recent studies were reported in the special issue of *Journal of Peace Research* where Nils Petter Gleditsch (2012, p.3) concludes: “Overall, the research reported here offers only limited support for viewing climate change as an important influence on armed conflict.”

The editors of *Climate Change, Human Security and Violent Conflict: Challenges for Societal Stability* stated moreover that “climate change has no automatic effect on human security, on societal stability, or on violent conflict. Rather, there are multiple links in the chain between changes in the natural environment and these phenomena, which mitigate or multiply the effects of climate change” (Scheffran *et al.*, 2012, p.797).

This paper attempts to respond to a critical question that we believe has not been addressed comprehensively so far in the literature: Why, contrary to the theoretical perceptions and expectations, might climate change and its consequent resource scarcity *not* lead to conflict and when they do, why might climate-induced conflicts not be as severe as anticipated?

To respond to this question, instead of investigating case studies or analyzing large-N datasets which has caused controversy in this area so far, we present a theoretical computational model based on a well-known economic framework which, borrowing Schelling's (1978) terms, associates individuals' micro-motives with emergent macro-behaviors of conflict.

Next section introduces the unsettled literature on the climate-conflict (CC) link and briefly reviews the current state of debate. After introducing our theoretical framework and analytical approach, the model is introduced and its verification and basic outputs are presented. Finally, the scarcity scenarios and their impacts on the results are discussed, followed by conclusions where we adress our primary research question.

2. The Debate

The security aspects of climate change have been highlighted by high-ranking policymakers and institutions. According to the *Washington Post* (Lynch, 2007), U.N. Secretary-General Ban Ki-Moon first addressed the U.N. General Assembly on the issue in 2007, stating that future extreme climatic events such as droughts, floods our constant inundations may lead to scarcity of arable land and so drive war and conflict[1]. In September 2009, *New York Times* also published Barak Obama's speech on climate change at the U.N. General Assembly, warning against "conflict in places where hunger and conflict already thrive" (Obama, 2009). In July 2011, *The Guardian* reported on a UN Security Council meeting discussing the formation of "green helmets" as a peacekeeping force to act when climate-induced conflicts occur (Goldenberg, 2011)[2].

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[1] The full statement is available on the UN news centre at:
http://www.un.org/apps/news/story.asp?NewsID=21720&Cr=global&Cr1=warming

[2] For further details see: Security Council 6587th meeting documents at:
http://www.un.org/News/Press/docs/2011/sc10332.doc.htm

Researchers are not as confident as politicians, since the issue of resource-driven conflicts has been source of disagreement, when the impacts of both resource abundance and resource scarcity are investigated.

In the final years of the last century, two studies, Sachs and Warner (1995) and Collier and Hoeffler (1998), caused a wave of academic debate by showing how natural resource abundance can lead to lower levels of economic growth and higher risks of war.

Over the next decade, many studies tried to better investigate the channels which may link resource abundance to conflict and as time passed more evidence was presented concluding that in the majority of cases, it is the institutional capacity of a country or a region in managing its natural resource wealth which determines its growth and security, and not the resource abundance *per se* (Ross, 1999; Maxwell and Reuveny, 2000; Mehlum *et al*. 2006; Brunnschweiler, 2008; Brunnschweiler and Bulte 2009).

The same story can be observed for resource scarcity. The potential links between resource scarcity and conflict, especially scarcity driven by climate change, have been discussed widely over the last couple of decades and almost every paper published in this area over the past few years has briefly or extensively reviewed how different studies have reached diverse, and sometimes even contradictory conclusions[3].

For instance, while authors such as Grossman and Mendoza (2003) and Homer-Dixon (1991 and 1994) used theoretical and empirical models to associate resource scarcity and conflict, interestingly, many recent studies such as Adano *et al.* (2012), Benjaminsen *et al*. (2012), Butler (2012) and Buhaug and Theisen (2012) highlights the social, economic and political institutions as the main factors affecting the conflict decisions of individuals, communities or states. Raleigh and Urdal (2007, p.674) concluded that: "political and economic factors far outweigh those between local

[3] We avoid repeating the entire literature here since it has been broadly covered by Theisen (2008), Salehyan (2008), Brauch (2009) and Scheffran *et al.* (2012).

level demographic/environmental factors and conflict". Nevertheless, there are still studies published recently, showing how conflict is significantly affected by resource scarcity such as freshwater availability, land degradation and rainfall (Hendrix and Salehyan, 2012; Urdal, 2008).[4]

In this paper, we apply a widely-used economic framework, called the theory of Production and Conflict[5] (P&C) and implement it by developing an agent-based computational model to examine what circumstances in which climate change might or might not cause conflict.

3. Theory and Modeling Approach

The building blocks of production and conflict theory are simple. According to this theory, economic entities do not merely allocate effort to produce goods and services, but they may also allocate some unproductive effort to predate others' resources (raw materilas), final products, rights and wealth, or protect themselves from being predated by others (Hirshleifer, 1988; Grossman, 1998, 2001).

While these types of models were originally developed to study topics in property rights protection, later versions were applied to explore issues such as rent-seeking behavior and resource conflicts (Garfinkel and Skaperdas, 2007; Hausken, 2005; Lahiri, 2010; Muthoo, 2004).

At least three studies have used this framework so far to explore the relations between resource access and conflict. Grossman and Mendoza (2003) presented an equation-based model of this theory where they found that resource scarcity, especially when it is transitory leads to further appropriative competition. Reuveny *et al.* (2011) developed a game theoretic model based on this theory and being able to replicate some of the real-world patterns and trends, concluded that "increasing the resource carrying capacity and growth rate intensifies the fighting" (p.709). Butler

[4] Authors such as Hartmann (2010), Brauch (2009) and Oels (2012) have warned against the securitization of climate change. Slettebak (2012, p.163) satates that "one worrying facet of the claims that environmental factors cause conflict is that they may contribute to directing attention away from more important conflict-promoting factors, such as poor governance and poverty." It has also been claimed that scarcity can even lead to cooperation among stakeholders and provide motivation for innovation in the affected communities (Dinar, 2009, 2011).

[5] As called by Hausken (2005)

and Gates (2012) also introduced a model partially based on this theory and showed that conflict is sensitive to property rights protection asymmetries.

In order to analyze the complexity of conflict decision at the micro and macro level, we have applied an agent-based model to simulate how individuals interact in an environment where they can both produce and predate. Agent-based modeling is "the computational study of systems of interacting autonomous entities, each with dynamic behavior and heterogeneous characteristics" (Heckbert, *et al.*, 2010, p.40). In economics, this approach is also known as *Agent-based Computational Economics* defined by Tesfatsion (2003, p.264) as "the computational study of economies modeled as evolving systems of autonomous interacting agents."[6]

In agent-based models, the computer provides a "flight-simulator-like interface" (Holland, 1992, p.29) where agents can represent entities such as individuals, communities, firms, cars, agricultural crops or climatic factors. Each agent is defined based on some features and functions and various embedded rules which control its actions and reactions. This approach provides the opportunity of taking into local interactions between heterogeneous autonomous players which can generate non-equilibrium states which better explain the nature of a system (Epstein, 2006).

Various studies have discussed the advantages of using agent-based models, including being able to address unsatisfactory features of conventional approaches such as the perfect rationality of the agents (Axtell, 2000). Agent-based models are highly flexible and so are better able to represent the "natural description of a system" (Bonabeau, 2002), especially when we want to present the human-environment relations (Li and Liu, 2008).

Many authors suggest that the conflict analyses should be undertaken at more disaggregated levels. Allouche (2011) believes that while long-term high-level data, such as international wars datasets, can provide insights into how scarcity may lead to conflict, moving toward applying short-term data

[6] Other definitions and introductory material on ABM are presented by Axelrod (1997) and also the second volume of *Handbook of Computational Economics* (Tesfatsion and Judd, 2006), Macal and North (2010), Heath *et al.* (2009) and Squazzoni (2009).

at more disaggregated levels can be more beneficial, especially when food and water security are studied. This has been echoed by other authors such as Nordås and Gleditsch (2007), Trombetta (2012), Scheffran *et al.* (2012), Hendrix and Glaser (2007) and Theisen (2008), who suggest that local, sub-national, small-scale and less intense conflicts should be taken in to account in CC analysis[7].

ABMs can also address the data limitation challenges that scholars face in CC research (Buhaug and Theisen, 2012; Scheffran *et al.* 2012), by providing the opportunity to run the model under different scenarios and study a range of possible outcomes.

Moreover, analyzing the associations between climate change and conflict, we are dealing with a complex adaptive system (Brauch and Scheffran, 2012; Nardulli and Leetaru, 2012; Butler and Gates, 2012). Following Ramalingam *et al.*'s (2008) framework of defining a complex system, different features of complexity can be identified in our model:

Firstly, conflict as discussed in this paper, is an interaction between at least two parties (Hirshleifer, 1988) and so an agent's decisions will directly and indirectly affect others' conflict decisions. This interdependence among system actors may lead to the formation of feedback loops such as violence leading to further violence (Adano, *et al.,* 2012). Also, as Trombetta (2012) discusses, assigning deterministic behavior to humans in CC models and then aggregating them, is one of the issues which needs to be corrected in these types of models since, as Grossman and Kim (2000) and Reuveny (2011) discuss, the complex outcomes of these models at the macro level emerge from the interactions among the individuals rather than decisions being aggregated.

Secondly, nonlinear patterns of behavior have been found in at least at two different levels in CC models. Hendrix and Salehyan (2012) show how there is a nonlinear relation between rainfall and social conflict in their studied group of countries in Africa and Scheffran *et al.* (2012) remind us of

[7] It has been argued that what is concluded from micro-level conflicts can be considered as a warning for problems at higher levels of aggregation considering their "incremental destabilizing effects" (Nardulli and Leetaru, 2012, p.73).

the "possible tipping points" and "possible critical thresholds" that may exist in agents' behaviors that are capable of triggering climate-induced conflicts.

Conflict models also present high dependency on initial conditions and heterogeneity of features. Beardsley and McQuinn (2009) comprehensively studied the history and characteristics of two rebel groups in Asia, the Free Aceh Movement (GAM) in Indonesia and the Tamil Tiger (Liberation Tigers of Tamil Eelam, LTTE) in Sri Lanka and explore how the differences among the groups led to two totally different outcomes in the aftermath of the 2004 Indian Ocean earthquake and tsunami.

ABMs have been widely used in modeling conflict, as presented by Rousseau and van der Veen (2005), Epstein (2002), and Bhavnani and Miodownik (2009) and Hassani-Mahmooei and Parris (2009, 2013).

4. Model

To ensure that the model is replicable, it is described using the Overview, Design concepts, and Details (ODD) protocol (Grimm 2006; Grimm, *et al.,* 2010). The associated Unified Modeling Language (UML) diagrams (Booch, *et al.,* 2005) are also provided as supplementary material. Among numerous platforms available for implementing an agent-based model, we have used NetLogo (Wilensky, 1999). Studies have shown that NetLogo is well equipped with the features necessary for modeling in the social sciences (Blikstein, *et al.,* 2005; Railsback, *et al.,* 2006).

4.1. Purpose

The main purpose of this model is to implement an agent-based environment which is capable of simulating effort allocation decisions between productive and conflict activities which is then used to investigate how resource scarcity is likely to affect agents' effort allocation between production and predation.

4.2. Entities, state variables, and scales

The model has four main entities including the agent, the network, the environment and the resource.

Each agent represents an individual with six main variables. The variable *mxage* holds the maximum expected *age* of the agent. Over time *age*, which is initially 1, increases and when it reaches to *mxage*, the agent leaves *child* number of offspring and dies. *child* holds an integer with uniform distribution which minimum and maximum values are determined based on the population scenarios. *mxage* is a normally distributed random value. To associate agents' allocation decisions with their heterogeneous attitude, each agent has a variable which determines its risk taking level, *rsktl*. When *rsktl* is higher, agents are more likely to allocate further effort to predation and less to protection.

Over the simulation, agents select an effort allocation strategy from the pool of strategies. The strategy is represented using a bit vector [X1 X2 X3 X4], where: X1 stands for a binary variable representing predation of resource type 1, X2 similarly represents predation of resource type 2, X3 is for product predation and X4 shows whether the agents produces or not. So, if a bit is 1, the agent allocates effort to that option and if 0, it does not. For example, the [0 0 1 1] strategy means an agent predates other agents' products along with producing itself. In the models which have just one type of resource, the first two bits are combined and the strategy takes the [X1 X2 X3] format. For simplicity, a strategy like [1 0 1] is presented as S101 from now on.

Agents are connected to each other through an undirected incomplete network where if *A* is connected to *B*, *B* is connected to *A* as well. The connection priority is set so that agents will connect to the agents spatially closer to them. Sensitivity analyses show that while this does not affect the results, it improves the model interface. The links are fixed and if a link is broken for any reason the agent will not attempt to establish new links, unless all of them are broken. The average number of links an agent creates is proportional to the population.

The environment is a 50 × 50 bounded square grid where each cell is called a patch. Patches all have the same physical size in the model's graphical user interface, representing an area able to accommodate only one agent.

In our model, four different types of resources are studied. *Land* which represents agricultural land is a private resource which can be accumulated and stored by the agent over the long-term and be inherited between generations. *Water-D* represents a resource such as drinking water which has only consumption usage. It is a common resource and can be preserved over a predefined short-term. *Water-P* on the other hand has similar features to *Water-D*, but it represents irrigation water since it yields utility through the production function. Finally, *Water-B* (water for Both uses) can be directly consumed and can also be used in the production process.

The resource scarcity scenarios are mainly controlled by two variables: 1) the Duration of the resource scarcity, *D*, and 2) the spatial Area which is affected by the resource scarcity, *A*. We also allow for single or multiple occurrences of scarcity, the impacts of which are discussed later.

4.3. Process overview and scheduling

The model runs for 25,000 ticks, where each tick is the smallest discrete unit of time in the model. During a tick there is a non-zero probability of all of the modules of the model being executed at least once. Model outputs are recorded every 10 ticks and the first 500 observations are discarded since they are highly affected by the initial conditions, finally leading to 2000 data points. Each agent goes through seven steps as described below:

1. Measuring Insecurity: During each tick each agent measures the insecurity in its surrounding environment. Equation 1 shows how insecurity (*insec*) is measured for the agent *i*, at each point of time *T*, where $attkd_{it-1}$ shows how intensively the agent *i* has been attachked predated in round $t - 1$. The intensity of predation is the previous rounds is determined by how much effort the predators have allocated to predate agent *i*.

$$insec_{iT} = \frac{1}{1 + e^{-\sigma \sum_{0}^{T} \left(\frac{attkd_{it-1}}{\vartheta}\right)^{T-t+1}}} \quad (1)$$

In Equation 1, by using $\left\{-\sigma \sum_{1}^{T} \left(\frac{attkd_{it-1}}{\vartheta}\right)^{T-t+1}\right\}$, at every point of time (*T*), the agent takes into account his experience of being predated from time = 0 to time = *T* and measures a weighted average value of those experiences by giving more attention to more recent incidents. The process is adjusted using ϑ and σ. This is then taken to a logistic function to provide a nonlinear distribution of values between zero and one. After calibrating the module, we have selected $\vartheta = 0.02$ and $\sigma = 1.001$ based on the life-span of each agent.

2. Allocate resources: Each agent has one unit of effort to allocate during each tick. The first decision an agent makes is about how much resources it wants to allocate to protection. Equation 2 shows the resources allocated to protection (*protn*) based on insecurity (*insec*) and risk-taking level (*rsktl*) of agent *i* at time *t*.

$$protn_{it} = insec_{it} \times (1 - rsktl_i) \quad (2)$$

Considering Equations 1 and 2, agents who are more risk-averse and have been frequently attacked recently, allocate more effort to protection.

After deciding on the amount of effort to allocate to protection, the agent is left with (1– *protn*) units of effort. This will be allocated between production, resource predation and product predation as shown in Table 1. In this table, the allocation of effort is presented when only one resource is in the model. If we have two types of resources, there are three steps for dividing the resource predation effort (*rprdn*): 1) agents measure how much of the resource of they have, 2) agents calculate how important each of these resources as a factor in their production function are, and 3) agents consider the average of both step 1 and step 2. So, each agent at any point of time measures the comparative benefit of predating *Water-B* against *Land*, and also considers how much *Land* and *Water-B* it already owns to decide how it should allocate its resource predation efforts.

Table 1: Effort allocation patterns based on the strategy selected by the agents

	Protection *protn*	**Production** *prodn*	**R-Predation** *rprdn*	**P-Predation** *pprdn*
S001	*insec*	0	0	0
S001	*insec*	1 – *protn*	0	0
S010	*insec*	0	1 – *protn*	0
S011	*insec*	1 – (*protn* + *predn*)	0	(1 – *protn*) * *rsktl*
S100	*insec*	0	0	1 – *protn*
S101	*insec*	1 – (*protn* + *predn*)	(1 – *protn*) * *rsktl*	0
S110	*insec*	0	(1 – *protn*) / 2	(1 – *protn*) / 2
S111	*insec*	1 – (*protn* + *predn*)	((1 – *protn*) * *rsktl*) / 2	((1 – *protn*) * *rsktl*) / 2

Strategy: SXYZ, where: X = 1 if the agent predates other agents' resources and 0 if it does not; Y = 1 if the agent predates other agents' products and 0 if it does not; and Z = 1 if the agent engages in production and 0 if it does not. *insec* = Insecurity, *protn* = Protection, *predn* = Predation, *rsktl* = Risk-taking Level

3. Predate resources: Equation 3 is an extended standard success function, showing how the subject of a particular conflict, such as the resource, is transferred from one agent to another during a conflict. For a conflict between agents *i* and *j*, the transfers from agent *i* to agent *j* are a function of their mutual predation and protection efforts and wealth, where θ is the predation factor and the relative value of σ and τ determines the effectiveness of the prey's protective efforts against the attacker's predatory effort. Wealth is measured as the accumulation of income.

$$transfer_{ij} = \frac{rprdn_j^{\theta_i}}{rprdn_j^{\theta_i} + (\sigma . protn_i^{\theta_i} + \tau . rprdn_i^{\theta_i})} \times \frac{welth_j^{\theta_i}}{welth_i^{\theta_i} + welth_j^{\theta_i}} \quad (3)$$

By including both the allocation options (*predn* and *protn*) and wealth (*welth*), we ensure the financial powers of the parties are considered as well as their individual effort. Predating resources takes place before the production in each tick so the stolen resources can be used.

4. Produce: Equation 4 shows a Cobb-Douglas production function, where *prodn* represents the effort allocated to production, *techy* is the technology, *spcln* is the agent's degree of specialization in production, *welth* is its wealth and *resrs* is its resources.

$$prodd_{it} = prodn_{it}^{\alpha}(techy_{it}(1 + spcln_{it}) . \sqrt{welth_{it}})^{\beta}(1 + resrs_{it})^{\gamma} \quad (4)$$

Total capital, $(techy_{it}(1 + spcln_{it}).\sqrt{welth_{it}})$, is measured by combining an agent's access to technology with its degree of production specialization and its wealth (financial capital). In Equation 4, α, β and γ are random variables normally distributed in a way to ensure decreasing returns to production factors for the majority of agents. At the end, *prodd* will contain the total amount of goods produced by the agent *i* at time *t*.

5. Predate production: The process of predating products is similar to what was discussed for resource predation, only the objects of predation are the products produced by the prey, rather than the raw material as in resource predation.

6. Record: Over time, agents continuously observe their output based on different combinations of strategies and allocation levels and keep records of the strategy which on average yields the greatest returns, which is called the best strategy (*bstry*). In other words, *bstry*, which is initially set to [0 0 0] or [0 0 0 0], always contains the strategy with the highest outcome resulting from production and predation.

The learning module is then implemented through three genetic operators: 1) a mutation which continuously introduces random changes into agents' strategies, thereby guaranteeing that each agent tries different strategies while looking for the strategy yielding the highest returns; 2) a crossover between the parent's strategy and the child's strategy which provides strategy inheritance; and 3) another crossover which occurs between an agent's most recent strategy and its best strategy (*bstry*), implementing the genetic learning process. The probability of each of these operations to occur is controlled using mutation-rate, inheritance-rate and crossover-rate, respectively.

7- Check age and reproduce: at the final step, agents increase their age by one. If *age* is equal to *mxage*, new agents are born. The offspring select a new random location and inherit their parent's resources, wealth, strategy and best strategy. The model stops if time is equal to 25000 ticks.

4.4. Design concepts

As Grimm *et al.* (2010, p. 2765) mention, this design concepts section "does not describe the model *per se*" but it is an attempt to review the main "characteristics" of the model.

Basic principles: As discussed earlier, the basic principles of actions and interactions in the model are based on the theory of production and conflict, which shows how effort can be allocated between productive and unproductive activities.

Emergence: We expect the final resource allocation trends to emerge from individual actions and interactions rather than simply being the aggregation of micro-level effort allocation decisions.

Adaptation: The adaptive traits in the model can be direct and indirect. One direct adaptation occurs when agents increase their protection in response to higher predation from their neighbors. Also, in response to the changes in the environment such as population, technology or resource access, agents can change their strategy and so their effort allocation patterns, to ensure that they gain the highest outcome.

Objectives: The main objective of agent is to increase its outcome by taking into account its personal features such as risk taking level and its neighbors' and environment's characteristics.

Learning: As our strategy framework revealed earlier, we have applied three genetic operators to embed learning in our agent. This allows us to easily change the number of strategies and at the same time to implement agents with bounded rationality, since they do not reflect on each strategy at every point of time (Brenner, 2006), but instead search for a better situation over time and are affected by a random process which manages the mutation and crossover probabilities. The strategy framework with genetic operator also enables us to have inter-generational learning.

Prediction: The main prediction that the agent does is using a weighted measurement of its history of being-attacked to form expectations about future insecurity.

Sensing: The agents detect the resource availability in the environment, the number of their neighbors, whether the patches are occupied or not, and other global values.

Interaction: The main interaction channel between the agents is through the predation process where resources or products are transferred between them.

Stochasticity: The probability values for the genetic operators are considered to be random. Also a random variable is also embedded in the predation function to control the success rate of predation.

Collectives: No collective actions are implemented in the model.

Observation: Two main sets of variables are observed in the model, including the mean efforts allocated by all agents to each activity, production, resource predation, product predation and protection and the share of each strategy selected from the pool.

4.5. Simulation Details

The further details of the model, especially the initial conditions and sensitivity analysis are presented in this section.

The model starts with 25 agents in a 50 by 50 cell environment. The main variables and their initial values are listed in Table 3. Resources, agents and their children are distributed randomly in the environment. The land regime is set in a way that the children can not only inherit land, but they can also gain their own land over time. The mean value of initial resources in each cell is 10 and the model has only one type of agent.

The Cobb-Douglas production function powers from Equation 4, α, β and γ, are all distributed normally with mean = 0.3 and *s.d* = 0.05, which means that less than 10% of the entities experience constant or increasing returns to scale.

4.5.1 Sensitivity Analysis

We ran a set of sensitivity analysis simulations to select the appropriate initial conditions for some of the variables. As expected, changes in mutation, optimization and inheritance rates significantly affect the model outputs since they determine how frequently agents' bit patterns are updated over time. High mutation and low inheritance rates increase the stochastic behavior, decreasing the opportunity for adaptation for agents, but at the same time improving their chances of finding the most beneficial strategy. On the other hand, while frequent optimization can ensure that agents follow the best strategy, it prevents them from searching for global optimums.

Based on the calibration results and considering each agents' life cycle, the value of the mutation rate is set in a way to guarantee, on average, four mutations over its life time. Based on this, the optimization rate is set to ensure that between each two mutations, on average, ten optimizations are undertaken. Finally, the value of the inheritance rate is assigned to provide a 50% probability of the agent following its parent across the whole bit thread.

The predation success rates for both product and resource are 25%. As expected, lower rates of predation success decrease agents' interest in attacking others, but since lower predation is a factor encouraging agents to predate more as others protect themselves less and returns to predation are high, the success rate impacts are not as high as expected, but still statistically significant.

Table 2: Sample initial conditions

Title	**Value**	**Title**	**Value**
Environment Variables			
Resource Distribution	Random (Uniform)	Agent Distribution	Random (Uniform)
Land Regime	Increasing	Child Placement	Random
Initial agents	25	Mean Initial Resource	10
Agent Types	1	Simulation Length	25000 ticks
Production Function Factors			
α (mean)	0.3	α (s.d.)	0.05
β (mean)	0.3	β (s.d.)	0.05
γ (mean)	0.3	γ (s.d.)	0.05
Learning and Activity Rates			
Mutation Rate	0.04% per tick	Max degradation rate	0.5% per tick
Optimization Rate	0.4% per tick	Cycle Length	50 ticks
Strategy Trans Rate	50% per tick	Risk Taking Level	Uniform (0,1)
PPred Success Rate	25% per tick	RPred Success Rate	25% per tick
Agent Variables			
Initial Strategy	[0 0 0]	Initial BEST	[0 0 0]
Average Children	1.5	Life Length	N (2500, 300)
Avg. Initial Wealth	5	Initial Technology	1
Linking	5%	Initial age	Random *ELIFE*

Agents are each linked to 5% of the population in the environment. The impacts of different levels of connectivity are mixed. While a higher level of connectivity leads to an increase in the chances of predating, since the agents have more options to attack, it decreases the probability of one agent being predated by one specific neighbor over time and these forces neutralize each other and the changes in connectivity do not significantly affect the model output.

4.5.2. Randomness Sensitivity Analysis

The model is affected by two sets of factors. Firstly, the initial conditions which were reviewed in the previous section, as well as the random seed which is selected by the software package. NetLogo uses a pseudo-random number generating system which means that while the random numbers are "random", their generation process is deterministic, so choosing the same random seed in different simulations ensures that the final thread of numbers produced will be the same. As these differences can affect our results, we checked how sensitive the model is to the random seeds, by running the model 30 times, each with a different random seed.

The results are presented in Figure1. Here, there are one line for each x and y coordinate making a grid line of 900 crossovers when the lines cross. When a x crosses a y line, it produces a black area if the two seed outputs are statistically significantly different[8]. Then, we consider all of these 870 values (900 observations minus 30 of them where a series is compared with itself) as one single dataset and test if the mean of this sample is more than 0.01 which is rejected at 99% concluding that there in not enough evidence to claim that the model outputs are significantly different under different random seeds.

[8] When a series is compared to itself, we have manually taken the value to zero.

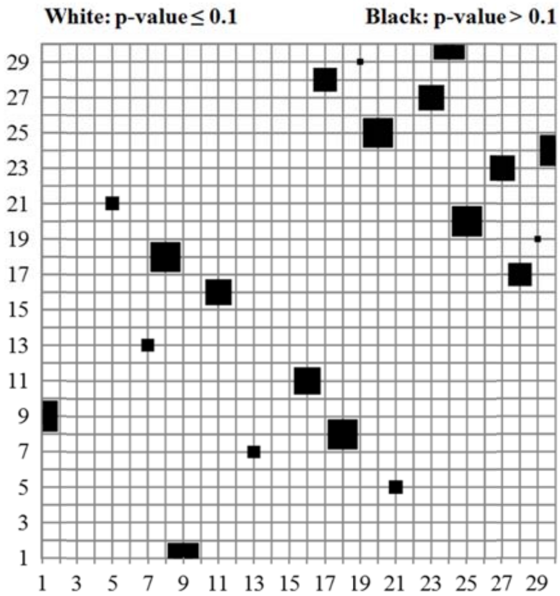

Figure 1: One-to-one sensitivity analysis results for independence from random seed variations and equal means over the simulations. H0: Equal means of any two simulations. Larger squares show higher values.

Based on these results, it can be said that the model is not significantly sensitive to changes in the initial conditions imposed by different random seeds. In other words, while using different random seeds provides the chance of having different experiments, it does not change the model outputs significantly and so the results can be analyzed independently.

4.6. Basic Model Verification

Before presenting the results, we first review a few outputs from the basic model where the scarcity scenarios are not active. This is done to verify the code and also better clarify the impacts of scarcity scenarios.

Figure 2 presents the variations in the proportion of agents who think being pure producers (S001), pure product predators (S010), or pure resource predators (S100) is the best strategy. The variations, whether short-run volatilities or long-run cyclical behavior, are observed in every single simulation, and mainly result from how agents select their strategies based on their personal attributes, their neighbors' decisions and how different environment variables change at the local and global levels. Pure resource predation stays close to zero, since there is no direct return to only predating and having resources.

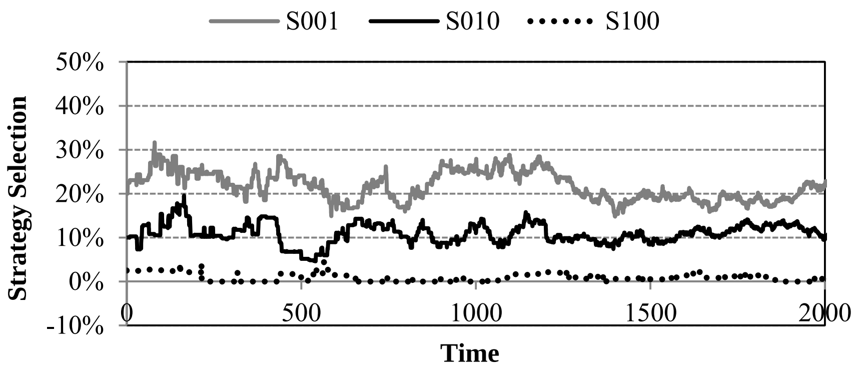

Figure 2: Trends of pure production (S001), pure product predation (S010), and pure resource predation (S100).

Regressing the productive allocations against the strategies (excluding the S000), Table 3 shows that majority of the strategies have significant impacts on the agents' productive effort allocation decision. As expected, the pure product predation strategy has the highest negative and the pure production strategy has relatively the highest positive impact on the productive allocations, while the dual production-predation strategies have lower or even insignificant effects. The insignificance of the triple and dual strategies is due to the fact that these strategies, by omitting the protective efforts, divide the rest of the effort between production and predation and so have unclear impacts on productive allocations. The insignificant effect of S100 is due to the fact that the strategy is not practiced by many agents and so its proportion value is close to zero.

Table 3: Productive allocation against the main strategies

Y: Productive Allocation			
Durbin-Watson stat	2.087326	Standard Error	0.007744
R Square	0.957432	Observations	2150
	Coefficients	*Standard Error*	*t Stat*
Intercept	0.2866	0.05859	4.8932
S001	0.2240	0.0628	3.5654
S010	-0.1945	0.0690	-2.819
S011	0.0985	0.0655	1.5023
S100	-0.0770	0.1055	-0.7304
S101	0.1072	0.0625	1.7131
S110	-0.1670	0.0696	-2.3976
S111	0.0545	0.0646	0.8442

Figure 3 presents the mutual resource allocation patterns between each pair of options. As expected there is a negative relation between production and each of predation options, and between protection and production, and both predation options lead to higher levels of protection.

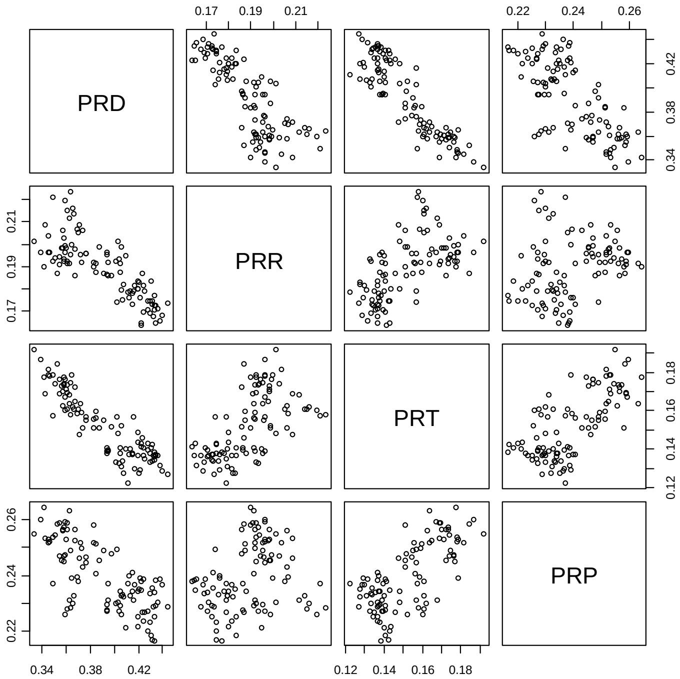

Figure 3: Mutual relations between any two effort allocation options for random observations.

In addition to the presented outputs and also using NetLogo debugging capabilities, each module was tested separately, to ensure that the intended design is implemented correctly based on a simple version of what is called abstract interpretation (Hermenegildo, 2005) in computer science, as well as running the model under two sample agents to ensure correct communications and interactions.

5. Scarcity Models' Results

The model provides us with an extended set of results which cannot all be presented in the course of this paper. As a result, we only discuss the major outputs.

5.1. Land Scarcity

In Figure 4 the vertical dash of lines indicate the start and the end of a medium-intensity resource shock period.

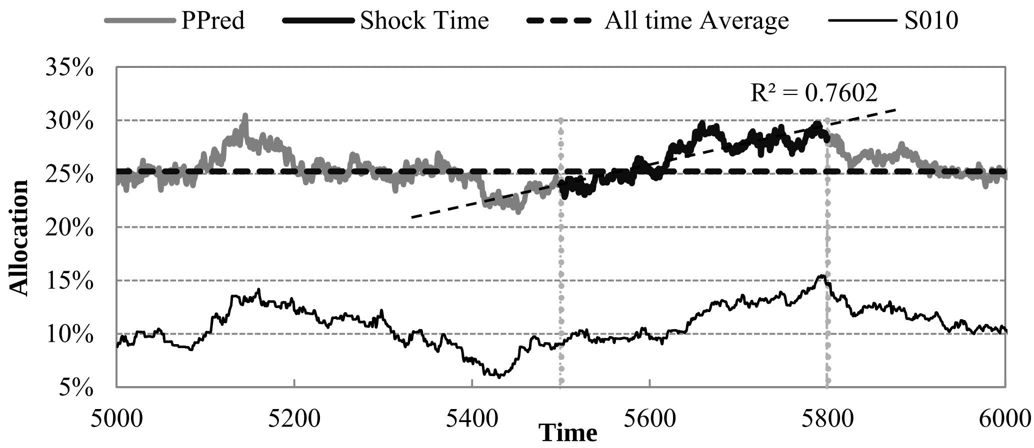

Figure 4: Changes in the efforts of all agents allocated to product predation (PPred) and percentage of product predators (S010) in the population in a simulation with medium shock

Two main issues can be seen in the figure. On one hand, during the resource scarcity period, there is an upward trend in product predation resource allocation, which finishes as soon as the shock disappears. But this 25% increase in product predation is not unprecedented since as can be seen in the figure, between times 5100 and 5200 another increase with similar amplitude but shorter time period is experienced where no scarcity scenario is active. When the model is run under a set of weak, medium and severe scarcity scenarios and the average of all is measured, at 95% confidence level, the trends are similar to the models without any scarcity.

To better explore the role of *Land* shocks in the changes observed in the predatory trend, we analyze the impulse responses in two different models. First, the model is run with one resource shock at a predetermined time (t = 1100), while in the second, the model is hit by four shocks (t = 300, 700, 1100, 1400).

Confirming our initial findings, analyzing the impulse impacts shows that in the majority of cases the changes in the allocation trends are temporary, if not insignificant and according to the results, less than 5% of the changes in effort allocation patterns can be attributed to the resource shocks. The model also shows that a single shock is more likely to cause a structural break in the effort allocation trends, compared to multiple shocks.

To study the impacts of *Land* scarcity more precisely, the environment was divided into 10 different regions as shown in Figure 5 and the shocks were arranged to only affect the 40% of patches on the left side (shadowed area). The effort allocation patterns were then monitored separately for the agents located in each region to see whether there was any significant variation across the environment.

In Figure 5 each black dot shows the average effort allocated to product predation by agents located in that area. It is clear that in a simulation where the average effort allocated to product predation is around 25%, in the affected areas average product predation is higher than the global average by almost 15%. The highest rate of predatory effort is observed in Region 1, which is not only affected by the shock, but is also the farthest region from the unaffected area. These results are important considering that in models with random shocks, there are no statistically significant differences in effort allocation across the environment.

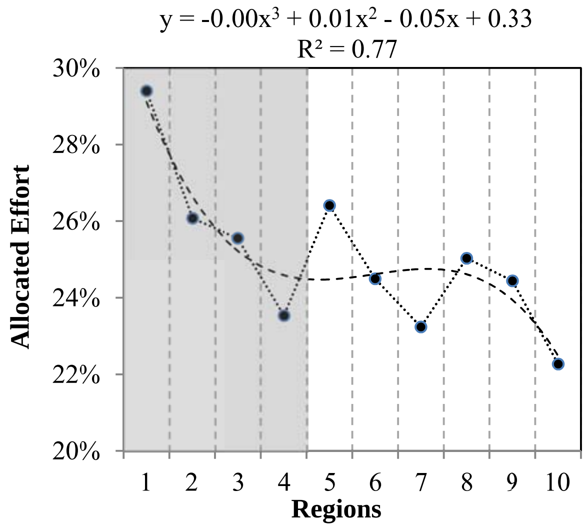

Figure 5: Changes in the product predation effort allocation in a model with regional shocks. The model environment is divided into 10 regions and only four of them, the shadowed area, are affected by the shock which takes their resource level to zero.

5.2. *Water-D* Scarcity

As introduced in Section 4-2, *Water-D* (representing resources such as drinking water) is a resource type which can only be consumed directly. Figure 6 shows how an increase in the area affected by a

Water-D shock changes the average proportion of agents who prefer to be pure producers. As can be seen, when the affected area extends, more agents decide to leave the pure production strategy and become predator by enabling their predation bit.

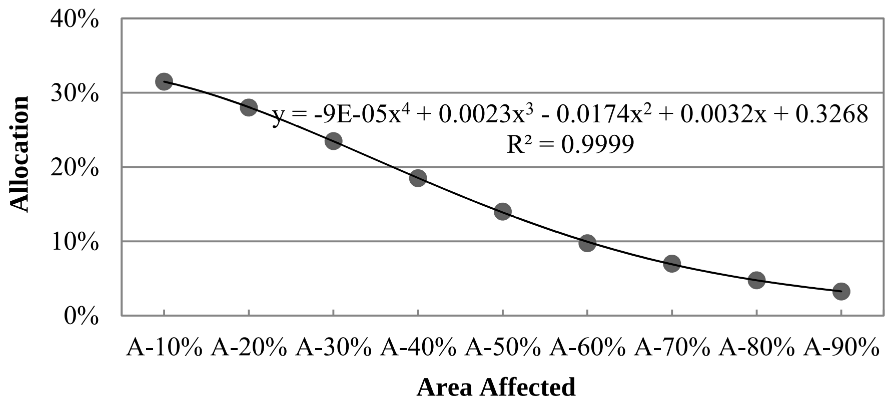

Figure 6: The final value for the proportion of pure producers in simulations with different levels of affected areas affected by the shock.

To analyze the shock thoroughly, a set of impulse response tests was undertaken for all six main strategies (leaving out S000 and S100) to investigate the short- and long-run impacts of the shocks, at different levels of scarcity. Table 4 contains the results for these tests.

Table 4: Agent populations' selection of different strategies in reaction to the Water-D shocks for different spatial extents. NS = Not Significant, TD = Temporarily Decreasing, TI = Temporarily Increasing, PD: = Permanently Decreasing, PI = Permanently Increasing.

		Strategy					
		S001	**S010**	**S011**	**S101**	**S110**	**S111**
Shock Extent (% of area)	**10%**	TD	NS	NS	TI	NS	NS
	20%	PD	NS	NS	PI	NS	NS
	30%	PD	NS	TD	PI	NS	TI
	40%	PD	NS	TD	PI	NS	TI
	50%	PD	TD	PD	PI	NS	PI
	60%	PD	TD	PD	PI	TI	PI
	70%	PD	PD	PD	PI	TI	PI
	80%	PD	PD	PD	PI	PI	PI
	90%	PD	PD	PD	PI	PI	PI

As the table suggests, at the lower levels of shocks the producer agents (SXX1) temporarily switch from just producing to predating *Water-D* as well as producing. At 20% level of shock, a similar impact is found, but this time it is permanent since a bigger group of agents experience the shock. As the shocks become more extensive the second group of non-resource-predating agents (S0XX) gradually joins the formerly-pure producers, by first temporarily and then permanently allocating effort to predating others' resources. The results show that after the shock level passes 50% of the area, almost all non-resource-predating agents are affected, since they attack others to gain *Water-D* and survive. This becomes permanent when the shock is at its full extent, so model responses changes in the long term changes.

To identify possible structural breaks, the Chow test is applied to the allocation trends. As presented in Figure 7, low intensity scenarios do not cause any breaks immediately after the shock, while when the shocks become severe, the model responds by a significant change in the output trends.

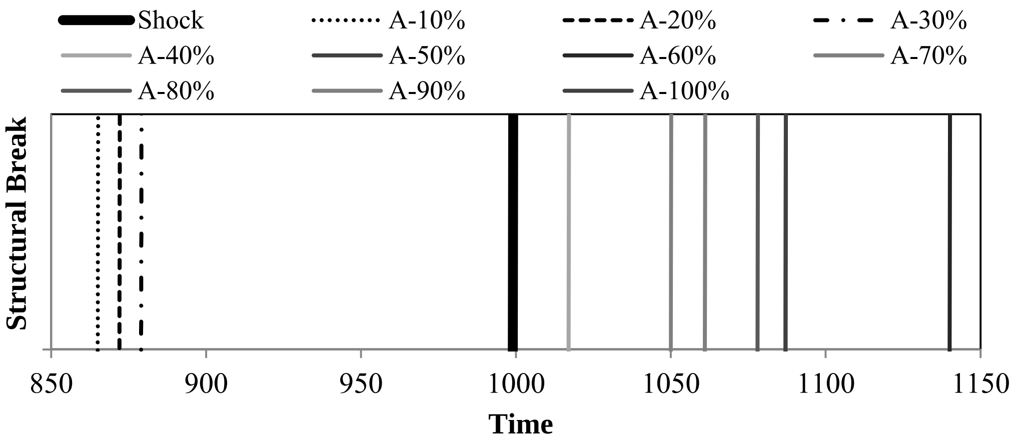

Figure 7: Shock and structural breaks in a sample run with Water-D as the resource - single run.

While the severe scarcity of a resource such as *Water-D* should lead to severe consequences for the agents, such as death, we did not allow the agents to die due to resource scarcity in the initial model in order to be able to follow the dynamics of their strategy selection over time. When we relax that constraint allowing the extremely thirsty agents die after passing a pre-defined threshold, the population trends react as shown in Figure 8. As the figure shows, while *Water-D* scarcity does not affect population trends at low or medium levels of shock intensity, at higher levels the population drops very fast during the simulation.

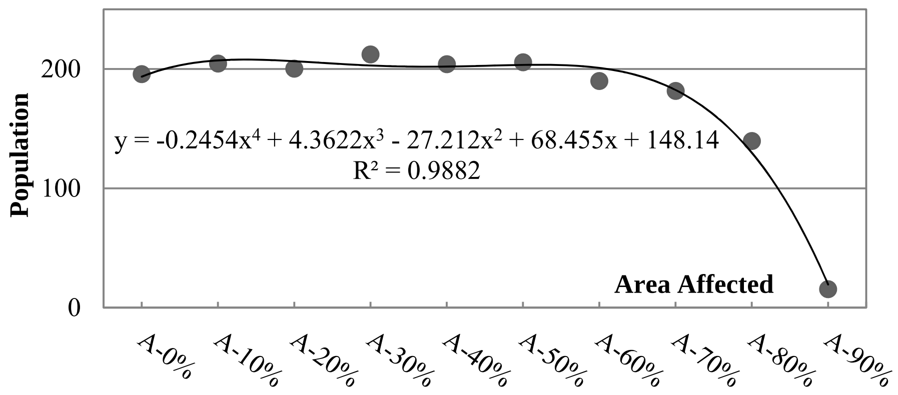

Figure 8: Final population and affected area in a *Water-D* model with death – 30 runs

We relax another limitation by allowing the agents to move in response to *Water-D* scarcity, searching for resources in the environment. As can be seen in Figure 9 where the natural log of the number of movements is presented against the affected area, the number of movements increases exponentially as a result of increasingly severe resource scarcities.

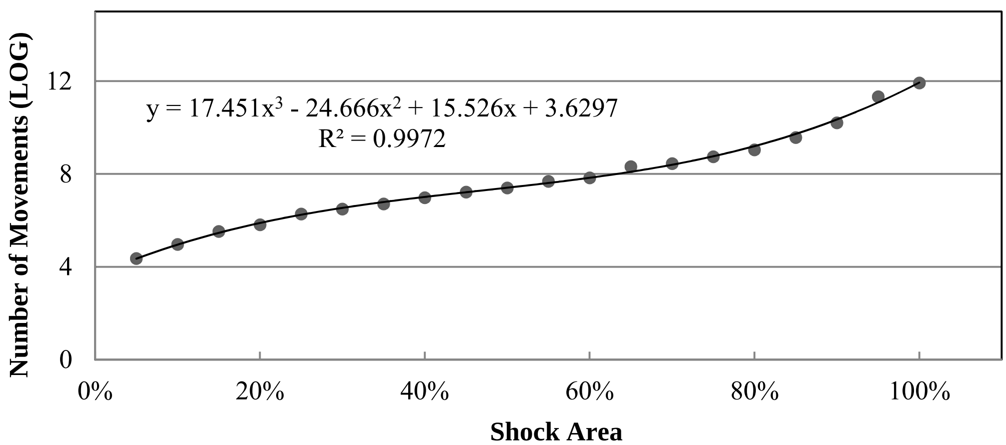

Figure 9: Changes in the number of moves in the model based on the different levels of scarcity – Multiple run.

Migration is an effective strategy also as Figure 10 shows, in the models with the migration option active (white boxplots), the effort allocated to productive action has decreased less due to different extents of shock, compared to the equivalent cases where migration is not allowed (grey boxplots).

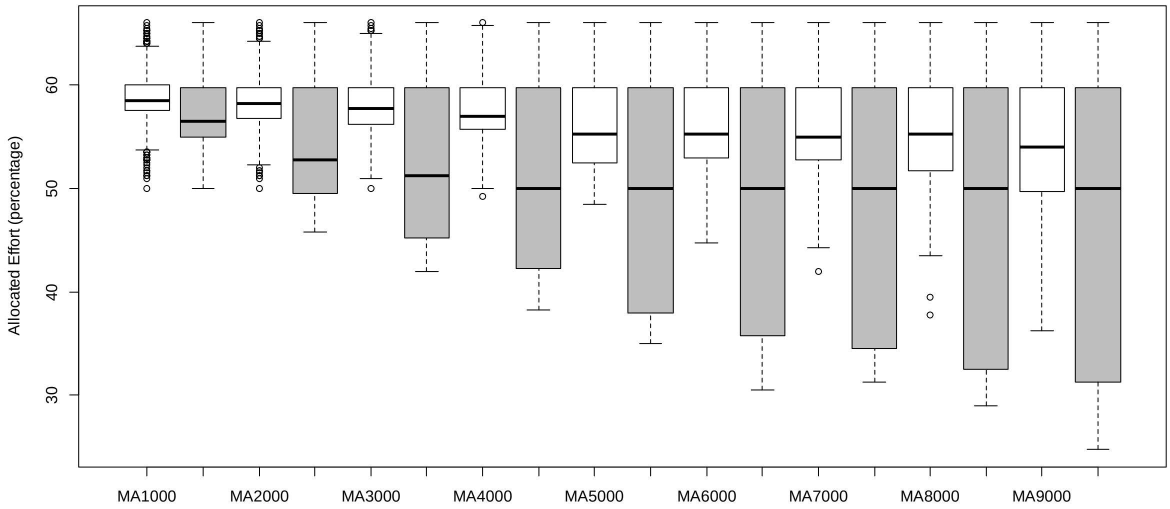

Figure 10: Decreases in productive allocation when migration is active (white) and inactive (grey).

5.3. Water-P Scarcity

Figure 11 shows how allocation trends react to a *Water-P* (such as water for production) scarcity scenario. As can be seen, during the shock, productive efforts are replaced by product predation, which increases gradually when the shock starts and to a large extent disappears after the shock finishes. As for the strategies, the significant increases in S010 (product predation) and S011 (product predation and production) are considerable, while effort allocated to the pure productive strategy falls when the shock starts and returns to its top position when the shock fades out.

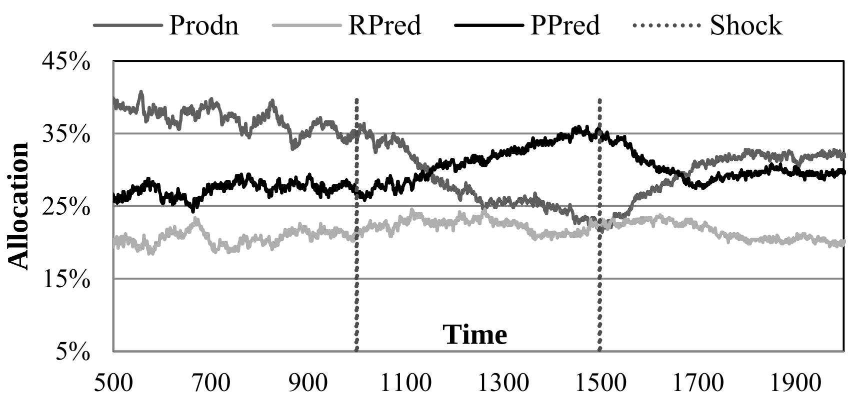

Figure 11: Changes in a sample individual-run effort allocation due to Water-P shock – single run.

Figure 12 shows how different levels of resource shock can affect the average proportion of effort allocated to production in a model with *Water-P* as the resource.

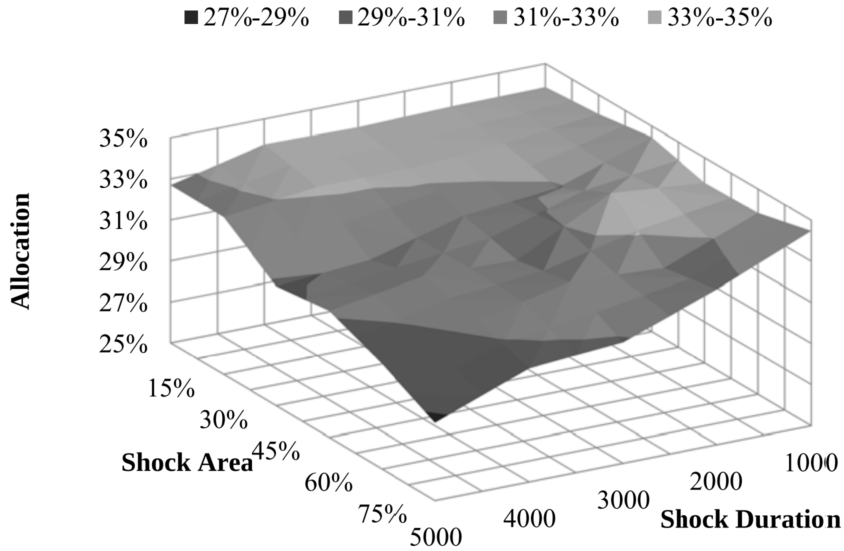

Figure 12: Changes in the average productive efforts in Water-P shocks multiple run.

As can be seen, the productive allocation which was more than 35% in the basic model without shocks, changes to almost 30% in less intense shock scenarios, then to slightly over 25% when the shocks become longer and affect a larger area. The results show a 25% decrease in productive efforts when the basic scenario is compared with very severe shocks.

According to the results, the decrease in the productive efforts mainly lead to more effort being allocated to product predation, since further resource predation is not efficient for the agents. The overall results show that as for *Land*, resource shocks to *Water-P* shift the effort from production to product predation, since the returns to resource predation decrease due to the shock and also considering the fact that *Water*, as a common resource in this model, cannot be stored for a long time and so agents need to constantly allocate effort to its predation.

We have also tested for the existence of a structural break in the model outputs over the scenarios. If there has been a break immediately within 100 ticks after the shock at 99% confidence level, we give the scenario a score of 1, and otherwise 0. The tests were undertaken using the 100-tick moving average of the data.

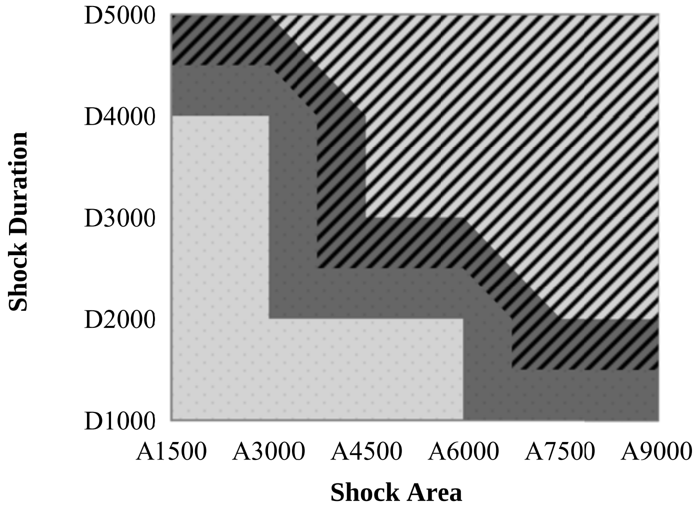

Figure 13: Testing for the existence of structural break due to *Water-P* resource shock scenarios. The dashed area with value of 1, shows scenario combinations which have caused a structural break.

Figure 13 shows that as the shocks become more powerful, the probability of a structural break increases as well. In the results, no structural breaks are experienced for limited shock durations and less extensive areas, but with longer and more extensive shocks the existence of a structural break in the effort allocation patterns becomes more likely. Despite testing for different scenario setups, we did not find any clear relation between the shock intensity and the timing of the break occurrence.

5.4. Water-B Scarcity

Figure 14 (top) illustrates how productive efforts decline due to resource shocks in a model with a resource for both consumption and production, *Water-B*. As can be seen, again the combined impacts of shock duration and area have significant effects on the agents' decisions whether to produce or not. The middle and bottom panels respectively show how average resource predation and product predation trends react to the scarcity. Resource predation does no change significantly while product predation increases at high levels of shock intensity.

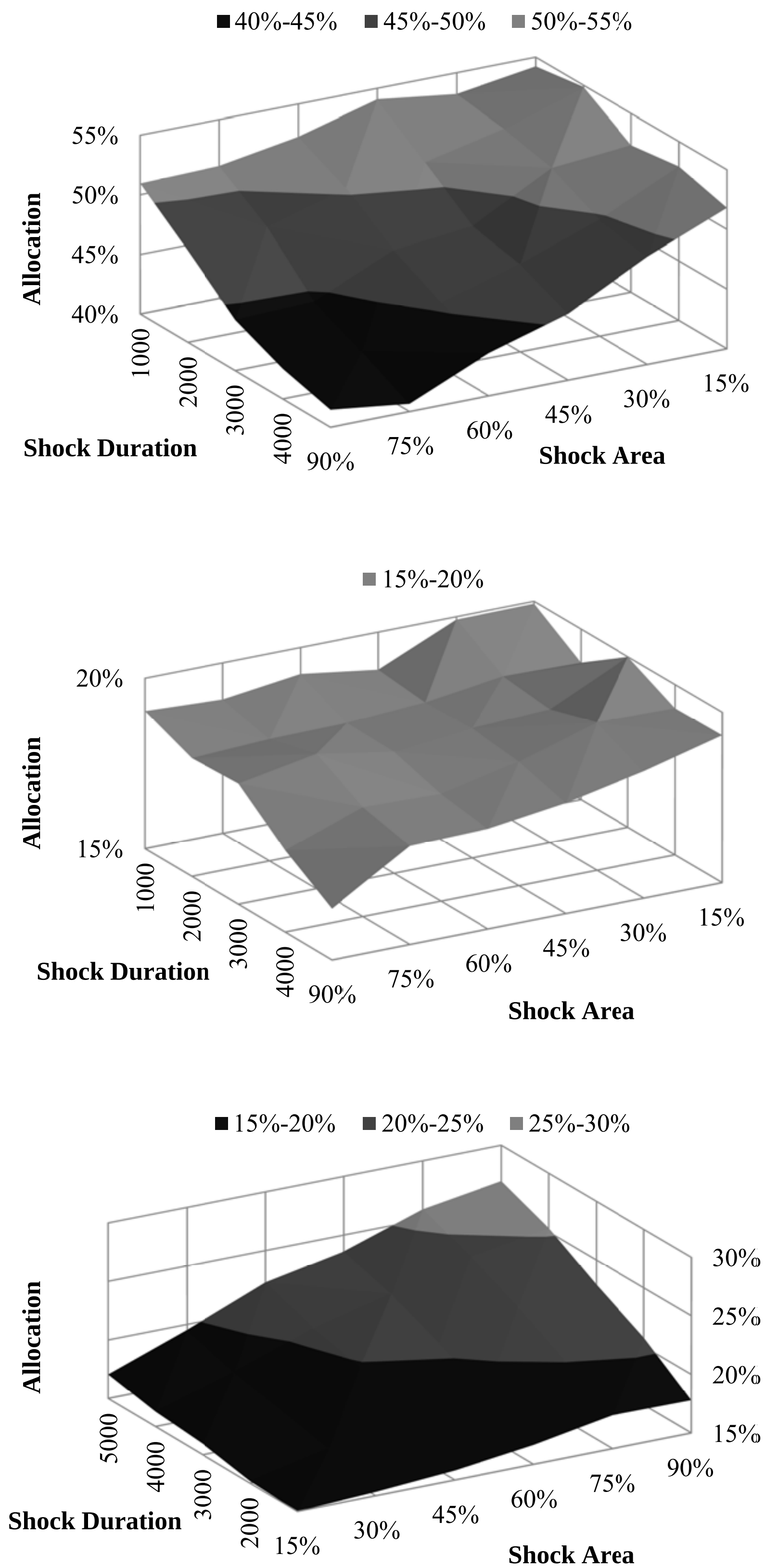

Figure 14: Changes in effort allocation due to *Water-B* resource shocks. Top: productive efforts; Middle: Resource Predation; Bottom: Product Predation

As we presented in previous cases, applying the impulse response tests shows that the impacts are only significant when severe shocks affect the model.

5.5. Land and Water-B Scarcity

To measure the possible impacts of parallel *Land* and *Water* scarcities on how agents allocate their efforts, different scenarios were designed based on low-, medium- and high-intensity *Land* and *Water* scarcity combinations. The model was then run 30 times and the average results over different random seeds were calculated separately for every scenario.

According to the results, when the productive effort allocation is regressed against the scarcity of each resource, the coefficients are 0.004 and 0.003 for *Land* and *Water*, respectively. While the closeness of the values can be attributed to the fact that both resources, on average, have similar roles in linking the production function to scarcity, the larger coefficient of *Land* can be attributed to the agents' abilities to preserve their *Land* over time, which makes its predation more desirable.

Figure 15 shows how the productive allocation effort coefficients are distributed for *Water* and *Land* over the 54 scenarios. As can be seen, while the *Land* coefficient distribution is close to a normal distribution, the *Water* coefficient distribution is skewed. This shows that while *Land*, on average, contributes more to the production process in this model, its role in production is less sensitive to the scenarios, compared to *Water* which can generate utility via either predation or consumption.

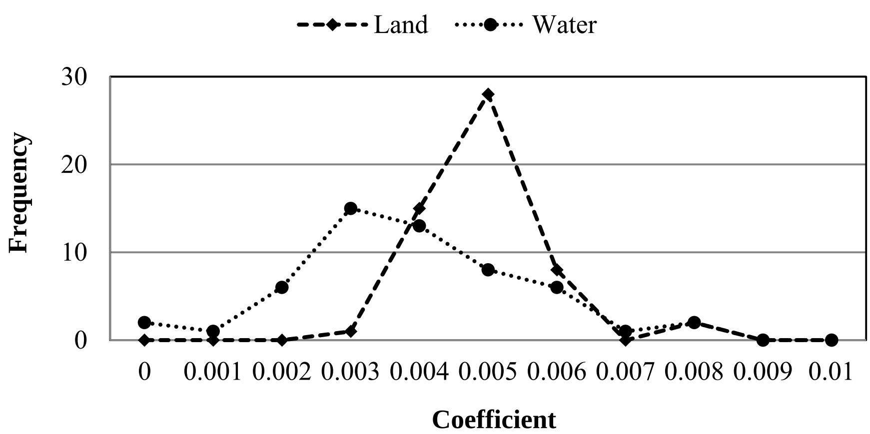

Figure 15: Distribution of regression coefficients for Land and Water

Individual regressions for each of the strategies were run against *Water-B* and *Land* levels in the model. The results are presented in Table 5.

Table 5: Strategy selection changes resulting from *Land* and *Water* variations. Dependent variable = strategies, e.g. S0001 = f (Land, Water). SWXYZ: W: Water-B, X: Land, Y: Product Predation and Z: Production.

SWXYZ	Land	Water	R^2	SWXYZ	Land	Water	R^2
S0000	N/A	N/A	N/A	**S1000**	-0.00067 (-47.8874)	-0.00085 (-11.5988)	0.590902
S0001	0.00349 (70.63291)	0.002721 (10.4183)	0.739972	**S1001**	-1.5E-05 (-0.66624)	-0.0021 (-17.178)	0.131499
S0010	-0.00083 (-55.9514)	0.000227 (2.894349)	0.597578	**S1010**	**-0.00095 (-65.549)**	**-0.00067 (-8.74781)**	**0.707277**
S0011	0.000987 (40.40638)	0.001007 (7.797153)	0.493947	**S1011**	0.000439 (17.46697)	-0.00041 (-3.07252)	0.117016
S0100	-0.0002 (-18.6174)	-0.00012 (-2.12893)	0.160524	**S1100**	-0.00025 (-19.3265)	-0.00094 (-13.8646)	0.284082
S0101	-0.00017 (-6.96071)	0.001391 (10.97296)	0.048042	**S1101**	-0.00086 (-44.0739)	-0.00116 (-11.3017)	0.554038
S0110	-0.00044 (-29.5389)	-0.00028 (-3.49163)	0.325794	**S1110**	-0.00057 (-36.5186)	-0.00089 (-10.724)	0.470349
S0111	0.000195 (7.560805)	0.002493 (18.31933)	0.203077	**S1111**	-0.00027 (-8.84087)	-0.00055 (-3.33685)	0.053989

According to the results, the pure production strategy, S0001, is significantly correlated with *Land* and *Water* access, enjoying the highest levels of significance and R^2. This clearly shows that the number of producers decreases due to resource scarcity in the model. Pure product predation is negatively correlated with *Land* and positively with *Water* since *Water* scarcity shift efforts to resource predation rather than product predation. The positive, statistically significant and highly correlated coefficients for S0011 (production and product predation) illustrate the fact that during the time of scarcity, since production levels fall, there may not be enough incentives for agents to predate what others have produced, and it can also be due to the fact that this strategy is not capable of providing *Water* for direct consumption.

Pure resource predation strategies, S0100, S1000 and S1100, all increase due to scarcity, but since *Land* cannot generate utility individually, the R^2 is much higher for the cases where *Water* predation is included in the strategy, S1XXX.

Two more interesting findings can be observed in Table 5. First, S1010, or *Water* and product predation has a significant negative correlation with both *Land* and *Water* access. It seems that during times of scarcity, agents prefer to predate *Water* and the final product to survive, rather than *Water* and *Land* and produce themselves. The coefficients of S1101 (predating both resources and producing) and S1110 (predating both resources and product predation) are comparatively high, indicating that resource predation that is accompanied by either production or product predation seems to be a popular strategy when resources get scarcer.

6. Discussion and Conclusions

It is widely believed that climate-induced resource scarcity is the main factor causing climate-driven conflicts. Applying the theory of production and conflict and using agent-based modeling enabled us to address three challenges that have been highlighted in the literature. First, following the suggestions by many researchers in this field, we applied disaggregated analysis to investigate the possible links between climate change and conflict. Secondly, we addressed a challenge highlighted by studies such as Theisen *et. al* (2011) and Scheffran *et al.* (2012) as we considered different levels of intensity for resource scarcity. Finally, we took into account the complexities involved in modeling conflict which arises from the interactions, feedback loops, thresholds and nonlinearities which exist when conflict decisions are made.

In line with empirical studies such as Theisen (2008) and Raleigh and Urdal (2007), which claim that only high or very high levels of land and water scarcity are likely to cause conflict, we showed that while low levels of scarcity does not affect the effort allocation patterns significantly and medium-level scenarios only cause temporary changes in the dynamics of allocation, when the scarcity becomes severe, in duration, spatial area or affected population, the impacts on allocation trends become substantial, since many agents develop predatory behavior.

Our findings on the links between the duration of scarcity and the likelihood of conflict also follow the historical patterns McMichael (2012) has reviewed: while societies can adapt to "recurring" short-term climatic events, medium- and long-term changes are more likely to cause social, health, economic or political challenges.

Figure 16 (left) summarizes our results in a sample case where decreases in the share of pure-producer agents in the population are shown based on different levels of scarcity. As can be seen, while in almost 50% of the cases (the dotted area), resource scarcity does not lead to any substantial changes in strategy selection patterns, in the other half, significant levels of decrease in production can be identified. Based on our results, we believe that there is a nonlinear relation between resource scarcity and conflict, as presented in Figure 16 (right), where the probability of conflict increases as the resource shocks become more severe due to higher portion of agents deciding to allocate effort to predating others rather than producing.

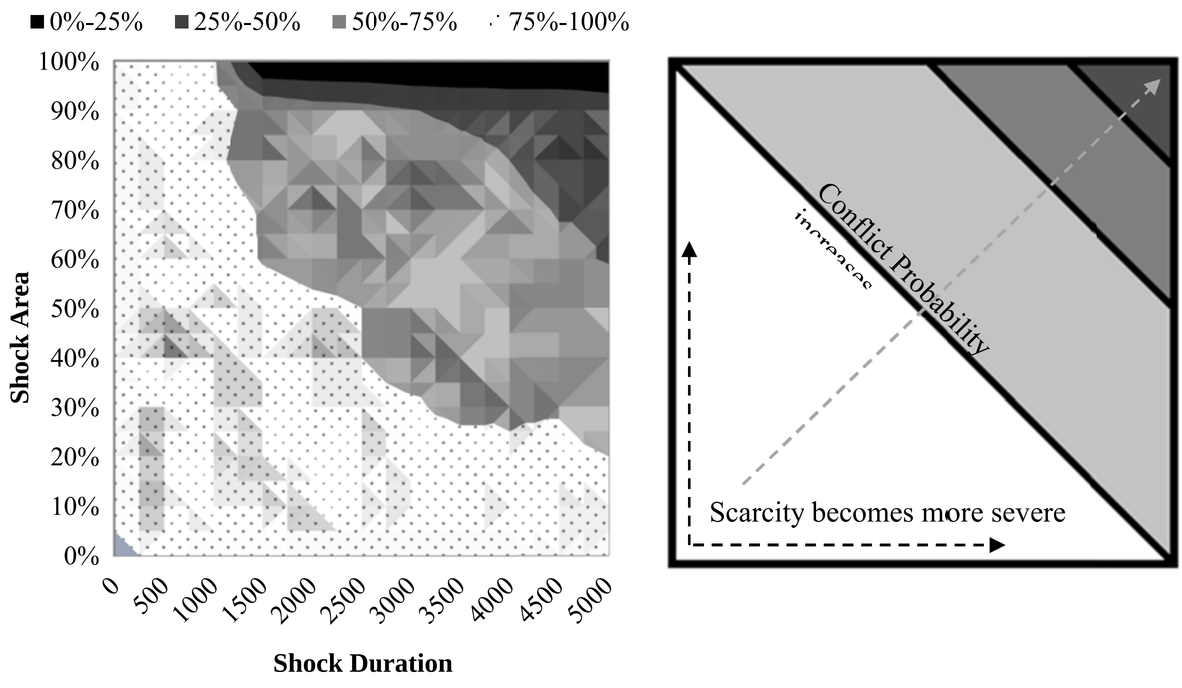

Figure 16: Share of pure producers due to different levels of resource shocks compared to the basic model without resource scarcity.

As was shown and discussed across the paper, higher order polynomials are more successful in capturing the trends and relations of the agents' conflict decisions, highlighting the nonlinearities and thresholds that may exist in real world when individuals or communities respond to climate-driven resource scarcity.

Considering our model results, it is time to respond to our main research question, namely: "Why, contrary to the theoretical perceptions and expectations, might climate change and its consequent resource scarcity not lead to conflict and when they do, why might climate-induced conflicts not be as severe as anticipated?" We highlight four main factors:

1. The first factor that discourages agents from predating others' resources or products is the protective efforts undertaken by the agents being attacked. Protection decreases the returns to predation for the predator in our model and a virtual economic limit emerges from such a reaction which acts as a negative feedback loop.

2. Our results can also be attributed to the adaptive actions which are undertaken by the agents. In the other words, agents know that when resource access levels decrease temporarily, adaptation can be a better solution than predation. Interestingly, when agents are equipped with better adaptation capabilities, such as being able to migrate to unaffected areas, resource scarcity even leads to less increase in conflict than when migration is unavailable.

3. Beyond the protective and adaptive capacities which can decrease the drivers for conflict, as has been mentioned in the literature (Benjaminsen *et al.,* 2012; Theisen, 2012; Witsenburg and Adano, 2009) and investigated in our paper, decreases in resource access or health levels acts as a negative feedback loop itself, discouraging the agents to predate others.

4. To our knowledge, this is the first study which has separated the objects of conflict showing that when resource become scarcer, it is more likely for a conflict to occur over the products made out of a resource rather than the resource itself. Among different types of resources, the agents would

engage in conflicts mainly over more vital, more durable, more easily storable, and more privately owned resources.

This model can be improved and extended by adding institutions such as government and also being modified to match the conditions of a specific country or region.

Acknowledgments

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