Agent Based Modelling of Migration Decision-Making

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Abstract. Attempts to quantify the numbers of migrants generated by changes in climate have commonly been calculated by projecting physical climate changes on an exposed population. These studies generally make simplistic assumptions about the response of an individual to variations in climate. However, empirical evidence of environmentally induced migration does not support such a structural approach and recognises that migration decisions are usually both multicausal and shaped through individual agency. As such, agent-based modelling offers a robust method to simulate the autonomous decision-making process relating to environmental migration. The Theory of Planned Behaviour provides a basis that can be used to effectively break down the reasoning process relating to the development of a behavioural intention. By developing an agent-based model of environmental migration on the basis of a combination of such theoretical developments and data analysis we further investigate the role of the environment in the decision to migrate.

Keywords: Agent-Based Model, Simulation, Decision-Making, Theory of Planned Behaviour, Climate Change, Human Migration.

1 Introduction

Climate change has become widely accepted as a challenge that humans will face in the not-too-distant future. Although uncertainty remains as to the precise nature and extent of these changes, scientific evidence suggests that they are inevitable [1]. The likely manifestations of climate change include rising sea levels, deforestation, dryland degradation and natural disasters. Such environmental events and processes are expected to pose significant challenges for society in terms of their effect on development and livelihoods, settlement options, food production and disease. As well as the large volume of research aimed at investigating the nature and occurrence of future climate change, much current research focuses on the challenges posed to society by climate change and the adaptations necessary for human populations to withstand them. One such adaptation strategy is the migration of people away from affected areas. It has been predicted that challenges to livelihoods in vulnerable regions worldwide will lead to the large-scale displacement of people, both internally and internationally with estimates of some 200 million to 1 billion climate change induced migrants by 2050 [2,3,4].

The variation in migratory response to changes in climate has been shown by a number of events. At one extreme, the experience of the US Gulf coast with Hurricane Katrina in 2005 showed the ability of a single climate event to induce considerable displacement of a human population [5]. By contrast, studies of migration of agricultural populations in the Sahel have shown that rather than encouraging migration, decreases in rainfall (and the subsequent bad harvests) tend to limit the ability of households to invest in long-distance movement [6,7]. As a result it has been argued that there is considerable uncertainty in the prediction of climate change induced migration [8,9]. The first major source for this uncertainty results from ambiguities in the extent and magnitude of the climate signals responsible for pushing and pulling migrants. The second contributing source of uncertainty results from variation in the individual contexts, perceptions and behaviour of the people upon whom the climate signals act.

Studies of climate-induced migration in the past have commonly calculated the numbers of ‘environmental refugees’ by projecting physical climate changes, such as sea-level rise, on an exposed population [10,11,12]. These studies assume that a person’s ability to cope with variations in climate is proportional to growth in Gross Domestic Product (GDP). In reality migration responses are the result of a far more complex combination of multiple pressures and opportunities that shape the behavioural decisions of individuals. Previous approaches to understanding such behavioural decisions have not successfully isolated environmental influences from the multitude of other factors that influence migration at the individual or household level. Empirical modelling techniques present the only way to effectively simulate such a behavioural process and predict the scale and impact of displacement as a result of climate change. By applying an agent-based modelling technique to the migration and climate change nexus, the influence of environmental factors upon the migratory response may be better understood. In creating such a model, the sensitivity of the migratory process to climate variability and change may be further investigated and assessed.

The latest Intergovernmental Panel on Climate Change (IPCC) report [1] suggests that projected reductions in yield in some African countries could be as much as 50 per cent by 2020. With small-scale farmers being the most likely to be affected the impact of this reduction in yield upon human settlements is likely to be significant. As one of the poorest countries in the world, the population and economy of Burkina Faso depend largely upon rain-fed agriculture and cattle-raising. The large number of people who rely upon subsistence agriculture and small-scale farming are thus very sensitive to changes in climate. As a nation with a historically mobile population whose livelihoods are sensitive to changes in climate variables such as rainfall, Burkina Faso presents an appropriate case-study for investigation into the issue of environmentally induced displacement.

This paper presents the development and testing of an agent-based model designed to replicate 1970-2000 climate migration in Burkina Faso and simulate migration flows forwards to 2060. The agent model we present has been developed using existing theoretical developments in the fields of human migration and climate change adaptation. These theoretical foundations are combined with advances in the field of social psychology to develop a conceptual basis for agent cognition in the model. At this early stage in the development of the model, agents in the modelled environment of Burkina Faso interact with one another and their environment to develop intentions to adapt to changes in rainfall through migration. The likelihood of an agent migrating is affected by both their individual attributes and their placement in a social network within which changes in rainfall are discussed.

2 The Decision to Migrate

Migration has always been a fundamental component of human history. Following years of academic consideration the topic has been the subject of much theoretical debate. Such notions as those of the ‘push’ and ‘pull’ factors of origins and destinations and the “intervening obstacles” that stand between an individual and their migration aims [13] have been developed to provide a simplistic analysis of migrant motives. The decision made by an individual to move from one location to another is however a personal choice formed as a result of a unique combination of circumstances. While in-depth survey-based approaches have been developed that work to disentangle the multiple factors influencing migration at the household/individual level, they do not allow predictions of migrant numbers in the future or under different conditions from those under which the original surveys were performed. However, dynamic approaches such as agent-based modelling provide a means to adjust various parameters to further investigate situational changes and future scenarios.

In modelling the migration decision, agents can be used to represent either individuals or households and are programmed to act on the stimuli they receive throughout the simulation. The agents used in an ABM are situated within a simulation environment that, in this instance, represents the geographic location. As they move around the environment agents come into contact and communicate with other agents whose circumstances and migration history may differ from their own. Through such agent-agent interaction, one individual may affect the later choices of another by, for example, sharing a positive experience of migration to location l, under rainfall conditions rc. An individual agent can therefore learn from their surroundings, personal experience and that of other agents through a rational thought process and adapt their behaviour accordingly. In order to represent these agent processes and incorporate them into an agent-based model, we first develop a conceptual basis for individual decision making within the model.

Grothmann and Patt [14] present a process model of private proactive adaptation to climate change (MPPACC) which separates out the psychological steps to taking action in response to perceptions of climate. The MPPACC provides a useful basis from which to develop a conceptual model of the reasoning undertaken by an agent in their migration decision. In seeking a basis from which to develop the MPPACC into a conceptual model to suit an ABM we draw upon theoretical developments made in the field of social psychology.

The Theory of Reasoned Action was developed by Fishbein and Ajzen [15] as an expectancy-value model that recognises attitudes as just one determinant of behaviour within a network of predictor variables. The theory proposes that the proximal cause of behaviour is ‘behavioural intention’, a conscious decision to engage in certain behaviour. Making up this behavioural intention is the attitude toward the behaviour) and the subjective norm (the belief that a significant other thinks one should perform the behaviour and the motivation to please this person). By extending the theoretical model to incorporate the additional parameter of perceived behavioural control, Ajzen [16] proposes the Theory of Planned Behaviour. Intended to aid prediction of behaviours over which a person does not have complete voluntary control, perceived behavioural control was conceptualised as the expected ease of actually performing the intended behaviour. Including attitudes toward behaviour, a subjective norm and perceived behavioural control (as well as the beliefs held by an individual that make up these components), the Theory of Planned Behaviour can be used to effectively break down the reasoning process relating to the development of a behavioural intention in the context of the migration decision.

3 Conceptual Model of Migration Adaptation to Rainfall Change

Developed from the MPPACC and the Theory of Planned Behaviour, we present an agent-oriented model of an individual's migration decision making as an adaptation strategy used in response to changes in climate. The conceptual model of Migration Adaptation to Rainfall Change (MARC) (Figure 1) is divided into four component levels: structural, institutional, individual and household. The central "individual" level of the model displays the reasoning processes proposed as undertaken by an individual, the "household" level permits interaction between members of a household to develop a group strategy, while the "structural" and "institutional" levels provide information used by the agent in their reasoning process. Although migration is a multifaceted process with multiple interacting components contributing to an individual's migration decision, for the purposes of this study, MARC focuses on rainfall variability and change as the key structural component affecting the migration decision. Other core structural components that may also affect migration but are beyond the scope of this study are shown in grey in Figure 1.

At the institutional level a social discourse inputs institution level views on the structural components in question (in this case rainfall variability and change) to the individual. This allows each individual decision-maker to be aware of and potentially share community views on issues such as the severity of a drought period and the potential implications this might have upon harvest yield. As the individual performs their own assessment of the rainfall conditions and the adaptation options available to them, they are able to consider the value of their potential actions in the eyes of the community through the consideration of this social discourse.

Following an appraisal of the potential impacts resulting from perceived changes in rainfall at the structural level, each individual considers their adaptation options on the basis of the three components borrowed from the Theory of Planned Behaviour: their attitude toward adaptation behaviours, their subjective norm (or assessment of the expectations of others), and their perceived behavioural control (or perceived adaptive capacity). The agent uses each of these components to consider each adaptation option available to them. On the basis of an individual's characteristics, migration probability values are used that reflect the normative likelihood of such an individual undertaking each adaptation option. For example, a young single male is more likely to migrate internationally than a married older woman and will be assigned the relevant attitude value to reflect this.

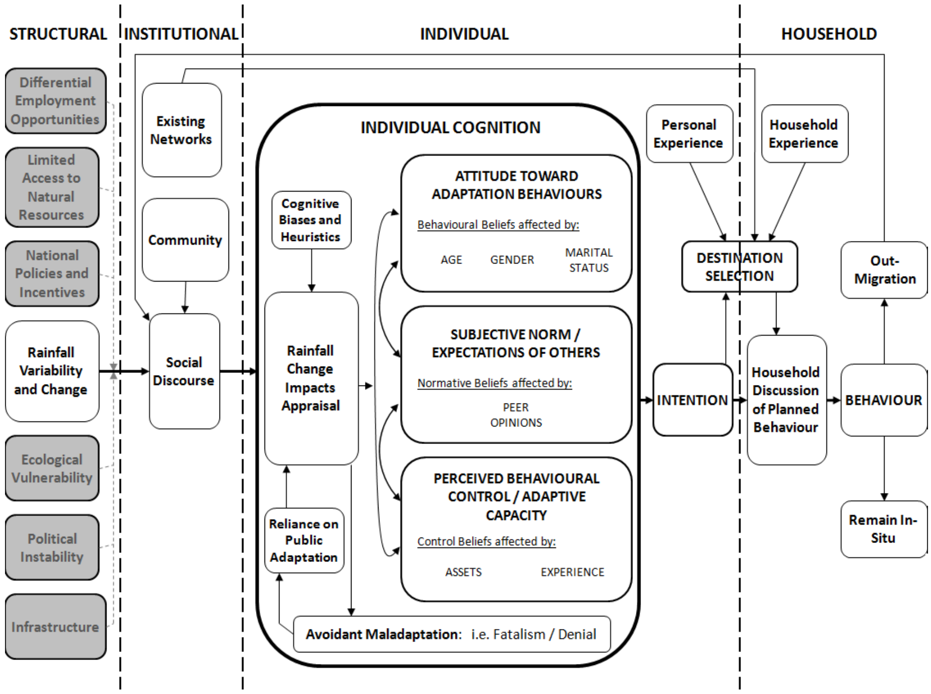

Fig. 1. Model of Migration Adaptation to Rainfall Change (MARC).

The subjective norm component of an individual's reasoning is based upon both visual changes to their surroundings and the choices made by their peers. An agent living in a particular location will therefore consider the actions of others (subjective norm) as a component for consideration in determining their chosen adaptation strategy. For example, if an individual is connected to ten others in a form of social network whereby information such as migration destinations is shared, the preferences of an agent's peers may influence, either positively or negatively, their perceptions of an adaptation option and therefore their willingness to follow that choice.

The final core component of the individual decision-making process presented by MARC is the perceived behavioural control, or ability to undertake a selected adaptation option, of the individual. Determined on the basis of an individual's ability to invest the necessary capital in migration and their previous experience of such activity, the conceptual model proposes that an individual perceives the ease with which they can undertake migration as an adaptation option. On the basis of this combination of the individual's attitude towards each adaptation option, subjective norm and perceived behavioural control, an individual assesses the options available to them and develops an intention to act according to the favoured option. This intention may, for example, result in an individual selecting international migration as the most appropriate adaptation strategy available to them in response to the structural conditions they are experiencing.

The final level of MARC that plays a part in the migration decision making process of an individual is that of the household. At this level, interaction between household members can result in the intentions of individuals being realised or reassessed according to household dynamics such as the overarching influence of a matriarch or patriarch. Following a household discussion of the individual's intentions that results in the selection of a suitable migration destination, the final stage of the model permits the resulting behaviour to be performed (such as remaining in-situ or migrating to a new location). This decision then affects the later decisions of other individuals by altering the institutional level of the model.

The MARC decision-making process that each agent undertakes in their consideration of climate stimuli, and their resulting selection of appropriate adaptation strategies, underpins the formation of the ABM in this paper. However, the individual context of each agent's unique combination of experiences, biases, assets and perceptions defines the heterogeneity of agents and their different responses to both environmental stimuli and the actions of others. The translation of the conceptual processes defined in Figure 1 into thresholds and attributes that inform the construction of an ABM is based on analysis of retrospective migration history data from Burkina Faso.

4 Defining Agent Attributes

The *Enquête Migration, Insertion Urbaine et Environnement au Burkina Faso* (EMIUB), a retrospective multi-level family-type survey conducted in 2000-2001, provides detailed spatio-temporal migration flow data relating to places of residence, work activities, matrimonial unions and offspring of respondents. The data was collected as a nationwide representative survey from over 600 locations throughout the country and included over 8,000 respondents from more than 3,500 households. From this survey data the attributes (age, gender, marital status) of the initial modelled agents, their probability-based attitudes towards migration behaviours, and relevant peer opinion thresholds for subjective norm were defined.

The EMIUB dataset provides us with core attribute information relating to 8,260 individuals recorded as living in Burkina Faso in 1970. These individuals can be divided into their five separate birth locations; Ouagadougou, Bobo Dioulasso, Sahel, Centre and Southwest. On model startup therefore we can locate each of these real agents into their respective zones and assign them the three core attributes used in the modelled migration decision: age, gender and marital status. These zones of origin form the basis for geographical representation throughout the model with different thresholds applying to agents in different zones. In addition to the initial attributes assigned to agents from the EMIUB data, statistical analysis of this resource also provides values for agent attitudes and subjective norms in the decision-making structure of the ABM.

The attitude value an agent in the model assigns to a particular migration option available to them is largely dependent upon their core. Through analysis of the EMIUB dataset, the probability of an agent born in origin location l, with current age, gender and marital status values a, g and s, defines the attitude value of that agent. Probability values for each combination of agent origin zone (birthplace), potential migration destination and combination of attributes under wet, dry and average rainfall conditions are stored within the ABM and are referenced by agents according to the circumstances they are assessing.

The subjective norm (or consideration of the expectations of others) values used by agents in the final ABM are also determined, in part, through analysis of the EMIUB dataset. This component of the conceptual model deals with the interactions between agents and the influence of an individual's peers upon their own migration decision. Where possible therefore, we use quantitative data analysis to inform the agent based model of migration adaptation to rainfall change. The EMIUB dataset provides a useful basis from which to gain such quantitative values. However, as the data was not collected for the specific purpose of constructing an ABM, it was not perfectly suited to the task and was not complete in a way that could permit the inclusion of a greater number of variables (such as ethnicity and status within the household) in the formation of an attitude value. For the purpose of testing the ability of ABM to replicate the migration decision-making process in Burkina Faso however, the data resource provides a valuable basis for model construction and testing.

5 Model of Agent Migration Adaptation to Rainfall Change

The agent model presented here is implemented in AnyLogic 6 University Edition, version 6.5.1. Constructed using five sets of agents defined according to their birthplace or "origin zone", the model environment is that of Burkina Faso with migration being defined as the relocation by an agent from their zone of origin to either one of the other four origin zones or out of the country.

The control of time steps in AnyLogic ABMs is defined using an "event". Using a recurrent time of 1 day, the event component of the model controls agent birth, ageing, marriage and death on a monthly basis. As a result, each month agents can be born into all five origin zones of the model at a rate defined by a birth rate function at model startup. Those agents already initialised into the model will age by 0.083 ($1/12^{th}$) of a year each month and agents with appropriate existing age and marital status attributes will marry and die according to marriage rate and death rate functions also established at startup. Also controlled through the event component but, for simplicity's sake, only occurring once a year at the end of the wet season in September, is the migration decision undertaken by agents. Taken on the basis of the structural rainfall conditions affecting an agent's location, this migration decision follows the basis of the decision-making structure presented by MARC in Figure 1.

The migration decision of agents within any origin zone of the model is therefore comprised of three core components; behavioural attitude, subjective norm and perceived behavioural control. In order to develop a preferred course of action in response to the structural rainfall conditions affecting an individual, each agent will score the five active options (migrate to one of the four other zones, or migrate internationally) available to them on the basis of these core components. With over 8,000 agents initialised into the model, the migration decision is computationally quite demanding. As a result, in this version of the model, the migration decision is only performed once a year. However, in reality, and in future versions of the model, an individual will continually assess the options available to them for some time prior to actually being placed in the situation where migration may become a necessity.

The behavioural attitude (BA), subjective norm (SN), and perceived behavioural control (PBC) values calculated by agents contribute to their behavioural intention (I) towards the migration option being considered. As shown in Equation 1, an agent's behavioural attitude is adjusted according to the combined impact of their networked peers (subjective norm) and their perception of whether or not they have the assets/experience necessary to undertake the migration (perceived behavioural control). Agents perform the intention calculation for each of the migration adaptation options available to them.

$$I = (BA \times SN) \times PBC \tag{1}$$

5.1 Perceived Behavioural Control

The perceived behavioural control (PBC) of an agent, or their perception of whether or not they have the assets/capability to undertake a migration adaptation option, is made up of two components. The first of these involves an assessment of whether or not the agent has the assets necessary to undertake the migration option. The second considers whether or not an agent has previous experience of migration. The final outcome of the PBC calculation is a binary result that denotes whether or not the agent believes they have the means/experience necessary to undertake the migration option being considered. As agents in the model are largely subsistence farmers, and a common measure of wealth across Burkina Faso is livestock, the primary determinants of assets in the model are livestock. Calculated on the basis of a household's stock of poultry, sheep, goats, donkeys and cattle, livestock assets (la) in the dataset range from 0.02 (1 chicken) to 45.6 (a herd of 228 cattle).

Although the EMIUB does not provide time dependent data on the assets of individual migrants, the survey includes information on the year 2000 assets of respondents. As a result we have data on the ratio of asset distribution in each of the model zones in 2000 as well as migration rates of respondents for that year. Assets are therefore assigned to agents in the model according to this rate and their impact upon the PBC value towards an option is measured using an asset rate (ar).

For agents not employed within the agricultural and craft sectors (around 25% of the population of each zone), livestock assets make up the total input to the asset rate. However, the income of those individuals working within the agricultural sector, and, to a lesser extent, those closely linked to this sector, are largely controlled by the success of harvests, and the assets amassed by such workers may be less than those in more steady employment (such as individuals designated as government employees within the data). Agents employed in such jobs therefore incorporate an additional measure of rainfall assets (ra) into the calculation of their PBC values.

Rainfall assets (ra) are calculated on the basis of the current year's ($r1$) and two previous years' ($r2, r3$) regional rainfall (measured in millimetres per month) according to whether they were below, on, or above average (scoring 1, 2 and 3 respectively). Rainfall assets are calculated by each agent on the basis of Equation 2.

$$ra = r1 + r2 + r3 \tag{2}$$

Agents initialised into the model at startup in 1970, as well as retrieving age, gender and marital status values from the data, retrieve job type according to the individual they represent. Those agents born into the model post-startup are assigned jobs at the rate by which they are distributed in the EMIUB data. As a result, the asset rate (ar) that an agent uses in the calculation of their PBC value incorporates both livestock assets (la) and rainfall assets (ra) and is dependent upon occupation (oc) (Equation 3). Because of the varied impact of rainfall upon the income/rainfall assets of agents employed in different sectors, oc values range from 0.0333 for agricultural workers whose income is most affected be regional rainfall, to 0.0 for individuals employed outside the agricultural and craft (*Artisanat* in the EMIUB) sectors.

$$ar = la + (ra \times oc) \tag{3}$$

The experience component of the PBC calculation permits an agent to return a higher value towards a migration option if they have previous experience of migration, either to the destination in question or another. Calculation of the experience rate (er), defined on the basis of an agent's experience of migration to the destination in question (de) and their experience of migration in general (ge) is performed on the basis of Equation 4. In the formation of an experience rate that contributes to the PBC value, prior experience of migration to the destination in question (de) is scaled to be of greater value to the experience rate than prior experience of migration to other destinations (ge). Both values represent the number of times an agent has migrated to each classification of destination and, throughout the duration of model execution, ordinarily range from 0 to a maximum of 10.

$$er = \frac{de}{100} + \frac{ge}{1000} \tag{4}$$

A calculation of behavioural control (BC) is performed using the asset rate (ar) as the primary indicator and the experience rate (er) as a secondary value in the manner shown in Equation 5.

$$BC = 0.75(ar) + 0.25(er) \tag{5}$$

If a random number (rn) between zero and one generated by the model is less than the resulting BC value, a binary score of 1 is allocated to PBC, migration is perceived by the agent to be within their means, and they continue to develop an intention value towards that option through Equation 1. Otherwise a value of 0 is assigned to PBC and there will therefore be no intention to migrate. The agents' perceptions of their behavioural control return a binary outcome in order to aid clarification of the migration decision. Rather than an agent thinking they 'might' have the capability to migrate, we define their consideration of an option as a yes/no decision formed on the basis of assets and experience. This enables clearer definition of an agent's options and a greater ability of the model to quantify the 'able' population.

5.2 Behavioural Attitude

The behavioural attitude (BA) component of the decision to migrate is, for each agent, selected from a matrix on the basis of the origin location (l) of the agent, the structural rainfall conditions (rc) that year and the current age (a) gender (g) and marital status (s) attributes of the agent. The origin location ranges from 1 (Ouagadougou) to 5 (Southwest) in the model while rainfall conditions range from 1 (dry) to 3 (wet). The probability value (PV) used by an agent is calculated from the number of agents with defined attributes a, g, and s who are migrants (m) from location l, under the prevalent rainfall conditions rc, divided by the population (p) of that location with the same defined attributes (Equation 6). The probability values stored within the matrix are derived from analysis of the EMIUB dataset and represent the likelihood of an agent with the same characteristics undertaking migration as an adaptation strategy in the face of the existing conditions.

$$PV(a, g, s, l, rc) = \frac{m(a, g, s, l, rc)}{p(a, g, s, l)} \tag{6}$$

The probability values retrieved by each agent reflect the likelihood of any agent with age, gender and marital status characteristics a, g and s migrating. However, as only those agents who perceive that they are able to complete the migration in question will actually do so, we need to adjust these values to represent the increased likelihood of an agent within this reduced ‘able’ population migrating. Such agents are those that return a PBC value of 1 towards the option in question and so consider themselves capable of migrating as a result of the behavioural control (BC) value calculated in Equation 5. The adjusted probability value represents the behavioural attitude (BA) of the agent and is calculated on the basis of Equation 7 using the probability value for the relevant population of the agent’s origin location (PV) and the population of agents that have scored 1 for their PBC value towards that option (op) in the current model cycle.

$$BA = \frac{PV(a, g, s, l, rc)}{op} \tag{7}$$

5.3 Subjective Norm

The subjective norm component of the decision to migrate is derived through an agent’s consideration of the opinions of their networked peers (po) (Equation 8). Each agent in the model is linked to ten others through a network defined at model startup. In a continuous 2-dimensional environment such as that used in the model, the network can be defined as random/scale-free/ring-lattice. Networked agents pass messages between themselves that inform one another of their most recent migration decisions. On the basis of the messages received by an agent from their peers, a scoring system is used to assign peer opinion values to each of the migration options being considered. However, as the number of peer messages an agent is likely to need to persuade them to migrate to a new location is dependent upon their individual circumstances, a multiplier function (f) is used to weight the values. For example, an agent migrating internally from the Sahel will have a different norm affecting their behaviour (perhaps due to the reluctance of Fulani people inhabiting the Sahel region to leave their homes) than an agent considering the same migration but living in the Southwest (where annual migration to neighbouring Côte d'Ivoire is commonplace).

$$SN = f(po) \tag{8}$$

Analysis of the EMIUB dataset reveals the range of probabilities of an agent migrating either internally or internationally in the top ten most populated locations in each of the five zones in 1990. The probability of an individual migrating from these locations is used to suggest the range of the peer impact component (po) of the subjective norm. For example, the lowest probability of migrating internally from a location (individual village/town) within the Sahel is 0.029 while the maximum probability provided by another location is 0.068. By ranking the migration probability values for the top 10 most inhabited locations in the region in this manner and dividing each by the probability of migrating in the whole of the Sahel zone we can develop a multiplier function.

When the top 10 most inhabited locations in the Sahel are ranked according to the probability of a member of their community migrating either internally or internationally, the multiplier functions calculated accordingly show a linear R^2 value of 0.9742 and 0.8893 respectively when plotted as a line graph. As a result, we conclude that the factor values calculated provide a fair representation of the impact of an agent's peers upon their likelihood to migrate.

From the line plots of the calculated multiplier functions we use the function equations from trend lines placed through the data to scale the influence of the opinions of an agent's peers in the model. Using these equations, agents in the model will scale the impact of their networked peers' opinions using the multiplier function (f) relevant to their own cultural reference.

Although agents are networked with 10 of their peers, it is very unlikely that all 10 would have last migrated to the same location. As a result we scale the multiplier functions so that each score for a location has twice the impact. For example, if 5 or more of an agent's peers favour one location, the agent will use the maximum multiplier function available from the data, thereby increasing the likelihood that the agent will favour that migration option.

An agent originating in the Sahel with four peers favouring migration to the southwest as an adaptation option will therefore generate a peer opinion value towards their subjective norm of 1.04 for that option. If the same agent has four peers who favour international migration, their peer opinion score will be 1.69. In both scenarios the impact of the subjective norm component is to increase the likelihood of the agent migrating to the considered destinations when used in the development of a behavioural intention (Equation 1). The more peers an agent has that favour a particular migration option, the greater the subjective norm value.

5.4 Behavioural Intention

By calculating behavioural intention on the basis of Equation 1, each agent stores intention values relating to the five migration options available for their consideration. Comparing each of the intention values an agent has assigned to each of the migration options available to them and identifying the highest scoring option, enables an agent to then make a behavioural choice. Starting with the highest scoring migration option considered, each agent effectively rolls a dice to see if their intention is realised. If a random number between 0 and 1 is generated that is less than the final intention score, the agent will follow that course of action. If however the random number is greater than the intention value the agent moves on to consider the next highest scoring migration option they have considered. Without this step, agents would generally migrate to the location for which they score the highest attitude value. While this is, in essence, the desired outcome, if agents with specific age, gender and marital status values retrieve an attitude score of, for example, 0.0075 for one migration option and 0.0074 for another, without this additional 'roll of the dice', disproportionately more agents would migrate to the marginally higher scoring location.

At this early stage of model development an agent will only ever migrate for a period of 7 months before they return to their origin location. Although this may not represent the real world migration of Burkinabé people, for the sake of model simplicity and transparency of results at this stage, we apply this standard rule to all agents. Performing the agent migration decision in September of each year and commanding all agents to return in May does however broadly represent a large number of annual migrations undertaken by Burkinabé people. Field interviews [17] conducted in Burkina Faso revealed that many people across the country reside at home for the duration of the wet season, only migrating following the harvest in August/September.

5.5 Model Cycles and Feedbacks

Through feedbacks built into the model, events that occur as it runs through each year of the simulation play a part in later events. As an agent goes through the process of ageing and getting married, their attributes change and the attitude they apply to the migration decision changes. Equally, as an agent gains experience of migration to various destinations, their perceived behavioural control value for repeating that action again increases. As these values change, so too do the messages that agents send to their peers regarding their preference for each option, therefore impacting the subjective norm values used by agents in their own decisions. It is these interacting components within the ABM that can produce emergent behaviour beyond that anticipated by a more linear statistical analysis.

As time progresses in the model, the structural rainfall conditions affecting migrants also change. These changes in rainfall affect the migration decisions of individuals. Using IPCC rainfall scenario data to 2060, the model can be run under different future rainfall scenarios to test the sensitivity of migration in Burkina Faso to rainfall. However, the first step in testing the ability of the model to replicate the migration decision is to run the model for a period during which migration flow data is available.

6 Early Model Validation

In a decision-making context such as adaptation to rainfall change in Burkina Faso it is possible to assess model validity by comparing the quantitative migration output to migration data for the region. On this basis, if the model data relates well with the experimental data, it is generally assumed that the model fits the human data well and that the model is externally valid. As a result of the emergent nature of the outcomes of agent-based models, a number of ensemble model runs should be performed to test the variation in outcomes generated. Doing this reveals how the context and circumstances of agents has a considerable impact upon their behaviour according to the rules specified.

By analysing data from only the period 1990-1999 to populate the model with agents that can retrieve appropriate values for both their behavioural attitude probabilities and subjective norm migration functions we leave a considerable amount of data available for model validation. Data on the movements of the same population from 1970-1989 were therefore used to see if the model is capable of accurately using a component part of the EMIUB data to reproduce the past. Table 1 displays the total observed and total modeled migration flux generated by three runs of the Agent Migration Adaptation to Rainfall Conditions (AMARC) model. Figure 2 shows the total mean migration flow result from the three runs of the model compared to the observed migration flux recorded in the EMIUB data.

Table 1. Table of observed and modelled Burkina Faso total migration data for the 8,260 agents initialised into the AMARC model at 1970. Model run for the period 1970-1989.

Year	Observed Data	Modelled Data Run 1	Modelled Data Run 2	Modelled Data Run 3
1970	144	151	171	161
1971	109	99	97	98
1972	142	107	96	95
1973	137	97	80	94
1974	184	118	112	123
1975	172	95	90	125
1976	188	101	100	102
1977	185	117	95	112
1978	205	98	122	112
1979	204	121	103	128
1980	309	169	170	198
1981	207	170	169	189
1982	251	170	162	162
1983	258	148	160	135
1984	295	219	181	211
1985	314	190	203	189
1986	294	187	146	151
1987	331	174	167	165
1988	339	242	206	257
1989	299	240	239	241

Mean correlation coefficient of the modelled and observed datasets: 0.8 (1970-1989)

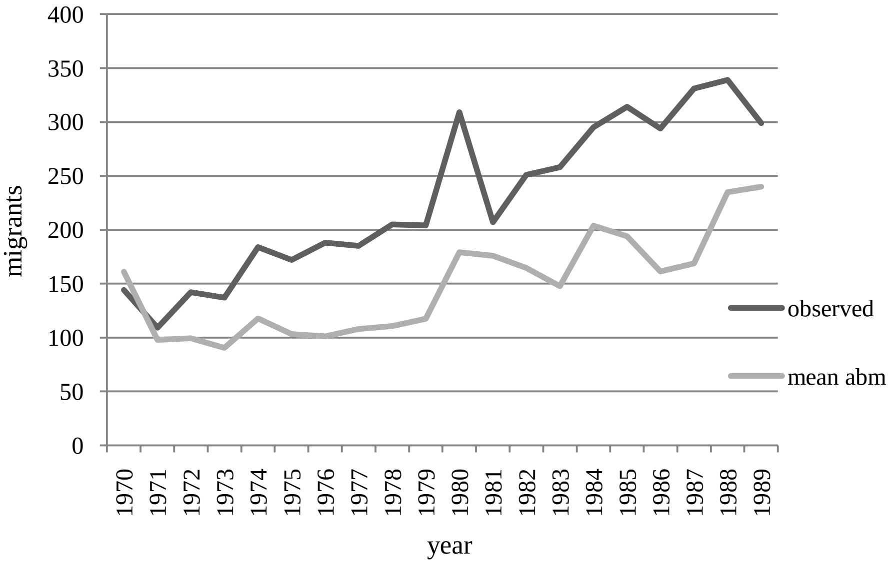

Fig. 2. Mean results of three validation runs of the AMARC model: annual variation in total migrant flux from 1970-1989 as simulated by the ABM and observed.

The observed and modelled data displayed in Table 1 and Figure 2 have a mean correlation coefficient of 0.8 for the test period 1970-1989. This degree of correlation suggests that the model is, over the 20 year test period, managing to relatively accurately recreate the migration decision in Burkina Faso.

Although a strong correlation between observed and modeled data has been observed at this stage, further development and testing of the model is required before it can be reliably used to infer future migration flows. The ability of the model to replicate known migration flows will alter throughout the development of the model as further parameters are added to the migration decision of agents.

7 Conclusion

Previous attempts to model the impact of climate stimuli on human migration have been largely inadequate. This is, in the main, as a result of the issues associated with modelling such a complex and multifaceted process. When developed on the basis of observed empirical data that reflects a real-world situation, agent-based modelling provides a realistic and promising opportunity to integrate the multiple variables involved in migration and manipulate these variables in order to obtain simulations of future migration patterns. The influence of the unique responses and attitudes of individuals towards manifestations of climate is of considerable importance in identifying the livelihood impact they perceive and the importance of these in their current and future existence. It is hoped that further development of the AMARC model will provide a basis from which future attempts to quantify the impact of changes in climate upon migration can draw upon.

References

1. Boko, M., Niang, I., Nyong, A., Vogel, C., Githeko, A., Medany, M., Osman-Elasha, B., Tabo, R., Yanda, P.: Africa. Climate Change 2007: Impacts, Adaptation and Vulnerability. Intergovernmental Panel on Climate Change. Cambridge (2007)
2. Myers, N.: Environmental Refugees. Population and Environment. 19, 167-182 (1997)
3. Myers, N.: Environmental refugees: a growing phenomenon of the 21st century. Philosophical Transactions of the Royal Society. 357, 609-613 (2002)
4. Stern, N.: The Economics of Climate Change – The Stern Review. Cambridge University Press. Cambridge. (2007)
5. Kniveton, D., Schmitt-Verkerk, K., Smith, C., Black, R.: Climate Change and Migration: Improving Methodologies to Estimate Flows. International Organization for Migration . Migration Research Series, No. 33 (2008)
6. Findley, S.: Does Drought Increase Migration? A Study of Migration from Rural Mali during the 1983-1985 Drought. International Migration Review. 28, 539-553, (1994)
7. Henry, S., Schoumaker, B., Beauchemin, C.: The Impact of Rainfall on the First Out-Migration: A Multi-Level Event History Analysis on Burkina Faso. Population and Environment. 25, 423-460 (2004)
8. Kibreab, G.: Environmental Causes and Impacts of Refugee Movements: A Critique of the Current Debate. Disasters. 21, 20-38 (1997)
9. Black, R.: Environmental refugees: myth or reality. UNHCR. Geneva. (2001)
10. TERI: The economic impact of a one-metre sea level rise on the Indian coastline: method and case studies from New Delhi. Tata Energy Research Institute. Bangalore. (1996)
11. Nicholls, R.J., Tol, R.S.J.: Impacts and responses to sea-level rise: a global analysis of the SRES scenarios over the twenty-first century. Philosophical Transactions of the Royal Society A – Mathematical, Physical and Engineering Sciences. 364, 1073-1095 (2006)
12. Warren, R., Arnell, N., Nicholls, R.J., Levy, P., Price, J.: Understanding the regional impacts of climate change. Research report prepared for the Stern Review. Tyndall Centre. Norwich. (2006)
13. Lee, E.: A Theory of Migration. Demography. 3, 47-57 (1966)
14. Grothmann, T., Patt, A.: Adaptive Capacity and Human Cognition: The process of Individual Adaptation to Climate Change. Global Environmental Change. 15 (3), 199-213 (2005)
15. Ajzen, I., Fishbein, M.: Understanding attitudes and predicting social behaviour. Prentice-Hall. Englewood Cliffs, NJ. (1980)
16. Ajzen, I.: The Theory of Planned Behavior. Organizational Behavior and Human Decision Processes. 50, 179-211 (1991)
17. Smith, C.: Field Notes from Burkina Faso, January – March 2009. Unpublished