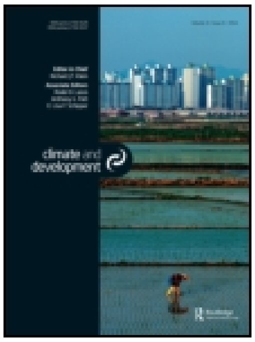

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Modelling migration futures: development and testing of the Rainfalls Agent-Based Migration Model – Tanzania

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This paper describes the conceptual and practical development and testing of the Rainfalls Agent-Based Migration Model – Tanzania (RABMM-T). Drawing upon the literature on the process of developing and parameterizing a social simulation in the absence of spatio-temporal data, the paper outlines the translation of the conceptual framework into a working agent-based model. The possible impact of a change in local rainfall variability and mean upon household income, food production, and therefore the resilience and migration of members, is simulated to permit consideration of the possible impact of the artificial scenarios tested. In addition to the influence of changing rainfall, other non-rainfall scenarios are tested to explore the scale of the changes simulated. It is proposed that while a relatively clear impact of rainfall scenarios upon household resilience is simulated, the impact upon migration of household members is generally less clear. Furthermore, demographic and societal changes to the model are also seen to clearly contribute to the simulation outputs generated. The paper concludes that RABMM-T offers the first step in developing a potentially valuable resource for producing comparable migration forecasts that consider a range of contributory mechanisms. However, careful parameterization is required to ensure the quality and value of model outputs.

Keywords: rainfall migration; Tanzania; agent-based model; parameterization; social networks.

Introduction

The findings of each of the Intergovernmental Panel on Climate Change's Assessment Reports draw upon global climate models that project future change on the basis of well-established physical principles. Between each assessment report, improvements have been made in developing the resolution, computational techniques and processes of parameterization used in model construction. From such advances Randall et al. (2007) were able conclude there was, considerable confidence that Atmosphere-Ocean General Circulation Models (AOGCMs) provide credible quantitative estimates of future climate change, particularly at continental and larger scales. Within that statement the elements that provide legitimacy to the claim are the degrees of confidence and credibility that may be conveyed. In this context 'confidence' refers to the quantification of model errors, themselves derived from how well the model performs in an ensemble of tests. From a high degree of confidence, credibility may be achieved through thorough and open model assessment and refers to how worthy of trust model results may be.

Our capacity to model and project changes to physical systems is of considerable value to governments and decision-makers tasked with facilitating mitigation and/or adaptation measures in response to future changes in climate. However, AOGCM outputs generally exist at some degree of separation from the human systems they impact. For credible estimates of future climate change to be of use to policy-makers, the separation between climate model outputs and their projected impact upon human systems must be addressed. However, forging a link between anticipated changes in a complex physical process such as precipitation and its impact upon human livelihoods at a scale of analysis useful to policy-makers remains a challenge. While the science of climate change has developed models that are based on well-established and detailed physical principles, the social scientific understanding of behavioural change lacks an equivalent degree of reliably re-applicable and re-scalable principles. Indeed, Perch-Nielsen (2004) found that the types of models used in climate and migration research were very different, to the extent that existing models could not be linked. Furthermore, Perch-Nielsen, Bättig and Imboden (2008) suggested that the connection between climate change and migration is by no means deterministic and aligned with a 'common sense' approach but depends upon numerous factors relating to both the people and the region in question.

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The readily apparent attributes of individuals (such as age, gender and marital status) are generally accepted within the modern literature as resulting in different degrees of resilience towards environmental change. The distribution of such attributes within a population is referred to within this paper as its *evident heterogeneity*. However, an inevitable outcome of a group of individuals inhabiting an environment within which interaction can occur is the formation of some sort of society. Such societies often take the form of complex adaptive systems as a result of the multiple nonlinear interactions that can occur between members and lead to complex global patterns with new properties. In addition to the evident heterogeneity of individuals, the more subtle influence of what this paper terms *societal heterogeneity* is therefore proposed to affect behaviour and potentially lead to otherwise unexpected, or emergent, outcomes. Due to the latent impact of societal heterogeneity upon the outcomes of behavioural decisions, this paper proposes that the explicit consideration of such factors is central to credible projections of how physical changes may affect human systems.

Agent-based models

Described by Buchanan (2009) as the social science analogue of the computational simulations now routinely used elsewhere to explore complex nonlinear processes such as the global climate, ABMs may present a viable means of projecting the impact of physical changes upon human systems. A form of social simulation, an agent-based approach represents a computational technique for the study and modelling of social interactions and communications (Li, Mao, Zeng, & Wang, 2008). Alongside more traditional representations of evident heterogeneity, an ABM can include direct consideration of societal influences.

Although not widely used for simulating climate change impacts and adaptation, the potential contribution of ABMs to the field has been reported. Within recent analyses of developments in methodological approaches to linking climate change, environmental degradation and migration, both Piguet (2010) and McLeman (2012) cite the potential for ABMs to contribute to our understanding of the process. Within the climate–migration field, Kniveton, Smith, and Wood (2011) and Kniveton, Smith, and Black (2012) draw upon migration history and rainfall data and the social psychological theory of planned behaviour to develop an ABM that serves as a heuristic device to understand the characteristics of aggregate migration behaviour. Such an approach is described by Piguet (2012) as having the potential to significantly improve our understanding of the population displacements linked to climate change.

Despite the potential of Kniveton et al.'s agent-based approach, national-scale representative migration history data such as that used by the authors are both rare and difficult to collect. As such, the development of an alternative means of using an agent-based system to model the impact of changes in rainfall upon human migration is sought. This paper presents the development and testing of an ABM of livelihood stress and migration using survey data collected by the 'Where the Rain Falls' (hereinafter 'Rainfalls') (Warner et al., 2012) project in three villages of Same District, Kilimanjaro Region, Tanzania.

Livelihoods and migration in the Kilimanjaro Region of Tanzania

A wealth of literature exists on the nature of the environment–migration nexus found across Africa. Jónsson (2010), for example, offers a review of the environmental factor in migration dynamics across 13 case studies in the Sahel region. Barrios, Bertinelli, and Strobl (2006) also explore the influence that climatic changes might have had in shaping the pattern of urbanization in sub-Saharan countries compared to the rest of the developing world. Numerous authors have also explored more in-depth environment–migration dynamics in more restricted geographical regions, such as the work of Henry, Schoumaker, and Beauchemin (2004) and Konseiga (2006) in Burkina Faso. However, few publications focus specifically on the environment and migration nexus in Tanzania.

In this special issue, Afifi, Liwenga, and Kwezi (2013) provide an in-depth exploration of the nature of rainfall-induced crop failure, food insecurity and out-migration in Same, Kilimanjaro, Tanzania using the same sources of data used by this research. The authors identify a positive relationship between rainfall shortage and out-migration in the district with rainfall variability found to affect human mobility through livelihood/food insecurity. For a more in-depth discussion of the causal links at play between rainfall variability and human migration and a presentation of empirical data from the case study region, see Afifi, Liwenga, and Kwezi (2013).

Conceptual framing

While the initial contributions made by ABMs were theoretical and abstract, Janssen and Ostrom (2006) report an increasing drive to combine models with empirical methods, both quantitative and qualitative. The authors go on to suggest that dimensions of social influence, agent cognition and temporal dynamics are central to the development of an empirically informed ABM. Under the guidance of these three core considerations, the conceptual framework for the Rainfalls Agent-Based Migration Model – Tanzania (RABMM-T) is proposed. Figure 1 displays the conceptual framework developed by this research for translation into RABMM-T. The framework defines the level of abstraction adopted by the research in appropriately

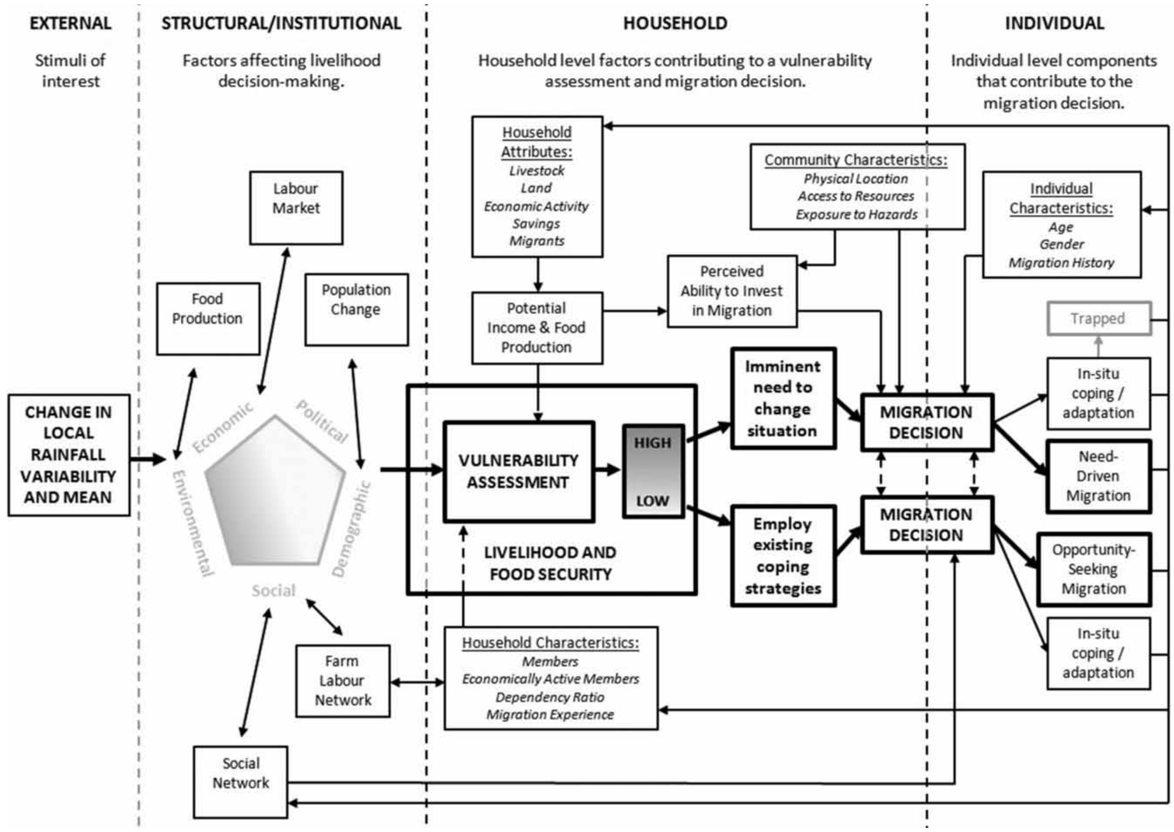

Figure 1. RABMM conceptual framework, adapted from Warner et al. (2012).

representing, without exhaustively reproducing, the true degree of complexity present in migration decision-making in the face of rainfall change.

With four levels of analysis: external; structural/institutional; household and individual, the conceptual framework sets out the range of components included at each level of analysis. At the 'external' level the change in local rainfall variability and mean experienced by a location is input. This change is seen to affect a pentagon of 'drivers of migration' (Black, Bennet, Thomas, & Beddington, 2011), a number of subcomponents of which are identified for explicit inclusion in the model.

At the household level, the foremost component is the 'vulnerability assessment', from which a household determines their resilience at time *t*. On the basis of the interdependencies identified by Afifi, Liwenga, and Kwezi (2013) as at play in the case study region, this assessment is framed by the degree of structural/institutional livelihood and food security their community is experiencing, their own characteristics (members, economically active members, dependency ratio and migration experience), and their income and food production (determined by attributes such as livestock, land, savings and the economic and migration activities of members). Regardless of the degree of resilience a household identifies, migration represents an opportunity to increase household livelihood and food security. Within the conceptual framework, migration is proposed to result from an individual decision mediated by the household. While an individual's migration decision is thus affected by their household's ability to invest in migration (itself affected by income and community characteristics) the propensity of an individual towards migration is driven by characteristics of age, gender, migration experience and the social network.

In line with the three dimensions of an empirically informed ABM identified above, the conceptual framework incorporates social influence at multiple levels of analysis through the social and farm labour networks that allow the sharing of views on migration between peers and a means to distribute farm labour between members of the community. Processes of agent cognition are also included through the consideration of both household and individual levels of decision-making within the bounded rationality of human actors. Finally, a temporal dynamic is included as a result of the social feedback mechanisms that permit internal changes to the system over time. These feedbacks both adjust the social sphere within which decisions are being modelled to take place (by informing household members and peers of migration actions) and affect an individual's tendency towards migration in the future. As in a real-world system, the behaviour of one agent thus affects the later actions of others. Further details of the interactions and dependencies presented within the framework diagram may be found in Warner et al. (2012).

Model parameterization

The conceptual framework sets out the level of detail and abstraction used to represent the complex phenomena under scrutiny. However, it is the process of parameterization that plays the largest part in controlling the confidence and credibility with which model results can be treated. Bonabeau (2002) suggests that finding the correct level of representation and complexity to appropriately model a system is an art more than a science. The more complicated a model, the more parameters and equations are required and, often, the more assumptions are needed to effectively bridge the divide between the true and simulated realities.

Janssen and Ostrom (2006) distinguish between four approaches to use empirical information: case studies; stylized facts; role play games and laboratory experiments. Where large *n* survey data with high-quality observations is available (such as the case of Kniveton et al., 2011, 2012), Janssen and Ostrom refer to the advantage of deriving statistical distributions and other stylized facts from the empirical data. Such data also provide a valuable resource for validation. However, in the absence of extensive spatio-temporal data a case study approach to model development may be pursued. In a case study context, the researcher has multiple but incomplete sources (census data, surveys, field observations and remotely sensed data) available to aid the development of different system components. Effectively used, such an approach can aid better understanding of the interactions between different components of a system and the impact of different scenarios.

Gray (2010) notes that research on migration and the environment has been limited by both disciplinary boundaries and a lack of appropriate data sets. With longitudinal migration data being far from the norm, this research does not benefit from the sort of representative retrospective life history data that lends itself to a stylized fact approach to parameterization. However, the Rainfalls project survey and participatory rural appraisal activities conducted in the Kilimanjaro region of Tanzania (Liwenga, Kwezi, & Afifi, 2012) offer data that may contribute to a case study format. Although covering more than 1000 individuals from 165 randomly sampled households in three communities, the survey data collected in Tanzania are not representative at any larger scale and only provides comprehensive data on the attributes and actions of respondents at the time of data collection in 2012. In spite of the fact that such data provide a wealth of information that is useful for the parameterization of model variables at the start of a simulation, it fails to provide an adequate basis from which to quantify the degree of change in such variables given some form of external change over time. Because of these data limitations, the conceptual framework described above is designed to accommodate a less data-driven and more heuristic case study-based approach that uses survey data and recent literature to explore the role of rainfall in shaping the drivers of migration within the communities surveyed.

To capture the unique situation captured by the Rainfalls research in the Tanzania case study study location, the process of parameterization begins with an analysis of the available data to explore significant relationships and dependencies within the system of interest. Logistic regression analyses were conducted to identify the variables that contribute significantly to the prediction of migration being used by a household. Variables for which the resulting univariate regression coefficient was not significantly different from zero are listed in Table 1 and regression coefficient values displayed for both univariate and multivariate regression analyses.

Table 1. Variables identified using univariate logistic regression analyses as contributing significantly to the prediction of migration being used by a household surveyed in the Kilimanjaro Region of Tanzania.

Variable	Univariate binomial logistic regression $P>$	Multivariate (ALL) binomial logistic regression $P>$
Land category	.003***	.004***
Family size	.001***	.412
Average age of householders	.081* (–)	.185 (–)
Economically active members	.000***	.219
Participate in farming	.006***	.468 (–)
Participate in non-farm work	.025**	.717
Work on others' land	.011** (–)	.120 (–)

* = $P>$ 90%.
** = $P>$ 95%.
*** = $P>$ 99%.
(–) = inverse relationship.

Whether or not a surveyed household had ever had migrants is seen to be significantly determined by numerous variables when tested using univariate models. These include variables relating to land ownership, demographic attributes and the economic activities undertaken by household members. However, when combined into a multivariate model, only the category of land owned by a household remains as a significant contributory variable. Used as a means to classify land areas reported as owned by survey respondents into discrete units, the land category variable represents the total land area owned by households. On the basis of the significant contribution of land category to the prediction of the use of migration by a household, Table 2 explores the variables that contribute significantly to the prediction of the category of land owned by a household.

Prediction of the category of land owned by a household is significantly contributed to by a series of variables at the level of a univariate analysis. These include variables relating to both household attributes and demography. However, when combined into a multivariate model only two of the original variables remain significant: the presence of household members that work on land not owned by the household, and the number of years the household have been living in the district.

On the basis of the above analysis, if a purely statistically derived model of migration in the case study region were to be developed, the pertinent multivariate variables for inclusion could be narrowed down to a household's land category, the employment of members on others' land and the length of time they have inhabited the area. However, because of the heuristic and case study based approach adopted by this research, and the requirement to elucidate the temporal influence of rainfall upon migration tendencies, each of those components identified as significant at the univariate level is included in the heuristic reasoning of RABMM-T. As such, it is proposed that those variables listed in Tables 1 and 2 contribute to the likelihood that a household surveyed by the Rainfalls Project in Tanzania will send migrants.

Table 2. Variables identified using univariate logistic regression analyses as contributing significantly to prediction of the category of land owned by a household surveyed in the Kilimanjaro Region of Tanzania.

Variable	Univariate binomial logistic regression	Multivariate (ALL) binomial logistic regression
Years living in the district	.016**	.071*
Economically active members	.003***	.132
Livestock ownership	.005***	.188
Work on others' land	.007*	.951 (−)
Work on shared land	.072*	.012**
Participate in farming	.004***	.757 (−)

* = $P > 90\%$.
** = $P > 95\%$.
*** = $P > 99\%$.
(−) = inverse relationship.

External

Changes in local rainfall variability and mean at a monthly timescale provide the external change input to RABMM-T. To develop as clear a picture as possible of the relationship between rainfall, livelihoods and migration, a Monte Carlo method of repeated random sampling provides artificial scenarios of monthly change applied to historical data from Same Meteorological Station between 1950 and 2010. DRY and WET scenarios replicate those developed by Arndt, Farmer, Strzepek, and Thurlow (2012) for Tanzania to 2050. These represent −11.14% and +13.3% changes in mean rainfall, respectively, by 2050. In addition, two scenarios of more extreme change are used that do not represent any change anticipated to occur in the region but can assist in providing a clearer interpretation of modelled trends. Named EXTRDRY and EXTRWET, these scenarios represent double the changes simulated by DRY and WET with −22.28% and +26.6% changes in mean rainfall, respectively, by 2050. All four scenarios use the same degree of deviation around the mean as the historical data with their respective changes in mean achieved by 2050 through an equal annual proportional change.

Structural and institutional

Within the conceptual framework, the influence of rainfall upon livelihoods and migration is manifested through changes to labour markets (L) and food production (F). These then influence the capacity of households to securely inhabit the region under current conditions. The relationship between rainfall and L or F is, in reality, highly complex. However, rather than attempt to recreate the true complexity and risk failing to represent the overall relationship, a more simplistic and transparent approach is adopted. The impact of rainfall upon L or F is thus pared down to a probability function that represents the approximate nature of the relationship in question. Assumptions made as to shape and scale of the influence of rainfall are thus clear and readily adjustable.

If the model presented here were to be used in any sort of predictive capacity, the precise shape and scale of the influence of rainfall change upon L and F would be instrumental in ensuring confident and credible model outputs. In its current form RABMM-T can use one of two probability function shapes: non-scaled normal or sigmoid. With the range of influence of any rainfall value upon L or F ranging from zero (no available labour or food production) to one (maximum available labour and food production,

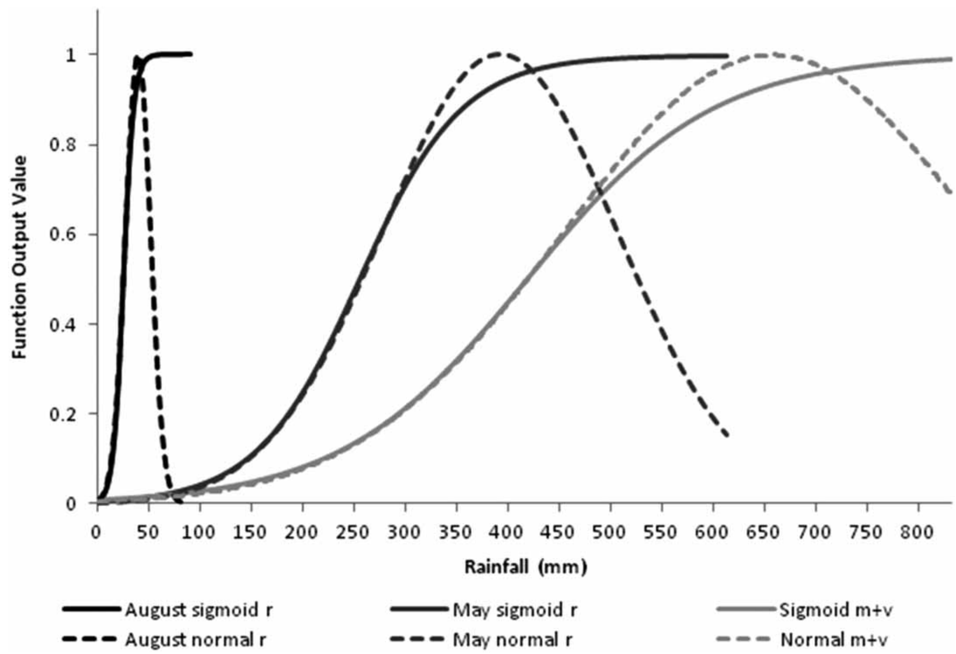

Figure 2. Graphical illustration of the range of sigmoid and non-scaled normal probability function values generated by three-month rainfall (R) for May and August as well for the Masika+Vuli period (October to May).

restricted by the scale of the systems in question), a sigmoid probability function gives a standard rate of increase in L or F with increasing rainfall that tails off as it nears the maximum value. A non-scaled normal probability function meanwhile gives the same form of standard rate of increase with increasing rainfall up to the point at which one is reached. However, past this optimal rainfall value, an equivalent decrease in L or F is seen that represents the potentially negative influence of too much rainfall (Figure 2). The two probability functions described here apply a simple assumed relationship between L or F and rainfall. By making such clear assumptions no attempt is being made to explain the precise changes taking place. Instead the approximate natures of the complex interaction effects at play are being simply reproduced.

Afifi, Liwenga, and Kwezi (2013) describe the Same District of Tanzania as a semi-arid zone characterized by a bimodal rainfall pattern made up of the Masika (long rains from March to May) and Vuli (short rains from October to December) rainy seasons. The nature of the rainfall patterns experienced provides the basis for interpretation of monthly rainfall into values that can be used within RABMM-T to affect L and F. While both the Masika (M) and Vuli (V) rainy seasons are proposed to affect agricultural yield, the wider labour market is proposed to be more continuously affected by rainfall as a rolling three-month control (R). From these variables, sigmoid or non-scaled normal probability functions may thus be calculated that scale the influence of a period of rainfall (R, M or V) as multiplier values (r, m and v) between zero and one. The closer that r, m or v falls to one, the closer to optimal yield a household will, for example, be able to gain from agricultural land or livestock.

Bardsley and Hugo (2010) suggest that communities affected by environmental change will reach thresholds beyond which migration will become central to an effective adaptation response. In this context, the shape and scale of the probability function used, and the point at which optimal and sub-optimal conditions are reached, is important to the outcomes of the model. On this basis, the probability function approach presented here is not intended as a fix all solution but as a means to explore the sensitivity of the modelled system to changes in the shape (non-scaled normal or sigmoid) and scale (point at which optimal yield is achieved) of the relationship between rainfall, livelihood/food security and migration. In such a way, rather than being based upon a known threshold (that is, as yet, unknown) future versions of RABMM-T may be used as a tool to investigate when a critical threshold within such a system may be neared and the steps that may be taken to manage or avoid such an occurrence.

Using the investigative approach adopted here, in order to derive the shape of the non-scaled normal probability distribution of the impact of R, M or V upon household-level components, relevant historical (1950–2010) mean (μ) and variance (σ^2) values were required (Table 3). As no negative rainfall values can occur, the σ^2 used for

Table 3. Mean (μ), maximum, true σ^2, q, adjusted σ^2, k and j values used in non-scaled normal and sigmoid probability functions.

	μ[a]	Max.[b]	True σ^2[a]	q[c]	Adjusted σ^2[c]	k[c]	j[c]
January R	178.32 mm	394.17 mm	27,066 mm	8	3383 mm	0.04	4.4
February R	164.30 mm	325.03 mm	22,542 mm	8	2818 mm	0.045	4.6
March R	188.14 mm	355.19 mm	33,782 mm	8	4223 mm	0.035	3.9
April R	243.35 mm	437.85 mm	36,833 mm	6	6139 mm	0.03	4.5
May R	257.55 mm	612.70 mm	39,231 mm	6	6539 mm	0.03	4.9
June R	183.51 mm	426.44 mm	17,437 mm	6	2906 mm	0.04	4.8
July R	78.10 mm	227.34 mm	5922 mm	10	592 mm	0.095	4.7
August R	25.12 mm	89.91 mm	1468 mm	20	73 mm	0.26	4
September R	26.47 mm	78.07 mm	1806 mm	20	90 mm	0.23	3.5
October R	60.17 mm	195.58 mm	5947 mm	16	371 mm	0.12	4.5
November R	112.97 mm	251.71 mm	15,376 mm	12	1281 mm	0.065	4.6
December R	161.82 mm	357.64 mm	23,155 mm	8	2894 mm	0.045	4.5
Vuli	216.45 mm	428.66 mm	42,729 mm	8	5341 mm	0.03	3.9
Masika	306.20 mm	612.70 mm	60,132 mm	6	10,022 mm	0.023	4.3
Masika + Vuli	522.65 mm	831.56 mm	204,240 mm	6	34,040 mm	0.012	3.7

[a]Values measured from historical data.
[b]Values measured from Monte Carlo model simulations.
[c]Values derived from calibration.

each non-scaled normal equation was adjusted (divided by q) from the recorded value to provide a normal shape of distribution that output an approximately zero multiplier value at zero rainfall. Using μ and σ^2 adjusted by q, non-scaled normally distributed values of r, m and v (collectively n) were derived using Equation (1) (where N represents R, M, V or $M + V$).

$$n = \exp\left(-\frac{-(N-\mu)^2}{2\sigma^2}\right). \tag{1}$$

In Equation (1), μ controls the N value at which a multiplier of one is reached while σ^2 controls the shape of the normal distribution and thus the rate of transition between zero and one. For the equivalent sigmoid probability functions, the shape and scale of the transition between zero and one with increasing R, M or V (collectively S) are controlled by adjuster variables k (slope) and j (scale) to generate relevant values of r, m and v (collectively s). To replicate the rate of change produced by the corresponding non-scaled normal distribution, k and i are appropriately calibrated (Table 3) for each application of Equation (2)

$$s = \frac{1}{1 + \exp^{-(k(S)+j)}}. \tag{2}$$

Figure 2 displays a graphical representation of the non-scaled normal and sigmoid r given R (three-month rolling rainfall) probability distributions for both May (highest three-month historical mean rainfall) and August (lowest three-month historical mean rainfall) as well as the relevant values for $m + v$ given $M + V$ (combined Masika and Vuli rainfall periods). Table 3 displays the μ, σ^2, k and i adjuster variables calculated from historical data or subsequently calibrated for the non-scaled normal and sigmoid functions used monthly for R and annually for M, V and $M + V$.

Household

Within the RABMM conceptual framework, the resilience of a household in each of the Tanzanian villages under study (Ruvu Mferejini, Bangalala and Vudee) to the circumstances affecting them is determined by their income (i) and food production (f) each month. Contributing to i are crop yield for sale (c_1), livestock yield for sale (l_1), farm labouring opportunities taken on by household members (w) and migrant remittances (d) (Equation (3)). Similarly, f is contributed to by crop yield for consumption (c_2) and livestock yield for consumption (l_2) (Equation (4))

$$i = c_1 + l_1 + w + d, \tag{3}$$

$$f = c_2 + l_2. \tag{4}$$

The Rainfalls research conducted in Tanzania (Warner et al., 2012) included a household survey that provides a valuable resource for the construction of an ABM. Using household-level attributes gained from the survey data, the impact of changes in r, m and v upon the i and f of households can be parameterized. Household-level attributes (livestock, land, economic activity, savings and migrants) and characteristics (members, employment, dependency ratio and migration experience) are proposed to contribute to the resilience of a household to changes in their environment. Year 2012 values for these attributes and characteristics are taken from the survey data, providing a genuine basis from which changes to the circumstances of households may be simulated. However, to apply such changes in appropriate proportions, household attributes require scoring in terms of their relative value

Table 4. Relative values assigned to household attributes in RABMM-T.

Attribute:	Relative value
Crop yield per hectare of land (y)	20 per year
Livestock score (v)	
1×Cow	1 per year
1×Donkey	0.5 per year
1×Oxen	1 per year
1×Pig	0.25 per year
1×Goat	0.25 per year
1×Chicken	0.1 per year
Return for daily wage (x)	1 per month
	0.05 per day
Max return on migrant labour (z)	1 per month

to households. In this instance the scoring system (Table 4) is derived from evidence contained within the Tanzania case study report (Liwenga et al., 2012) on the relative value of relevant items in Tanzanian Shillings.

Depending upon the shape of impact of rainfall being simulated (non-scaled normal or sigmoid), the relevant n or s value is applied to the attributes of a household to determine their resilience at time t. Due to the different altitudes of the three villages studied, the rainy seasons that affect crop yields (c) differ. The irrigation systems in place in Ruvu Mferejini (lowland) lead Liwenga et al. (2012) to describe relative year-round availability of food. As such, the three-month rainfall measure, R, is used to determine the influence of rainfall upon crop yields in Ruvu Mferejini. While Liwenga et al. go on to describe the midland village of Bangalala as benefitting from both the Masika and Vuli seasons ($M + V$), the highland village of Vudee is described as only benefitting from Vuli (V). The relevant n or s derived values of r, $m + v$ and v (ranging from zero to one depending upon rainfall at time t) are thus used to determine the impact of rainfall upon c (c_1 and c_2) using a standardized crop yield per acre value (y) and the area of land farmed by a household (p). In contrast to crop yields, livestock yield and the availability of farm labour are defined as being uniformly affected by R in all villages. Using the RABMM-T scoring system (Table 2), a household's livestock score (v) defines the maximum benefit available to the household which is then adjusted by r at time t.

Because of the crucial social element involved in the distribution of farm labour, R is deemed not to be the only controlling factor. For a household to accept farm labouring opportunities, they must be made available by another household within the simulation. For the purposes of this test model, the farm labour system is restricted to the three villages in question. Households recorded within the survey data as having a history of offering labouring opportunities to others do so at a rate (w_o) governed by R. In order for the range of w_o offered by the market system to be taken up by labourers, they must be informed of the opportunity. Within RABMM-T all households offering w_o inform their social network of the availability of work. A household that has potentially economically active members available for work that receives communication as to the existence of opportunities will then be able to offer themselves as a labourer and take up employment for an allocated number of days (w_t). Rather than introduce some form of merit-based competition into the model, the proportion of total system w_o is divided between appropriate labourers that have received communication as to the availability of employment (w_s) using an equal form of distribution between all appropriate individuals. Farm labouring activities (w) thus contribute to household income according the value of w_t and the standard return for daily wage labour (x) (Equation (5))

$$w = \frac{w_t x}{w_s}. \tag{5}$$

Household vulnerability assessment

Following calculation of each household's i and f, their livelihood resilience at time t is determined. As well as i and f, the resilience of a household is affected by the household size (h) and the relative cost of consumption by one person (e), set at 0.083 per month. The resilience of a household is thus determined by their surplus (d) post-consumption using Equation (6)

$$d = \frac{i + f}{h\ e}. \tag{6}$$

The average household size across those surveyed is six people. With e set at 0.083, and hypothesized to also represent the minimum non-food outgoings of a household, the average household is proposed to require a surplus each month of 0.5 to remain resilient. Following all outgoings each month, if a household has any remaining d, a standard savings rate of 60% (0.6 d) is retained in order to bolster resilience in later months.

Simulated household resilience

To test the influence of rainfall change upon household resilience classifications each month, the DRY, WET, EXTRDRY and EXTRWET rainfall scenarios are used as the external input to RABMM-T. Unless otherwise stated, demographic change is set at zero (equal birth and death) while the farm labour market is open across the system (all households communicate with all others). A base version of RABMM-T provides the foundation from which the resilience classifications output by the different scenarios can be compared. Within the base, scenario a standard value of 0.75 is consistently used as the multiplier values r, m+v and v. As a result L and F are consistently 75% of optimal, a level that provides a clear basis for later comparison. Figure 3 displays the 10 member ensemble, 5-year moving averaged rate at which modelled households are classified as resilient under the range of non-scaled normal (N-) and sigmoid (S-) scenarios, normalized against the base scenario. Error bars show the complete envelope of changes simulated across the ensembles for the S-range of scenarios.

In Figure 3 the EXTRWET and WET scenarios under both N- and S-rainfall structures generate a positive base-normalized rate of change. While N-EXTRWET produces the greatest positive change in resilient households, the second greatest comes from N-WET. Although also following this hierarchy, both S-EXTRWET and S-EXTRDRY produce generally smaller positive changes. In terms of drying, both S-EXTRDRY and N-EXTRDRY produce similarly negative normalized rates of change with lesser degrees simulated under S-DRY and N-DRY. By 2047, the highest positive change seen in Figure 3 is 0.034 (3.4%), while the negative changes peak at −0.054 (−5.4%). Although clear differences exist in the rate at which the 165 households remain resilient under the four artificial rainfall scenarios, deviations away from the base scenario are relatively small.

While still considering the household unit of analysis, the potential influences of both non-static demographic change and alterations to the household social network can be investigated within the structure of RABMM-T. In the case of demography, by applying UNPD (2010) medium variant crude birth and death rate forecasts to the model population, the influence of birth rates that consistently exceed death rates upon household resilience can be investigated. Changes to the social network of households, and the resultant impact upon the farm labour market, are more difficult to parameterize. The w achieved by a household (Equation (5)) is dependent upon the number of individuals seeking work (w_s) and whether the household has received notification of the availability of opportunities. In the base version of RABMM-T, households offering w_o inform all other households across all villages, thereby creating an open, inclusive and fair market structure. However, a more realistic scenario might be that such sharing of opportunities is either restricted to the social network of labour offering households (the size of which can be changed) or to the relevant village. Figure 4 displays the base-normalized rate at which households are classified as resilient under the: United Nations Department of Economic and Social Affairs (DESA) Population Division demographic scenario (UNDemog) with a standard inclusive network; static demographic scenario with each household networked with 10 others (Network10); static demography and 30 strong networks (Network30); static demography and 50 strong networks (Network50); and static demography with labour information sharing restricted to villages (RestrictionON).

At the start of the simulation, the RestrictionON scenario is seen to represent the greatest negative change in household resilience classifications with almost 8% fewer resilient households than the base scenario. However, this negative value is simulated to gradually decrease over time and achieves a maximum positive change of 6% by 2043. In contrast, the number of resilient households simulated by UNDemog decreases over time to peak at −5% by 2045, likely as a result of the changing dependency ratio of fast-growing households. All three network size scenarios show a positive base-normalized change in resilient household numbers over time with very little deviation between

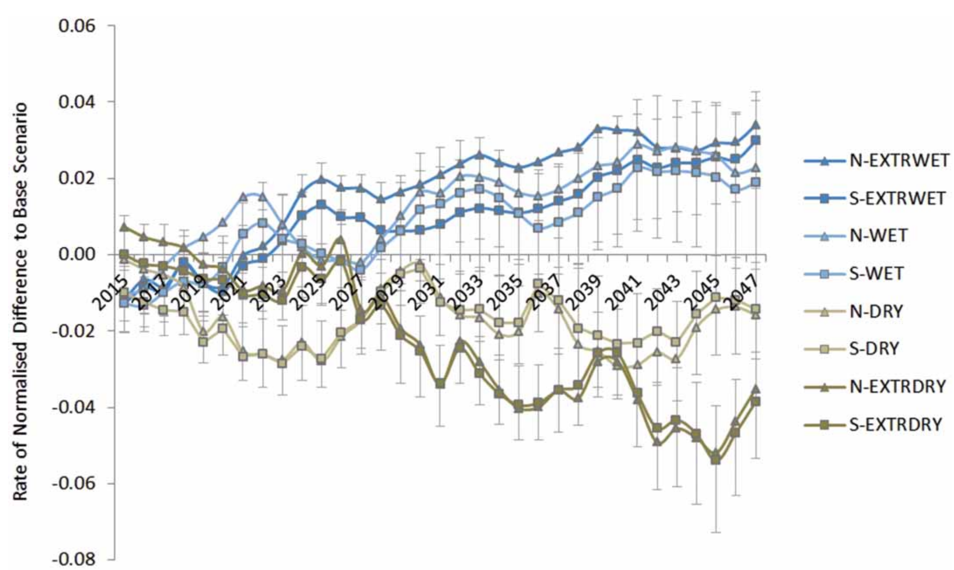

Figure 3. Ten member ensemble, five-year moving averaged base-normalized rate at which households are classified as resilient under the range of non-scaled normal (N-) and sigmoid (S-) rainfall scenarios.

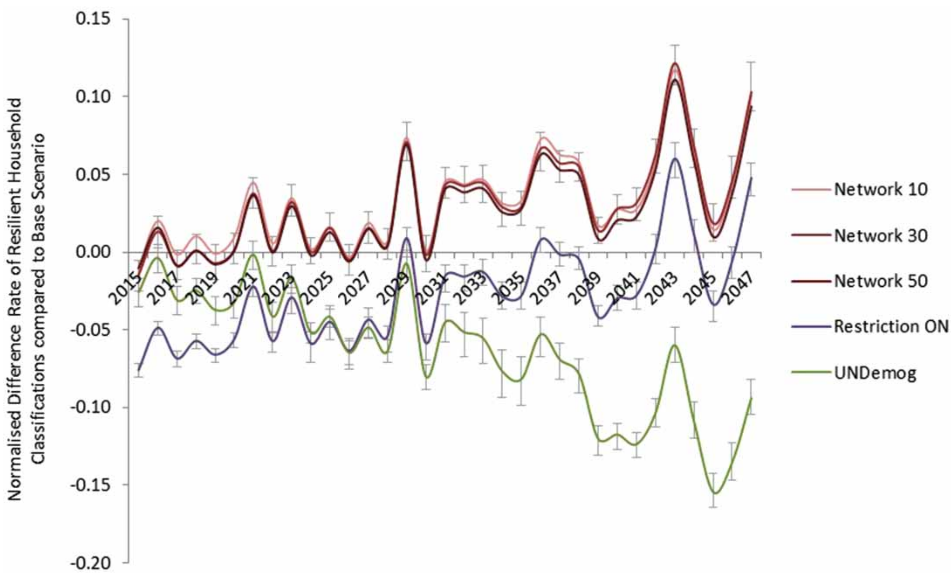

Figure 4. Ten member ensemble, five-year moving averaged base-normalized rate at which households are classified as resilient under non-rainfall scenarios tested, normalized. Error bars indicate the complete envelope of changes simulated for Network30, RestrictionON and UNDemog scenarios.

them and a peak change of approximately 12% by 2043. Comparing the scales of change simulated for the scenarios displayed in Figures 3 and 4 reveals that changes to the demographic and network state of the simulated households have a potentially more marked impact than the range of artificial rainfall scenarios tested. Furthermore, the degree of error shown in Figure 4 is relatively smaller than that seen in Figure 3.

Individual

Although the resilience of households to changes in their circumstances are of considerable interest, in the context of RABMM-T, such classifications are generated as a means to better understand the migration flows that represent the focus of this research. The migration decision is portrayed in the conceptual framework as an individual decision mediated by the household. Using the Theory of Planned Behaviour approach adopted by Kniveton et al. (2011), each RABMM-T agent aged 14 and over within a household develops a migration propensity (P) on the basis of their attitude (A) towards migration and the influence of their peers (S). While S is indicative of the proportion of the individual's household and social network (set to a default of 20 peers) that have already migrated, A is derived using the potential migrant's age (a), gender (g) and the estimated relative likelihood of an individual with those characteristics migrating from their village (o). In the absence of comprehensive temporal migration data, this likelihood is calculated from the Rainfalls survey data using information relating to the first and last migration trips of respondents. Due to the limited data available for the cohort in each village, the range of attitudes used is approximated from the equation generated by a second-order polynomial trend line placed through the available migration data. Figure 5 displays the second-order polynomial trend line derived estimations of the likelihood of model individuals migrating according to their attributes of age, gender and home village.

It can be clearly seen from Figure 5 that in all three study villages, males have a consistently greater maximum estimated likelihood of migrating, particularly in the village of Ruvu Mferejini. As well as revealing the age at which a villager's estimated migration propensity is greatest, Figure 5 also identifies the age at which the estimated likelihood of an individual migrating becomes zero. This is seen to range from approximately 64 years for males in Bangalala to 84 years for females in the same village. Although this approach to deriving and individual's A is constrained by the limited quantity of relevant migration data available to this research, it is used here as only as a comparative indicator of the relative likelihood of one individual undertaking migration compared to another. In all cases, both A and S values are calculated to be a value of 1 or lower and are combined evenly in this version of the model. However, their relative impacts can be adjusted using different values of b in Equation (7) to adjust the relative power of social influence hypothesized

$$P = \frac{b_1 A + b_2 S}{b_1 + b_2}. \tag{7}$$

In addition to A and S components that contribute to an individual's P, the mediating influence of a household arises from its ability and willingness to invest in sending

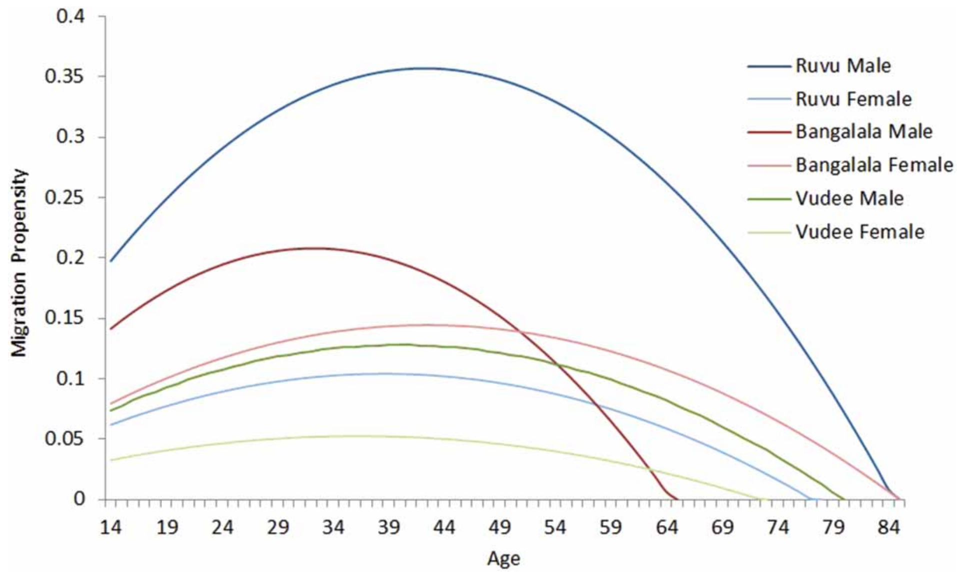

Figure 5. Second-order polynomial trend line derived estimations of the likelihood of model individuals migrating according to village, age and gender characteristics.

migrants. For a household to be able to invest in migration (in the order of ranked P values of members), the surplus (d) remaining each month following subsistence must be greater than the cost of opportunistic migration (o_1), derived from Liwenga et al. (2012) and set at 1.5. For more than one individual from a household to migrate, d must be greater than the number of migrants multiplied by o_1. Upon departure, o_1 is deducted from a household's monthly surplus. However, in later months, the absence of these individuals will contribute to household resilience through remittances (up to a monthly maximum of z, Table 2) and by reducing the number of members consuming resources at home. As well as needing to meet the cost of migration, a household's willingness to send migrants decreases with the departure of an individual in order to retain some economically active members at home and therefore maintain a buoyant dependency ratio.

With the resilience threshold set at 0.5 and the cost of migration at 1.5, non-resilient households cannot, by definition, send opportunistic migrants. However, in acknowledgement of the potential for people to migrate under desperate circumstances at little or no cost, potential exists for non-resilient model households to send migrants. For such households, the cost of need-driven migration (o_2) is set at 0.25 with the same underlying process of migrant selection undertaken by ranking member P values. Using the DRY, WET, EXTRDRY and EXTRWET rainfall scenarios, the total numbers of migrants (from resilient and non-resilient households) are simulated and compared to those modelled under the base scenario. Figure 6 displays the 10 member ensemble, 5-year averaged base-normalized rate of total migration.

The general trend of increased migration under wetting and decreased migration under drying seen in Figure 6 broadly reflects the pattern seen for household classifications in Figure 3. However, the scale of change in migrant numbers simulated is greater than that seen for household classifications with maximum positive and negative changes compared to the base scenario of +7.7% and −11.4%, more than double that simulated for household resilience classifications. Despite the greater extent of the change simulated, the results are less clear for migration with more overlap between the error bars of different scenarios leading to lower degrees of confidence in the precise change seen. Furthermore, while the N-interpretation of scenarios led to consistently more extreme household classifications than the sigmoid alternatives, no such trend is replicated for migration. In order to unpack the relationship between migration and rainfall under RABMM-T, Figures 6 and 7 display the base-normalized rate of change in migration from non-resilient and resilient households, respectively.

In the case of migration from non-resilient households, almost all of the rainfall scenarios tested result in a simulated rate of migration greater than that of the base scenario. Only S-EXTRWET produces a rate of migration lower than that of the base. By 2047 the greatest positive changes in non-resilient migration are modelled as occurring under both EXTRDRY scenarios, likely due to the reductions in i and f that render more households non-resilient over time and lead to need-driven migration. Although the error bars in Figure 7 suggest a relatively low degree of confidence in the non-resilient migration trends modelled, the scale of change simulated is far greater than anything witnessed thus far with a maximum positive change of 48.5%.

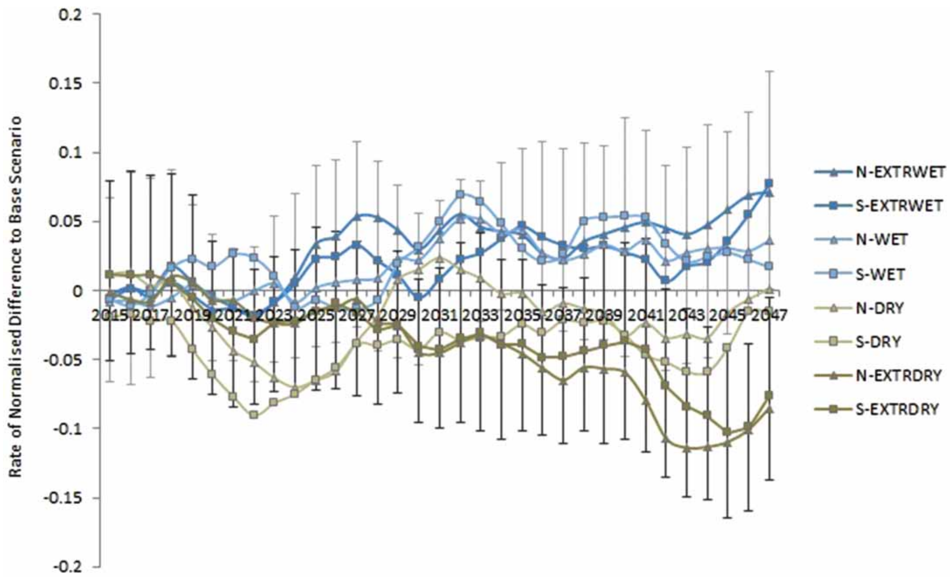

Figure 6. Ten member ensemble, five-year moving averaged base-normalized rate of total migration under the range of non-scaled normal (N-) and sigmoid (S-) rainfall scenarios tested. Error bars indicate the complete envelope of changes simulated for S-EXTRWET and S-EXTRDRY.

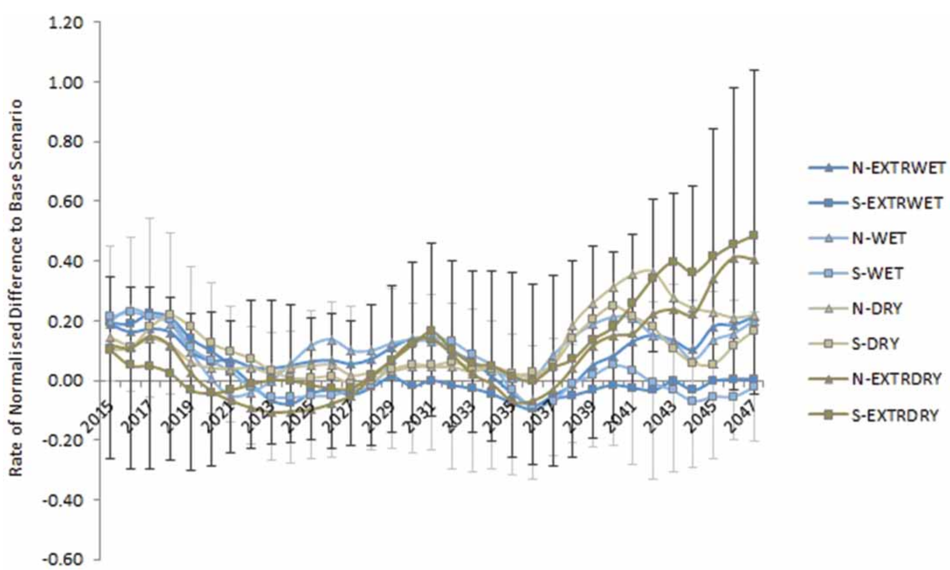

Figure 7. Ten member ensemble, five-year moving averaged base-normalized rate of migration from non-resilient households under the range of non-scaled normal (N-) and sigmoid (S-) scenarios tested. Error bars indicate the complete envelope of changes simulated for S-EXTRWET and S-EXTRDRY.

Although offering more clarity in terms of the contrasting influence of drying (leading to negative changes compared to the base) and wetting (leading to positive changes compared to the base), the scale of change in migration from resilient households in Figure 8 suggests a lesser influence from rainfall. Compared to the 48.5% increase in non-resilient migration described above, the maximum positive change in migration from resilient households peaks at 8.4% under S-EXTRWET. However, a greater negative change is seen in migration from resilient households, peaking at −15.2% under both S-EXTRDRY and N-EXTRDRY.

Results from RABMM-T therefore suggest that, under the range of artificial rainfall scenarios tested, total migration flows greater than those simulated under the base scenario result from wetting while lesser flows result from drying. It is clear from a direct comparison of Figures 6 and 8 that the trend in total modelled migration

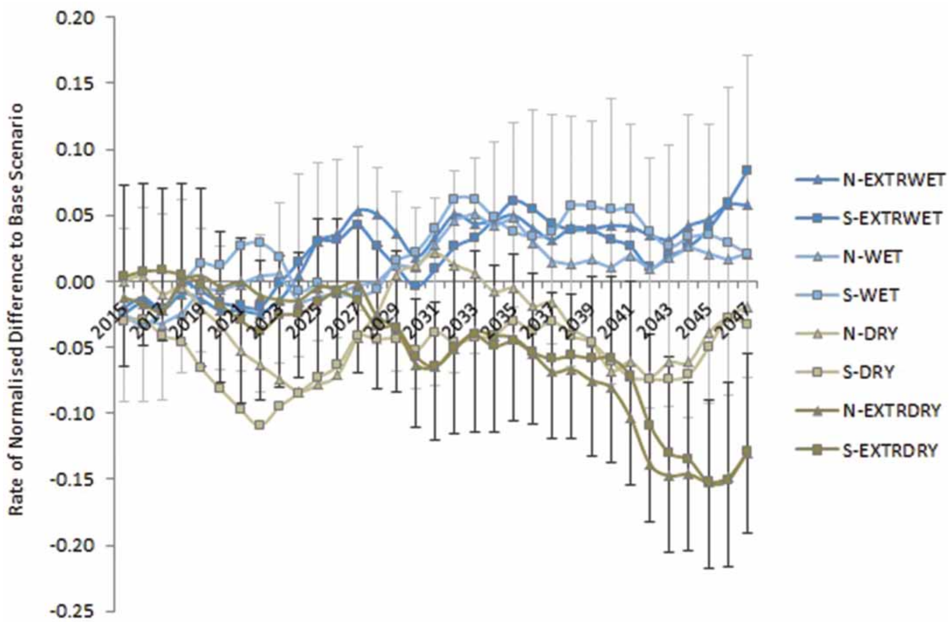

Figure 8. Ten member ensemble, five-year moving averaged base-normalized rate of migration from resilient households under the range of non-scaled normal (N-) and sigmoid (S-) scenarios tested. Error bars indicate the complete envelope of changes simulated for S-EXTRWET and S-EXTRDRY.

seen is driven by changes to migration flows from resilient households under each of the rainfall scenarios tested. Despite the proportional changes in migration from non-resilient households far exceeding those from resilient households, the relatively small actual numbers affected means that the situation of such households is lost at the higher level of analysis used for total migration. If found to replicate the true situation found in the case study region such a finding could have potentially important implications for decision-makers working in the region. However, as with the household classification results presented above, in order to place the influence of rainfall variability upon the total migration flows simulated into a

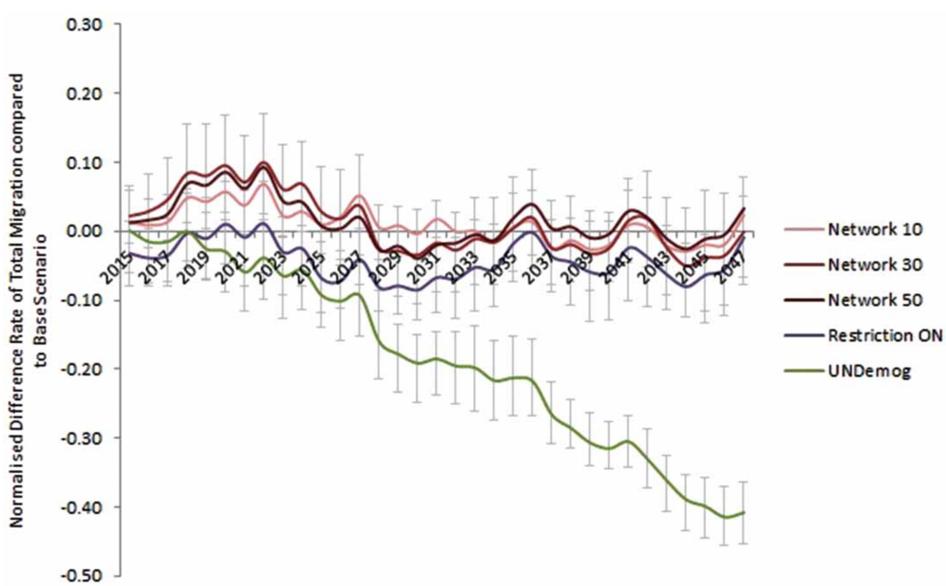

Figure 9. Ten member ensemble, five-year moving averaged base-normalized rate of total migration under the range of demographic and network scenarios tested. Error bars indicate the complete envelope of changes simulated for Network30, RestrictionON and UNDemog scenarios.

wider context, Figure 9 displays the influence of the non-rainfall scenarios tested upon total migration.

In contrast to the equivalent household resilience classification shown in Figure 4, the total flow of migrants simulated under the RestrictionON scenario remains consistently just below the base scenario. As such, while more households were simulated as becoming resilient over time under the scenario, this did not have a marked impact upon the total migration flows modelled. In the case of the range of network scenarios, while the differences between the three scenarios are again small, the general trend of fewer total modelled migrants accords well with the increasing household resilience classifications simulated.

Within Figure 9, the UNDemog scenario stands out. While household resilience was seen to decrease gradually over time in Figure 4, the total number of migrants simulated decreases markedly from around 2025 onwards, peaking at −41.5% in 2046. It is likely that such a phenomenon is modelled by RABMM-T as the population growth rate predicted by UNPD (2010) places more individuals within households, worsening their dependency ratio and leaving fewer households with the capacity to invest in either opportunistic or need-driven migration. Such an outcome is highly dependent upon the model structure used by RABMM-T which does not accommodate the creation of new households within the model system. As such, existing households grow with no capacity for separate self-supporting entities to be established. Although such a finding is thus limited and should be treated with appropriate caution until verified in the study location, it could indicate the power of demographic forces to influence household migration strategies in the future.

Conclusion

Designed to simulate migration decision-making within the context of the livelihood resilience of households within the communities studied, RABMM-T offers a means of exploring the likely impacts of scenarios of future rainfall change. Base-normalized results generated by the model reveal that the four artificial rainfall scenarios tested have a consistent modelled impact upon both household resilience and total migration. While the proportional change in total migrant numbers is simulated to be greater than the equivalent change in household resilience classifications, less confidence can be placed in these results due to the greater degree of intra-model variation simulated by 10 member ensembles. Although unfortunate from the perspective of migration research, such a finding should be anticipated due to the greater level of complexity involved in replicating a human decision-making process. Indeed, it is this uncertainty that has led to the debate surrounding the existence of environmental migrants and the identification of agent-based modelling as a potential means to address the degree of complexity required in any future-oriented study.

Broadly speaking, RABMM-T simulates increased household resilience and increased total migration under scenarios of wetting and opposing results under scenarios of drying. However, analysis of the migration flows simulated from resilient and non-resilient households within the study communities reveals that migration modelled from non-resilient households does not follow this pattern with a clear increase in such migration simulated to occur, particularly under the scenario of extreme drying. Such findings suggest that the needs of those communities most vulnerable to the impacts of environmental change could be hidden from view under a study format that focuses only on total migration. If the existence of such a phenomenon were to be positively identified from further investigation led by simulation results such as these, the needs of the most vulnerable communities could be more appropriately identified and planned for.

Despite the focus of this research being to investigate the role of rainfall upon livelihoods and migration, a series of non-rainfall scenarios were also tested. Comparison of simulation outputs generated by both rainfall and non-rainfall scenarios reveals that alterations to the demographic and network state of model households have the potential to produce changes in both resilience classifications and migration flows that are equal to, and in some cases greater than, those simulated under changing rainfall. Such a finding highlights the importance of appropriately parameterizing the base conditions upon which external changes input to a model are required to act.

Given the potential impact of the complex adaptive nature of societies upon modelling future migration, the potential explorative power of ABMs and the rarity of comprehensive spatio-temporal migration data with which to work, the process of model development described in this paper is intended as a viable alternative means of investigation. Although a case study approach to model development may limit the potential for findings to be extrapolated to different conditions and circumstances, this research provides a step in understanding the potential for later development of wider reaching models that may offer greater value to policy-makers. It is proposed that, although this work presents a technique that shows potential for future application as a tool to aid decision-makers, the quality of the data available to the research and the lack of an appropriate means of validation render it only as indicative of the potential that future applications may have.

In order to generate model outputs of real value to policy-makers, adequate measures must be put in place to deal with the additional complexity introduced by non-rainfall parameters while carefully parameterizing and controlling all other variables. From the experience gained through completion of this research, it is clear that any form of data collection proposed to be undertaken to establish an empirical basis for future simulation efforts must appropriately address the numerous areas of uncertainty identified throughout the RABMM-T development process. Only by adequately understanding and quantifying the multiple and interconnected components that contribute to livelihoods and migration decision-making at appropriate spatial and temporal resolutions may we construct models that offer the confidence and credibility required to be of practical assistance to decision-makers.

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