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Monitored versus experience-based perceptions of environmental change: evidence from coastal Tanzania

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The impacts of climate change are likely to exacerbate many problems that coastal areas already face. In this study, we used multinomial logistic regression to examine human perception of climate change based on a cross-sectional survey of 1253 individuals in coastal regions of Tanzania. This was complemented with time series analysis of 50-year meteorological data. The results indicate that self-rated ability to handle work pressure, self-rated ability to handle personal pressure and unexpected difficulties, age, region and educational status were significant predictors of perceived temperature change unlike ethnicity and gender. A disproportionately large percentage of respondents of all ages indicated that temperature was getting hotter between the past 10 and 30 years. This observation was supported by the time series analysis. Although respondents also alluded to changes in rainfall patterns in the past 10–30 years, time series analysis of rainfall revealed a different scenario except for Mtwara region of Tanzania. Because there is agreement between respondents' perceptions of temperature and available scientific climatic evidence over the 50-year period, this study argues that when meteorological records are incomplete or unavailable, local perceptions of climatic changes can be used to complement scientific climatic evidence. Based on the spatial differentials in climate change perception observed in this study, there is opportunity for a more locally oriented adaptation dimension to climate policy integration, which has hitherto been underserved by both academics and policymakers.

Keywords: time series; multinomial regression; climate change; policy; temperature; rainfall

Introduction

Based on longstanding association with their environment, local communities have generated a sophisticated body of knowledge regarding different changes to their environment, which were obtained via experience and passed on from one generation to the other. Experiential climate change, in the context of this paper, refers to the climate-related knowledge individuals and groups have acquired, over time, by their relationship to their natural and immediate environment. Because all people are unique and have

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unique experiences, every group will be different in terms of their climate-related knowledge and have a different dynamic even within the same society.

The debate between experiential climate change and meteorologically measured climate change is longstanding. The conventional explanation for this controversy emphasizes impediments to public understanding: limited popular knowledge of science, the inability of ordinary citizens to assess technical information and the resulting widespread use of unreliable cognitive heuristics to assess risk (Braman et al. 2011). Climate change is intrinsically probabilistic and is often regarded as an issue that is beyond human perception (see Rebetez 1996; Weber 2006; Blennow et al. 2012). In this context, it is normative to use time series analysis of climate variables, notably precipitation (rainfall) and temperature data spanning 30 years or more. That is, studies on climate change usually put more emphasis on descriptions of weather events and the question of whether human observations meet rainfall data sets and other measurable variables (see Chaudhary and Bawa 2011). Such research usually attempts to determine whether human observations are correct, that is, conform to meteorological measurements (Kemausuor et al. 2011; Rademacher-Schulz and Mahama 2012).

However, climate change research documents the importance of local, place-based evidence of climate change gained through experiential learning to be as or more effective than simply studying analytical climate change data to increase climate change literacy. Adaptation to climate change essentially involves people deciding to do things differently. In this regard, local perceptions are likely most meaningful and therefore useful to individuals adapting and responding to climate change. While this is so, the dominant narrative values scientific and technical understandings of climate change more highly. The technical approach is useful and rightly requires emphasis. Yet, it is people's perception of climate change (based on experiential knowledge) that will play a large if not the largest role in mitigation and adaptation efforts, but this is not necessarily without some degree of scientific thinking (Ruddell et al. 2012).

The distinction between personal experience of possible climate change outcomes and statistical description of possible climate change outcomes has received recent attention because, presumably, the same information about the consequences of decisions and their likelihoods can lead to different perceptions and actions, depending on how the information is acquired (Swim et al. 2009). The two approaches are not mutually exclusive and may be considered as complementary mechanisms by which humans examine and know their environment. Personal experience of climate change by humans differs from the occurrence of climate change or climate extremes in the biophysical environment (Leiserowitz 2006). Weber (2006) distinguishes the one from the other conceptually and indicates that cognitive processes (e.g. perceptions) are experience-based while stochastic (probabilistic) processes are description-based. Human information processing and decision-making are also influenced by affect and emotions (Lazarus 2000), which form the basis of the experiential system. Furthermore, humans have entirely different time horizons. The recall bias, of the sort that humans are predisposed to, is not the same for the biophysical environment (Hahn et al. 2009). The memory of the biophysical environment is different from human memory. In humans, memory is rather short even for events (such as floods and episodic hot temperature) that appear to be indelible in the minds of those who have previously experienced it.

Perception is inextricably linked to human action (Brody et al. 2008). Human action, here, includes coping, adaptation, mitigation, risk aversion, etc. Thus, we will fail to elicit a comprehensive understanding of the issue of climate change without partly focusing on human perception (climate change in people's minds) (Leiserowitz et al. 2010). Local experiences of climate change could help not only efforts to adapt, but can influence individual mitigation behaviour and policy support. Public opinion about climate change appears to shift with personal experience. But what is the relationship between climate change and what people experience? This is far more difficult to answer, but may be obtainable with more data on people's long-term experiences of climate. Although this is certainly useful for understanding how to develop adequate policies for addressing environmental change due to climate, it also shows that people's experience of climate in the short-term is much more likely to incite changes in behaviour than changes that are likely to take place in the longer term.

With few exceptions, little consideration has been given to how cognitive processes such as climate change perceptions mediate or shape human action. Yet, human action is predominantly a function of perception or cognition rather than stochastic considerations (Weber 2010). Understanding public perceptions of climate change is fundamental to both climate science and policy because it defines local and global sociopolitical contexts within which policymakers and scientists operate (Burch and Robinson 2007). The greatest barrier to public recognition of human-made climate change is probably the natural variability of local climate (Hansen et al. 2012). How can a person discern long-term climate change, given the notorious variability of local weather and climate from day to day and year to year? In response to a general lack of inquiry into experiential climate change especially in the sub-Saharan African context, we use multinomial regression techniques to examine the degree of perception of climate change in coastal Tanzania. Climate change could affect coastal areas in a variety of ways. Coasts are sensitive to sea level rise, salt water intrusion into local soils, changes in the frequency and intensity of storms, increases in precipitation and warmer ocean temperatures (Moser et al. 2012). We analyse multiple measures of climate change using time series analysis along with socioeconomic, demographic and attitudinal variables derived from a cross-sectional survey that examines variation in climate change risk perception. By combining time series analysis and multinomial logistic regression, our approach allows us to (a) empirically test theoretical propositions on the determinants of human perception of climate change, (b) statistically unpack the compositional, physical and geographic factors triggering public perception of climate change and (c) provide direction to planners and policymakers on how to garner public support for government initiatives meant to reduce the adverse changes associated with climate change. It has been argued that validation of experiential knowledge is essentially political (Agrawal 2002). Some studies have used meteorological data to validate human perception of climate change (see Chaudhary and Bawa 2011); we do not adopt this methodology because we situate the two approaches in distinct but complementary paradigms although we also model times series of temperature and rainfall data in this study. Furthermore, in the discussion, we compare the two approaches but only because we seek to demonstrate diversity in acquiring knowledge on the human environment and not to validate one approach (climate change in the people's minds) with the other approach (descriptive statistics of meteorological data).

Theoretical context

The literature is replete with competing theories on climate change perception. Two of such theories of interest to this study are *science comprehension theory* and *cultural cognition theory*. Science comprehension theory is rooted in three key postulates: the public form perceptions of climate change based on sound scientific information; the public lack sound scientific information about climate change; bounded rationality (limits to technical reasoning capacity) forces the public to rely on heuristics like cultural worldviews (e.g. conservative or liberal values) to assess the risks of climate change (see Bord et al. 2000; Kahan et al. 2012; Young and Neill 2013). Cultural cognition theory hinges on two distinct but interrelated principles: the public primarily form perceptions of climate change based on the worldviews of groups with which they most strongly identify, not sound scientific information, and that cultural worldviews are not heuristic devices, but deeply ingrained ways people fit in society that cannot be easily overcome by increasing knowledge or technical reasoning ability (see Parker et al. 2003; Tomasello 2009; Young and Neill 2013).

The theory on cultural cognition posits that beliefs of environmental (climate) risks should be expected to diminish as worldviews become simultaneously more hierarchical and individualistic, and increase as worldviews become simultaneously more egalitarian and communitarian (Braman et al. 2011; Kahan et al. 2012). Within this theoretical milieu, it is argued that perceptions about climate change differ for individuals since their perceived world is subjectively constructed and is influenced by previous experience, type of education and other socioeconomic characteristics (Otto-Banaszak et al. 2011). According Swim et al. (2009), evidence from the health literature, the social psychological literature and the risk communication literature suggests that social and cultural processes serve to modify perceptions of climate risk in a manner that can both augment or decrease response in ways that are presumably socially adaptive. Research in cognitive psychology suggests that certain perceived characteristics of climate change (e.g. that it is 'natural', not new, and in principle controllable) may lead citizens as well as policymakers to underestimate the magnitude of the risks (Swim et al. 2009). An individual's perceptions of climate change impacts can be moderated by social norms (Leiserowitz 2005) and by their environmental identity (a sense of identity that transcends the individual and encompasses one's position as part of a living environment).

Decisions from repeated personal experience with climate outcomes involve associative and often affective processes, which are fast and automatic (Weber et al. 2004). Processing statistical descriptions, on the other hand, requires analytic techniques that need to be learned and require cognitive effort. People's choices can differ dramatically under the two information conditions, especially when the small-probability events are involved, which is certainly the case with climate risks (Swim et al. 2009). Several researchers suggest that the rational processing system is analytic, logical, and deliberative and encodes reality in abstract symbols, words and numbers (see Epstein and Pacini 1999; Slovic et al. 2004; Leiserowitz 2005; Lowe et al. 2006). In contrast, the experiential system is holistic, affective and intuitive and encodes reality in concrete images, metaphors and narratives linked in associative networks (Slovic et al. 2004; Epstein 2008). Summarizing the convergent findings of numerous research studies, Epstein posits that experientially derived knowledge is often more compelling and more likely to influence behaviour than is abstract knowledge. Likewise, Nisbet (2009) argues that vivid, concrete information has a greater influence on perceptions and inferences than technical information. The preceding theoretical discussion informs our analysis on the relationship between perceived environmental change on the one hand, and compositional, contextual and psychosocial factors, on the other hand.

Materials and method

Study area

Tanzania is a coastal country lying between longitude 29° and 49° East and latitude 1° and 12° south of the Equator (Francis and Bryceson 2001). The marine waters comprise

64,000 km^2 as territorial waters and 223,000 km^2 as offshore waters (EEZ) (Mngulwi 2003). Tanzania's coastline stretches for 800 km. It has five coastal regions – Tanga, Pwani, Dar es Salaam, Lindi and Mtwara. The five coastal regions cover about 15% of the country's total land area and are home to approximately 25% of the country's population. According to the 2012 Population and Housing census, the total population was 44,928,923 compared with 12,313,469 in 1967 (National Bureau of Statistics 2013), reflecting an annual growth rate of 2.9%. The under 15 age group represented 44.1% of the population, with 35.5% being in the 15–35 age group, 52.2% being in the 15–64 age group and 3.8% being older than 64 (National Bureau of Statistics 2013). Overall Tanzania on average is sparsely populated with population density of 51 persons/km^2, lower significant variation exists across regions. The population density varies from 1 person/km^2 in arid regions to 51/km^2 in the mainland's well-watered highlands to 134/km^2 in Zanzibar (United Republic of Tanzania 2013). The population density for the Dar es Salaam region is 3133 persons/km^2 and that of Lindi is only 13.1 persons/km^2 (National Bureau of Statistics 2013). This suggests wide disparities in population density across regions (Plate 1).

Study design

The study is part of Indian Ocean World (East Africa, the Near and Middle East, and Southeast Asia) which is the broader region of interest. Within this broader milieu, the

Plate 1. Map of United Republic of Tanzania showing the study areas.

study is interested in demarcating the specific connections between select contemporary changes in these regions and their historical antecedents, particularly the historical circumstances associated with environmental factors, both direct (drought, flood, etc.) and indirect (migration, resource scarcity). The reasons for selecting the study areas are threefold. First, Tanzania was selected because of its historical and geopolitical significance in East Africa. Second, anecdotal evidence suggests that the climate along the coastline of Tanzania is changing. In response to this change, central and local governments in Tanzania have initiated steps to address climate change threats and combined local impacts of increased flooding due to increased precipitation and coastal and infrastructure erosion due to increased tidal activity and storm surges. However, no major survey of the perceptions, attitudes and adaptation behaviour of the public in relation to climate change had been undertaken up to January 2013 in the study area although perception is critical to adaptive responses by the public. Third, the biosocial and sociocultural factors that influence perceived climate change along the coastline of Tanzania are not well understood. Theory and experience shows that it is the poorest, who are most dependent on natural resources for livelihood, that are most exposed to climate hazards and changes affecting the environment. Yet, they are also the ones least equipped to deal with the consequences. By studying the public perceptions of climate change in coastal Tanzania, we theoretically situate this study in culture and by extension, we argue that perceptions about climate change differ for individuals since their perceived world is subjectively constructed and is influenced by previous experience, type of education and other compositional characteristics.

The study design was approved by the Committee of Research Ethics of the University of Western Ontario, Canada. Research approval was also granted by the Commission on Science and Technology (COSTECH) in Tanzania. A cross-sectional survey was conducted with 1253 individuals in three regions along the coastline of Tanzania. The data were collected between March and September 2013. The scope of the survey was to learn about perceptions, attitudes and behaviour to climate change in Dar es Salaam and Zanzibar, which were considered as a unit, and Pwani and Tanga. The sampling distribution between Dar es Salaam and Zanzibar was 3:1. The study population included male (606) and female (647) participants between the ages of 18 and 70 years. The study used multistage sampling to obtain representative estimates of the population of residents of the three regions. Within each region, a list of villages based on the 2012 Population and Housing Census was divided further into households. The list of villages was also divided into clusters ensuring that each cluster would provide adequate numbers of eligible respondents to be included in the survey. This approach both corrects for sampling bias and weights the cases to match census percentages of males and females of various age groups and by ethnicity. The enumeration areas (EAs) and their total number of households were listed geographically by urban and rural areas. Where EAs did not include the minimum number of households, geographically adjacent EAs were amalgamated to yield sufficient households. This provided the frame for selecting the clusters to be included in the survey according to a stratified systematic sampling technique in which the probability for the selection of any cluster was proportional to its size. A sampling interval was calculated by dividing the total number households by the number of clusters. A random number between 1 and the sampling interval was computer generated. The EA in which the random number fell was identified as the first selected cluster. The sampling interval was applied to that number and then progressively until the 20 (urban) and 15 (rural) clusters were identified. These clusters made up the sample for the survey. Individuals in the households were randomly selected from these clusters for interview.

Data collection

The recruitment of the participants in the pilot study was random. The survey was pre-tested and piloted under one-to-one supervised interview with 30 people of varied backgrounds and ages (at least 18 years old). The face-to-face interview was conducted in English by five local research assistants from the University of Dar es Salaam. The pilot study highlighted any unclear sections of the questionnaire, which were altered to ensure consistency and clarity. The questionnaire was subdivided into sections, which cover socioeconomic and demographic questions, attitudes to life and environmental issues, personal views on climate change, measures on climate change, trust and responsibility, and informational requirements. Respondents were asked whether they had noticed long-term changes in temperature and rainfall over the past 10 years and 30 years. In designing the survey instrument, particular consideration was given to item and question framing, and response options, as it was important, where possible and within the constraints of comparability and standardized items, to frame questions in an unbiased way, and to use response formats and scales that had sufficient sensitivity and face and construct validity to allow for a reasonable and defensible measurement of responses and the constructs and variables of interest.

In order to model description-based climatic change, precipitation (hereafter rainfall) and temperature data spanning 1960–2010 were obtained from the Tanzania Meteorological Agency.

Measures

Dependent variable

A polytomous nominal response variable, perceived temperature change consisting of four mutually exclusive categories, that is, getting hotter, getting colder, short and long spells of hot temperature and short and long spells of cold temperature, is the outcome variable. Getting hotter was used as the baseline comparison group. Because outcomes are unordered, arbitrarily shifting 'baseline' makes no difference.

Independent variables

Independent variables were selected based on theoretical relevance, experience, parsimony and model fit. Previous research highlights differentials in the perception of climate change based on compositional factors, that is, both biosocial and sociocultural factors (Hartter et al. 2012). Therefore, perceptions of climate change may vary based on the number of years spent in an area or residence time (Hartter 2010), amount of formal education (Maddison 2007), wealth (Hartter and Goldman 2011), gender (Hartter 2010; McCright 2010) and age (Zahran et al. 2006), among other factors. Similarly, Wolf and Moser (2011) argue that status in society (as indicated by gender, age, socioeconomic status and other social variables) may play an important role in these differentiated judgements of climate change by various groups. For this reason, biosocial factors including age, gender (both inherently biological) and ethnicity (inherently cultural) were taken into consideration in this study. Ethnic groups found in the coastal regions in which the survey was conducted included Zaramo, Sambaa and others such as the Haya, Hehe, Sukuma, Nyamwezi, and Makonde. Based on their relative proportions in the sample, we coded Zaramo and Sambaa as 1 and 2, respectively. All other ethnicities were coded as 3. Climate change perception is subjective and value-laden. Such values may vary among rural people and urban communities, depending on local context factors such as community well-being, occupations, and key resident characteristics. For example, according to Leiserowitz (2005), concern about climate change tends to be higher for people who are urban female, and with higher levels of education. For this reason, sociocultural factors including education, residential locality, residence time and region were accounted for by including them in the multinomial regression models.

Statistical analyses

Inferential statistics

Survey data were processed in IBM SPSS version 20 and analysed using STATA version 13 (StataCorp, TX 2013). We used non-parametric tests (Pearson chi-square and Cramer's V statistic) to determine whether the observed differences in perception of temperature change and rainfall patterns on the one hand, and compositional factors on the other hand, were independent (statistical significance was set to$\alpha \leq 0.05$). The outputs were presented as contingency tables in the results.

Multinomial logistic regression

Multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical membership. Multinomial logistic regression was used to predict categorical placement in or the probability of category membership on the dependent variable based on multiple independent variables in the survey data. Multicollinearity was evaluated with simple correlations among the independent variables. Also, multivariate diagnostics (i.e. standard multiple regression) was used to assess for multivariate outliers and for the exclusion of outliers or influential cases. Sample size guidelines for multinomial logistic regression indicate a minimum of 10 cases per independent variable (Schwab 2002). This requirement was met for the data. Multinomial logistic regression is often considered an attractive analysis because it does not assume normality, linearity or homoscedasticity. It does have assumptions, such as the assumption of independence among the dependent variable choices. This assumption states that the choice of or membership in one category is not related to the choice or membership of another category (i.e. the dependent variable). In this study, the assumption of independence was tested with the Hausman-McFadden test. Furthermore, multinomial logistic regression also assumes non-perfect separation. If the groups of the outcome variable are perfectly separated by the predictor(s), then unrealistic coefficients will be estimated and effect sizes will be greatly exaggerated. Variable selection or model specification methods for this study was based on theoretical relevance and sequential logistic regression analysis.

For the dependent variable (perceived temperature change), we considered the response to be multinomial. That is, the "response" for row $i, y_i = (y_i1, y_i2, \ldots y_ir)^{\mathrm{T}}$, is assumed to have a multinomial distribution with index $n_i = \Sigma_{j=1}^{r} y_{ij}$ and parameter $\pi_i = (\pi_i1, \pi_i2, \ldots, \pi_ir)^{\mathrm{T}}$.

In this case, the data are grouped so n_i is the total number of "observations" in the ith row of the dataset, and y_{ij} is the number of observations in which outcome j occurred.

The output of the regression model has three parts, labelled with the categories of the outcome variable (perceived temperature change). They correspond to the three equations below:

$$
\begin{aligned}
&ln(P(perceived\ temperature\ change = \text{getting colder})P(perceived\ temperature\ change \\
&\quad = \text{getting hotter})) = b_{10} + b_{11}SRPD + b_{12}SRWP + b_{13}(age = 36\text{–}50) \\
&\quad\quad + b_{13}(age = 51\text{–}65) + b_{13}(age = \text{more than } 65) + b_{14}(Ethnicity = \text{Sambaa}) \\
&\quad\quad + b_{14}(Ethnicity = \text{others}) + b_{15}(Residential\ Locality = \text{rural}) + b_{16}(Region = \text{Pwani}) \\
&\quad\quad + b_{16}(Region = \text{Tanga}) + b_{17}Income + b_{18}(Educational\ Status = \text{primary}) \\
&\quad\quad + b_{18}(Educational\ Status = \text{secondary}) + b_{18}(Educational\ Status = \text{tertiary})
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&ln(P(perceived\ temperature\ change = short\ and\ long\ spells\ of\ hot\ temperature) \\
&\quad P(perceived\ temperature\ change = getting\ hotter)) = b_{20} + b_{21}SRPD + b_{22}SRWP \\
&\quad + b_{23}(age = 36 - 50) + b_{23}(age = 51 - 65) + b_{23}(age = \text{more than } 65) \\
&\quad + b_{24}(Ethnicity = \text{Sambaa}) + b_{24}(Ethnicity = \text{others}) + b_{25}(Residential\ Locality = \text{rural}) \\
&\quad + b_{26}(Region = \text{Pwani}) + b_{26}(Region = \text{Tanga}) + b_{27}Income \\
&\quad + b_{28}(Educational\ Status = \text{primary}) + b_{28}(Educational\ Status = \text{secondary}) \\
&\quad + b_{28}(Educational\ Status = \text{tertiary})
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
&ln(P(perceived\ temperature\ change = short\ and\ long\ spells\ of\ cold\ temperature) \\
&\quad P(perceived\ temperature\ change = getting\ hotter)) = b_{30} + b_{31}SRPD + b_{32}SRWP \\
&\quad + b_{33}(age = 36\text{–}50) + b_{33}(age = 51\text{–}65) + b_{33}(age = \text{more than } 65) \\
&\quad + b_{34}(Ethnicity = \text{Sambaa}) + b_{34}(Ethnicity = \text{others}) \\
&\quad + b_{35}(Residential\ Locality = \text{rural}) + b_{36}(Region = \text{Pwani}) + b_{36}(Region = \text{Tanga}) \\
&\quad + b_{37}Income + b_{38}(Educational\ Status = \text{primary}) \\
&\quad + b_{38}(Educational\ Status = \text{secondary}) + b_{38}(Educational\ Status = \text{tertiary})
\end{aligned}
\tag{3}
$$

where b's are the regression coefficients; SRPD is self-rated ability to handle personal pressure and unexpected difficulties and SRWP is self-rated ability to handle work pressure and responsibilities. The ratio of the probability of choosing one outcome category (out of four groups in perceived temperature change) over the probability of choosing the baseline category is the relative risk. Relative risk was obtained by exponentiating the linear equations above, yielding regression coefficients that are relative risk ratios for a unit change in perceived temperature change.

Time series analysis of meteorological (rainfall and temperature) data

Monthly rainfall and mean temperature data from weather stations in four regions were used. The stations satisfied the following criteria: the records were sufficiently long for the analysis and included the standard reference period of 1960–2009, less than 20% of the monthly values were missing in each year. In all cases, the station had been located at a single site during the period of record, the station, in all cases, had a documented history of changes such as those involving instrumentation, observation practices and the station's immediate environment (metadata). The eligibility criteria are important because according to Longobardi and Villani (2010), most long-term climatic series are affected by non-climatic factors indeed: changes in instruments, station location, station environment and so on make climate data unrepresentative of temporal climate variability. Based on these criteria, climate data from Pwani and Tanga were eliminated from the preliminary analysis although respondents were surveyed in these two locations. Data for three coastal locations namely Dar es Salaam, Mtwara and Zanzibar were however retained because they met the inclusion criteria and a large number of respondents surveyed either originated from there or had previously lived in that area. Data for Mwanza (non-coastal location) were also included as counterfactual evidence. As a preliminary step, tests of data homogeneity were carried out to ascertain outliers (see Longobardi and Villani 2010). If a time series can be characterized as the sum of a stationary stochastic process and a linear time trend, then the appropriate test for a trend is to regress the series on a linear trend and carry out a *t*-test on the slope (Hay et al. 2002). An annual time series of each index was computed for each station, without removing the seasonal cycle of temperature or rainfall. Decomposition of the seasonal trend and residual analysis were carried out for each of the four locations based on the 50-year monthly rainfall and temperature data. Trend detection analysis was then performed through parametric and non-parametric tests only for the homogeneous data. Parametric *t*-test was used to assess whether the slope coefficient of the fitted linear regression was significantly different from zero, indicating the presence of a linear trend in this case. The slope coefficient sign would then indicate whether it is a positive or a negative trend. The Mann–Kendall non-parametric test was used to confirm the existence of a positive or negative trend at the 95% confidence level. Trends were analysed both at the annual and at the seasonal scale.

Results

Adjusted predictions of compositional factors for categories of perceived temperature change

Probabilities for each category (getting hotter, getting colder, short and long spells of hot temperature and short and long spells of cold temperature) of perceived temperature change by educational status, ethnicity, region, residence time, residential locality and respondent age were predicted. We found variations in perceived temperature change for various categories of some compositional factors. The predictions are shown in Figures 1–6. Overlap of any two categories in each variable indicates non-statistical significance and vice versa. For example, in Figure 1, respondents with no education do not overlap with respondents who have tertiary education in terms of their perception of temperature change indicating the differences in perceived temperature change between these two groups are statistically significant. The predictions in Figures 1–6 are very important in examining within group differences. For instance, in Figure 1, there are statistically significant differences among individuals with primary education, who perceived temperature to be getting colder, short and long spells of hot temperature and short and long spells of cold temperature. However, for individuals with no education there were no statistically significant differences between those who perceived temperature change to be short and long spells of hot temperature and those who perceived temperature change to be short and long spells of cold temperature.

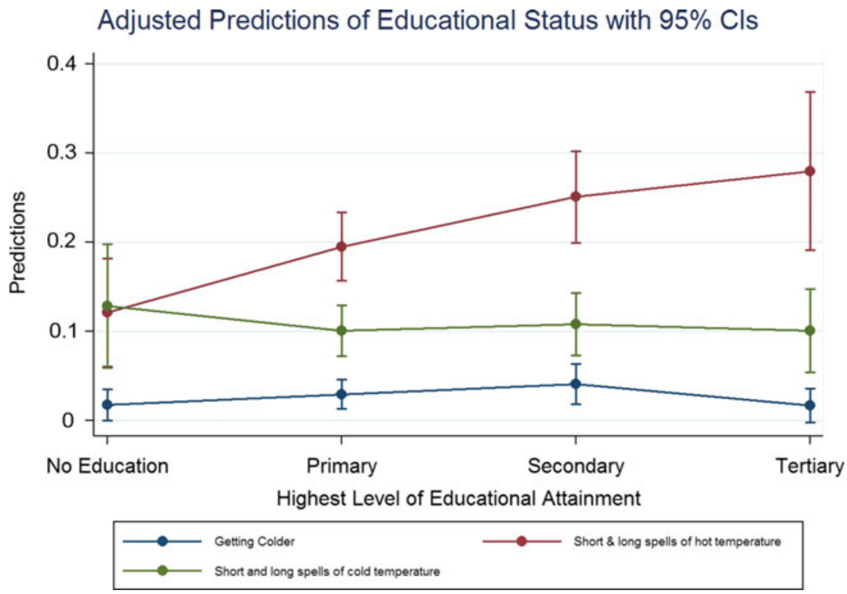


Figure 1. Prediction of perceived temperature change by highest educational status.

Association between perceived temperature change and compositional factors

The chi-square statistic reported for compositional factors except sex and education firmly reject the hypothesis that perceived temperature change and categories of age, residence time, region, ethnicity and residential locality are independent (Table 1). Similarly, the chi-square statistic reported for self-rated abilities to handle work pressure, personal pressure and unexpected difficulties rejects the hypothesis that perceived temperature change and categories of these two variables are independent. However, Cramer's V

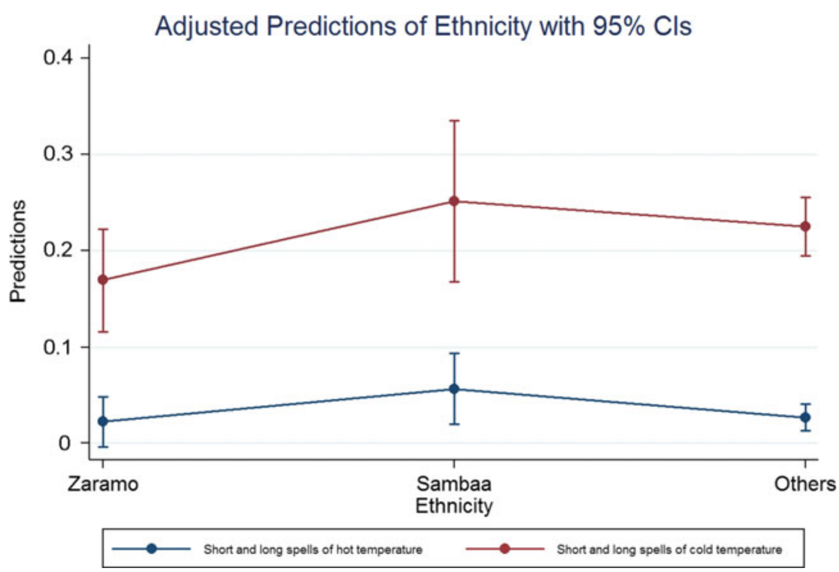


Figure 2. Prediction of perceived temperature change by ethnicity.

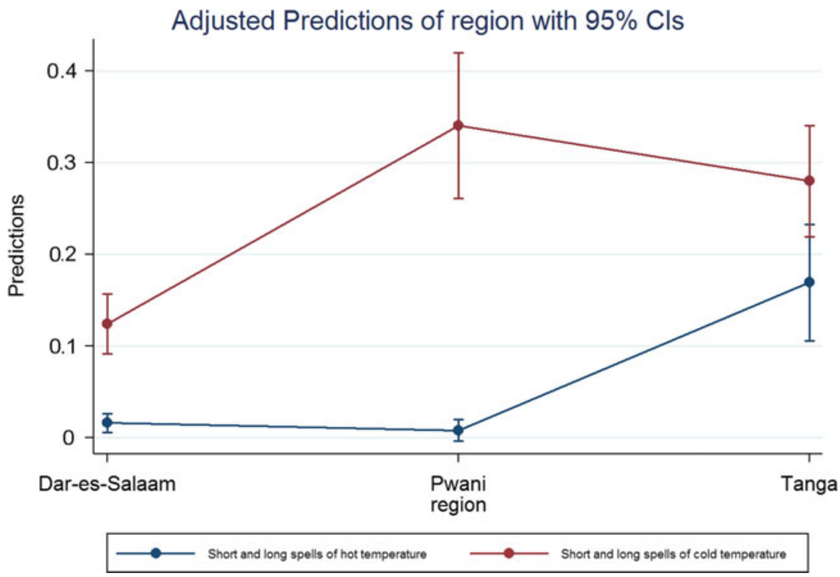


Figure 3. Prediction of perceived temperature change by coastal region.

statistic values are all less than 0.3, indicating that the association between perceived temperature change and each of the compositional measures is weak.

We found statistically significant differences in perceived temperature change at various time periods across age categories ($p \leq 0.0001$) as shown in Table 2. However, Cramer's V statistic showed a weak association between perceived temperature change and age categories.

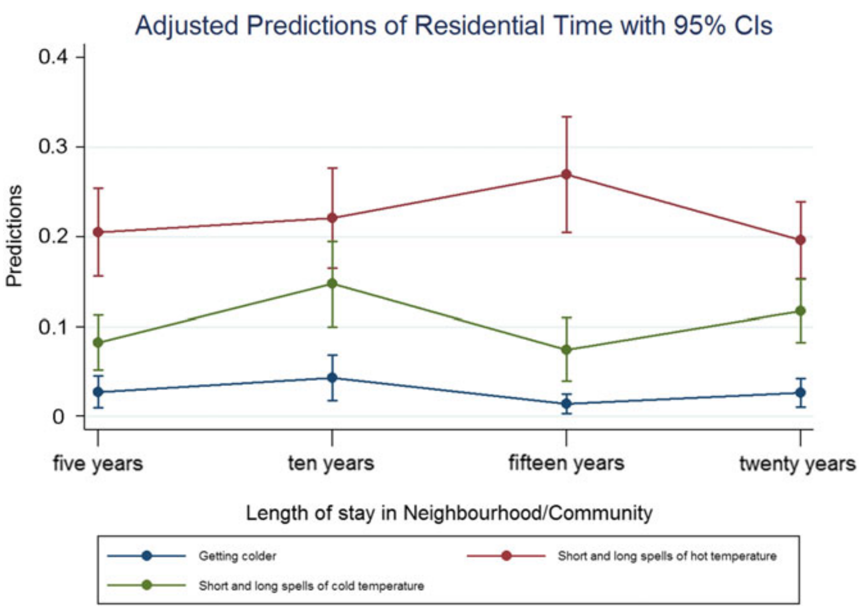


Figure 4. Prediction of perceived temperature change by residence time.

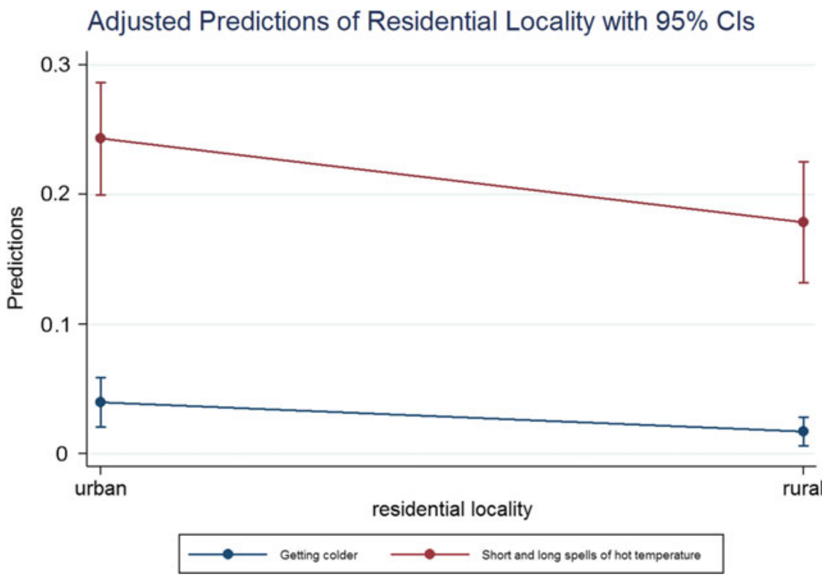


Figure 5. Prediction of perceived temperature change by rural-urban status.

Perceived temperature change at various time periods differed across coastal regions in Tanzania (Table 3) although Cramer's V suggested a weak association between perceived temperature change and region of residence.

Association between perceived changes in rainfall pattern and compositional factors

The chi-square statistic reported for age rejects the hypothesis that perceived changes in the pattern of rainfall at various time periods and categories of respondents' age are

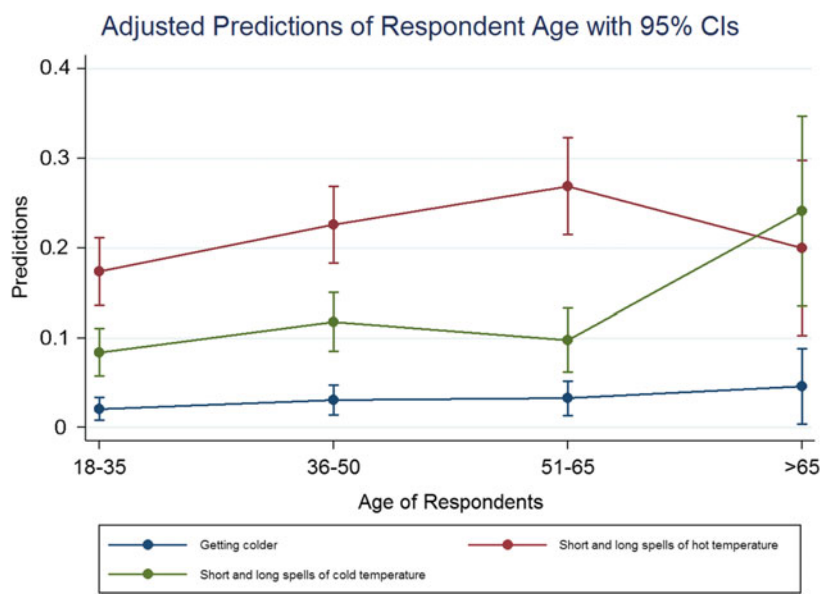


Figure 6. Prediction of perceived temperature change by age of respondents.

Table 1. Distribution of perceived temperature change by compositional factors (n = 1253).

Variables	Getting hotter (%)	Getting colder (%)	Short and Long spells of hot temperature (%)	Short and long spells of cold temperature (%)	χ^2 (df)	Cramer's V
Age					(9) = 30.7472; Pr = 0.000	0.0904
18–35	66.14	3.84	17.61	12.42		
36–50	55.48	7.62	22.14	14.76		
51–65	56.03	8.14	25.08	10.75		
More than 65	49.4	8.43	16.87	25.3		
Residence time					(9) = 28.3478; Pr = 0.001	0.0868
0–5	67.12	4.93	17.53	10.41		
6–10	53.25	9.35	20.73	16.67		
11–15	57.14	5.24	28.10	9.52		
16 or more years	56.25	6.71	20.37	16.67		
Ethnicity					(6) = 51.1785; Pr = 0.000	0.1429
Zaramo	62.45	1.22	19.59	16.73		
Sambaa	47.33	19.08	24.43	9.16		
Others	59.75	6.04	20.75	13.45		
Sex					(3) = 4.6430; Pr = 0.200	0.0609
Male	62.05	5.94	19.14	12.87		
Female	56.11	6.96	22.57	14.37		
Res. Locality					(3) = 21.2759; Pr = 0.000	0.1303
Rural	55.29	8.63	25.29	10.78		
Urban	61.51	4.98	17.9	15.61		
Region					6) = 165.5302; Pr = 0.000	0.257
Dar es Salaam	65.89	2.33	14.81	16.97		
Pwani	55.48	0.66	27.24	16.61		
Tanga	50.14	18.52	25.93	5.41		
Education					(9) = 14.9038; Pr = 0.094	0.063
No education	59.81	6.54	16.82	16.82		
Primary	57.83	8.09	21.86	12.22		
Secondary	57.43	6.71	21.87	13.99		
Tertiary	63.96	1.8	18.92	15.32		
SRWP					(3) = 47.4120; Pr = 0.000	0.1945
Poor	64.07	8.58	21.56	5.79		
Good	55.59	5.05	20.48	18.88		
SRPD					(3) = 44.4151; Pr = 0.000	0.1883
Poor	60.73	7.03	23.34	8.91		
Good	55.92	5.48	16.67	21.93		

Table 2. Differences in perceived frequency of temperature change by age of respondents ($n = 1253$).

Variables	18–35 (%)	36–50 (%)	51–65 (%)	More than 65 (%)	χ^2 (df)	Cramer's V
Perceived temperature change in past 10 years					(9) = 125.3359; Pr = 0.000	0.1827
Never	28.57	14.29	14.29	42.86		
1–3 times	45.21	31.12	19.95	3.72		
4–5 times	20.52	38.21	32.55	8.73		
More than 5 times	18.84	33.33	26.09	21.74		
Perceived temperature change between 10 and 20 years					(9) = 152.6711; Pr = 0.000	0.2015
Never	53.3	26.93	15.44	4.33		
1–3 times	20.8	43.74	28.84	6.62		
4–5 times	23.39	29.84	36.29	10.48		
More than 5 times	27.45	35.29	25.49	11.76		
Perceived temperature change between 20 and 30 years					(9) = 200.7904; Pr = 0.000	0.2311
Never	47.3	30.15	18.3	4.26		
1–3 times	6.77	39.04	42.63	11.55		
4–5 times	10.71	47.32	29.46	12.5		
More than 5 times	14.29	33.33	38.1	14.29		
Perceived temperature change between 30 and 40 years					(9) = 165.4476; Pr = 0.000	0.2098
Never	40.15	34.12	21.17	4.56		
1–3 times	2.22	21.11	54.44	22.22		
4–5 times	1.69	42.37	35.59	20.34		
More than 5 times	0	25	62.5	12.5		
Perceived temperature change between 40 and 50 years					(9) = 201.3526; Pr = 0.000	0.2314
Never	36.53	34.71	23.72	5.04		
1–3 times	0	3.85	30.77	65.38		
4–5 times	0	0	66.67	33.33		
More than 5 times	0	0	100	0		
Perceived temperature change between 50 and 60 years					(6) = 130.9394; Pr = 0.000	0.2286
Never	35.65	33.87	24.68	5.81		
1–3 times	0	0	0	100		
4–5 times	0	0	0	100		
More than 5 times	0	0	0	0		

independent (Table 4). Except perceived changes in rainfall in the past 10 years, Cramer's V statistic values range between 0.23 and 0.26, indicating that the association between perceived changes in rainfall and age is moderate to moderately strong.

Table 5 shows the distribution of perceived rainfall patterns by coastal regions. The chi-square statistic reported for Dar es Salaam, Pwani and Tanga rejects the hypothesis that perceived rainfall patterns and coastal regions are independent although based on the Cramer's V statistic values the association is weak.

Results of multinomial logistic regression of perceived temperature on compositional factors are shown in Table 6. Both coefficients and relative risk ratios are shown in the

Table 3. Differences in perceived frequency of temperature change by region of respondents ($n = 1253$).

Variables	Dar es Salaam (%)	Pwani (%)	Tanga (%)	χ^2 (df)	Cramer's V
Perceived temperature change during past 10 years				(6) = 34.8274; Pr = 0.000	0.1179
Never	100	0	0		
1–3 times	50	24.47	25.53		
4–5 times	40.09	24.76	35.14		
More than 5 times	68.12	17.39	14.49		
Perceived temperature change between 10 and 20 years				(6) = 65.3332; Pr = 0.000	0.1615
Never	56.5	16.2	27.31		
1–3 times	40.9	34.28	24.82		
4–5 times	38.71	23.39	37.9		
More than 5 times	62.75	23.53	13.73		
Perceived temperature change between 20 and 30 years				6) = 54.4901; Pr = 0.000	0.1475
Never	52.82	21.29	25.89		
1–3 times	28.69	32.67	38.65		
4–5 times	49.11	25	25.89		
More than 5 times	71.43	28.57	0		
Perceived temperature change between 30 and 40 years				(6) = 23.0435; Pr = 0.001	0.0959
Never	49.54	22.63	27.83		
1–3 times	32.22	32.22	35.56		
4–5 times	37.29	38.98	23.73		
More than 5 times	87.5	12.5	0		
Perceived temperature change between 40 and 50 years				(6) = 16.5619; Pr = 0.011	0.0813
Never	48.6	23.22	28.18		
1–3 times	19.23	53.85	26.92		
4–5 times	46.67	33.33	20		
More than 5 times	50	50	0		
Perceived temperature change between 50 and 60 years				(4) = 15.4333; Pr = 0.004	0.0785
Never	48.31	23.55	28.15		
1–3 times	10	70	20		
4–5 times	33.33	66.67	0		
More than 5 times	0	0	0		

table. The model converged in five iterations. The likelihood ratio chi-square of 304.7 with a p-value < 0.0001 indicates that the model as a whole fits significantly better than the null or intercept only model.

Age, residential locality and region were statistically significant for respondents who perceived temperature to be getting colder compared with getting hotter. The relative risk ratio of switching from the 18–35 age categories to the more than 65 age category is 3.118 for being in the getting colder vs. getting hotter group (Table 6). In other words, the expected risk of reporting that temperature is higher for respondents who are older compared with their counterparts who are 18–35 years old. The relative risk ratio of switching from urban to rural is 0.361 for being in the getting colder group vs. getting

Table 4. Differences in perceived patterns (starting and ending time) of rainfall by age of respondents ($n = 1253$).

Variables	18–35 (%)	36–50 (%)	51–65 (%)	More than 65 (%)	χ^2 (df)	Cramer's V
Perceived changes in rainfall in past 10 years					(9) = 133.3436; Pr = 0.000	0.1884
Never	46.34	29.27	14.63	9.76		
1–3 times	42.77	33.53	18.84	4.86		
4–5 times	15.2	37.16	39.19	8.45		
More than 5 times	18	16	42	24		
Perceived changes in rainfall between 10 and 20 years					(9) = 208.2891; Pr = 0.000	0.2354
Never	54.55	27.27	14.97	3.21		
1–3 times	21.76	41.32	29.43	7.5		
4–5 times	12.32	29.71	42.03	15.94		
More than 5 times	14.29	0	57.14	28.57		
Perceived changes in rainfall between 20 and 30 years					(9) = 213.3617; Pr = 0.000	0.2382
Never	46.31	31.24	18.92	3.52		
1–3 times	7.17	39.25	39.25	14.33		
4–5 times	2.04	42.86	38.78	16.33		
More than 5 times	0	0	50	50		
Perceived changes in rainfall between 30 and 40 years					(6) = 165.4228; Pr = 0.000	0.2569
Never	39.57	34.11	21.93	4.39		
1–3 times	0.87	29.57	42.61	26.96		
4–5 times	0	23.81	61.9	14.29		
More than 5 times	0	0	0	0		
Perceived changes in rainfall between 40 and 50 years					(6) = 143.9755; Pr = 0.000	0.2397
Never	36.28	34.23	24.16	5.32		
1–3 times	0	0	42.31	57.69		
4–5 times	0	0	50.0	50.0		
More than 5 times	0	0	0	0		
Perceived changes in rainfall between 50 and 60 years					(6) = 158.8534; Pr = 0.000	0.2518
Never	35.78	33.93	24.64	5.65		
1–3 times	0	0	15.38	84.62		
4–5 times	0	0	0	100		
More than 5 times	0	0	0	0		

hotter group. That is, the expected risk of staying in the getting colder group is lower for respondents who reside in rural areas compared with their urban counterparts. The relative risk ratio of switching from Dar es Salaam to Tanga is 2.727 for being in the getting colder vs. getting hotter group. The expected risk of staying in the getting colder group is higher for respondents who originate from Tanga compared with their counterparts who originate from Dar es Salaam.

Self-rated ability to handle work pressure, self-rated ability to handle personal pressure and unexpected difficulties, age, region and educational status were statistically significant for respondents who perceived temperature change as short and long spells of hot temperature compared with getting hotter. The relative risk ratio of switching from poor to

Table 5. Differences in patterns (starting and ending time) of rainfall by region of respondents ($n = 1253$).

Variables	Dar es Salaam (%)	Pwani (%)	Tanga (%)	χ^2 (df)	Cramer's V
Perceived changes in rainfall during past 10 years				(6) = 49.5061; Pr = 0.000	0.1406
Never	80.49	4.88	14.63		
1–3 times	47.17	25.2	27.63		
4–5 times	40.2	26.01	33.78		
More than 5 times	82	8	10		
Perceived changes in rainfall between 10 and 20 years				(6) = 62.2792; Pr = 0.000	0.1576
Never	56.86	15.86	27.27		
1–3 times	39.67	33.46	26.87		
4–5 times	45.65	21.01	33.33		
More than 5 times	28.57	0	71.43		
Perceived changes in rainfall between 20 and 30 years				(6) = 46.3117; Pr = 0.000	0.1359
Never	53.58	21.01	25.41		
1–3 times	32.08	33.79	34.13		
4–5 times	38.78	22.45	38.78		
More than 5 times	50	0	50		
Perceived changes in rainfall between 30 and 40 years				(4) = 30.4308; Pr = 0.000	0.1102
Never	50.31	22.02	27.66		
1–3 times	26.96	41.74	31.3		
4–5 times	38.1	33.33	28.57		
More than 5 times	0	0	0		
Perceived changes in rainfall between 40 and 50 years				(4) = 28.5207; Pr = 0.000	0.1067
Never	48.3	23.67	28.03		
1–3 times	15.38	53.85	30.77		
4–5 times	50	50	0		
More than 5 times	0	0	0		
Perceived changes in rainfall between 50 and 60 years				(4) = 8.9442; Pr = 0.063	0.0597
never	48.3	23.67	28.03		
1–3 times	15.38	53.85	30.77		
4–5 times	50	50	0		
More than 5 times	0	0	0		

good self-rated ability to handle personal pressure and unexpected difficulties is 0.649 for being in the short and long spells of hot temperature category vs. getting hotter group. Therefore, expected risk of staying in the short and long spells of hot temperature category is lower for respondents with good self-rated ability to handle personal pressure and unexpected difficulties compared with their counterparts with poor self-rated ability to handle personal pressure and unexpected difficulties.

The relative risk ratio of switching from poor to good self-rated ability to handle work pressure and responsibilities is 1.468 for being in the short and long spells of hot temperature category vs. getting hotter group. Therefore, expected risk of staying in the short and long spells of hot temperature category is higher for respondents with good self-rated ability to

Table 6. Multinomial logistic regression model predicting perceived temperature change of respondents ($n = 1253$).

Perceived temperature change	B	RRR exp (β)	SE	z	$p > \|z\|$	[95% Confidence Interval]	
Pseudo $R^2 = 0.1202$	Parameter estimates						
	Base comparison group (getting hotter)						
Variables	Getting Colder						
Self-rated ability to handle personal pressure and unexpected difficulties (ref: poor)	−0.226	0.797	0.281	−0.64	0.521	0.3996	1.5909
Self-rated ability to handle work pressure and responsibilities (ref: poor)	−0.347	0.707	0.232	−1.06	0.291	0.3711	1.3454
Age (ref: 18–35)							
36–50	0.525	1.690	0.574	1.55	0.122	0.8685	3.2903
51–65	0.639	1.895	0.680	1.78	0.075	0.9378	3.8298
More than 65	**1.137**	**3.118**	**1.704**	**2.08**	**0.037**	**1.0685**	**9.0990**
Ethnicity (ref: Zaramo)							
Sambaa	1.121	3.067	2.217	1.55	0.121	0.7435	12.6511
Others	0.270	1.310	0.886	0.4	0.690	0.3480	4.9338
Residential locality (ref: urban)							
Rural	**−1.018**	**0.361**	**0.131**	**−2.81**	**0.005**	**0.1774**	**0.7351**
Region (ref: Dar es Salaam)							
Pwani	−0.287	0.750	0.636	−0.34	0.735	0.1426	3.9470
Tanga	**2.727**	**15.283**	**6.475**	**6.44**	**0.000**	**6.6618**	**35.0624**
Income	−9.77E-07	0.999	6.28E-07	−1.56	0.119	0.9999	1.0000
Educational status							
Primary	0.609	1.838	0.889	1.26	0.208	0.7120	4.7429
Secondary	1.052	2.862	1.572	1.92	0.055	0.9757	8.3971
Tertiary	0.160	1.173	0.949	0.2	0.844	0.2401	5.7304
_cons		0.016	0.014	−4.85	**0.000**	0.0030	0.0855

(Continued)

	Short and long spells of hot temperature						
Self-rated ability to handle personal pressure and unexpected difficulties (ref: poor)	−0.432	0.649	0.123	−2.27	**0.023**	0.4476	0.9420
Self-rated ability to handle work pressure and responsibilities (ref: poor)	0.384	1.468	0.265	2.13	**0.033**	1.0305	2.0905
Age (ref: 18–35)							
36–50	0.404	1.498	0.277	2.19	**0.029**	1.0432	2.1525
51–65	0.619	1.857	0.373	3.08	**0.002**	1.2532	2.7524
More than 65	0.482	1.619	0.577	1.35	0.176	0.8054	3.2540
Ethnicity (ref: Zaramo)							
Sambaa	0.592	1.807	0.576	1.86	0.063	0.9674	3.3764
Others	0.379	1.461	0.324	1.71	0.087	0.9461	2.2575
Residential locality (ref: urban)							
Rural	−0.472	0.624	0.155	−1.9	0.057	0.3836	1.0145
Region (Dar es Salaam)							
Pwani	1.417	4.124	1.189	4.91	**0.000**	2.3437	7.2555
Tanga	1.165	3.206	0.811	4.61	**0.000**	1.9526	5.2635
q100	−5.65E-07	0.999999	2.95E-07	−1.91	0.056	0.9999989	1.000
Educational status (ref: no education)							
Primary	0.561	1.753	0.529	1.86	0.063	0.9704	3.1665
Secondary	0.930	2.534	0.848	2.78	**0.005**	1.3149	4.8816
Tertiary	1.034	2.812	1.146	2.54	**0.011**	1.2652	6.2520
_cons		0.060	0.025	−6.76	**0.000**	0.0265	0.1356
	Short and long spells of cold temperature						
Self-rated ability to handle personal pressure and unexpected difficulties (ref: poor)	0.718	2.051	0.421	3.5	**0.000**	1.3720	3.0668
Self-rated ability to handle work pressure and responsibilities (ref: poor)	1.164	3.201	0.818	4.55	**0.000**	1.9402	5.2823

(*Continued*)

Age (ref: 18–35)							
36–50	0.478	1.613	0.350	2.2	**0.028**	1.0541	2.4686
51–65	0.330	1.391	0.358	1.28	0.200	0.8394	2.3041
More than 65	1.395	4.034	1.419	3.97	**0.000**	2.0247	8.0386
Ethnicity							
Sambaa	0.289	1.335	0.550	0.7	0.484	0.5951	2.9938
Others	0.143	1.154	0.285	0.58	0.562	0.7111	1.8735
Residential locality (ref: urban)							
Rural	−0.341	0.711	0.264	−0.92	0.358	0.3435	1.4714
Region (ref: Dar es Salaam)							
Pwani	0.647	1.911	0.757	1.63	0.102	0.8789	4.1534
Tanga	**− 0.909**	**0.403**	**0.147**	**− 2.49**	**0.013**	**0.1968**	**0.8252**
Income	**− 7.13E-07**	**0.9999**	**3.27E-07**	**− 2.18**	**0.029**	**0.9998**	**0.9999**
Educational status (ref: no education)							
Primary	−0.156	0.856	0.290	−0.46	0.645	0.4407	1.6607
Secondary	0.025	1.025	0.383	0.07	0.946	0.4930	2.1327
Tertiary	−0.047	0.955	0.423	−0.1	0.916	0.4002	2.2767
_cons	−2.698	0.067	0.032	−5.66	0.000	0.0264	0.1714

Note: Bold values denote statistically significant relationships.

handle work pressure and responsibilities compared with their counterparts with poor self-rated ability to handle personal pressure and unexpected difficulties.

The relative risk ratio of switching from the 18–35 age categories to the 36–50 age category is 1.498 for being in the short and long spells of hot temperature vs. getting hotter group. In other words, the expected risk of staying in the short and long spells of hot temperature group is higher for respondents who are older compared to their counterparts who are 18–35 years old. Similarly, the relative risk ratio of switching from the 18–35 age categories to the 51–65 age category is 1.857 for being in the short and long spells of hot temperature vs. getting hotter group. That is, the expected risk of staying in the short and long spells of hot temperature group is higher for respondents who are 50 years and above compared with their counterparts who are 18–35 years old.

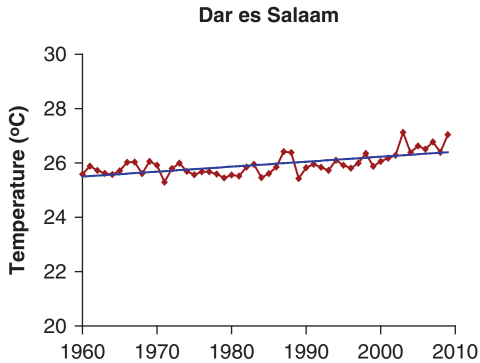
The relative risk ratio of switching from Dar es Salaam to Pwani is 4.124 for being in the short and long spells of hot temperature group vs. getting hotter group. The expected risk of staying in the short and long spells of hot temperature group is higher for respondents who originate from Pwani compared with their counterparts who originate from Dar es Salaam. Likewise, the relative risk ratio of switching from Dar es Salaam to Tanga is 3.206 for being in the short and long spells of hot temperature group vs. getting hotter group. The expected risk of staying in the short and long spells of hot temperature group is higher for respondents who originate from Tanga compared with their counterparts who originate from Dar es Salaam.

The relative risk ratio of switching from the no education category to the secondary education category is 2.534 for being in the short and long spells of hot temperature vs. getting hotter group. In other words, the expected risk of staying in the short and long spells of hot temperature group is higher for respondents who have secondary education compared with their counterparts with no education. Similarly, the relative risk ratio of switching from the no education category to the tertiary education category is 2.812 for being in the short and long spells of hot temperature vs. getting hotter group. That is, the expected risk of staying in the short and long spells of hot temperature group is higher for respondents with secondary education and above compared with their counterparts with no education.

Ethnicity, income, self-rated ability to handle work pressure, self-rated ability to handle personal pressure and unexpected difficulties, age and region were statistically significant for respondents who perceived temperature change as short and long spells of cold temperature compared with getting hotter.

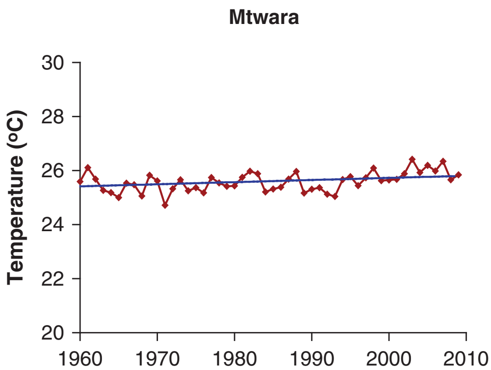
The relative risk ratio of switching from poor to good self-rated ability to handle personal pressure and unexpected difficulties is 2.051 for being in the short and long spells of cold temperature category vs. getting hotter group. Therefore, expected risk of staying in the short and long spells of cold temperature category is higher for respondents with good self-rated ability to handle personal pressure and unexpected difficulties compared with their counterparts with poor self-rated ability to handle personal pressure and unexpected difficulties. Also, the relative risk ratio of switching from poor to good self-rated ability to handle work pressure and responsibilities is 3.201 for being in the short and long spells of cold temperature category vs. getting hotter group. Therefore, expected risk of staying in the short and long spells of cold temperature category is higher for respondents with good self-rated ability to handle work pressure and responsibilities compared with their counterparts with poor self-rated ability to handle personal pressure and unexpected difficulties.

The relative risk ratio of switching from the 18–35 age categories to the 36–50 age category is 1.613 for being in the short and long spells of cold temperature vs. getting hotter group. In other words, the expected risk of staying in the short and long spells of cold temperature group is higher for respondents who are older compared with their



Best-fit values	
Slope	0.018 ± 0.0030
Y-intercept when X=0.0	−10 ± 6.0
X-intercept when Y=0.0	570
1/slope	55
95% Confidence Intervals	
Slope	0.012 to 0.024
Y-intercept when X=0.0	−23 to 1.8
X-intercept when Y=0.0	−140 to 920
Goodness of Fit	
r^2	0.43
Sy.x	0.31
Is slope significantly non-zero?	
F	36
DFn, DFd	1.0, 48
P value	< 0.0001
Deviation from zero?	Significant

Figure 7. Statistical and trend analysis for mean monthly temperature data (Dar es Salaam).



Best-fit values	
Slope	0.0078 ± 0.0032
Y-intercept when X=0.0	10 ± 6.4
X-intercept when Y=0.0	−1300
1/slope	130
95% Confidence Intervals	
Slope	0.0014 to 0.014
Y-intercept when X=0.0	−2.8 to 23
X-intercept when Y=0.0	−17000 to 200
Goodness oFit	
r^2	0.11
Sy.x	0.35
Is slope significantly non-zero?	
F	5.9
DFn, DFd	1.0, 50
P value	0.0187
Deviation from zero?	Significant

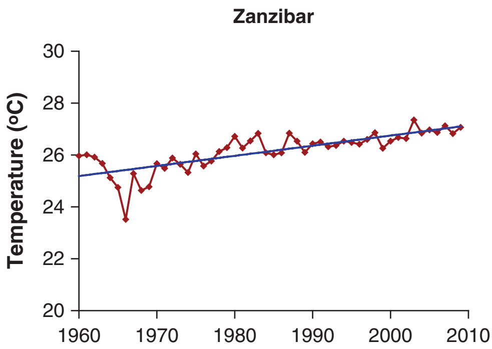
Figure 8. Statistical and trend analysis for mean monthly temperature data (Mtwara).

counterparts who are 18–35 years old. Similarly, the relative risk ratio of switching from the 18–35 age categories to the more than 65 years category is 4.034 for being in the short and long spells of cold temperature vs. getting hotter group. That is, the expected risk of staying in the short and long spells of cold temperature group is higher for respondents who are above 65 years compared with their counterparts who are 18–35 years old.

The relative risk ratio for a one-unit increase in income of respondents is 0.999 for being the short and long spells of cold temperature group vs. getting hotter group. That is, the expected risk of staying in the short and long spells of cold temperature group is lower for respondents with higher income compared with their counterparts with lower income.

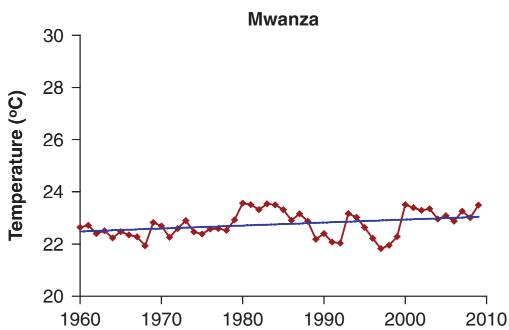
Time series analysis of temperature

Figures 7–10 show statistical and trend analysis for mean monthly temperature data for Dar es Salaam, Mtwara, Zanzibar and Mwanza, respectively. The corresponding



Best-fit values	
Slope	0.039 ± 0.0046
Y-intercept when X=0.0	–51 ± 9.1
X-intercept when Y=0.0	1300
1/slope	26
95% Confidence Intervals	
Slope	0.030 to 0.048
Y-intercept when X=0.0	–70 to –33
X-intercept when Y=0.0	1100 to 1400
Goodness of Fit	
r^2	0.60
Sy.x	0.47
Is slope significantly non-zero?	
F	73
DFn, DFd	1.0, 48
P value	< 0.0001
Deviation from zero?	Significant

Figure 9. Statistical and trend analysis for mean monthly temperature data (Zanzibar).



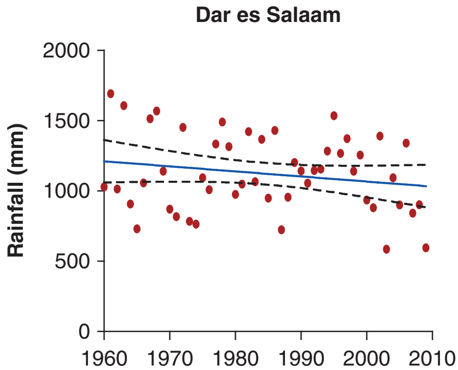
Best-fit values	
Slope	0.011 ± 0.0046
Y-intercept when X=0.0	0.16 ± 9.1
X-intercept when Y=0.0	–14
1/slope	88
95% Confidence Intervals	
Slope	0.0021 to 0.021
Y-intercept when X=0.0	–18 to 19
X-intercept when Y=0.0	–8600 to 880
Goodness of Fit	
r^2	0.11
Sy.x	0.47
Is slope significantly non-zero?	
F	6.2
DFn, DFd	1.0, 48
P value	0.0167
Deviation from zero?	Significant

Figure 10. Statistical and trend analysis for mean monthly temperature data (Mwanza). For *p*-values < 0.05, the hypothesis that the slope is non-zero is accepted and vice versa.

interpolated regression line for each region is also plotted. At α-level of 0.05, the deviation from zero is statistically significant for Dar es Salaam ($p < 0.0001$), Mtwara ($p < 0.05$), Zanzibar ($p < 0.0001$) and Mwanza ($p < 0.05$) indicating overall increase in mean monthly temperature in the four regions of Tanzania. The slopes for each of the four areas were positive indicating an overall increase in annual temperature over the 50-year period (1960–2009) for Dar es Salaam, Mtwara, Zanzibar and Mwanza. The models explained 43%, 11%, 60% and 11% of the total variance in the temperature data for Dar es Salaam, Mtwara, Zanzibar and Mwanza, respectively.

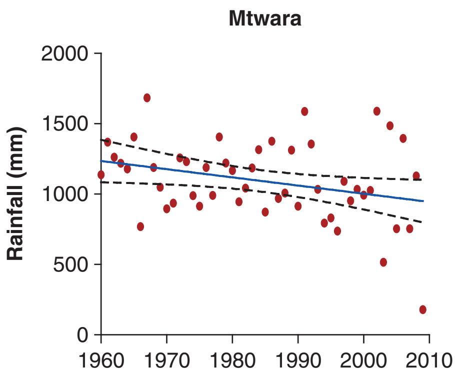
Time series analysis of rainfall

The annual rainfall time series averaged over the whole dataset, for Dar es Salaam, Mtwara, Zanzibar and Mwanza are illustrated in Figures 11–14. The corresponding interpolated regression line for each region is also plotted. The slopes for each of the four areas were negative indicating an overall decrease in annual rainfall. However, except for



Best-fit values	
Slope	–3.6 ± 2.6
Y-intercept when X=0.0	8300 ± 5300
X-intercept when Y=0.0	2300
1/slope	–0.28
95% Confidence Intervals	
Slope	–8.9 to 1.7
Y-intercept when X=0.0	–2300 to 19000
X-intercept when Y=0.0	2100 to +infinity
Goodness of Fit	
r^2	0.037
Sy.x	270
Is slope significantly non-zero?	
F	1.9
DFn, DFd	1.0, 48
P value	0.1794
Deviation from zero?	Not Significant

Figure 11. Statistical and trend analysis of mean annual rainfall data (Dar es Salaam).



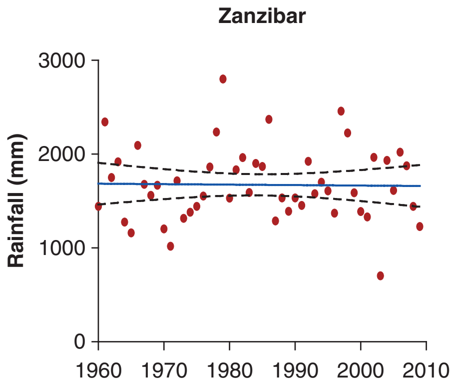
Best-fit values	
Slope	–5.8 ± 2.6
Y-intercept when X=0.0	13000 ± 5200
X-intercept when Y=0.0	2200
1/slope	–0.17
95% Confidence Intervals	
Slope	–11 to –0.51
Y-intercept when X=0.0	2100 to 23000
X-intercept when Y=0.0	2100 to 4100
Goodness of Fit	
r^2	0.092
Sy.x	270
Is slope significantly non-zero?	
F	4.9
DFn, DFd	1.0, 48
P value	0.0323
Deviation from zero?	Significant

Figure 12. Statistical and trend analysis of mean annual rainfall data (Mtwara).

Mtwara, the decrease in rainfall is not statistically significant indicating that in terms of precipitation (rainfall), the climate of Dar es Salaam, Zanzibar and Mwanza has not changed over the 50-year period (1960–2009). The variability around the mean value in Mtwara, that is about 1200 mm, is rather marked, despite the smoothing effect induced by the average computation over a large area, and a decrease in the annual average rainfall is evident, given the slope of the regression line. Residual plots for rainfall of Dar es Salaam, Mtwara, Zanzibar and Mwanza are also illustrated in Figures 15–18.

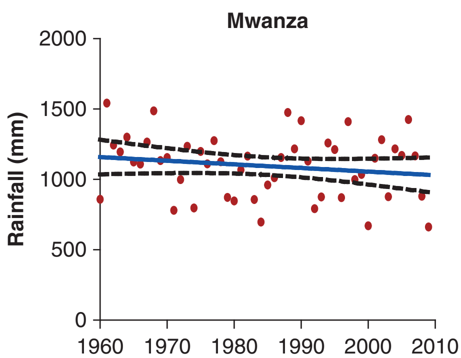
Discussion

In this study, we examined the effects of respondents' characteristics on their choice of perceived climate change outcomes. We also carried out time series analysis of rainfall and temperature over a 50-year period (1960–2009) to ascertain whether there are trends and if so, whether these trends are linear and whether the slopes for rainfall and



Best-fit values	
Slope	–0.50 ± 3.9
Y-intercept when X=0.0	2700 ± 7700
X-intercept when Y=0.0	5400
1/slope	–2.0
95% Confidence Intervals	
Slope	–8.3 to 7.3
Y-intercept when X=0.0	–13000 to 18000
X-intercept when Y=0.0	2200 to +infinity
Goodness of Fit	
r^2	0.00034
Sy.x	400
Is slope significantly non-zero?	
F	0.016
DFn, DFd	1.0, 48
P value	0.8992
Deviation from zero?	Not Significant

Figure 13. Statistical and trend analysis of mean annual rainfall data (Zanzibar).



Best-fit values	
Slope	–2.6 ± 2.2
Y-intercept when X=0.0	6200 ± 4300
X-intercept when Y=0.0	2400
1/slope	–0.39
95% Confidence Intervals	
Slope	–6.9 to 1.8
Y-intercept when X=0.0	–2400 to 15000
X-intercept when Y=0.0	2100 to +infinity
Goodness of Fit	
r^2	0.029
Sy.x	220
Is slope significantly non-zero?	
F	1.4
DFn, DFd	1.0, 48
P value	0.2372
Deviation from zero?	Not Significant

Figure 14. Statistical and trend analysis of mean annual rainfall data (Mwanza).

temperature over the period deviate from zero (statistically significant) or not. We then related the experience-based perceptions to the description-based (monitored) climate change.

Multinomial logistic regression

The results of the multinomial analysis show that region, residential locality and education are strongly associated with respondents' perception of temperature change. That is, whether temperature in the past 10 and 30 years was getting hotter, getting colder, short and long spells of hot temperature or short and long spells of cold temperature. The strong relationship between these variables and perceived temperature change suggests that actions intended to shape perception and by extension, behavioural change should take into account these compositional factors. Interestingly, older respondents (more than 65 years old), living in rural areas of Tanga region were more likely to perceive temperature

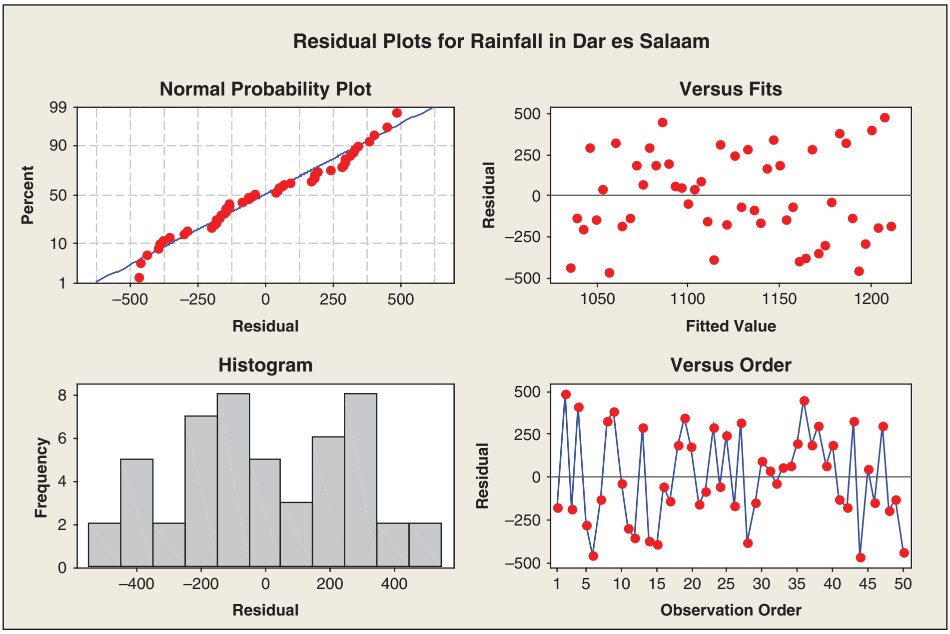


Figure 15. Residual plots of annual rainfall (Dar es Salaam).

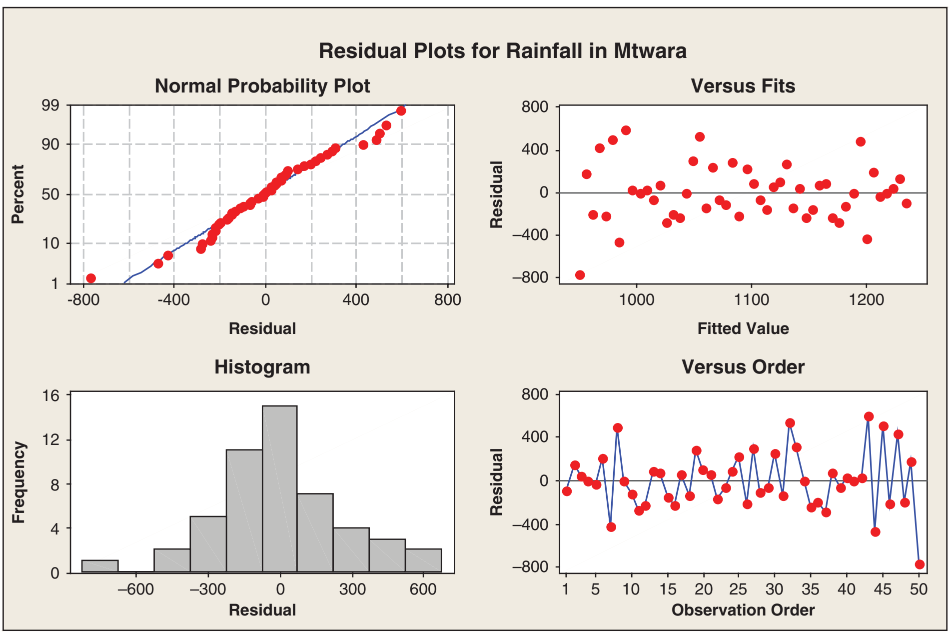


Figure 16. Residual plots of annual rainfall (Mtwara).

as getting colder rather than getting hotter when compared with younger people who were 18–35 years old, living in urban areas in Dar es Salaam. This indicates the importance of age, educational status and spatial differentials in the perception of temperature change.

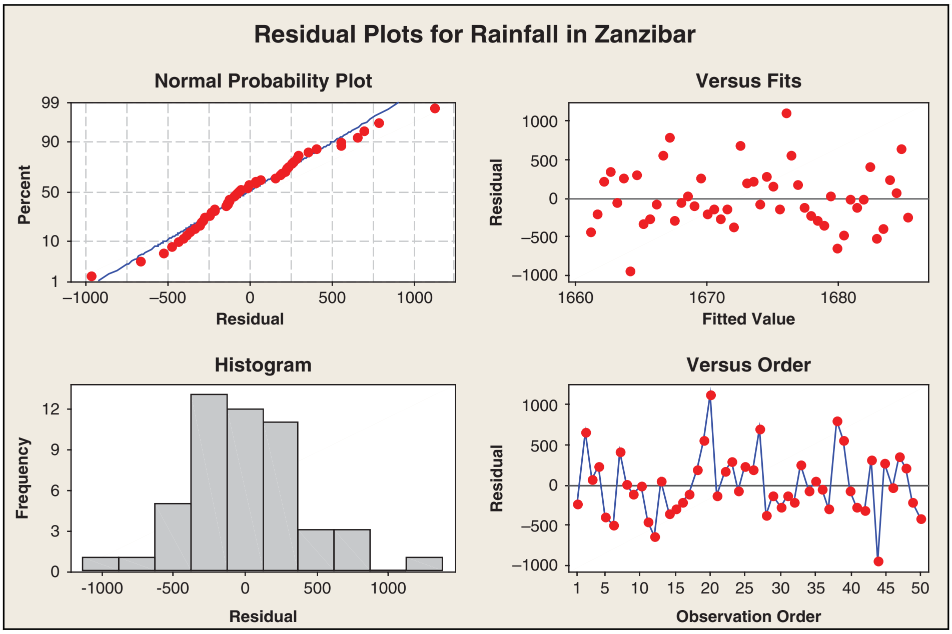


Figure 17. Residual plots of annual rainfall (Zanzibar).

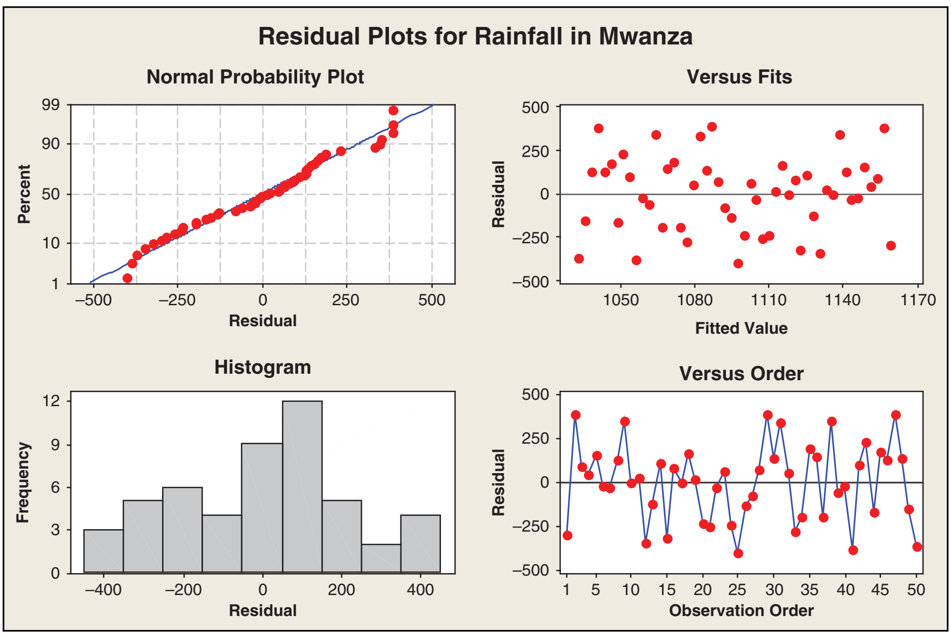


Figure 18. Residual plots of annual rainfall (Mwanza).

Our result on age of respondents and perceived climate change is consistent with several studies. Age has been frequently associated with climate risk perception (see Grothmann and Reusswig 2006; Lindell and Hwang 2008; Kellens et al. 2011). Similarly, several researchers highlight the role of education in shaping perceived climate risks (see

Leiserowitz 2006; Brody et al. 2008). Consistent with previous work (see Leiserowitz 2006; Semenza et al. 2008), we observed that people with higher levels of education perceive a lower risk associated with climate change. Our finding on spatial (regional, rural-urban) differentials in perceived climate change is also supported in the extant literature (see Thomas et al. 2007; Hamilton and Keim 2009; Sanchez et al. 2012).

The significance of coping capacity in terms of self-rated ability to handle work pressure and responsibilities as well as self-rated ability to handle personal pressure and unexpected difficulties suggest the importance and complexity of the two psychosocial factors in shaping perception of climate change. For instance, respondents who reported good self-rated ability to handle personal pressure and unexpected difficulties were less likely to perceive temperature change as short and long spells of hot temperature rather than getting hotter compared with their counterparts who had poor self-rated ability to handle personal pressure and unexpected difficulties. However, the situation is different in terms of self-rated ability to handle work pressure and responsibilities. Respondents who reported good self-rated ability to handle work pressure and responsibilities were more likely to perceive temperature change as short and long spells of hot temperature rather than getting hotter compared with their counterparts who had poor self-rated ability to handle work pressure and responsibilities. Reporting good rather than poor self-rated ability on both psychosocial measures were associated with higher likelihood of perceiving temperature change as short and long spells of cold temperature than perceiving temperature change as getting hotter. It is difficult to compare these results with the literature given that previous work has not focused on the use of multinomial techniques in assessing the relationship between perceived environmental changes on the one hand, and compositional, contextual and psychosocial factors, on the other hand.

Interestingly, we did not find any gender differentials in perceived temperature (climate) change. However, some emerging research works suggest that perceptions of risk, including climate risk perception, are gendered, and that this affects women's and men's responses to those risks. For instance, Brody et al. (2008) and Sanchez et al. (2012) suggested that females perceive a greater risk associated with global climate change. Also, women express slightly more concern about climate change than do men (McCright 2010), as other climate change public opinion studies find (e.g. Leiserowitz 2006; Hamilton 2008; Malka et al. 2009). Women's perceptions of risk also tend to be given less attention than those of their male counterparts (Kellens et al. 2011).

This study did not find any income group differentials in perceived temperature (climate) change except for those who reported short and long spells of cold temperature. Inconsistent with previous literature, we did not find income to be negatively associated with climate change risk perceptions as suggested by some researchers (see Leiserowitz 2006; Brody et al. 2008; Semenza et al. 2008) that people with higher household income will perceive a lower risk associated with global climate change. The differences between our findings and previous studies are likely due to contextual and the techniques used to establish statistical associations between the outcome and independent variables.

Unlike previous research work (Sanchez et al. 2012), we did not observe any differentials among ethnic groups in their perception of climate (temperature) change. However, our findings are consistent with the results of Nielsen and Reenberg (2010) in Northern Burkina Faso. It has been frequently suggested that different cultural, ethnic, gender and age groups will not necessarily exhibit the same attitudes of knowledge or concerns about climate change (Lowe et al. 2006; Crona et al. 2013). Ethnicity is inherently cultural and since interaction of humans with their local environment as well as the production of knowledge on local climate is rooted in distinct cultures (Crona et al.

2013), it is unsurprising that some studies report differences in perceived climate change across cultures.

Time series analysis

The time series analysis of historical temperature and rainfall data together with the preceding evidence-based perceptions provides a nuanced understanding of perceived climate change. The analyses show that in Dar es Salaam, Mtwara Zanzibar and Mwanza climate change (in terms of temperature) has taken place in all four areas of Tanzania. Temperature has invariably increased over the 50-year period. Respondents in coastal Tanzania indicated that temperature change has occurred in the past 10–30 years. Besides, as shown in Table 1, a disproportionately large percentage of respondents of all ages indicated that the temperature is getting hotter. Given that there is agreement between respondents' perceptions of temperature over the 50-year period and available scientific climatic evidence, this study argues that when meteorological records are incomplete or unavailable, local perceptions of climatic changes may be considered in determining climate change policy pointers (see Boissière et al. 2013). The time series analysis of rainfall data, however, show that climate change in terms of the amount of rainfall has not taken place in any of the four areas except in Mtwara. Although the amount of rainfall decreased in all four areas over the 50-year period, this decrease was only significant in Mtwara. This observation was also made by some respondents, especially the older ones. However, the perception of respondents that changes in rainfall patterns over the past 10 and 30 years had taken place in Dar es Salaam and Zanzibar is rather inconsistent with the findings of the time series analysis on rainfall data. This does not necessarily invalidate the perception of respondents rather it is complementary to the information provided by the meteorological data.

The findings of this study have significant implications for climate policy. It is often suggested that achieving public engagement with climate change is difficult because it is not a matter that is relevant to people's daily lives or concerns. The results of this study challenge this assertion. During the past decade, climate change has become much more than an environmental issue. It is a global challenge whose repercussions are felt in all facets of our society. It is therefore of the utmost importance for developing countries, who are hypothesized to experience climate impacts disproportionately, to develop knowledge of this emerging risk, by providing research about its physical nature, its social and economic consequences, and its implications in terms of policy and governance. This study highlights the importance of doing quantitative survey research on public perceptions of climate change within developing countries. The findings underscore the need to focus not only on technical aspects but also social dimensions such as perceptions of communities in the design and implementation of climate change adaptation initiatives. Based on the spatial differentials in climate change perception observed in this study, there is opportunity for a more locally oriented adaptation dimension to climate policy integration, which has hitherto been underserved by both academics and policymakers.

Conclusion

In this paper, we have demonstrated the usefulness of complementing time series analysis with cross-sectional survey on perceived climate change in our bid to elicit a comprehensive understanding of the phenomenon of climate change in the human mind.

Time series analysis indicated that temperature had increased over a 50-year period in coastal Tanzania. Multinomial regression also showed that respondents of all ages observed that the temperature was getting hotter. This observation by respondents is consistent with the meteorological data and demonstrates that local perception of climate change is complementary to scientific evidence on climate change. The use of multinomial regression and time series analysis has, thus, provided a much more nuanced understanding of climate change risk perception in coastal Tanzania. Such studies of local manifestations and climate perceptions can assist in identifying what technical and socioeconomic assistance is needed from the local to the national level in Tanzania and other developing country contexts. The formulation of sound national policies that embrace both technical and social dimensions of climate change hinges on a comprehensive understanding of the various facets of climate change including both experiential and descriptive. This understanding will eventually enhance capacities to deal with adverse psychosocial outcomes that are climate-induced in coastal areas, which are potential hotspots of adverse climate impacts.

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Notes

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