

## EFFECTS OF TOURISM VULNERABILITY TO DROUGHT ON PERFORMANCE OF WILDLIFE TOURISM IN MAASAI MARA, KENYA

<sup>1</sup>Richard Mose , <sup>2</sup>Christopher Ngacho, <sup>3</sup>Pius Odunga

<sup>1</sup>Adjunct lecturer, Kisii University, School of Business and Economics, Department of Tourism and Hospitality Management, Kenya; moserk2005@gmail.com, ORCID: 0000-0003-4957-0349

<sup>2</sup>Associate professor, Kisii University, School of Business and Economics, Department of Management Science, Kenya; cngacho@kisiiversity.ac.ke, ORCID: 0000-0001-8433-5307

<sup>3</sup>Professor, Kirinyaga University, School of Business and Economics, Department of Tourism and Hospitality Management, Kenya; podunga5@gmail.com, ORCID: 0000-0002-7949-7798

### ABSTRACT

The study aimed at determining the effects of sector vulnerability to climate change on performance of wildlife tourism. Drought was chosen as an indicator of climate change in Maasai Mara. A pragmatic approach using mixed methods research design was adapted for the study. Quantitative data were collected using a questionnaire that was randomly administered to 783 respondents stratified into tourists and community members in the study area. Qualitative data were also collected from 30 key informants purposively sampled for study. The questionnaire response rate was 58.51%. Quantitative data were analyzed by use of SPSS version 22 and AMOS version 21. Measurement and structural equation models were developed for the analysis. The results show that vulnerability mediated the relationship between drought and tourism  $\beta = -0.143$ ,  $t = -3.666$ ,  $P < .05$ . The results of the study are important to wildlife tourism policy makers as a guide for future research and decision making because climate change is global new normal.

*Keywords: climate change, drought, vulnerability, wildlife tourism*



Received: 20 December 2023

Accepted: 04 February 2024

Published: 16 April 2024

## A TURIZMUS ASZÁLYAL SZEMBENI SEBEZHETŐSÉGÉNEK HATÁSA A KENYAI MAASAI MARA SZAFARI TURIZMUSÁNAK TELJESÍTMÉNYÉRE

<sup>1</sup>Richard Mose ✉, <sup>2</sup>Christopher Ngacho, <sup>3</sup>Pius Odunga

<sup>1</sup>Egyetemi adjunktus, Kisii Egyetem, Üzleti és Közgazdaságtudományi Iskola, Turizmus és Vendéglátás-menedzsment Tanszék, Kenya; moserk2005@gmail.com, ORCID: 0000-0003-4957-0349

<sup>2</sup>Egyetemi docens, Kisii Egyetem, Üzleti és Közgazdaságtudományi Iskola, Vezetéstudományi Tanszék, Kenya; cngacho@kisiiversity.ac.ke, ORCID: 0000-0001-8433-5307

<sup>3</sup>Egyetemi tanár, Kirinyaga Egyetem, Üzleti és Közgazdaságtudományi Iskola, Turizmus és Vendéglátás-menedzsment Tanszék, Kenya; podunga5@gmail.com, ORCID: 0000-0002-7949-7798

### ABSZTRAKT

A tanulmány célja, hogy meghatározza az ágazat éghajlatváltozással szembeni sebezhetőségének hatását a szafari turizmus teljesítményére. A kutatás keretében az aszályt választottuk a Maasai Mara éghajlatváltozást jelző mutatójának, pragmatikus megközelítést alkalmazva, amelyet vegyes módszertani kutatási elemekkel egészítettünk ki. A kvantitatív adatok gyűjtése kérdőív segítségével történt, amelyet véletlenszerűen osztottunk ki 783 válaszadónak, a vizsgált terület turistái és a közösség tagjai között. Minőségi adatokat is gyűjtöttünk 30, a felméréshez célzottan kiválasztott kulcsinformátortól. A kérdőív kitöltöttségi aránya 58,51% volt. A kvantitatív adatokat az SPSS 22-es verziója és az AMOS 21-es verziója segítségével elemeztük, melyhez mérési és strukturális egyenletmodelleket dolgoztunk ki. Az eredmények azt mutatják, hogy a sebezhetőség befolyásolja az aszály és a turizmus közötti kapcsolatot  $\beta = -0,143$ ,  $t = -3,666$ ,  $P < ,05$ . A tanulmány eredményei útmutató jellegűek lehetnek a szafari turizmussal foglalkozó szakpolitikusok számára a jövőbeli kutatáshoz és döntéshozatalhoz, hiszen az éghajlatváltozás egy új globális trendként értelmezhető.

*Kulcsszavak: éghajlatváltozás, aszály, sebezhetőség, szafari turizmus*

*Benyújtva: 2023. december 20.*

*Elfogadva: 2024. február 4.*

*Publikálva: 2024. április 16.*

## **1. Introduction**

Kenya is a mega diverse ecosystem. The country is blessed with numerous species of flora and fauna forming a rich diversity of wildlife. The wildlife is found in game reserves, national parks, conservancies, and animal sanctuaries. With strict conservation laws, consumptive use of wildlife in the country is highly restricted: legally regulated or prohibited (The Wildlife Conservation and Management Act, 2013). The wildlife is mainly utilized through non-consumptive ways such as wildlife tourism. The tourism industry, which mainly relies on wildlife in Kenya, contributes an average of 10% to the country's GDP and accounts for an average of six in every 100 jobs in the formal employment sector of the country (KNBS, 2023). The sector is an economic enabler that spurs the growth of other sectors such as infrastructure, social and economic development (The Wildlife Conservation and Management Act, 2013). However, most wildlife in Kenya is found in arid and semi-arid areas. These areas are the most vulnerable to the effects of climate change (Ogotu et al., 2011; Mose, 2017; IPCC, 2023). Located in Narok County, a semi-arid region of Kenya, the Maasai Mara ecosystem is one such area. The Maasai Mara is the most popular game reserve in the country, attracting an average of 10% of the total number of wildlife tourists visiting Kenya annually. The game reserve has one of the highest concentrations of diverse species of wildlife in East Africa. It is home to the spectacular annual migration of the charismatic wildebeest along with other ungulates, across the crocodile infested transboundary Mara River. This is the phenomenon that attracts tourists to the Maasai Mara. Extreme climatic events such as drought that reduces water volumes of the Mara River may make wildlife tourism in Maasai Mara to be less attractive. Drought reduces the volume of water in the river, which makes the crossing of wildlife across the river less spectacular as low water levels make it easy for crocodiles to capture crossing ungulates. Thus, the spectacular struggle for life by the ungulates across the river as they try to evade marauding crocodiles is lost.

### **1.2. Study area**

The study was carried out in the Maasai Mara ecosystem, Narok County, coordinates: 1°29'24"S 35°8'38"E. The Maasai Mara ecosystem comprises an area of 1510 km<sup>2</sup>. It is located in the south-western part of Kenya and occupies the northern part of the trans-boundary Mara-Serengeti ecosystem traversing two countries, Kenya and Tanzania. The total area covered by the Mara-Serengeti ecosystem is approximately 25,000 km<sup>2</sup> in these two countries.

### **1.3. Objectives and hypothesis of the study**

The objective of the present study was to determine the role of sector vulnerability in the relationship between drought and wildlife tourism sector performance. It was based on a null hypothesis (H<sub>0</sub>), stating that Sector vulnerability does not mediate the relationship between drought and wildlife tourism sector performance in the Maasai Mara ecosystem.

## 2. Literature review

The impacts of climate change are not homogenous (Susanto et al., 2020), but rather, they are heterogeneous: region-, sector-, and context-specific (Scott et al., 2020; Liu et al., 2020). Some of the indicators include rainfall, melting of the glaciers, cyclones, rise in temperature, and drought (IPCC, 2023). About 3.6 million people or almost half of the world's population live under conditions that make them extremely vulnerable to the effects of climate change (IPCC, 2023). Ecosystem vulnerability and human vulnerabilities are interdependent on one another (IPCC, 2023). Even though they contribute the least to the causes of climate change, developing countries and island countries are the most vulnerable to the effects of climate change (IPCC, 2023). Indigenous communities and communities that depend on nature for their livelihoods are the most vulnerable to the effects of climate change (Liu et al., 2020). Sectors of the economy depending on rain-fed agriculture and nature-based tourism are most vulnerable to climate change (Scott et al., 2020). The tourism sector is highly climate-sensitive and vulnerable (Smith & Fitchett, 2020). The effects of drought on tourism are highly heterogeneous and vary from region to region (Susanto et al., 2020). Drought will put pressure on water resources, pitting tourists against local communities as they compete for scarce water resources (Layne, 2017; Susanto et al., 2020). Drought affects the migration of wildlife into and out of Maasai Mara (Mose, 2017). Once the migration is affected it sways the attractiveness of Maasai Mara as a tourist destination (Ogotu et al., 2011). Frequent drought has been seen to affect the tourism industry in the Caribbean (Dube & Nhamo, 2020). However, drought does not seem to affect nature-based tourism in Southern Africa (Scott et al., 2020; Smith & Fitchett, 2020). Drought in the Maasai Mara ecosystem is becoming more frequent and severe with an increase in temperature in recent years (Ogotu et al., 2011). Drought frequency patterns are on the increase in the Maasai Mara ecosystem and are having extreme impacts on the wildlife populations and migrations of wildlife (Ng'etich, 2018). Drought reduces water levels of the crocodile infested Mara River. The reduced levels of water make the wildebeest crossing less spectacular and less attractive as a tourist activity, thus reducing the performance of wildlife tourism in Maasai Mara (Mose, 2017).

## 3. Methodology and data collection instruments

The study employed a mixed-methods research design using both qualitative and quantitative research methods (Creswell, 2011, 2014; Cameroon, 2011). A pragmatic research approach that advocates for what works in research was adapted for the study. There were three variables (constructs) in the study: drought effects (a climate change indicator), wildlife tourism sector vulnerability, and wildlife tourism sector performance. Data were collected via questionnaires that had both open- and closed-ended items. Drought effects were measured using six closed-ended questionnaire items, vulnerability was measured using seven closed-ended questionnaire items, while performance was

measured using eight closed-ended items. The closed-ended items were ranked using a five-step Likert-scale.

The questionnaires were administered to 783 respondents, stratified into community members and tourists. The respondents were randomly sampled for the study. 466 useable questionnaires were returned, a response rate of 58.5%. Interviews were conducted with 30 key informants purposively sampled from managers of conservancies, hotels, and lodges, as well as Kenya Wildlife Service and conservation nongovernmental organizations (NGOs) working in the Maasai Mara ecosystem. Qualitative data collected via open-ended questions in the questionnaires and through interviews were explored by use of content analysis, whereas quantitative data were analyzed through exploratory factor analysis (EFA) using SPSS version 22 and by use of measurement and structural equation models using IBM AMOS version 21. The results were then presented in tables and models.

### **3.1. Wildlife tourism performance**

Performance can be defined as an achievement, an accomplishment or lack of it or that act of attaining or missing a set goal or objective (Anula, 2020). Tourism businesses will usually have financial, social, and environmental goals to achieve. For this reason, measuring performance for the tourism industry is somewhat more complex. For most tourism businesses, performance involves the measuring of economic, social, and environmental impacts of their activities. These elements are also of interest to community members involved in and dependent on tourism, especially wildlife tourism. It is for this reason that in this study the tourism performance indicators used were categorized into social, economic, and environmental indices. To measure performance, eight questionnaire items themed around economic, social, and environmental gains were developed and used for the study. The items were coded PERF 1 to 8 and a Likert-scale of 1 to 5 was used to rate the items. Further, open-ended questions in the questionnaire gave respondents a chance to give their unrestricted views.

### **3.2. Wildlife tourism sector vulnerability**

Vulnerability can be defined as the degree to which biological, geophysical, and socio-economic systems are susceptible to, and are unable to cope with, adverse effects of climate change (IPCC, 2023). For this study vulnerability was taken to mean wildlife tourism sector susceptibility to the effects of climate change, more specifically, drought. Not many studies have been carried out to investigate the impacts of climate change for communities in arid and semi-arid areas also known as range lands, where most wildlife tourism occurs in East Africa (IPCC, 2023). Seven questionnaire items were used to collect respondents' views on sector climate change vulnerability in Maasai Mara ecosystem. The questionnaire items were themed around community vulnerability, tourist vulnerability, and tourism businesses vulnerabilities. The items were coded VULN 1 to 7, and a Likert-scale of 1 to 5

was used to rate the items. Open-ended questions in the questionnaire gave the respondents a chance to give their unrestricted views.

### 3.3. Drought effects on wildlife tourism

There are several ways of defining drought. Definitions may include water deficiency in the soil, rainfall deficiency, periods of low rainfall, low water levels in streams, rivers, lakes and reservoirs, and low ground water. From all these definitions the common feature is low or deficit water levels (Bartzke et al., 2018). Also, drought can broadly be classified into two types: wet season drought which comes in the rainy season due to reduced rainfall, and dry season drought which comes in the dry season due to severely reduced rainfall (Bartzke et al., 2018). This study focused on the effects of drought on wildlife tourism in Maasai Mara. The views of both community members and tourists visiting the Maasai Mara during the study period were sought using a questionnaire. Six questionnaire items themed round community effects and tourists' effects were used. The items were coded DRGT 1 to 6. The questionnaire items were ranked using a Likert-scale of 1 to 5. Here, too, there were open-ended questions to give respondents a chance to give their unrestricted views.

## 4. Results and analysis

Quantitative data collected using questionnaires were analyzed in three steps. The first step involved an exploratory factor analysis (EFA) to establish factor structure and sampling adequacy. This was done using SPSS version 22, followed by confirmatory factor analysis (CFA) where a measurement model was developed using AMOS version 21. The model was tested for model fit and was used to test the data for reliability and validity. Finally, a structural equation model (SEM) was developed again using AMOS version 21. This model was used for hypothesis and mediation testing.

### 4.1. Exploratory factor analysis for drought, vulnerability, and performance

To test for the role of vulnerability in the drought and wildlife tourism performance relationship, an exploratory factor analysis (EFA) using the maximum likelihood method with Varimax rotation was used for analyzing the factor structure and correlation between items used in the study.

Table 1. Drought vulnerability performance relationship KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.878
Bartlett's Test of Sphericity	Approx. Chi-Square	4531.693
	Df	120
	Sig.	.000

Source: Field Survey (2023).

According to Collier (2020), data with Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) values above 0.800 are considered appropriate for factor analysis. As shown on

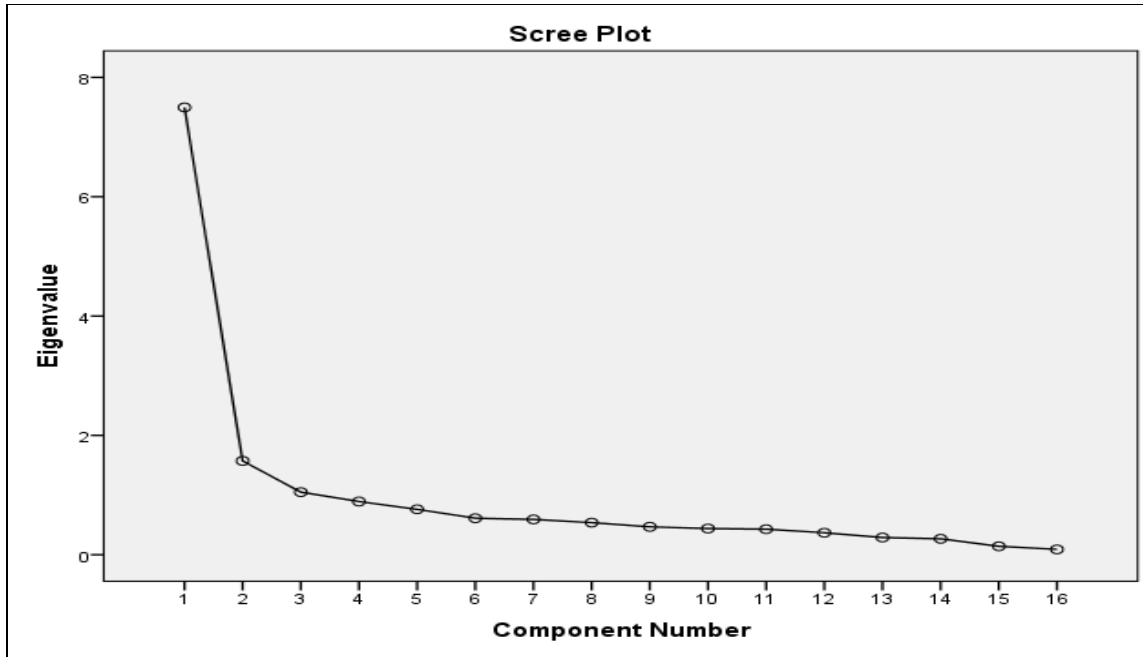
Table 1, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) for drought vulnerability and performance was .878, which is above 0.80; thus, the criterion of sampling adequacy was met. The Bartlett test of sphericity was statistically significant ( $P < .001$ ), thus the correlation matrix was statistically different from the identity matrix.

Table 2. Drought vulnerability performance relationship total variance

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	7.497	46.853	46.853	7.497	46.853	46.853	4.489	28.057	28.057
2	1.572	9.827	56.681	1.572	9.827	56.681	3.152	19.701	47.758
3	1.049	6.557	63.237	1.049	6.557	63.237	2.477	15.479	63.237
4	.892	5.574	68.811						
5	.761	4.754	73.565						
6	.612	3.825	77.390						
7	.592	3.698	81.088						
8	.538	3.362	84.449						
9	.468	2.923	87.372						
10	.439	2.744	90.116						
11	.427	2.672	92.788						
12	.369	2.304	95.091						
13	.288	1.799	96.890						
14	.267	1.667	98.557						
15	.141	.882	99.439						
16	.090	.561	100.000						

Source: Field Survey (2023).

Figure 1. Drought vulnerability performance relationship scree plot



Source: Field Survey (2023).

Table 3. Rotated component matrix

Item	Component		
	1	2	3
DRGT2		.742	
DRGT3		.769	
DRGT4		.639	
DRGT5		.753	
DRGT6		.509	.602
VULN3	.778		
VULN4	.720		
VULN5	.674		
VULN6	.627		
VULN7			.650
PERF1	.416		.532
PERF2	.661	.469	
PERF5	.773		.488
PERF7	.600	.487	
PERF8	.702		.465
VULN8	.401		.708

Source: Field Survey (2023).

As shown in Table 2 and the scree graph in Figure 1, the results of the exploratory factor analysis (EFA) exhibit that the solution was based on three factors. The three-factor



solution explains a 63.237% cumulative variance of the total variance. However, the results of the rotated component matrix illustrated in Table 3 show that the items for two of the constructs, drought and vulnerability, were loading well together, whereas the items for performance were not loading well together, with some having cross loading. Several items, such as DRGT 1, VULN 1 & 2 and PERF 3, 4 & 6, were eliminated since they did not load to any of the constructs.

Table 4. Communalities results

Item	Initial	Extraction
DRGT2	1.000	.656
DRGT3	1.000	.691
DRGT4	1.000	.580
DRGT5	1.000	.615
DRGT6	1.000	.621
VULN3	1.000	.671
VULN4	1.000	.586
VULN5	1.000	.610
VULN6	1.000	.522
VULN7	1.000	.534
PERF1	1.000	.479
PERF2	1.000	.662
PERF5	1.000	.872
PERF7	1.000	.604
PERF8	1.000	.755
VULN8	1.000	.661

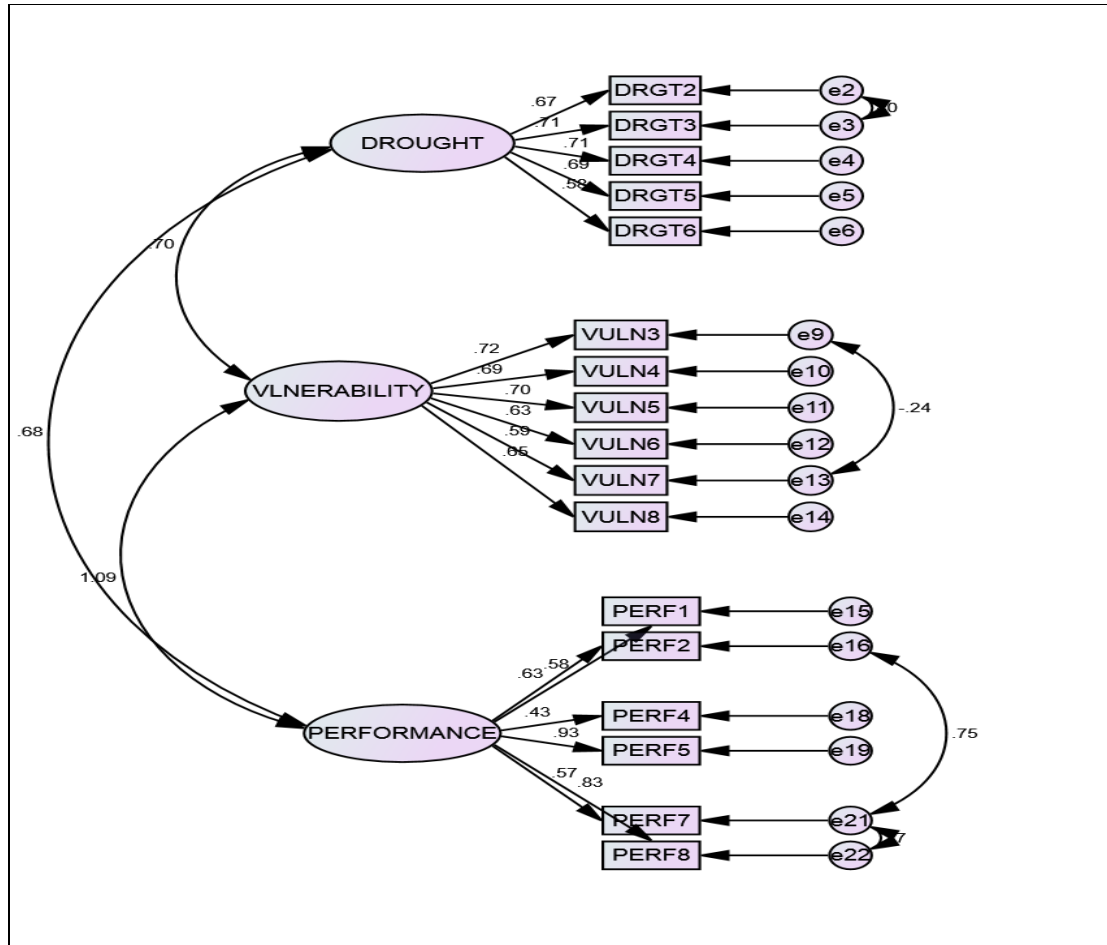
Source: Field Survey (2023).

As shown in Table 3, the factor communalities for all the items except PERF1 were found to be above 0.5. The results of the exploratory factor analysis for the relationship between drought and wildlife tourism sector performance with sector vulnerability being a mediator show that the factors have a good level of validity and can be used for further analysis.

#### 4.2. Confirmatory factor analysis

AMOS version 21 was used to perform a confirmatory factor analysis (CFA) for the relationship between drought, vulnerability, and performance. A measurement model illustrated by Figure 2 was developed and assessed for normality, model fit, reliability, and convergent validity. Model modification indices were used to improve model fit for the measurement model.

Figure 2. Drought vulnerability performance relationship measurement model



Source: Field Survey (2023).

### 4.3. Assessment of normality

An assessment of normality was conducted by testing the skewness and kurtosis of the data using Maximum Likelihood Estimator (MLE). According to Collier (2020), for sample sizes larger than 200, an absolute skewness of up to +/-2 is acceptable, while a kurtosis range of -10 to +10 is acceptable (Collier, 2020). Based on this and considering that our sample size was 466, the data were found to be within the acceptable normal range, as shown in Table 5.

Table 5. Normality test

Variable	Min	Max	Skew	c.r	Kurtosis	c.r
PERF8	1.000	3.000	-.549	-4.835	-1.175	-5.176
PERF7	1.000	3.000	-.433	-3.816	-1.354	-5.968
PERF5	1.000	4.000	.497	4.379	-.394	-1.738
PERF4	1.000	5.000	.795	7.007	-.192	-.844
PERF2	1.000	5.000	.441	3.883	-.299	-1.319
PERF1	1.000	5.000	.179	1.575	-.227	-1.002
VULN8	1.000	5.000	.968	8.527	.692	3.048

Variable	Min	Max	Skew	c.r	Kurtosis	c.r
VULN7	1.000	5.000	1.342	11.829	2.411	10.623
VULN6	1.000	5.000	1.363	12.016	1.114	4.910
VULN5	1.000	5.000	1.284	11.319	.846	3.729
VULN4	1.000	5.000	.945	8.331	-.219	-.967
VULN3	1.000	5.000	.757	6.668	-.392	-1.727
DRGT6	1.000	5.000	1.051	9.261	1.292	5.694
DRGT5	1.000	5.000	1.468	12.935	1.252	5.519
DRGT4	1.000	5.000	.881	7.760	-.283	-1.247
DRGT3	1.000	5.000	1.588	13.992	1.764	7.771
DRGT2	1.000	5.000	1.330	11.724	.906	3.991

Source: Field Survey (2023).

#### 4.4. Model fit statistics

From the measurement model developed for confirmatory factor analysis (CFA), factor loadings for each of the questionnaire items were assessed. To improve model fit, model modification indices were used. To further improve model fit, five items (DRGT1, VULN1, VULN2, PERF3, and PERF6) were removed because they had low factor loadings (< .50). Model-fit indices were then used to assess the model's goodness of fit. All the indices were found to be within the respective common acceptance levels (Collier, 2020; Ullman, 2001; Hu & Bentler, 1998; Bentler, 1990). The three-factor model (drought, vulnerability, and performance) gave a good fit as shown in Table 6.

Table 6. Model fit results

Evaluation index	Model Goodness of Fit Index	General Rule for Acceptable Fit	Default model
Absolute fit index	Chi square/df	< 5	3.292
	SRMR	< 0.05	.0613
	RMR	< 0.05	.053
	RMSEA Value	0 indicates no fit while 1 is perfect fit	.070
	GFI Value	0 indicates no fit while 1 is perfect fit	.911
Relative fit index	NFI Value	0 indicates no fit while 1 is perfect fit	.922
	IFI Value	0 indicates no fit while 1 is perfect fit	.944
	TLI		.932

	CFI Value	0 indicates no fit while 1 is perfect fit	.944
Parsimonious fit index	PNFI Value	>0.5	.759
	PCFI Value	>0.5	.778

Note: SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index. Source: Field Survey (2023).

#### 4.5. Construct reliability

Construct reliability was assessed using Cronbach's Alpha and Composite Reliability. As shown in Table 7, Cronbach Alpha for each construct in the study was found to be over the required limit of .70 (Nunnally & Bernstein, 1994). Composite reliabilities ranged from 0.806 to .830, which was above the 0.70 benchmark (Hair et al., 2011). Hence, construct reliability was established for each construct in the study.

Table 7. Reliability test

Item	Variable/Construct	Factor Loading	Default model Cronbach's Alpha	Benchmark	Default model Composite Reliability	Benchmark
DRGT2	DROUGHT	.668				
DRGT3	DROUGHT	.713				
DRGT4	DROUGHT	.707				
DRGT5	DROUGHT	.692				
DRGT6	DROUGHT	.584	.781	>0.70	0.806	>0.70
VULN3	VULNERABILITY	.723				
VULN4	VULNERABILITY	.694				
VULN5	VULNERABILITY	.695				
VULN6	VULNERABILITY	.631				
VULN7	VULNERABILITY	.587				
VULN8	VULNERABILITY	.645	.805	>0.70	0.825	>0.70
PERF1	PERFORMANCE	.575				
PERF2	PERFORMANCE	.629				
PERF4	PERFORMANCE	.431				
PERF5	PERFORMANCE	.929				
PERF7	PERFORMANCE	.573				
PERF8	PERFORMANCE	.826	.856	>0.70	0.830	>0.70

Source: Field Survey (2023).

#### 4.6. Convergent and divergent (discriminant) validity

A test for convergent validity of the scale questionnaire items was done using average variance extracted (AVE) (Fornell & Larcker, 1981; Wencui, 2014). The results showed that AVE values for all the scale questionnaire items were above the benchmark value of above 0.5, as suggested by Fornell and Larcker (1981) and Wencui (2014). Therefore, the scales for the questionnaire items used for the study to develop the measurement model were found to have the required convergent validity. The results are shown in *Table 8*.

*Table 8. Convergent validity test*

Item	Construct	Factor Loading	AVE	Benchmark
DRGT2	DROUGHT	.668		
DRGT3	DROUGHT	.713		
DRGT4	DROUGHT	.707		
DRGT5	DROUGHT	.692		
DRGT6	DROUGHT	.584	0.674	> 0.5
VULN3	VULNERABILITY	.723		
VULN4	VULNERABILITY	.694		
VULN5	VULNERABILITY	.695		
VULN6	VULNERABILITY	.631		
VULN7	VULNERABILITY	.587		
VULN8	VULNERABILITY	.645		
PERF1	PERFORMANCE	.575	.664	> 0.5
PERF2	PERFORMANCE	.629		
PERF4	PERFORMANCE	.431		
PERF5	PERFORMANCE	.929		
PERF7	PERFORMANCE	.573		
PERF8	PERFORMANCE	.826	.681	> 0.5

*Source: Field Survey (2023)*

Discriminant validity is a measure of correlations between two constructs that are not similar. It indicates the extent to which on construct differs from the others. In this study, a heterotrait-monotrait ratio of correlations (HTMT) was used to determine discriminant validity between constructs. According to Ringle et al. (2023) and Collier (2020), an HTMT value of below 0.90 indicates that there is discriminant validity between two constructs. The HTMT ratios for the drought, vulnerability, and performance constructs indicate that the HTMT criterion is detecting multicollinearity among performance–drought and vulnerability–drought constructs since their ratios are above 0.90, while performance–vulnerability has good discriminant validity at .6163, as indicated in *Table 9*. Since the AVE values were good enough, a decision was made to proceed with further analysis.

Table 9. Discriminant validity

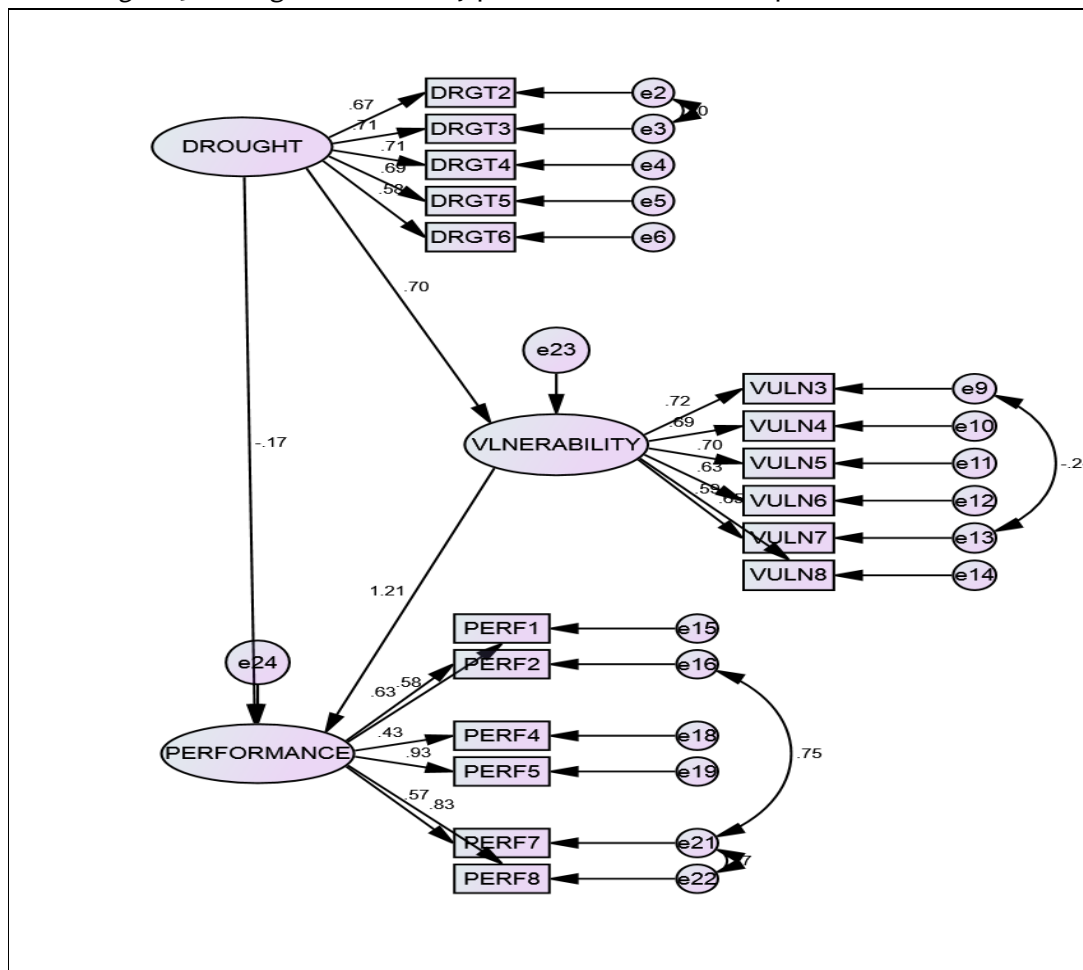
	Performance	Vulnerability	Drought
Performance			
Vulnerability	0.6163		
Drought	0.9677	0.9843	

Source: Field Survey (2023).

#### 4.7. Mediation analysis and hypothesis testing

For mediation analysis and hypothesis testing, a structural equation model (SEM) was developed (Figure 3). The study assessed the mediating role of wildlife tourism sector vulnerability on the relationship between drought and wildlife tourism sector performance. The mediation analysis was conducted by treating drought as independent variable and wildlife tourism sector performance as independent variable, while wildlife tourism sector vulnerability was treated as a mediator.

Figure 3. Drought vulnerability performance relationship structural model



Source: Field Survey (2023).

#### 4.8. Mediation analysis

A mediation analysis was based on the analysis of indirect effects based on the guidelines given by Baron and Kenny’s approach (Baron & Kenny, 1986). Mediation analysis was performed by using the total, direct and indirect effects based on bootstrap procedures (3000 samples) and based on a bias-corrected bootstrap confidence interval of 95% The results obtained were that the direct (unmediated) effect of drought on performance when vulnerability is a mediator is -.143. That is, due to the direct (unmediated) effect of drought on performance, when drought goes up by 1, performance goes down by 0.143. This is in addition to any indirect (mediated) effect that drought may have on performance. The indirect (mediated) effect of drought on performance when vulnerability is a mediator is .734. That is, due to the indirect (mediated) effect of drought on performance, when drought goes up by 1, performance goes up by 0.734. This is in addition to any direct (unmediated) effect that drought may have on performance. The indirect (mediated) effect of drought on performance is significantly different from zero at the 0.001 level ( $p = .001$  two-tailed). This is a statistical relationship which simply means that in Maasai Mara ecosystem performance and drought are inversely related.

Table 10. Mediation analysis

H. No.	Path	Total effects	Direct effects	Indirect effects	Remarks
Ho	DRGT>VULN>PERF	.591*** P< .001	-.143* P<.05	.734*** P<.001	Partial mediation

Notes: \* =  $P < .05$ , \*\* =  $P < .01$ , \*\*\* =  $P < .001$ . Source: Field Survey (2023).

The result shows that climate change vulnerability is partially mediating the relationship between drought and wildlife tourism sector performance as the indirect effects are statistically significant  $\beta = .734$ ,  $P < .001$ , as shown in Table 10.

#### 4.9. Hypothesis test results

Hypotheses test results based on path analysis show that drought in the presence of sector adaptability as a mediator is negatively and significantly associated with wildlife tourism sector performance ( $\beta = -0.143$ ,  $t = -3.666$ ,  $P < .05$ ). Based on these results, Hypothesis Ho (Sector vulnerability does not mediate the relationship between drought and wildlife tourism sector performance in Maasai Mara ecosystem) was rejected, as shown in Table 11

Table 11. Hypothesis test results

H. No.	Paths	Estimate ( $\beta$ )	S.E.	C.R.(t)	P	Remarks
Ho	Drought > vulnerability > performance	-0.143	.039	-3.666	< .05	Hypothesis Ho was rejected

Source: Field Survey (2023)

#### **4.10. Qualitative data analysis**

Qualitative data collected from interviews were organized into themes, while responses to open-ended questions of the questionnaire were explored through content analysis. Most of the key informants were concerned about the rising drought events in recent years. Respondents from community members indicated that they are being forced to diversify to other economic activities due to extreme events of drought. Key informants from the conservation sector and hotels and lodges noted that increased events of drought have intensified competition for resources between wildlife and communities and, as a result, cases of human – wildlife conflicts have multiplied. The tourists were concerned with the numerous carcasses seen in the game reserve after drought. They were concerned about the pungent smell arising from the carcasses during drought.

### **5. Conclusion**

The study revealed that vulnerability partially mediates the relationship between drought and wildlife tourism performance in the Maasai Mara ecosystem  $\beta = -.143$ ,  $t = -3.666$   $P = <.001$ . Due to these findings, the null hypothesis, which stated that sector vulnerability does not mediate the relationship between drought and wildlife tourism performance in the Maasai Mara ecosystem, was rejected. Qualitative data complemented the findings of quantitative data. The study is important because it adds to existing literature on the effects of climate change on tourism. The study specifically focuses on effects of climate change, more specifically drought on wildlife tourism, an area that has not been extensively studied previously, and thus the findings of this study are important to policy makers in the areas of tourism and wildlife.

#### **5.1. Implications for policy makers**

The findings of this study can be claimed to be important for policy makers in that they can be used to inform decisions on adaptations and mitigations of climate change effects on wildlife tourism. To improve performance, be it economic, social, or environmental, policy makers can come up with such mechanisms of reducing the effects of drought as water recycling, use of renewable energy, and tapping into the Maasai culture as a tourism product to complement wildlife tourism.

#### **5.2. Recommendations**

Further studies in the area are recommended, especially for focusing on the specific stakeholders of the wildlife tourism industry in Maasai Mara ecosystem: tourists, community members, and tourism businesses.



## References

- Baron, R. M. & Kenny, D. A. (1986). The moderator mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology* 51 (6): 1173–1182. DOI: 10.1037/0022-3514.51.6.1173
- Bartzke, G. S., Ogutu, J. O., Mukhopadhyay, S., Mtui, D., Dublin, H. T. & Piepho, H-P. (2018). Rainfall trends and variation in the Maasai Mara ecosystem and their implications for animal population and biodiversity dynamics. *PLOS ONE* 13 (9): e0202814. DOI: 10.1371/journal.pone.0202814
- Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin* 107 (2): 238–246. DOI: 10.1037/0033-2909.107.2.238
- Cameron, R. (2011). Mixed Methods Research: the Five Ps Framework. *Electronic Journal of Business Research Methods* 9 (2): 96–108.  
<https://academic-publishing.org/index.php/ejbrm/article/view/1272/>
- Creswell, J. W. (2014). *A concise introduction to mixed methods research*. Los Angeles etc.: SAGE Publications, 152 p.
- Creswell, J. & Clark P. V. (2011). *Designing and Conducting Mixed Methods Research*. Thousand Oaks, CA: Sage Publications, 488 p.
- Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*. New York & London: Routledge, 366 p.
- Dube, K. & Nhamo, G. (2020). Vulnerability of nature-based tourism to climate variability and change: case of Kariba resort town, Zimbabwe. *Journal of Outdoor Recreation and Tourism* 29: 100281. DOI: 10.1016/j.jort.2020.100281
- Fornell, C. & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research* 18 (3): 382–388. DOI: 10.1177/002224378101800313
- Hair, J. F., Ringle, Ch. M. & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *The Journal of Marketing Theory and Practice* 19 (2): 139–152. DOI: 10.2753/MTP1069-6679190202
- Hu, L. T. & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods* 3 (4): 424–453. DOI: 10.1037/1082-989X.3.4.424
- IPCC (2023). *Climate Change 2023 Synthesis Report*. Geneva: Intergovernmental Panel on Climate Change, 169 p.  
[https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC\\_AR6\\_SYR\\_FullVolume.pdf/](https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_FullVolume.pdf/)
- KNBS (2023). *Economic Survey 2023*. Nairobi: Kenya National Bureau of Statistics.  
<https://www.knbs.or.ke/download/economic-survey-2023/>
- Layne, D. (2017). Impacts of Climate Change on Tourism in the Coastal and Marine Environments of Caribbean Small Island Developing States (SIDS). *Caribbean Marine Climate Change Report Card: Science Review 2017*: 174–184.  
[https://assets.publishing.service.gov.uk/media/5a82a85840f0b6230269c051/12.\\_Tourism.pdf/](https://assets.publishing.service.gov.uk/media/5a82a85840f0b6230269c051/12._Tourism.pdf/)

- Liu, J., Cheng, H., Jiang, D. & Huang, L. (2019). Impact of climate-related changes to the timing of autumn foliage colouration on tourism in Japan. *Tourism Management* 70: 262–272. FOI: 10.1016/j.tourman.2018.08.021
- Mose, R. K. (2017). Vulnerability and Impacts assessment of Wildlife Tourism to Climate Change. A Study of the Maasai Mara Ecosystem. In: Heshimati, A. (ed.) *Economic Transformation for Poverty Reduction in Africa*. London: Routledge, pp. 36–57.
- Nunnally, J.C & Bernstein, I. H. (1994). *Psychometric theory*. New York: McGraw Hill, 752 p.
- Ogutu, J., Owen-Smith, N., Piepho, H. P. & Said, M. Y. (2011). Continuing Wildlife Population Declines and Range Contraction in the Mara Region of Kenya during 1977-2009. *Journal of Zoology* 285 (2): 99–109. DOI: 10.1111/j.1469-7998.2011.00818.x
- Ringle, C. M., Sarstedt, M., Sinkovics, N. & Sinkovics, R. R. (2023). A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief* 48: 109074. DOI: 10.1016/j.dib.2023.109074
- Scott, D., Steiger, R., Knowles, N. & Fang, Y. (2020). Regional ski tourism risk to climate change: an inter-comparison of Eastern Canada and US Northeast markets. *Journal of Sustainable Tourism* 28 (4): 568–586. DOI: 10.1080/09669582.2019.168493
- Smith, T. & Fitchett, J.M. (2020). Drought challenges for nature tourism in the Sabi Sands Game Reserve in the eastern region of South Africa. *African Journal of Range & Forage Science* 37 (1): 107–117. DOI: 10.2989/10220119.2019.1700162
- Susanto J., Zheng X., Liu Y. & Wang C. (2020). The impacts of climate variables and climate-related extreme events on island country's tourism: Evidence from Indonesia. *Journal of Cleaner Production* 276: 124204. DOI: 10.1016/j.jclepro.2020.124204
- The Wildlife Conservation and Management Act (2013). *Kenya Gazette Supplement*, 27 December 2013. <https://faolex.fao.org/docs/pdf/ken134375.pdf/>
- Ullman, J. B. (2001). Structural equation modeling. In: Tabachnick, B. G. & Fidell, L. S. (ed.) *Using Multivariate Statistics*. Needham Heights, MA: Allyn & Bacon, pp. 653–771.
- Wencui, Z. (2014). *A structural equation modeling approach to factors that influence farmers' behaviour and behavioural intentions towards water policy changes*. PhD thesis. Lethbridge, Alta: University of Lethbridge, Dept. of Economics. <https://opus.uleth.ca/items/24406582-of6a-4d6b-aa3f-ea334ce0fa46/>
- WTTC (2023). *Travel & Tourism Economic Impact*. World Travel & Tourism Council. [https://assets-global.website-files.com/6329bc97af73223b575983ac/647df24b7c4bf560880560f9\\_EIR2023-APEC.pdf/](https://assets-global.website-files.com/6329bc97af73223b575983ac/647df24b7c4bf560880560f9_EIR2023-APEC.pdf/)

### Online sources

- Anula, G. (2020). *How to measure Tourism Impacts*. Available online: <http://www.linkedin.com/pulse/how-measure-tourism-impact-anula-galewska/>  
Accessed on 13 December 2023.

Ng'etich J. (2018). Queries after fire delays wildebeest migration to Mara. *The Standard*. Available online: <https://www.standardmedia.co.ke/article/2001302190/wildebeest-delay-and-blame-game/> Accessed on 15 December 2023.