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Effect of Sector Vulnerability in the Rainfall, Wildlife Tourism Sector Performance Relationship in Maasai Mara Ecosystem, Kenya

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Abstract

This study sought to examine the role of sector vulnerability in the relationship between rainfall and wildlife tourism sector performance in Maasai Mara ecosystem, Kenya. This study is important because the Maasai Mara being a semi arid area is extremely vulnerable to the effects of climate change. The study adapted a pragmatic research approach that advocates for mixed methods research design. The study was based on a null hypothesis that sector vulnerability does not mediate the relationship between rainfall and wildlife tourism performance. Qualitative and quantitative data was collected using a questionnaire that was randomly administered to 466 respondents. Further qualitative data was collected by use interviews from 30 key informants purposively selected for the study. The results were analyzed using SPSS version 22 and AMOS version 21. The results showed that sector vulnerability mediated the relationship between rainfall and wildlife tourism performance β = - 0.439, t= -4.179, P<.001 this results were further collaborated by content analysis of qualitative data. The study concludes that wildlife tourism is extremely vulnerable to climate change indicator such as rainfall thus sector specific studies should be carried out so as to develop sector specific adaptations.

Keywords: *Vulnerability, climate change, rainfall, wildlife tourism performance*

Introduction

Globally, the tourism industry accounted for 7.6 % of the world's GDP in the year 2022. This was slightly lower than the 10.4% global GDP contributed by the sector in 2019 just before the COVID -19. Further in same year (2022) the tourism industry was responsible for 22 million new jobs globally (WTTC, 2023). In Africa, the tourism industry contributed 7% to the global GDP and accounted for 5.6 % or 25.1 million jobs directly and indirectly in the year 2022 (WTTC, 2023).

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In Kenya the tourism industry was responsible for 10.39% of the Kenyan GDP in the year 2022. (Tourism Research Institute, 2022). The sector accounted for 5.5 % of country's total formal employment meaning that almost 6 in every 100 jobs in the country were based on tourism in the year 2022. The sector contributed 4.2 % of Kenya's Gross fixed capital formation in the same year, which means 4 out of 100 new investments were attributed to tourism (WTTC, 2023). It is important to note that about 70% of tourism in Kenya is wildlife based.

The Maasai Mara received 249,900 tourists out of the 2,543,000 tourists who visited the numerous national parks and game reserves in Kenya. This amounted to about 9.8% of the total number of wildlife tourism tourists in the country, easily making the Maasai Mara the most preferred destination for wildlife tourism enthusiasts (KNBS, 2023).

Situated in a semi arid area, the Maasai Mara is extremely vulnerable to climate change. Arid and semi arid regions will be vulnerable to climate change(IPCC, 2023).. Climate dependent sectors will be particularly vulnerable to climate change (IPCC, 2023). It is for this reason that this study is important to all stakeholders involved in the wildlife tourism sector so that they can use the findings of this study to inform decision making. The study was guided by one hypothesis which was that: sector vulnerability does not mediate the relationship between rainfall and wildlife tourism performance.

Objective and Hypothesis of the study

The objective of the study was to determine the role of sector vulnerability in the relationship between rainfall and wildlife tourism sector performance in Maasai Mara ecosystem Kenya. While the hypothesis of the study was: Ho. Sector vulnerability does not mediate the relationship between rainfall and wildlife tourism sector performance in Maasai Mara ecosystem.

Literature review

Rainfall is an important factor in nature based tourism (Dube , Nhamo, 2020). At the same time, the tourism sector especially nature based tourism such as wildlife tourism is extremely vulnerable to the effects of climate change. The vulnerabilities and risks of wildlife tourism to climate change range from: infrastructure damage, loss of heritage, loss of habitat, unpredictable wildlife migrations, disease and loss of income among community members who are dependent on wildlife tourism (Gossling, 2012; IPCC, 2023; Mose, 2017; Ng'etich, 2018; Susanto et al., 2020). Extreme unpredictable rainfall makes tourism destinations unattractive (Dube, Nhamo, 2020). Lack of sufficient rainfall leads to water scarcity which increases human wildlife conflicts in conservation areas (Ogutu et al., 2011). For sectors that are dependent on climate such as tourism, their vulnerability to extreme climate indicators such as rainfall will increase in the coming years in developing countries (IPCC, 2023).

Methodology

The study adapted a pragmatic research approach that advocates for mixed methods research design. Mixed methods research design combines qualitative and quantitative data collection, analysis and interpretation. The study also adapted an objective ontology and value free axiology. (Cameron, 2011; Creswell, 2014; Creswell, Clark, 2011). Quantitative and qualitative data were collected by use of a questionnaire that was composed of closed and open ended questionnaire items. The questionnaire items were measured using a 1 to 5 Likert scale. 783 respondents stratified into tourists and community members were randomly selected for the Sstudy. 466 questionnaires were returned accounting for 66.5 % questionnaire return rate. Qualitative data was further collected using an interview schedule from 30 key informants purposively sampled for the study. The data was divided into two randomly with one half of the data being subjected to exploratory factor analysis and the other half being subjected to confirmatory factor analysis. Quantitative data was analyzed using SPSS version 25 and by use of measurement and structural equation models in AMOS version 25, while qualitative data was organized into themes and analyzed through content analysis. The hypothesis was tested using p values. A p value greater than .05 could be used not to reject the null hypothesis. While a p value of less than .05 could result in the rejection of the null hypothesis.

Study area

This study was conducted in the Maasai Mara ecosystem, Narok County, Kenya. Coordinates: 1°29'24"S 35°8'38"E. As illustrated by figure 1, the Maasai Mara ecosystem covers an area of 1,510 km^2. It is located in the south-western part of Kenya and it occupies the northern-most part of the Mara-Serengeti ecosystem. The Mara-Serengeti ecosystem traverses two countries and covers some 25,000 km2 in Tanzania and Kenya.

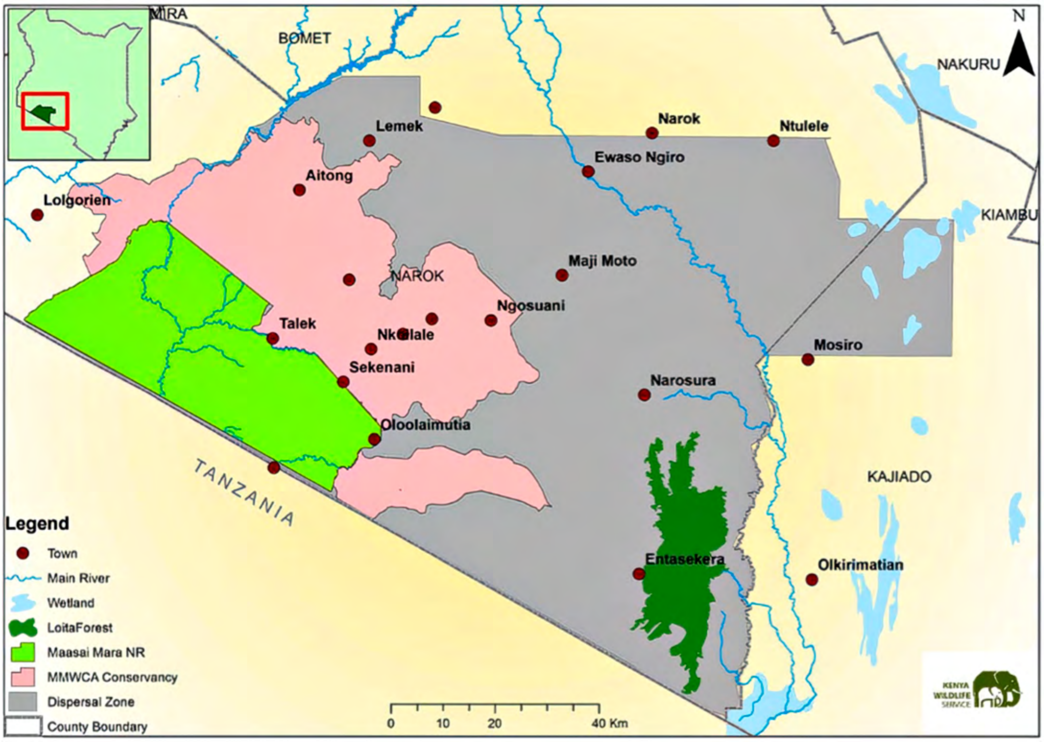

Figure 1. The Maasai Mara ecosystem
Source: Adopted from Mwiu et al., (2019)

Study Findings

Exploratory Factor Analysis (EFA)

To assess the factor structure in the relationship between rainfall, vulnerability and wildlife tourism sector performance, an EFA was performed using the principal component analysis (PCA) and varimax rotation. SPSS version 25 was used to perform EFA.

The EFA analysis for the rainfall, vulnerability and sector performance items gave a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) result of .880 while the Bartlett's Test of Sphericity results were statistically significant (P <.001) as shown on table 1. According to Collier (2020), MSA values that are above 0.800 and with Bartlett's Test of Sphericity P <0.05 are considered good for factor analysis. Thus the data was good for further analysis.

Table 1. *Rainfall, vulnerability performance relationship KMO and Bartlett's Test*

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.880
Bartlett's Test of Sphericity	Approx. Chi-Square	2636.935
	Df	91
	Sig.	.000

Source: Field Survey (2023)

Table 2. *Rainfall, vulnerability performance relationship total variance test*

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	6.340	42.266	42.266	6.340	42.266	42.266	3.587	23.912	23.912
2	1.551	10.340	52.606	1.551	10.340	52.606	2.918	19.456	43.369
3	1.013	6.755	59.361	1.013	6.755	59.361	2.399	15.993	59.361
4	.958	6.390	65.751						
5	.781	5.207	70.958						
6	.729	4.860	75.818						
7	.665	4.433	80.251						
8	.577	3.847	84.099						
9	.513	3.420	87.519						
10	.458	3.053	90.572						
11	.427	2.850	93.422						
12	.402	2.678	96.100						
13	.335	2.232	98.332						
14	.152	1.013	99.346						
15	.098	.654	100.000						

Extraction Method: Principal Component Analysis.

Source: Field Survey (2023)

Further, the EFA analysis indicated a three component analysis with a total cumulative variance value of 59.361 % as shown on table 2. The results of the rotated component matrix using the Varimax rotation with a Kaiser Normalization, showed the items loading together to give three constructs which are; Rainfall, vulnerability and performance as illustrated on Table 3.

Table 3. *Rainfall, vulnerability performance relationship rotated component matrix*

Item	Component		
	1	2	3
RAIN1			.577
RAIN3			.644
RAIN5			.793
RAIN6			.705
VULN3	.641		
VULN4	.781		
VULN5	.758		
VULN6	.628		
VULN7			
VULN8			
PERF2		.831	
PERF3		.638	
PERF4		.571	
PERF7		.859	
PERF5	.818		

Source: Field Survey (2023)

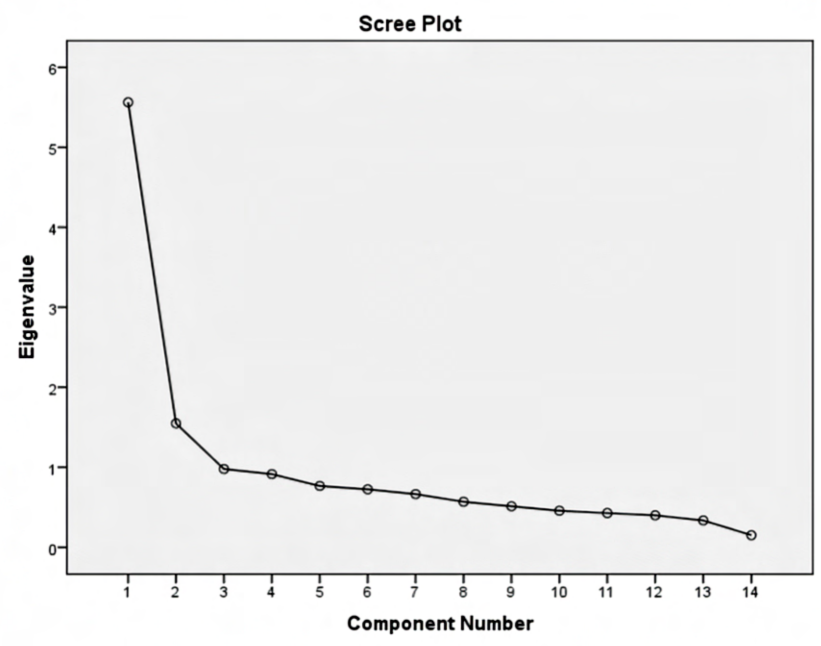

Figure 2. Rainfall, vulnerability performance relationship scree plot
Source: Field Survey (2023)

Collier, (2020) posits that, components with Eigen values which are above 1 should be considered for analysis. For this study, the scree graph obtained from the EFA analysis indicated a 3 factor analysis since three components were found to have a value of above 1 as shown on Figure 2.

Table 4. *Rainfall, vulnerability performance relationship communalities test*

Item	Initial	Extraction
RAIN1	1.000	.504
RAIN3	1.000	.516
RAIN5	1.000	.558
RAIN6	1.000	.518
VULN3	1.000	.535
VULN4	1.000	.469
VULN5	1.000	.585
VULN6	1.000	.477
VULN7	1.000	.335
VULN8	1.000	.446
PERF2	1.000	.670
PERF3	1.000	.478
PERF4	1.000	.397
PERF7	1.000	.623

Source: Field Survey (2023)

The EFA analysis further indicated that the communalities for majority of the items were above 0.5 as shown on table 4. This means that at least 50% information could be extracted from most of the questionnaire items for the study.

Confirmatory Factor Analysis (CFA)

For CFA, a measurement model was developed in AMOS version 25 and the model was assessed for model fit, normality and reliability, convergent and divergent validity. Model modification indices were used to improve model fit for the measurement model (figure 3).

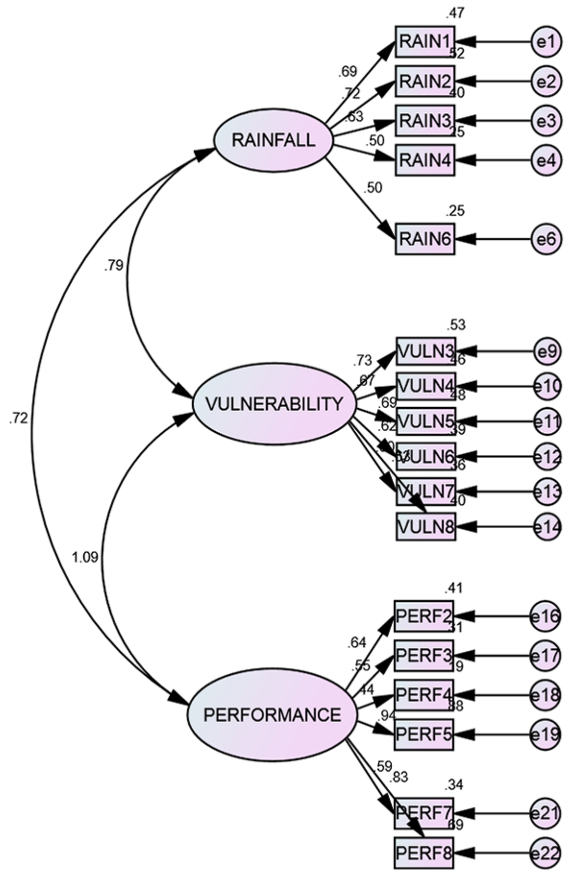

Figure 3. Rainfall, vulnerability performance relationship measurement model
Source: Field Survey (2023)

Assessment of normality

An assessment of normality was done by testing the skewness and kurtosis of the data using Maximum Likelihood Estimator (MLE). Collier (2020) opines that, for sample sizes that are more than 200, an absolute skewness of up to +/-2 is good and acceptable. While a Kurtosis range of between –10 to +10 is acceptable (Collier, 2020). Based on this, the data was found to be within the acceptable normal range as shown on table 5.

Table 5. *Rainfall, vulnerability performance relationship 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
PERF3	1.000	5.000	.942	8.306	.534	2.353
PERF2	1.000	5.000	.441	3.883	-.299	-1.319
VULN8	1.000	5.000	.968	8.527	.692	3.048
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
RAIN6	1.000	5.000	.259	2.281	-1.078	-4.750
RAIN4	1.000	5.000	2.498	22.016	5.897	25.984
RAIN3	1.000	5.000	-.022	-.197	-1.321	-5.822
RAIN2	1.000	5.000	1.251	11.027	.458	2.020
RAIN1	1.000	5.000	.409	3.606	-.887	-3.908
Multivariate					75.412	32.025

Source: Field Survey (2023)

Model Fit Statistics

To test for model fit, factor loadings for each of the questionnaire items were assessed. Model-fit indices were used to assess the model's goodness of fit. Five items (RAIN5, VULN1, VULN2, PERF 1 and PERF6) were removed because they had low factor loadings of < .50. After these items were removed, all the indices were then found to be within the respective common acceptance levels (Bentler, 1990; Collier, 2020; Hu, Bentler, 1998; Ullman, 2001).The three-factor model (Humidity, adaptability, and performance) gave a good model fit as shown on Table 6.

Table 6. *Rainfall, vulnerability performance relationship model fit*

<table>
<tr><th>Evaluation index</th><th>Model Goodness of Fit Index</th><th>General Rule for Acceptable Fit</th><th>Default model</th></tr>
<tr><td rowspan="4"></td><td>Chi square/df</td><td>1 or 2 (Threshold < 5)</td><td>2.987</td></tr>
<tr><td>SRMR Value
RMR</td><td><0.05</td><td>.0473
.042</td></tr>
<tr><td>RMSEA Value</td><td><0.05 indicates very good fit (Threshold level=0.10)</td><td>.065</td></tr>
<tr><td>GFI Value</td><td>0 indicates no fit while 1 indicates perfect fit</td><td>.925</td></tr>
<tr><td rowspan="4">Relative fit index</td><td>NFI Value</td><td>0 indicates no fit while 1 indicates perfect fit</td><td>.928</td></tr>
<tr><td>IFI Value</td><td>0 indicates no fit while 1 indicates perfect fit</td><td>.951</td></tr>
<tr><td>TLI</td><td></td><td>.938</td></tr>
<tr><td>CFI Value</td><td>0 indicates no fit while 1 indicates perfect fit</td><td>.951</td></tr>
<tr><td rowspan="2">Parsimonious fit index</td><td>PNFI Value</td><td>>0.5</td><td>.737</td></tr>
<tr><td>PCFI Value</td><td>>0.5</td><td>.755</td></tr>
</table>

Source: Field Survey (2023)

Construct Reliability

For the study, construct reliability was assessed using Cronbach's Alpha and composite reliability. As shown on Table 7. Cronbach Alpha for each construct in the study was found to be over and above the required limit of .70 (Nunnally, Bernstein, 1994). Composite reliabilities ranged from 0.734 to 0.825, which was above the 0.70 benchmark (Hair et al., 2011). Thus, construct reliability for each construct in the study was established.

Table 7. *Rainfall, vulnerability performance relationship reliability test*

Item	Construct	Factor Loading	Default model Cronbach's Alpha	Bechmark	Default model Composite Reliability	Benchmark
RAIN1	RAINFALL	.633				
RAIN2	RAINFALL	.738				
RAIN3	RAINFALL	.571				
RAIN4	RAINFALL	.521				
RAIN6	RAINFALL	.506	.749	>0.70	0.734	>0.70
VULN3	VULNERABILITY	.704				
VULN4	VULNERABILITY	.684				
VULN5	VULNERABILITY	.704				
VULN6	VULNERABILITY	.625				
VULN7	VULNERABILITY	.572				
VULN8	VULNERABILITY	.622	.805	>0.70	0.81	>0.70
PERF2	PERFORMANCE	.623				
PERF3	PERFORMANCE	.541				
PERF4	PERFORMANCE	.423				
PERF5	PERFORMANCE	.932				
PERF7	PERFORMANCE	.573				
PERF8	PERFORMANCE	.828	.856	>0.70	0.825	>0.70

Source: Field Survey (2023)

Convergent validity

A test for convergent validity of all the scale questionnaire items was done using the Average Variance Extracted (AVE) (Fornell, Larcker, 1981). The results showed that the average variance-extracted (AVE) values for all the scale questionnaire items were above the benchmark required value of 0.50 as suggested by Fornell and Larcker (Fornell, Larcker, 1981; 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 on table 8.

Table 8. *Rainfall, vulnerability performance relationship validity test*

Item	Variable/construct	Factor Loading	AVE	Benchmark
RAIN1	RAINFALL	.633		
RAIN2	RAINFALL	.738		
RAIN3	RAINFALL	.571		
RAIN4	RAINFALL	.521		
RAIN6	RAINFALL	.506	0.600	> 0.5
VULN3	VULNERABILITY	.704		
VULN4	VULNERABILITY	.684		
VULN5	VULNERABILITY	.704		
VULN6	VULNERABILITY	.625		
VULN7	VULNERABILITY	.572		
VULN8	VULNERABILITY	.622	0.654	> 0.5
PERF2	PERFORMANCE	.623		
PERF3	PERFORMANCE	.541		
PERF4	PERFORMANCE	.423		
PERF5	PERFORMANCE	.932		
PERF7	PERFORMANCE	.573		
PERF8	PERFORMANCE	.828	0.676	> 0.5

Source: Field Survey (2023)

Divergent (Discriminant) Validity

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. Referring to table 9, the HTMT criterion detected poor discriminant validity between performance-rainfall constructs with a value above .90, while the other constructs that is rainfall-vulnerability and performance, vulnerability constructs indicate that the constructs did not have discriminant validity issues since they had values below .90.

Table 9. *Performance, vulnerability, rainfall discriminant validity test.*

	Performance	Vulnerability	Rainfall
Performance			
Vulnerability	0.6268		
Rainfall	0.9783	0.7646	

Source: Field Survey (2023)

Mediation analysis and hypothesis test

After the confirmatory factor analysis, a structural equation model (SEM) was developed for the mediation analysis and hypothesis testing as illustrated by figure 4. The study assessed the mediating role of wildlife tourism sector vulnerability on the relationship between rainfall and wildlife tourism sector performance.

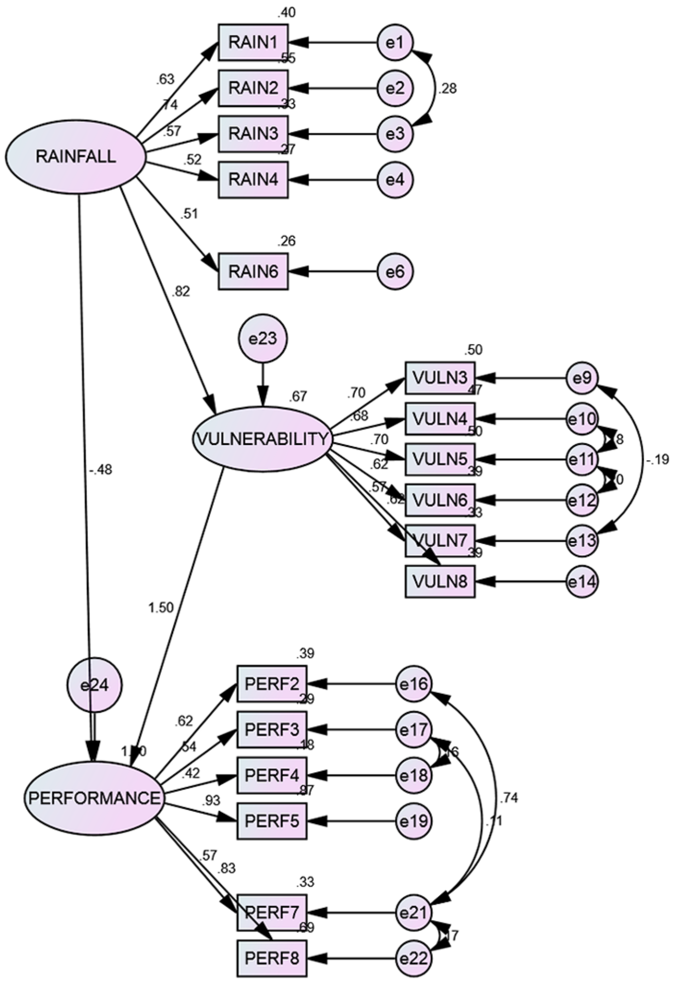

Figure 4. Rainfall, vulnerability performance relationship structural equation model.
Source: Field Survey (2023)

Mediation analysis

A mediation analysis was conducted by treating rainfall and wildlife tourism sector performance as independent variables and dependent variable respectively. While wildlife tourism sector vulnerability was treated as a mediator. The mediation analysis was based on the analysis of indirect effects based on the guidelines given by Baron and Kenny classical approach (Baron, Kenny, 1986). The mediation test was based on the total, direct and indirect effects based on bootstrap sampling procedures. 3000 bootstrap samples were used based on a bias-corrected bootstrap sampling confidence interval of 95%. The results obtained were that; the direct (unmediated) effect of rainfall on performance with vulnerability being a mediator is -.439. That is, due to the direct (unmediated) effect of rainfall on performance, when rainfall goes up by 1, performance goes down by 0.439. This is in addition to any indirect (mediated) effect that rainfall may have on performance. The indirect (mediated) effect of rainfall on performance is 1.123. That is, due to the indirect (mediated) effect of rainfall on performance, when rainfall goes up by 1, performance goes up by 1.123. This is in addition to any direct (unmediated) effect that rainfall may have on performance. Also, the indirect (mediated) effect of rainfall on performance is significantly different from zero at the 0.001 level (p=.001 two-tailed).

From this result, it is concluded that vulnerability was partially mediating the relationship between rainfall and wildlife tourism sector performance since the indirect effects are statistically significant β = 1.123, P<.001 as shown on Table 10.

Table 10. *Rainfall, vulnerability performance relationship mediation test*

H. No.	Path	Total Effects	Direct Effects	Indirect Effects	Remarks
H0	RAIN>VULN>PERF	.684*** P<.001	-.439*** P<.001	1.123*** P<.001	Partial Mediation

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

Hypothesis test results

Hypotheses test results based on path analysis showed that rainfall in the presence of sector vulnerability as a mediator is negatively and significantly associated with wildlife tourism sector performance (β = - 0.439, t= -4.179, P<.001). Based on these result: Hypothesis Ho: Sector vulnerability does not mediate the relationship between rainfall and wildlife tourism sector performance in Maasai Mara ecosystem was rejected as illustrated by Table 11.

Table 11. *Rainfall, vulnerability performance relationship hypothesis test*

H. No.	Paths	Estimate(β)	S.E.	C.R.(t)	P	Remarks
H0	Rainfall>vulnerability>performance	-0.439	.105	-4.179	***	Hypothesis H0 rejected

Source: Field Survey (2023)

Qualitative data analysis

Content analysis was used to analyze qualitative data from open ended questions on the questionnaires. Majority of the respondents opined that extreme rainfall negatively affected wildlife tourism in Maasai Mara. Responses from community members brought out the fact that excess rainfall led to water logging of the Maasai Mara game reserve since the soils there are clay soils. Water logging led to foot rot disease among ungulates resulting in the animals leaving the Maasai Mara earlier than normal. Further, the respondents posited that delayed rainfall or rainfall of insufficient quantities resulted in delayed migration of the wildlife especially the charismatic wildebeest into the Maasai Mara from Serengeti. Low rainfall also reduced the volume of water in the Mara River which made the crossing of the crocodile infested Mara River by the wildebeest, a phenomena that has been declared the eighth wonder of the world, less spectacular thus less attractive to tourists who like seeing the wildebeest struggling to escape the jaws to marauding hungry crocodiles. The sentiments were collaborated by information collected from key informants who further opined that unreliable rainfall which was becoming a common occurrence, was negatively affecting wildlife tourism in Maasai Mara.

Discussion and conclusion

The study findings indicate that wildlife rainfall is statistically significantly related to wildlife tourism performance with sector vulnerability being a mediator. Content analysis of qualitative data collected during the study also supports this quantitative data results. Consequently the null hypothesis for the study was rejected. Since the direct effects were still significant after mediation it is therefore concluded that sector vulnerability partially mediated the relationship between rainfall and wildlife tourism sector performance.

It is concluded that while rainfall is very important in Maasai Mara ecosystem. The wildlife tourism sector in the area is highly vulnerable to extreme and unpredictable rainfall which is a characteristic feature of climate change. Sector vulnerability partially mediates the relationship between rainfall and wildlife tourism performance $\beta = -0.439$, $t = -4.179$, $P<.001$ for this reason the stakeholders involved in wildlife tourism in the Maasai Mara require to put more efforts and resources in studying and understanding the specific effects of climate change on wildlife tourism so that sector specific adaptations can be formulated. This is because climate change vulnerabilities and risks are sector and context specific.

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