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# Livelihood vulnerability increases human–wildlife interactions

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**Research Paper**

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## Summary

Human–wildlife interactions (HWIs) occur in many rural African communities, with potential impacts on livelihood vulnerability. High livelihood vulnerability may force communities to employ strategies that increase the risk of negative HWIs, yet the extent to which HWIs drive or are driven by vulnerability is unclear. We hypothesized that more vulnerable households are more likely to be exposed to wildlife and experience negative interactions. To test this hypothesis, we calculated the Livelihood Vulnerability Index (LVI) of rural households in and around Quirimbas National Park (north-eastern Mozambique) and assessed whether there is a link between livelihood vulnerability and HWIs. We found a two-way association between LVI and HWIs, with more vulnerable households indeed taking greater risks and encountering wildlife when fetching water from rivers, whereas less vulnerable households tended not to employ strategies likely to increase wildlife encounters. We also observed that HWIs exert a strong effect on livelihood vulnerability, suggesting that HWIs should be included as an exposure factor in vulnerability assessments for rural households. We recommend that livelihood strategies and community vulnerability should be considered when designing HWI mitigation schemes and implementing conservation measures.

## Introduction

Human population growth can increase the vulnerability of local communities to food and water scarcity, poverty and climate change (Mondal 2019). Although strategies such as building a highly connected social network are very successful in reducing vulnerability (Chambers & Conway 1992), other strategies, such as collection of non-timber forest resources for commercial purposes, may alleviate vulnerability in one way but exacerbate it in others (Duffy et al. 2016), such as by increasing the frequency of human–wildlife interactions (HWIs) (Khumalo & Yung 2015). Globally, millions of people are at risk of negative HWIs, such as human fatalities or crop and livestock losses (Barua et al. 2013). However, most vulnerability assessments have primarily focused on climate change risks (e.g., Hanh et al. 2009) rather than the more immediate vulnerability risks associated with negative HWIs. Some recent studies have taken a more holistic approach to vulnerability assessments (e.g., Yadava & Sinha 2020, Notelid & Ekblom 2021), including a variety of stress scenarios such as variability in crop yield and price (Jezeer et al. 2019, Junquera & Grêt-Regamey 2020). Projected climate-driven changes in human migration and wildlife range shifts suggest that HWIs may become more frequent, so a better understanding of the relationship between HWIs and livelihood vulnerability is fundamental (Khumalo & Yung 2015).

Some studies of HWIs have already explored the role of livelihood vulnerability in wildlife interactions for particular regions and social groups (Ogra 2008, Khumalo & Yung 2015, Seoraj-Pillai & Pillay 2017). It is widely recognized that living alongside wildlife brings many benefits and services to communities, such as through the provision of food and other resources (Cox & Gaston 2018), pest control (Morales-Reyes et al. 2015), tourism revenue (Naidoo et al. 2016) and cultural and recreational value (Bateman & Glew 2010). However, proximity to wildlife may also engender costs and disservices (Ceauşu et al. 2019) through property damage (Lamichhane et al. 2018), competition for food and land (Treves 2009), disease transmission (Blair & Meredith 2018) and human injury or loss of life (Ratnayeke et al. 2014). These costs may differ with levels of wildlife exposure and with community vulnerability (Ogra 2008). Vulnerable communities may adopt livelihood strategies that escalate negative HWIs, as vulnerability can force their

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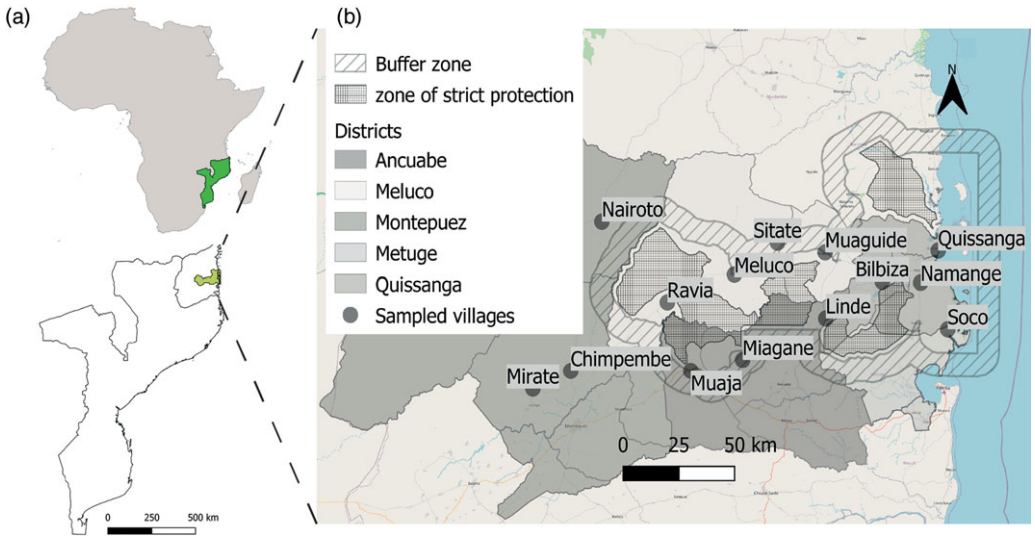



**Fig. 1.** (a) Location of Quirimbas National Park (QNP) in the Republic of Mozambique on the African continent. (b) Sampled villages within and close to QNP.

adoption of risky behaviours to obtain essential resources and/or to increase income (e.g., bushmeat hunting, poaching), in turn increasing wildlife exposure (Bevan 2000) and retaliation (Inskip et al. 2013). Moreover, socio-economic characteristics (e.g., age, gender, wealth, occupation, education, religion), individuals' emotions (e.g., fear) and perceptions of risk, social norms and political inequalities (Bond 2014, Bhatia et al. 2019) can all contribute to escalating or alleviating HWIs. Communities and households with alternative sources of income and/or with a highly connected social network (e.g., who cooperate in crop damage prevention and mitigation (Stone et al. 2019), share resources and participate in group protection) are less vulnerable to negative HWIs (Butt et al. 2009).

In Africa, 60% of the population lives in rural areas, and of this, 43% live in extreme poverty (World Bank 2018) and are highly dependent on natural resources for subsistence. African wildlife populations are among the most diverse and dense in the world, and the overlap between wildlife habitat and human-occupied areas is substantial. Africa accounts for 66% of the negative HWIs reported globally (Seoraj-Pillai & Pillay 2017). Damage by and encounters with wildlife have forced rural communities to adopt non-agricultural livelihoods to reduce their vulnerability (Gupta 2013). Since wildlife presence is an important driver of change for rural livelihoods (Gupta 2013), there is a need to better understand how livelihoods and vulnerability relate to HWIs.

In this study, we aim to understand whether and how HWIs and livelihood vulnerability are linked in a case study in Mozambique (southern Africa), an impoverished country with recent protected areas and where rural communities are living alongside wildlife (Merz et al. 2021). Mozambique's plan for protection requires reduced use of protected areas as well as maintaining and improving wildlife populations and minimizing HWIs (Anderson & Pariela 2015). The country has experienced a growing incidence of HWIs as people scout the landscape for the natural resources necessary for their livelihoods (Le Bel et al. 2014). This likely increases potential encounters with freely roaming wildlife (Dunham et al. 2010). We hypothesized that more vulnerable households are more likely to be exposed to wildlife and to experience negative interactions. More specifically, individuals and communities displaying higher sensitivity (the degree to which individuals and communities may be affected by climate change and HWIs) and lower adaptive capacity (a lower ability to take action to reduce exposure and sensitivity) will be more vulnerable to negative HWIs (Majale 2002). We explore how livelihood vulnerability varies across communities and evaluate which drivers have the greatest influence on such vulnerability, its components (i.e., exposure, sensitivity and adaptive capacity) and, ultimately, HWIs. Finally, we assess how HWIs and livelihood vulnerability influence each other by examining whether HWIs are either external drivers or internal components of that vulnerability. Our approach expands upon previous vulnerability analyses by considering the interaction between HWIs and livelihood vulnerability. This approach is crucial for understanding the links between livelihood vulnerability and biodiversity conservation (García-Frapolli et al. 2018), as well as for guiding biodiversity management and sustainable development.

## Methods

### *Study area*

We studied communities living within and close to Quirimbas National Park (QNP; Province of Cabo Delgado, north-eastern Mozambique; −12°30'0 S, 39°24'0 E) (Fig. 1a). There are 153 villages in QNP, harbouring a total of *c.* 200 000 people, 57% of whom live within the Park, and the remainder inhabit its buffer zone (Appendix A; MITADER 2012). We also included three villages located outside QNP encompassing an estimated combined population of 8786 residents.

### *Data collection*

#### *Sampling design*

We sampled villages inside the Park (n = 9), in the buffer zone (n = 2) and bordering or outside the Park (n = 3) (Fig. 1b). We used structured questionnaires (n = 224) that included both closed and open-ended questions. We selected villages according to their geographical location so that they would be representative of socio-demographic characteristics (e.g., religion and ethnicity), as well as for accessibility to QNP and its surroundings (see Appendix A). Upon arrival in a village, we first consulted with the community leaders to explain the purpose of the project and

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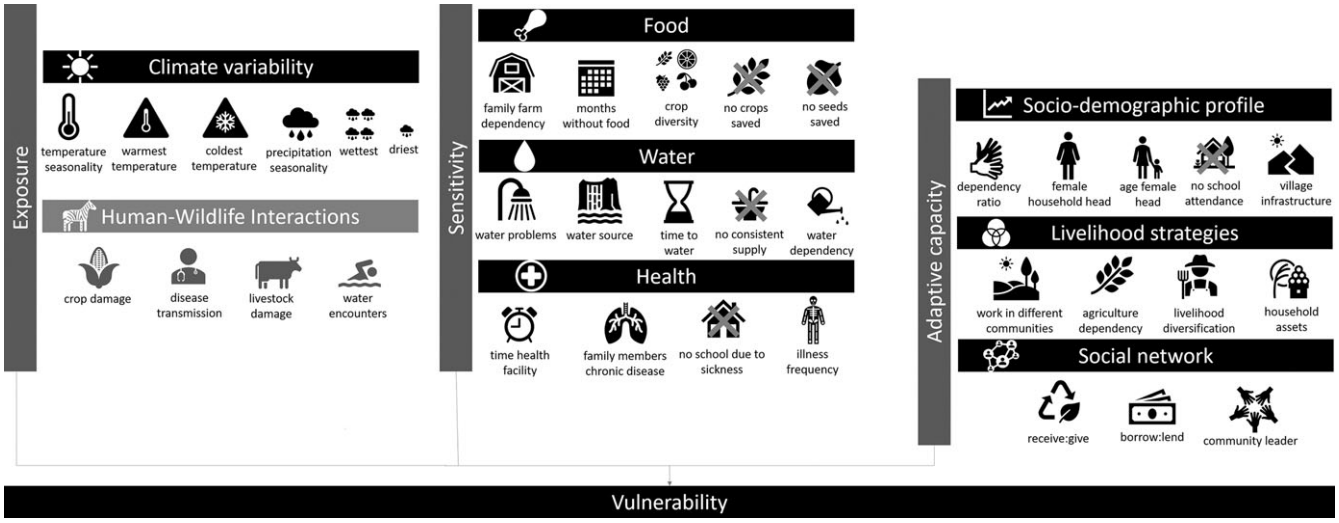



**Fig. 2.** The Livelihood Vulnerability Index (LVI) components and specific indicators, organized according to contributory factors to the Intergovernmental Panel on Climate Change's (IPCC) Vulnerability Assessment Framework (i.e., exposure, sensitivity and adaptive capacity). The framework considers human–wildlife interactions as a possible component of exposure in the LVI, as examined in our analysis. The figure has been generated according to the IPCC's Fourth Assessment Report (AR4) on climate change vulnerability.

to obtain permission to visit households. We used two questionnaires (Appendix B), one for community leaders (n = 14) and another for households (n = 210), enabling us to capture the respective leaders' specialized knowledge about village dynamics, characteristics and problems, as well as the perceptions of householders. We randomly selected 15 households and interviewed the heads of the households (typically men) to obtain information on livelihoods and vulnerability. To ensure a balanced sex ratio (Inskip et al. 2013), we also interviewed the partners of the heads of the households, resulting in a sample set of 118 men (56%) and 94 women (44%). Participants were informed about the purpose of the study, its anonymity and that participation was voluntary, before requesting signed or fingerprinted consent. We limited identifying information to village name and questionnaire number. The study was approved by the Ethics Committee for the Collection and Protection of Scientific Data ('Comissão de Ética para Recolha e Protecção de Dados de Ciências' – CERPDC) of the University of Lisbon, Portugal. Each interview lasted 35 minutes on average (range = 15–45 minutes; SD = 0.006) and had a response rate of 100%. Interviews were conducted in Portuguese by the lead author or in Makua by local native speakers hired for the project, or they were translated into the local dialect by a person from the community hired to work on the survey. All interviewers were trained in the sampling design, survey technique, confidentiality and participation consent protocol.

### *Questionnaire structure*

For community leaders, we collected information on population size and village infrastructure (e.g., schools, healthcare centres, hospitals, markets, religious places, water fountains, electricity and telephone networks). For households, we obtained information to calculate the LVI (see the 'Livelihood Vulnerability Index' section; Fig. 2 & Appendix C). Our household questionnaire was based on that of Hanh et al. (2009), which was adapted for our context and field conditions. The questionnaire included seven sections: household demographics, livelihood strategies, social networks, health and health services, food security, access to water and community problems. For instance, we removed questions from the Hanh et al. (2009) questionnaire that referred to sensitive topics (e.g., percentage of households with orphans) or that we considered irrelevant to our study (e.g., average malaria exposure). We included questions about HWIs within the sections on health, food security and access to water by enquiring about household risk perception of zoonotic diseases (Decker et al. 2010), crop damage by wildlife, attacks on domestic animals by wildlife and wildlife encounters. We also collected socio-demographic data from individuals with respect to gender, ethnicity, religion, household size and number of family members with any level of education. To better describe the local context, we calculated the village development index (Sahn & Stifel 2003) and the intensity of healthcare requirements (Chambers & Conway 1992).

## *Additional data*

### *Village characteristics*

We obtained the most recent geographical information for QNP (2012) from the National Administration for Conservation Areas (ANAC) that manages QNP to measure village distance to roads, distance to the nearest strict protection area and location (within or outside the park or in the buffer zone). Distance to the nearest strict protection area was measured as the Euclidean distance from the centroid of the village to the centroid of the nearest protected area (Madsen & Broekhuis 2018). We used the centroid instead of the edge because animal population densities are likely be higher at the core of protected areas (Kiffner et al. 2013). We also calculated a village accessibility index as a combination of road class (primary (connecting provincial capitals), secondary (connecting primary roads and economic centres) and tertiary (connecting secondary roads and residential areas); INE 2017), road type (asphalt or unpaved), road condition (good, reasonable) and distance to the nearest primary road (<5 km, 5–10 km, >10 km). For road class, we also considered a subcategory of road types (national (N; major intercity roads), regional (R; connecting towns/localities)). All distance metrics were calculated in *QGIS* 3.6.1 (QGIS Development Team 2018).

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### Climate data

Climate data at 1-km$^2$ resolution were obtained from the global database 'WorldClim version 2' (http://worldclim.org/). We used variables that reflected monthly variation in temperature and rainfall during 1970–2000, namely: temperature seasonality ($BIO_4$), mean temperature of warmest quarter ($BIO_{10}$), mean temperature of coldest quarter ($BIO_{11}$), precipitation seasonality ($BIO_{15}$), precipitation of warmest quarter ($BIO_{16}$) and precipitation of coldest quarter ($BIO_{17}$). We calculated the average of each bioclimatic variable for the area of the village and used it as an indicator of 'climate variability'.

## Data analysis

### Livelihood Vulnerability Index

We used the LVI developed by Hahn et al. (2009) to measure livelihood vulnerability for the selected communities. The LVI is an additive indicator combining seven components deemed to influence livelihoods, namely: 'socio-demographic profile', 'livelihood strategies', 'social networks', 'health', 'food', 'water' and 'climate variability' (Fig. 2 & Appendix C). The LVI builds on the Intergovernmental Panel on Climate Change (IPCC) vulnerability assessment framework, which considers exposure, sensitivity and adaptive capacity as factors contributing to vulnerability (IPCC 2001). We calculated the LVI and its components as standardized scores following the approach of Hahn et al. (2009), which considers exposure as 'climate variability' (e.g., bioclimatic variables); sensitivity as a combination of access to 'health' (e.g., distance to health facility, percentage of family members with chronic disease), 'food' (e.g., crop diversity, number of months without food) and 'water' (e.g., distance to water source, percentage of households without daily water availability); and adaptive capacity as a combination of 'livelihood strategies' (e.g., livelihood diversification, percentage of households solely dependent on agriculture), 'social network' (e.g., percentage of households lending and/or borrowing money, percentage of households asking for help from community leaders) and 'socio-demographic profile' (e.g., percentage of female heads of households, dependency ratio) (Hanh et al. 2009). We further explored the possibility of adding HWIs as a factor of exposure (see the 'Relationship between the LVI and HWIs' section).

### Human–wildlife interactions

Four parameters relating to HWIs (percentage of households whose agricultural fields were damaged by wildlife, percentage of households who became ill due to wildlife-transmitted diseases, percentage of households whose livestock production had been affected by wildlife, percentage of households who encountered wildlife at water sources) were used to calculate standardized HWI scores and a respective average per household.

### Drivers of the LVI and HWIs

We used a non-parametric Kruskal–Wallis analysis of variance (Zar 2010) to test whether the variance in the LVIs differed between villages and districts. We performed a *post hoc* comparison of the pair-wise means using Tukey's honest significant difference test (Tukey 1949).

First, we used a principal component analysis (PCA; Jolliffe 2002) to examine whether the LVI components and HWIs are related in a multidimensional space. Then, we used a set of linear mixed-effects models (LMMs; Zuur et al. 2009) to quantify the effects of potential drivers on the LVI and its components. We explored three sets of variables (socio-demographics, village characteristics and HWIs) as potential drivers of the LVI. Similarly, we explored the same sets of variables as drivers of the LVI components, except that we added additional LVI components to HWIs. In this 'HWI + other LVI components model', we tested the effects of the LVI components on each other. For example, if 'food' was the response variable, then the components 'water', 'health', 'socio-demographic profile', 'social network', 'livelihood strategies', 'climate' and 'HWI' were added as predictors. Lastly, for the model with 'HWI' as the response, we considered four sets of variables (i.e., socio-demographics, village characteristics, LVI components and 'LVI'). The variables 'village' and 'district' were included in all of the models as nested random effects (i.e., 'village' nested within 'district').

We used a multiple-stage modelling approach, whereby initially we built independent sets of models and then built a combined model encompassing the variables included in the best-performing models from the previous stage for which coefficients had been reliably estimated (Morin et al. 2020). We tested for collinearity between variables using a variance inflation factor (Zuur et al. 2007), prompting us to remove one variable ('local zone') from the analysis. We selected the best-performing models from each set of models using Akaike's information criterion corrected for small sample sizes ($AIC_c$; Akaike 1974). We chose $\Delta AIC_c < 5$ to identify the best models, and final parameter and error estimates were calculated by model averaging of the best model(s) (Burnham & Anderson 2002). We only report variables for which it was possible to reliably estimate an effect (i.e., the 95% confidence interval (95% CI) around the respective coefficient (β) did not encompass zero; see Appendix D for additional results). For the variables included in the best models, we estimated relative importance (RI) as the cumulative model weights of all models that included those variables (Arnold 2010).

### Relationship between the LVI and HWIs

For the LVI components having an effect on the LVI (i.e., those contributing to the best models), we examined whether their indicators were related to HWIs. We developed an additional LMM in which 'HWI' acted as the response variable and individual indicators were the predictors, and we followed the same procedure as detailed above.

We also examined whether HWIs exerted an indirect (as an external driver) or direct (as a component within the LVI) effect on the LVI. We assessed an indirect HWI effect by generating a LMM to test the impact of HWIs on exposure, sensitivity and adaptive capacity individually. Next, we tested whether HWIs are a direct component of the LVI by adding HWIs as an indicator of exposure. We built three LMMs to test the effect of this expanded parameter of exposure on sensitivity. We used three variable sets for exposure – (1) HWI, (2) Climate and (3) HWI + Climate – and used the same modelling approach as detailed above.

Statistical analysis was performed in *R* software (R Core Team 2019) using the packages *Hmisc* (Harrell & Frank 2015), *lme4* (Bates et al. 2015), *MuMIn* (Bartón 2019), *FactoMiner* (Le et al. 2008), *Factoextra* (Kassambara & Mundt 2016) and *missMDA* (Husson & Josse 2016).

## Results

Almost all (96%) of the interviewed households reported that their crops had been damaged by wildlife, a majority of which (59%) indicated that it was a daily occurrence. The interviewees identified

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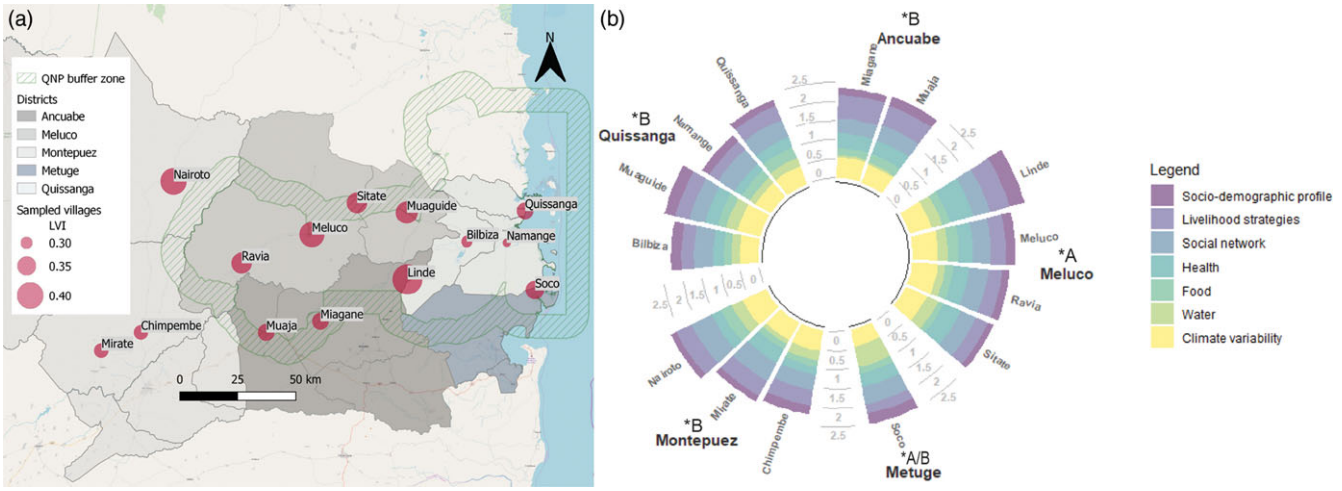



**Fig. 3.** (a) The Livelihood Vulnerability Index (LVI) for sampled villages within and close to Quirimbas National Park (QNP). Bubble size illustrates index values, ranging from 0.29 (less vulnerable) to 0.43 (more vulnerable). (b) The radar graph displays the scores for the LVI components in different colours. Cumulative scores per village are represented by individual bars. The villages have been grouped by district. Significantly different mean LVI scores after the Tukey's honest significant difference test for each district are represented by asterisks and are grouped by letter case.

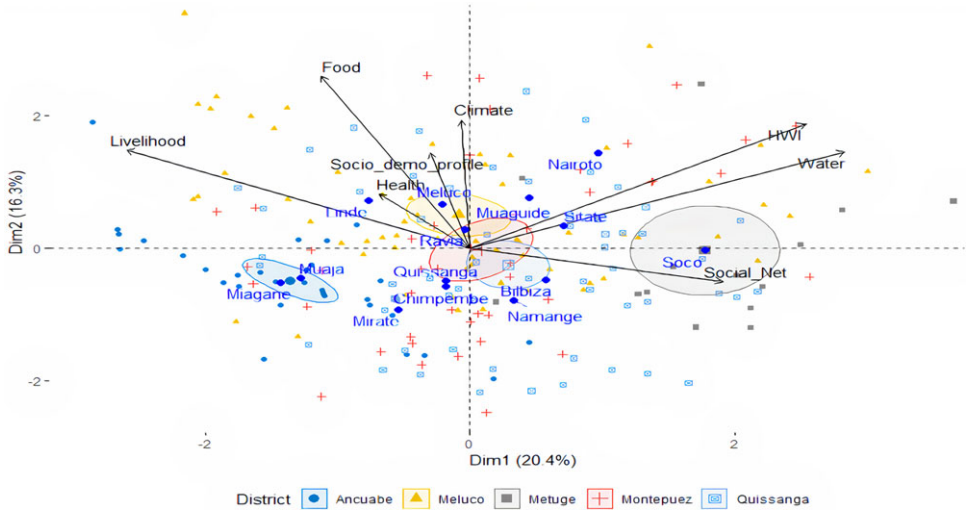



**Fig. 4.** Principal component analysis plot in which primary contributing components to the Livelihood Vulnerability Index are displayed as arrows, questionnaires per district are represented by different symbols and ellipses represent the 95% confidence interval. The blue dots are the centroids of the villages.

six crop-raiding species, including baboons (*Papio cynocephalus*; 47%), bush pigs (*Potamochoerus porcus*) and/or warthogs (*Phacochoerus aethiopicus*; 32%), vervet monkey (*Chlorocebus pygerythrus*; 13%), elephants (*Loxodonta africana*; 7%) and a single case of hippopotamus (*Hippopotamus amphibius*; 1%). Apart from crop-raiding events, 35% of the households mentioned encountering wildlife when collecting water from nearby rivers. Only 3% of respondents associated zoonotic diseases with family illness, and another 4% reported attacks by wildlife on domestic animals.

### *Livelihood vulnerability across QNP*

Livelihood vulnerability was similar among districts (LVI range = 0.33–0.39; Table C.1 & Appendix E) and villages (LVI range = 0.29–0.43), but with high intra-village variability (LVI range = 0.21–0.53; Fig. 3a, Table C.2 & Appendix E). We observed considerable variability in LVI components across villages (Fig. 3b). In particular, the parameters 'socio-demographics' (range: 0.008–0.8), 'livelihood strategies' (range: 0.04–1.0) and 'water' (range: 0–0.8) presented the widest ranges.

We identified a link between 'HWI', 'water' and 'social network', as these three variables were all positioned on the positive side of PCA axis 1 (Fig. 4). In contrast, 'livelihood strategies', 'health' and 'food' appeared on the negative side of the PCA axis 1. PCA axis 2 further separated 'livelihood strategies' from 'social network'. Together, the two PCA axes accounted for 36.7% of the total variance in the data (PCA1 = 20.4% and PCA2 = 16.3%). The variables most contributing to the two PCA axes were 'water' (21.1%), 'HWI' (20.7%), 'livelihood strategies' (18.6%) and 'food' (16.7%). Village segregation across the two PCA axes implies a contribution of different livelihood vulnerability components to data variability (Figs 3b & 4).

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**Table 1.** Averaged model coefficients for variables included in the best combined models ($\Delta AIC_c < 5$). The variables with a 95% confidence interval not including zero are highlighted in bold.

| | β | SE | z-value | p-value | 95% CI | RI |
|---|---|---|---|---|---|---|
| *LVI model* | | | | | | |
| Intercept | 0.35 | 0.02 | 15.35 | <0.001 | 0.30, 0.39 | – |
| **HWI** | **0.07** | **0.02** | **2.87** | **0.004** | **−0.02, 0.11** | **0.56** |
| **Gender (male)** | **−0.04** | **0.00** | **3.25** | **0.001** | **−0.04, −0.01** | **0.55** |
| **Accessibility** | **0.08** | **0.03** | **2.80** | **0.005** | **0.03, 0.13** | **0.29** |
| **Population size** | **−0.08** | **0.03** | **2.65** | **0.008** | **−0.13, 0.06** | **0.23** |
| *HWI model* | | | | | | |
| Intercept | 0.23 | 0.10 | 2.40 | 0.02 | 0.04, 0.42 | – |
| **LVI** | **0.51** | **0.21** | **2.34** | **0.02** | **0.18, 0.93** | **0.73** |
| **Water** | **0.18** | **0.08** | **2.28** | **0.02** | **0.07, 0.61** | **0.45** |
| *HWI vulnerability categories* | | | | | | |
| Intercept | 0.26 | 0.17 | 1.56 | – | −0.07, 0.60 | – |
| **Sensitivity** | **0.34** | **0.12** | **2.84** | **<0.001** | **0.11, 0.58** | **0.92** |
| Exposure | 0.20 | 0.50 | 0.40 | 0.69 | −0.77, 0.17 | 0.29 |
| Adaptive Capacity | 0.14 | 0.11 | 1.20 | 0.23 | −0.09, 0.37 | 0.16 |

$AIC_c$ = Akaike's information criterion corrected for small sample sizes; CI = confidence interval; HWI = human–wildlife interaction; LVI = Livelihood Vulnerability Index; RI = relative importance.

### *Drivers of livelihood vulnerability across QNP*

Our LMM results showed that livelihood vulnerability was best predicted by 'HWI', 'gender', 'accessibility' and 'population size'. More vulnerable households tended to be more exposed to 'HWI' and men were less vulnerable than women. Villages with better access to main roads were also more vulnerable, whereas villages with larger population sizes were less vulnerable. Of all the variables we considered, 'HWI' and 'gender' had the strongest positive effect on the LVI (Table 1, LVI model; Appendix F Fig. F.1).

### *Drivers of components of livelihood vulnerability*

#### *Exposure*

None of our variables constituted good predictors of 'climate variability'. The null model was the only model selected from a total of 190 models.

#### Sensitivity

'Food' was negatively associated with 'age' of the household head, implying that older people experienced lower food scarcity. 'Food' was also positively associated with 'livelihood strategies', indicating that households with greater food scarcity were less resilient (Appendix F Figs F.1a & F.1b & Table F.1). We also found that access to water was positively associated with the interaction between 'household size' and 'HWI'. In other words, larger households with limited access to water had greater exposure to HWIs (Appendix F Fig. F.1c & Table F.2). None of the variables were good predictors of 'health' sensitivity (only the null model was selected).

#### *Adaptive capacity*

The 'socio-demographic profile' of households was negatively associated with 'gender' of the head of household and positively associated with village 'accessibility' (Appendix F Figs F.1d & F.1e & Table F.3), with women prone to having a more vulnerable socio-demographic profile. 'Food' was also positively associated with 'livelihood strategies', as food scarcity enhanced the likelihood of vulnerable 'livelihood strategies' (Appendix F Fig. F.1f & Table F.4). Finally, the 'social network' of households was negatively affected by 'socio-demographic profile' and 'livelihood strategies' (Appendix E Figs F.1f & F.1h & Table F.5).

### *Drivers of HWIs*

More vulnerable households, in particular those with more restricted access to water, were also more exposed to HWIs. We found that 'HWI' was best explained by 'LVI' and 'water', with both of those variables exerting a positive effect on 'HWI' (Table 1, HWI model; Appendix G Fig. G.1 & Table G.1).

The type of 'water source' (river/lake/lagoon or village well) was the only variable with an effect on the average best model (Appendix G Fig. G.2 & Table G.2), revealing that HWI risk was greater when households fetched water from a river, lake or lagoon than when they used wells in the village.

### *HWIs as a component of livelihood vulnerability*

We identified a positive association between 'HWI' and livelihood 'sensitivity', with households more exposed to 'HWI' being the ones displaying higher sensitivity. In fact, the variable 'sensitivity' was present in the best four models, out of a total of eight models, and it was reliably estimated (Table 1, see HWI vulnerability categories). 'Exposure' and 'adaptive capacity' were present in just two of the eight best models, but the respective coefficients were not reliably estimated (Appendix H Table H.1). Furthermore, the models of 'sensitivity' as a function of 'HWI' and of 'sensitivity' as a function of 'climate' were both weaker than models of sensitivity as a function of 'climate' plus 'HWI', with this latter reflecting exposure (Fig. 5).

## Discussion

We show the extent to which HWIs and livelihood vulnerability are linked in QNP, Mozambique. We found that high sensitivity and low adaptive capacity render individuals and communities more vulnerable to risks from wildlife. Furthermore, we show that HWIs, such as crop raiding or wildlife encounters when fetching water from rivers, were prevalent and almost daily occurrences in the study area. Although in many cases these encounters were not serious, some involved potentially dangerous species such as elephants (33%), crocodiles (*Crocodylus niloticus*; 13%), carnivores (lion (*Panthera leo*), leopard (*Panthera pardus*), hyenas (*Crocuta crocuta*); 4%) and hippopotamus (only one report). Moreover, when we included HWIs as a factor of exposure, we found that it was strongly related to sensitivity and overall livelihood vulnerability.

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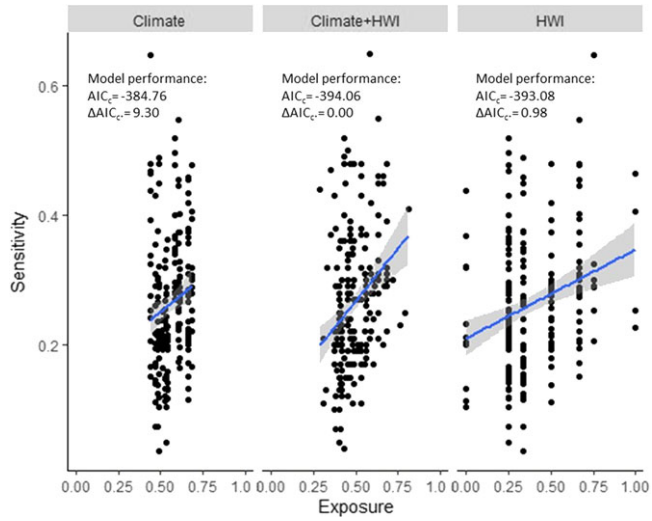



**Fig. 5.** Sensitivity as a function of Exposure to 'Climate', 'Climate + HWI' and 'HWI'. Model performance metrics include Akaike's information criterion corrected for small sample sizes ($AIC_c$) and $\Delta AIC_c$. The null model had an $AIC_c = -385.43$. HWI = human–wildlife interaction.

On average, communities living in QNP (LVI = 0.37) seem to have higher livelihood vulnerability than those inhabiting some other districts of Mozambique (e.g., Moma, LVI = 0.316; Mabote, LVI = 0.326; Hahn et al. 2009), but they are likely less vulnerable than communities in Limpopo National Park (also in Mozambique). In Limpopo, communities were qualitatively classified as exceedingly vulnerable to climate change and very exposed to wildlife damage (Notelid & Ekblom 2021). These results suggest that a larger number of factors can increase vulnerability, and in some cases the contribution of protected areas and HWIs to the overall livelihood vulnerability might be minor.

Fundamentally, the livelihood vulnerability of communities in QNP is enhanced by water scarcity, as communities take risks while fetching water. Rivers are attractive areas for wildlife and they are used as dispersal corridors. Accordingly, it is not surprising that we uncovered a higher probability of HWIs when communities used these water sources (Madsen & Broekhuis 2018). To counteract this problem, we advocate increasing the number of communal closed wells near villages, thereby reducing the need to retrieve water from nearby rivers and, consequently, decreasing the risk of potentially negative HWIs. In addition, the association between the variables 'HWI', 'water' and 'social network' (Fig. 4) indicates that households with less social support struggled to manage their water resources, so they displayed an increased need to retrieve water from rivers, exposing them to HWIs. In other words, households with a strong social network were more likely to fetch water in groups, reducing their exposure to wildlife encounters and boosting security. Indeed, a critical role for social ties in reducing vulnerability to water scarcity has been demonstrated previously, such as by enabling water resources to be shared among households in ways that are beneficial to the social network and the wider community (Faurès & Santini 2009) through increased communication (e.g., on weather) and partnerships (Dickson et al. 2016). Our modelling results have revealed that the relationship between water scarcity and HWIs is stronger for larger households, most likely because such households need more water (Angoua et al. 2018). Moreover, since access to wells in QNP villages is limited (i.e., a limited number of community wells and a large number of users), a greater number of households must fetch water more frequently, engendering a greater risk of HWIs.

Surprisingly, and despite 96% of householders reporting crop-raiding events, we did not find evidence for a relationship between food security and HWIs. This outcome contrasts with the findings of other similar studies (e.g., Barua et al. 2013). We believe that this result could be due to the indicator of crop damage that we used (percentage of households whose agricultural fields were damaged by wildlife) not being sufficiently sensitive to the intensity or extent of such events. Since every respondent household suffered crop damage at least once a month, with a consequent reduction in food supply, all households displayed maximum vulnerability for this indicator.

We found that women had higher livelihood vulnerability than men. More specifically, young women who acted as the head of a household were the most vulnerable. Young women in rural communities are less empowered, are less likely to have undertaken formal education and are more restricted in their activities due to rigidly defined gender roles (Khumalo & Yung 2015). Thus, most women are unlikely to have a direct source of income, hindering their potential to invest in alternative activities to diversify their livelihoods (Khumalo & Yung 2015). Accordingly, they are less able to recover from or adopt strategies to overcome crop losses (Naughton-Treves 1997). Moreover, these vulnerable women are also more exposed to HWIs, especially as they are frequently responsible for fetching water and for the maintenance of agricultural fields very often visited by wildlife (Mwangi et al. 2016), and they are less effective at guarding against and preventing crop damage (Naughton-Treves 1997).

Our analyses have also revealed that households in villages with more access to nearby cities suffered greater livelihood vulnerability. This outcome is contrary to the common expectation that remote villages are more highly vulnerable because they lack assets and business opportunities (Salerno 2016). However, villages closer to primary roads may suffer more rapid resource depletion, with negative consequences for the livelihoods of their communities (Mwangi et al. 2016). We found that villages with greater road access presented more vulnerable socio-demographic profiles and lower development indices, reinforcing the evidence for a negative influence of road proximity (Appendix I.1). Furthermore, the presence of a road system does not necessarily mean greater mobility between villages (Asafo-Adjei & Iyer-Raniga 2017). For the communities in QNP, mobility remains very limited, since almost no villager owns a car or motorcycle and public transportation is non-existent. Our data show that villages with larger population sizes tended to display a lower LVI than smaller villages, with this finding potentially being related to the greater capacity for development and infrastructure of the former (International Monetary Fund 2008) and their greater access to health facilities and water sources (Appendix I.2).

Although the LVI incorporates different components of livelihood vulnerability, it still has some limitations. The LVI oversimplifies the complex reality of livelihoods into indices and indicators that are difficult to validate (Hanh et al. 2009). Furthermore, in the case of HWIs, our results suggest caution regarding the type of indicator of HWIs used in LVI assessments, such as crop damage intensity. We propose that spatial modelling of the probability of HWIs and their effects on the LVI could improve our understanding of the HWI–LVI bidirectional relationship. However, currently available data on wildlife ranges and habitat use (MITADER 2012) are insufficient for proper analyses of species distributions. Other relevant indicators for the study area may also be lacking

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(e.g., human migration) because the underlying socio-economic, cultural and ecological contexts are still poorly understood.

## Conclusions

Understanding the relationship between livelihood vulnerability and HWIs is fundamental to attaining improved management and conservation of wildlife populations and the sustainable development of rural populations throughout Africa. We found evidence of a strong relationship between livelihood vulnerability and HWIs, implying that this dependency needs to be better addressed if both of these goals are to be met. Based on our results, simple measures such as enhancing cooperation in water and food activities within communities and adding closed wells near villages could quickly diminish exposure to HWIs. In the long term, households could be encouraged to invest in crops that are more resistant to wildlife damage and to switch from agriculture-based activities, although this latter would have land-use impacts elsewhere. We also recommend that community livelihoods and sensitivities must be considered when designing HWI mitigation schemes and implementing conservation actions. Furthermore, our study highlights that the problem of HWIs cannot be addressed without addressing the root causes of livelihood vulnerability. Accordingly, we propose that HWIs should be included as a component of exposure by extending the LVI framework proposed by Hanh et al. (2009). Finally, in order to address the multiple dimensions of livelihood vulnerability, specifically where HWIs have a profound impact on poor rural communities and given that HWIs affect millions of people globally, communities should be provided with the capacity to respond to the risks of HWIs.

**Supplementary material.** To view supplementary material for this article, please visit https://doi.org/10.1017/S037689292100028X.

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**Ethical standards.** The authors assert that all procedures contributing to this work comply with applicable ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

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