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Changes in Wild Meat Hunting and Use by Rural Communities During the COVID-19 Socio-economic Shock

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Abstract

There is limited quantitative evidence of the effects of socio-economic shocks on biological resource use. Focusing on wild meat hunting, a substantial livelihood and food source in tropical regions, we evaluated the impacts of the shock from Nigeria's COVID-19 lockdown on species exploitation around a global biodiversity hotspot. Using a three-year quantitative dataset collected during and after the lockdown (covering 1,008 hunter-months) and matching by time of year, we found that successful hunting trip rates were more frequent during lockdown, with a corresponding increase in the monthly number, mass, and value of animals caught. Moreover, hunters consumed a larger proportion of wild meat and sold less during lockdown compared to non-lockdown periods. These results suggest that local communities relied on wild meat to supplement reduced food and income during lockdown, buffering COVID-19's socio-economic shock. Our findings also indicate that wild species may be especially vulnerable to increased hunting pressure during such shocks.

Introduction

The hunting of wild animals for food (hereafter 'wild meat') is one of the biggest threats to biodiversity globally (Schulze et al., 2018; Abernethy et al., 2013) while also providing income and food to many rural communities across the tropics and subtropics (Coad et al., 2019). Wild meat is an accessible resource with relatively low entry costs compared to other livelihood activities (Schulte-Herbrüggen et al., 2013) and therefore provides an important safety net for rural communities during socio-economic crises, civil conflicts or other shocks that are usually characterised by reductions in livelihood opportunities and market access (UNDP, 2023). The economic importance of wild meat to rural communities is well known (Nielsen et al., 2017; Schulte-Herbrüggen et al., 2013), but there is limited quantitative evidence of its use during shocks, potentially because of their unpredictability and hence the lack of comparable data before, during, and afterwards.

The 2019 coronavirus disease (COVID-19) triggered one of the greatest global shocks in modern human history (World Bank, 2022), with the disease linked to ~ 6.9 million human deaths worldwide (as of March 2023; JHU, 2023) and a global economic shrinkage of 3.5% in 2020 (World Bank, 2022). Many countries implemented national lockdowns that reduced transmission rates (Balmford et al., 2020; Hsiang et al., 2020), but with adverse economic effects (World Bank, 2022).

McNamara et al. (2020) proposed that the COVID-19 lockdowns may have reduced urban demand for wild meat due to decreased spending power and increased costs for traders. Conversely, rural families, facing restricted livelihood options and increased urban-rural migration during the pandemic, may have increasingly relied on wild meat as a crucial source of food and income. Nonetheless, McNamara et al.'s hypotheses are yet to be tested quantitatively: previous attempts to assess the impacts of the COVID-19 shock on wild meat extraction and use mostly used qualitative interviews collected retrospectively and often focusing on single species (Enns et al., 2023; Mendiratta et al., 2022; Vliet et al., 2022; Kamogne Tagne et al., 2022; Briceño-Méndez et al., 2021).

Here we investigated the impacts of the shock created by the COVID-19 pandemic on patterns of wild meat hunting and use in two rural communities around Nigeria's Cross River National Park (CRNP). Using quantitative data from 28 hunters collected during and after Nigeria's lockdown, and covering 1,008 hunter-months, we compare the frequency of successful hunting trips – trips in which at least one animal was captured – and their outcomes (number, mass, value, and use of animals caught) during and after the lockdown. In line with McNamara et al.'s hypothesis, we expect that the frequency of successful trips and these outcomes will be higher in lockdown compared to other periods. Given reported disruptions in protected area management during lockdown (Eklund et al., 2022; Singh et al., 2021), we also investigate changes in ranger patrol efforts in CRNP and further assessed whether hunting locations (i.e., within and outside the park) changed during lockdown. Our results provide quantitative evidence of the importance of wild meat to local communities and the vulnerability of wild animal populations during shocks, which can help to inform policies for withstanding future disruptions.

Methods

Data Collection

We tracked 33 male hunters each recruited from a different household around CRNP, south-east Nigeria, for three years (1 April 2020-31 March 2023), but here we only used data from 28 hunters followed continuously. The communities (~ 10 km apart) border Oban Division of CRNP, one of the largest remaining forest blocks in the Guinean Forest biodiversity hotspot (Myers et al., 2000; Figure 1). We recruited hunters through community hunter associations, focusing on formal hunters (those who primarily hunt with guns) as casual hunters (who mainly use snares to trap animals) were not members. After each hunting trip, we conducted structured interviews administered by trained local field assistants.

The data collected included trip duration (in days), the number and species of animals captured, and, for each animal, its intended use (household consumption, gift, ceremonial use, or commercial purpose), mass, and price (for carcasses not intended for sale, we requested the likely price if sold). In cases where hunters had already slaughtered an animal, we recorded its mass and price per piece. Additionally, we inquired about any captures consumed during the trip, though we had missing data for mass in such cases. We also recorded the location of capture as follows a) plantation, b) community forests, and c) protected forests. During lockdown, we recorded only those trips on which animals were caught, and hence our analyses here focus on the frequency and outcomes of successful trips, restricting us from assessing variations across all hunts irrespective of outcome. However, this limitation does not hinder us from testing McNamara et al. (2020) hypothesis of elevated harvesting of wild meat during lockdown. Note that all hunts within CRNP or that involved killing a protected species were illegal. An ethics statement is provided in Appendix A.

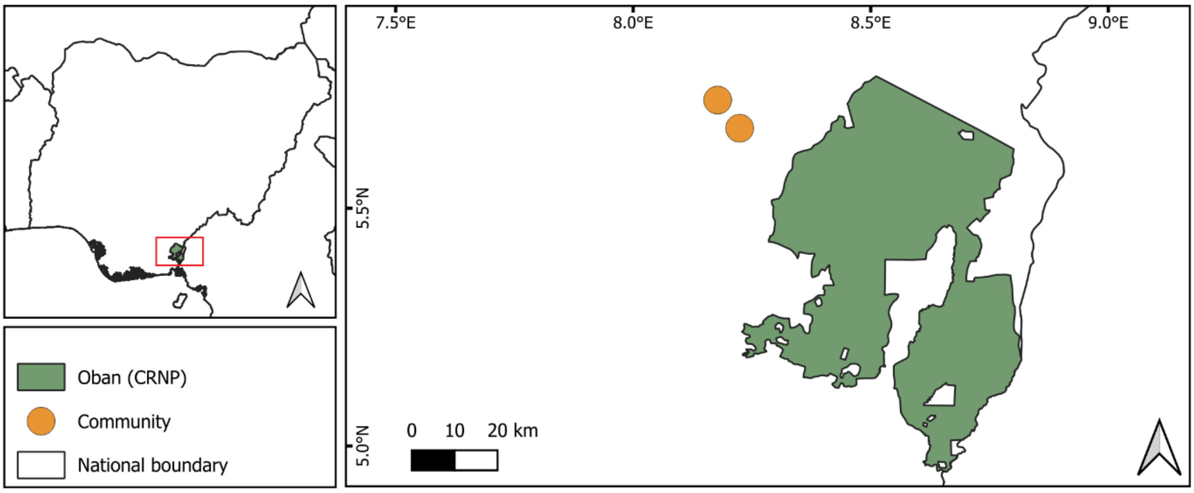

Figure 1: Approximate locations of the study communities around Oban Division of Nigeria's Cross River National Park. The red rectangle in the top left map highlights the study location within Nigeria.

Analysis

We first split our data into three periods: 'lockdown' (30 March to 3 September 2020; 5.2 months), 'matched non-lockdown' (corresponding lockdown dates in 2021 and 2022, totalling 10.4 months; note these included minor restrictions on people's movements), and 'other non-lockdown' (other days in 2020-2023, totalling 20.6 months; see Appendix B for more details). Next, we used a Chi-square test to compare a) species composition of the catch across periods (using data on 13 species as we dropped those with expected values per period <5) and b) location of captures across the periods (we merged plantation with secondary forests as community forest and compared captures here with CRNP). We then examined how wild meat offtake and use varied with lockdown by fitting eight generalised linear mixed models to examine changes in hunting behaviour and outcomes. The first four models examined variations in hunter behaviour and hunting outcomes across our three periods, while the second set assessed the uses of the captured animals, providing insights into observed patterns in the earlier models. The response variables of the models were: a) number of successful trips, b) number of animals captured, c) mass of wild meat harvested, d) value of wild meat harvested, e) mass of wild meat consumed in hunter's household (hereafter mass eaten), f) mass of wild meat sold, g) proportion of mass eaten, and h) proportion of mass sold.

We summed the number of successful trips and animals captured per hunter for each period and calculated the mass and value of animals caught by multiplying each hunter's total number of animals per species in the relevant period by their median mass and median price, respectively (using period-specific values). We corrected the values of these response variables (models a-f) for differences in each period's duration by dividing them by their respective lengths. We fitted the models as a function of period (lockdown, matched non-lockdown, and other non-lockdown) and four hunter-level variables: 1) hunter's annual household income excluding hunting-related income ($\log_{10}$-transformed), 2) hunter's experience in years ($\log_{10}$-transformed; models a-d only), 3) their household's well-being index (WBI; L'Roe et al., 2023), and 4) their household size expressed in adult male equivalents (AME), which describes a household's energy needs by accounting for the sex, age, and physiology of its members relative to the average adult male's energy requirements (Weisell & Dop, 2012). The rationale for including each predictor and their derivation is set out in Appendix B. All hunter-level covariates were gathered in May 2022. Univariate plots of the response variables and predictors are in Figures S1-8 presented in the order in which we described the models above. We used a Gaussian model to explore, using one data point per hunter for each period, the log-transformed number of successful trips and animals captured, mass and value of wild meat harvested, mass eaten, and mass sold (each expressed per hunter-month). Where only a part of an animal was eaten or sold, we used the median mass of the relevant part, as we could not record the mass of every part. To include zero values for the total mass of meat eaten or sold in a period, we added 0.0005 to all the records. We accounted for inflation in the value model – adjusting nominal prices in 2020-22 to reflect current prices (i.e., real prices in 2023) using inflation rates based on Nigeria's consumer price index (Trading Economics, 2023; World Bank, 2023). For the models of proportions of mass eaten and sold, we used beta regression with a logit link function, transforming the response variables to meet the open interval assumption of the beta distribution (Smithson & Verkuilen, 2006) . In all models, we examined collinearity among the predictors (variance inflation factor threshold = 3; Zuur et al., 2013) before and after fitting the model, standardised all continuous predictors, and used simulated residuals (Dunn & Smyth, 1996) to visually assess model fit (Figures S9-16; see Equations S1-8 presented in the order in which we described the models above; software and packages in the Supplementary Material).

To check that the patterns we observed in our main analyses are not driven by any long-run declines in animal populations, we ran another mixed-effects model to infer temporal trends in animal availability, using mass harvested per trip (restricted to each hunter's last lockdown and first post-lockdown trips) as the response variable. Here we hypothesise that decreased mass per trip following the lockdown suggests that potential lower offtake rates post-lockdown was driven by diminished prey availability, possibly due to overhunting in lockdown. We used the following as predictor variables: period (lockdown and other non-lockdown), trip duration in days (accounting for effort), and the hunter-level covariates in previous models (Figures S17-18 and Equation S9). Finally, we analysed CRNP ranger patrol data provided by Wildlife Conservation Society to compare patrol efforts (see units below) during lockdown and matched days in 2019 (matched pre-lockdown) and 2021 (matched post-lockdown). Using Kruskal-Wallis tests and Dunn's post hoc, we examined variations in the monthly median a) patrol frequency, b) rangers per patrol, c) distance covered, and d) active patrol time (duration) across these periods (five data points per period; see additional information in Appendix B). We did not include the ranger data as a predictor in models a-h because the patrols occurred within the park whereas most of the hunting trips took place in community forests.

Results

The 28 hunters made 1,398 successful hunting trips (433 during lockdown, 340 in matched non-lockdown, and 625 in other non-lockdown; period length adjustments = 83, 33, and 31, respectively). Together they captured 2,369 animals of 39 different species (five birds, five reptiles, and 29 mammals) with a combined estimated mass of 13,870 kg and total value of ₦17,941,000 (US$23,921 at $1 = ₦750). The adjusted monthly capture rate summed across our sampled hunters was 130, 53, and 56 animals in lockdown, matched non-lockdown, and other non-lockdown periods, respectively. Note that here and afterwards, 'rate' refers to monthly offtake within successful trips only. Approximately 85% of all captures occurred in community forests, while the remained took place in the park. Hunters consumed 8% of the total mass, selling 91% (with gifting and ceremonial use together accounting for 1%).

The proportional composition of the catch across species differed significantly between periods (χ^2 = 106.81, df = 24, p < 0.001). Of the 13 species used in the test, African brush-tailed porcupine (*Atherurus africanus*), African palm civet (*Nandinia binotata*), blue duiker (*Philantomba monticola*), greater cane rat (*Thryonomys swinderianus*), sitatunga (*Tragelaphus scriptus*), mona monkey (*Cercopithecus mona*), sitatunga (*Tragelaphus spekii gratus*) and white-bellied pangolin (*Phataginus tricuspis*) were caught disproportionately more in lockdown than non-lockdown periods (Figure S19; see species monthly capture rate per period in Figure S20). We also found that the number of animals captured in CRNP and community forests differed significantly across the periods (χ^2 = 493.4, df = 2, p < 0.001). There were more captures in CRNP during lockdown than expected based on the distribution of captures across all periods (observed count: 284, expected count: 108), with 42% occurring there during lockdown compared with 0% during matched non-lockdown Nonetheless, the observed count in community forests (388) during lockdown was higher than the expected count there (284; Figure S21).

We found a higher number of successful trips per month in COVID-19 lockdown than in matched non-lockdown (β = -1.08, *SE* = 0.11, p < 0.001) or other non-lockdown periods (β = -1.05, *SE* = 0.11, p < 0.001; Figure 2a; overall model r^2 = 0.79; full details in Table S1). There was no significant difference in the average number of successful trips conducted between the two non-lockdown periods, and the number did not significantly vary with hunter's experience, or the income, WBI or AME of their households. These patterns were similar in the model exploring the number of animals caught: hunter's monthly capture rates were higher in lockdown than in matched non-lockdown and other non-lockdown periods (β = -1.06, SE = 0.12, $p < 0.001$ and β = -0.94, SE = 0.12, $p < 0.001$, respectively; Figure 2b; overall model r^2 = 0.76; Table S2), with no significant difference in capture rates between the two non-lockdown periods or across hunter-level predictors.

Our models of the mass and value of animals caught corroborated these findings. In the mass model, hunters harvested more wild meat per month during lockdown compared to the matched non-lockdown (β = -1.05, SE = 0.13, $p < 0.001$) and other non-lockdown periods (β = -0.98, SE = 0.13, $p < 0.001$; Figure 2c; overall model r^2 = 0.73; Table S3). The value model showed that each hunter's total value of wild meat harvested monthly was higher during lockdown than in matched non-lockdown (β = -0.88, SE = 014, $p < 0.001$) and other non-lockdown periods (β = -0.84, SE = 0.14, p = < 0.001, Figure 2d; overall model r^2 = 0.67; Table S4). The two non-lockdown periods did not differ in both these models, and no hunter-level covariates were statistically associated with the response variables.

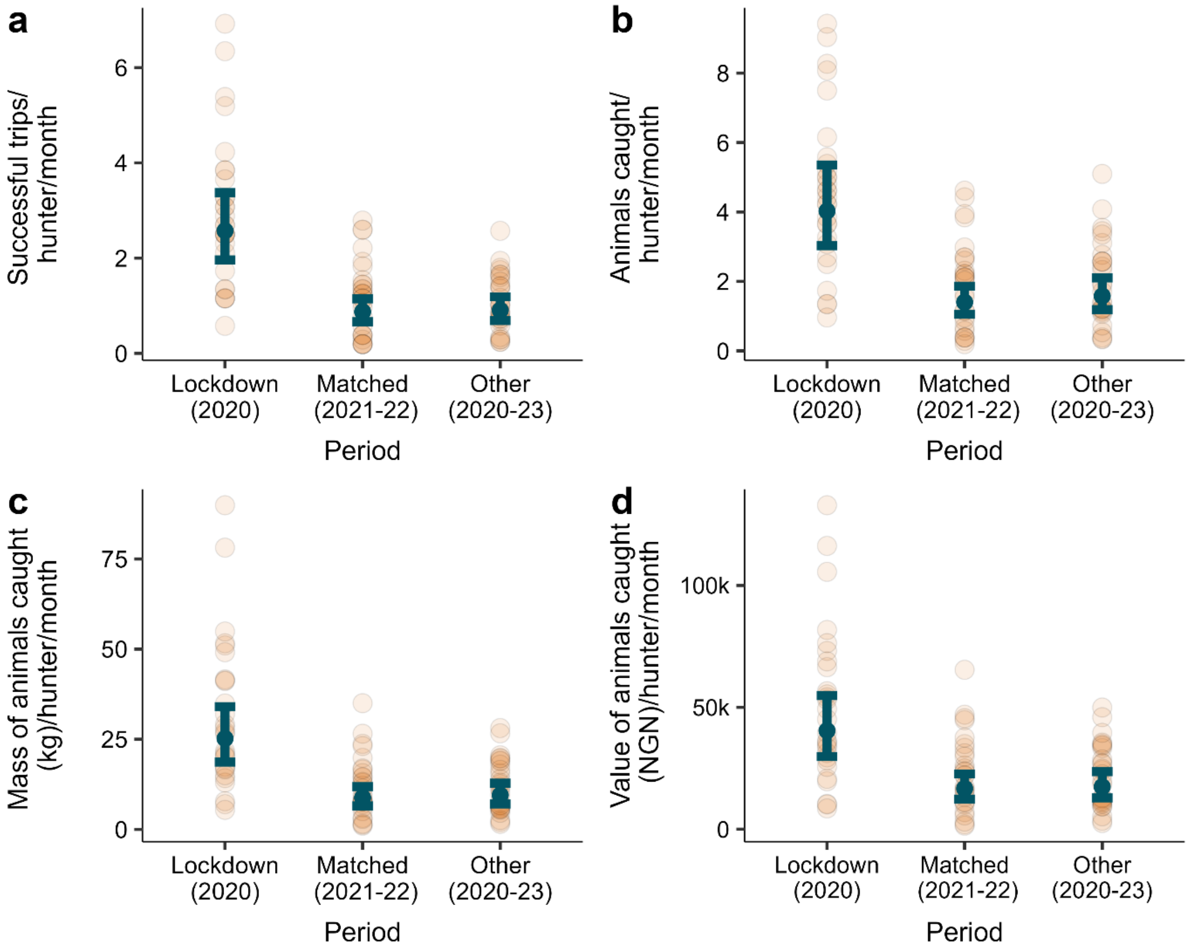

Figure 2: The monthly number of successful hunting trips and number, mass and value of animals caught were higher during the COVID-19 lockdown than in matched non-lockdown and other non-lockdown (a-d, respectively). There were no differences between matched and other (a-d). Green points show marginal

predictions (error bars = 95% confidence intervals) taken from models, with other covariates held constant: a) annual household income, b) hunting experience, c) household's well-being index, and d) household size (expressed in adult male equivalents). Pale brown circles show observed data for each period for 28 hunters in two communities adjacent to Nigeria's Cross River National Park (April 2020-March 2023).

The model exploring variation in the mass of wild meat eaten per month showed that hunters consumed more wild meat in their homes in lockdown compared to matched non-lockdown (β = -2.79, SE = 0.43, p < 0.001) and non-matched non-lockdown periods (β = -1.63, SE = 0.43, p = < 0.001; Figure 3a; overall model r^2 = 0.56; Table S5). Unlike in other models, the mass eaten during matched non-lockdown was lower than in other non-lockdown periods, but only weakly (β = 1.16, SE = 0.44, p = 0.03). The model of the mass of wild meat sold per month revealed similar patterns: more mass was sold during lockdown than in matched non-lockdown (β = -0.97, SE = 0.15, p < 0.001) and other non-lockdown (β = -0.91, SE = 0.15, p < 0.001; Figure 3b; overall model r^2 = 0.70; Table S6), with no difference between the two non-lockdown periods. Wild meat trade during the lockdown happened within each community but did not involve wider trading because markets were shut (S. Agbor, pers. comms). None of the hunter-level covariates in either model were significantly associated with the response variables.

Our models on the proportions of wild meat mass eaten and sold revealed opposite patterns. The model of the proportion of wild meat eaten showed an increase in household consumption during the lockdown relative to matched non-lockdown (β = -0.89, SE = 0.14, p < 0.001) and other non-lockdown periods (β = -0.59, SE = 0.13, p < 0.001; Figure 3c; overall model r^2 = 0.62; Table S7). The model of the proportion of meat sold revealed that, on average, hunters sold a smaller proportion of the wild meat they caught during the lockdown compared with the other two periods (β = 0.95, SE = 0.15, p < 0.001 and β = 0.59, SE = 0.14, p < 0.001 respectively; Figure 3d; overall model r^2 = 0.75; Table S8). Neither proportion model showed differences in the non-lockdown periods, and no hunter-level covariates were significantly associated with the response variables.

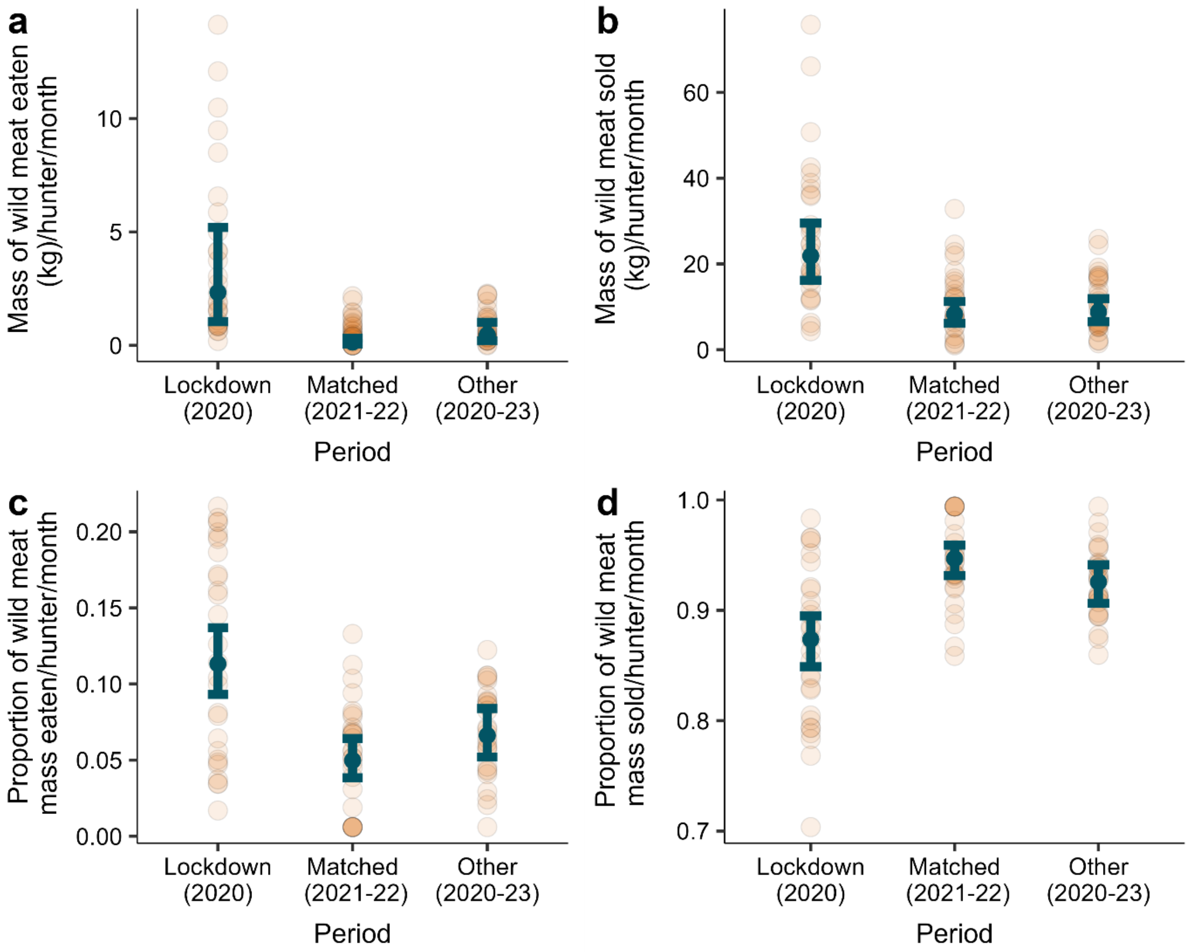

Figure 3: The mass of wild meat eaten within hunter households and the mass sold were higher during the COVID-19 lockdown than matched non-lockdown and other non-lockdown (a and b, respectively). In proportional terms, hunters ate more of the mass of animals they caught in their homes and sold less during the lockdown compared to matched and other (c and d, respectively). Only in b was there a difference between matched and other non-lockdown periods. Green points show marginal predictions (error bars = 95% confidence intervals) taken from models, with other covariates held constant: a) annual household income, b) household's well-being index, and c) household size (expressed in adult male equivalents). Pale brown circles show observed data for each period for 28 hunters in two communities adjacent to Nigeria's Cross River National Park (April 2020-March 2023).

The model of mass per trip indicated no significant difference in the mass (kg) harvested by each hunter on the last trip during lockdown and first trip after lockdown, suggesting consistent prey stock throughout the study (Table S9). Finally, Kruskal-Wallis tests revealed that ranger patrol duration and the number of rangers per patrol were comparable across periods (lockdown, matched pre-lockdown [2019] and matched post-lockdown [2021]; $\chi^2 = 4.69$, df = 2, $p = 0.10$ and $\chi^2 = 4.91$, df = 2, $p = 0.09$, respectively). However, we found differences in patrol frequency and distance covered ($\chi^2 = 9.10$, df = 2, $p = 0.01$ and $\chi^2 = 9.53$, df = 2, $p = 0.009$, respectively), with higher rates after the lockdown compared to other periods, which both had comparable frequency and distance covered (Table S10).

Discussion

We quantitatively investigated how wild meat hunting and use varied during the coronavirus pandemic in southeast Nigeria and found that the lockdown, implemented to curtail the spread of the virus, was associated with increased rates of successful hunting trips, higher hunting offtakes (number, mass and value of animals caught), and greater wild meat consumption by rural hunters' households. These findings support McNamara et al.'s (2020) hypothesis of elevated hunting in rural areas during the pandemic. Our results suggest that increased household demand for meat probably intensified hunting efforts, underscoring the importance of wild meat as a safety net during socio-economic shocks. Turning to our analysis on protected area management, we found that patrol activities in CRNP remained consistent before and during lockdown (increased funding for patrols 2020-2021 explains the elevated efforts post-lockdown; I. Imong, pers. obs.). This finding suggests sustained park management activities in CRNP during lockdown, which differs from other areas, including Madagascar, where elevated forest fires correlated with reduced management activities during lockdown (Eklund et al., 2022).

We propose that four factors may have contributed to higher hunter offtake rates in lockdown. First, market closures presumably reduced the supply of domesticated meat to villages, leading to greater reliance on wild meat. Second, food requirements in rural households probably increased due to elevated urban-rural migration (Kamogne Tagne et al., 2022). In line with both these suggestions, we found that hunters consumed a larger proportion of wild meat and sold less in lockdown. Third, the economic shock of the lockdown probably reduced labour opportunities for hunters, lowering the opportunity cost of hunting. Fourth, the apparent increase in hunting in the park in lockdown, where animals are conceivably more abundant (Novaro et al., 2000), may have facilitated the elevated offtake rates which we observed then. Although ranger activities in CRNP remained consistent during the lockdown, it is conceivable that hunters' perception, rather than the reality, of reduced site-based law enforcement during lockdown contributed to an increase in hunting activities within the park.

Our study has three main limitations. The first is the possibility of social desirability bias arising from self-reporting (Kormos & Gifford, 2014). However, hunters had no incentive to inflate reports to our observers, as this would mean admitting to violating government guidelines. Second, we focused exclusively on formal hunters because casual hunters were more diffused and, hence harder to follow. However, in the landscape, we estimated that casual hunters account for 40% of the total offtake, on average (Supplementary Methods and Table S11). Lastly, the absence of pre-lockdown data could mean that the observed post-lockdown declines in hunting arose from long-term temporal changes in hunter behaviour or wild animal availability, potentially exacerbated by overhunting in lockdown. Nevertheless, the absence of a difference in mass harvested on each hunter’s last trip in lockdown and the first trip after lockdown contradicts the notion of changes in prey availability.

There are several conservation implications of our work. First, given our finding that local communities consumed a higher proportion of the wild meat they caught during the COVID-19 lockdown, we suggest that in future health, climatic, socio-political, or economic crises, policy interventions that disrupt everyday socio-economic activities should consider the likely impacts on food insecurity of rural communities, especially those without access to hunting areas. Such impacts could be mitigated by providing local communities with alternative protein sources. Similarly, given the dependence on wild meat, restrictive interventions, such as blanket bans on hunting and consuming wild meat, could be counterproductive (Tylianakis et al., 2021). Second, the increased offtake rates during lockdown have likely further reduced the sustainability of hunting, especially for already vulnerable groups such as pangolins and primates. Therefore, the biodiversity effects of policies during shocks should be considered and mitigated (McCleery et al., 2020). Third, the resilience of local communities and of wildlife populations are interlinked. In the medium term, both rely on reducing hunting pressure during normal conditions (e.g., by promoting sustainable hunting practices and investing in site-based law enforcement in protected areas). Thus, without progress in reducing hunting pressures during less disrupted times, it is probable that future shocks will result in even greater economic and ecological impacts. Lastly, community-centred conservation interventions should anticipate shock-triggered changes that could disrupt otherwise successful efforts.

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Conflict of Interests Statement

Charles A. Emogor is a conservation fellow at Wildlife Conservation Society (WCS) and Diane Detoeuf, Inaoyom Imong and Andrew Dunn are employees of the organisation: WCS provided ranger patrol data for this study.

Data Availability Statement

The data supporting this study's findings are not publicly available due to privacy and ethical restrictions, but are available on request from the corresponding author.

Author Contribution Statement

Charles A. Emogor: Conceptualization, methodology, investigation, formal analysis, writing – original draft, funding acquisition. Lauren Coad: Conceptualisation, methodology, writing – original draft, supervision. Ben Balmford: Conceptualisation, methodology, writing – review and editing. Daniel J. Ingram: Methodology, writing – review and editing. Diane Detoeuf: Investigation, writing – review and editing. Robert Fletcher Jr: Conceptualization, methodology, writing – review and editing. Inaoyom Imong: Resources, writing – original draft. Andrew Dunn: Resources, writing – original draft. Andrew Balmford: Conceptualization, methodology, writing – original draft, funding acquisition, supervision.

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Appendix A: Ethics Statement

Research ethics were assessed and approved by Cambridge University's Psychology Research Ethics Committee (applications: PRE.2020.095 and PRE.2021.071). Before collecting data, we sought permission from community leaders following a presentation of the study objectives. We then met with hunters through their community hunter associations, where we explained the study, detailing the nature of data collection, and asked for volunteers. We stressed voluntary participation, data anonymisation, and participants' rights to withdraw from the study. Each respondent granted written free and informed consent before data collection commenced; we only worked with hunters above 18 years of age. Note that data collection during lockdown was in line with government guidelines, as the researchers lived in the study communities and there were no restrictions on movements within local communities.

Appendix B: Supplementary Methods

Derivation of Period Variable

Although Nigeria's first of three lockdown phases (effective on 30 March 2020) only concerned Lagos, Abuja, and Ogun states (Presidential Task Force, 2020a), Cross River state (our study location) also announced a state-wide lockdown that began on the same date (Vanguard News, 2020). The first and second lockdown phases in the country (which coincided with Cross River state's lockdown) lasted ~ 5 months (30 March-3 September 2020) and featured restrictions in human movements, closure of public and private institutions, and curfews (Presidential Task Force, 2020a, 2020c). In the third phase of the lockdown (3 September-20 December 2020), regular commercial and social activities, including international flights, resumed, but a national curfew was placed from midnight to 4 am (Presidential Task Force, 2020b).

In creating our primary variable of interest (i.e., period), we treated only the first two phases as lockdown (i.e., COVID-19–induced lockdown days in the study location in 2020; 5.2 months). We then matched the lockdown period in 2020 with corresponding days in 2021-22, calling that period matched non-lockdown (10.4 months). Finally, we created a third period to cover days in 2020-2023 that were neither lockdown nor matched non-lockdown (other non-lockdown; 20.6 months).

Derivation of Hunter-level Variables and Rationale for Inclusion in the Models

The hunter-level covariates were: hunter's annual household income, excluding hunting-related income, experience (in years), their household's well-being index (WBI) and their household size (expressed in adult male equivalents; AME). We derived non-hunting income by asking and summing monthly estimates (in Naira) of earnings over the past year (March 2021-April 2022) from agriculture, timber and non-timber forest product trade, business and employment. To assess experience, we asked each hunter how long they had been active hunters. We derived an index of household-level well-being with a protocol that uses access to services and affordability of necessary goods to develop a composite measure of a household's socio-economic security (i.e., wealth; Detoeuf et al., 2020). The protocol assesses goods and services identified as 'essential' by the focal communities. We created this list through workshops in four local communities (surrounding CRNP) in 2017 and conducted the assessment with the hunters in May 2022. The BNS survey can be assessed through this link https://ee.kobotoolbox.org/x/L12MXi3d. Protocol for deriving the index is described in L'Roe et al. (2023). We used income and WBI in the same model as income is limited to financial earnings, while the latter provides a more holistic assessment of wealth (they both had a variance inflation factor of 1). AME measures household dietary requirement, standardising food consumption using household size (number) and composition (sex and age; Weisell & Dop, 2012). We included wealth and income in the model because of established associations between wealth and wild meat consumption (Brashares et al., 2011) and hypothesised that more experienced hunters would have more successful trips and consequently higher hunting returns. Further, an increase in household AME has been shown to positively co-vary with higher protein consumption (Godoy et al., 2010).

Model Specifications

The equation for the model predicting the variation in the number of successful trips is given by

$$log(Number\ of\ successful\ trips_{ij}) = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + log(\beta_3 Experience_i) + \beta_4 WBI_i + \beta_5 AME_i + \alpha_{ij} \tag{1}$$

where $Number\ of\ successful\ trips_{ij}$ is the total number of trips where hunter *i* captured at least one animal in period *j*; β_0 is the intercept; β_{1-5} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the number of animals captured is given by

$$log(Number\ of\ animals\ captured)_{ij} = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + log(\beta_3 Experience_i) + \beta_4 WBI_i + \beta_5 AME_i + \alpha_{ij} \quad (2)$$

where $Number\ of\ animals\ captured_{ij}$ is the total number of animals hunted by hunter *i* in period *j*; β_0 is the intercept; β_{1-5} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the mass of wild meat harvested is given by

$$log(Mass\ of\ wild\ meat_{ij}) = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + log(\beta_3 Experience_i) + \beta_4 WBI_i + \beta_5 AME_i + \alpha_{ij} \quad (3)$$

where $Mass\ of\ wild\ meat_{ij}$ is the total mass of animals harvested by hunter *i* in period *j*; β_0 is the intercept; β_{1-5} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the value of wild meat harvested is given by

$$log(Value\ of\ wild\ meat_{ij}) = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + log(\beta_3 Experience_i) + \beta_4 WBI_i + \beta_5 AME_i + \alpha_{ij} \quad (4)$$

where $Value\ of\ wild\ meat_{ij}$ is the total value (in Naira) of animals harvested by hunter *i* in period *j*; β_0 is the intercept; β_{1-5} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the mass of wild meat eaten in hunter household is given by

$$log(Mass\ eaten_{ij}) = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + \beta_3 WBI_i + \beta_4 AME_i + \alpha_{ij} \quad (5)$$

where $Mass\ eaten_{ij}$ is the total mass of wild meat eaten by hunter *i* in period *j*; β_0 is the intercept; β_{1-4} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the mass of wild meat sold is given by

$$log(Mass\ sold_{ij}) = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + \beta_3 WBI_i + \beta_4 AME_i + \alpha_{ij} \qquad (6)$$

where $Mass\ sold_{ij}$ is the total mass of wild sold by hunter *i* in period *j*; β_0 is the intercept; β_{1-4} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

The equation for the model predicting the proportion of the mass of wild meat eaten in hunter households is given by

$$Proportion\ of\ mass\ eaten_{ij} = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + \beta_3 WBI_i + \beta_4 AME_i + \alpha_{ij} \qquad (7)$$

where $Mass\ eaten_{ij}$ is the proportion of the mass eaten by hunter *i* in period *j*; β_0 is the intercept; β_{1-4} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Beta distribution.

The equation for the model predicting the proportion of the mass of wild meat sold is given by

$$Proportion\ of\ mass\ sold_{ij} = \beta_0 + \beta_1 Period_j + log(\beta_2 Income_i) + \beta_3 WBI_i + \beta_4 AME_i + \alpha_{ij} \qquad (8)$$

where $Mass\ sold_{ij}$ is the proportion of the mass sold by hunter *i* in period *j*; β_0 is the intercept; β_{1-4} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Beta distribution.

The equation for the model predicting the mass of wild meat harvested per trip (last trip during lockdown and first trip after lockdown only) is given by

$$log(Mass\ of\ wild\ meat_{ij}) = \beta_0 + \beta_1 Period_k + log(\beta_2 Income_i) + log(\beta_3 Experience_i) + \beta_4 WBI_i + \beta_5 AME_i + \beta_6 Duration_j + \alpha_{ij} \qquad (9)$$

where $Mass\ of\ wild\ meat_{ij}$ is the mass of harvested by hunter *i* on trip *j* in period *k*; β_0 is the intercept; β_{1-6} are the slopes of the respective predictors; α_{ij} is random intercept; and we assume that the errors follow a Gaussian distribution.

Changes in Patrol Effort and Derivation of Variable

We derived data on patrol effort data from the Nigeria program of Wildlife Conservation Society (WCS), supporting CRNP's management. Ranger patrols are conducted monthly using spatial monitoring and reporting tool (https://smartconservationtools.org/; SMART), allowing automated data collection on the distance covered, time spent travelling, and patrol route. The number of rangers per patrol was also derived from SMART records inputted by the patrol team at the start of patrols. We matched the data by time of year to drive three corresponding periods: lockdown (2020), pre-lockdown (2019), and post-lockdown (2021). We obtained 78 patrol records across the periods, which we used to derive monthly averages for a) patrol frequency, b) rangers per patrol, c) distance covered, and d) active patrol time (duration).

Note that SMART aggregates all patrols conducted on the same date as one patrol, with corresponding information for separate patrols conducted on the same day summed. For example, the distance covered by four different patrols that began on a given date would be aggregated and presented alongside the sum of patrols conducted on the said date.

Proximate Offtake Between Formal and Casual Hunters

Forming part of a different strand of research in the Cross River landscape, we collected data from 590 hunters (392 formal and 198 casual) to understand their relative contributions to the total wild meat offtake in the regions. Formal hunters refer to those who primarily hunt with gun while casual hunters are those whose predominant hunting method is trap, mainly wire snares. We asked each hunter the average number of individuals for African brush-tailed porcupine (*Atherurus africana*), black-bellied (*Phataginus tetradactyla*), blue duiker (*Philantomba monticola*), red river hog (*Potamochoerus porcus*), and white-bellied pangolins (*P. tricuspis*) that they killed in the wet (April-October) and dry seasons (November-March) over the past three years. We conducted this survey in 20 communities in southeast Nigeria's Cross River Forest landscape in October-November 2023. The landscape includes three protected areas occurring there: Afi Mountain Wildlife Sanctuary (100 km²), Mbe Mountains Community Forest (86 km²), and Cross River National Park (CRNP; 3,640 km²), comprising Oban and Okwangwo divisions (~ 65 km apart). We received ethics approval for this study from Cambridge University's Psychology Research Ethics Committee (applications: PRE.2023.097).

To select our study communities, we divided each of the CRNP divisions into four geographic quadrants (hereafter strata), capturing other protected areas in our stratification. We then randomly selected 12 communities from each stratum (2-4 per stratum based on their total number of communities), except in southeastern stratum of Okwangwo where no community occurs. The remaining eight communities were purposefully selected to include communities wherein we have ongoing projects, including the two communities where we tracked the hunters for this study. We recruited hunters at their homes, but first informed community leaders of the study's objectives and protocols for data collection and requested their permission to conduct our surveys. We then counted all households (defined as groups of people living under the same roof and sharing the same meals in each community (n = 9,510 across the communities). During the count, we asked about the number of people in the household and the number of hunters by category. We then returned to all the households with hunters to interview them individually – but did not capture all hunters as some declined to take part and others were absent during our visit. We estimate that our final survey sample represents 43% of hunters in the landscape, based on our household-level records.

To obtain the contribution of casual hunters to the overall captures in the landscape, we calculated the percentage of annual captures by casual hunters (Supplementary Table 13) for each species (using the median per species) and then extracted the median percentage across the five species.

Software and Packages

All analyses were done using R v 4.2.2 (R Core Team, 2022), with lme4 (Bates et al., 2015) for Gaussian models, glmmTMB (Brooks et al., 2017) for Beta models, and emmeans (Lenth, 2023) for posthoc tests. Performance package (Lüdecke et al., 2021) was used for model validation.

Appendix C: Figures

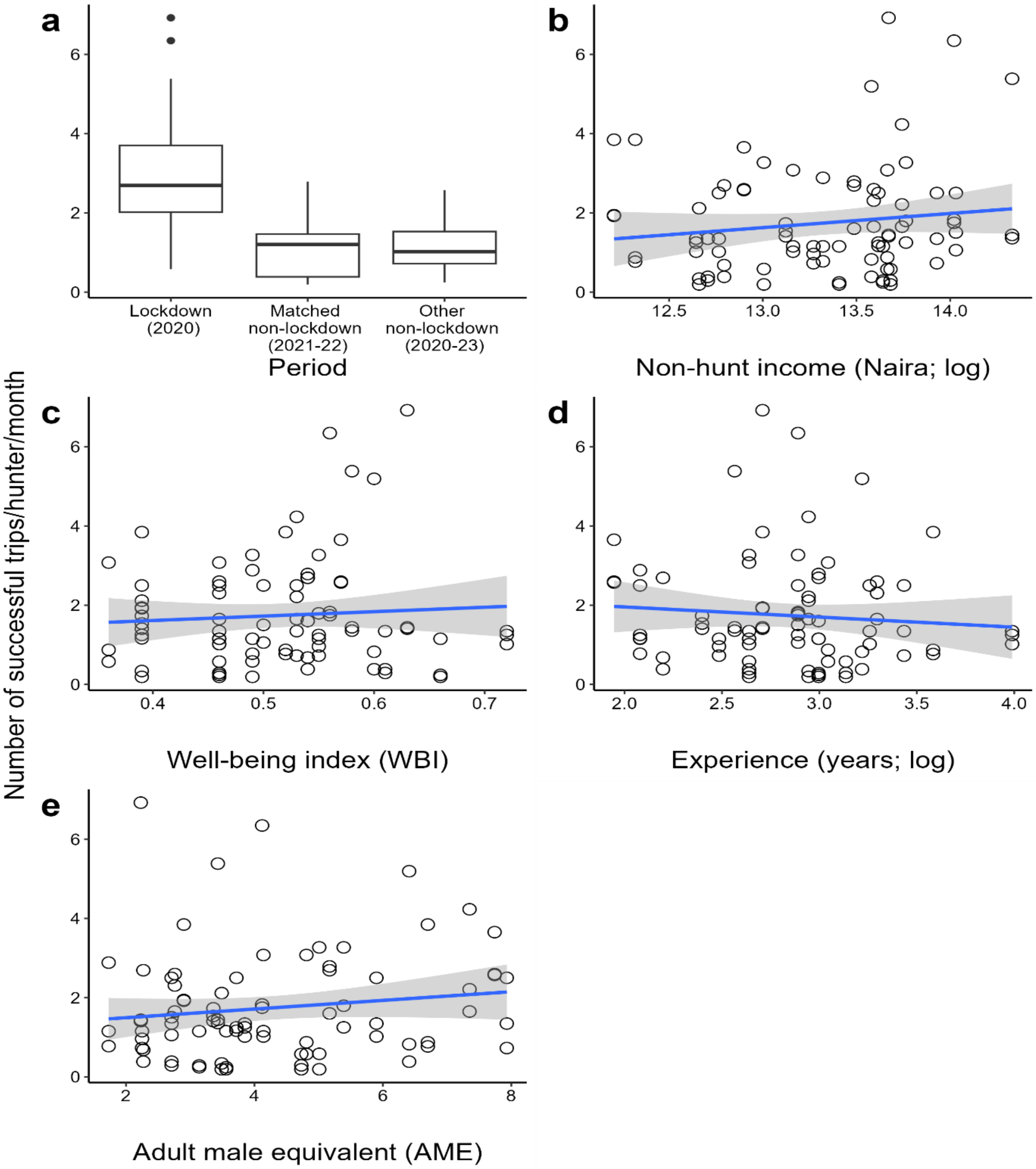

Figure S1: The distribution of the predictors used to model the number of successful hunting trips (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b and d. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers. Circles in b-e are raw data points.

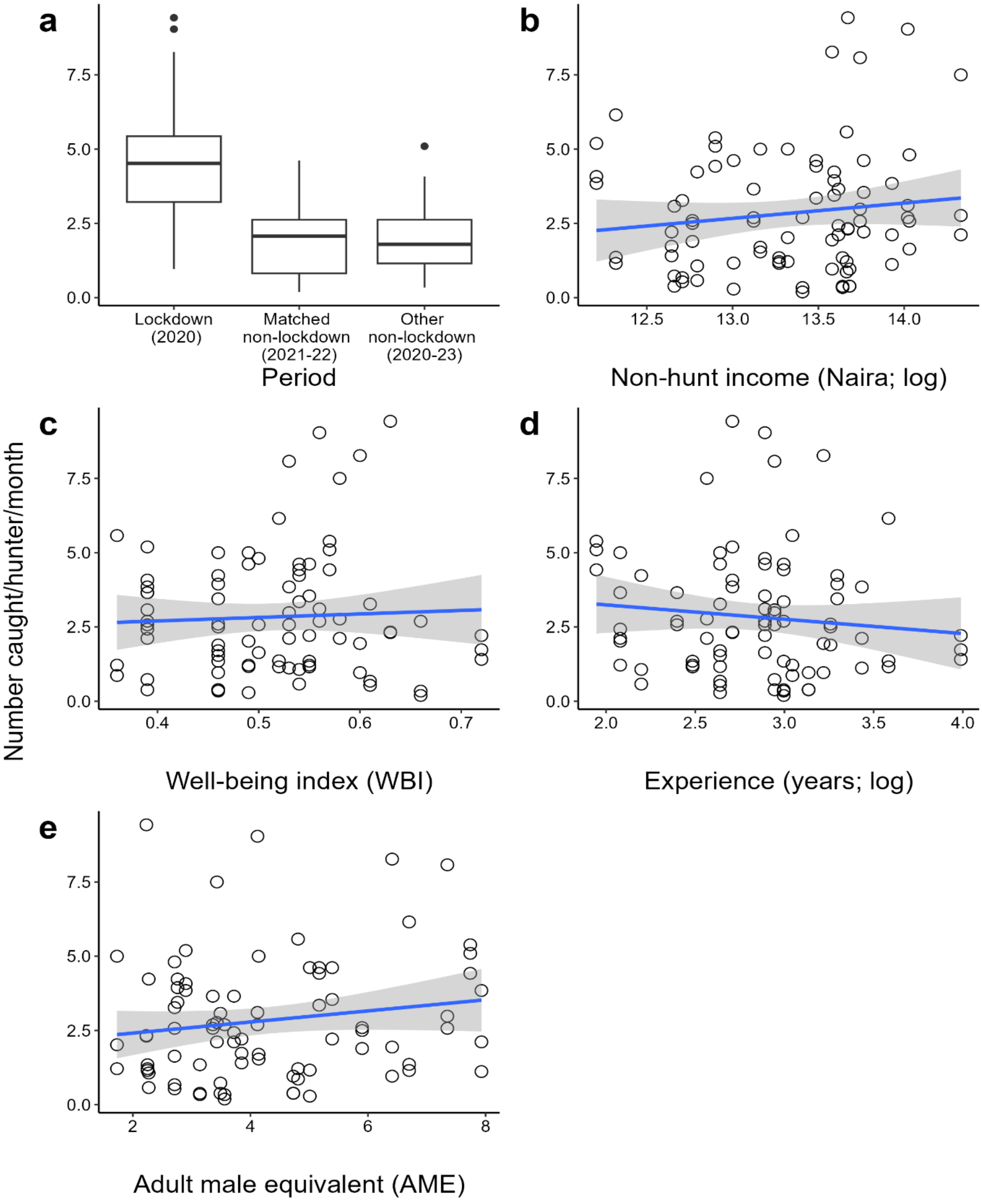

Figure S2: The distribution of the predictors used to model the number of each animal captured (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b and d. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-e) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-e).

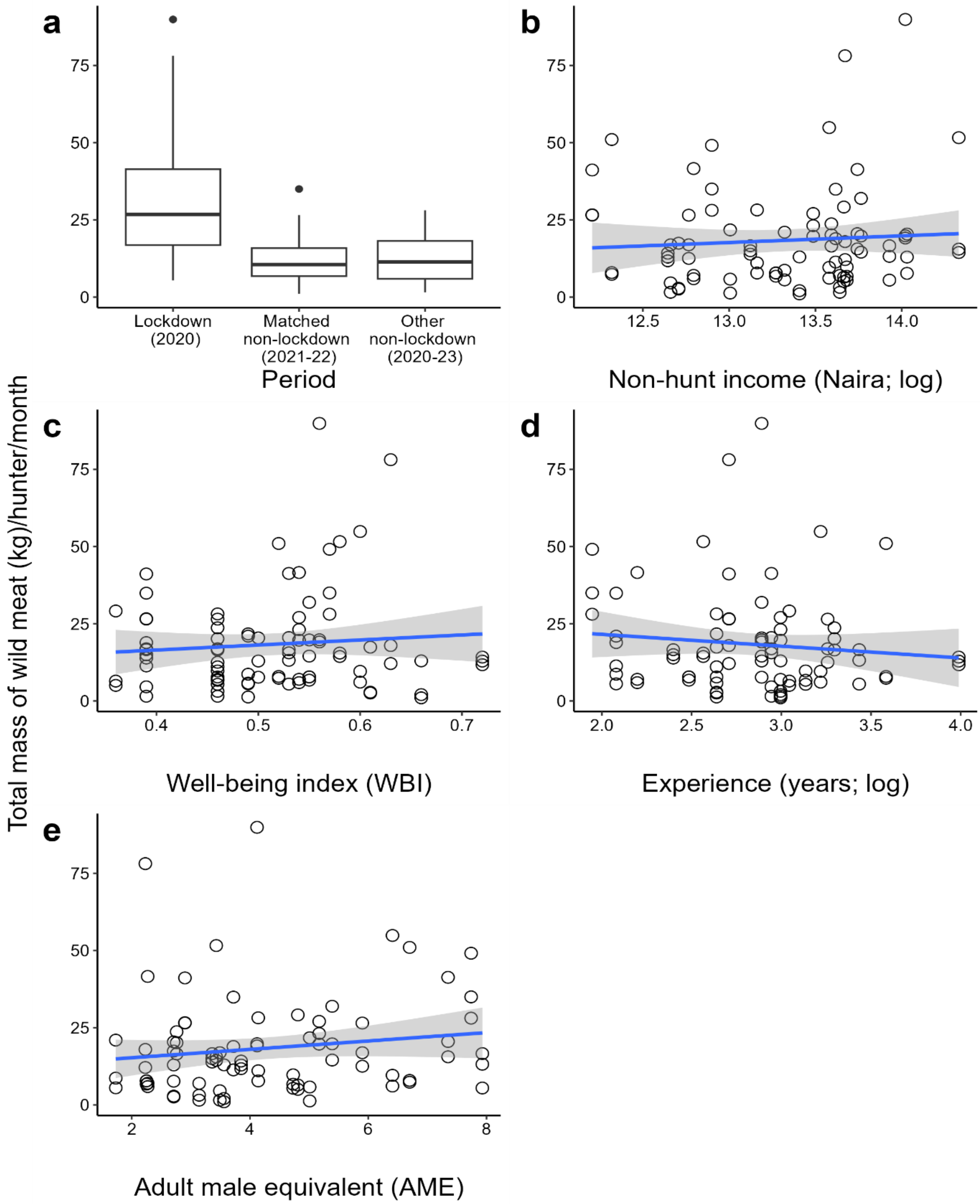

Figure S3: The distributions of the predictors used to model the mass of wild meat harvested (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b and d. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-e) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-e).

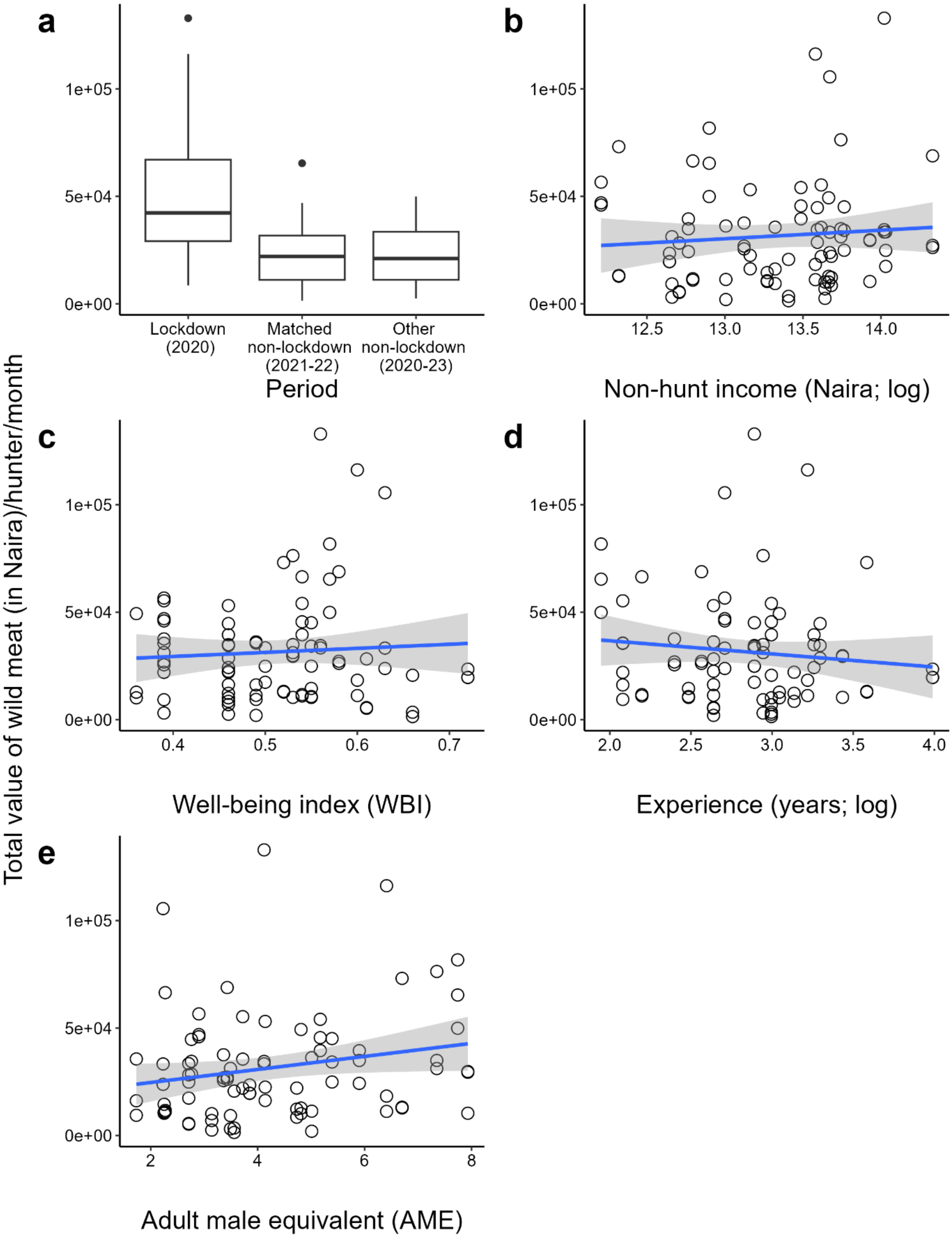

Figure S4: The distributions of the predictors used to model the value of wild meat harvested (see y-axis labels for predictor names). We used log_{10} transformation in b and d. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-e) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-e).

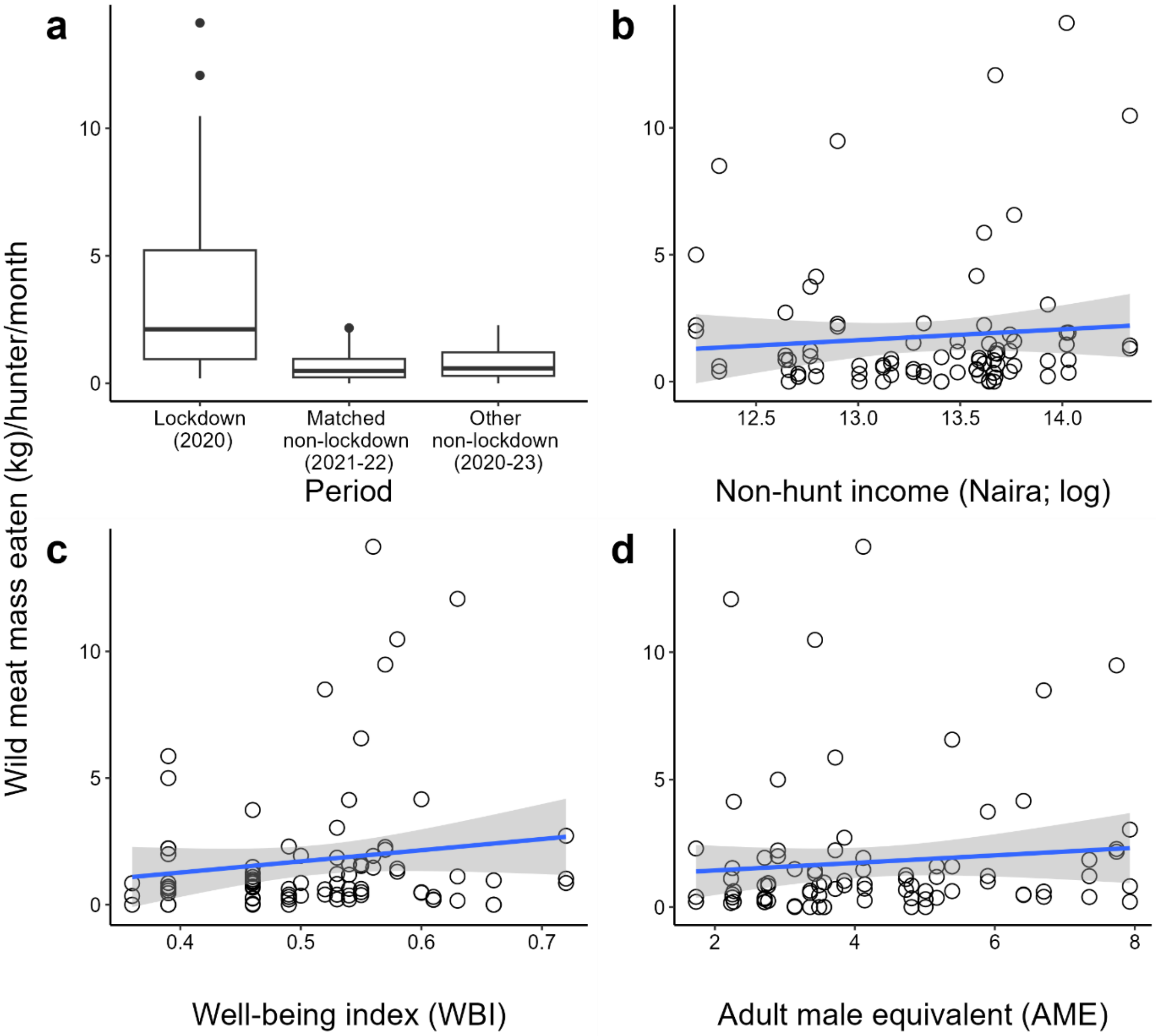

Figure S5: The distributions of the predictors used to model the mass of wild meat eaten in hunter households (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-d) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-d).

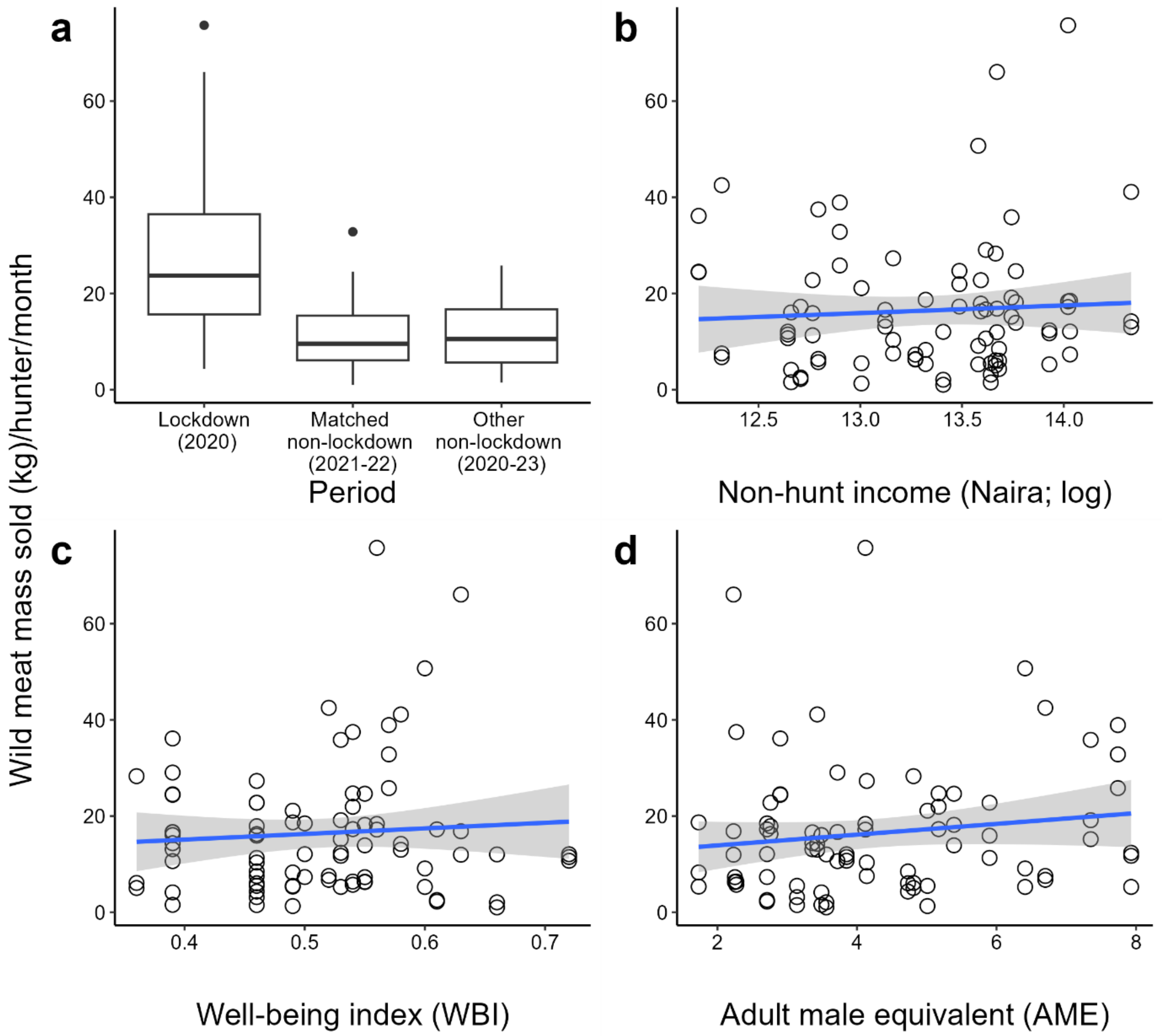

Figure S6: The distributions of the predictors used to model the mass of wild meat sold (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-d) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-d).

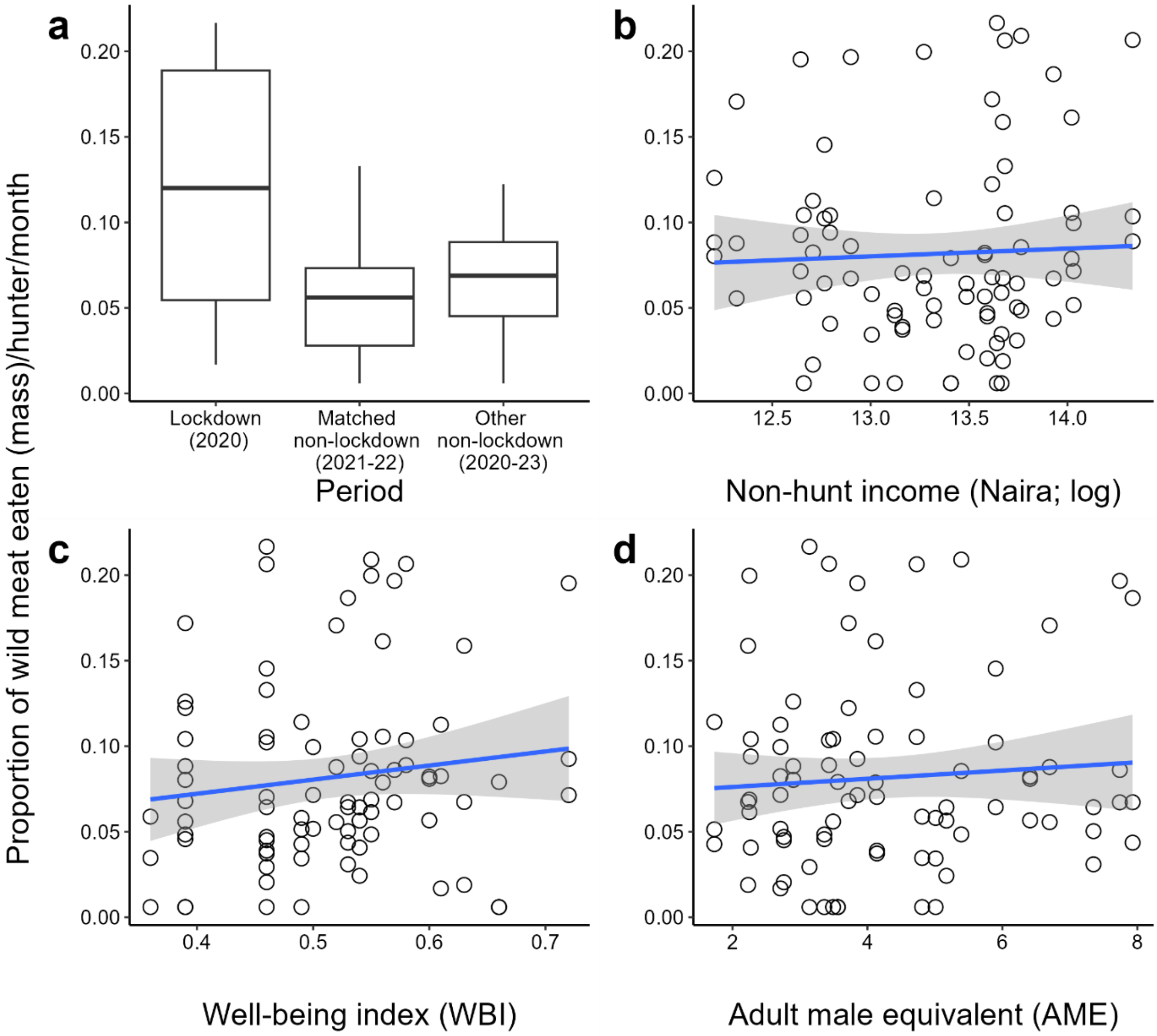

Figure S7: The distributions of the predictors used to model the proportions of wild meat mass eaten in hunter households (see y-axis labels for predictor names). We used log_{10} transformation in b. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-e) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Blue lines (b-d) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-d).

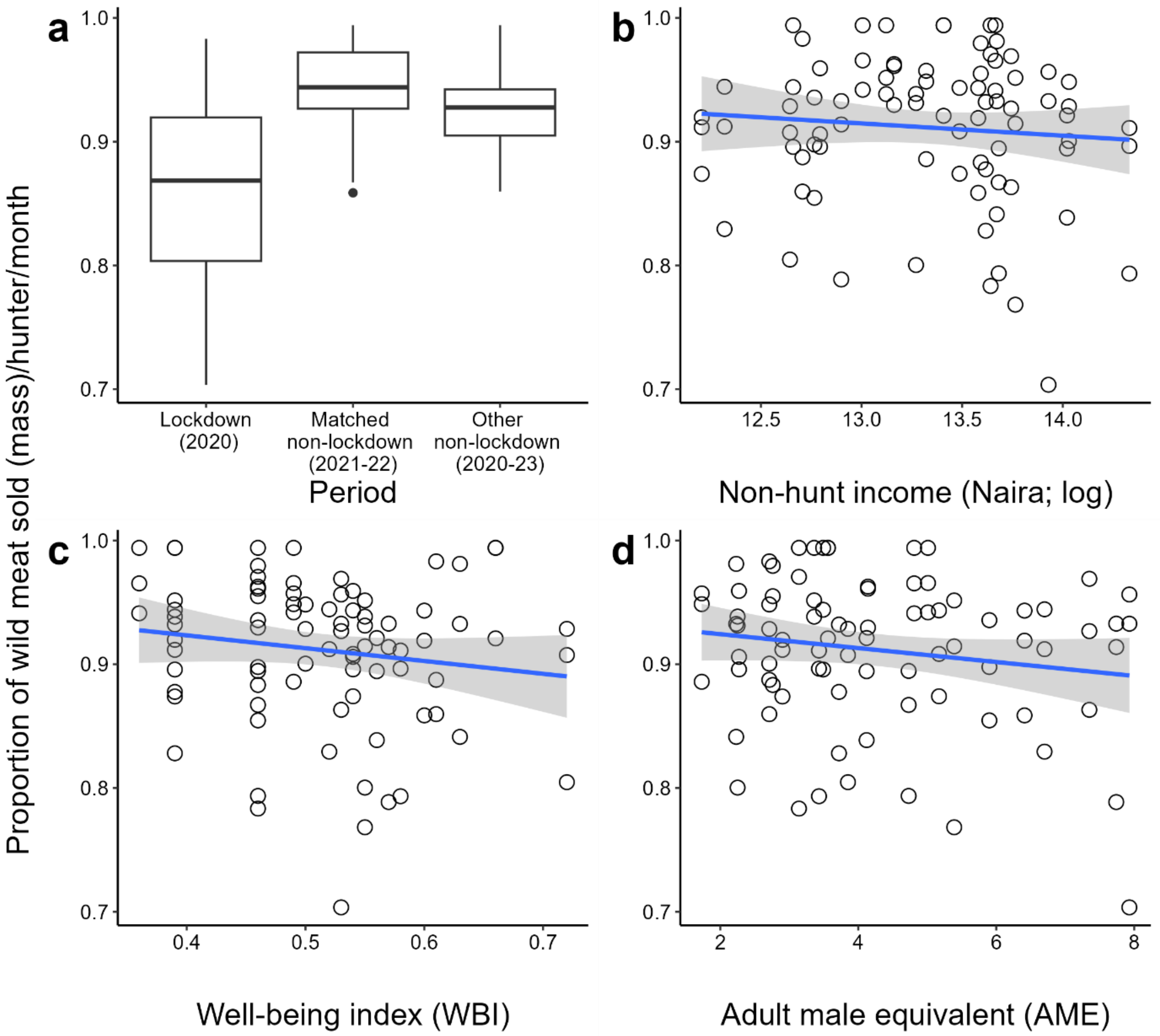

Figure S8: The distributions of the predictors used to model the proportions of wild meat mass sold (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-d) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-d).

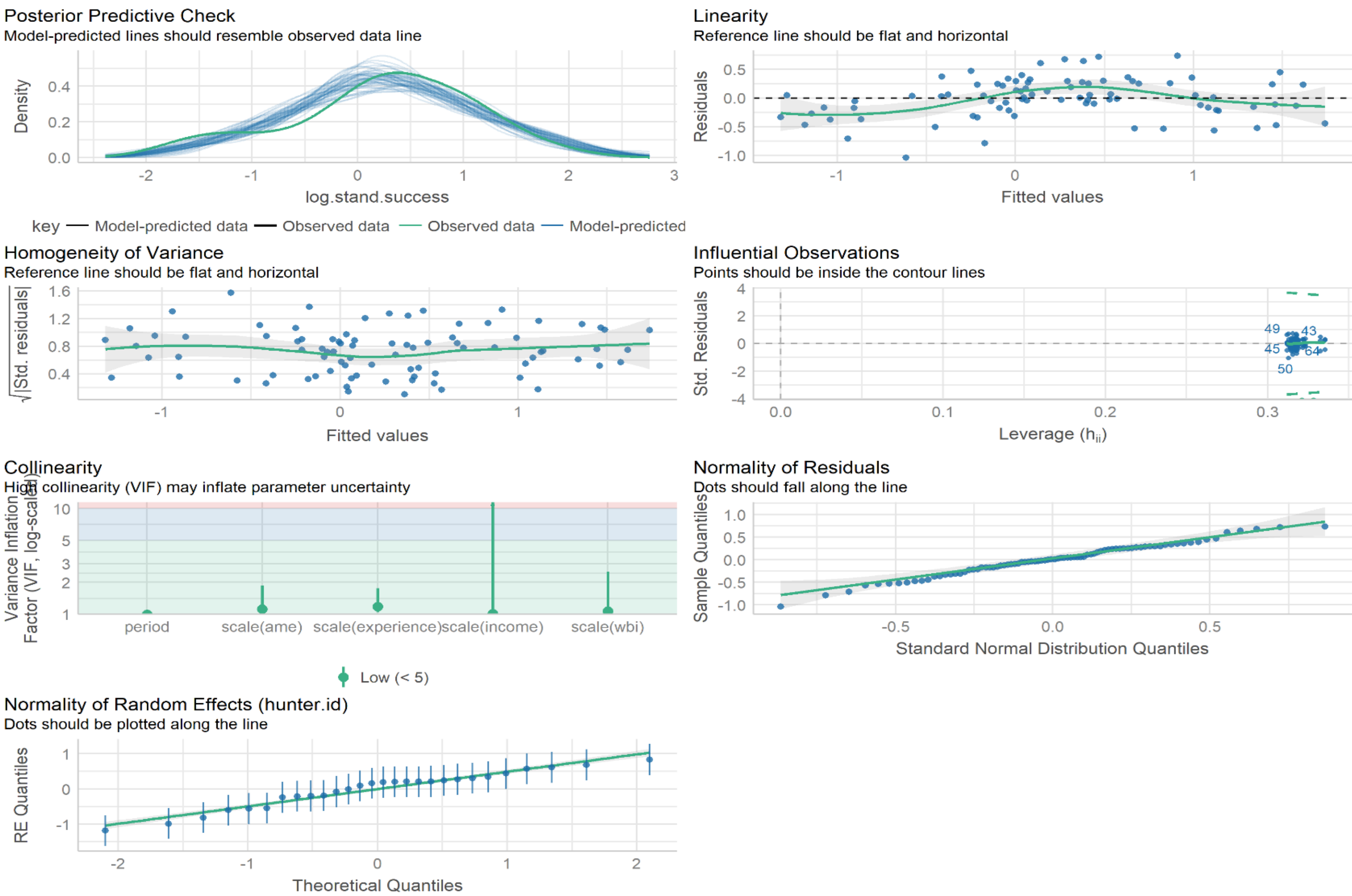

Figure S9: Diagnostics of the model predicting the total number of each hunter's successful trips per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

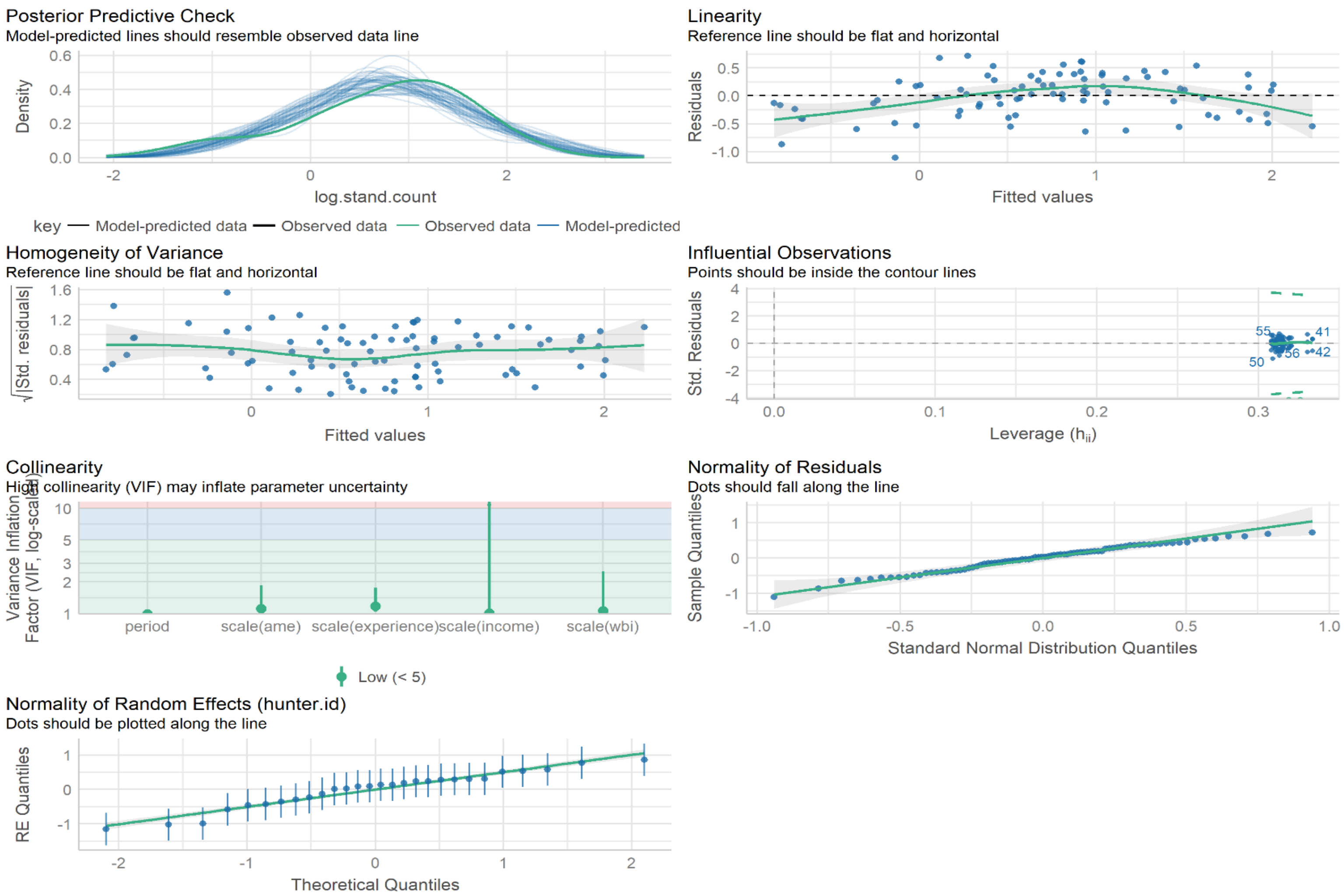

Figure S10: Diagnostics of the model predicting the total number of animals each hunter captured per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

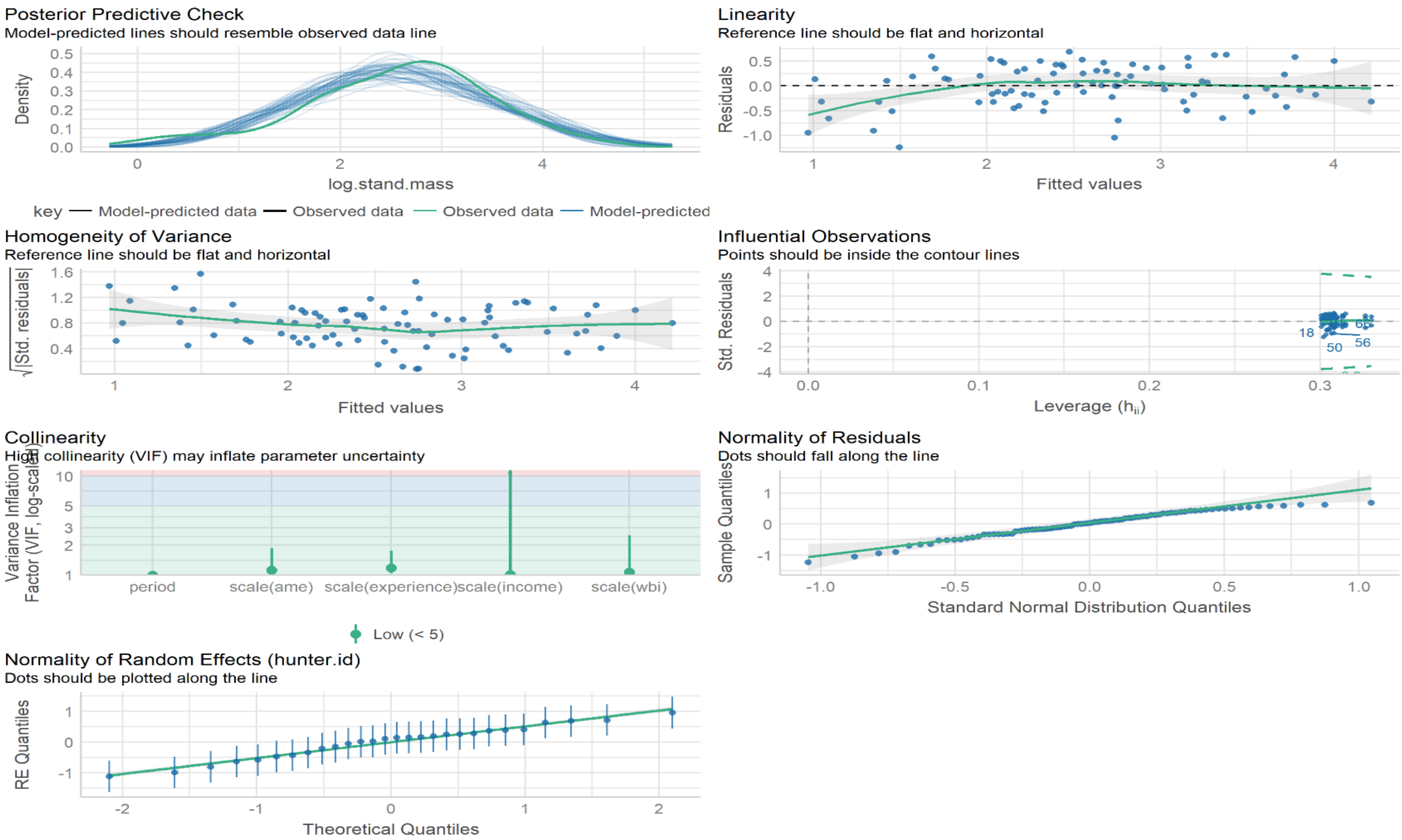

Figure S11: Diagnostics of the model predicting the total mass of wild meat caught by each hunter per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

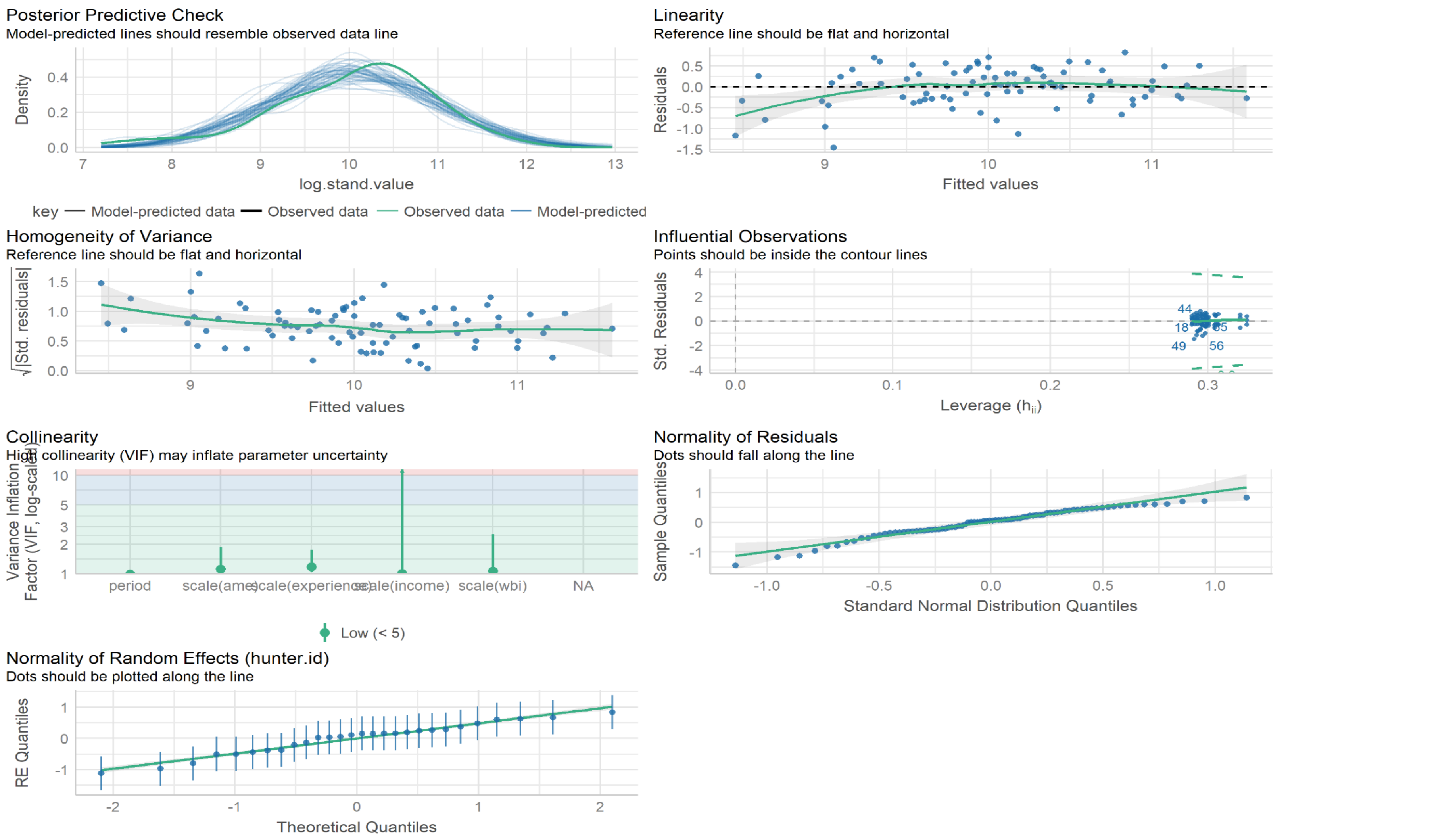

Figure S12: Diagnostics of the model predicting the total value of animals captured per hunter per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

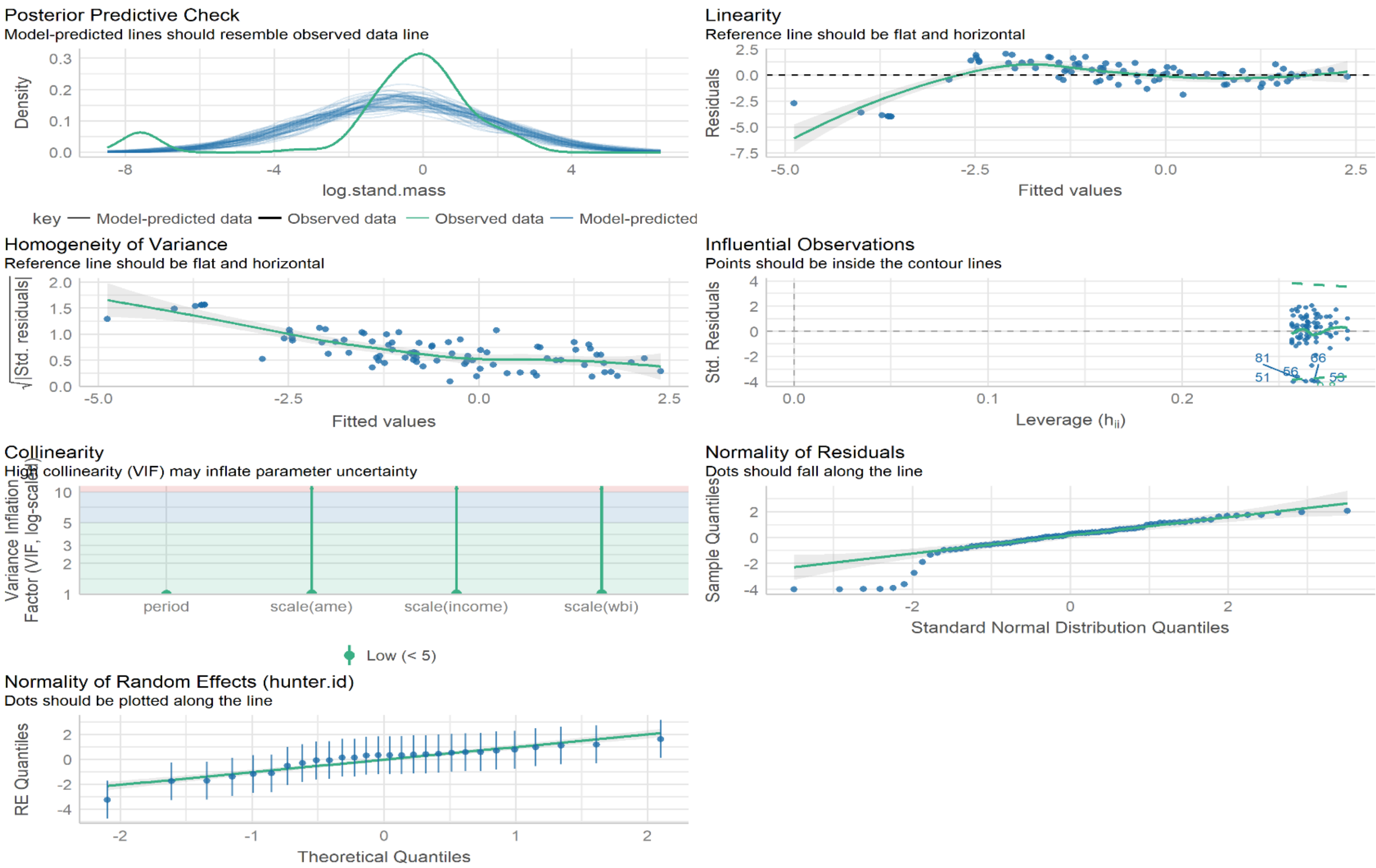

Figure S13: Diagnostics of the model predicting the mass of wild meat eaten in hunter households per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

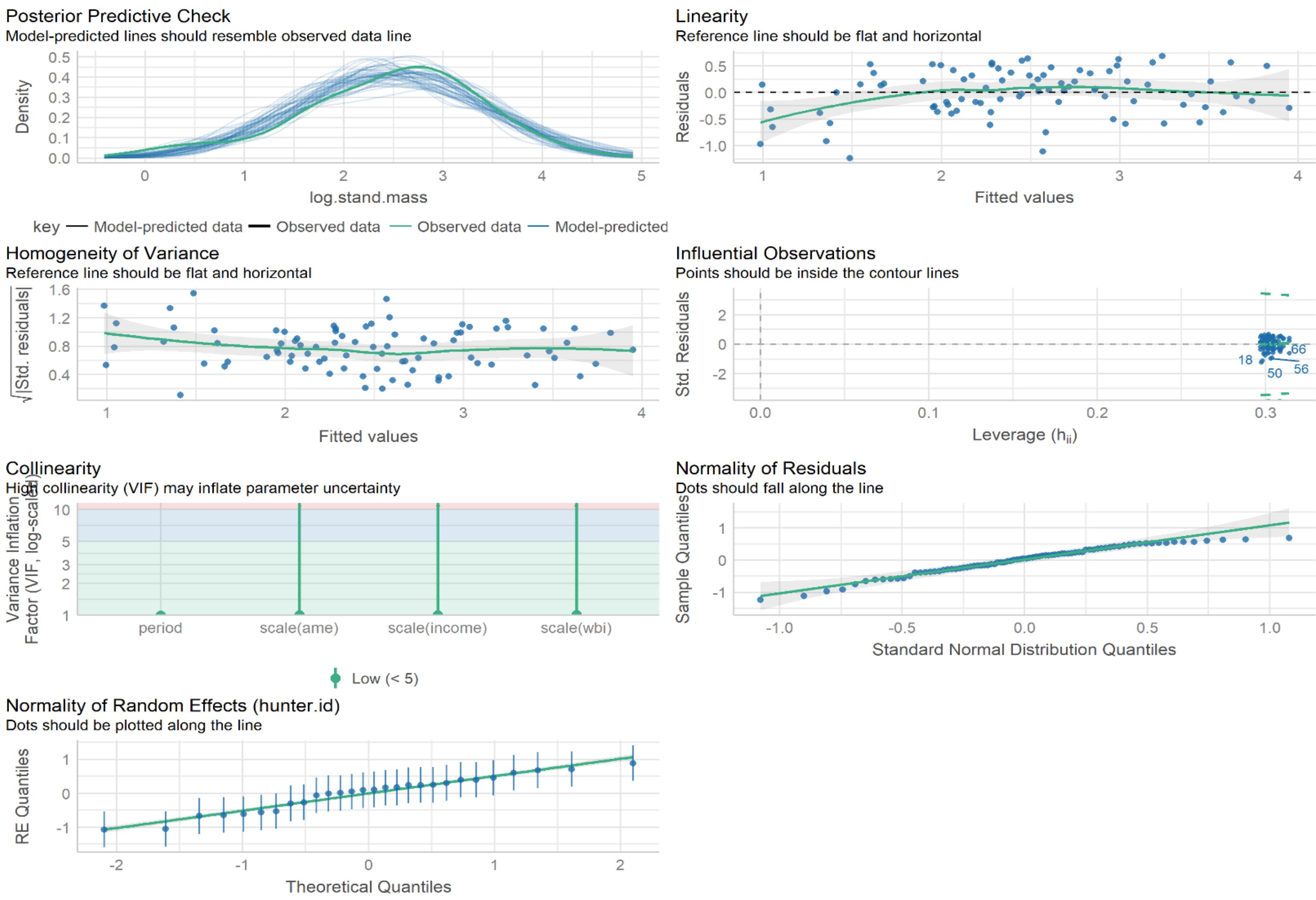

Figure S14: Diagnostics of the model predicting the mass of wild meat sold per hunter per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

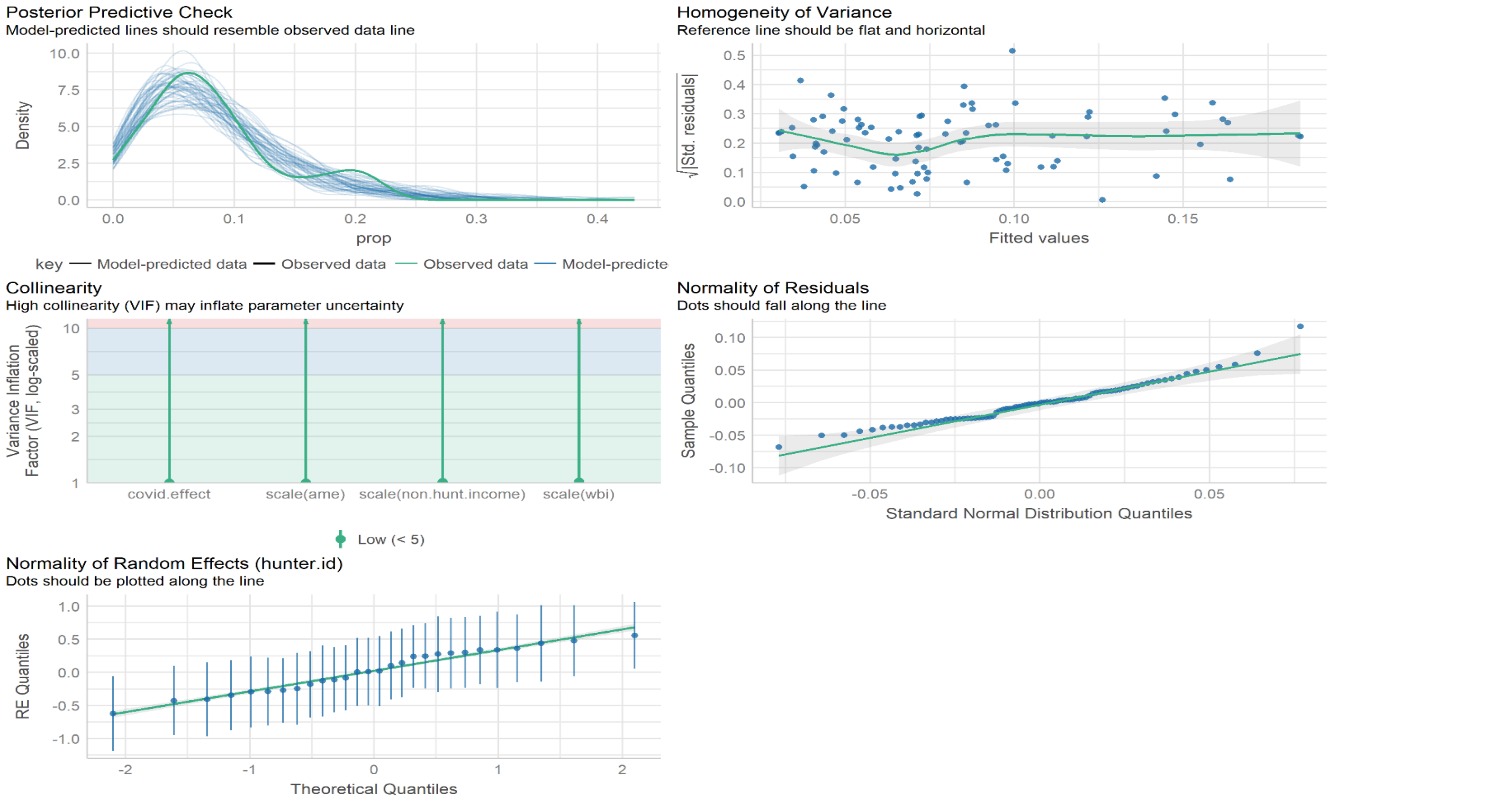

Figure S15: Diagnostics of the model predicting the proportion of wild meat mass eaten in hunter households per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

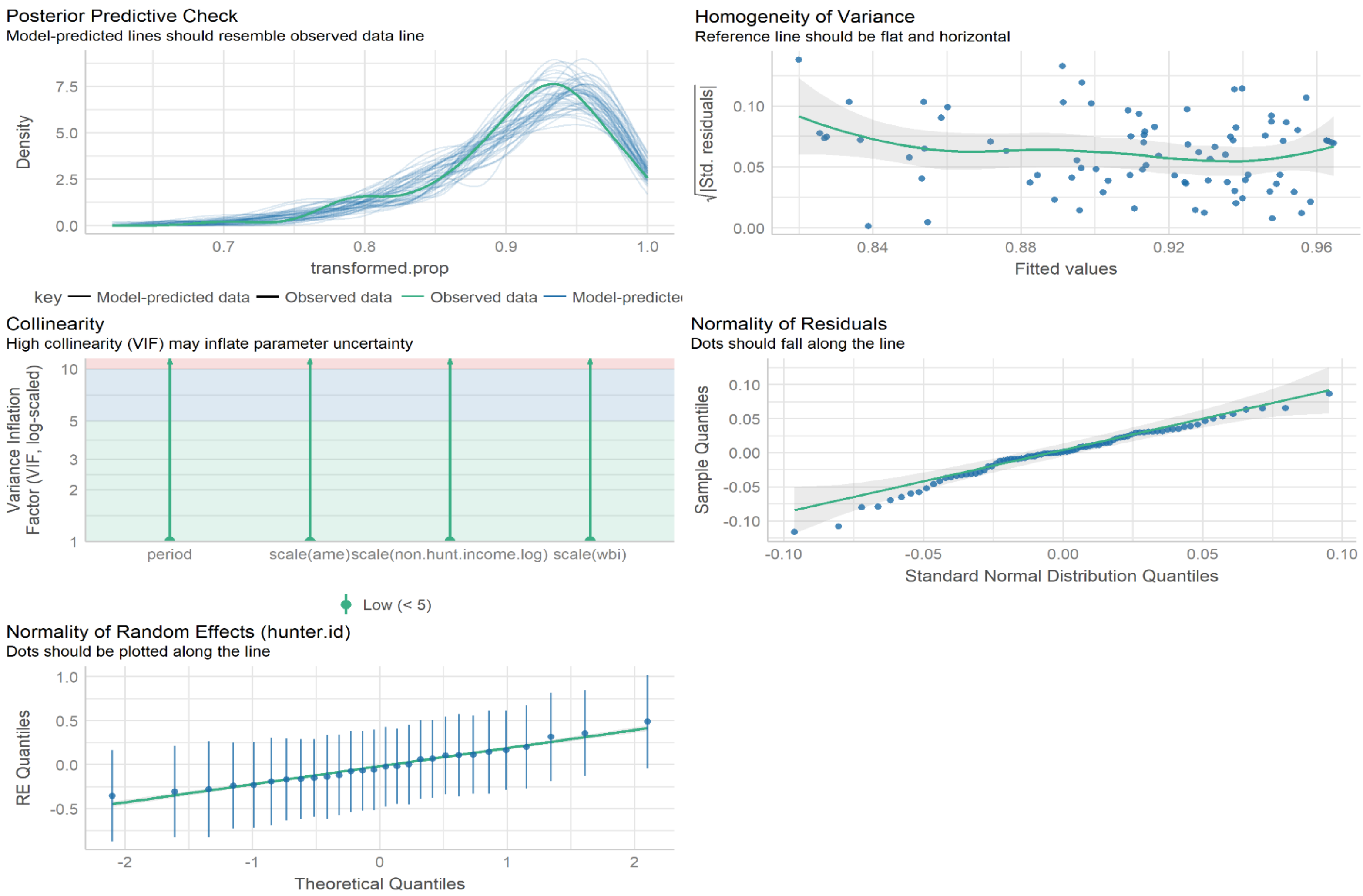

Figure S16: Diagnostics of the model predicting the proportion of wild meat mass sold per month. Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

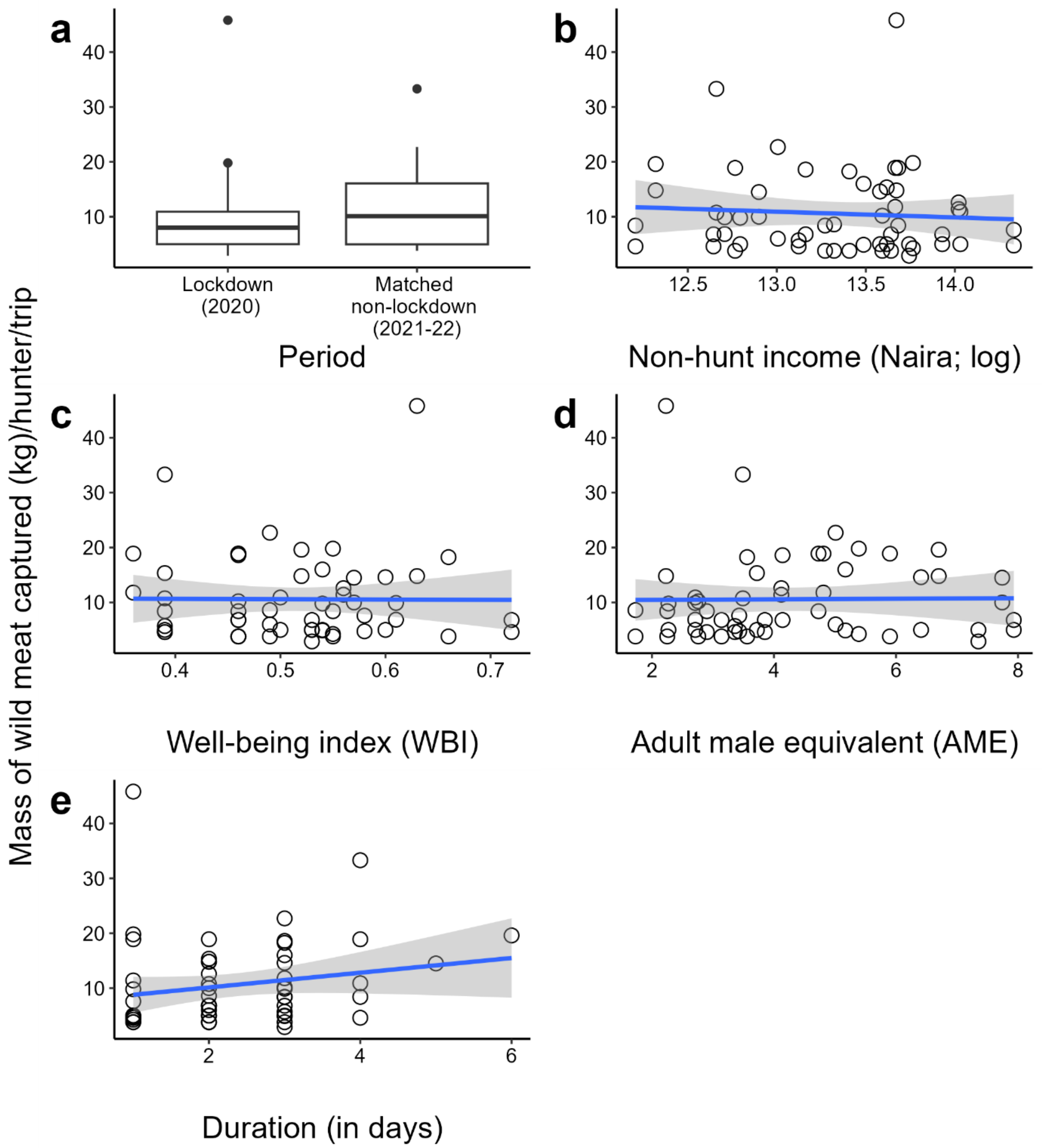

Figure S17: The distributions of the predictors used to model the mass of wild meat caught by each hunter in the last trip during lockdown and first trip post-lockdown (see y-axis labels for predictor names). We used $\log_{10}$ transformation in b. In a, each boxplot corresponds to the average number per hunter for the relevant period, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers (a). Blue lines (b-e) represent the corresponding relationships (using the linear model smoother function in R) and grey ribbon are 95% credible interval. Circles are raw data points (b-e)

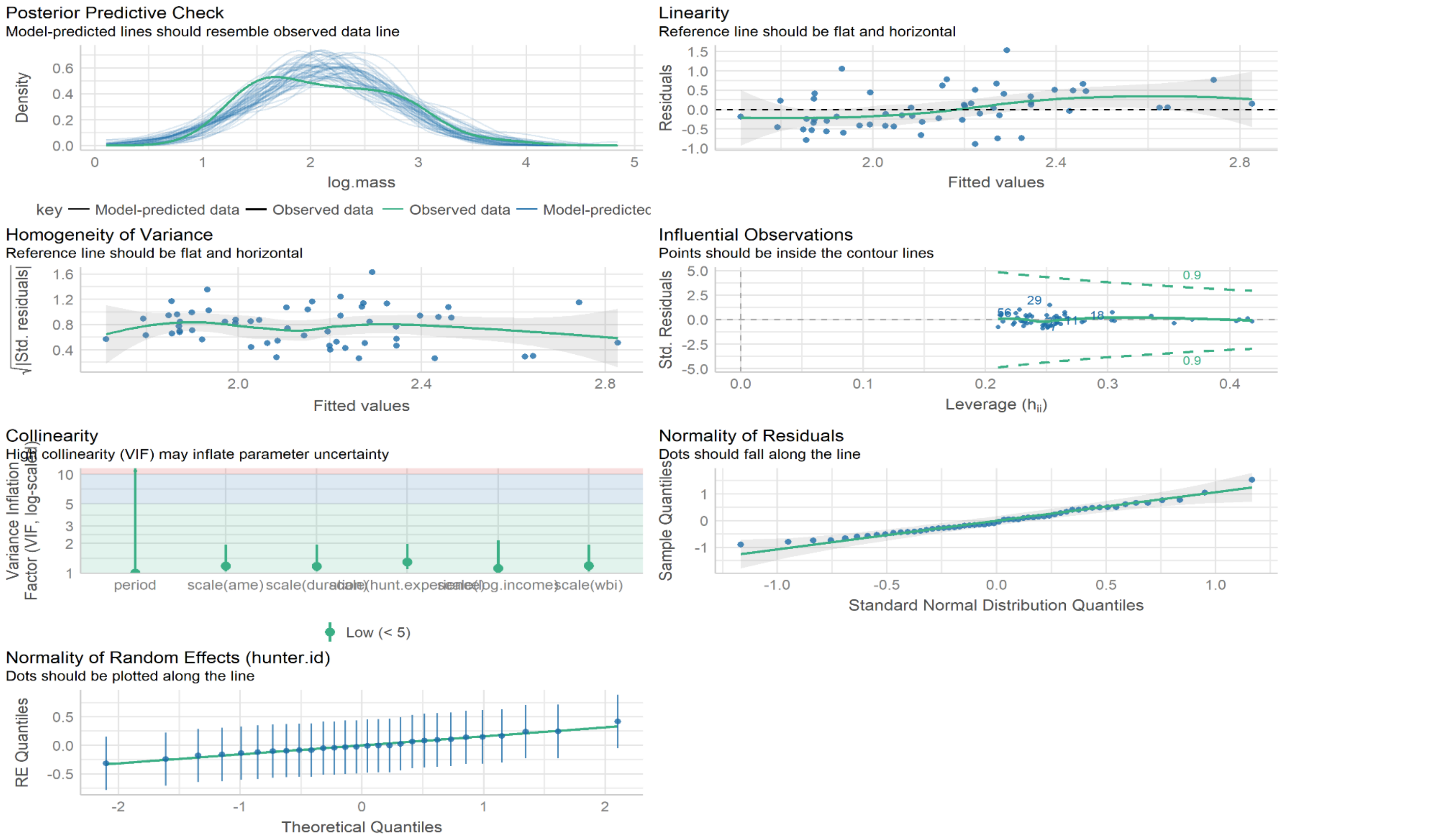

Figure S18: Diagnostics of the model predicting the mass caught per hunter per trip (last trip during lockdown and first trip after lockdown only). Diagnostic parameters and interpretation of the plot are provided on top of each panel. Model assessment conducted using Performance package.

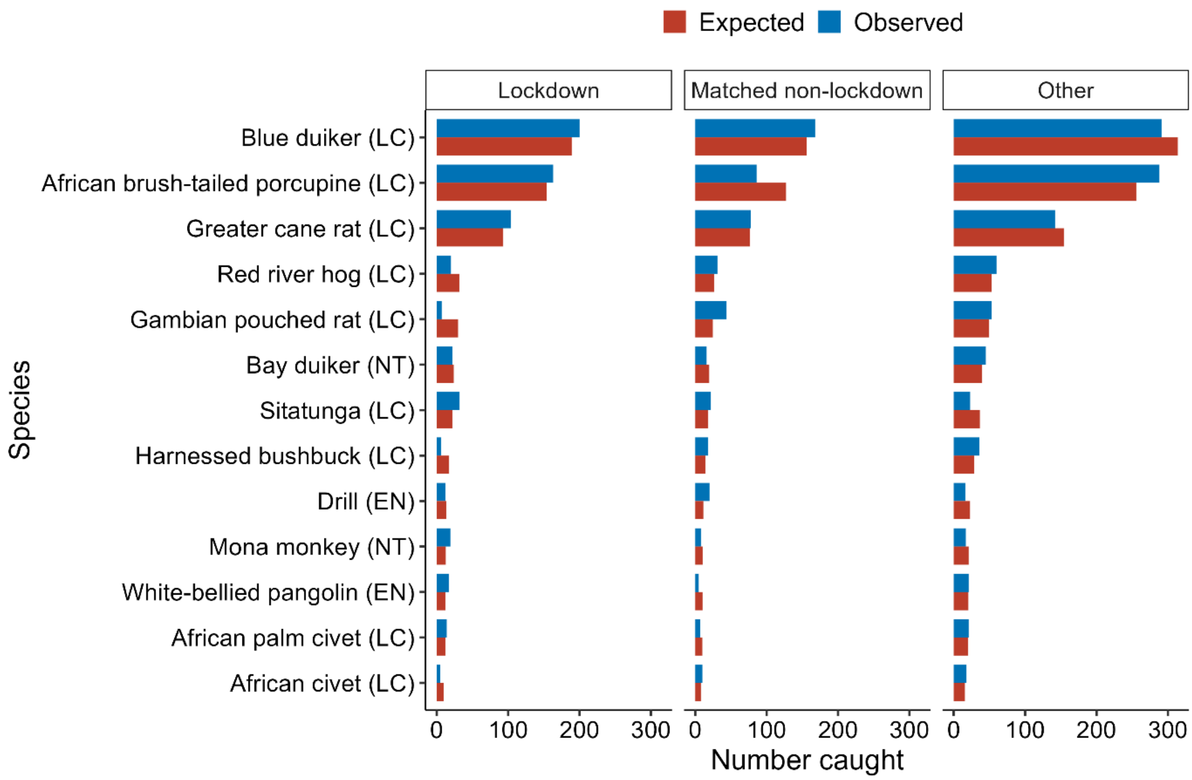

Figure S19: Observed (actual data) and expected frequencies (what would be expected if the variables were independent) per species for each period. The expected values were derived from a Chi-square estimation (χ^2 = 106.81, df = 24, p < 0.001). 'Lockdown (2020)' refers to 5.2 months of COVID–induced lockdowns in Nigeria in 2020, 'Matched (2021-22)' is 10.4 month in 2021 and 2022 that correspond with the 2020 lockdown, while 'Other (2020-2023)' refers to periods that were neither lockdown nor matched with lockdown (20.6 months). IUCN categories are in brackets: LC = Least Concern, NT = Near Threatened, VU = Vulnerable, EN = Endangered, and CR = Critically Endangered.

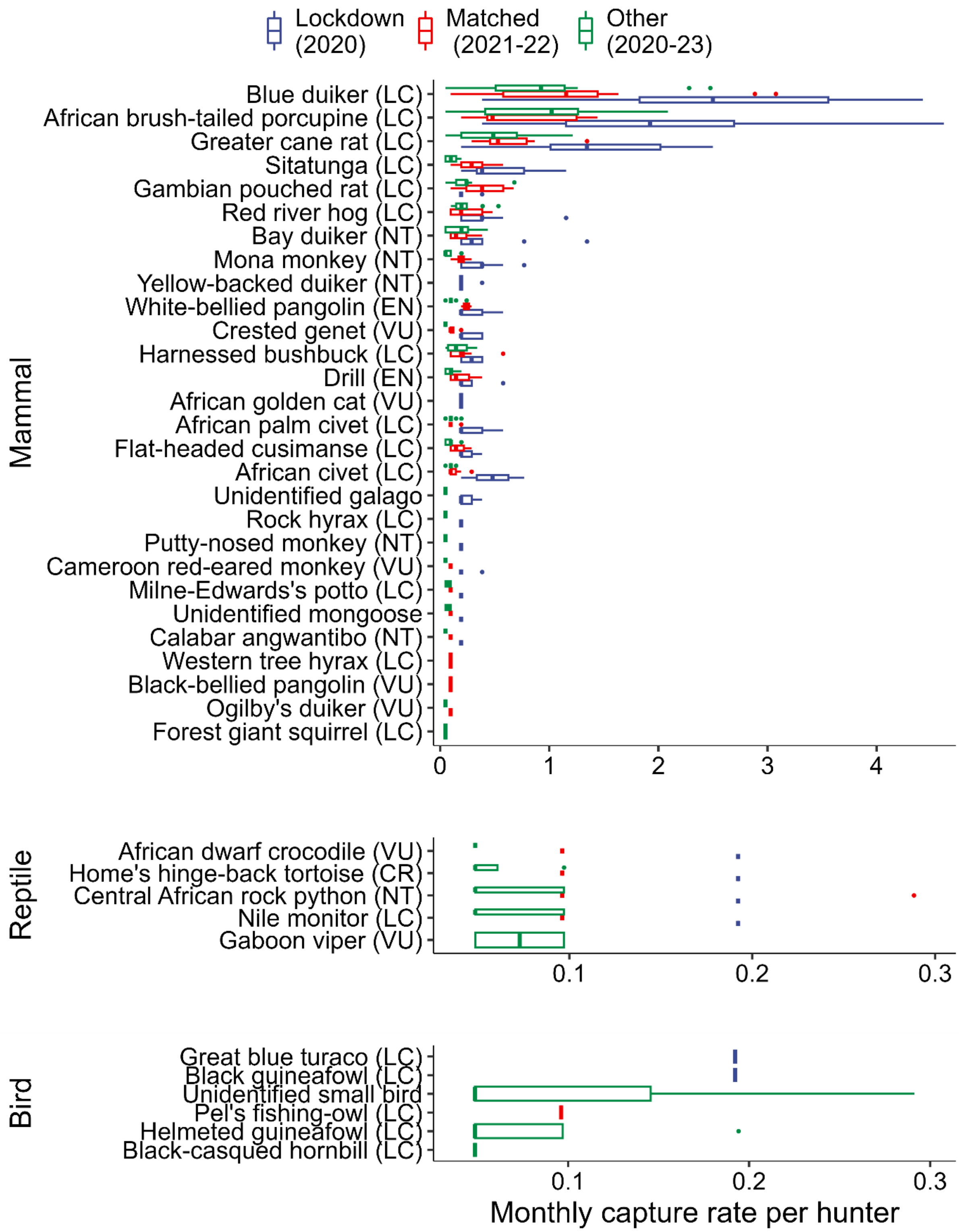

Figure S20: Average monthly capture rate per hunter (individuals captured per hunter for each of the three periods – normalised by number of months per period). Each boxplot corresponds to the average offtake of a species, with the rectangular box representing the interquartile range (IQR) and the vertical line showing the distribution's median. The lines (whiskers) extending from the boxplot show 1.5 times the IQR from the box. Individual dots beyond the whiskers indicate outliers. Symbology as in Supplementary Figure 19.

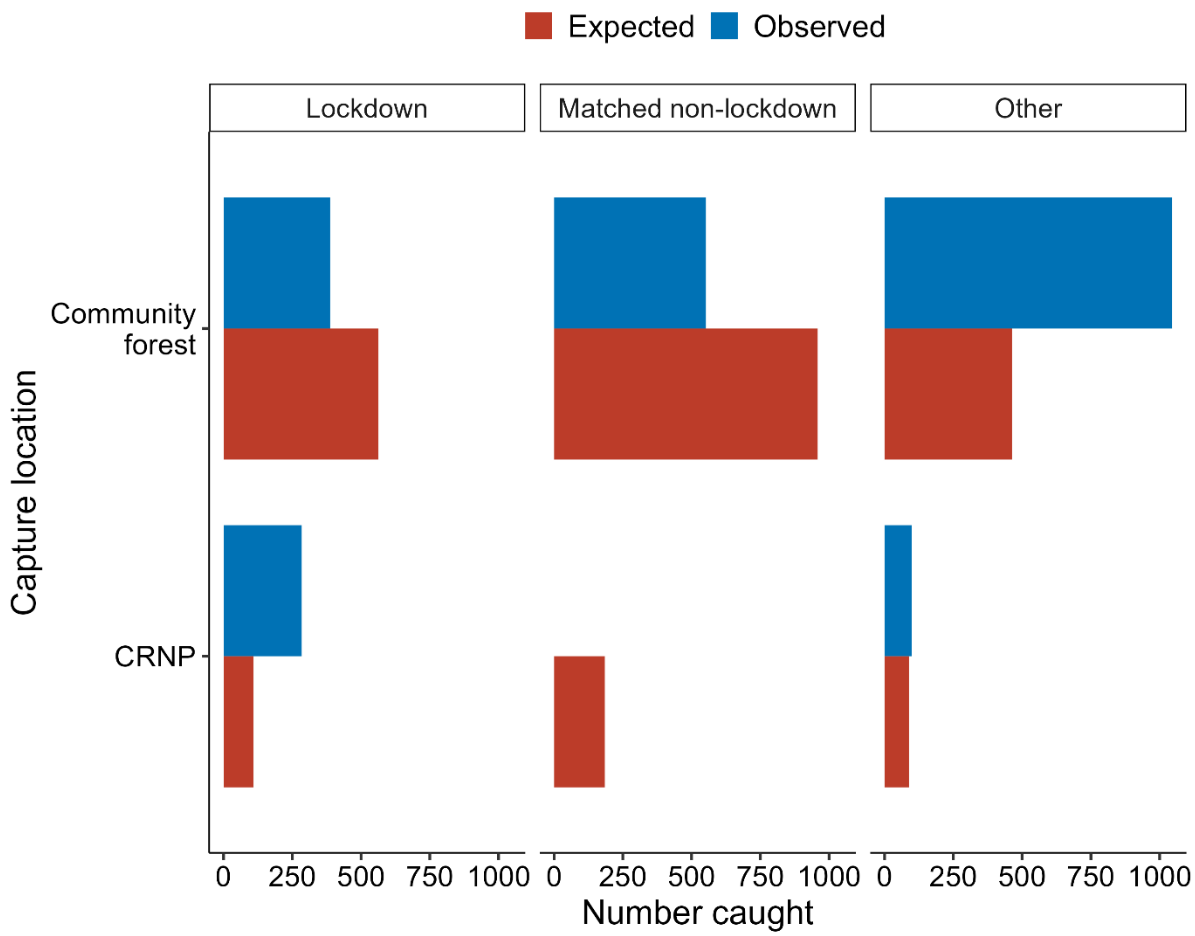

Figure S21: Observed and expected frequencies per capture location for each period. The expected values were derived from a Chi-square estimation (χ^2 = 106.81, df = 24, p < 0.001). Symbology as in Supplementary Figure 19.

Appendix D: Tables

Table S1a: Gaussian-based mixed effects model predicting the number of successful monthly trips. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.345	0.588		
Residual		0.174	0.417		
Fixed effects:					
Terms	**Estimate (β)**	**Std. error (*SE*)**	**Degree of freedom (DF)**	**T ratio**	**P value**
Intercept	0.946	0.136	36.819	6.943	< 0.001
Period: Matched non-lockdown	-1.081	0.111	54	-9.704	< 0.001
Period: Other non-lockdown	-1.046	0.111	54	-9.389	< 0.001
WBI	0.027	0.125	23	0.216	0.831
AME	0.177	0.128	23	1.383	0.180
Experience (log_{10})	-0.147	0.131	23	-1.116	0.276
Income (log_{10})	0.089	0.121	23	0.735	0.470

Table S1b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting each hunter's monthly successful trip rate.

Pair	***β***	***SE***	***t* ratio**	***P* value**
Lockdown - Matched non-lockdown	1.081	0.111	9.704	< 0.001
Lockdown - Other non-lockdown	1.046	0.111	9.389	< 0.001
Matched non-lockdown - Other non-lockdown	-0.035	0.111	-0.316	0.967

Table S2a: Gaussian-based mixed effects model predicting hunter monthly capture rate. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.369	0.607		
Residual		0.204	0.452		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	1.393	0.143	37.997	9.741	< 0.001
Period: Matched non-lockdown	-1.055	0.121	54	-8.741	< 0.001
Period: Other non-lockdown	-0.936	0.121	54	-7.750	< 0.001
WBI	0.014	0.130	23	0.107	0.916
AME	0.191	0.133	23	1.438	0.164
Experience ($\log_{10}$)	-0.164	0.137	23	-1.200	0.242
Income ($\log_{10}$)	0.078	0.126	23	0.618	0.543

Table S2b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting each hunter's number monthly capture rate.

Pair	***β***	***SE***	***t* ratio**	***P* value**
Lockdown - Matched non-lockdown	1.055	0.121	8.741	< 0.001
Lockdown - Other non-lockdown	0.936	0.121	7.750	< 0.001
Matched non-lockdown - Other non-lockdown	-0.120	0.121	-0.991	0.586

Table S3a: Gaussian-based mixed effects model predicting the mass of wild meat harvested per month. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.385	0.621		
Residual		0.251	0.500		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	3.227	0.151	40.149	21.412	< 0.001
Period: Matched non-lockdown	-1.054	0.134	54	-7.874	< 0.001
Period: Other non-lockdown	-0.976	0.134	54	-7.294	< 0.001
WBI	0.027	0.135	23	0.201	0.842
AME	0.222	0.138	23	1.611	0.121
Experience ($\log_{10}$)	-0.161	0.142	23	-1.139	0.266
Income ($\log_{10}$)	0.060	0.131	23	0.455	0.654

Table S3b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting each hunter's total mass of wild meat per month.

Pair	***β***	***SE***	***t* ratio**	***P* value**
Lockdown - Matched non-lockdown	1.054	0.134	7.874	< 0.001
Lockdown - Other non-lockdown	0.976	0.134	7.294	< 0.001
Matched non-lockdown - Other non-lockdown	-0.078	0.134	-0.580	0.831

Table S4a: Gaussian-based mixed effects model predicting value of wild meat each hunter harvested per month. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.361	0.601		
Residual		0.293	0.542		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	10.608	0.153	43.431	69.385	< 0.001
Period: Matched non-lockdown	-0.883	0.145	54.000	-6.099	< 0.001
Period: Other non-lockdown	-0.842	0.145	54.000	-5.817	< 0.001
WBI	-0.008	0.133	23.000	-0.058	0.954
AME	0.242	0.136	23.000	1.774	0.089
Experience (log_{10})	-0.159	0.140	23.000	-1.133	0.269
Income (log_{10})	0.073	0.130	23.000	0.565	0.578

Table S4b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting value of wild meat each hunter harvested per month.

Pair	***β***	***SE***	***t* ratio**	***P* value**
Lockdown - Matched non-lockdown	0.883	0.145	6.099	< 0.001
Lockdown - Other non-lockdown	0.842	0.145	5.817	< 0.001
Matched non-lockdown - Other non-lockdown	-0.041	0.145	-0.282	0.957

Table S5a: Gaussian-based mixed effects model predicting mass of wild meat eaten in hunter household per month. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	1.889	1.374		
Residual		2.648	1.627		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	0.847	0.403	54.488	2.104	0.040
Period: Matched non-lockdown	-2.787	0.435	54	-6.408	< 0.001
Period: Other non-lockdown	-1.631	0.435	54	-3.750	< 0.001
WBI	0.243	0.318	24	0.765	0.452
AME	0.329	0.317	24	1.036	0.310
Income ($\log_{10}$)	0.075	0.318	24	0.237	0.815

Table S5b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting the mass of wild meat eaten in hunter household per month.

Pair	***β***	***SE***	***t* ratio**	***P* value**
Lockdown - Matched non-lockdown	2.79	0.435	6.408	< 0.001
Lockdown - Other non-lockdown	1.63	0.435	3.750	0.001
Matched non-lockdown - Other non-lockdown	-1.16	0.435	-2.659	0.027

Table S6a: Gaussian-based mixed effects model predicting mass of wild meat sold per month. Number of observations = 84.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.372	0.612		
Residual		0.264	0.514		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	3.085	0.151	43.054	20.456	< 0.001
Period: Matched non-lockdown	-0.965	0.137	54	-7.027	< 0.001
Period: Other non-lockdown	-0.907	0.137	54	-6.604	< 0.001
WBI	-0.018	0.130	24	-0.141	0.889
AME	0.161	0.129	24	1.245	0.225
Income ($\log_{10}$)	0.064	0.130	24	0.491	0.628

Table S6b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting the mass of wild meat sold per month.

Pair	***β***	***SE***	**T ratio**	**P value**
Lockdown - Matched non-lockdown	0.965	0.137	7.027	< 0.001
Lockdown - Other non-lockdown	0.907	0.137	6.604	< 0.001
Matched non-lockdown - Other non-lockdown	-0.058	0.137	-0.423	0.906

Table S7a: Beta-based mixed effects model predicting the proportion wild meat mass eaten in hunter household per month. Number of observations = 84. Dispersion parameter = 48.4.

Random effect:				
Groups	**Term**	**Variance**	**Std. dev**	
Hunter ID	Intercept	0.149	0.387	
Fixed effects:				
Terms	**β**	***SE***	**Z ratio**	**P value**
Intercept	-2.058	0.111	-18.525	< 0.001
Period: Matched non-lockdown	-0.892	0.141	-6.332	< 0.001
Period: Other non-lockdown	-0.589	0.132	-4.456	< 0.001
WBI	0.087	0.094	0.931	0.352
AME	0.073	0.092	0.798	0.425
Income ($\log_{10}$)	0.094	0.092	1.024	0.306

Table S7b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting the mass of wild meat eaten in hunter household per month.

Pair	***β***	***SE***	**Z ratio**	**P value**
Lockdown - Matched non-lockdown	0.892	0.141	6.332	< 0.001
Lockdown - Other non-lockdown	0.589	0.141	4.456	< 0.001
Matched non-lockdown - Other non-lockdown	-0.303	0.141	-2.005	0.110

Table 8a: Beta-based mixed effects model predicting the proportion wild meat mass sold per month. Number of observations = 84. Dispersion parameter = 37.4.

Random effect:				
Groups	**Term**	**Variance**	**Std. dev**	
Hunter ID	Intercept	0.087	0.295	
Fixed effects:				
Terms	**β**	***SE***	**Z ratio**	**P value**
Intercept	1.934	0.106	18.215	< 0.001
Period: Matched non-lockdown	0.947	0.153	6.204	< 0.001
Period: Other non-lockdown	0.589	0.143	4.111	< 0.001
WBI	-0.093	0.083	-1.123	0.261
AME	-0.124	0.082	-1.525	0.127
Income (log_{10})	-0.063	0.084	-0.748	0.455

Table S8b: Pairwise post-hoc Tukey test of levels of the period variable used in predicting the mass of wild meat sold per month.

Pair	***β***	***SE***	**Z ratio**	**P value**
Lockdown - Matched non-lockdown	-0.947	0.153	-6.204	< 0.001
Lockdown - Other non-lockdown	-0.589	0.143	-4.111	< 0.001
Matched non-lockdown - Other non-lockdown	0.358	0.161	-2.005	0.073

Table S9: Linear mixed effects model of mass captured per trip.

Random effect:					
Groups	**Term**	**Variance**	**Std. dev**		
Hunter ID	Intercept	0.087	0.295		
Residual		0.330	0.574		
Fixed effects:					
Terms	**β**	***SE***	**DF**	**T ratio**	**P value**
Intercept	2.062	0.122	45.188	16.89	< 0.001
Period: Other non-lockdown	0.173	0.154	25.489	1.122	0.272
Duration	0.199	0.092	42.333	2.164	0.036
WBI	0.032	0.105	23.071	0.310	0.759
AME	-0.002	0.104	23.820	-0.021	0.983
Experience (log_{10})	-0.032	0.109	21.904	-0.293	0.772
Income (log_{10})	-0.012	0.101	24.037	-0.116	0.909

Table S10: Pair-wise post-hoc comparisons of the number of patrols, distance covered, and number of rangers per team in lockdown, matched pre-lockdown in 2019, and matched post-lockdown in 2021.

Number of patrols			
Comparison	*Z*	*p* (unadjusted)	*p* (adjusted)
Lockdown - Matched post-lockdown	-2.450	0.014	0.029
Lockdown - Matched pre-lockdown	0.301	0.763	0.763
Matched post-lockdown - Matched pre-lockdown	2.751	0.060	0.018
Distance covered			
Comparison	*Z*	*p* (unadjusted)	*p* (adjusted)
Lockdown - Matched post-lockdown	-2.479	0.013	0.026
Lockdown - Matched pre-lockdown	0.354	0.723	0.723
Matched post-lockdown - Matched pre-lockdown	2.833	0.004	0.013

Table S11: The median number of individuals caught per year by formal and casual hunters.

Species	Average number (formal hunter)	Average number (casual hunter)
African brush-tailed porcupine	25	17
Black-bellied pangolin	3	3
Blue duiker	30	16
Red river hog	4	2
White-bellied pangolin	6	5

Appendix E: Appendix References

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