Report

Current Biology

Wildlife impacts and changing climate pose compounding threats to human food security

Highlights

- KAZA households experience diverse factors constraining livelihoods
- Marginal agriculture is further limited by recent changes in precipitation patterns
- Crop depredation by wildlife is widespread and compounds food insecurity
- Inclusive policies conserving wildlife and supporting people are needed

Authors

Jonathan Salerno, Forrest R. Stevens, Andrea E. Gaughan, ..., Kyle Woodward, Nicholas Kolarik, Joel Hartter

Correspondence

jonathan.salerno@colostate.edu

In brief

Salerno et al. quantify impacts of changing rainfall and wildlife crop depredation across multiple nation sites in KAZA. Crops lost to wildlife, primarily elephants, cause significant increases in food insecurity, beyond observed impacts from shortened rainy seasons. Findings articulate the need for inclusive policies supporting wildlife and people.

Salerno et al., 2021, Current Biology *31*, 5077–5085
November 22, 2021
https://doi.org/10.1016/j.cub.2021.08.074

Current Biology

CellPress

Report

Wildlife impacts and changing climate pose compounding threats to human food security

Jonathan Salerno,[1,16,*] Forrest R. Stevens,[2] Andrea E. Gaughan,[2] Tom Hilton,[1] Karen Bailey,[3] Timothy Bowles,[4] Lin Cassidy,[5] Patricia Mupeta-Muyamwa,[6] Duan Biggs,[7,8,9,10,15] Narcisa Pricope,[11] Alfons Wahabe Mosimane,[12] Luwaya Maseka Henry,[13] Michael Drake,[3] Ariel Weaver,[2] Selma Kosmas,[14] Kyle Woodward,[11] Nicholas Kolarik,[2] and Joel Hartter[3]

[1]Department of Human Dimensions of Natural Resources, Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO 80523-1480, USA
[2]Department of Geographic and Environmental Sciences, University of Louisville, Louisville, KY 40292, USA
[3]Environmental Studies Program, University of Colorado Boulder, Boulder, CO 80303, USA
[4]Department of Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, CA 94720, USA
[5]Okavango Research Institute, University of Botswana, Maun, Botswana
[6]The Nature Conservancy South Africa, Cape Town, South Africa
[7]School of Earth and Sustainability, Northern Arizona University, Flagstaff, AZ 86011, USA
[8]Resilient Conservation, Centre for Planetary Health and Food Security, School of Environment and Science, Griffith University, Nathan, QLD 4111, Australia
[9]Department of Conservation Ecology and Entomology, Stellenbosch University, Matieland 7602, South Africa
[10]Centre for Complex Systems in Transition, School of Public Leadership, Stellenbosch University, Stellenbosch 7600, South Africa
[11]Department of Earth and Ocean Sciences, University of North Carolina Wilmington, Wilmington, NC 28403, USA
[12]Multi-Disciplinary Research Centre, University of Namibia, Neudamm Campus, Windhoek, Namibia
[13]Department of National Parks and Wildlife, Chilanga, Lusaka, Zambia
[14]Department of Wildlife Management and Ecotourism, Katima Mulilo Campus, University of Namibia, Windhoek, Namibia
[15]Twitter: @duanbiggs
[16]Lead contact
*Correspondence: jonathan.salerno@colostate.edu
https://doi.org/10.1016/j.cub.2021.08.074

SUMMARY

High-level policy debates surrounding elephant management often dominate global conservation headlines, yet realities for people living with wildlife are not adequately incorporated into policymaking or evident in related discourse.[1,2] Human health and livelihoods can be severely impacted by wildlife and indirectly by policy outcomes.[3] In landscapes where growing human and elephant (*Loxodonta spp.* and *Elephas maximus*) populations compete over limited resources, human-elephant conflict causes crop loss, human injury and death, and retaliatory killing of wildlife.[4–6] Across Africa, these problems may be increasingly compounded by climate change, which intensifies resource competition and food insecurity.[6–9] Here, we examine how human-wildlife impacts interact with climate change and household food insecurity across the Kavango-Zambezi Transfrontier Conservation Area, the world's largest terrestrial transboundary conservation area, spanning five African nations. We use hierarchical Bayesian statistical models to analyze multi-country household data together with longitudinal satellite-based climate measures relevant to rainfed agriculture. We find that crop depredation by wildlife, primarily elephants, impacts 58% of sampled households annually and is associated with significant increases in food insecurity. These wildlife impacts compound effects of changing climate on food insecurity, most notably observed as a 5-day shortening of the rainy season per 10 years across the data record (1981–2018). To advance sustainability goals, global conservation policy must better integrate empirical evidence on the challenges of human-wildlife coexistence into longer term strategies at transboundary scales, specifically in the context of climate change.[3,9–11]

RESULTS

Negative wildlife impacts on people, such as crop and livestock depredation, can undermine conservation goals by fostering negative attitudes and intolerance toward wildlife, particularly where community cooperation is vital for conservation.[12–14] In response, increasing emphasis is being placed on the science of human-wildlife coexistence.[15] However, the lack of empirical evidence on wildlife impacts in many systems, and at appropriate scales, hinders integration of coexistence science with policy and management and with broader approaches to sustainability challenges like food insecurity and climate change.[9,10,16]

Such is the case with conservation of African savanna elephants (*Loxodonta africana*) and African forest elephants

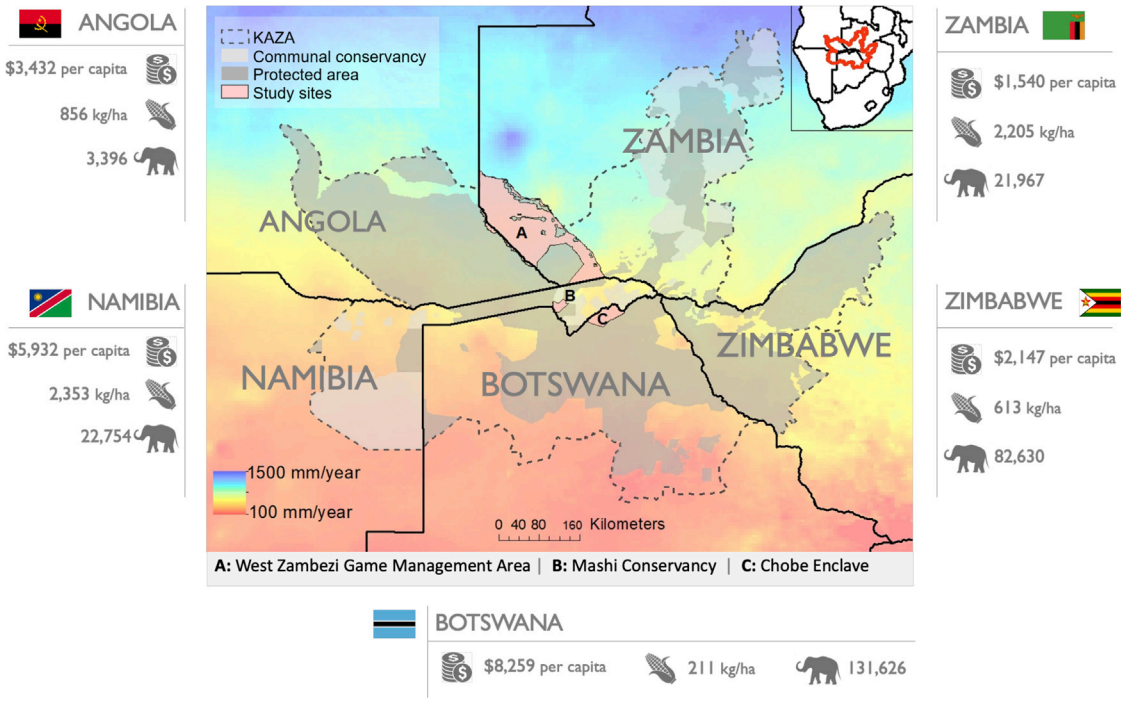

Figure 1. Kavango-Zambezi Transfrontier Conservation Area (KAZA)

Wildlife movement is largely unrestricted across national borders and the ~520,000 km^2 of protected areas, communal lands, and private holdings (study sites: A, West Zambezi; B, Mashi; C, Chobe Enclave). Mean annual precipitation, per capita GDP, and average maize yield vary markedly at the national level.

(*Loxodonta cyclotis*), as they range widely over both protected and human-occupied lands, experience diverse threats (e.g., habitat loss, retaliatory killings, poaching for ivory, and climate change), and can cause significant damage to human lives and livelihoods.[17–19] In this study, we focus on smallholder farmers and examine how human-wildlife impacts interact with climate change and food insecurity challenges across three countries in the Kavango-Zambezi Transfrontier Conservation Area (KAZA) (Figure 1), which spans ~520,000 km^2 and protects nearly half of the world's remaining savanna elephants.[20,21] We evaluate household food insecurity outcomes as a function of crop depredation and livelihood data (n = 726) associated with longitudinal satellite-based rainfall measures (1981–2018)[22,23] using Bayesian multilevel statistical modeling.

Household survey data and rainfall analyses show that people across all sites experience substantial food insecurity, exacerbated by increasingly shorter, drier rainy seasons and widespread crop depredation by wildlife, primarily elephants (Figure 2). Applying the Food Insecurity Experience Scale (FIES), an indicator adopted by the United Nations to measure sustainable development goal 2 (end hunger),[24] we estimate the prevalence of moderate to severe food insecurity in the study area at 71% (all main text analyses are based on this measure of experiencing moderate to severe food insecurity). Further, households report high interannual yield variance, with many relying on food sharing and humanitarian aid to meet basic needs following poor harvests.

Study communities are characterized by low agricultural productivity, with yields of maize—the primary subsistence crop—just 490 kg ha^{-1} on the average 2.5-ha farm plot. Elsewhere in southern Africa, areas with similar rainfall but better soils, inputs, and intensive management have recorded maize yields over 5,000 kg ha^{-1} (Table S1).[25]

Lower and less predictable rainfall exacerbates food insecurity through impacts on agricultural productivity. Satellite-based rainfall analysis from 1981 to 2018 shows mean annual precipitation of ~500–800 mm across sites, with significant variation in timing, amount, and duration of rains (Figure 3). Since 1981, the majority of pixels containing study households show an increase in dry dekads (periods of 10 days or more without rainfall) during the rainy season, from an average of 6.9 (1981–1985) to 9.2 dry dekads (2013–2018) per year (Figure 3E). Many households experience a significant trend toward shorter rain seasons, with the average duration falling by 10% from 152 (1981–1985) to 137 days (2013–2018) per year (Figure 3F). Supplementary temperature analysis showed no significant trends in peak daily temperatures (>30°C) and insufficient variation over the study period to explain household-level food insecurity outcomes, although projected increases in mean and extreme temperature are still likely to reduce maize yields,[26,27] especially when heat coincides with low soil moisture.[28]

The statistical model estimates a credible relationship between trends in rainy season length and household food insecurity. Given the mean observed 5-day shortening of the rainy season over the past 10 years, the model predicts the average household that experiences this trend to be 3.61 times more likely to be food insecure, all else being equal (Figures 2, 3, and 4). This result must be treated with caution, however,

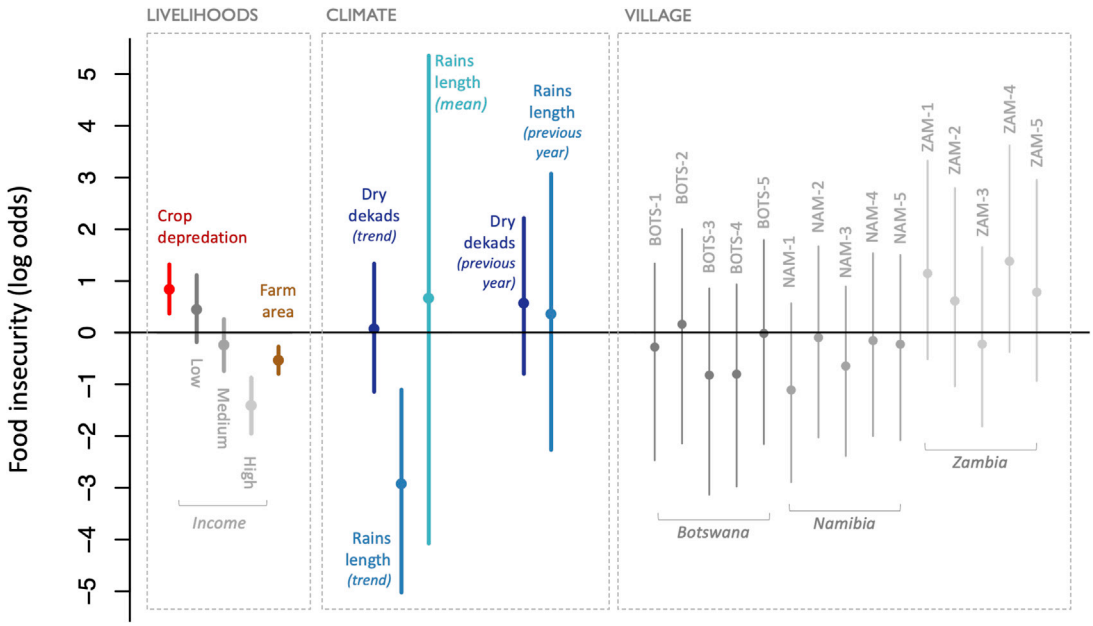

Figure 2. Statistical model results predicting household food insecurity from livelihood, climate, and community-level effects

The main binomial model predicts the odds of households experiencing moderate to severe food insecurity. Livelihood and climate effects are estimated at the household level; community- and site-level varying (i.e., random) effects are combined and plotted for each community, representing community-wide adjustments to household food insecurity outcomes. Mean coefficient estimates and 95% credibility intervals are drawn from the joint-posterior density of the main model. Estimates can be interpreted as credibly or significantly associated with odds of higher or lower food insecurity based on their credibility intervals (lines extending from points) not crossing the zero line.

due to the coarseness of the rainfall data, and observed trends may be correlated with other factors at the 1-km^2 pixel scale, such as land-use zoning or market access. Nevertheless, appreciable variability in rainy season length trends exists within sites, such that pixel-level values of season length trend explain variance in food insecurity outcomes left unattributed to community-level varying effects. Although we would expect the significant increases in dry dekads (Figures 3B and 3E) to also be associated with greater odds of food insecurity, it is likely that noise in the data contributes to this imprecise estimate in the model.

The challenges associated with low productivity agriculture under shortening rains are further compounded by frequent wildlife crop depredation. Depredation is widespread, with 58% of households reporting substantial crop damage by wildlife, averaging 0.57 ha of lost crops per household in the previous year. Elephants were the primary problem species in 67% of maize depredation cases, with many households experiencing multiple events annually.

The model estimates that crop depredation is associated with a credible increase in food insecurity, with 1 ha of damage corresponding to 2.31 times the likelihood of experiencing food insecurity, all else being equal (Figure 2). These wildlife impacts may be felt on top of the effects of shorter rainy seasons, with 1 ha of crop depredation on top of a 5-day shortening of rains (sample mean) corresponding to more than 8 times the likelihood of experiencing food insecurity, all else being equal (Figure 4). Despite appreciable differences in economic development levels across sites (Figure 1), the community-level varying intercept effects of the model do not show marked differences in baseline food insecurity (Figure 2). Notably, in a separate model, the interaction between rainy season length trend and crop depredation suggests that households already experiencing shorter seasons suffer even greater impacts of crop depredation, but the effect is only credible at 90% and the model is less parsimonious than our primary model.

DISCUSSION

Our study shows that climate-stressed livelihoods are further impacted by negative interactions with wildlife. Throughout the continent, similar impacts risk undermining conservation goals—poor yields motivate stressed households to expand cultivation, potentially encroaching on wildlife habitat and further isolating protected areas, encouraging further wildlife impacts.[9] Notably, our study sites feature high dry-season elephant density; such conflict hotspots are common near perennial water sources where humans and wildlife compete over scarce resources.[29,30] These hotspots must be the focus of efforts to support coexistence landscapes.[3,6]

Impacts will likely intensify across Africa, as climate change is expected to pose increasing threats to agriculture and food security,[31] and corresponding changes to available water and vegetation will shift wildlife space use and the potential for conflict.[9] Already, climate stress is negatively impacting both savanna and forest elephant populations within parks.[19,32] Indeed, the vast extent of KAZA was designed to allow for climate-induced wildlife movement, but this would likely involve elephant range shift to the north, from core protected areas into lands dominated by agriculture (Figure 1).[21,33]

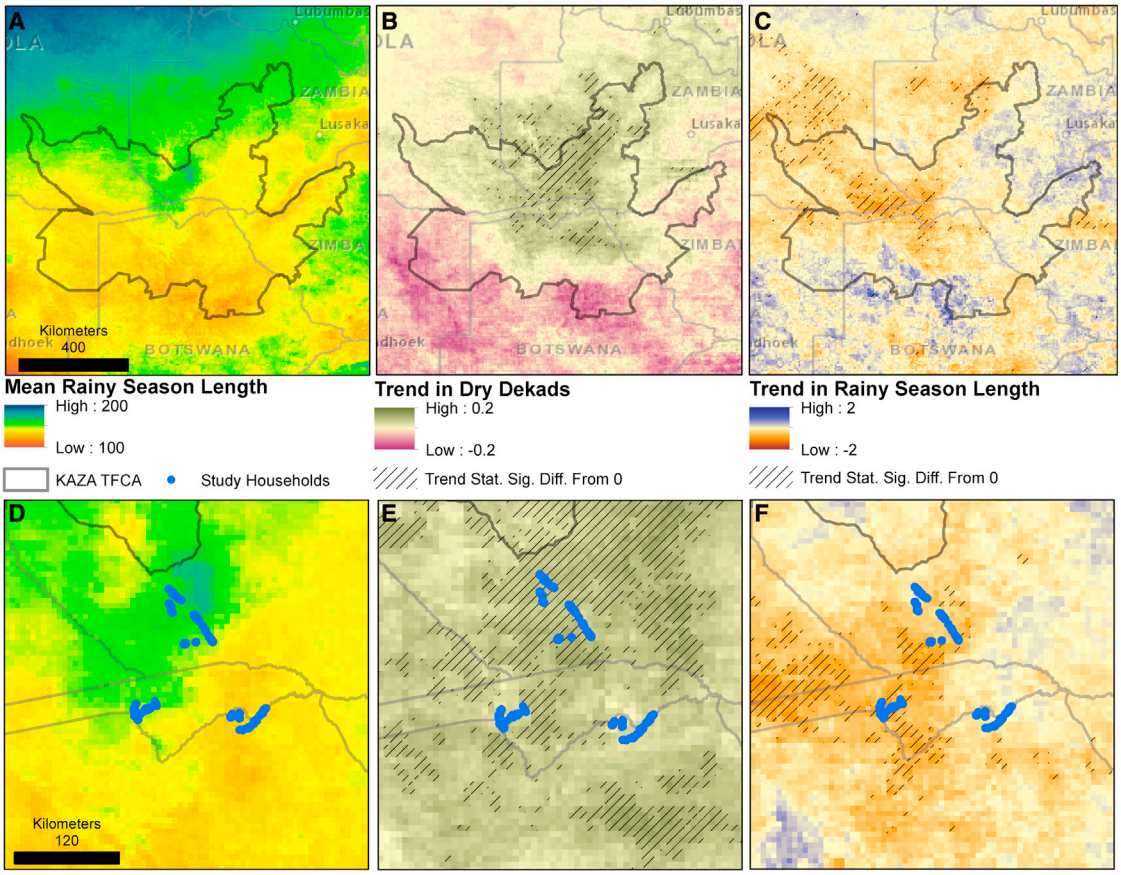

Figure 3. Satellite-based daily rainfall analysis (1981–2018)

Rainfall data were processed to produce three variables describing conditions relevant for rainfed maize production: mean rainy season length (A and D); trend in dry dekads during the rainy season (i.e., 10-day periods without rain; B and E); and trend in rainy season length (C and F). Panels show identical rainfall analyses at the KAZA-wide extent (A–C) and at the more limited study area extent (D–F); household locations, blue dots. Hatching indicates significant ($p < 0.05$) trends in dry dekads (B and E) and rainy season length (C and F).

Shorter rainy seasons, increasing dry periods, and increasing variability are projected to persist, driven by anomalous climate modes and sea-surface temperatures, further modulated by regional factors.[8,34] Shorter rainy seasons with increasing dry periods constrain maize yields, especially if dry periods coincide with key developmental stages like flowering.[35] Increasing frequency in high temperature extremes will further limit crop production.[35,36] However, because observed yields in our study are well below regional estimates of maize water-limited yield potential,[35] closing these yield gaps and increasing adaptive capacity are both possible and essential to increasing food security.[37] Promising interventions include soil management and legume diversification to improve yields and yield stability under climate stress, supported through participatory approaches (Tables S1 and S2).[37–39]

Meanwhile, elephant conservation efforts (e.g., reducing poaching, protecting habitat, and connectivity) have seen some populations stabilizing—in Botswana alone, the elephant population has tripled since 1990.[21] Although these successes are to be lauded and maintained, successful conservation places substantial pressure on people living with wildlife. As is all too common, local people bear the disproportionate costs of conserving globally valued wildlife.[3,4]

Communities on the frontlines of wildlife impacts play a critical role in stemming poaching and the illegal wildlife trade.[9,12] If effective conservation comes at the price of increased crop depredation and more severe food insecurity, then conservation not only faces an ethical dilemma, but people will be more easily incentivized to participate in poaching and other conservation-harmful activities.[13] Conversely, communities who share in the benefits of conservation can become wildlife advocates.[40] To date, KAZA has been exemplary of effective conservation management, protecting ecosystems and community wellbeing, reducing poaching, and promoting tourism.[20,21,41] However, unless pressures faced by local communities are reduced, sustainability may be jeopardized. This is critical in light of the coronavirus disease 2019 (COVID-19) pandemic, which will likely have long-term negative impacts on conservation revenue, both from tourism and donors, although the health impacts of the pandemic on KAZA communities remain unclear.[42,43]

To support human-wildlife coexistence, meaningful and inclusive stakeholder dialog is needed to work toward equitable

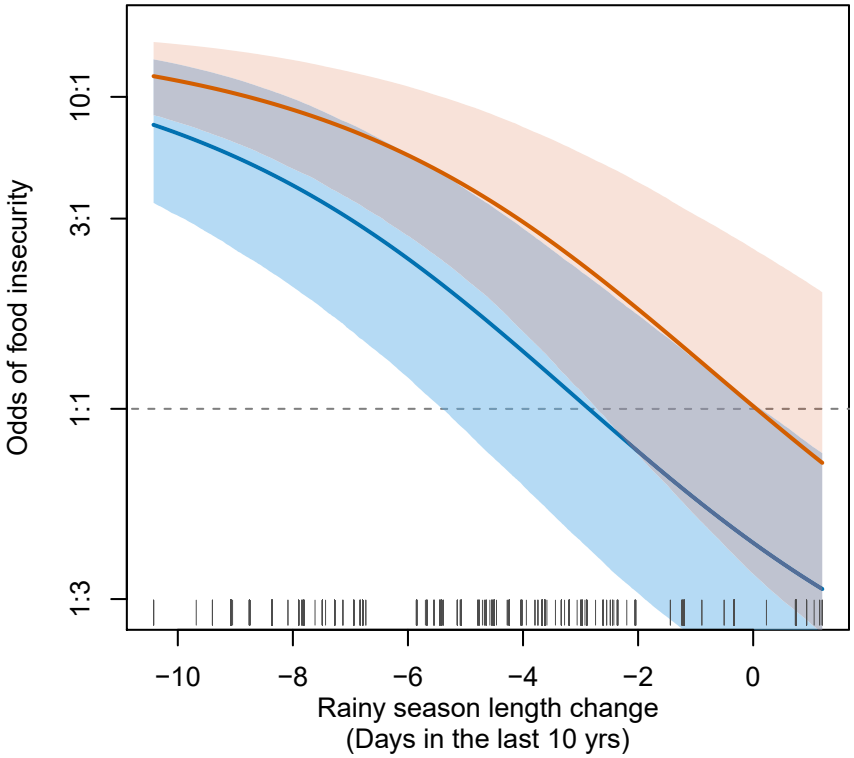

Figure 4. Model predictions for the effect of observed rainy season shortening and crop depredation on food insecurity

The mean effect of trend in rainy season length on the odds of food insecurity (blue line; odds ratio as odds of moderately to severely food insecure:mildly food insecure to food secure) and 80% prediction interval are plotted with observed values (gray ticks), holding crop depredation at 0 and all other variables at mean or modal values. Otherwise identical households experiencing 1 ha of crops destroyed by wildlife (red line) have the added effect of further increased odds of food insecurity.

management.[1,44] This dialog must include global conservation interests, state-level policy makers, and local residents alike.[3] Efforts must be accelerated to balance the cost-benefit distribution and governance of wildlife conservation, while institutionalized in relevant policy fora, such as the Conference of Parties to the Convention on the International Trade of Endangered Species (CITES).[12,45]

These higher level policy processes should be accompanied by steps on the ground to promote better outcomes for people and wildlife, also guided by community voices,[40] and focused on the root causes of conflict.[9,46] Strategies to promote community-based conservation and *in situ* impact mitigation will be key to bridging priorities across stakeholder interests at multiple levels.[3,14] Indeed, existing community-based conservation institutions can link local actors across landscapes to support adaptation and wildlife protection,[40,47] and in KAZA, these local institutions could form the structure of a stronger learning network for managing the complex challenge of achieving sustainable human-wildlife coexistence. However, challenges persist in effectively devolving rights and authority to communities,[48] as well as effectively addressing livelihood vulnerability like from climate stress, as our findings highlight. Solutions will undoubtedly require diverse approaches, and each must be evaluated in context. These may include dynamic land-use plans,[6,29] crop depredation mitigation and compensation,[9,49] sustainable wildlife consumption,[45] and integrated agroecological strategies (Table S2).[37] For instance, combining better understanding of wildlife behavior and movement patterns will enable communities to employ more effective deterrent strategies while prioritizing agricultural land use zones to minimize space-use overlap and crop depredation.[30,46] Enabling more flexible land access and sustainable natural resource harvest will support livelihood diversification in the event of food insecurity.[18]

Importantly, international advocates and practitioners of wildlife conservation must support such approaches. KAZA embodies the global Anthropocene challenges of biodiversity conservation, climate change, and food insecurity, and indeed, further research is needed to advance evidence-based priorities.[10,50] As with most people-nature tradeoffs globally, unresolved livelihood challenges can hinder lasting policy and management solutions.[10,40] Progress toward landscapes where wildlife and people coexist will be achieved through coalitions and compromise, centered on those most impacted by wildlife.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- EXPERIMENTAL MODEL AND SUBJECT DETAILS
  - Summary and ethics statement
- METHOD DETAILS
  - Study region
  - Household survey data
  - Climate data and analyses
- QUANTIFICATION AND STATISTICAL ANALYSIS

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.cub.2021.08.074.

ACKNOWLEDGMENTS

Research was supported by the US National Science Foundation (no. 1560700). We sincerely thank the leaders and residents of the study communities for their contributions, along with S. Baitsile, L. Sitoboha, B. Likukela,

and M. Nyoni. Collaborators with the KAZA Secretariat, IRDNC Namibia, and Zambian Department of National Parks and Wildlife provided essential support. For their assistance in data collection, we are grateful to N. Libuku, E. Mabuta, O. Xao, S. Muyakwabo, T. Samatombo, M. Nyoka, S. Sikume, B. Makando, E. Lishoni, S. Malatulelo, E. Kuhumelo, J. Shilling, A. Mupuo, M.K. Kabilima, L. Imbula, M. Maele, S. Simasiku, M.M. Lifalalo, L. Musiwa, and P.M. Muliokela. B. Bruyere, M. Gavin, and J. Neff provided helpful comments on earlier versions of this paper. We also thank Z. Weller and the Franklin A. Graybill Statistics and Data Science Laboratory at Colorado State University.

AUTHOR CONTRIBUTIONS

J.S., F.R.S., A.E.G., L.C., P.M.-M., N.P., and J.H. designed the research. J.S., F.R.S., A.E.G., L.C., P.M.-M., N.P., A.W.M., L.M.H., M.D., A.W., S.K., K.W., N.K., and J.H. contributed to data collection and field support. J.S., F.R.S., A.E.G., L.C., T.H., and K.B. analyzed data. J.S., F.R.S., A.E.G., T.H., K.B., T.B., L.C., and D.B. drafted the manuscript. All authors revised the paper and approved the final draft.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We worked to ensure gender balance in the recruitment of human subjects. We worked to ensure ethnic or other types of diversity in the recruitment of human subjects. We worked to ensure that the study questionnaires were prepared in an inclusive way. One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. One or more of the authors of this paper received support from a program designed to increase minority representation in science. The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

Received: June 18, 2021
Revised: August 16, 2021
Accepted: August 31, 2021
Published: September 24, 2021

REFERENCES

1. Mokobela, M.J., Kerley, G., and Wasserman, R.J. (2019). Foster local expertise in Botswana's elephant-hunting debate. Nature *573*, 346.
2. Croome, H., and Wilkinson, C. (2021). How African is the African elephant?: reflections on elephant poaching and conservation in African and UK newspapers. In Communicating Endangered Species, , E. Freedman, S. Shipley Hiles, and D.B. Sachsman, eds. (Routledge), pp. 67–84.
3. Cassidy, L., and Salerno, J. (2020). The need for a more inclusive science of elephant conservation. Conserv. Lett. *13*, e12717.
4. Barua, M., Bhagwat, S.A., and Jadhav, S. (2013). The hidden dimensions of human–wildlife conflict: Health impacts, opportunity and transaction costs. Biol. Conserv. *157*, 309–316.
5. Hoare, R. (2015). Lessons from 20 years of human–elephant conflict mitigation in Africa. Hum. Dimens. Wildl. *20*, 289–295.
6. Stoldt, M., Göttert, T., Mann, C., and Zeller, U. (2020). Transfrontier conservation areas and human-wildlife conflict: the case of the Namibian component of the Kavango-Zambezi (KAZA) TFCA. Sci. Rep. *10*, 7964.
7. Palm, C.A., Smukler, S.M., Sullivan, C.C., Mutuo, P.K., Nyadzi, G.I., and Walsh, M.G. (2010). Identifying potential synergies and trade-offs for meeting food security and climate change objectives in sub-Saharan Africa. Proc. Natl. Acad. Sci. USA *107*, 19661–19666.
8. Conway, D., van Garderen, E.A., Deryng, D., Dorling, S., Krueger, T., Landman, W., Lankford, B., Lebek, K., Osborn, T., Ringler, C., et al. (2015). Climate and southern Africa's water–energy–food nexus. Nat. Clim. Chang. *5*, 837–846.
9. Shaffer, L.J., Khadka, K.K., Van Den Hoek, J., and Naithani, K.J. (2019). Human-elephant conflict: a review of current management strategies and future directions. Front. Ecol. Evol. *6*, 235.
10. Kremen, C., and Merenlender, A.M. (2018). Landscapes that work for biodiversity and people. Science *362*, eaau6020.
11. Liu, J., Hull, V., Godfray, H.C.J., Tilman, D., Gleick, P., Hoff, H., Pahl-Wostl, C., Xu, Z., Chung, M.G., Sun, J., et al. (2018). Nexus approaches to global sustainable development. Nat. Sustain. *1*, 466–476.
12. Biggs, D., Cooney, R., Roe, D., Dublin, H.T., Allan, J.R., Challender, D.W.S., and Skinner, D. (2017). Developing a theory of change for a community-based response to illegal wildlife trade. Conserv. Biol. *31*, 5–12.
13. Cooney, R., Roe, D., Dublin, H., Phelps, J., Wilkie, D., Keane, A., Travers, H., Skinner, D., Challender, D.W.S., Allan, J.R., et al. (2017). From poachers to protectors: engaging local communities in solutions to illegal wildlife trade. Conserv. Lett. *10*, 367–374.
14. Salerno, J., Romulo, C., Galvin, K.A., Brooks, J., Mupeta-Muyamwa, P., and Glew, L. (2021). Adaptation and evolution of institutions and governance in community-based conservation. Conserv. Sci. Pract. *3*, e355.
15. Nyhus, P.J. (2016). Human–wildlife conflict and coexistence. Annu. Rev. Environ. Resour. *41*, 143–171.
16. Redpath, S.M., Young, J., Evely, A., Adams, W.M., Sutherland, W.J., Whitehouse, A., Amar, A., Lambert, R.A., Linnell, J.D.C., Watt, A., and Gutiérrez, R.J. (2013). Understanding and managing conservation conflicts. Trends Ecol. Evol. *28*, 100–109.
17. Wall, J., Wittemyer, G., Klinkenberg, B., LeMay, V., Blake, S., Strindberg, S., Henley, M., Vollrath, F., Maisels, F., Ferwerda, J., and Douglas-Hamilton, I. (2021). Human footprint and protected areas shape elephant range across Africa. Curr. Biol. *31*, 2437–2445.e4.
18. Salerno, J., Bailey, K., Gaughan, A.E., Stevens, F.R., Hilton, T., Cassidy, L., Drake, M.D., Pricope, N.G., and Hartter, J. (2020). Wildlife impacts and vulnerable livelihoods in a transfrontier conservation landscape. Conserv. Biol. *34*, 891–902.
19. Bush, E.R., Whytock, R.C., Bahaa-El-Din, L., Bourgeois, S., Bunnefeld, N., Cardoso, A.W., Dikangadissi, J.T., Dimbonda, P., Dimoto, E., Edzang Ndong, J., et al. (2020). Long-term collapse in fruit availability threatens Central African forest megafauna. Science *370*, 1219–1222.
20. KAZA-TFCA (2014). Kavango-Zambezi Transfrontier Conservation Area Master Integrated Development Plan, 2015-2020 (KAZA TFCA Secretariat).
21. Thouless, C., Dublin, H.T., Blanc, J., Skinner, D., Daniel, T., Taylor, R., Maisels, F., Frederick, H., and Bouche, P. (2016). African Elephant Status Report 2016 (International Union for the Conservation of Nature).
22. Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations–a new environmental record for monitoring extremes. Sci. Data *2*, 150066.
23. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens. Environ. *202*, 18–27.
24. Cafiero, C., Viviani, S., and Nord, M. (2018). Food security measurement in a global context: the food insecurity experience scale. Measurement *116*, 146–152.
25. Snapp, S.S., Grabowski, P., Chikowo, R., Smith, A., Anders, E., Sirrine, D., Chimonyo, V., and Bekunda, M. (2018). Maize yield and profitability tradeoffs with social, human and environmental performance: is sustainable intensification feasible? Agric. Syst. *162*, 77–88.
26. Waha, K., Müller, C., and Rolinski, S. (2013). Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid- to late-21st century. Global Planet. Change *106*, 1–12.

27. Burke, M.B., Lobell, D.B., and Guarino, L. (2009). Shifts in African crop climates by 2050, and the implications for crop improvement and genetic resources conservation. Glob. Environ. Change *19*, 317–325.

28. Lobell, D.B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. Nat. Clim. Chang. *1*, 42–45.

29. Naidoo, R., Kilian, J.W., Du Preez, P., Beytell, P., Aschenborn, O., Taylor, R.D., and Stuart-Hill, G. (2018). Evaluating the effectiveness of local- and regional-scale wildlife corridors using quantitative metrics of functional connectivity. Biol. Conserv. *217*, 96–103.

30. Pozo, R.A., Cusack, J.J., McCulloch, G., Stronza, A., Songhurst, A., and Coulson, T. (2018). Elephant space-use is not a good predictor of crop-damage. Biol. Conserv. *228*, 241–251.

31. Müller, C., Cramer, W., Hare, W.L., and Lotze-Campen, H. (2011). Climate change risks for African agriculture. Proc. Natl. Acad. Sci. USA *108*, 4313–4315.

32. Wato, Y.A., Heitkönig, I.M.A., van Wieren, S.E., Wahungu, G., Prins, H.H.T., and van Langevelde, F. (2016). Prolonged drought results in starvation of African elephant (*Loxodonta africana*). Biol. Conserv. *203*, 89–96.

33. Engelbrecht, C.J., and Engelbrecht, F.A. (2016). Shifts in Köppen-Geiger climate zones over southern Africa in relation to key global temperature goals. Theor. Appl. Climatol. *123*, 247–261.

34. Dunning, C.M., Black, E., and Allan, R.P. (2018). Later wet seasons with more intense rainfall over Africa under future climate change. J. Clim. *31*, 9719–9738.

35. Rattalino Edreira, J.I., Guilpart, N., Sadras, V., Cassman, K.G., van Ittersum, M.K., Schils, R.L.M., and Grassini, P. (2018). Water productivity of rainfed maize and wheat: a local to global perspective. Agric. Meteorol. *259*, 364–373.

36. Nhamo, L., Matchaya, G., Mabhaudhi, T., Nhlengethwa, S., Nhemachena, C., and Mpandeli, S. (2019). Cereal production trends under climate change: impacts and adaptation strategies in southern Africa. Agriculture *9*, 30.

37. Snapp, S.S., Blackie, M.J., Gilbert, R.A., Bezner-Kerr, R., and Kanyama-Phiri, G.Y. (2010). Biodiversity can support a greener revolution in Africa. Proc. Natl. Acad. Sci. USA *107*, 20840–20845.

38. Snapp, S.S., DeDecker, J., and Davis, A.S. (2019). Farmer participatory research advances sustainable agriculture: lessons from Michigan and Malawi. Agron. J. *111*, 2681–2691.

39. Steward, P.R., Dougill, A.J., Thierfelder, C., Pittelkow, C.M., Stringer, L.C., Kudzala, M., and Shackelford, G.E. (2018). The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: a meta-regression of yields. Agric. Ecosyst. Environ. *251*, 194–202.

40. Biggs, D., Ban, N.C., Castilla, J.C., Gelcich, S., Mills, M., Gandiwa, E., Etienne, M., Knight, A.T., Marquet, P.A., and Possingham, H.P. (2019). Insights on fostering the emergence of robust conservation actions from Zimbabwe's CAMPFIRE program. Glob. Ecol. Conserv. *17*, e00538.

41. Salerno, J., Cassidy, L., Drake, M., and Hartter, J. (2018). Living in an elephant landscape. Am. Sci. *106*, 34–41.

42. Lindsey, P., Allan, J., Brehony, P., Dickman, A., Robson, A., Begg, C., Bhammar, H., Blanken, L., Breuer, T., Fitzgerald, K., et al. (2020). Conserving Africa's wildlife and wildlands through the COVID-19 crisis and beyond. Nat. Ecol. Evol. *4*, 1300–1310.

43. Stone, L.S., Stone, M.T., Mogomotsi, P.K., and Mogomotsi, G.E.J. (2021). The impacts of Covid-19 on nature-based tourism in Botswana: implications for community development. Tour. Rev. Int. *25*, 263–278.

44. Madden, F., and McQuinn, B. (2014). Conservation's blind spot: the case for conflict transformation in wildlife conservation. Biol. Conserv. *178*, 97–106.

45. Biggs, D., Holden, M.H., Braczkowski, A., Cook, C.N., Milner-Gulland, E.J., Phelps, J., Scholes, R.J., Smith, R.J., Underwood, F.M., Adams, V.M., et al. (2017). Breaking the deadlock on ivory. Science *358*, 1378–1381.

46. Mumby, H.S., and Plotnik, J.M. (2018). Taking the elephants' perspective: remembering elephant behavior, cognition and ecology in human-elephant conflict mitigation. Front. Ecol. Evol. *6*, 122.

47. Galvin, K.A., Beeton, T.A., and Luizza, M.W. (2018). African community-based conservation: a systematic review of social and ecological outcomes. Ecol. Soc. *23*, 39.

48. Cassidy, L. (2021). Power dynamics and new directions in the recent evolution of CBNRM in Botswana. Conserv. Sci. Pract. *3*, e205.

49. Ravenelle, J., and Nyhus, P.J. (2017). Global patterns and trends in human-wildlife conflict compensation. Conserv. Biol. *31*, 1247–1256.

50. Gaughan, E.A., Stevens, F.R., Pricope, G.N., Hartter, J., Cassidy, L., and Salerno, J. (2019). Operationalizing vulnerability: land system dynamics in a transfrontier conservation area. Land (Basel) *8*, 111.

51. Salerno, J., Cassidy, L., Hartter, J., Gaughan, A.E., Pricope, N.G., and Stevens, F.R. (2020). KAZAVA household survey data for food insecurity. https://figshare.com/articles/dataset/KAZAVA_Household_Survey_Data_for_Food_Insecurity/13217843.

52. R Development Core Team (2020). R: A language and environment for statistical computing (R Foundation for Statistical Computing. https://www.R-project.org/.

53. Stan Development Team (2021). RStan: the R interface to Stan. R package version 2.26.1, https://mc-stan.org/rstan/index.html.

54. Stevens, F.R. (2020). CHIRPS combined precipitation analysis in Google Earth Engine, 1981-2019. https://figshare.com/articles/code/CHIRPS_Combined_Precipitation_Analysis_in_Google_Earth_Engine/7223999.

55. Stevens, F.R. (2020). ERA5 Daily Aggregate Temperature Analysis in Google Earth Engine, 1979-2020, https://figshare.com/articles/software/ERA5_Daily_Aggregate_Temperature_Analysis_in_Google_Earth_Engine_1979-2020/13202984.

56. MEA (2005). Millenium Ecosystem Assessment: Ecosystems and Human Well-Being (Island).

57. Barrett, C.B. (2010). Measuring food insecurity. Science *327*, 825–828.

58. Cafiero, C., Nord, M., Viviani, S., Del Grosso, M.E., Ballard, T., Kepple, A., Miller, M., and Nwosu, C. (2016). Voices of the Hungry: Methods for Estimating Comparable Prevalence Rates of Food Insecurity Experienced by Adults throughout the World (Food and Agriculture Association of the United Nations).

59. McElreath, R. (2015). Statistical Rethinking: A Bayesian Course with Examples in R and Stan (Chapman & Hall/CRC).

60. Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. *146*, 1999–2049.

61. Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P., and Naylor, R.L. (2008). Prioritizing climate change adaptation needs for food security in 2030. Science *319*, 607–610.

62. Nkemelang, T., New, M., and Zaroug, M. (2018). Temperature and precipitation extremes under current, 1.5 °C and 2.0 °C global warming above pre-industrial levels over Botswana, and implications for climate change vulnerability. Environ. Res. Lett. *13*, 065016.

63. Collomb, J.G.E., Mupeta, P., Barnes, G., and Child, B. (2010). Integrating governance and socioeconomic indicators to assess the performance of community-based natural resources management in Caprivi (Namibia). Environ. Conserv. *37*, 303–309.

64. Bailey, K.M., Drake, M.D., Salerno, J., Cassidy, L., Gaughan, A.E., Stevens, F.R., Pricope, N.G., Woodward, K.D., Luwaya, H.M., and Hartter, J. (2020). Mapping natural resource collection areas from household survey data in Southern Africa. Appl. Geogr. *125*, 102326.

65. Archibald, S., and Scholes, R.J. (2007). Leaf green-up in a semi-arid African savanna -separating tree and grass responses to environmental cues. J. Veg. Sci. *18*, 583–594.

66. Metcalfe, S., and Kepe, T. (2008). "Your elephant on our land": the struggle to manage wildlife mobility on Zambian communal land in the Kavango-Zambezi Transfrontier Conservation Area. J. Environ. Dev. *17*, 99–117.
67. Taylor, R. (2009). Community based natural resource management in Zimbabwe: the experience of CAMPFIRE. Biodivers. Conserv. *18*, 2563–2583.
68. Songhurst, A., McCulloch, G., and Coulson, T. (2016). Finding pathways to human–elephant coexistence: a risky business. Oryx *50*, 713–720.
69. Young, J.C., Marzano, M., White, R.M., McCracken, D.I., Redpath, S.M., Carss, D.N., Quine, C.P., and Watt, A.D. (2010). The emergence of biodiversity conflicts from biodiversity impacts: characteristics and management strategies. Biodivers. Conserv. *19*, 3973–3990.
70. Songhurst, A. (2017). Measuring human–wildlife conflicts: comparing insights from different monitoring approaches. Wildl. Soc. Bull. *41*, 351–361.
71. West, P., Igoe, J., and Brockington, D. (2006). Parks and peoples: the social impact of protected areas. Annu. Rev. Anthropol. *35*, 251–277.
72. Stevens, F.R., Gaughan, A.E., Linard, C., and Tatem, A.J. (2015). Disaggregating census data for population mapping using random forests with remotely-sensed and ancillary data. PLoS ONE *10*, e0107042.
73. DeMotts, R., and Hoon, P. (2012). Whose elephants? Conserving, compensating, and competing in Northern Botswana. Soc. Nat. Resour. *25*, 837–851.
74. Gupta, A.C. (2013). Elephants, safety nets and agrarian culture: understanding human-wildlife conflict and rural livelihoods around Chobe National Park, Botswana. J. Polit. Ecol. *20*, 238–254.
75. Suich, H. (2013). The effectiveness of economic incentives for sustaining community based natural resource management. Land Use Policy *31*, 441–449.
76. Brooks, J.S. (2017). Design features and project age contribute to joint success in social, ecological, and economic outcomes of community-based conservation projects. Conserv. Lett. *10*, 23–32.
77. Hanks, J., and Myburgh, W. (2015). The evolution and progression of transfrontier conservation areas in the Southern African development community. In Institutional Arrangements for Conservation, Development and Tourism in Eastern and Southern Africa, , R. van der Duim, M. Lamers, and J. van Wijk, eds. (Springer), pp. 157–179.
78. Muntifering, J.R., Linklater, W.L., Clark, S.G., Uri-Khob, S., Kasaona, J.K., Uiseb, K., Du Preez, P., Kasaona, K., Beytell, P., Ketji, J., et al. (2017). Harnessing values to save the rhinoceros: insights from Namibia. Oryx *51*, 98–105.
79. Lotter, W., and Clark, K. (2014). Community involvement and joint operations aid effective anti-poaching in Tanzania. Parks *20*, 19–28.
80. Bernard, H.B. (1988). Research Methods in Cultural Anthropology (Sage Publications).
81. AAA (2012). American Anthropological Association Statement on Ethics (American Anthropological Association).
82. Brittain, S., Ibbett, H., de Lange, E., Dorward, L., Hoyte, S., Marino, A., Milner-Gulland, E.J., Newth, J., Rakotonarivo, S., Veríssimo, D., and Lewis, J. (2020). Ethical considerations when conservation research involves people. Conserv. Biol. *34*, 925–933.
83. Pinstrup-Andersen, P. (2009). Food security: definition and measurement. Food Secur. *1*, 5–7.
84. Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., and Toulmin, C. (2010). Food security: the challenge of feeding 9 billion people. Science *327*, 812–818.
85. United Nations General Assembly (2015). Transforming our world: the 2030 agenda for sustainable development. https://sdgs.un.org/2030agenda.
86. Cafiero, C., Viviani, S., and Nord, M. (2018). RM.weights: weighted Rasch modeling and extensions using conditional maximum likelihood. https://cran.r-project.org/web/packages/RM.weights/index.html.
87. Ballard, T.J., Kepple, A.W., and Cafiero, C. (2013). The Food Insecurity Experience Scale: Development of a Global Standard for Monitoring Hunger Worldwide (FAO).
88. FAO (2016). Modeling Food Insecurity in Bivariate and Regression Analyses, Guidelines Prepared by the Voices of the Hungry Team (Food and Agriculture Association of the United Nations).
89. Ebadi, N., Ahmadi, D., Sirkeci, I., and Melgar-Quiñonez, H. (2018). The impact of remittances on food security status in the global South. Remit. Rev. *3*, 135–150.
90. Sadiddin, A., Cattaneo, A., Cirillo, M., and Miller, M. (2019). Food insecurity as a determinant of international migration: evidence from Sub-Saharan Africa. Food Secur. *11*, 515–530.
91. Coates, J., Swindale, A., and Bilinsky, P. (2007). Household Food Insecurity Access Scale (HFIAS) for Measurement of Food Access: Indicator Guide (United States Agency for International Development).
92. Collins, S., Dent, N., Binns, P., Bahwere, P., Sadler, K., and Hallam, A. (2006). Management of severe acute malnutrition in children. Lancet *368*, 1992–2000.
93. Black, R.E., Allen, L.H., Bhutta, Z.A., Caulfield, L.E., de Onis, M., Ezzati, M., Mathers, C., and Rivera, J.; Maternal and Child Undernutrition Study Group (2008). Maternal and child undernutrition: global and regional exposures and health consequences. Lancet *371*, 243–260.
94. Rubin, L.P. (2016). Maternal and pediatric health and disease: integrating biopsychosocial models and epigenetics. Pediatr. Res. *79*, 127–135.
95. Hertel, T.W., Burke, M.B., and Lobell, D.B. (2010). The poverty implications of climate-induced crop yield changes by 2030. Glob. Environ. Change *20*, 577–585.
96. Wheeler, T., and von Braun, J. (2013). Climate change impacts on global food security. Science *341*, 508–513.
97. Hertel, T.W. (2016). Food security under climate change. Nat. Clim. Chang. *6*, 10–13.
98. Bhatia, S., Redpath, S.M., Suryawanshi, K., and Mishra, C. (2020). Beyond conflict: exploring the spectrum of human–wildlife interactions and their underlying mechanisms. Oryx *54*, 621–628.
99. Hoare, R.E. (1999). A Standardised Data Collection and Analysis Protocol for Human–Elephant Conflict Situations in Africa (IUCN African Elephant Specialist Group).
100. Siex, K.S., and Struhsaker, T.T. (1999). Colobus monkeys and coconuts: a study of perceived human–wildlife conflicts. J. Appl. Ecol. *36*, 1009–1020.
101. Hill, C.M. (2004). Farmers' perspectives of conflict at the wildlife–agriculture boundary: some lessons learned from African subsistence farmers. Hum. Dimens. Wildl. *9*, 279–286.
102. Mackenzie, C.A., and Ahabyona, P. (2012). Elephants in the garden: financial and social costs of crop raiding. Ecol. Econ. *75*, 72–82.
103. Gillingham, S., and Lee, P.C. (2003). People and protected areas: a study of local perceptions of wildlife crop-damage conflict in an area bordering the Selous Game Reserve, Tanzania. Oryx *37*, 316–325.
104. Fernando, P., Wikramanayake, E., Weerakoon, D., Jayasinghe, L.K.A., Gunawardene, M., and Janaka, H.K. (2005). Perceptions and patterns of human–elephant conflict in old and new settlements in Sri Lanka: insights for mitigation and management. Biodivers. Conserv. *14*, 2465–2481.
105. Wang, S.W., Curtis, P.D., and Lassoie, J.P. (2006). Farmer perceptions of crop damage by wildlife in Jigme Singye Wangchuck National Park, Bhutan. Wildl. Soc. Bull. *34*, 359–365.
106. Chambers, R., and Conway, G.R. (1992). Sustainable Rural Livelihoods: Practical Concepts for the 21st Century (Institute of Development Studies).
107. Scoones, I. (1998). Sustainable Rural Livelihoods: A Framework for Analysis (Institute of Development Studies).

108. Misselhorn, A.A. (2005). What drives food insecurity in southern Africa? A meta-analysis of household economy studies. Glob. Environ. Change *15*, 33–43.

109. Matshe, I. (2009). Boosting smallholder production for food security: some approaches and evidence from studies in sub-Saharan Africa. Agrekon *48*, 483–511.

110. Cassidy, L., and Barnes, G.D. (2012). Understanding household connectivity and resilience in marginal rural communities through social network analysis in the village of Habu, Botswana. Ecol. Soc. *17*, 11.

111. Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N.J., Bauch, S., Börner, J., Smith-Hall, C., and Wunder, S. (2014). Environmental income and rural livelihoods: a global-comparative analysis. World Dev. *64* (*Suppl 1*), S12–S28.

112. Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., and Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over Eastern Africa. Q. J. R. Meteorol. Soc. *144*, 292–312.

113. Muthoni, F.K., Odongo, V.O., Ochieng, J., Mugalavai, E.M., Mourice, S.K., Hoesche-Zeledon, I., Mwila, M., and Bekunda, M. (2019). Long-term spatial-temporal trends and variability of rainfall over Eastern and Southern Africa. Theor. Appl. Climatol. *137*, 1869–1882.

114. Marchant, R., Mumbi, C., Behera, S., and Yamagata, T. (2007). The Indian Ocean dipole – the unsung driver of climatic variability in East Africa. Afr. J. Ecol. *45*, 4–16.

115. Nicholson, S.E. (2018). The ITCZ and the seasonal cycle over equatorial Africa. Bull. Am. Meteorol. Soc. *99*, 337–348.

116. Broccoli, A.J., Dahl, K.A., and Stouffer, R.J. (2006). Response of the ITCZ to Northern Hemisphere cooling. Geophys. Res. Lett. *33*, L01702.

117. Boyard-Micheau, J., Camberlin, P., Philippon, N., and Moron, V. (2013). Regional-scale rainy season onset detection: a new approach based on multivariate analysis. J. Clim. *26*, 8916–8928.

118. Daryanto, S., Wang, L., and Jacinthe, P.-A. (2016). Global synthesis of drought effects on maize and wheat production. PLoS ONE *11*, e0156362.

119. Connolly-Boutin, L., and Smit, B. (2016). Climate change, food security, and livelihoods in sub-Saharan Africa. Reg. Environ. Change *16*, 385–399.

120. Schlenker, W., and Lobell, D.B. (2010). Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. *5*, 014010.

121. Funk, C., Peterson, P., Peterson, S., Shukla, S., Davenport, F., Michaelsen, J., Knapp, K.R., Landsfeld, M., Husak, G., Harrison, L., et al. (2019). A high-resolution 1983–2016 T_{max} climate data record based on infrared temperatures and stations by the climate hazard center. J. Clim. *32*, 5639–5658.

122. Gelman, A., Hwang, J., and Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. Stat. Comput. *24*, 997–1016.

123. Goldstein, H. (1987). Multilevel Models in Education and Social Research (Oxford University).

124. Carpenter, B., Gelman, A., Hoffman, M.D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., and Riddell, A. (2017). Stan: a probabilistic programming language. J. Stat. Softw. *76*, 1–32.

125. Gelman, A., Carlin, J.B., Stern, H.S., and Rubin, D.B. (2013). Bayesian Data Analysis, Third Edition (Chapman and Hall/CRC).

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Deidentified household data	This paper[51]	https://figshare.com/articles/dataset/KAZAVA_Household_Survey_Data_for_Food_Insecurity/13217843
Software and algorithms		
R: A language and environment for statistical computing	R Core Team 2020[52]	https://www.r-project.org/
RStan: the R interface to Stan	Stan Development Team 2021[53]	https://mc-stan.org/
Rainfall analysis (JavaScript code for analysis in Google Earth Engine)	This paper[54]	https://figshare.com/articles/CHIRPS_Combined_Precipitation_Analysis_in_Google_Earth_Engine_1981-2019/12358034/1
Temperature analysis (JavaScript code for analysis in Google Earth Engine)	This paper[55]	https://figshare.com/articles/software/ERA5_Daily_Aggregate_Temperature_Analysis_in_Google_Earth_Engine_1979-2020/13202984

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Jonathan Salerno (jonathan.salerno@colostate.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

Original data and code have been deposited at figshare and are publicly available. URLs are listed in the Key resources table. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Summary and ethics statement

We examine impacts of wildlife crop depredation and climate change on communities in KAZA, the largest terrestrial transfrontier conservation areas on Earth.[20] We do this by focusing on a fundamental measure of human wellbeing: food security.[7,56–58] Research protocols followed recognized codes of conduct and were approved by community leadership, Traditional Authorities, national research councils, and the University of Colorado Institutional Review Board (#16-0126). The analytical framework included fitting Bayesian multilevel statistical models to household and climate data,[59] and interpreting model results alongside satellite-based rainfall (1981-2018) and temperature (1979-2018) analyses.[22,23,60]

METHOD DETAILS

Study region

KAZA spans c. 520,000 km^2 across five member nations: Angola, Botswana, Namibia, Zambia, and Zimbabwe. Vegetation communities are predominantly semi-arid savanna woodland interspersed with seasonal floodplains. Land use policy and management are independently implemented by member nations, while the KAZA Secretariat serves as an overarching coordinating institution.[20] Land use designation includes IUCN category I-VI protected areas, along with private and communal lands. As such, KAZA is a patchwork of lands for people and lands for wildlife, with considerable mobility and overlap of land uses. The mean annual precipitation (MAP) gradient spans c. 400-1,000 mm, with rains typically falling from November to March, but with significant interannual variability.[22] Variability in temperature and precipitation extremes is projected to increase, with implications for the region's livelihoods and economy.[61,62]

KAZA spans three major watersheds: the Okavango (Cubango), Kwando, and Zambezi. Major rivers serve as critical dry season water sources for wildlife and primary sites of human settlement.[30,41] KAZA contains c. 250,000 savanna elephants, roughly half of the global population.[21] Associated wildlife tourism contributes significantly to the region's economy.[20,41,48] National elephant population totals are estimated as follows for KAZA member states: Angola 3,396 [95% CI: 1,734, 5,058]; Botswana,131,626 [119,118, 144,134]; Namibia, 22,754 [18,358, 27150]; Zambia, 21,967 [16,999, 26,935]; Zimbabwe, 82,630 [72,321, 92,939].[21] The human population of the KAZA region as a whole is c. 2.3 M people, including both rural and urban areas.[50]

Across KAZA, the dominant land uses are smallholder agriculture, livestock keeping, and natural resource harvest, in addition to wildlife conservation.[50,63] Resource harvest includes food (e.g., fish, edible plants) and other products (e.g., fuelwood, building poles, medicinal plants).[64] Harvested resources are used in the household and also sold.[18] Off-farm employment opportunities are scarce, and households earn limited cash from the sale of surplus crops and livestock.[41] Local and national land management policies, grazing by wildlife and livestock, and soil-nutrient characteristics further influence landscape heterogeneity, with implications for both livelihoods and wildlife.[65,66]

Human-wildlife interactions resulting in negative impacts are common, including wildlife damaging or destroying crops.[63,66–68] We term this impact "crop depredation," acknowledging the use of other terms (e.g., crop raiding, crop loss, human-wildlife conflict generally).[16,30,69] Crop depredation, while rarely quantified,[9,70] can cause significant impact on people across conservation landscapes globally.[15,71] Offsetting crop depredation impacts remains a key goal of conservation efforts in Africa, with the hope of ultimately supporting less negative relationships between people and protected wildlife.[47,49]

Research sites were identified as three community-based conservation (CBC) areas in KAZA: Chobe Enclave Conservation Trust in Botswana (Chobe), Mashi Conservancy in Namibia (Mashi), and the Lower West Zambezi (LWZ) Game Management Area in Zambia (see section below for sampling frame). Similar to land management noted above, CBC policy is defined and implemented independently by each KAZA national government. Individual CBC areas are comprised of multiple participating communities, which in theory jointly participate in governance over wildlife and resources (but see below). Therefore, our study sites are represented by a geographic area and also a governing body. Human population in the respective study sites is estimated at 3,747 in Chobe (0.024 people/ha, 2017), 2,900 in Mashi (0.066 people/ha, 2017), and 10,155 in LWZ (0.070 people/ha, 2018).[72]

Communities play little if any active role in land and wildlife management at the level of the multi-country KAZA Secretariat.[3,20,41] While communities generally have limited engagement with national-level natural resource decision-making, there are notable differences in the degree to which CBC-participating communities are able to govern their own resources. For example, Namibian community wildlife and land use laws are relatively decentralized compared to the top-down authority maintained by the national government in Botswana.[48,63,73–75] Zambian CBC policy was established under a co-management structure with joint management shared between communities and the national government; however, *de facto* Zambian CBC governance is relatively underdeveloped.[66]

In the study sites, CBC participation is associated with few direct benefits to households (e.g., substantial cash payments, permanent employment), which is a common challenge with CBC efforts across Africa.[47] Our data show that CBC households in Namibia reported direct payments from conservation activities of approximately US$10 annually. Households in Botswana and Zambia reported no CBC payments. However, CBC as a conservation and development strategy can still support strengthened institutions, social networks among members, and increased opportunity for economic gain in the presence of certain enabling conditions.[14,76] For example, CBC in KAZA may help to organize members to produce crafts and other products for tourism markets, potentially in collaboration with associated conservation projects, while also supporting community-level developments with indirect benefits to households.[63,77] Moreover, evidence suggests that well-resourced and decision-enabled CBC efforts can be effective at combating illegal poaching of wildlife.[78,79] For these reasons, we posit that existing CBC areas are necessary bridging institutions for more inclusive governance within KAZA to support people living with wildlife.[3]

Household survey data

Research protocols were designed and approved by community government and Traditional Authorities following recognized codes of conduct.[80–82] All human data collection adhered to ethical standards that were reviewed and approved by the University of Colorado Institutional Review Board (#16-0126). Protocols included gaining verbal informed consent from all participants prior to data collection. Consent was verbal due to low literacy rates in the study population. Participants were assured anonymity. All data used in the study and made public are anonymous, including household locations, which were spatially jittered (i.e., applying a randomly generated spatial offset of approximately 100 m, to prevent distinguishing between specific households) following spatial referencing to remote sensing data for analysis. During a pilot effort in 2016, researchers introduced the project and gained permission to conduct activities at higher levels of authority (e.g., national research councils, KAZA Secretariat, Traditional Authorities, Council Chiefs). Key informant interviews and focus group discussions in communities aided in survey instrument development. Household data collection took place in 2017-2018 in three KAZA member nations, Botswana, Namibia, and Zambia. Prior to sampling, researchers presented letters of introduction and gained permission for research from local authorities in each sample community.

Key informant interviews and focus group discussions produced qualitative data regarding livelihoods in the communities. While these data are not formally presented in the main text, they support qualitative observations such as households reporting generally high yield variance, as well as various strategies to supplement food security (e.g., temporary out-migration to return remittances, food sharing through relational or kin networks within the community).

Household survey protocols followed a stratified random sampling procedure, with sites, villages, and wards in each country-site as strata. The purposeful selection of the three study sites, and the strata within them, was conducted in collaboration with partner institutions, including the KAZA Secretariat, Traditional Authorities, and community officials. Site selection prioritized representativeness across social-ecological conditions relevant to the goals of this study (i.e., meaningfully describing the variation in human-wildlife interactions in areas of shared land use, wildlife movement, and various conservation area designations). Data collection occurred under the broader umbrella of a research initiative investigating vulnerability and adaptation to land-use and climate change.[50]

CBC areas were selected as geographically bounded sites (i.e., conservancies, wildlife trusts), in which sampling could be structured. Sampling was balanced across the three sites, with the sample comprised of five communities and c. 50 households per community in each site (complete data: Botswana, n = 240; Namibia, n = 241; Zambia, n = 245; total, n = 726). The sampling intensity is therefore estimated at 27.7% in Botswana (site population: 3,747), 37.9% in Namibia (site population: 2,900), and 13.8% in Zambia (site population: 10,155); calculations apply mean household size from survey data in each site, which includes household members permanently living in the household. For the population estimates, we draw on data from https://www.worldpop.org, which applies dasymetric methods relying on a random forest model.[72] It is notable that the available national census data that underlie these estimates are of very different spatial and temporal resolution (i.e., coarse resolution in Zambia, relatively fine resolution in Botswana and Namibia). While the WorldPop estimates produce the most comparable data available across nation-sites, and also allow for estimates specific to our study years, there is inherently greater uncertainty with the Zambian population estimates than with those from the other two sites.

To sample households in each community, we conducted a spatially random sampling procedure. Local authorities provided household counts and distributions within sub-areas (wards). Based on total households and community spatial arrangement (e.g., households clustered around a community center versus distributed along a linear main road), every *n*th household was selected for sampling to reach the balanced sample of 50, ensuring that households both central and dispersed were sampled. Field teams counted outward as they moved away from the community head offices in a systematic pattern along paths and roads, approaching each *n*th household to request participation. If household heads or spouses were absent, enumerators returned later or located the respondent in their fields; if households were permanently absent, enumerators selected the nearest neighbor. Surveys were conducted by trained local enumerators residing in the larger site; individual enumerators did not conduct interviews in their home communities. Surveys were conducted in the Setswana language in Botswana, and in Lozi in Namibia and Zambia, though enumerators translated into local languages when appropriate.

Surveys recorded data regarding household composition, livelihood, natural resource harvest and use, and interactions with wildlife. For this study we extract measures of food insecurity, crop depredation by wildlife, cash income, and land area farmed.

Our outcome variable is food insecurity, a widely accepted measure of livelihood vulnerability and wellbeing.[56,57,83–85] We estimate food insecurity based on the Food Insecurity Experience Scale (FIES), which classifies individuals into one of four categories of food insecurity and quantifies prevalence of food insecurity in populations.[58] FIES is based on responses to the following survey questions:

During the last 12 months, was there a time when you...

...were worried you would not have enough food to eat? (WORRIED)
...were unable to eat healthy and nutritious food? (HEALTHY)
...ate only a few kinds of foods? (FEWFOOD)
...had to skip a meal? (SKIPPED)
...ate less than you thought you should? (ATELESS)
...ran out of food? (RUNOUT)
...were hungry but did not eat? (HUNGRY)
...went without eating for a whole day? (WHLDAY)

We conducted validation of FIES responses following the FIES technical guidance and using the {RM.weights} package in R.[86] Specifically, internal validity is assessed using thresholds of acceptability of four key statistics: infit [0.7,], outfit [, 2], residual correlation [, 0.4], and reliability [0.7,]. Our FIES data meet all of these validity thresholds (Table S3). Adjusting our scale to the FIES global reference scale as per the FIES technical guidance, we find that our sample indicates prevalence rates of 71.2% likely to be either moderately or severely food insecure (Mod+Sev), and 48.1% likely to be severely food insecure (Sev) (Table S3).

Because our analyses require household-level food insecurity measures, we apply the binary FIES questions raw scores (number of positive responses, 0-8) to assign each household to a category using the suggested thresholds: score of 0 as "food secure," score of 1-3 as "mildly food insecure," score of 4-6 as "moderately food insecure," and score of 7-8 as "severely food insecure."[87] This application of raw scores is recommended specifically for regression analysis such as ours with food insecurity as the dependent variable,[88] as has been done in similar studies.[89,90] In the main text, we present all analyses based on households experiencing moderate to severe food insecurity, unless otherwise noted.

For the initial survey, questions were based on a similar measure, the Household Food Insecurity and Access Scale (HFIAS).[91] Our surveys adapted HFIAS questions to pertain to the previous 12-month period, in part because focus group respondents felt this was a more relevant time frame (HFIAS protocols refer to the previous 4-week period). Generally, eight of the nine HFIAS questions map directly onto the eight FIES questions; we omit the HFIAS question regarding disliked foods in our analysis. While slight differences

in English language structure exist between the HFIAS and FIES questions, one of the advantages of the FIES approach is that the validation process accounts for varied translation and implementation across cultural contexts[58,87] To test for sensitivity of our results based on HFIAS versus FIES specification, we report results of alternative models below (model estimates are nearly identical).

We justify our use of food insecurity as an outcome variable because it is an important dimension of health and wellbeing.[7,57,83–85] FIES in particular is integrated into the United Nations Sustainable Development Goals as a global standard.[24] Reduced food security and malnutrition cause diverse negative outcomes. Acute malnutrition, such as from the loss of a family's food crop, can lead to wasting and severe health consequences and/or mortality, especially in children.[92] Early-childhood malnutrition impairs cognitive development, school performance, and subsequent physical capabilities; these effects have clear impacts on the long-term social and economic development of individuals and communities.[93] Further, evidence suggests that the impacts of malnutrition may be intergenerational, with malnourished parents adversely affecting their children through epigenetic pathways, independent of prenatal nutrition.[94] Following others, we therefore assert that food insecurity is a necessary element of human wellbeing and relevant within the broader context of livelihoods and changing climate in this system.[95–97] We do, however, acknowledge other wide-ranging impacts of human-wildlife interactions on people, both direct and indirect, that may be experienced variably among households.[4,98]

Our focal analysis uses 10 predictor covariates, with 5 of these drawn from the household survey, and 5 drawn from the climate analyses described below. We measure a proxy for intensity of *crop depredation* as the reported total area of crops damaged or destroyed by wildlife during the previous growing season. Respondents are asked to report estimates of damaged area for each crop type, and values are summed to give total damaged area (maize represented the large majority of damage reports). We acknowledge that household self-reporting of crops destroyed by wildlife is subject to error or bias. For example, households may inaccurately report crop area affected due to incorrect estimation or poor event recall. Respondents may also intentionally overestimate or exaggerate reports.[99,100] To minimize error, survey responses were examined for internal validity during questioning (e.g., checking that summed areas of crop types grown and crop area damaged from pests, livestock and disease together represented plausible scenarios). In addition, many surveys were conducted in fields where farmers could spatially indicate or even show crop area damaged.[41] An alternative to measuring crop depredation through direct questioning is to take physical measurements, but physical measurement of crop area damaged by wildlife has been demonstrated to produce error as well, due to variation in acceptable and implemented protocols.[70,99] It also must be acknowledged that any attempt to quantify crop depredation impacts through crop area damaged, including our own, ignores the associated direct and opportunity costs of crop guarding and defense.[4,9,101,102] While acknowledging potential for error, we follow other studies and argue that respondent-reported measurement is an appropriate proxy of relative crop predation by wildlife.[103–105] Descriptive values from the household data are provided in Table S4.

As control covariates, we measure *total land farmed* during the previous growing season, and *total cash income* from all sources (permanent salary, wage labor, small business activities, sale of crops and livestock, sale of harvested natural resources, remittances, social welfare payments; total cash income is binned as quantiles for the statistical models, see below). This measure of total cash income was based on an operationalization of the Households Livelihood Framework, which understands that households possess wealth or assets in many forms, specifically financial, human, natural, physical, and social capitals.[106,107] This framework informed data collection, and cash sources from livelihood capital types were identified and measured across various household activities.[50] To make these livelihood assets comparable and a suitable control covariate, we pooled all sources together (permanent salary, wage labor, sale of natural resources, remittances, social welfare payments, small business income), including non-cash sources (e.g., food aid), which were converted to a US$ equivalent. While this may mask the differential impacts of, for instance, small business income and cash from selling gathered firewood, these differences are not within our scope of examination. Further, in our study population, dependent on marginal agriculture and few jobs, the vast majority of household capital is invested in food security, through crop production for consumption and purchased food.[4,63,74,108–111] This literature supports that our formulation of income, when combined with other control covariates, adequately describes the variation in livelihoods and their expected relationship with food security.

For comparison, the main text reports yields from other regions receiving similar mean annual precipitation, and under various management regimes. These comparison sites are located in Malawi, Zambia, Zimbabwe, and the U.S.A; Table S1 reports yields and mean annual precipitation in these sites.

Climate data and analyses

We analyze and present climate information spatially, while also integrating climate covariates into the household-level statistical models. Rainfall analyses, described below, yield five covariates: mean length of rainy season; trend in length of rainy season; trend in dry 10-day periods (i.e., dekads) occurring during the rainy season; and, two control covariates for season length and dry dekads in the year preceding households surveys. Rainfall data are estimated as pentadal sums from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS v 2.0; 0.05 arc-degree spatial resolution),[22] and analyzed over the 1981-2018 period. With a spatial grain of 0.05° x 0.05° on a fixed latitude-longitude grid, CHIRPS is a blend of five infrared satellite products and available station precipitation observations. Noting the paucity of spatial and temporal ground station coverage for much of the KAZA region,[112,113] CHIRPS provides a comparable dataset option that appeals for its finer spatial resolution and the combination of satellite-based and station-based estimates. We also consider temperature measures in a supplementary analysis, described below following the rainfall measures derivation.

Households are assigned values corresponding to the five precipitation variables for analysis. Figure 3 presents analyses of rainfall and trends in precipitation that we further discuss in relation to food security and crop depredation. These data were accessed and

analyzed via Google Earth Engine.[23] Analyses were conducted using a series of script-based statistical aggregations of pentad-based rainfall aggregations, estimated for the water years between 1981 and 2018, and exported for visualization at a nominal resolution of 6 km grid cell resolution.

For the study region, precipitation ranges between approximately 550 mm/year in the southeastern Botswana communities to 850 mm/year in the northern-most Zambian communities sampled. This is a narrower mean annual precipitation range than is present across the full extent of the KAZA landscape. The mean annual rainfall accumulations represent a gradient determined by the rain belt over central and southern Africa, noted primarily in the literature by the migration of the Intertropical Convergence Zone (ITCZ) and its seasonal location,[114] but note recent research questioning that paradigm.[115] The ITCZ creates unimodal temporal rainfall patterns with a high degree of interannual variability in timing and location, and potential evidence suggests a long term shift in ITCZ behavior that may affect annual rainfall amount and timing for the region.[116]

To characterize precipitation variability we estimated a conservative rainy season length for each water year (Figures 3A and 3D). We designated the start of a water year as October 1st (Julian day 275). For each water year we subset the pentadal data between Julian day 275 and Julian day 181 of the following year (June 30th in non-leap years), which conservatively excludes the dry season that receives near-zero precipitation. For each year, we define the rainy season start by identifying the first pentad receiving 10 mm or more rainfall after October 1st. We define the season end as the last pentad in the following year which is estimated to have 10 mm or more rainfall. Rainy season length is then calculated as the number of days between these pentads for each year. Figures 3C and 3F shows the trend in rainy season length over the data record.

Ten millimeters was chosen as a threshold to define a significant rainfall event as it reflects on average a 1% rainfall accumulation per pixel, as aggregated across the region. The pentads occurring before and after those exceeding this threshold would therefore receive on average less than 98% of the annual rainfall total. We acknowledge alternative ways to calculate rainy season onset and ending.[117] However, we present a very conservative estimate, which could be applied regionally across the rainfall gradient. Our approach is simple yet relevant to agricultural practices and wildlife movements that may be sensitive to these small but significant rainfall accumulations.

Figures 3B and 3E presents the trend in the number of dry dekads (10-day periods without measurable rainfall) occurring during the rainy season. For each rainy season we summed the number of dekads between the start and end day of each rainy season in which zero rainfall was estimated. The number of these dry dekads represent significant dry periods that are important for cereal crop germination, flowering, and seed-set setting[35,118] but may also represent periods of increasing intra-annual variation.

For both the length of the estimated rainy season and number of dry dekads in each year, for each pixel, we estimate a simple annual linear trend across all years. Significant negative trends are represented in Figure 3 as hashed cells (estimated trend coefficient, $p < 0.05$ for $n = 37$). Code to reproduce rainfall analyses are publicly available[54]

Although we place the climate focus on precipitation due to the strong dependence on rainfall for subsistence farming and the projected declines and increased variability in rainfall for southern Africa,[61,119] temperature is also an important variable that influences crop yields[27,28,120], as noted in the Results and Discussion. In rainfed systems across sub-Saharan Africa, evidence suggests that each additional growing degree day above 30°C reduces maize yield by 1% when soil water availability is not limiting, and 1.7% under drought conditions.[28] To assess the suitability of incorporating temperature data, we analyzed daily maximum temperatures using the ERA5 gridded climate reanalysis product (0.25° x 0.25°, 1979-2018)[60] in Google Earth Engine. While a higher spatial resolution product exists[121], it is downscaled from and largely informed by the ERA5 product and, in areas such as our study region, lacks a reasonable density of station data (i.e., the apparent increase in spatial resolution is largely a function of interpolation). Thus, the interpolated temperature data for the region are spatially coarse, creating a likely scale mismatch in our household-level analysis.

Focusing on temperature exceedance thresholds, we produced six temperature measures: mean days per year exceeding 30°C; trend in days per year exceeding 30°C; mean season length between first and last days exceeding 30°C; trend in season length between first and last days exceeding 30°C; and two control covariates for previous year's days exceeding 30°C and previous year's season length between first and last days exceeding 30°C. Code to reproduce temperature analyses are publicly available.[55] Over the period of examination, there is no significant trend in exceedance values and little variation across study sites (Figure S1). We include the set of all six temperature covariates in an exploratory statistical model (see below section describing the main model); unsurprisingly, temperature coefficient estimates are near zero with broad credibility intervals, and the model less parsimonious than the main model (WAIC scores, 731.4 versus 737.1).[59,122] For these reasons, we do not include temperature measures in our main analysis; however, given the availability of more precise longitudinal temperature data for the region, this is an important line of future investigation.

QUANTIFICATION AND STATISTICAL ANALYSIS

We evaluate the impact of crop depredation and climate change on food insecurity by estimating a multilevel binomial logistic regression model. The use of this model is informed by the structure of our data, with household samples from a multilevel, hierarchically structured population[123] We estimate the statistical model with Bayesian methods and a Hamiltonian Monte Carlo procedure in Stan, called through the R Statistical Environment.[52,53,124] This approach is informed by three main considerations: (i) *a priori*, there is reason to expect that focal human-wildlife relationships vary substantially between communities and sites (i.e., between and among different levels of the model), and Bayesian methods allow for a more precise examination of these multilevel relationships and their

uncertainty than likelihood-only methods;[125] (ii) the computational efficiency of the Bayesian approach, in particular, a Hamiltonian Monte Carlo process;[124] and (iii), the relative ease of specifying and estimating complex models using "off-the-shelf" methods.[59]

We fit a multilevel binomial logistic regression model to 717 complete household observations. Data are structured as households in communities and communities in sites (see sample description, above). Varying intercept parameters (i.e., random effects) are included for communities and sites, and these effects are combined and illustrated graphically as community-level effects in Figure 2. These varying effects capture unobserved variation in food insecurity outcomes shared by communities and sites, such as might be influenced by strength of local governance, quality of natural resource areas, or land use zoning.

The modeled outcome variable, *food insecurity*, is specified as a binary variable for households categorized on the FIES scale as moderately and severely food insecure, following recommended methods.[88]

The main binomial model presented in the main text estimates the log-odds of a household, h, being food insecure, fi, as the function,

$$fi_h \sim \text{Binomial}(1, p_h)$$

$$\text{logit}(p_h) = \alpha + \alpha_{\text{community}[h]} + \alpha_{\text{site}[h]} + \beta W_h C_h + \delta T_h + \varepsilon D_h + \zeta L_h + \gamma F_h + oG_h + \iota I_h + \kappa A_h$$

where α is the grand intercept, $\alpha_{\text{community}[h]}$ is the varying intercept for each community, and $\alpha_{\text{site}[h]}$ is the varying intercept for each nation site; β is the effect of wildlife impact, W (i.e., crop depredation), multiplied by a binary variable indicating the household cultivated crops, C; δ is the effect of total rainy season length, T; ε is the effect of trend in dry dekads during the rainy season, D, 1981-2018; ζ is the effect of trend in rainy season length, L, 1981-2018; γ is the effect of rainy season length during the previous year, F; o is the effect of dry dekads in the previous year, G; ι is the effect of total household cash income, L (modeled as 3 binary wealth quartiles); and κ is the effect of total area of land farmed, A.

The following transformations are implemented for household-level predictor variables: square root of crop depredation (ha), square root of farmed area (ha), log of trend in dry dekads (change of days per year), log of mean rainy season length, log of dry dekads in the previous year, and log of rainy season length in the previous year; trend in mean rainy season length is retained on the original scale. Wealth is binned by quartiles, with the three highest quartiles included as binary, or dummy, variables. We examine predictor variables for multicolinearity via correlation matrix of the transformed variables included in the main binomial model (Table S5). We further examine the relationship between wealth, farm size, and crop depredation by plotting the distributions of farm size and crop depredation disaggregated by the binary wealth variables used in the model (Figure S2).

Priors on all household-level fixed effects are Gaussian, with mean of 0 and standard deviation of 1. Priors on all varying effects are Gaussian with mean of zero and variance hyperparameters; priors on hyperparameters are half-Cauchy with location of 0 and scale of 1. The model is coded and estimated following published methods.[59] Deidentified data to reproduce household analyses are provided below via public repository.[51]

Model estimation is computed with a 10,000-iteration burn-in and harvesting 10,000 posterior samples. This estimation for the fully parameterized main model requires approximately 4.9 hours on an Intel Xeon E5 3.6 (4.5) GHz 8-core processor, with 64 GB of memory, running macOS v10.15.6. Examination of traceplots and kernel densities indicate adequate mixing. Additional evaluation of convergence is performed through the examination of Rhat and n_eff model diagnostics, and we conduct posterior predictive checks.[59,125] Together, these diagnostic steps indicate adequate model fit.

We evaluate our research question regarding the association of crop predation with household food insecurity in the presence of rainfall trends through graphical and tabular representations of the joint posterior density of household-level fixed effects estimates, in the context of community- and site-level varying intercept effects estimates. Coefficient estimates are reported in Table S6.

To assess sensitivity of our outcome variable specification, we fit 2 additional statistical models. First, we fit a binomial model predicting the FIES-derived food insecurity outcome specified as a binary variable for only those households experiencing *severe* food insecurity. Second, we fit an ordinal logistic model predicting the HFIAS-derived four-category food insecurity outcome. Both models use an identically specified linear predictor (i.e., righthand-side function) and prior specification as the main binomial model presented in the main text. Coefficient estimates from these models are relatively similar to the main model and support the main findings (Figures S3, S4, and 2).

As noted above in the description of the climate analyses and in Results, we fit an additional statistical model including 6 temperature covariates, but otherwise identical to the main binomial model. Covariates describe trends in exceedance thresholds based on days > 30°C, as well as controls for the previous year. Coefficient estimates for the focal predictors in this model (crop depredation, rainfall, controls) are similar to those presented in the main model, while the temperature covariates are largely uninformative (near 0 with large credibility intervals), and WAIC model comparison ranks this model as less parsimonious than our main model (WAIC scores: 731.4 versus 737.1). Also noted in the main text, we fit an additional statistical model including interaction effects between crop depredation and the 3 main rainfall covariates (mean season length, season length trend, and dry dekads trend). The model estimated an effect of depredation*season length trend that was credible at 90%, indicating that households already experiencing shorter seasons may suffer even greater impacts of crop depredation. However, the model was less parsimonious than our main model (WAIC scores: 731.4 versus 732.7); therefore, and due to the lower credibility of the interaction effect, we do not present this as a main finding. Further research is needed to examine these relationships.