Dehorning reduces rhino poaching

Timothy Kuiper[1,2], Sharon Haussmann[3], Steven Whitfield[4] , Daniel Polakow[5], Cathy Dreyer[4], Sam Ferreira[4], Markus Hofmeyr[6], Jo Shaw[7], Jed Bird[8], Mark Bourn[9], Wayne Boyd[10], Zianca Greeff[3], Zala Hartman[3], Kim Lester[11], Ian Nowak[12], Iain Olivier[11], Edwin Pierce[13], Colin Rowles[14], Sandra Snelling[4], Martin van Tonder[15], Ellery Worth[16], Hannes Zowitsky[17], E.J. Milner-Gulland[18] and Res Altwegg[2]

[1]Department of Conservation Management, Nelson Mandela University, George, South Africa

[2]University of Cape Town, Centre for Statistics in Ecology, Environment, and Conservation, Cape Town, South Africa

[3]Greater Kruger Environmental Protection Foundation, Hoedspruit, South Africa

[4]South African National Parks, South Africa

[5]University of Stellenbosch, Departments of Statistics and Actuarial Science, Stellenbosch, South Africa, and University of Cape Town, School of Actuarial Science, Cape Town, South Africa.

[6]Rhino Recovery Fund, Wildlife Conservation Network, South Africa

[7]Save the Rhino International, London, UK

[8]Sabie Game Reserve, South Africa

[9]Manyeleti Provincial Nature Reserve, South Africa

[10]Mala Mala Game Reserve, South Africa

[11]Sabi Sand Nature Reserve, South Africa

[12]Balule Nature Reserve, South Africa

[13]Timbavati Private Nature Reserve, South Africa

[14]Klaserie Private Nature Reserve, South Africa

[15]Umbabat Private Nature Reserve, South Africa

[16]Karingani Private Nature Reserve, Mozambique

[17]Thornybush Private Nature Reserve, South Africa

[18]University of Oxford, Department of Biology, Oxford, UK

Abstract

Across 11 southern African reserves protecting the world's largest rhino population, we documented the poaching of 1,985 rhinos (2017-2023, ~6.5% of the population annually) despite ~$74 million spent on anti-poaching. Most investment focused on reactive law enforcement—rangers, tracking dogs, access controls, and detection cameras—helping achieve >700 poacher arrests. Yet we found no statistical evidence that these interventions reduced poaching (horn demand, wealth inequality, embedded criminal syndicates, and corruption likely combine to drive even high-risk poaching). By contrast, reducing poacher reward through dehorning (2,284 rhinos across eight reserves) achieved large (~78%) and abrupt reductions in poaching using 1.2% of the budget. Some poaching of dehorned rhino continued as poachers targeted horn stumps and regrowth, signalling the need for regular dehorning alongside judicious use of law enforcement.

One sentence summary: Dehorning rhinos is associated with large and abrupt reductions in poaching.

Main text

Rethinking strategies to tackle the poaching of high-value wildlife

Despite decades of conservation effort, poaching for international trade continues to threaten the existence of the world's five rhinoceros species (*1*, *2*), while also reducing tourism revenues (*3*), entrenching criminal syndicates (*4*), threatening ecosystem function (*5*), and leading to loss of human life due to violent contacts between rangers and poachers (*6*). In the Greater Kruger ecosystem of southern Africa (a critical global stronghold that protected 27% of all Africa's rhinos in 2017; *2*), we documented the poaching of 1,985 rhinos between 2017 and 2023 (Fig. 1). This has rapidly reduced both black (*Diceros bicornis*) and white (*Ceratotherium simum*) rhino populations (*1*, *7*, *8*). Poaching has persisted despite the investment of ~USD 74 million in diverse anti-poaching interventions (Fig. 3B). Political instability, local poverty, police criminality, an ineffective justice system (with poachers often let out on bail), and involvement of conservation staff with criminal syndicates have enabled wildlife crime to thrive in the region (*4*, *9*).

In his seminal work in the 1950s, Becker argued that crime can be reduced by increasing the probability (e.g., more police patrols) or the severity (e.g., longer prison sentences) of punishment (*10*). Researchers of wildlife poaching and trade have since applied this thinking to model poacher behaviour as a function of both the risks, and the costs and benefits, of poaching behaviour (*11*, *12*). Further evidence in behavioural economics suggests that the certainty of the cost or benefit has a strong influence on human decision-making in general (*13*, *14*).

Globally, as in our study area, efforts to combat the illegal wildlife trade have for decades focused on increasing the risk of incurring a penalty, through law enforcement measures such as militarized ranger patrols and advanced surveillance technologies (*15–17;* Fig. 2). Yet consumer demand and local poverty create financial incentives for poaching despite high risk (*9*, *18*, *19*). Also, corruption allows criminal poaching syndicates to circumvent detection and arrest through inside information on ranger and camera deployments (*4*, *20;* Fig. 2). Furthermore, ineffective criminal justice systems dampen the deterrence value of the penalty because sentences are seldom swift, fair and certain (*21*). Finally, raising the likelihood of detecting and arresting poachers — through measures like additional cameras, rangers, helicopters, and dogs — may be prohibitively expensive to implement at a scale and intensity large enough to significantly deter poacher behaviour across vast wildlife areas like those in our study (*10*, *12*; Fig. 3D). In summary, the overall expected cost to poachers (risk x penalty) achievable through law enforcement is hindered by several contingencies and extenuating factors and is therefore often too low to substantially deter poaching.

Given these complexities, rhino custodians across Africa and Asia are increasingly turning to proactive dehorning of rhinos as an entirely different approach to poaching deterrence: reducing rewards. The staggered implementation of dehorning across eight of our study reserves and over seven years (2,284 rhinos dehorned) has provided a unique opportunity to empirically evaluate the effectiveness of this approach. Based on the theoretical work and contextual factors referenced above, we predict that the large, direct, and unambiguous reduction in expected reward created by dehorning will exert a stronger influence on poacher behaviour in our study area than the less direct, less certain and more contingent increases in expected penalty achievable through law enforcement interventions (Fig. 2).

Evaluating the effectiveness of anti-poaching interventions

We used quarterly data collected over seven years (2017-2023) from eleven wildlife reserves in the Greater Kruger ecosystem to measure the effectiveness of rhino dehorning alongside traditional law

enforcement interventions (anti-poaching rangers, fences, security control rooms, tracking dogs, detection cameras, and others, see Fig. 2). Our unit of analysis was the poaching rate and intervention intensity per reserve, per year quarter (Fig. 1). Data were combined for black and white rhino species (black rhinos constituted ~8% of the total rhino population and poaching and dehorning rates were similar by species). The interventions were applied as part of ongoing management, rather than a controlled experiment. To reduce uncertainty in the attribution of changes in poaching to specific interventions in a complex system without experimental controls, we took an interdisciplinary approach that combined correlative and quasi-experimental quantitative models with structured qualitative attribution methods from policy program evaluation (*22*, *23*).

First, we built a baseline all-intervention model to test for empirical associations between poaching rates and the intensity of implementation of eleven anti-poaching interventions (Fig. 1B). We used process tracing (through interviews with reserve managers and intervention experts) to map out the causal pathways for each intervention and then tested these against our quantitative data (Fig. 2; fig s1). We used a hierarchical Bayesian regression model with reserve and year random effects, and model selection performed via regularisation to account for multiple testing (see materials and methods). Next, we quantified evidence for intermediate steps along hypothesised pathways, such as the number of poachers arrested using tracking dogs. Finally, we used contribution analysis through structured results workshops to further appraise the empirical support for intervention pathways and to interrogate how and under which conditions interventions worked or did not work as intended (*21*). See materials and methods for full details.

Second, we built a dehorning-focussed model to strengthen causal inference for our main intervention of interest. Although several tests confirmed no significant temporal or spatial autocorrelation in our all-intervention model residuals (figs. S3 to S8), this model was limited by the non-random application of multiple interventions that overlapped inconsistently in space and time. By contrast, seven reserves implemented dehorning abruptly (dehorning almost all rhinos present within 1-2 months; fig S11) and in a staggered fashion (two reserves in early 2019, two in late 2019, and three in mid-2022). This provided good spatial and temporal contrast, allowing us to conduct a quasi-experimental regression discontinuity in time analysis to test for abrupt changes in poaching in response to dehorning (*24–26*). Staggering of dehorning by site provided multiple replicates of potential discontinuity, helping us to separate dehorning effects from potential confounders (as in *25*). To account for pre-dehorning trends in poaching, our model included terms to measure immediate changes in poaching related to dehorning, as well as any change in the average poaching trend (see ref *26* and Fig. 4B). We also confirmed that none of the other interventions changed abruptly around the point of dehorning (fig. s9).

Finally, we computed the relative risk of poaching faced by dehorned versus horned individuals at the landscape level and individual rhinos level, as well as an estimate of the cost per rhino saved from poaching (see materials and methods and Fig. 5). Dehorning was conducted by a specialised veterinarian and an operational team, and involved sedation of the rhino, painless removal of both horns above the growth plate using a chainsaw, followed by an antidote. Maintenance dehorning was carried out whereby all rhinos were repeatedly dehorned at ~18-month intervals, due to the rate of horn regrowth (fig. S11). Research, though nascent, suggests limited effects of dehorning on rhino ecology, behaviour and reproduction (*27–30*).

Our approach: In our baseline all-intervention model, we tested for empirical associations between poaching rates and 11 anti-poaching interventions across 11 reserves and over 5 years (2017-2021). We then conducted a dehorning-focussed quasi-experimental regression discontinuity analysis to test for any abrupt changes in poaching in response to dehorning, using a wider period of data (2017-2023).

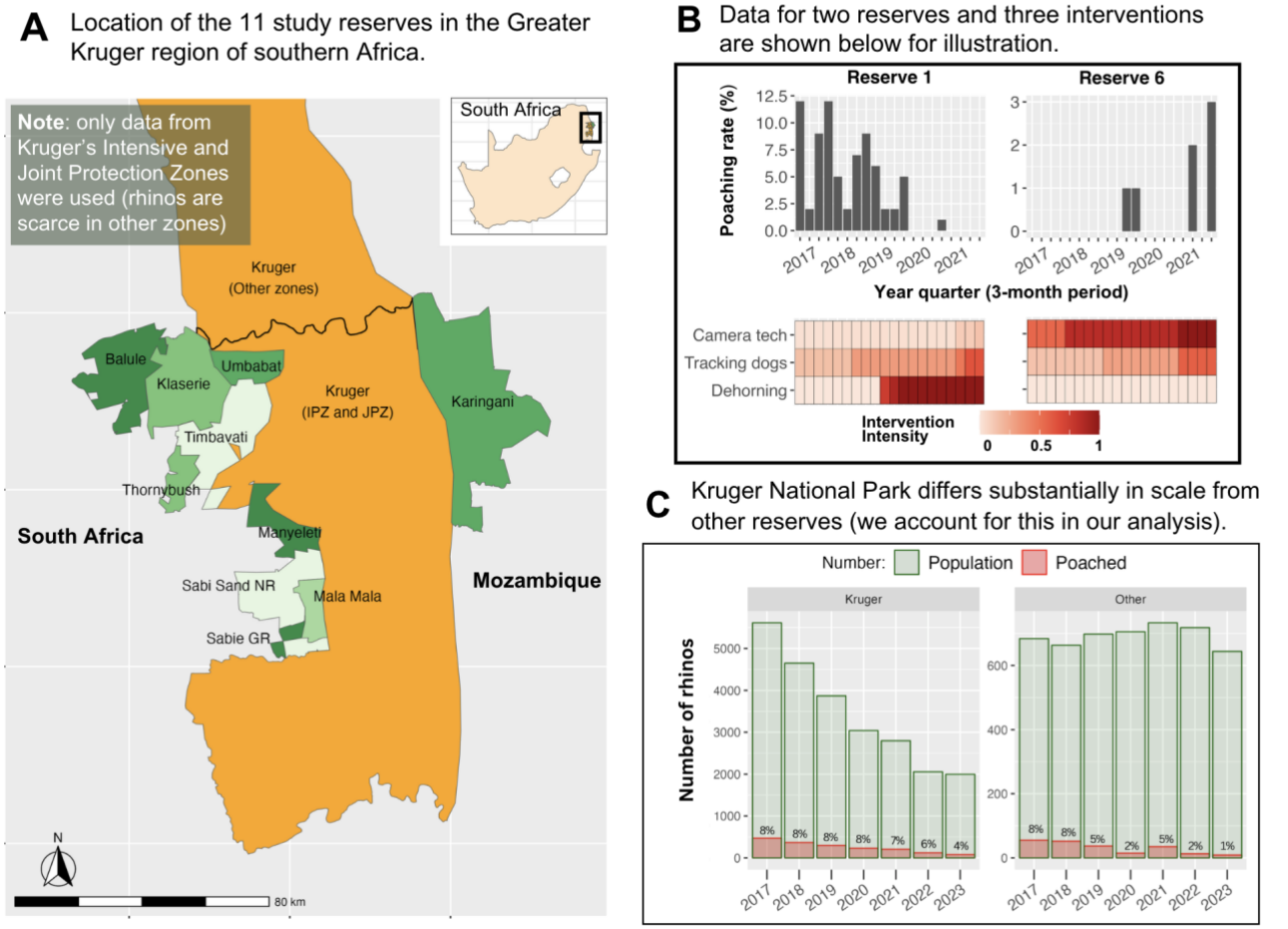


Figure 1. Overview of study area and analysis. A: We collated detailed quarterly data on poaching and interventions for eleven reserves from 2017-2021 (shades of green used to distinguish reserves visually). For Kruger National Park (Kruger NP, orange), we included data from the Intensive and Joint Protection Zones where, outside of which rhinos are scarce (IPZ and JPZ). The system has outer fences, but there is free movement of rhinos between reserves. The state manages Kruger NP and Manyeleti Game Reserve (GR), while the other nine reserves are privately managed. Mozambique borders Kruger NP in the east. Given the unique size and context of Kruger NP, we conducted analyses with and without Kruger NP (see materials and methods). **B:** Poaching rates and intensity of interventions varied across the reserves. **C:** Kruger NP experienced large rhino population declines over the study period, contrasted with stable populations on aggregate in the other ten reserves, despite similar poaching levels in earlier years. **D:** Overall costs per intervention across all reserves and years. Data were missing for a minority of intervention costs; hence the estimate is a minimum.

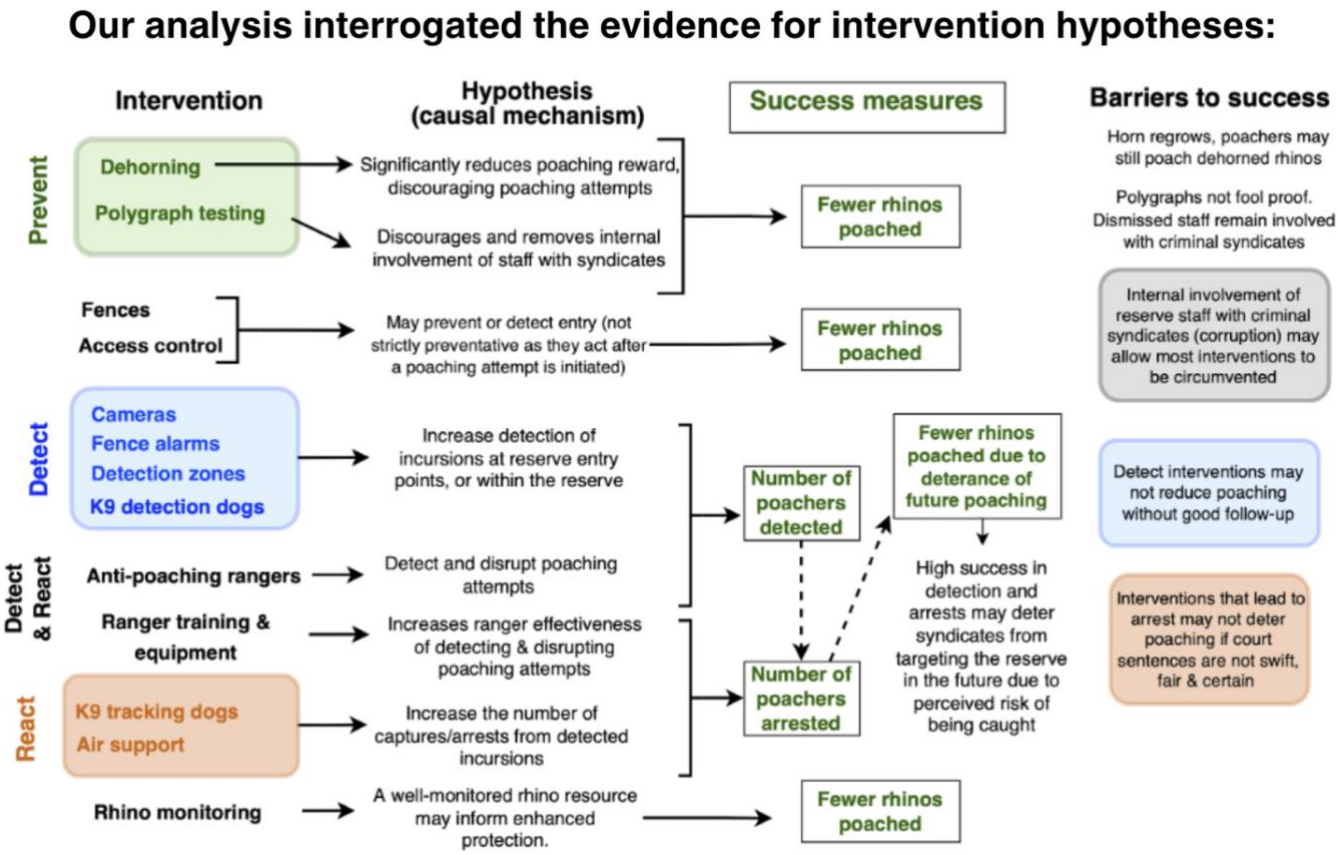


Figure 2. Hypothesised causal pathways as to how the different categories of interventions act to reduce rhino poaching, including potential barriers to success. This conceptual model was developed from workshops and interviews with reserve managers and other experts. The statistical model served to test the strength of evidence for these hypotheses. Interventions were classed into three groups based on their approach: (1) *Preventative interventions* are designed to stop poaching incursions before they happen; (2) *Detect interventions* are designed to detect poacher incursions into a reserve; and (3) *React interventions* are designed to react to detected incursions and help track, capture, and arrest poachers.

Results

Intervention implementation and cost

Across the eleven Greater Kruger reserves between 2017 and 2023, the horns of 2,284 rhinos were pro-actively removed (dehorning), 671 cameras of seven different types were installed to detect poachers, 5,562 polygraph tests were conducted (with 129 staff dismissed following the failure of a test), 45 detection dogs were deployed at reserve access points, 47 tracking dogs were deployed within reserves, 1,150km of detection zones were maintained and checked (roads or rivers checked for poacher footprints), and over 500 anti-poaching rangers were deployed at any one time.

To illustrate the complex environment in which interventions are implemented, and the strategies used by poachers to circumvent them, see Box S1 (supplementary material) for a description of how several interventions acted in concert to achieve the arrest of a core member of a poaching syndicate. An estimated minimum of USD 74 million (using the mid-2019 spot rate of 14.4 ZAR to 1 USD) was spent on interventions related to rhino protection across all reserves in the period 2017-2021 (Fig. 3D; cost data were not available for 2022 and 2023). This equated to an estimated USD 3,120 spent per

resident rhino per year. Across all reserves and years, higher total expenditure on interventions was weakly correlated with lower poaching rates (fig. S20).

Dehorning was associated with large and abrupt reductions in poaching

In our baseline all-intervention model, we found strong statistical evidence that dehorning reduced poaching (Fig. 3). On average, dehorning all rhinos present on a reserve reduced poaching by ~75% from pre-dehorning levels (95% credible interval: 57% to 87% reduction), having accounted for other interventions and random effects (Fig. 3B). Poacher incursions were also significantly lower after dehorning (fig. S24), supporting the hypothesis that poachers make fewer attempts to enter reserves with dehorned rhinos due to the perception of a significantly reduced reward from poaching (Fig. 2; fig. S1). Conclusions were the same (no significant intervention effects apart from dehorning) for supplementary models with flat Bayesian priors (fig. S2), excluding Kruger NP data (fig. S26), using the raw number of rhinos poached instead of the poaching rate (fig. S27), using bias-corrected population estimates (fig. S28), with combinations of intervention variables (fig. S29), and with lagged intervention effects (fig. S30).

For the seven reserves that implemented abrupt dehorning, we found strong evidence for a simultaneous and abrupt reduction in poaching as well as a change in the poaching trend (Fig. 4; Bayesian regression discontinuity effects exclude zero: Table S1). The estimated reduction in poaching for the regression discontinuity model was 78% (95% credible interval: 38-92%; Table S1). Given the different times at which dehorning was introduced on each reserve (two in early 2019, two in late 2019, and three in mid-2022) it is unlikely that some unmeasured factor could have explained these effects (*29*). Furthermore, any abrupt change in the other interventions around the dehorning event was ruled out as a possible explanation for the abrupt change in poaching (fig. S9).

Using data across all reserves and years, we estimated a 13% risk of an individual horned rhino being poached in a particular year, compared to 0.6% poaching risk for a dehorned rhino, representing a 95% reduction in relative poaching risk (Fig. 5A). Risk was also reduced at the landscape level, with higher annual levels of dehorning at the landscape level (all eleven reserves) associated with reduced poaching rates overall (Fig. 5B and fig. S22). Thus, while dehorning on one reserve may have displaced poaching pressure to others, overall poaching rates in the system did decline. By making several simplifying assumptions, we estimate that a total of between 70 and 134 rhinos were saved from poaching in the 12 months after dehorning across the eight implementing reserves, at a median cost of USD 7,133 per rhino saved (Table S2). Dehorning was also the most cost-efficient intervention (USD 570 per rhino operation), using ~1.2% of the USD 74 million total expenditure to achieve large reductions in poaching (Fig. 3, fig. S20 and S21).

Despite these strong effects, we recorded the poaching of 111 previously dehorned rhino, 107 of which were poached within Kruger NP in 2022-2023 (fig. S23). During these two years, only 50-55% of rhinos on Kruger had been dehorned in the previous 18 months, on average, and horned and dehorned rhinos were poached at similar rates (fig. S23). Evidently, while the overall poaching rate within Kruger NP declined from 7.5% to 3.4% after dehorning (Fig. 4; see Reserve 3), criminal syndicates remained willing to poach dehorned rhinos there at fairly high rates. A sizeable proportion of horn mass remains on the rhino after dehorning as veterinarians are only able to cut the horn up to the growth plate, leaving 5-15cm of basal horn length behind depending on the rhino's age (data from field measurements during dehorning operations). The specific targeting of Kruger might be explained by lower coverage and frequency of dehorning (fig. S23) and the comparatively easy access to the reserve from Mozambique, where poaching syndicates may be more willing to poach dehorned rhino and less

able to shift operations elsewhere (compared to South African syndicates). The effective rate and frequency of dehorning was also lower on Kruger (fig. S23).

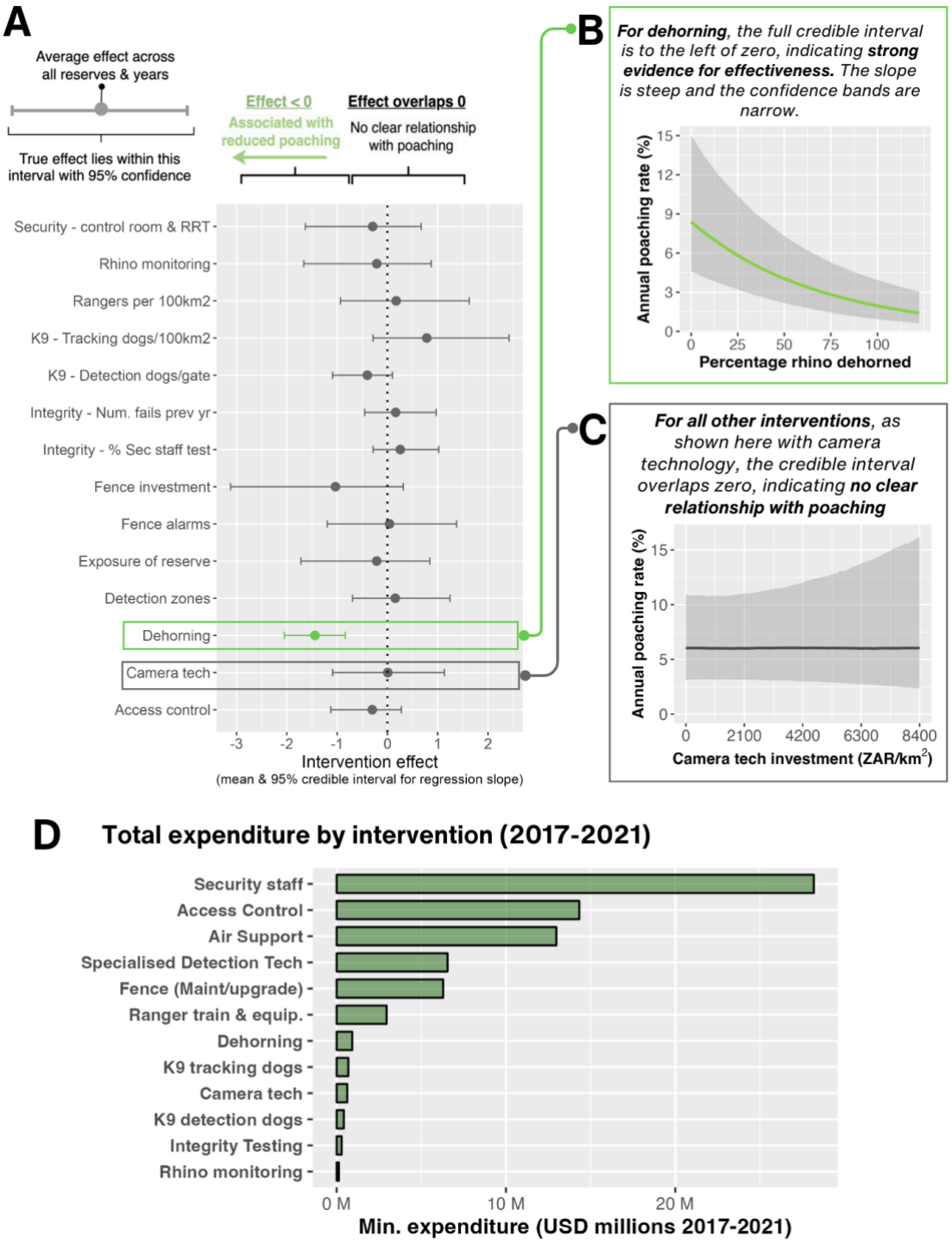


Figure 3. The effectiveness and cost of anti-poaching interventions. A: Effectiveness was measured as the slope of the relationship between the intensity of each intervention and the poaching rate, in a statistical model including all interventions together and with random effects to account for unmeasured confounding factors (see materials and methods). All intervention indices are standardised to the 0-1 scale to allow direct comparison. Some intervention indices were correlated, so the effects of ranger training and equipment, and tracking technology are shown in fig. S25. **B and C:** Conditional effects plots for the effect of dehorning and camera technology, respectively, having accounted for all other interventions and random effects.

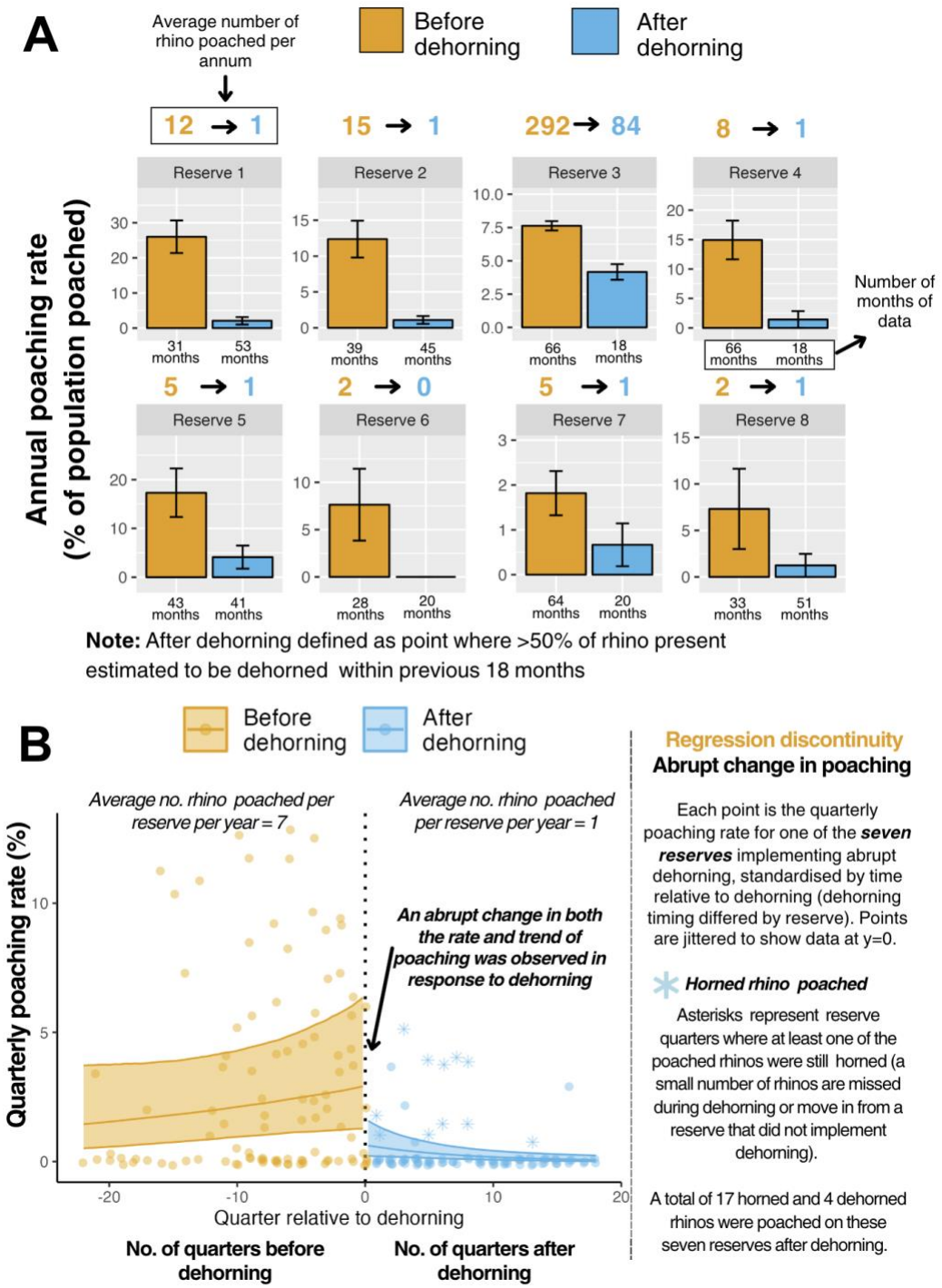


Figure 4. Dehorning associated with abrupt and significant reductions in poaching. **A:** Annual poaching rates before and after dehorning for the eight reserves implementing dehorning (mean ± SE). All these reserves implemented abrupt dehorning except Kruger NP (Reserve 3). **B:** Rhino poaching rates before and after dehorning, with data from the seven reserves implementing abrupt dehorning standardised by the year quarter relative to dehorning (dehorning was staggered across these reserves between 2019 and 2022, see materials and methods). The blue asterisks indicates that at least one of the rhinos poached on a particular reserve in a particular quarter was still horned (missed during dehorning or moving in from a reserve that had not dehorned its rhinos). Trend lines and discontinuity estimates are from the Bayesian regression discontinuity in time model that tested for an immediate dehorning effect as well as a change in the poaching trend (see materials and methods and Table S1).

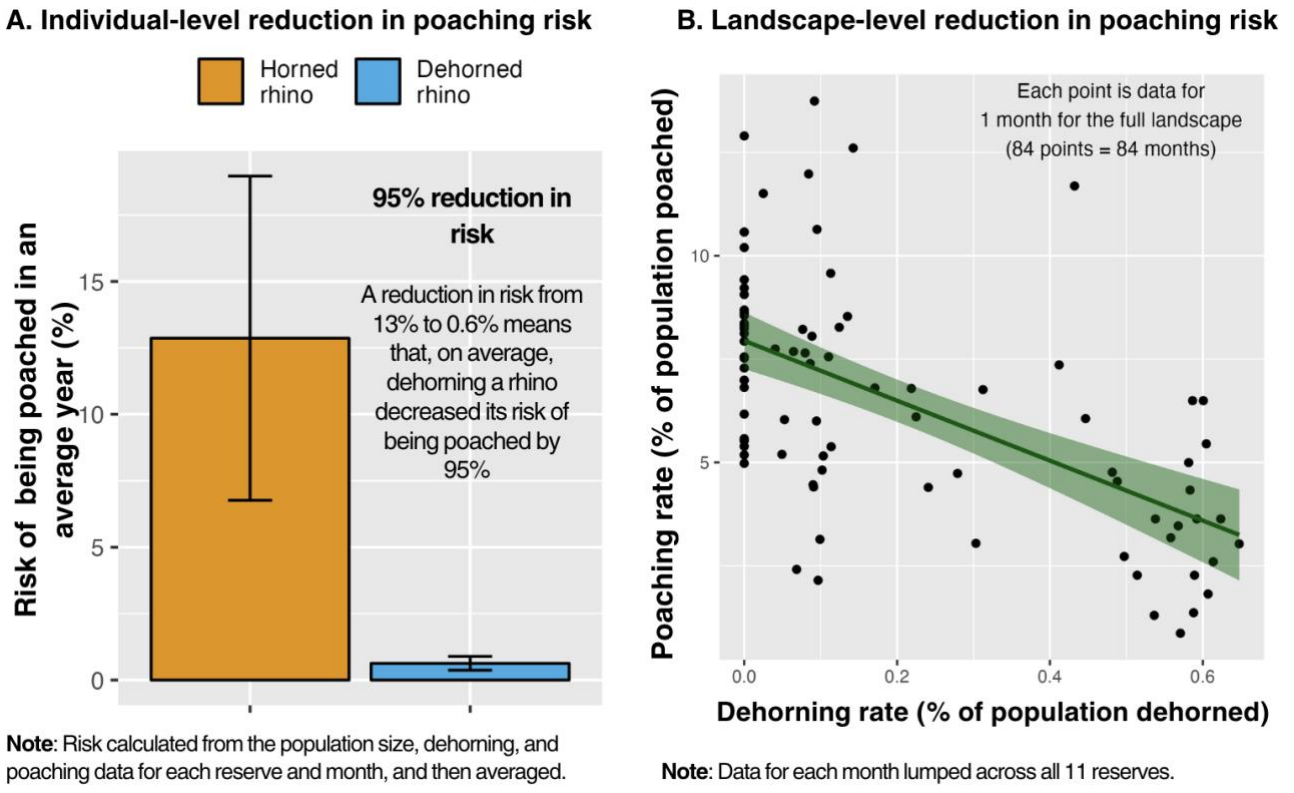


Figure 5. A. Risk ratios for dehorning effectiveness. Risk ratios compare the poaching rate of horned versus dehorned rhino, using data across all reserves and months (see materials and methods). **B.** the relationship between the monthly poaching and dehorning rate across 2017-2023 (84 months; data lumped across reserves).

Law enforcement interventions show less direct success

Apart from dehorning, the credible intervals for the effects of the other ten interventions overlapped zero, suggesting that greater intensity of these interventions was not associated with any significant change in poaching across the study (Fig. 3A and C). However, these results do not necessarily imply that the other interventions were ineffective. The credible intervals for all interventions are plausibly consistent with a positive effect, and the inconclusive results may reflect low power to detect impacts from a real-world data-sparse system in which interventions were implemented in a non-experimental way that did follow a strong experimental design. Many interventions were successful on their own terms, being associated with increased rates of poacher detection and arrest, sometimes prior to the poaching event (Fig. S31), even if this did not, on aggregate, translate to a significant effect across reserves. Detection cameras equipped with artificial intelligence detected numerous poachers, tracking dogs (K9) and air support helped track and arrest several hundred poachers, and polygraph testing led to the dismissal of 129 staff members after test failures suggested collusion with criminal syndicates (Fig. S31).

Discussion

Our results bring into sharp focus the limitations of reactive approaches to rhino poaching when poachers have already entered reserves. Interventions that work to aid poacher detection and arrest, while a necessary element of the anti-poaching toolkit, are compromised by several systemic factors that may dampen their effectiveness (Fig. 2). First, ongoing socio-economic inequality incentivises a large pool of vulnerable and motivated people to join, or poach for, criminal syndicates even when the risks are high (*4*, *9*). Second, entrenched corruption (among police, reserve staff and in the courts) allows offenders to circumvent many anti-poaching efforts, significantly compromising their deterrent value (*18*, *20*). Third, ineffective criminal justice systems mean that arrested offenders often escape punishment, with evidence from our study area of multiple repeat offenders (*4*). The fact that these conditions are by no means unique to our study area broadens the significance of our work (*31*, *32*).

Reactive approaches also raise inevitable human rights concerns, as apprehending armed poachers in the field carries a high risk of either rangers or poachers losing their lives (*33*). Addressing the socio-economic vulnerability of local communities, which allow syndicates to access a pool of poachers, is another critical strategic priority (requiring long-term collaborative efforts by government, civil society, and the private sector; *30*).

Dehorning was the only intervention for which we found strong evidence for effectiveness. Interventions that unambiguously reduce the revenues from poaching (such as dehorning) may be more robust to contextual complexity than interventions that act via actual or perceived costs and risks of poaching (*9*, *12–14*, *20;* and see Fig. 2). Our results align with work in behavioural economics, which suggest people respond more to outcomes that are more certain (a clear and substantial reduction in reward, such as through dehorning) than to those that are less certain (poacher detection, arrest and sentencing are all subject to high uncertainty) (*13*, *14*). Dehorning is also an example of a more general approach in situational crime prevention - that of reducing opportunities for crime by rendering it less rewarding, an approach with many analogues in the prevention of more traditional crimes (*37*, *38*). Another likely reason for the effectiveness of dehorning is that it is less easily thwarted by internal corruption. While cameras, dogs and rangers can be avoided by poachers with internal information, dehorning cannot.

While the removal of valuable body parts to reduce poaching is often not possible for other species threatened by the illegal wildlife trade, the broader approach of reducing opportunities for and rewards from poaching (as opposed to increasing risk) is generalisable. Researchers in Venezuela, for example, found that removing parrot nestlings from nests into safer areas at night and returning them in the morning led to large reductions in poaching (*35*). In Cape Town, conservationists paint indigenous trees to discourage illegal debarking for medicinal trade (*36*).

Our results make a strong case for dehorning as a strategy to reduce poaching, yet there are several caveats. First, dehorned rhinos were occasionally poached (particularly those with significant regrowth). Second, dehorning in the Greater Kruger may have displaced poaching pressure to horned populations elsewhere (with some evidence of a shift to the second largest stronghold for South African rhinos, namely Hluhluwe-iMfolozi Park; *35*). It remains to be seen whether dehorning would be as effective in the absence of horned populations elsewhere accessible to criminal syndicates. If dehorning had taken place in the total absence of other interventions, poaching for the stumps and regrowth would probably have continued given the lack of risk to poachers. It follows that the effective implementation of a suite of other interventions is probably necessary to ensure the ongoing effectiveness of dehorning, whether in our study system or elsewhere. Finally, effects of dehorning on

rhino biology are still unclear, with current research suggesting that dehorning may alter rhino space use, but not survival and reproduction (*27–30*)

Our results present a challenge to governments, funders, the private sector and NGOs to re- reassess their strategic approaches to wildlife crime in general and rhino poaching in particular. While detecting and arresting poachers is essential, strategies that focus on reducing opportunities for and rewards from poaching may be more effective. Demand reduction, by reducing the price of wildlife products, is one such strategy (*40*). Similarly, efforts to support the socio-economic resilience of local people may help create viable economic alternatives that render rewards from poaching less attractive (*34*). For practice and policy in global rhino conservation, our work makes a strong case for dehorning as a tool that may achieve large and immediate reductions in poaching in cases where law enforcement has not yielded the desired level of poacher deterrence. Yet the fact that poaching of dehorned rhinos continued at fairly high rates on Kruger National Parks suggests that horn stumps and regrowth remain attractive to criminal syndicates, pointing to the need for regular dehorning and ongoing prudent use of law enforcement.

Finally, our work is an example of both the value and difficulty of impact evaluation in conservation science and practice. We demonstrate how combining multiple lines of evidence (qualitative attribution methods through workshops and interviews, tailored statistical models, and quasi-experimental approaches) can help reduce uncertainty in the attribution of biodiversity outcomes to specific policies or interventions in messy contexts. Our work is also an example of a situation in which conservation practitioners reached out to scientists for support in addressing a perceived problem, rather than the scientists coming to an area with a question that may or may not be one of interest to local practitioners. This flipping of the scientist-practitioner relationship and the direction of knowledge exchange is still unusual (but see ref *41* for another example). Where possible, to maximise future learning and adaptation, we suggest that scientists and conservation practitioners co-design research that seeks to actively evaluate interventions in a more explicitly experimental way, the lack of which was a limitation of this current study.

References

1. J. A. J. Eikelboom, H. H. T. Prins, Poaching pressure on African rhinos is still at an all-time high. *Science Advances* **10**, eadl1482 (2024).

2. CITES, “Working document 75 for CoP19 of the Convention on the International Trade in Endangered Species: RHINOCEROSES (RHINOCEROTIDAE SPP.)” (2022); https://www.nature.com/articles/s41562-021-01267-6.

3. B. A. Lubbe, E. A. du Preez, A. Douglas, F. Fairer-Wessels, The impact of rhino poaching on tourist experiences and future visitation to National Parks in South Africa. *Current Issues in Tourism* **22**, 8–15 (2019).

4. Rademeyer, “Landscape of fear: Crime, corruption and murder in greater Kruger” (36, ENACT Africa Report, 2023); https://enactafrica.org/research/research-papers/landscape-of-fear-crime-corruption-and-murder-in-greater-kruger.

5. J. P. G. M. Cromsigt, M. te Beest, Restoration of a megaherbivore: landscape-level impacts of white rhinoceros in Kruger National Park, South Africa. *Journal of Ecology* **102**, 566–575 (2014).

6. M. Belecky, R. Singh, W. D. Moreto, Life on the frontline 2019: A global survey of the working conditions of rangers. *WWF report*, 1–70 (2019).

7. S. M. Ferreira, L. Dziba, Rhinoceros accounting in Kruger National Park, South Africa. *Journal for Nature Conservation* **72**, 126359 (2023).

8. S. M. Ferreira, C. Greaver, C. Simms, L. Dziba, The Impact of COVID-19 Government Responses on Rhinoceroses in Kruger National Park. *African Journal of Wildlife Research* **51**, 100–110 (2021).

9. A. M. Hübschle, The social economy of rhino poaching: Of economic freedom fighters, professional hunters and marginalized local people. *Current Sociology* **65**, 427–447 (2017).

10. G. S. Becker, Crime and Punishment: An Economic Approach. *Journal of Political Economy* **76**, 169–217 (1968).

11. E. H. Bulte, G. C. van Kooten, Economics of Antipoaching Enforcement and the Ivory Trade Ban. *American Journal of Agricultural Economics* **81**, 453–466 (1999).

12. E. . J. . Milner-Gulland, N. . Leader-Williams, A Model of Incentives for the Illegal Exploitation of Black Rhinos and Elephants : Poaching Pays in Luangwa Valley , Zambia. *Journal of Applied Ecology* **29**, 388–401 (1992).

13. M. Siegrist, J. Árvai, Risk Perception: Reflections on 40 Years of Research. *Risk Analysis* **40**, 2191–2206 (2020).

14. D. Kahneman, A. Tversky', Prospect Theory: An Analysis of Decision under Risk. *Econometrica* (1979).

15. D. W. S. Challender, D. C. MacMillan, Poaching is more than an enforcement problem. *Conservation Letters* **7** (2014).

16. World Bank, Analysis of international funding to tackle illegal wildlife trade. (2016).

17. F. Masse, J. Margulies, The geopolitical ecology of conservation: The emergence of illegal wildlife trade as national security interest and the re-shaping of US foreign conservation assistance. *World Development* **132**, 104958 (2020).

18. T. Kuiper, R. Altwegg, C. Beale, T. Carroll, H. T. Dublin, S. Hauenstein, M. Kshatriya, C. Schwarz, C. R. Thouless, A. Royle, E. J. Milner-Gulland, Drivers and facilitators of the illegal killing of elephants across 64 African sites. *Proc. R. Soc. B.* **290**, 20222270 (2023).

19. J. H. Liew, Z. Y. Kho, R. B. H. Lim, C. Dingle, T. C. Bonebrake, Y. H. Sung, D. Dudgeon, International socioeconomic inequality drives trade patterns in the global wildlife market. *Science Advances* **7**, 1–12 (2021).

20. D. P. Van Uhm, W. D. Moreto, Corruption Within the Illegal Wildlife Trade: A Symbiotic and Antithetical Enterprise. *British Journal of Criminology* **58**, 864–885 (2018).

21. WWF, "Crime prevention and high value poaching" (2020).

22. J. Zavaleta Cheek, J. Eklund, N. Merten, J. Brooks, D. C. Miller, A guide to qualitative attribution methods for evaluation in conservation. *Conservation Biology* **37**, e14071 (2023).

23. J. Mayne, Addressing Attribution through Contribution Analysis: Using Performance Measures Sensibly. *Canadian Journal of Program Evaluation* **16**, 1–24 (2001).

24. C. Hausman, D. S. Rapson, Regression Discontinuity in Time: Considerations for Empirical Applications. *Annual Review of Resource Economics* **10**, 533–552 (2018).

25. E. G. Frank, The economic impacts of ecosystem disruptions: Costs from substituting biological pest control. *Science* **385**, eadg0344 (2024).

26. N. Huntington-Klein, *The Effect: An Introduction to Research Design and Causality | The Effect* (Chapman and Hall/CRC, 2022; https://theeffectbook.net/).

27. L. C. Chimes, P. Beytell, J. R. Muntifering, B. Kötting, V. Neville, Effects of dehorning on population productivity in four Namibia sub-populations of black rhinoceros (Diceros bicornis bicornis). *Eur J Wildl Res* **68**, 58 (2022).

28. V. Pfannerstill, R. Härdtner, O. S. Maboga, N. Balkenhol, E. Bennitt, M. Scheumann, Dehorning impacts white rhinoceros behaviour less than social events: evidence from Botswana. *Journal of Zoology* **n/a** (2023).

29. S. G. Penny, M. Withey, R. L. White, D. M. Scott, L. MacTavish, A. P. Pernetta, Changes in social dominance in a group of subadult white rhinoceroses (Ceratotherium simum) after dehorning. *African Zoology* **57**, 32–42 (2022).

30. V. Duthé, K. Odendaal, R. Van der Westhuizen, B. Church, S. Naylor, S. Boshoff, M. Venter, M. Prinsloo, P. Ngwenya, C. Hanekom, C. P. Kelly, T. W. N. Walker, S. Rasmann, E. Defossez, Reductions in home-range size and social interactions among dehorned black rhinoceroses (*Diceros bicornis*). *Proceedings of the National Academy of Sciences* **120**, e2301727120 (2023).

31. M. t'Sas-Rolfes, D. W. S. Challender, A. Hinsley, D. Veríssimo, E. J. Milner-Gulland, Illegal Wildlife Trade: Scale, Processes, and Governance. *Annual Review of Environment and Resources* **44**, 201–228 (2019).

32. V. Felbab-Brown, *The Extinction Market: Wildlife Trafficking and How to Counter It* (Oxford University Press, 2017).

33. C. Galliers, R. Cole, R. Singh, J. Ohlfs, H. Aisha, A. Benoit Koutoua, C. Roodt, M. Á. Malvido, Conservation casualties: an analysis of on-duty ranger fatalities (2006-2021). *PARKS* **28**, 39 (2022).

34. R. Cooney, D. Roe, H. Dublin, J. Phelps, D. Wilkie, A. Keane, H. Travers, D. Skinner, D. W. S. Challender, From Poachers to Protectors: Engaging Local Communities in Solutions to Illegal Wildlife Trade. *Conservation letter*, doi: 10.1111/conl.12294 (2016).

35. J. M. Briceño-Linares, J. P. Rodríguez, K. M. Rodríguez-Clark, F. Rojas-Suárez, P. A. Millán, E. G. Vittori, M. Carrasco-Muñoz, Adapting to changing poaching intensity of yellow-shouldered parrot (Amazona barbadensis) nestlings in Margarita Island, Venezuela. *Biological Conservation* **144**, 1188–1193 (2011).

36. Pinnock, Don, A conversation with the man who paints trees to combat bark stripping, *Daily Maverick*. https://www.dailymaverick.co.za/article/2024-02-25-meet-the-man-who-paints-trees-to-combat-bark-stripping/.

37. A. Lemieux, *Situational Prevention of Poaching* (Taylor & Francis, 2014).

38. P. L. Brantingham, P. J. Brantingham, Environment, routine and situation: Toward a pattern theory of crime. *Advances in criminological theory* **5**, 259–294 (1993).

39. South African Government, South African Government Media Briefing Progress in fight against rhino poaching, 1 Aug (2023). https://www.gov.za/news/media-advisories/media-briefings/minister-barbara-creecy-outlines-progress-fight-against-rhino.

40. A. Olmedo, V. Sharif, E. J. Milner-Gulland, Evaluating the Design of Behaviour Change Interventions: A Case Study of Rhino Horn in Vietnam. *Conservation Letters*, doi: 10.1111/conl.12365 (2017).

41. J. Aini, P. West, Y. Amepou, M. L. Piskaut, C. Gasot, R. S. James, J. S. Roberts, P. Nason, A. E. Brachey, Reimagining conservation practice: Indigenous self-determination and collaboration in Papua New Guinea. *Oryx* **57**, 350–359 (2023).

42. Z. Kidwai, J. Jimenez, C. J. Louw, H. P. Nel, J. P. Marshal, Using N-mixture models to estimate abundance and temporal trends of black rhinoceros (Diceros bicornis L.) populations from aerial counts. *Global Ecology and Conservation* **19**, e00687 (2019).

43. American Sociological Association, "Code of Ethics" (2008); https://www.asanet.org/wp-content/uploads/savvy/images/asa/docs/pdf/CodeofEthics.pdf.

44. M. Norton-Griffiths, Counting animals. Handbooks on techniques currently used in African wildlife ecology. *African Wildlife Leadership Foundation, Nairobi* (1978).

45. G. Jolly, Sampling Methods for Aerial Censuses of Wildlife Populations. *East African Agricultural and Forestry Journal:* (1969).

46. G. Seber, *The Estimation of Animal Abundance and Related Parameters*, (Blackburn Pres, 2nd edition., 2002).

47. S. M. Ferreira, E. T. Crowhurst, C. Greaver, C. Simms, Resizing Kruger National Park: Trends in numbers of rhinoceroses within priority zones. *Koedoe* **66**, 9 (2024).

48. C. F. Dormann, J. Elith, S. Lautenbach, C. McClean, S. Bacher, A. K. Skidmore, C. Buchmann, B. Schröder, B. Reineking, P. E. Osborne, B. Gruber, D. Zurell, P. J. Leitão, G. Carl, B. Lafourcade, T. Münkemüller, G. Carré, J. R. G. Marquéz, Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* **36**, 27–46 (2012).

49. P.-C. Bürkner, **brms** : An *R* Package for Bayesian Multilevel Models Using *Stan*. *J. Stat. Soft.* **80** (2017).

50. C. M. Carvalho, N. G. Polson, J. G. Scott, "Handling Sparsity via the Horseshoe" in *Proceedings of the Twelth International Conference on Artificial Intelligence and Statistics* (PMLR, 2009; https://proceedings.mlr.press/v5/carvalho09a.html), pp. 73–80.

51. A. T. Tredennick, G. Hooker, S. P. Ellner, P. B. Adler, A practical guide to selecting models for exploration, inference, and prediction in ecology. *Ecology* **102** (2021).

52. R. Tibshirani, Regression Shrinkage and Selection via the Lasso. *Journal of the Royal Statistical Society, Series B (Methodogical)*, **58**, 267–288 (1996).

53. A. Gelman, J. Hill, *Data Analysis Using Regression and Multilevel/Hierarchical Models* (Cambridge university press, 2006).

54. P. Moraga, *Spatial Statistics for Data Science: Theory and Practice with R* (Routeledge, 2023; https://www.routledge.com/Spatial-Statistics-for-Data-Science-Theory-and-Practice-with-R/Moraga/p/book/9781032633510).

55. T. Kuiper. Supplementary Materials and Replication Folder for Kuiper et al. (2025), R code, Zenodo (2025); https://doi.org/ 10.5281/zenodo.15098035

Acknowledgements

The Greater Kruger reserve managers contributed hundreds of hours of combined time helping to design this project, consolidating the data required, and providing critical insight and experience to help interpret and contextualise the results. The steering committee provided expert oversight and much-needed direction to this project. The data collectors patiently and persistently tackled the mammoth task of gathering standardised data over countless reserve visits.

Funding: Grants from the Rhino Recovery Fund (part of the Wildlife Conservation Network, and the World Wildlife Fund South Africa Grant made this project possible. E.J.M.-G. acknowledges funding from the UK Research and Innovation's Global Challenges Research Fund (UKRI GCRF) through the Trade, Development, and the Environment Hub project (project number ES/S008160/1). T.K. is currently supported by a Postdoctoral Fellowship at the University of Cape Town, funded by the National Research Foundation in South Africa

Author contributions: T.K.: conceptualization, data curation, formal analysis, investigation, methodology, writing—original draft, writing—review and editing; S.H.: conceptualization, funding acquisition, project administration, resources, investigation, methodology, writing—review and editing; S.W.: conceptualization, funding acquisition, resources, investigation, methodology, writing—review and editing; C.D: conceptualization, investigation, methodology, writing—review and editing; M.H.: conceptualization, investigation, methodology, writing—review and editing; D.P.: conceptualization, investigation, methodology, formal analysis, writing—review and editing; J.S: conceptualization, funding acquisition, project administration, resources, investigation, methodology, writing—review and editing; S.F. conceptualization, investigation, methodology, writing—review and editing; J.B: conceptualization, investigation, methodology, writing—review and editing; M.B.: conceptualization, investigation, methodology, writing—review and editing; W.B.: conceptualization, investigation, methodology, writing—review and editing; Z.G.: investigation, methodology, data curation, , writing—review and editing; Z.H.: investigation, methodology, data curation; K.L.: investigation, methodology, data curation, , writing—review and editing; IN: conceptualization, investigation, methodology, writing—review and editing; I.O.: conceptualization, investigation, methodology, writing—review and editing; E.P.: conceptualization, investigation, methodology, writing—review and editing; C.L.: conceptualization, investigation, methodology, writing—review and editing; M.V.T: conceptualization, investigation, methodology, writing—review and editing; E.W.: conceptualization, investigation, methodology, writing—review and editing H.Z.:

conceptualization, investigation, methodology, writing—review and editing; SS: conceptualization, investigation, methodology, writing—review and editing; R.A: conceptualization, formal analysis, investigation, methodology, writing—review and editing; E.J.M.-G: methodology, validation, writing—review and editing; R.A: formal analysis, investigation, methodology, writing—original draft., writing—review and editing.

Competing interests: Authors declare that they have no competing interests

Data and materials availability: Given the sensitivity of the rhino poaching and intervention data, it is protected by a data sharing agreement. Queries related to data access can be directed to the Greater Kruger Environmental Protection Foundation info@gkepf.org. The R statistical programming code for reproducing the baseline all intervention model as well as the regression discontinuity model is available on Zenodo with the following DOI: 10.5281/zenodo.15098035 (see ref 55).

Supplementary Materials

Box S1
Tables S1and S2
Materials and Methods
Figs. S1 to S31
References

Figure 1. Overview of study area and analysis. A: We collated detailed quarterly data on poaching and interventions for eleven reserves from 2017-2021 (shades of green used to distinguish reserves visually). For Kruger National Park (Kruger NP, orange), we included data from the Intensive and Joint Protection Zones where, outside of which rhinos are scarce (IPZ and JPZ). The system has outer fences, but there is free movement of rhinos between reserves. The state manages Kruger NP and Manyeleti Game Reserve (GR), while the other nine reserves are privately managed. Mozambique borders Kruger NP in the east. Given the unique size and context of Kruger NP, we conducted analyses with and without Kruger NP (see materials and methods). **B:** Poaching rates and intensity of interventions varied across the reserves. **C:** Kruger NP experienced large rhino population declines over the study period, contrasted with stable populations on aggregate in the other ten reserves, despite similar poaching levels in earlier years. **D:** Overall costs per intervention across all reserves and years. Data were missing for a minority of intervention costs; hence the estimate is a minimum.

Figure 2. Hypothesised causal pathways as to how the different categories of interventions act to reduce rhino poaching, including potential barriers to success. This conceptual model was developed from workshops and interviews with reserve managers and other experts. The statistical model served to test the strength of evidence for these hypotheses. Interventions were classed into three groups based on their approach: (1) *Preventative interventions* are designed to stop poaching incursions before they happen; (2) *Detect interventions* are designed to detect poacher incursions into a reserve; and (3) *React interventions* are designed to react to detected incursions and help track, capture, and arrest poachers.

Figure 3. The effectiveness and cost of anti-poaching interventions. A: Effectiveness was measured as the slope of the relationship between the intensity of each intervention and the poaching rate, in a statistical model including all interventions together and with random effects to account for unmeasured confounding factors (see materials and methods). All intervention indices are standardised to the 0-1 scale to allow direct comparison. Some intervention indices were correlated, so the effects

of ranger training and equipment, and tracking technology are shown in fig. S25. **B and C:** Conditional effects plots for the effect of dehorning and camera technology, respectively, having accounted for all other interventions and random effects.

Figure 4. Dehorning associated with abrupt and significant reductions in poaching. A: Annual poaching rates before and after dehorning for the eight reserves implementing dehorning (mean $\pm$ SE). All these reserves implemented abrupt dehorning except Kruger NP (Reserve 3). **B:** Rhino poaching rates before and after dehorning, with data from the seven reserves implementing abrupt dehorning standardised by the year quarter relative to dehorning (dehorning was staggered across these reserves between 2019 and 2022, see materials and methods). The blue asterisks indicates that at least one of the rhinos poached on a particular reserve in a particular quarter was still horned (missed during dehorning or moving in from a reserve that had not dehorned its rhinos). Trend lines and discontinuity estimates are from the Bayesian regression discontinuity in time model that tested for an immediate dehorning effect as well as a change in the poaching trend (see materials and methods and Table S1).

Figure 5. A. Risk ratios for dehorning effectiveness. Risk ratios compare the poaching rate of horned versus dehorned rhino, using data across all reserves and months (see materials and methods). **B.** the relationship between the monthly poaching and dehorning rate across 2017-2023 (84 months; data lumped across reserves).



Supplementary Materials for

Dehorning reduces rhino poaching

Timothy Kuiper[1,2,*], Sharon Haussmann[3], Steven Whitfield[4] , Daniel Polakow[5], Cathy Dreyer[4], Sam Ferreira[4], Markus Hofmeyr[6], Jo Shaw[7], Jed Bird[8], Mark Bourn[9], Wayne Boyd[10], Zianca Greef[3], Zala Hartmann[3], Kim Lester[11], Ian Nowak[12], Iain Olivier[11], Edwin Pierce[13], Colin Rowles[14], Sandra Snyman[4], Martin van Tonder[15], Ellery Worth[16], Hannes Zowitsky[17], E.J. Milner-Gulland[2] and Res Altwegg[2]

*Corresponding author: timothykuiper@gmail.com

The PDF file includes:

Box S1
Tables S1 to S3
Materials and Methods
Figs. S1 to S31

Box S1: How the interventions worked in practice: contextualizing the empirical analyses

To complement our empirical results, this narrative of a high-level arrest of a core member of a rhino poaching syndicate in our study region illustrates the complex environment in which interventions (bold text) are implemented, and the external factors that influence intervention effectiveness. It is written by an experienced reserve manager and focuses on a single reserve.

During initial **polygraph testing** in 2018, an employee "John" (not his real name) failed his tests with regard to involvement in rhino poaching and was dismissed from the reserve. At the time he was employed in a region suffering high rates of poaching. On 5 October 2020, we received information that "John" and three others had illegally entered the reserve with the intent to kill a rhino. **Intensive rhino monitoring** revealed that there was a rhino bull with substantial regrowth (dehorned 18 months prior) in the area. At 3:50 am on 10 October 2020, we received an alert from our **AI camera network** that three individuals had been detected in the region in question. A **ranger reaction unit** which had a **tracking dog (K9)** was dispatched to perform the follow-up, by which time the rhino had been poached and its horn taken. The dog took the track immediately, and after three hours of follow up and with the support of a **helicopter** organised through the control room, contact was made with the poaching group on their way out of the reserve.

The group split into two and the decision was made to follow the group that had the bag that likely contained the horn that would be required for evidence. The helicopter hampered the movements of the primary target group while the ground team and K9 were in hot pursuit. The 'bag' group cleared the **reserve fence.** The suspect with the bag split in a different direction before he was apprehended and identified as John. Police responders opened the bag and found the horn, which later DNA tests linked the horn to the carcass found in the reserve.

The arrest of John was due to the careful adaptive management and cumulative effects of various critical interventions. It demonstrated the logic of polygraph testing, which indicated some 2 years prior to the incident that John had been involved in poaching for many years. After John's arrest, the reserve experienced a period of 1089 days without another rhino loss. However, the story does reveal the limitations of interventions. John's removal through polygraph testing did not prevent him from entering the reserve again and poaching the rhino in the above story. Also, the rhino poached had been **dehorned,** but there was significant regrowth. Finally, many similar arrests have involved suspects being released on bail only to be caught again poaching on the same or neighbouring reserve.

1
2

Table S1. Bayesian regression discontinuity results table for the effect of abrupt dehorning on poaching rates, across the seven reserves implementing abrupt dehorning. As with the all-intervention model, we used a Bayesian hierarchical regression model with random effects for year and quarter. The response variable was the number of rhinos poached (negative binomial fit), with the logarithm of population size as an offset (see materials and methods).

Parameter	**Estimate & 95% credible interval**
Quarters relative to dehorning (QRD; the running variable)	0.03 (0.02; 0.08)
Treatment variable (before/after dehorning)*	-1.53* (-2.51; -0.49)
QRD*Treatment (to test for change in slope before/after dehorning)	-0.16 (-0.28; -0.04)
Standard deviation for quarter random effect	0.21 (0.01; 0.56)
Standard deviation for reserve random effect	1.10 (0.55; 2.20)

**This equates to a median 78% reduction in the poaching rate (1- $e^{-1.53}$)*

Table S2. Estimating the number of rhinos that would have been poached in the year immediately after dehorning, across the eight implementing reserves, should dehorning not have been implemented. Model-based estimates of reduction in poaching are used for all reserves except Kruger National Park (NP) and several simplifying assumptions were made with associated uncertainty (see materials and methods).

Reserve	**Mean annual poach. rate before dehorning (A)**	**Pop. size just before dehorning (B)**	**Estimated reduction in poaching rate (C)**	**Estimated rhinos saved in year immediately after dehorning (A*B*C)**	**USD spent on dehorning[3]**	**USD per rhino saved**
1	26.5%	50	78% (38-92%)	5 (10-12)	$38,190	$7,638
2	14.7%	107	78% (38-92%)	12 (6-114)	$53,010	$4,418
3	7.6%	2054[1]	45% (32-57%)[2]	70 (50-89)	$463,980	$6,628
4	14.9%	53	78% (38-92%)	6 (3-7)	$21,660	$3,610
5	21.7%	30	78% (38-92%)	5 (2-6)	$19,950	$3,990
6	6.4%	22	78% (38-92%)	1 (1-1)	$9,690	$9,690
7	1.8%	246	78% (38-92%)	3 (2-4)	$122,550	$40,850
8	6.6%	23	78% (38-92%)	1 (1-1)	$19,380	$19,380
			Total	**108 (70-134)**	**Median**	**$7,133**

[1]Population size at the end of 2021, the year prior to widespread dehorning on Kruger NP (Reserve 3)
[2]For Reserve 3 (Kruger NP) we conservatively used the actual change in poaching rates after widespread dehorning rather than the modelled rate from the all-intervention model, which was likely an overestimate for Kruger as it continued to experience poaching of dehorned rhinos (see Materials and Methods).
[3]Actual expenditure based on the number of rhinos dehorned and a mean cost of USD 570/rhino

Table S3. Bayesian regression discontinuity results table for the effect of abrupt dehorning on poaching rates, across the seven reserves implementing abrupt dehorning, in a supplementary model in which population estimates were corrected for possible under-estimation of the rhino population size. Estimates were corrected upwards by a factor 1.245 following Kidwai et al. 2019 (see Supplementary text and ref *42*). As with the all-intervention model, we used a Bayesian hierarchical regression model with random effects for year and quarter. The response variable was the number of rhinos poached (negative binomial fit), with the logarithm of population size as an offset (see material and methods).

Parameter	**Estimate & 95% credible interval**
Quarters relative to dehorning (QRD; the running variable)	0.03 (-0.02; 0.09)
Treatment variable (before/after dehorning)*	-1.53* (-2.51; -0.49)
QRD*Treatment (to test for change in slope before/after dehorning)	-0.16 (-0.28; -0.04)
Standard deviation for quarter random effect	0.21 (0.01; 0.56)
Standard deviation for reserve random effect	1.11 (0.55; 2.18)

**This equates to a median 78% reduction in the poaching rate (1- $e^{-1.53}$)*

Materials and Methods

Quantifying the cost and effectiveness of interventions to protect rhino

We used quarterly data collected over seven years (2017-2023) from eleven wildlife reserves in the Greater Kruger Ecosystem to measure the effectiveness of dehorning alongside traditional law enforcement interventions (anti-poaching rangers, fences, security control rooms, K9 tracking dogs (K9), detection cameras, and others). To maximise insights into intervention effectiveness in the face of system complexity and the lack of explicit experimental controls, we conducted two complementary analyses:

1. **Baseline all-intervention model**: We first generated *a priori* (i.e. not based on the data used for this analysis) causal pathways behind each of the eleven anti-poaching interventions through workshops with reserve managers (see fig. S1 for our conceptual model and figs. S2 to S14 for intervention details). We then used a Bayesian regression model with spatial and temporal random effects to quantify the empirical association between poaching rates and eleven anti-poaching interventions. Finally, we quantified evidence for intermediate steps along hypothesised pathways, such as the number of poachers arrested using tracking dogs.

While informative, the baseline model was limited by the non-random application of multiple interventions that overlapped inconsistently in space and time, motivating a dehorning-focussed model.

2. **Dehorning-focussed analyses:** Seven reserves implemented dehorning abruptly (dehorning almost all rhinos present within 1-2 months; Fig. S5), allowing us to strengthen causal inference through a regression discontinuity in time analysis to identify discontinuous/abrupt changes in poaching in response to dehorning (*24*)). The staggered implementation of dehorning across reserves (two in early 2019, two in late 2019, and three in mid-2022) provided multiple replicates of potential discontinuity, helping us to separate any dehorning effects from other potential confounders that changed at the same time as dehorning. Finally, we computed the relative risk of poaching faced by dehorned versus horned rhinos at the landscape level (dehorned rhinos were poached in small numbers).

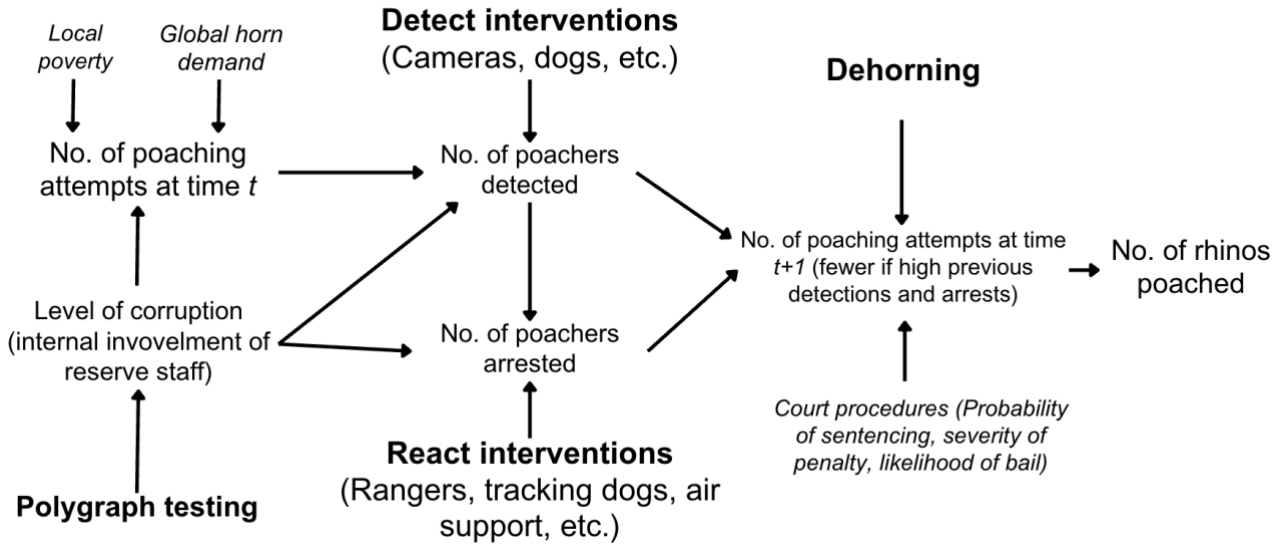


Figure S1. Directed Acyclic Graph with time step: Indicating assumptions about causal relationships between interventions (**bold**) and poaching outcomes (intermediate and final). Sources of exogenous variation are shown in *italics* (these affect poaching attempts at time t and t+1). Detect and react interventions are contingent on each other in achieving fewer poaching attempts. Corruption provides poachers with information to help them circumvent detect and react interventions.

Four-stages for the all-intervention baseline model

Central to our approach was the combination of (a) empirical analyses to quantify intervention effectiveness by statistically related poaching rates to intervention intensity, and (b) qualitative insight and attribution methods via interviews and workshops to better understand how and under which conditions interventions work or do not work as intended. This interdisciplinary approach was designed to reduce uncertainty in the attribution of changes in poaching to specific interventions, in the absence of randomised experimental data. Specifically, we used two well-established qualitative attribution methods: process tracing and contribution analysis (*22*, *23*) across four stages:

Stages 1 and 2 were facilitated through 15 workshops and 11 individual interviews with reserve managers and other expert stakeholders and focussed on:

1. Measuring intervention intensity and poaching rates: for each intervention, participants identified key variables to quantify the intensity of application of each intervention, standardised across reserves and years. Participants also decided how and at what scale variation in poaching would be measured.
2. Clarifying hypotheses linking interventions to poaching rates*:* Participants discussed and clarified the causal pathways for how interventions are meant to work to reduce poaching rates, including intermediate mechanisms. Participants helped categorise interventions into three classes based on their function (prevent, detect, react) and identified possible barriers to success (fig S1).

Stage 3 was the core empirical element of the work, the statistical analysis:

3. Empirical support for intervention mechanisms*:* Our statistical analysis was designed to test the level of empirical support for each of these assumed causal pathways, including evidence

for intermediate steps along pathways, such as the number of poacher arrests achieved using K9 tracking dogs. We used a tailored statistical approach to tease apart the contributions of overlapping interventions to variation in poaching rates. We used spatial (reserve identity) and temporal (three-month "quarters") random effects to help account for unmeasured confounders such as background trends in poaching and differences in baseline vulnerability among reserves. We fitted the model using a Bayesian framework (see the statistical analyses section below for more details).

Stage 4 sought to ensure robust interpretation of statistical results through additional workshops:

4. Evaluation of results considering feasible alternative explanations*:* Four separate workshops were held to critically interrogate and interpret results. Participants included two project statisticians, an independent scientist, three experts from non-governmental organisations working in rhino conservation in the landscape, three senior practitioners involved in counter-poaching in the region, and 16 reserve managers. The focus of these workshops was evaluating the degree to which the empirical analyses supported the intervention pathways (stage 2), while carefully considering alternative explanations for variation in poaching. For example, participants assessed whether some factor other than dehorning could feasibly explain the decline in poaching after the implementation of dehorning on five specific reserves. Similarly, participants discussed whether the lack of empirical support for a particular intervention might be explained by confounding factors that might have dampened an otherwise effective intervention.

It is important to note that the effects of some interventions were considered inconclusive given available data. Our empirical analysis and the qualitative attribution methods were designed to reduce our uncertainty about the link between an intervention and outcome by leveraging expert knowledge in a structured way. Crucially, this four-stage approach not only strengthened our confidence in intervention effects or lack thereof but also helped us understand the importance of context when interpreting results. For example, participants put forward several lines of evidence as to why the detect and capture/arrest interventions may be weakened by numerous external factors such as manager competence or the effectiveness of the judicial system.

The reserve managers and other stakeholders who participated in interviews or workshops provided free prior and informed consent to their participation, and the study followed the protocols in the *Code of Ethics of the American Sociological Association* (*43*). Many of these participants were part of the reserve manager group that first identified the need for an empirical evaluation of the effectiveness of anti-poaching interventions. Some managers may have had a conflict of interest in that their view of the effectiveness of certain interventions will have been shaped by their personal experiences. We managed this by foregrounding the quantitative results while also seeking to balance diverse perspectives from different managers.

Intervention and poaching data

Over a period of nine months, two dedicated data co-ordinators compiled standardised poaching and intervention data from each reserve for the period 2017-2021, through multiple visits to each reserve. The data collection template was devised based on a series of workshops hosted by the Greater Kruger Environmental Protection Foundation (GKEPF) involving various reserve managers and other staff (scientists, security managers, law enforcement staff, technology experts, etc) from the study reserves. Participants discussed the essential quantitative indicators for each intervention for which standardised and comparable data were accessible between reserves and over time. To mitigate any potential

misunderstanding or misinterpretation, the data collection was done in person on a one-on-one basis with a designated representative from each participating reserve. The data requirements were clearly defined and explained to avoid any potential ambiguity. Rhino poaching was a high priority threat on every participating reserve, so intensive monitoring of poaching was conducted, and participants estimate that over 95% of poached carcasses were detected within a few days of the event (facilitated by multiple signs of poaching such as footprints and gunshots, wide patrolling, and the substantial evidence that a large carcass constitutes).

1. Quantifying intervention success (the response variable)

Our primary success measure was a reduction in the poaching rate (the number of rhinos poached as a proportion of the population size). Reserves vary widely in terms of their rhino population size, and populations also change over time. The number of rhinos poached may be influenced by these fluctuations. For example, if the rhino population declines on a reserve over the five-year period, the absolute number of rhinos poached might decline too, but the proportion of available rhinos poached may remain stable or even increase over the same period. We used the raw number of rhinos poached as a secondary measure, because given the direct goal of the rhino protection interventions is to reduce poaching, a secondary measure of success is a reduction in the number of rhinos poached when an intervention is in place compared to when it is not. This measure has advantages because the absolute change in the number of rhinos poached is directly related to a reduction in the number of attempts made by syndicates/poachers to target the reserve, which points to intervention success.

2. Rhino population estimates

All reserves except Kruger NP used standardised annual total counts of both rhino species, via a helicopter census conducted over 2-4 days in September each year. The method used was the standard total count method with standardised helicopter flight paths (*44*, *45*). Each reserve was surveyed using a Bell 206 B Jet Ranger helicopter, with count marker bars fitted to each side of the aircraft. Each marker bar represents a 250m transect on each side of the aircraft when the target height of between 70-90m is reached. Flight paths were spaced 500m apart. In this way, the total reserve area was surveyed with directly adjacent strips. Double counting was avoided through careful logging of the GPS locations and exit time of each observed rhino location, allowing groups observed on previous transects to be excluded. Average flight speed was 90-100km/h. Count session duration was limited to the fuel capacity of the aircraft, with around 2-3 hours per session. The survey crew consisted of the pilot, Front Seat Observer (FSO) and two Rear Seat Observers (RSO). Navigation and data collection during the survey was done using the Capture software program, a multi-disciplinary geo-referencing and data capture program developed by Mike Pingo and Sunrise Aviation, South Africa.

Kruger NP uses a plot-based sampling technique via helicopter. A total of 439 3km x 3km blocks distributed randomly across Kruger, are sampled. Within each block, 400 m strip transects were conducted, with observations made 200m either side of the aircraft (a helicopter). A pilot, data recorder, and an observer on either side of the helicopter, with a 45m average flight height and an average speed of 120km/h. The pilot used an aviation geographic positioning system (GPS), Garmin aera 660, to navigate the blocks and strips. A sample estimator was used to estimate total population sizes of black and white rhino, from aerial sample counts (*46*). While standard errors were available for these counts, we used only the mean estimates to fit with the private reserve data. Full details for Kruger NP census and analysis methods are provided in ref (*47*)

A recent study on aerial helicopter counts of black rhino in two reserves similar in size and habitat to the reserves in the Greater Kruger studied in our analysis, found that helicopter counts under-estimated rhino population sizes (*42*). Based on N-mixture models that estimated imperfect detection using repeat annual census counts, the authors estimated that bias corrected population estimates were on average 24.5% higher than raw counts (*42*). To test the sensitivity of our results to any population under-estimation effect (which would affect calculation of poaching rates and dehorning rates) we conducted a supplementary analysis in which we corrected population counts upwards by a factor of 1.245. Although this correction factor is based on a different study system (Madikwe and Pilanesberg reserves in South Africa), the same aerial count methods (total helicopter counts) were used, the same/similar species were counted (counts of black rhino, where our study involved black and white rhino counts), and the reserves are similar in size and habitat type (savannah with large open woodlands and grasslands) to our Greater Kruger reserves. We did not however apply this correction to Kruger NP data due to the slightly different block count and extrapolation count method used on Kruger (see above), which already includes a correction for effects of vegetation cover on rhino detectability (*47*).

Results in the supplementary population-corrected models were very similar to the main results for the all-intervention model (see Fig. S28) and the regression-discontinuity model (see Table S3).

3. Quantifying intervention implementation (the explanatory variables)

A key challenge for this project was summarising the rich data collected for each intervention. For each reserve and year quarter we quantified 11 intervention indices constructed from standardised data: (1) Security index: the presence/absence of a control room and rapid response team, plus characteristics of each. (2) Anti-poaching rangers per 100km^2. (3) Rhino monitoring index: the number of dedicated staff, databases, and tracking devices. (4) Dehorning index: The proportion of the rhino population that was dehorned. (5) K9 dog unit: the number of tracking dogs per 100km^2. (6) K9 dog unit: the number of detection dogs per commercial gate. (7) Integrity/polygraph testing: (a) the proportion of security staff tested over the previous year, and (b) the number of staff removals/failures over the previous year. (8) Detection zone index: coverage and maintenance frequency. (9) Access control index: CCTV cameras, staff, boom gates, and other access technologies.(10) Fence investment index: quantifying fence type and add-ons. (11) Fence alarm index: quantifying the number of zones and distance between them. More details on the specific data used and how the indices were constructed is included below.

4. Interacting interventions, and lagged intervention effects

To lead to reduced poaching, those interventions that increase poacher detections (such as camera technologies and fence alarms) must interact with follow-up interventions that lead to increased poacher arrests (such as tracking dogs and rapid response teams). To account for this effect, we investigated the effectiveness of intervention combinations. Our data set was too small to have adequate statistical power to test all possible combinations of detect and capture interventions, so we instead tested the effect of a small subset of combinations identified by managers and other experts as important. These included the interactions between each of two detect interventions (camera technology and detections zones) and each of two react/arrest interventions (ranger density and tracking dogs) for a total of four interactions. Dehorning was also included in these models given its high explanatory power. Only one significant interaction was observed, though it invovled a positive association with poaching and may have resulted from the low statistical power issue described above (fig. S28).

For detect and arrest interventions, we might also expect that any effect on poaching is lagged by a number of months as poachers take time to become aware of the increased probability of detection on

reserves implementing these interventions. For these interventions, we therefore tested versions of the model in which the effect of these interventions was lagged by one and two quarters (three-month periods). The results of both these lagged models were not different from the main model (fig. S29).

A. Statistical analysis for the all-intervention baseline model

To match the data structure, we used a Bayesian hierarchical Generalized Linear Mixed Model (GLMM) with a Poisson error structure to relate rhino losses to intervention implementation. The Poisson distribution is often used when the response variable is a whole number count (in this case it is the number of rhinos lost).

We modelled rhino losses for each reserve and period (three-month quarter) by treating the number of rhinos lost ($N.poached_{rq}$) at each reserve (r) and quarter (q) as a Poisson random variable:

$$N.poached_{rq} \sim Poison(\lambda_{rq})$$

Where $N.poached_{rq}$is the total number of rhinos poached on each reserve in each quarter and λ represents the rate parameter and is both the mean and variance of the Poisson distribution. Using the log link function, we then modelled rhino losses as a function of the 11 intervention variables which represent the intensity with which each intervention was implemented on each reserve in each quarter. For each reserve (r) and quarter (q):

$$log(\lambda_{rq}) = \beta_0 + \sum_{k=1}^{11} \beta_k X_{rq} + \alpha(0, \sigma_r) + \gamma(0, \sigma_q) + offset(ln(pop))$$

Where β_k is the coefficient (estimated size) of the effect of intervention k on rhino poaching levels (on the log scale; these can be converted to factors if effects on the back-transformed scale are desired), X_{rq} is the index measuring how intensively intervention k was implemented on reserve r in period q, and α and γ are the normally distributed random effects for reserve and quarter respectively.

Importantly, we used the logarithm of the rhino population size (*pop*) as an offset, to account for the wide variability in rhino population sizes across reserves. We checked for correlations among the intervention variables and avoided including highly correlated variables in the same model, using a threshold of r=0.70 based on an extensive simulation study (based on ref *48*). We fitted the model using Markov Chain Monte Carlo (MCMC) sampling, implemented using Stan via the R package *brms* (*49*). A total of 2000 iterations with 1000 burn in was sufficient to achieve convergence as indicated by low *R-hat* values.

Use of quarter as the temporal unit: we chose to use quarter, rather than month, for two reasons. First, for some reserves and year the interventions data were only available at the quarterly scale. Secondly, for many interventions the timescales over which they reduce poaching is likely greater than 1 month (fig. S1).

Random effects helped us account for variability in poaching rates that was not related to interventions. We accounted for such variability across reserves (the spatial random effect) and quarters (the temporal random effect).

Bayesian priors were selected to achieve efficient model selection. In particular, we performed model selection via horseshoe regularization to help separate interventions with stronger and weaker evidence for effectiveness through a conservative prior distribution that shrunk weak effects towards zero, a

method that has become increasingly validated for Bayesian hierarchical models (*49*, *50*). We further tested LASSO (Least Absolute Shrinkage and Selection Operator) regularization methods, finding no change in model conclusions (*51*, *52*). We also ran a version of the model with flat/uninformative uniform priors to test the effects of model selection. One additional intervention variable (fence investment) became significant (95% credible interval excludes zero) in the baseline all-intervention model, when flat priors were used (fig. S2). But this effect was marginal, with the credible interval still very close to zero (fig. S2). This result shows the effect and advantage of Horseshoe model selection, in that interventions with uncertain (wide credible interval) effects like fence investment are conservatively reduced to protect against type 1 errors.

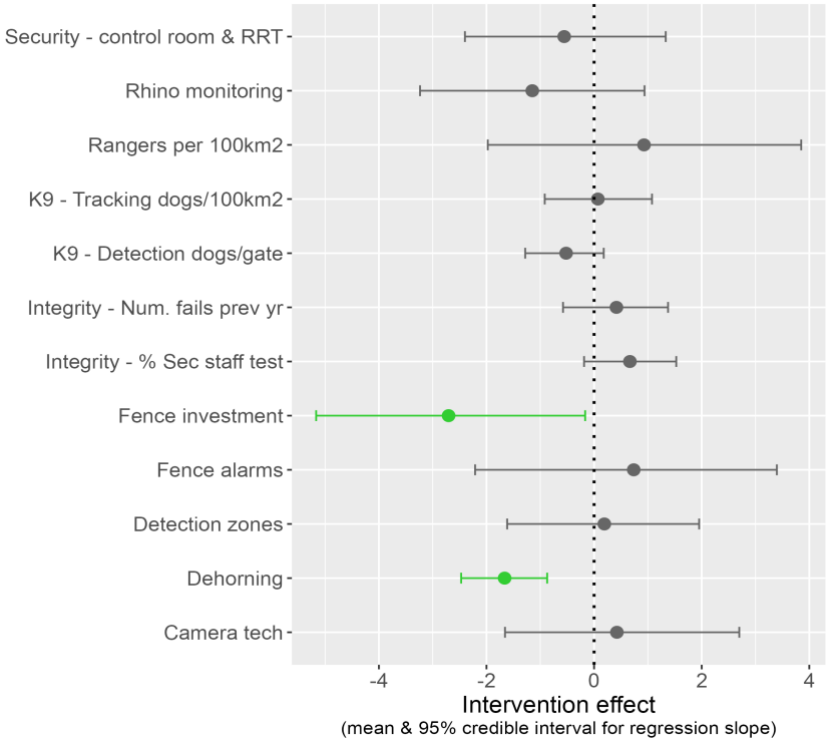


Figure S2. Supplementary model with flat uniform Bayesian priors (i.e. no model selection via Horseshoe prior regularisation). The estimated effect of each intervention on rhino poaching rates, based on statistical analysis of data across reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels.

Model fit was assessed using posterior predictive checks, a robust method available for Bayesian models that involves simulating replicate data under the fitted model and comparing it to the observed data (*53*) We initially used a Poisson model but found that a negative binomial model better fitted the data, based on leave-out-one cross validation and WAIC model weights, using the LOO and model_weights function in the brms package (11,15). Specifically, the kappa parameter indicated moderate overdispersion (posterior mean k=0.1; 95% credible interval: 0.01 - 0.30). In this case, using the Poisson model would risk underestimating standard errors and increase the type 1 error rate Thus, all results reported are from the negative binomial model.

The orthogonality of predictors was tested via spectral decomposition (see fig. S3). A principal component analysis was run to assess informational decay (fig. S1 Panel A), as well as the clustering of interventions by reserve (Panel B), over time (Panel C) by quarter (Panel D). Results indicate a healthy degree of informational decay, useful differentiation amongst interventions based on their

ordination and no unexpected clustering. For completeness, we note the first five principal components retain eigenvalues greater than 1 (fig. S3).

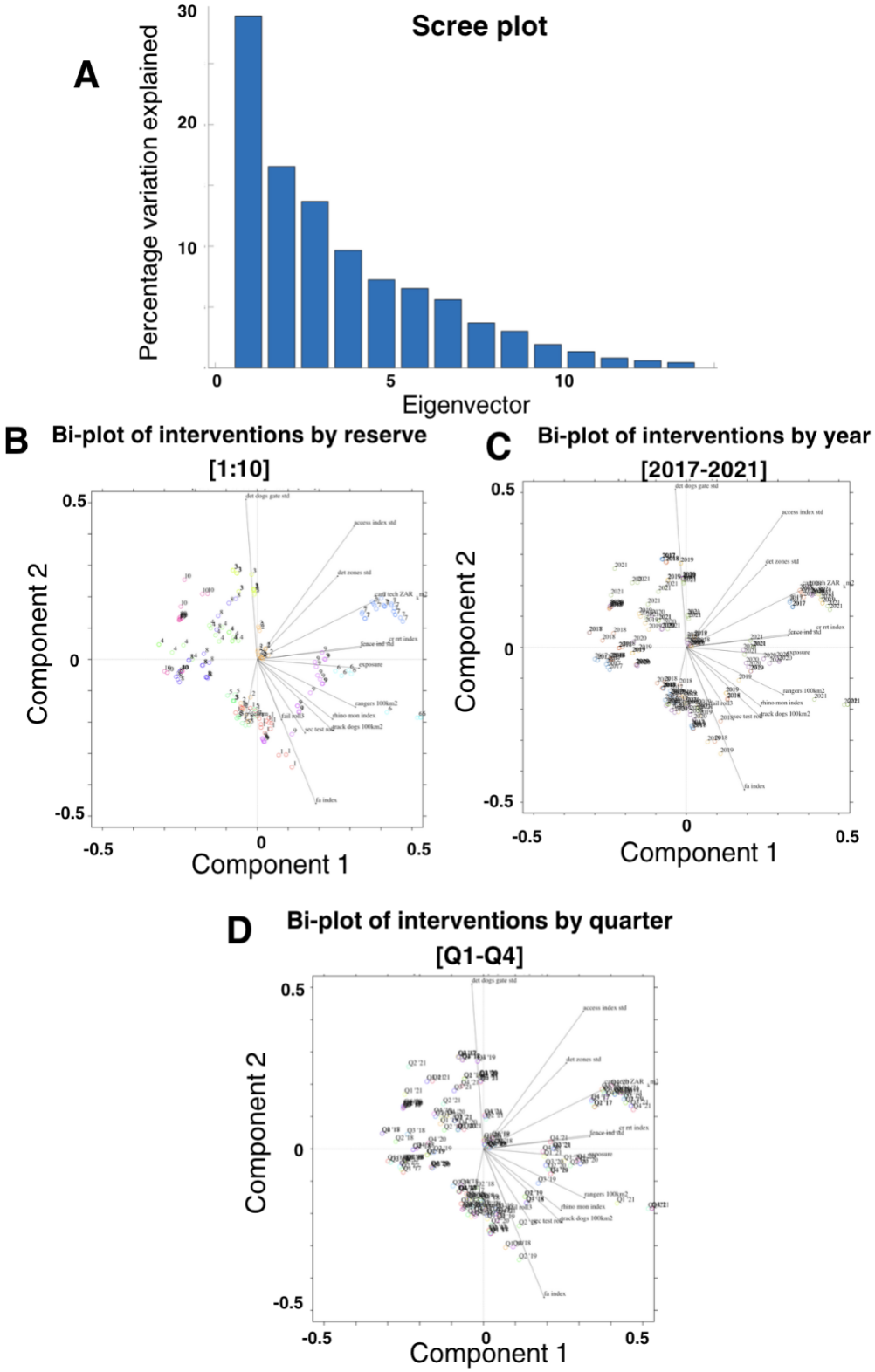


Figure S3. Results from principal component analyses to assess informational decay (Panel A), as well as the clustering of interventions by reserve (Panel B), over time (Panel C) by quarter (Panel D).

The reserve and quarter random effects were included to help account for non-independence of data within each reserve (across years), and within each quarter (across reserves). To examine issues with non-independence, we plotted the residuals of the all-intervention baseline model over space (reserves) and over time (year quarter) and checked for any correlation. There was no obvious concern (Fig. S4). Next, we computed the temporal autocorrelation model residuals by reserve, using the *acf* function in *R*, and found no correlations at any time lags (Fig. S5).

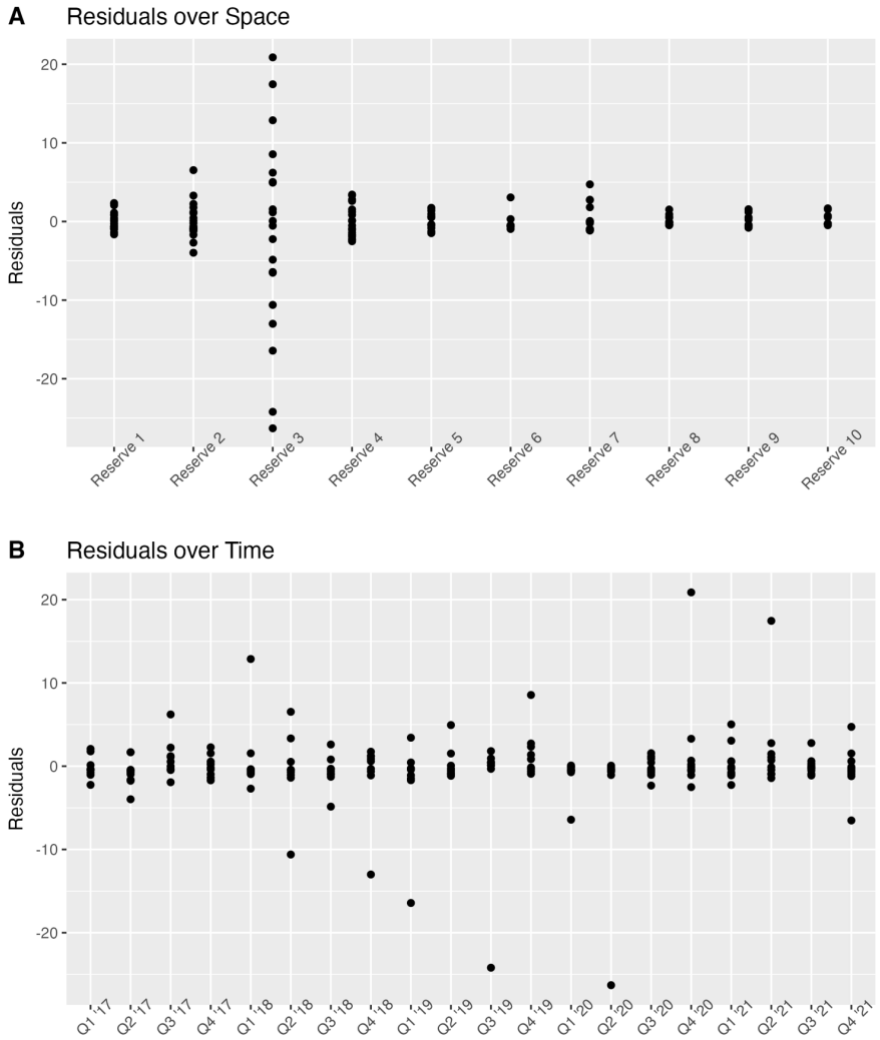


Fig. S4. The residuals of the all-intervention baseline model over (A) space (reserves), and (B) time (quarters).

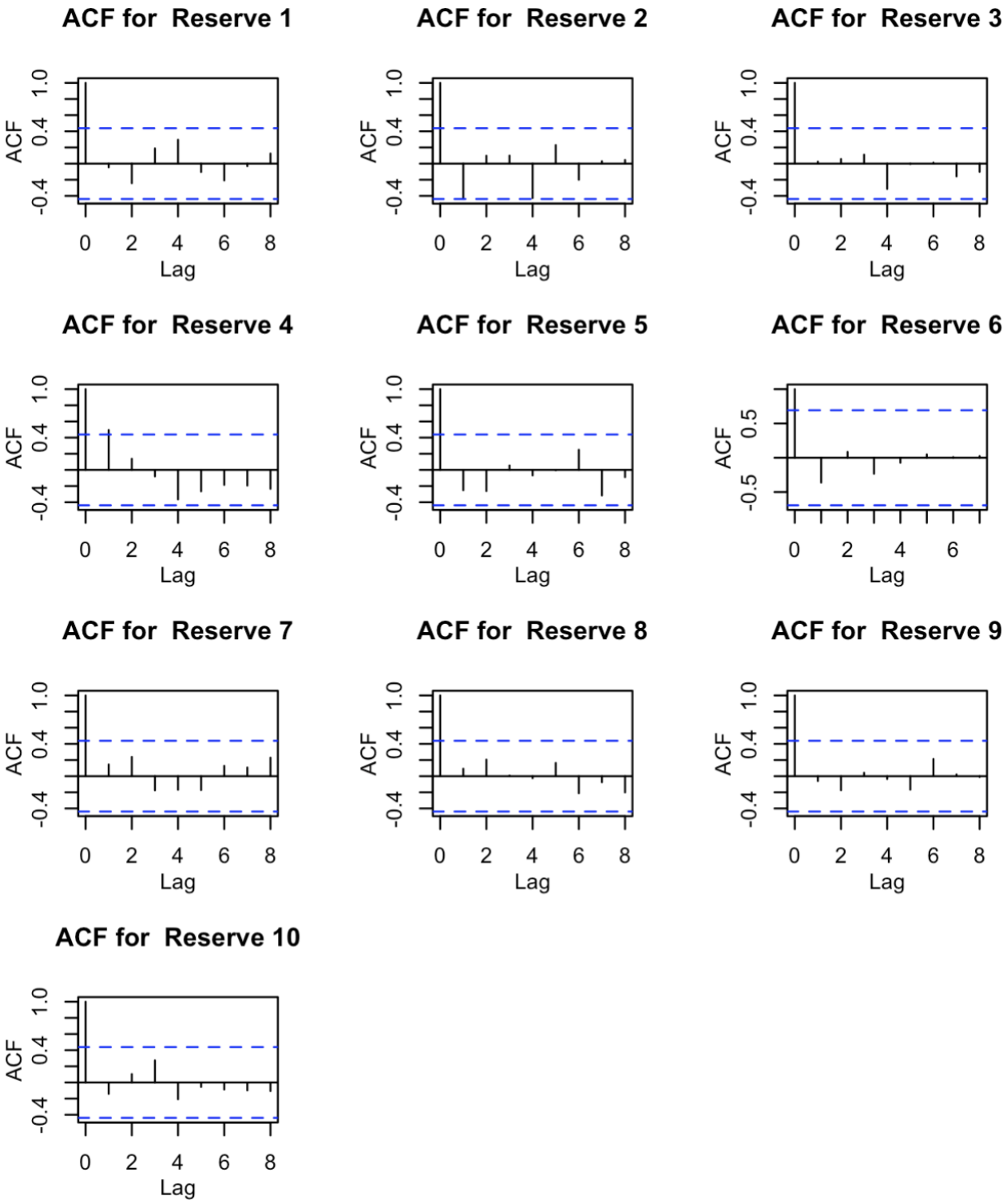


Figure S5. Autocorrelation function plots for the all-intervention baseline model, showing the correlations among residuals at different lags for each reserve separately. ACF values fall within blue bands for all lags on all reserves, indicating no significant autocorrelation.

We then used the spatial locations of reserves to test for spatial autocorrelation in the model residuals, using Moran's I test via the *moran.test()* function in the *spdep* package in R (*54*). We found no significant evidence for autocorrelation (fig. S6). Finally, we tested for spatial and temporal dependence effects by re-fitting two more versions of the all-intervention baseline model: (1) the first with reserve as a fixed effect rather than a random effect and, (2) the second with quarter as a fixed effect rather than a random effect. In both these models, the intervention effectiveness results were no different from the model with random effects for quarter and reserve – i.e., dehorning remains significant, and other interventions remain inconclusive (figs. S7 and S8).

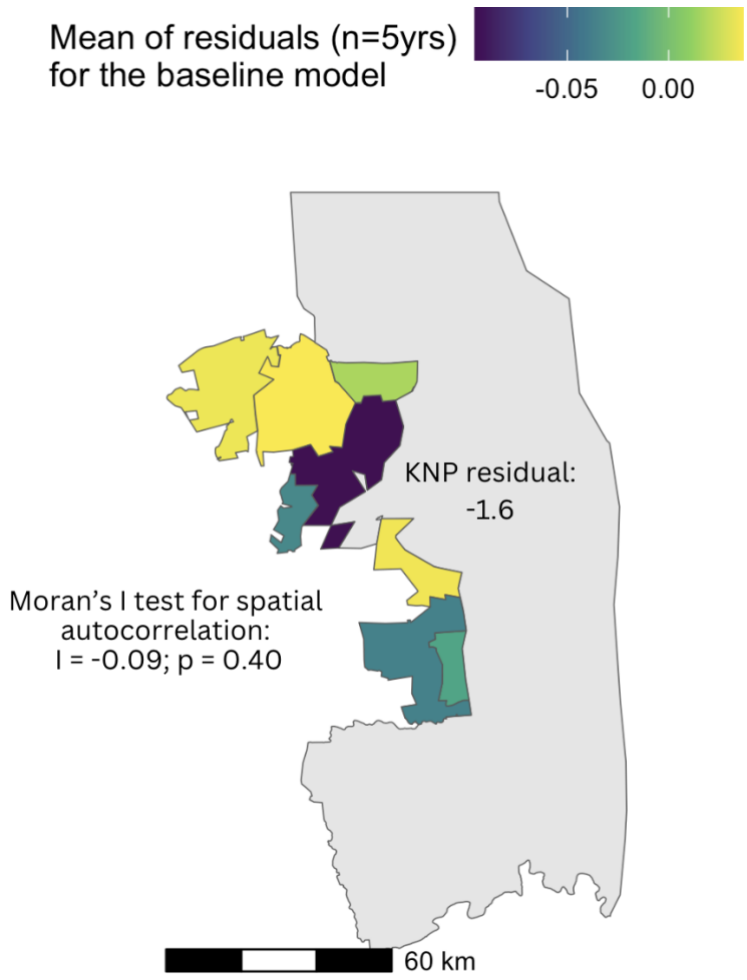


Figure S6. Residuals plotted spatially to visually examine potential spatial autocorrelation. The Moran's I test confirms there was no significant autocorrelation. Kruger National Park (KNP) mean residual was so large that the value was set to NA for visualisation (the true value was kept for the Moran's test).

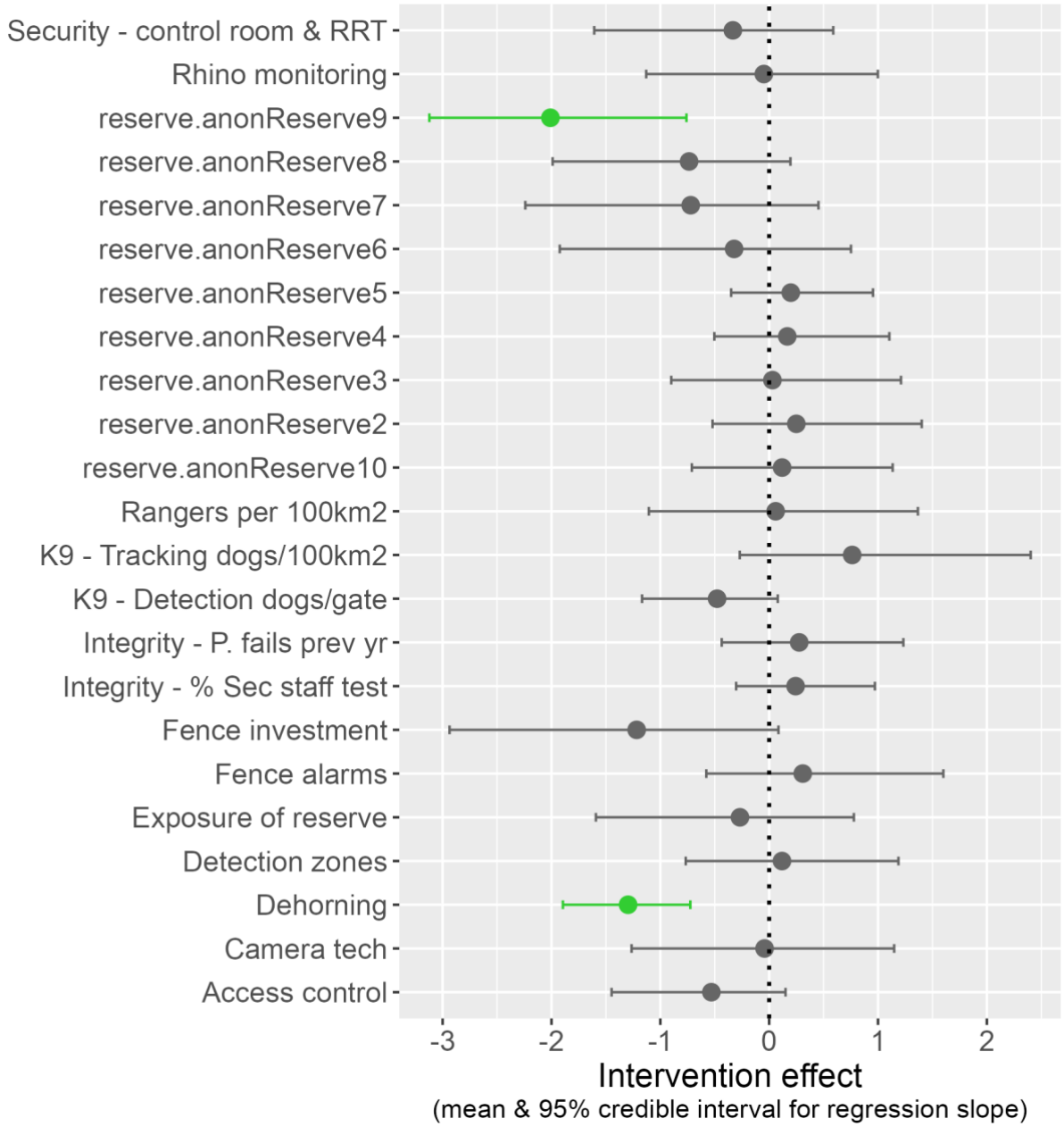


Fig S7. Coefficients estimated by the all-intervention model with reserve fitted as a fixed rather than a random effect.

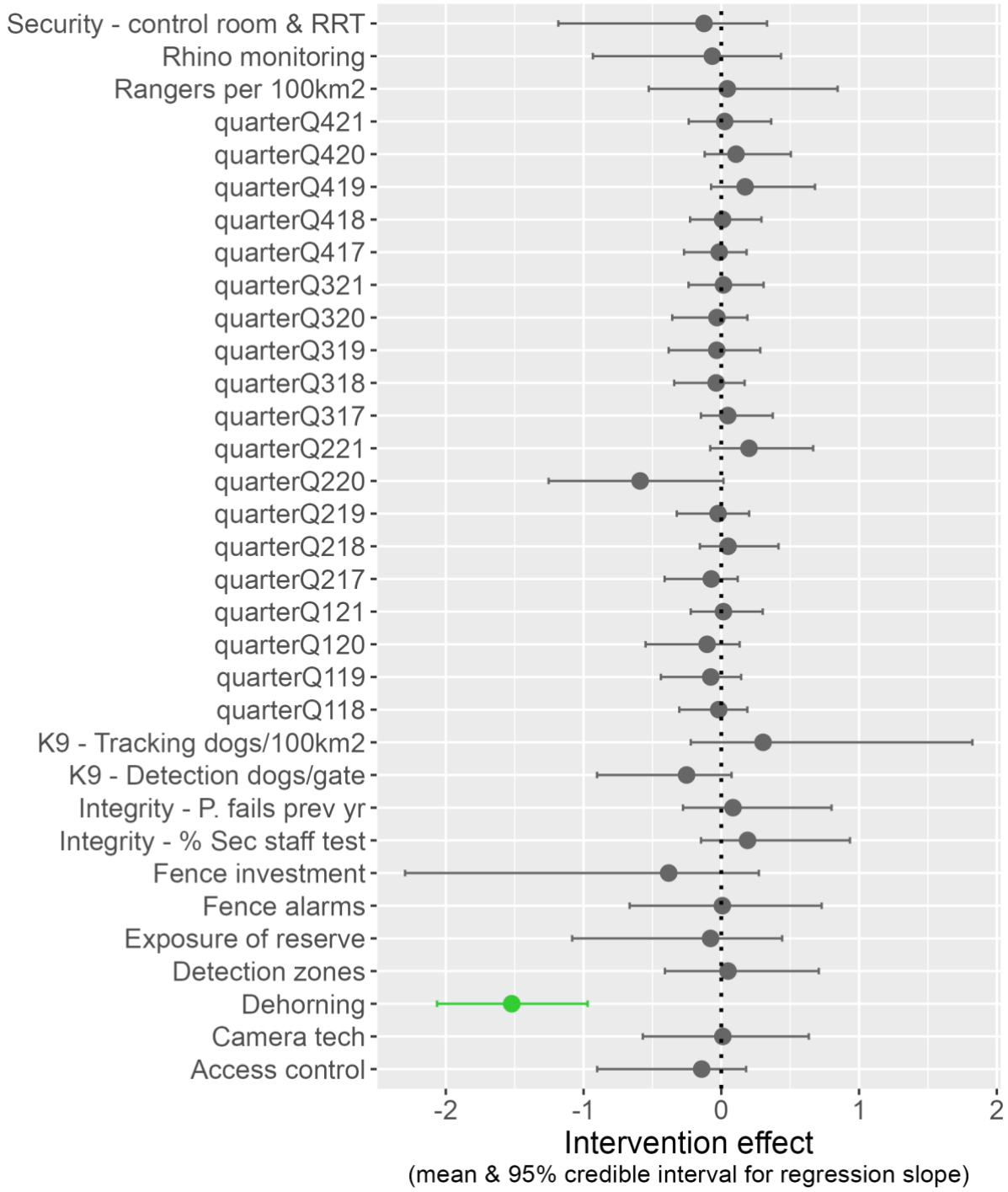


Fig S8. Coefficients estimated by the all-intervention model with quarter fitted as a fixed rather than a random effect.

Accounting for unique size and context of Kruger National Park

The dynamics of poacher activity and the protection interventions implemented in Kruger NP differed in important ways from the other 10 reserves:

- *Size*: The KNP data includes intervention and poaching data from 11 Sections which together form the Intensive Protection Zone and Joint Protection Zone regions and cover around 10 000km^2. Due to difficulties separating poaching and intervention data by section/zone, the KNP data was treated as one unit, which is an order of magnitude larger than many other reserves.
- *Poaching dynamics*: The large border with Mozambique means that much poaching in KNP is initiated on the Mozambique side, and poachers/syndicates may operate quite differently given the large area.
- *Dehorning*: KNP used strategic/partial dehorning during the 2017-2021 project period (25% of all rhinos by the end of the project period), whereas other dehorning reserves employed total dehorning.
- *Dog units*: The larger size of Kruger means that tracking dogs have far higher distances over which to operate, which increases success rates and make it difficult to compare with smaller reserves.
- *Perimeter:* KNP's fences are not for security and do not prevent incursions; the Park instead relies on detection zones and presents a situation quite different to private reserves.
- *Aerial support:* KNP has a significantly larger fleet of fixed and rotary wing support compared to the private reserves.

Give the above considerations, we took a two-pronged approach to the KNP data to ensure the most reliable results:

1. **KNP Included in main analysis**: KNP was simply included in the main statistical model and treated as an additional reserve unit alongside the private reserves
2. **KNP excluded in supplementary analyses:** The full statistical analysis was conducted again, but with the KNP data excluded.

Dehorning-focussed analyses

1. Regression discontinuity in time

We took advantage of the fact that seven of the eight reserves that implemented dehorning during our study period did so abruptly, dehorning almost all rhinos present within 1-2 month of starting dehorning. This allowed us to conduct a regression discontinuity in time (RDiT) analysis to test for abrupt changes in poaching in response to dehorning (*24*). Given the staggered implementation of dehorning across the implementing reserves, we computed a running variable that measured the number of quarters relative to the quarter in which dehorning was first implemented on each reserve. To test for an abrupt change in poaching as well as a change in the poaching trend, we built a Bayesian regression model with three main fixed effects. These were: quarters relative to dehorning, a dummy variable indicating whether a quarter was before or after dehorning, and the interaction between these two (following ref *26*). Reserve identity and year quarter were retained as random effects as in the baseline all-intervention model, and we also use the negative binomial error structure and population size offset as in the baseline model (see above).

To further strengthen inference around the causal effect of dehorning, we plotted the values of the other intervention indices (rangers, dogs, etc) against the quarters relative to the dehorning variable (Fig. S9). This was to see whether any confounding variable might explain the drop in poaching after dehorning. We also ran several regression discontinuity models using each of the other interventions as the response variable, and quarters relative to dehorning and the treatment variable (before/after dehorning) as explanatory variables. The only variable for which we found evidence for an abrupt change around the time of dehorning was staff removals after polygraph test failures (variable '*fail.roll3'* in fig. S9). However, the hypothesis for this variable was that less staff removals (which was the case after dehorning) would lead to more future poaching, so this is an unlikely confounding explanation of reduced poaching after dehorning. Furthermore, the effect of this variable was close to zero in the main all-intervention statistical model.

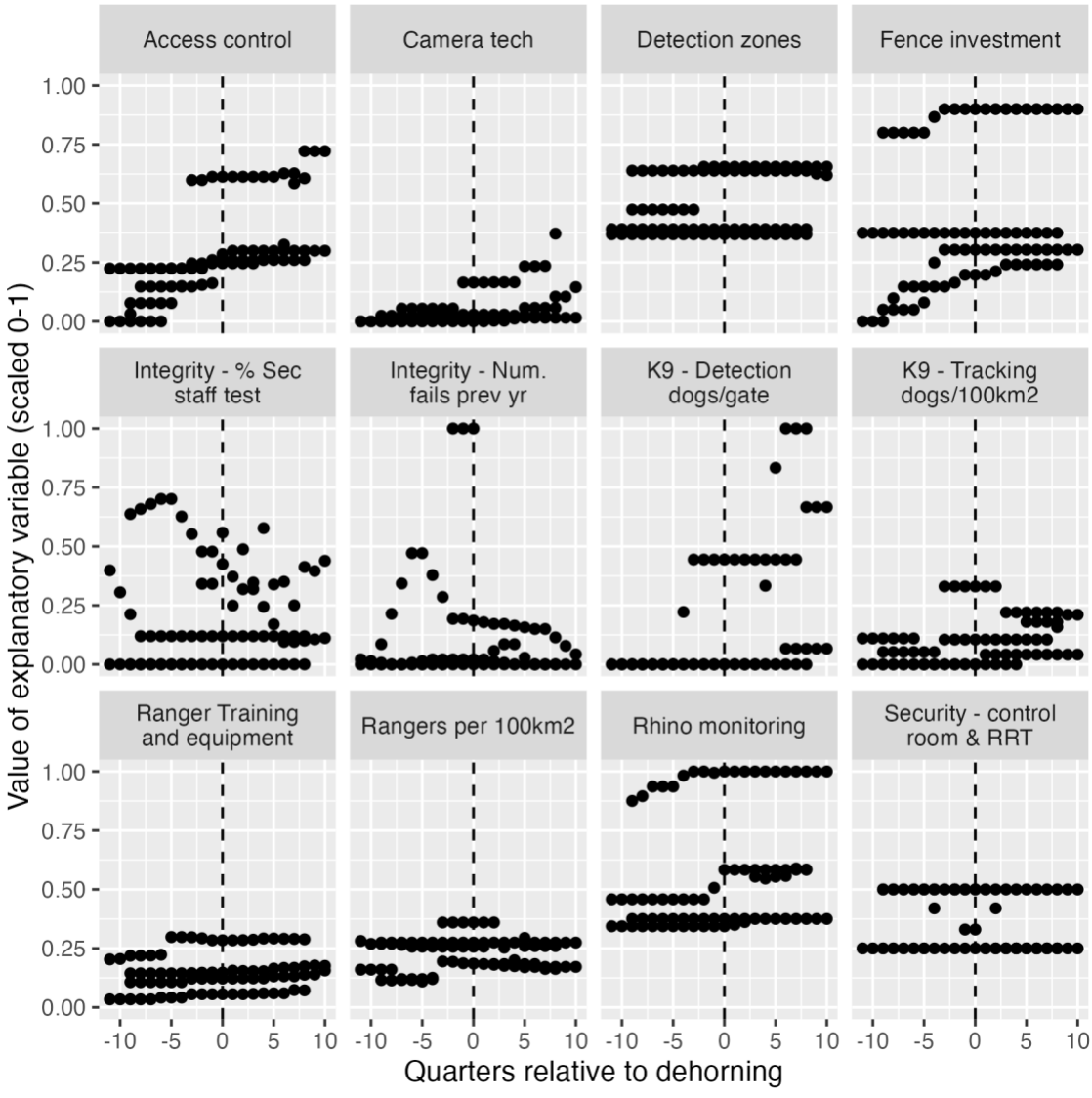


Figure S9. Examining whether any of the other intervention indices (other than dehorning) also changed abruptly around the dehorning (dotted vertical line) for the four reserves implementing abrupt dehorning during the 2017-2021 period (intervention data from 2022-2023 were not collected).

2. Estimating rhinos saved and cost per rhino saved

For each of the eight implementing reserves, we calculated the average annual poaching rate in the years before dehorning, as well as the population size immediately prior to dehorning. We then estimated the number of rhinos saved on each reserve by multiplying the poaching rate by the population size and the reduction in poaching rate estimated from the regression discontinuity model. We only estimate this for the year after dehorning, as it is likely that high poaching in the absence of dehorning would reduce population sizes overall and thus the number of rhinos saved in later years. We use the regression discontinuity estimates for all reserves except Kruger NP (which did not implement abrupt dehorning). For Kruger, we conservatively used the actual change in poaching rates after widespread dehorning rather than the modelled rate from the all-intervention model which was likely an overestimate for Kruger as it continued to experience poaching of dehorned rhinos. Finally, we used the actual number of rhinos dehorned to achieve widespread dehorning on each reserve and the average cost of dehorning a single rhino to estimate total expenditure per rhino saved, by reserve. These results are presented in Table S2.

This method is subject to significant uncertainty as we were not able to estimate the counterfactual directly (what would have happened in the absence of dehorning). We make the simplifying assumptions that the poaching rate and population size prior to dehorning would have prevailed over the next year in the absence of dehorning.

3. Relative risk ratios

We computed the relative risk ratio for dehorning by comparing the rate at which dehorned rhinos were poached to the rate at which horned rhinos were poached. To compute this, we estimated for each reserve and month (2017-2023), the number of dehorned and horned rhinos present, as well as the number of dehorned and horned rhinos poached on that reserve that month. We used a month time step for this analysis as dehorning and poaching data were available at the month level (unlike data from some interventions, hence the use of quarters in the all-intervention model). This allowed us to compute the below risk ratio:

$$Reduction\ in\ poaching\ risk\ due\ to\ dehorning = 1 - \frac{Poaching\ rate\ of dehorned\ rhino}{Poaching\ rate\ of\ horned\ rhino}$$

Where the poaching rate of dehorned rhinos represents the number of dehorned rhinos poached as a percentage of the total number of dehorned rhinos present, and similarly for horned rhinos. For example, a reserve may have 200 rhinos of which 100 are estimated to have been dehorned in the past 18 months. If eight horned rhino and two dehorned rhinos are poached, the poaching rate for dehorned rhino is 2% (two out of 100) and 8% for horned rhino (eight out of 100). Horned rhinos are thus poached at 4x the rate of dehorned rhinos in this example (8% versus 2%). Using the equation above and this hypothetical example, the *reduction in risk is this* $1 - \frac{0.02}{0.08} = 75\%$ reduction in risk of poaching for an individual rhino that is dehorned compared to a horned rhino.

A caveat for this approach is that it relies heavily on population estimates for computing the number of dehorned/horned rhino present, which is influenced by the reliability of the aerial survey estimates. It also relies on accurate designation of a poached rhino as being dehorned or horned priori to poaching. Given aerial population estimates are typically an underestimate, the number of horned rhino present is probably overestimated (computed as population size minus the number of dehorned rhinos, with the latter having more accurate data), and hence the poaching rate of horned rhino is underestimated.

However, the number of dehorned rhinos poached may also be slightly under-estimated as a poached rhino is only classified as being previously dehorned if evidence is conclusive. Thus, the numerator of the above equation is under-estimated, and so is the denominator, so the estimation errors should to a certain extent compensate for each other (or at least will not have multiplied each other).

Details for how the index for each intervention was selected and measured

Note: the weights for the different components of particular intervention indices were decided based on expert insight of reserve managers and intervention experts where appropriate. The goal was simple: to measure, for each intervention, how intensively and widely a particular intervention was implemented during each quarter on each reserve, compared to other quarters and reserves. Once initial indices were developed for each intervention, they were presented to managers and other stakeholders to elicit feedback.

a. Access Control

An equally weighted sum of the following indicators:

1. CCTV cameras: the number of operational cameras per commercial gate (weighted 75%) and whether or not these cameras are connected to a control room (25%). Scaled to 0-1.
2. Other access tech: the presence or absence of an electronic database of entries and exits, a biometric system, a technology boom gate, and licence plate recognition cameras. All weighted equally and scaled to 0-1.
3. Access staff: the number of security staff per commercial gate. Scaled to 0-1.

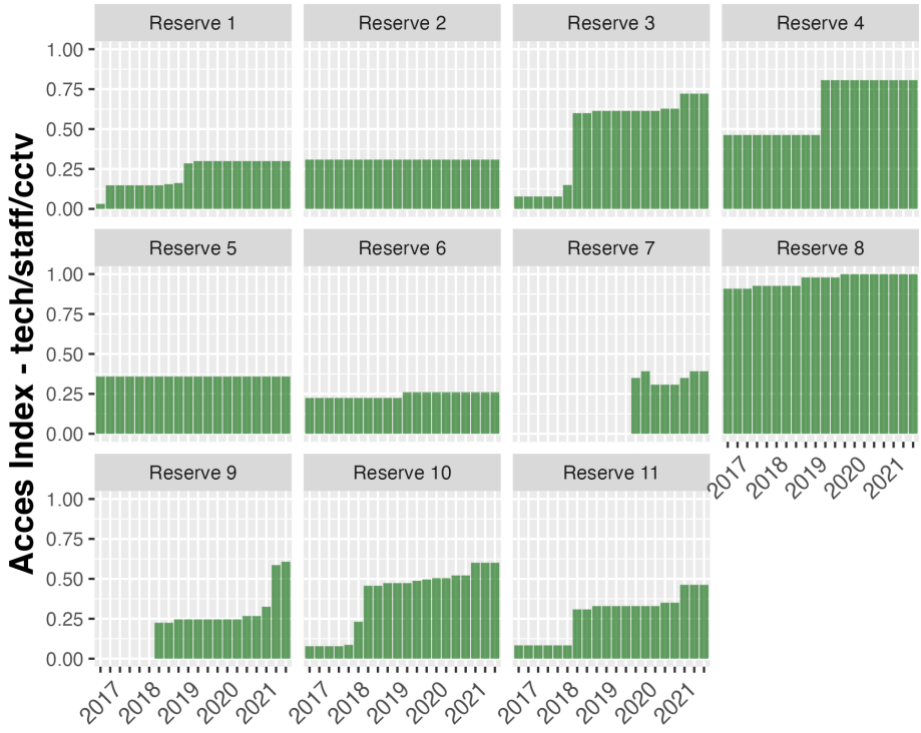


Figure S10. The intensity of implementation of the Access Control intervention. As described in the Materials and Methods text, access control was quantified as a combination of CCTV camera use, other access technologies, and security staff at access points. **Note:** For the access control intervention, there is a Control Gate Company that has two main gates, each of which serve 2-3 reserves. For these

reserves, the access control index included the access technology and staff from the relevant control gate company gates were enumerated.

b. Dehorning

Each dehorning reserve recorded the total number of rhinos dehorned each month, as well as annual population estimates. The chosen index was thus simply the total number of rhinos present that are dehorned on each reserve and in each quarter, as a proportion of all rhinos present.

We however acknowledge that population estimates are often an underestimate and did indeed find that dehorning numbers occasionally exceeded population estimates. To preserve relative changes in dehorning rates despite population underestimates, we allowed the index to vary slightly above 1. We tested the sensitivity of results to this approach by running a supplementary model in which dehorning proportions exceeding 1 were changed to equal 1, finding no difference in results. Furthermore, in supplementary models with population estimates corrected upwards (see page 12 of these supplementary materials), dehorning rates all fell below 1, and we again found no difference in the main results (Fig. S28 and Table S3).

Given that each reserve's policy was to dehorn 100% of their rhino, and that all reserves practiced active maintenance dehorning within 18 months (except KNP which only started dehorning in late 2020), we considered that a rhino remained in the dehorned state for the full project period once it was dehorned. We considered incorporating estimated horn re-growth by modelling horn regrowth for each dehorned individual and then estimating dehorning levels accounting for different levels of re-growth. We considered this to be unnecessary given maintenance dehorning and were concerned it may introduce more uncertainty relating to horn re-growth rates.

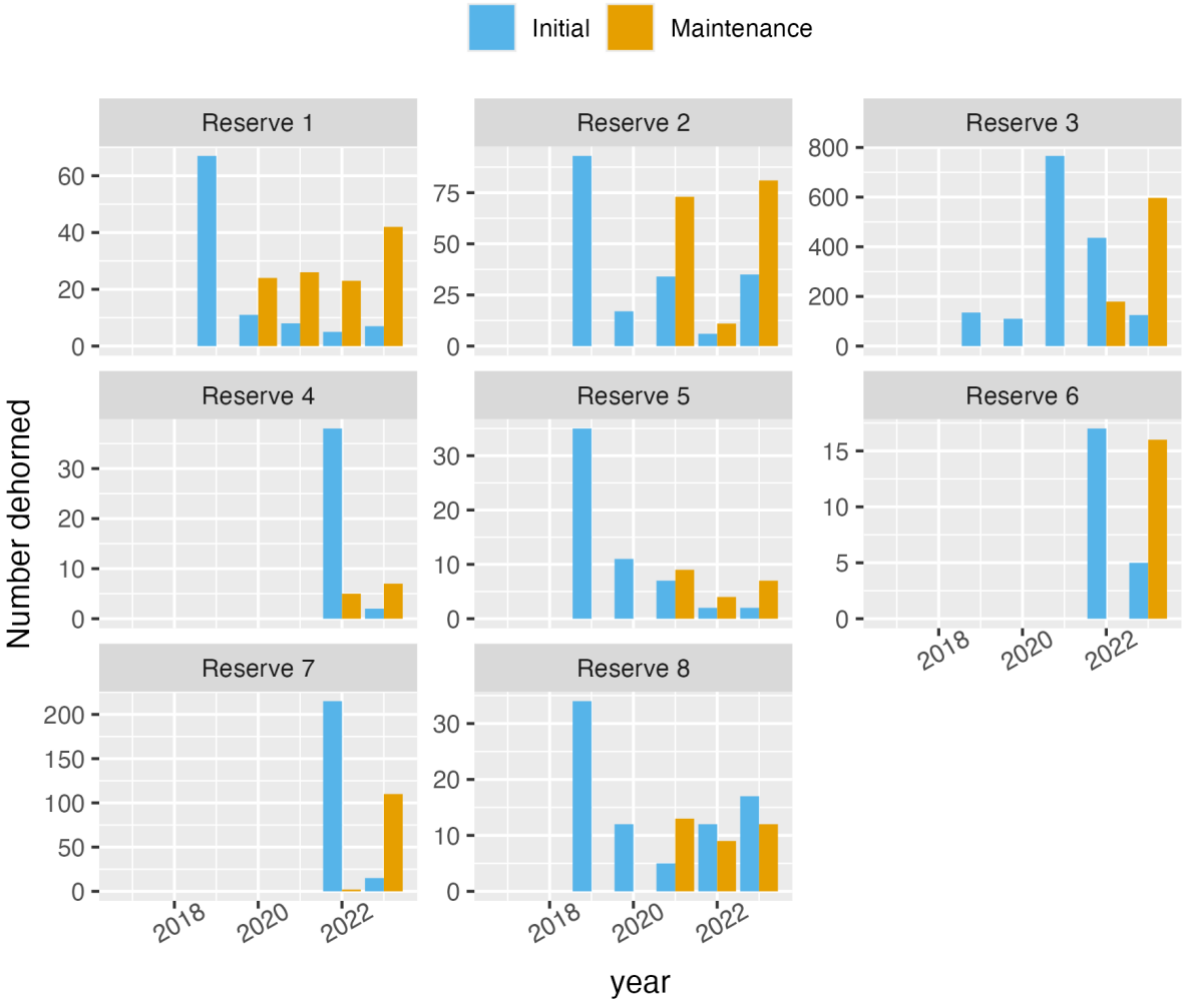


Figure S11. The total number of rhinos dehorned (black and white combined) in each year on each of the eight reserves that implemented dehorning during 2017-2023.

c. Polygraph/integrity testing

Our desired index increased in value when (a) a higher proportion of staff are tested, (b) staff are tested more regularly, and (c) there are clear consequences for test failures (staff removals). Furthermore, the hypothesis behind this intervention is that implementing integrity management in a particular month (polygraph tests and removal of those who fail the tests) will have a positive deterrence effect *for a number of months afterwards*, after which the effect may wane. With the above considerations in mind, we developed the following index. For each reserve and quarter, the intensity of integrity testing will be measured by a combination of:

1. The proportion of staff tested in that and the previous three quarters (summed together). This measures the extent and regularity of testing.
2. The number of staff removed from the reserve in the previous 3 quarters, expressed as a proportion of the total number of tests conducted. Note removals in the current quarter are excluded as they would be conflated with poaching.

Note on test failures and staff removals: Integrity test failures and staff removals may indicate that the integrity testing on a particular reserve is well-targeted, or the questions asked are effective at picking up involvement. The removal of staff also makes the consequence of integrity breaches very clear and

may be a strong deterrent. However, a low number of failed tests may also simply indicate low levels of internal involvement, and reserves that have no failures are not necessarily implementing integrity testing less intensively. Another challenge with measuring the effect of polygraph testing is that more tests may correlate positively with poaching because more tests are conducted around specific incidents. Results should be interpreted with these limitations in mind.

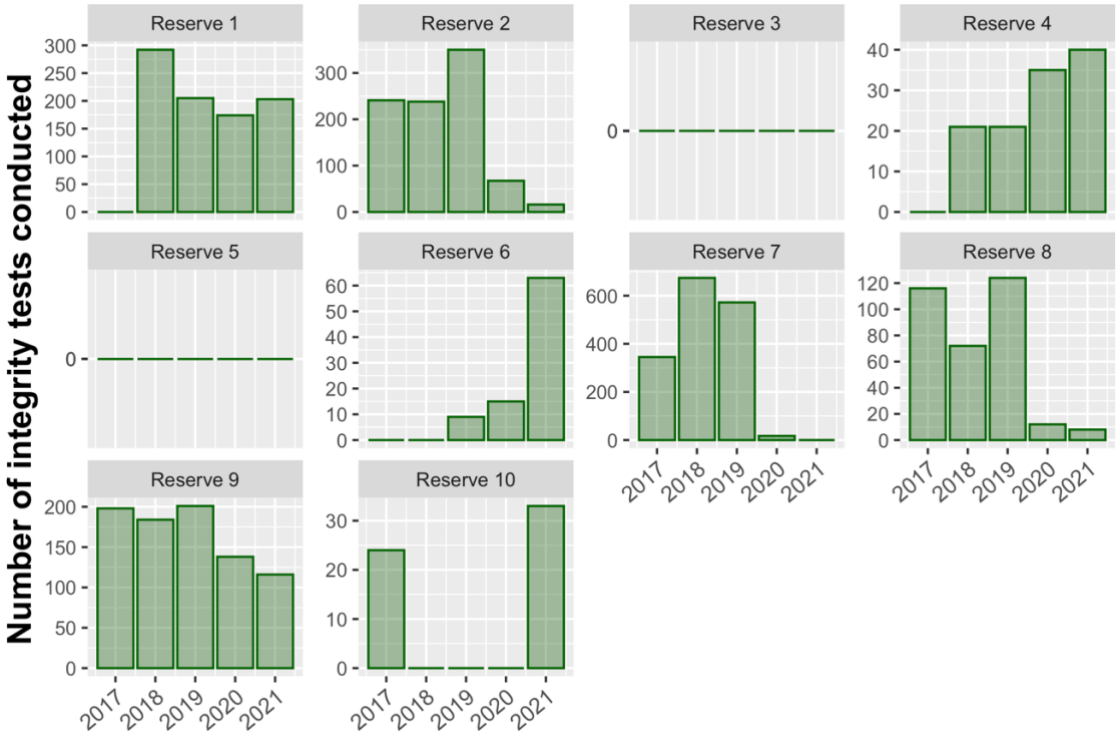


Figure S12. The number of annual integrity (polygraph) tests conducted on each reserve (2017-2021).

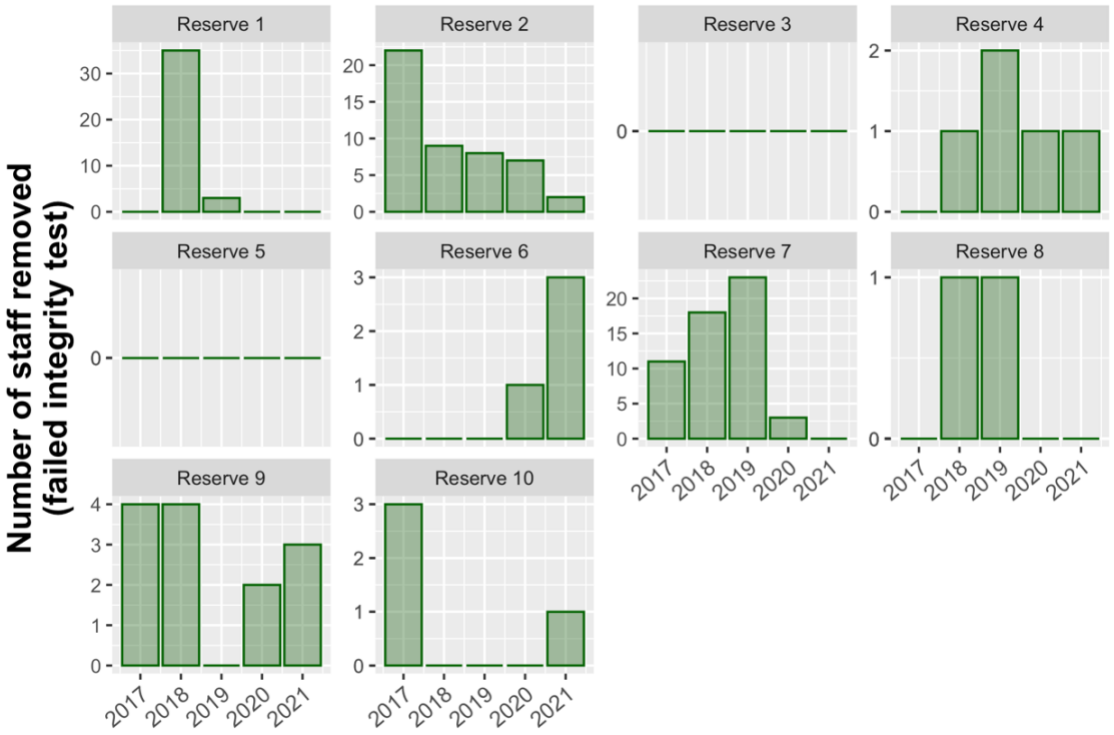


Figure S13. The annual number of staff removed for each reserve after a failed integrity test (2017-2021).

d. K9 (dog) units: detection and tracking dogs

The two K9 (dog) indices were

1. Number of detection dogs per commercial gate
2. The number of tracking dogs per 100km^2

The data collection sheets did include more detailed information on pro-active and reactive use, confiscation of firearms and/or rhino products after dog detection, and others. However, detailed information was not available for most reserves and could therefore not be included. Some reserves were serviced by a control gate company with its own K9 detection dog capacity. Enkhulu gate services three reserves, while Avoca gate services two reserves. These detection dogs were added to the implementation intensity for the relevant reserves.



Figure S14. The total number of operational K9-units (active handler and dog) across all reserves (2017-2021). Data for detection and tracking dogs are shown separately.

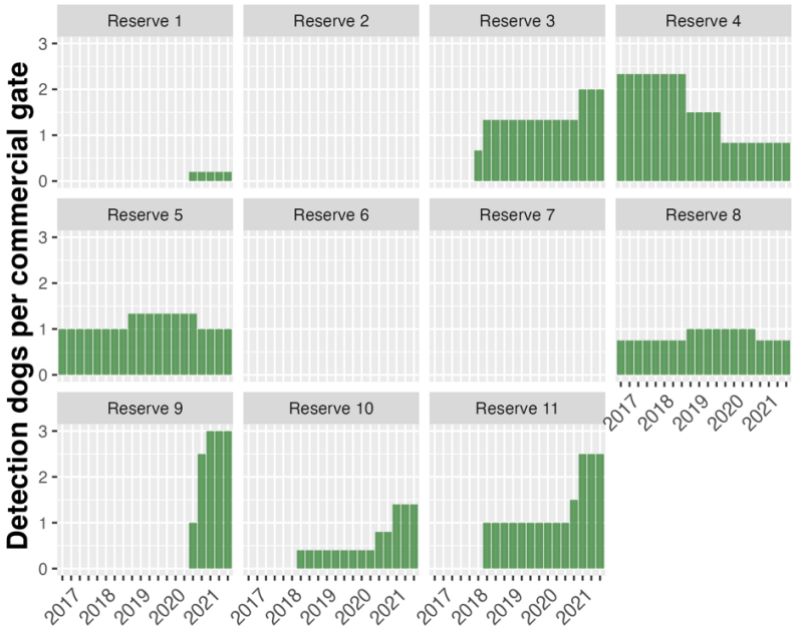


Figure S15. Operational detection K9-units (active handler and dog) per commercial gate across all reserves (2017-2021).

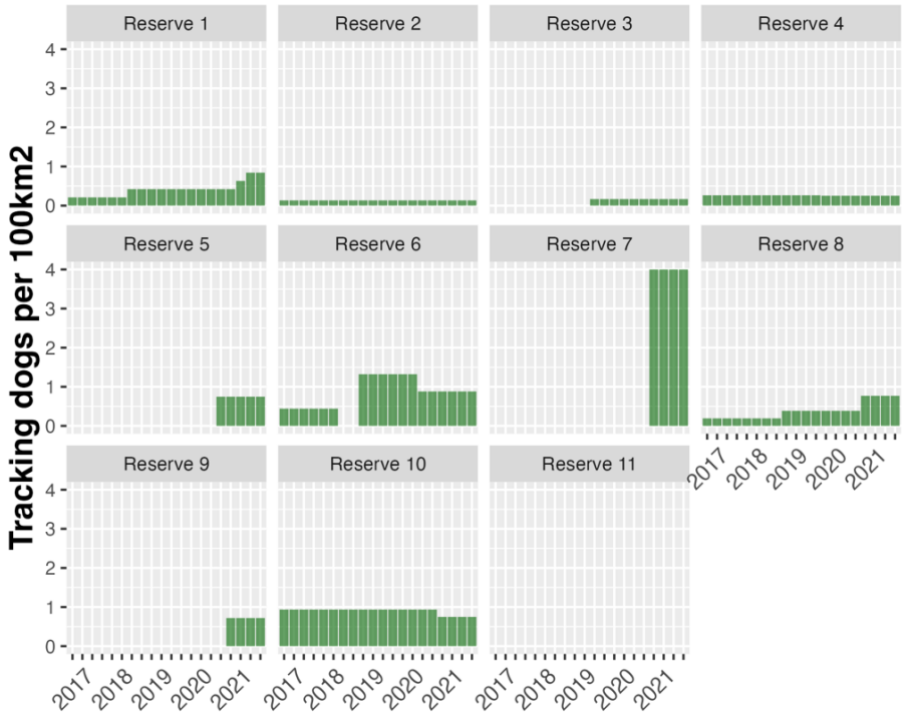


Figure S16. Operational tracking K9-units (active handler and dog) per 100km^2 across all reserves (2017-2021).

e. Fence index (maintenance and upgrades)

The index was a weighted sum of the following indicators. Scaled to the 0-1 scale.

1. *Fence general type* (75% weight) – normal fence, upgraded game fence, or new security. Proportion of fenced perimeter of each type (with security fence weighted twice the value of upgraded game fence, and normal fence rated zero as such fences have zero security function). Scaled to 0-1.
2. *Fence add-ons* (25% weight) - five different add-ons (razor, apron, overhang, loops, other). Compute how many of the 5 each reserve has each quarter. Average score then scaled 0-1.

Note for enclosed reserves, the fence index scores of buffering reserves were used, according to their proportion of buffer perimeter.

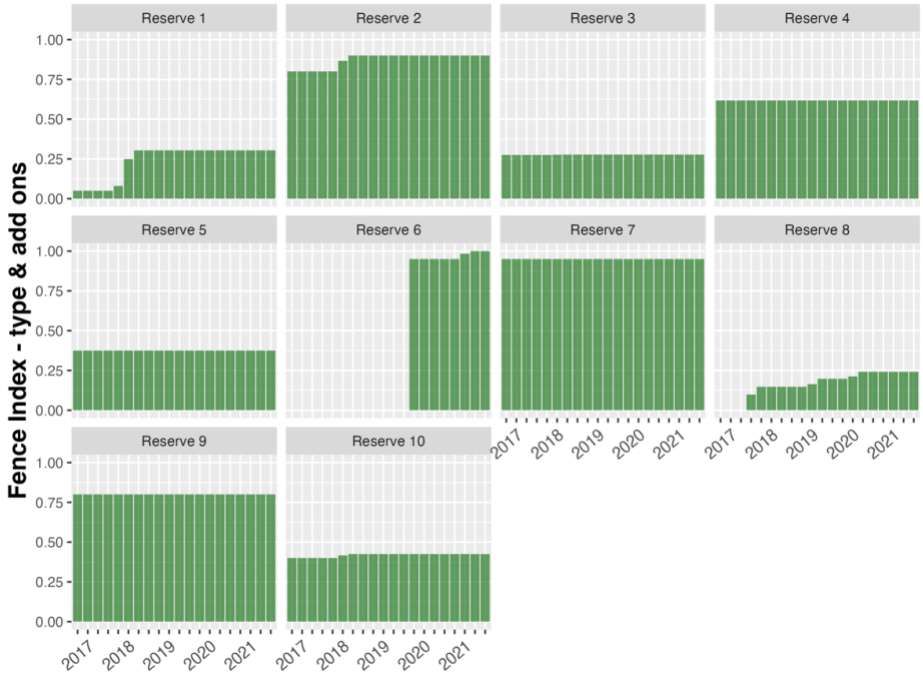


Figure S17. The intensity of implementation of perimeter fences: As described in the materials and methods this was quantified as an index of the type of fence (game or security) and the number of security add-ons. Note for enclosed reserves, the fence index scores of buffering reserves were used (see materials and methods).

f. Fence alarms

The index was computed as the weighted sum of two sub-indicators and then scaled to 0-1.

1. *Alarm presence* (weighted 75%) Whether or not alarm was present (0 or 1).
2. *The distance of each fence alarm detection "sector"* (weighted 25%). Smaller distance is better as it allows pinpointing of the incursion, therefore the score was inverted, then scaled to 0-1.

The presence of an active alarm system was deemed more important than the section distances, hence the above weightings.

g. Detection zone index

The index had three weighted components and was scaled 0-1 across reserve quarters.

1. Length (33% weighting): the sum of perimeter and primary detection zones if not the same, plus secondary zones. Divided by perimeter to account for different reserve sizes (not area, because zones are linear).
2. Frequency of checking (33%): how often the detection zone is inspected
    a. Incident specific (score 1), daily (score 2), or twice daily (score 3), scaled 0-1.
3. Frequency maintenance (33%) – how often the detection zone is maintained (dragged)
    a. The number of times a month the detection zone is maintained, scaled 0-1.

h. Specialised Security: control room and rapid response team index

The index was an equally weighted sum of the following two indicators, scaled to vary 0-1.

Control room: no control room score is 0, control roomed manned during day scores 0.5, and control room manned 24/7 is scored 1.

Rapid response team (RRT): if there is none the score is 0, a non-dedicated RRT has a score of 0.5, while a dedicated RRT scores 1.

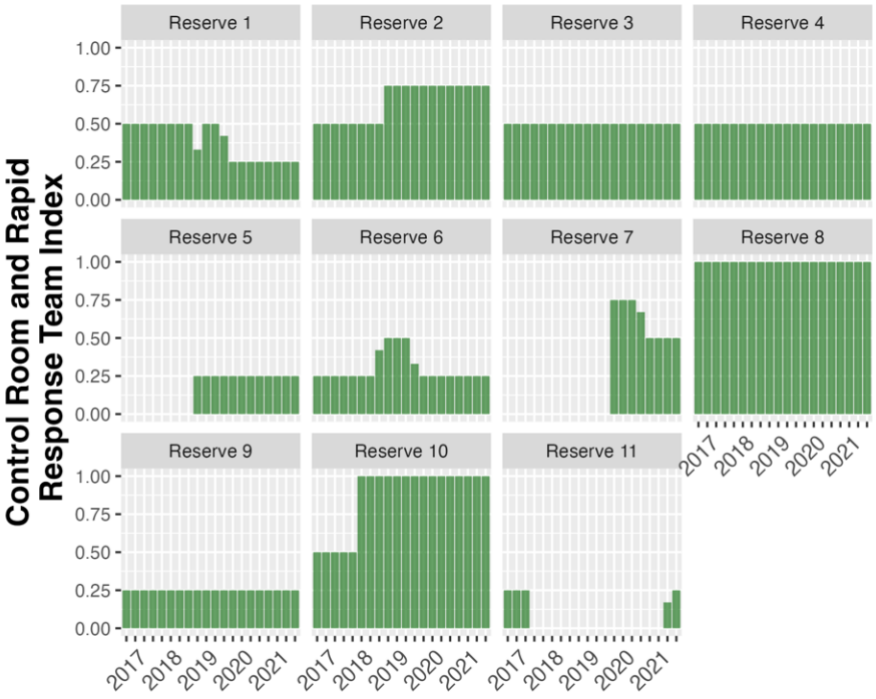


Figure S18. The intensity of implementation of specialised security: control room and rapid response teams across all 11 reserves (2017-2021). As described in the materials and methods, this was quantified as the presence/absence and intensity of each intervention on each reserve based on several variables.

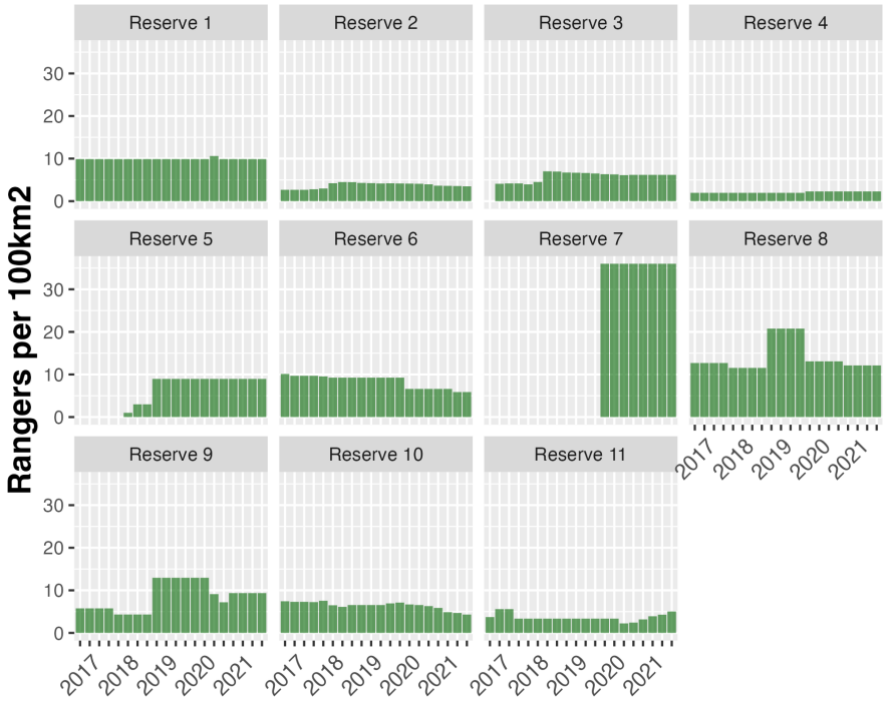


Figure S19. The density of anti-poaching rangers across all reserves (2017-2021).

i. Rhino monitoring index

The index was an equally weighted sum of the following two indicators:

1. Rhino monitoring staff (an equally weighted sum of the following two sub-indicators):
    a. Whether or not there is an analyst dedicated to rhino monitoring data (1 or 0)
    b. Whether or not there is a dedicated (score 1) or non-dedicated (score 0.5) staff member responsible for monitoring of black and white rhino. Total scores scaled to 0-1 scale.
2. Rhino monitoring details and technologies (each sub indicator below scaled to 0-1 scale).
    a. Whether or not there is dedicated rhino/asset monitoring for each species
    b. Whether or not each species is individually marked
    c. Whether or not the rhino monitoring data feed into security planning, and whether this is real-time, retrospective, or strategic
    d. The proportion of the rhino population that are microchipped

j. Ranger training and equipment index

The index was the equally weighted combination of the following four indicators (each scaled to 0-1):

1. *The proportion of security staff trained in each of 8 forms of training*: basic field ranger training, advanced field ranger training, tactical training, night tactical training, legal training, first aid training, and counselling). Fort each form of training and for each quarter on each reserve, the rolling sum of the proportion of staff that had been trained over the last year was calculated (assuming that training more than 1 year ago was less effective in the present). Then, the sum of these rolling sums was calculated over all forms of training. The score was then scaled to 0-1.
2. *General ranger equipment, per ranger*. There were 15 types of equipment across the 10 reserves labelled as: IR beacons strips, Thermals, Clip IR, Binoculars, Defence weapon

Sighting system, Compass, GPS, Navigation platforms (e.g., Alpine quest), Map, IR torch flashlight, Weapon mounted light White IR, IR laser, Night Vision Goggles, Cameras, Torches. Six reserve managers were contacted to rank these equipment types in terms of their importance for rhino security (low = 1, medium = 2, high = 3) and then the equipment score was calculated as the number of units of each equipment type, multiplied by this importance score, and then weighted by the number of rangers present on each reserve in each quarter. The score was then scaled to 0-1.

3. *Vehicles.* Three types of vehicles: standard vehicle, quad bike, and motorcycle. For each reserve and quarter, the number of vehicles per 100km^2 was calculated. Quads and motorcycles were weighted as 0.5 x standard vehicles because standard vehicles were deemed to be roughly twice as important as other vehicle types, on consultation. The score was then scaled to 0-1.
4. *Firearms.* For each reserve and quarter, the number of firearms per 100km^2. Did not use ranger density as this was so variable and would bias the index. The score was then scaled to 0-1.

k. Camera technology index

The index was computed as the sum of the number of cameras of each type multiplied by the average cost for each type of camera. We assumed that a higher cost of camera means a greater intensity of camera technology implementation, scaled according to reserve size to create an index of ZAR invested in camera technology per km^2. We tested the effect of an index with just the number of cameras, and in which cameras were categorized as "highly specialised" and "other" (Table S3) but this did not change the neutral effect of camera technology on poaching rates in the main statistical model.

A total of nine different camera types were deployed across the various reserves at different points in time (Table S3). Mobile live feed cameras with AI were the most widely deployed, with all reserves using them at some point and a total of 401 units (Table S3). Another widely used camera type was static live feed CCTV cameras (Table S3; mostly deployed at gates). There were a few highly specialised camera types (thermal, PTZ, etc) costing over R100k, but deployed only at a few reserves (see Table S3 rows r13, r15, r16, r22).

Table S3. The various camera types deployed across the various reserves

Row # in data sheet	Camera description	Mean Cost (ZAR)	Total # (all reserves)	Reserves
Highly specialised cameras (ZAR >200k)				
r13	Static live feed CCTV camera with AI (deployed in the field, not at access)	120 000	1	Only 1 reserve
r15	Static Pan Tilt Zoom camera	214 000	5	2 reserves
r16	Static thermal camera non-AI	220 000	13	Only 1 reserve
r22	Mobile thermal camera with AI	350 000	3	Only 1 reserve
Other cameras (<10k).				
r17	Static live feed CCTV camera no AI. Some deployed in field, otherwise recorded under access control.	11 008	84	All except 2
r19	Mobile live feed camera with AI	8 000	401	All reserves at some point
r25	Mobile live feed camera trap non-AI	5 567	7	2 Reserves
r26	Mobile manual camera trap non-AI	6 433	70	5 Reserves
r31	Dummy camera	273	87	8 Reserves

B. Data on intervention cost

For each intervention, detailed data were collected on the monthly expenditure on various aspects of that intervention. For example, for K9 dog units, expenditure on acquiring the dog, training the dog and handler, as well as revisionary and kennel costs were recorded (Fig. 20 C). Detailed ranger and other security staff salaries were available for each reserve annually. The cost of dehorning an individual rhino was very similar across reserves (USD 500-600) but the total expenditure varied widely among reserves according to the number of rhinos dehorned (Fig. 20 D; Reserve 3 is Kruger NP). For camera tech, the expenditure was enumerated as the total value of all cameras acquired, standardised by area (Table S3; Fig. S20E). Cost data represent minimum estimates as data on some elements of particular interventions were not available.

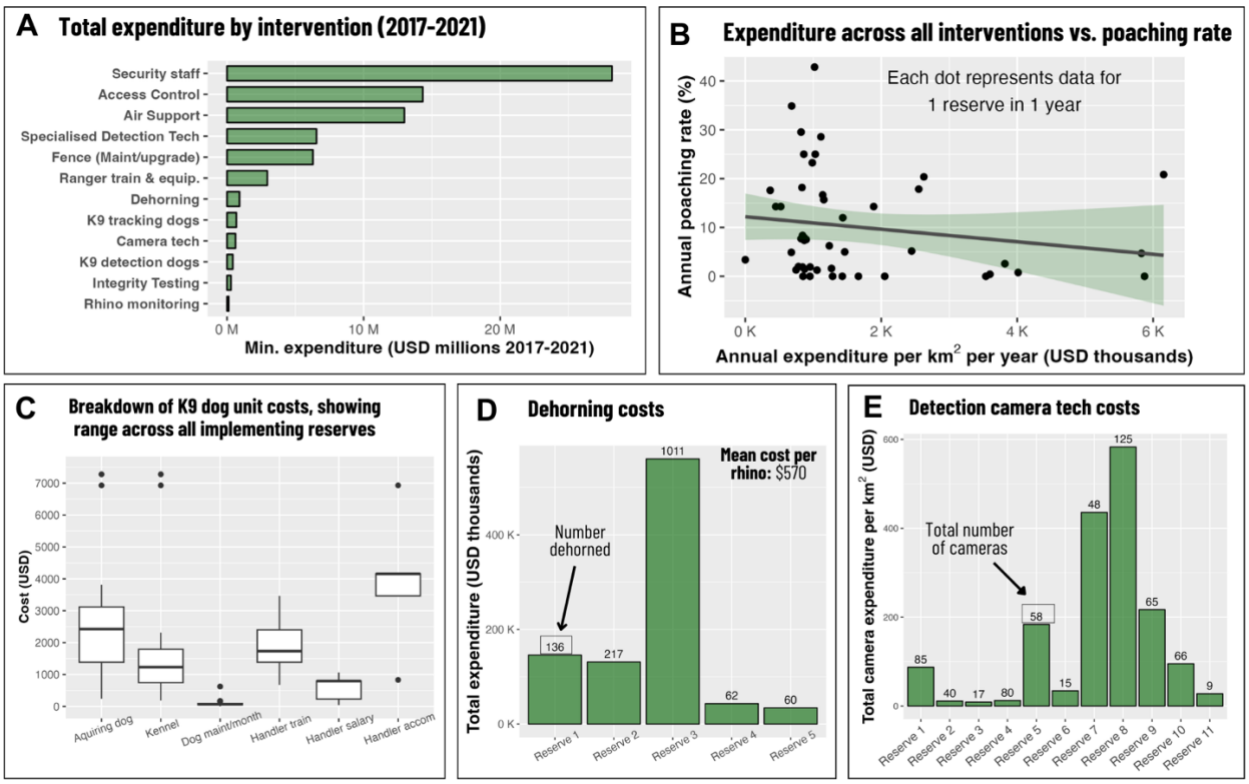


Figure S20. An overview of the financial investment in various anti-poaching interventions in the Greater Kruger landscape (2017-2021). **A**: Overall costs per intervention across all reserves and years. Estimates were collated from detailed expenditure data for each element of the intervention, with standardised cost data collected across reserves. Data were missing for a minority of intervention costs; hence the estimate is a minimum. **B:** The correlation between expenditure and poaching rates across all reserves and quarters (three-month period). Data were missing for a minority of intervention costs hence the estimate is a minimum. **C to E:** More detailed breakdowns of cost for three key interventions. **Note:** We did not quantify the intensity of aerial support in the main statistical model because each reserve other than Kruger NP had access to the same level of aerial support which serviced the entire region. Similarly, Kruger NP was the only reserve implementing specialised detection technologies such as the Wide Area Surveillance System, so this intervention could not be meaningfully included in the statistical analysis.

Additional supplementary results figures

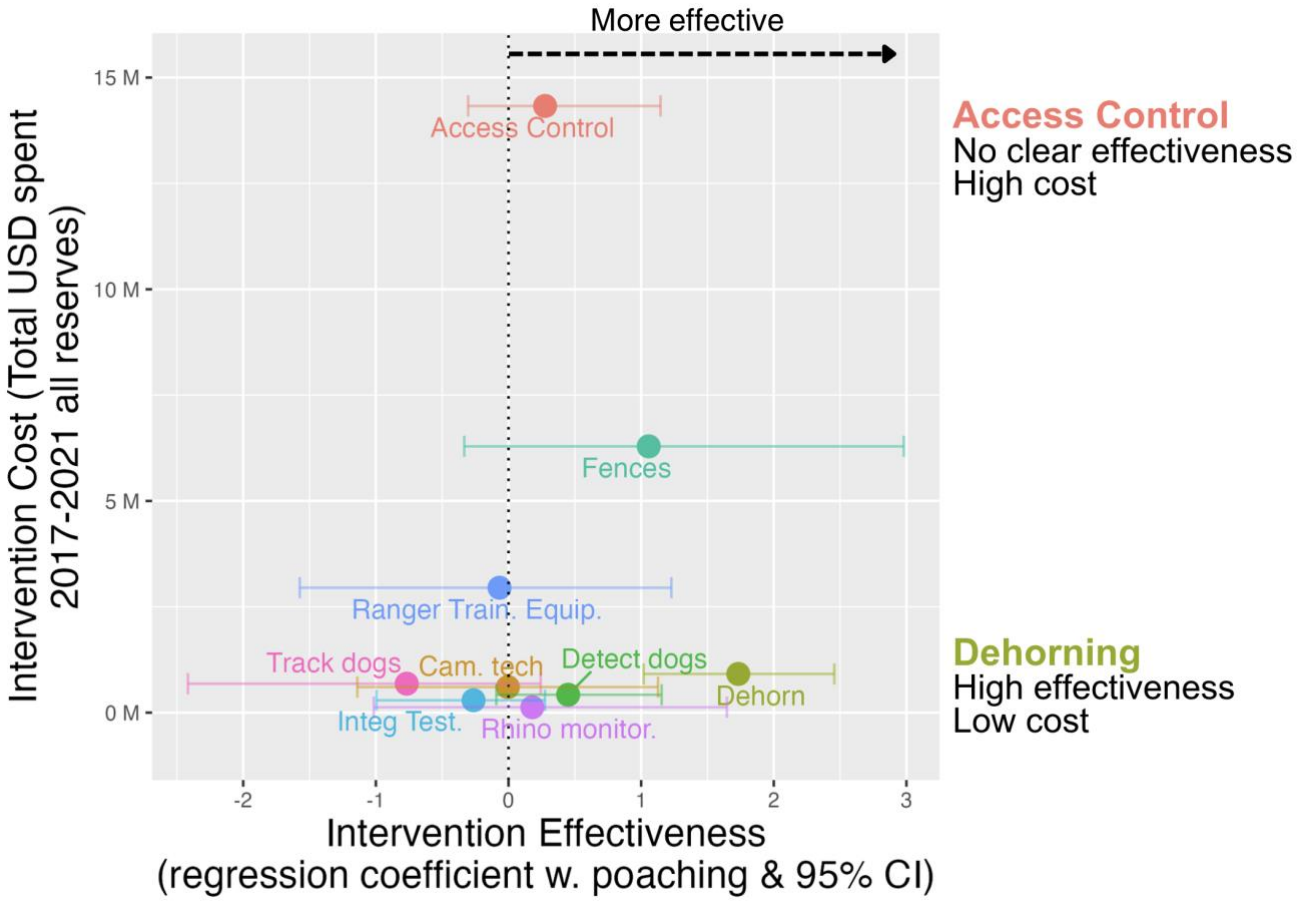


Figure S21. The total amount invested in each intervention between 2017-2021 and across all reserves, plotted against the effectiveness of each intervention as measured by the regression coefficient with poaching (values reversed such that those greater than zero represent more effective interventions).

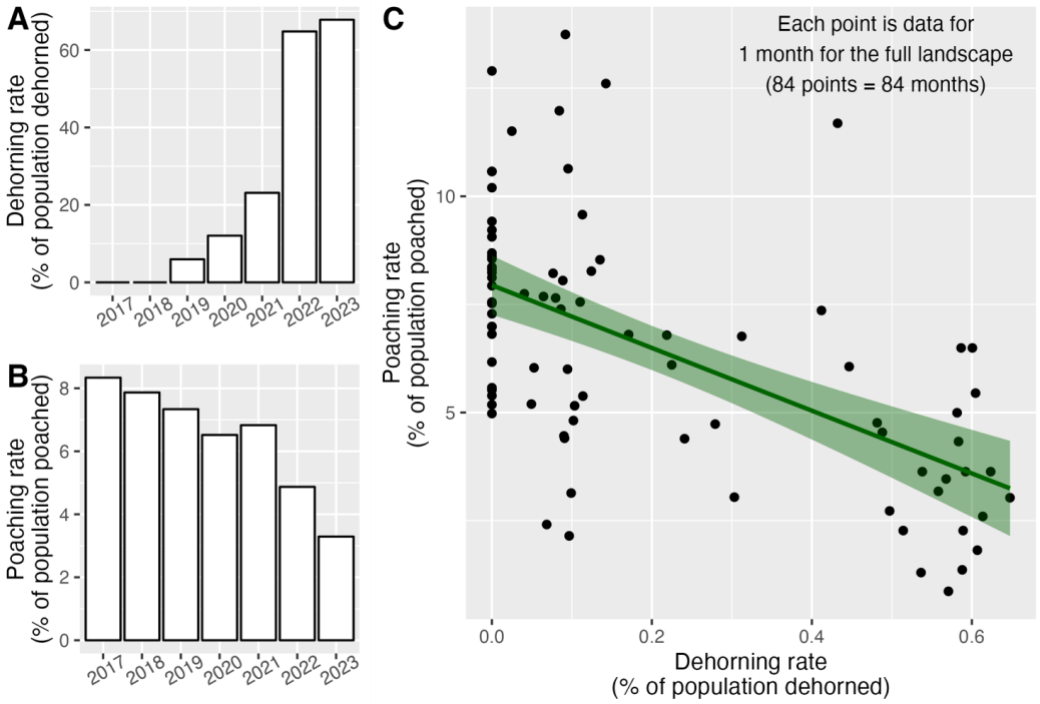


Figure S22. Landscape-level relationship between (A) the dehorning rate (% of all rhinos present dehorned), and (B) poaching rate (% of rhino poached) across the 11 Greater Kruger focal reserves over seven years (data lumped across reserves, 2017-2023). Panel C shows the relationship between the monthly poaching and dehorning rate across 7 years (84 months; data lumped across reserves).

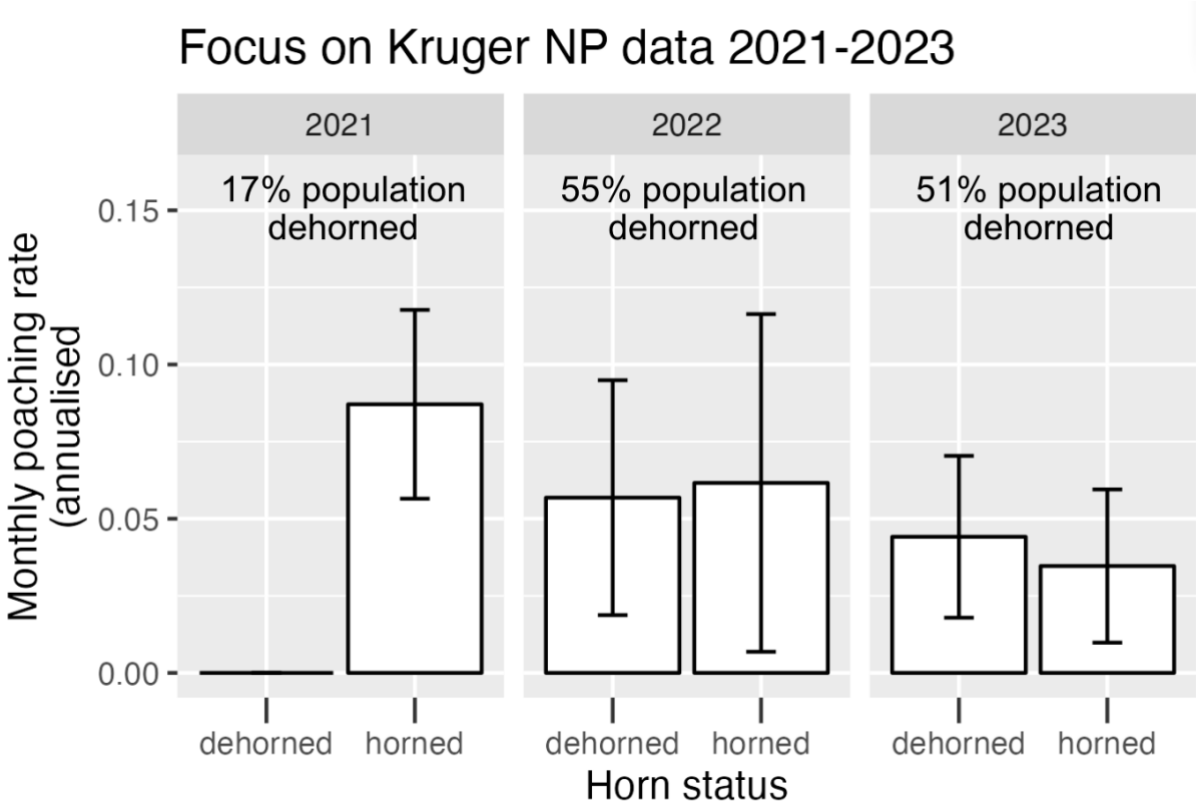


Figure S23. The poaching rate of horned versus dehorned rhino on Kruger NP between 2021 and 2023, with the percentage of all rhinos that were in the dehorned state (classified as being dehorned in the last 18 months) shown above the bars.

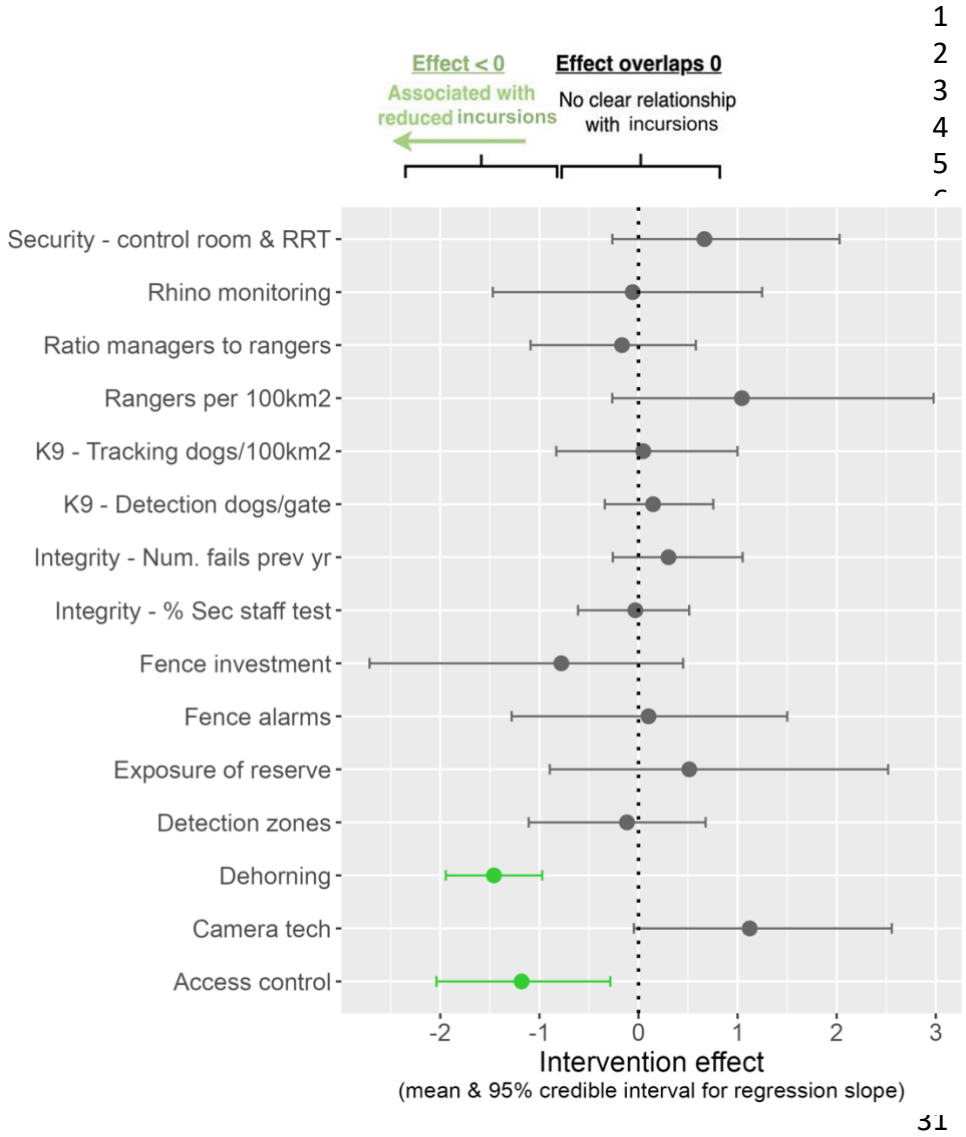


Figure S24. Supplementary model with incursions as the response variable: The estimated effect of each intervention on rates of incursions (incursions per unit area), based on statistical analysis of data across all reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

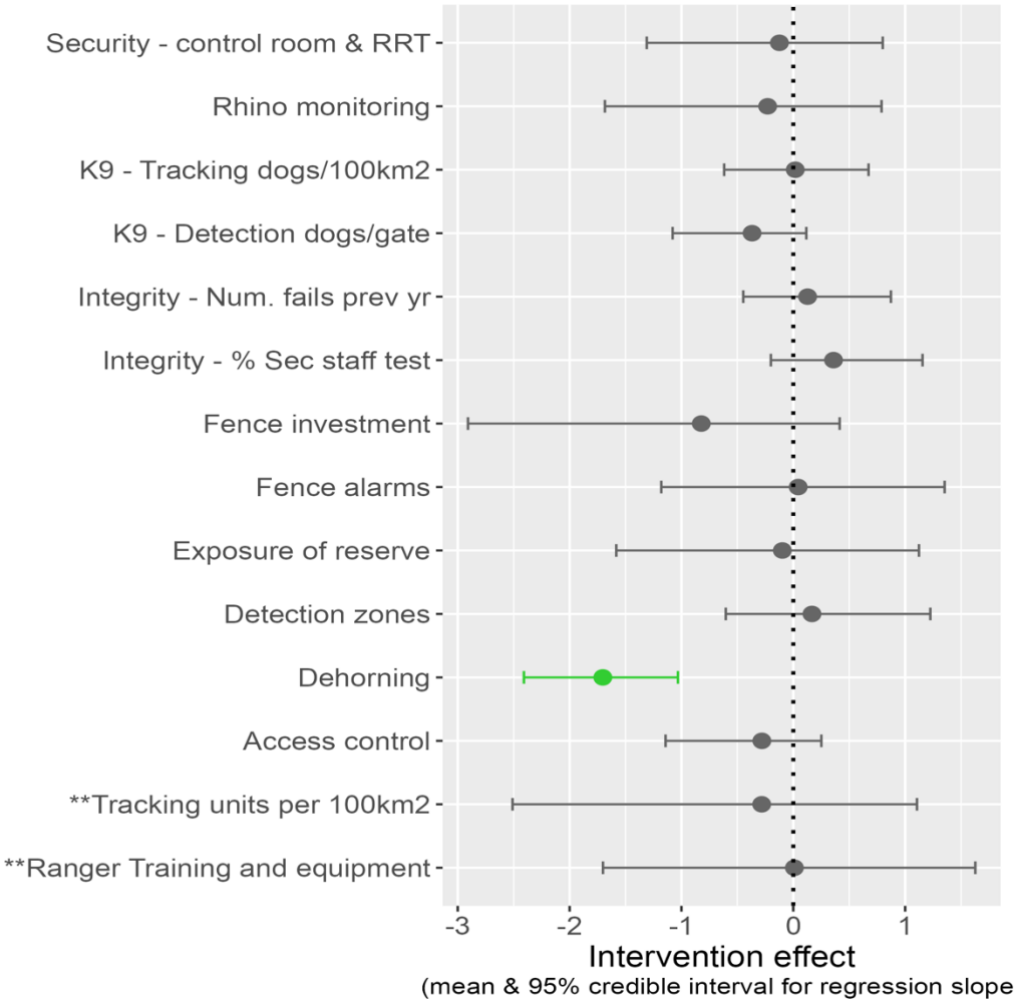


Figure S25. Supplementary model with ranger training and equipment, and tracking technology included (and correlated variables included). The estimated effect of each intervention on rhino poaching rates, based on statistical analysis of data across reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

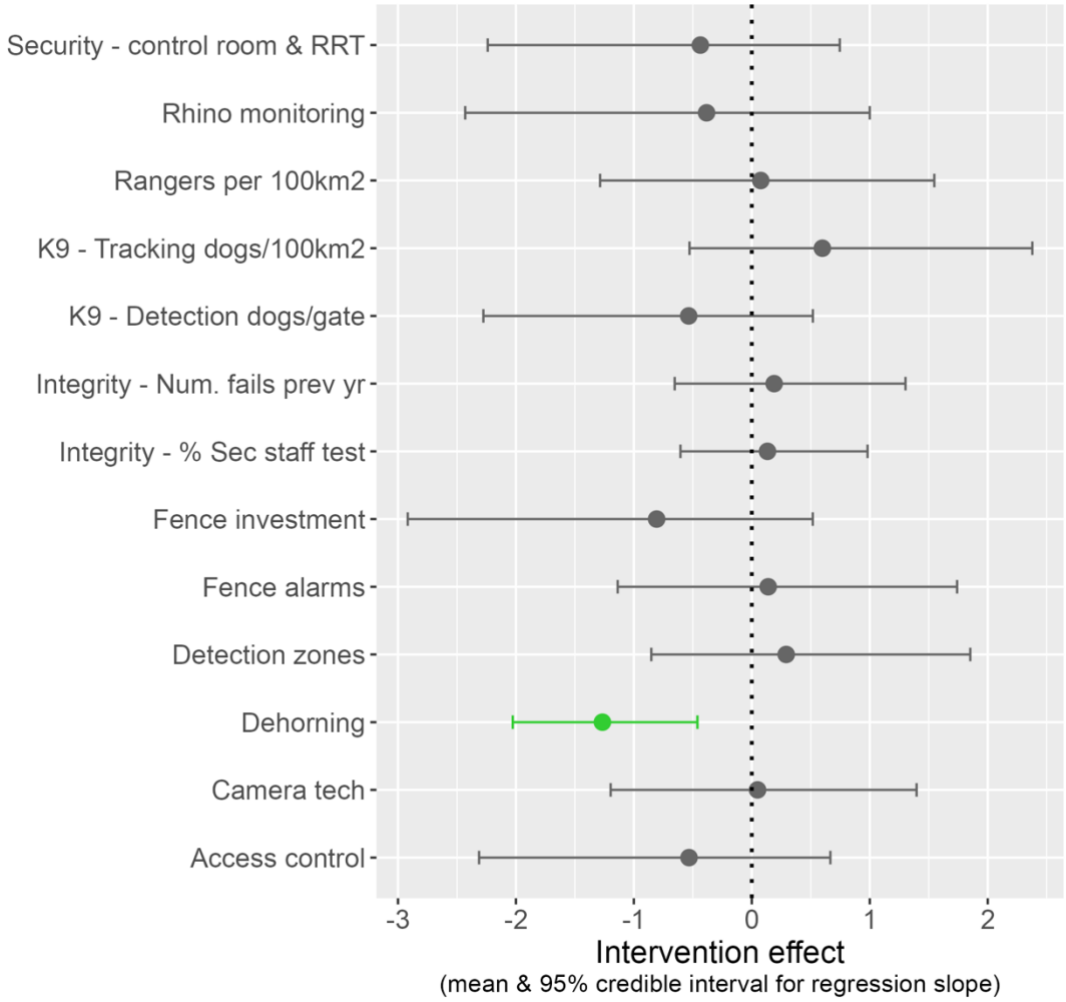


Figure S26. Supplementary model with Kruger NP excluded. The estimated effect of each intervention on rhino poaching rates, based on statistical analysis of data across reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

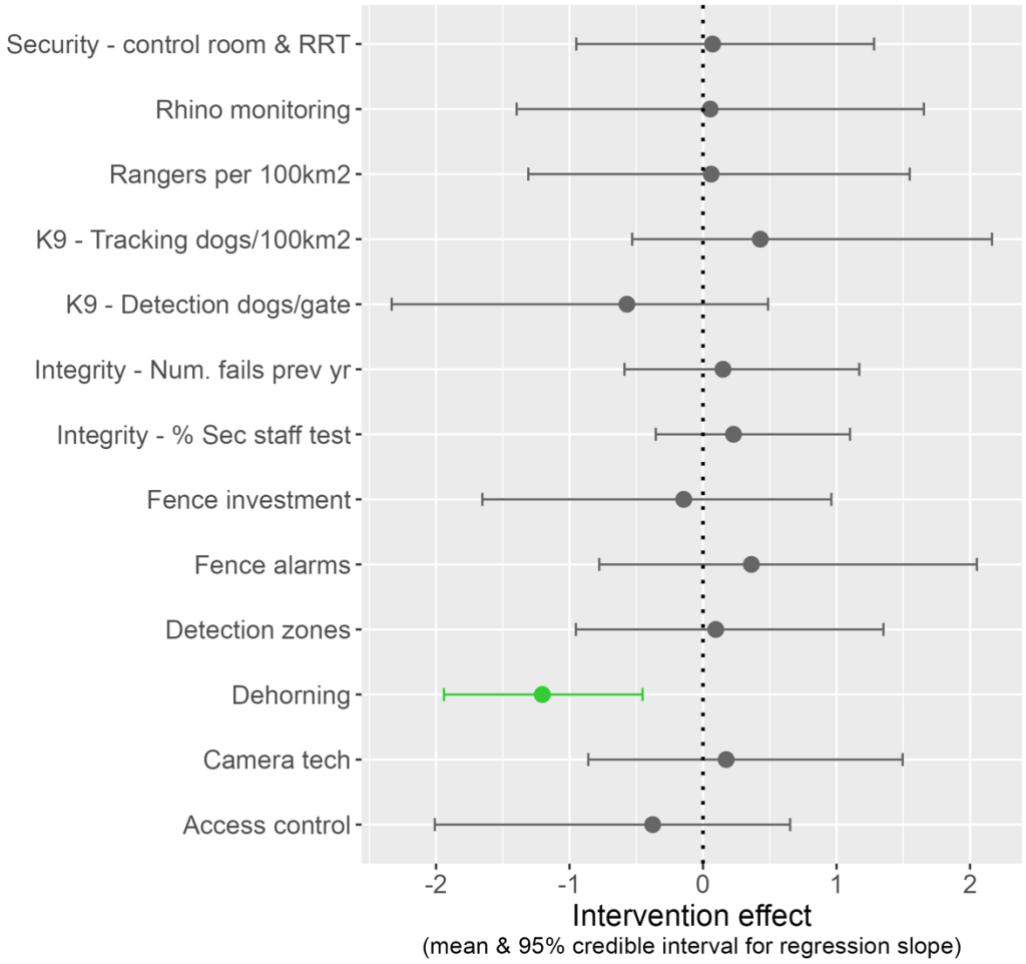


Figure S27. Supplementary model with the raw number of rhinos poached as the response variable. The estimated effect of each intervention on rhino poaching rates, based on statistical analysis of data across reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

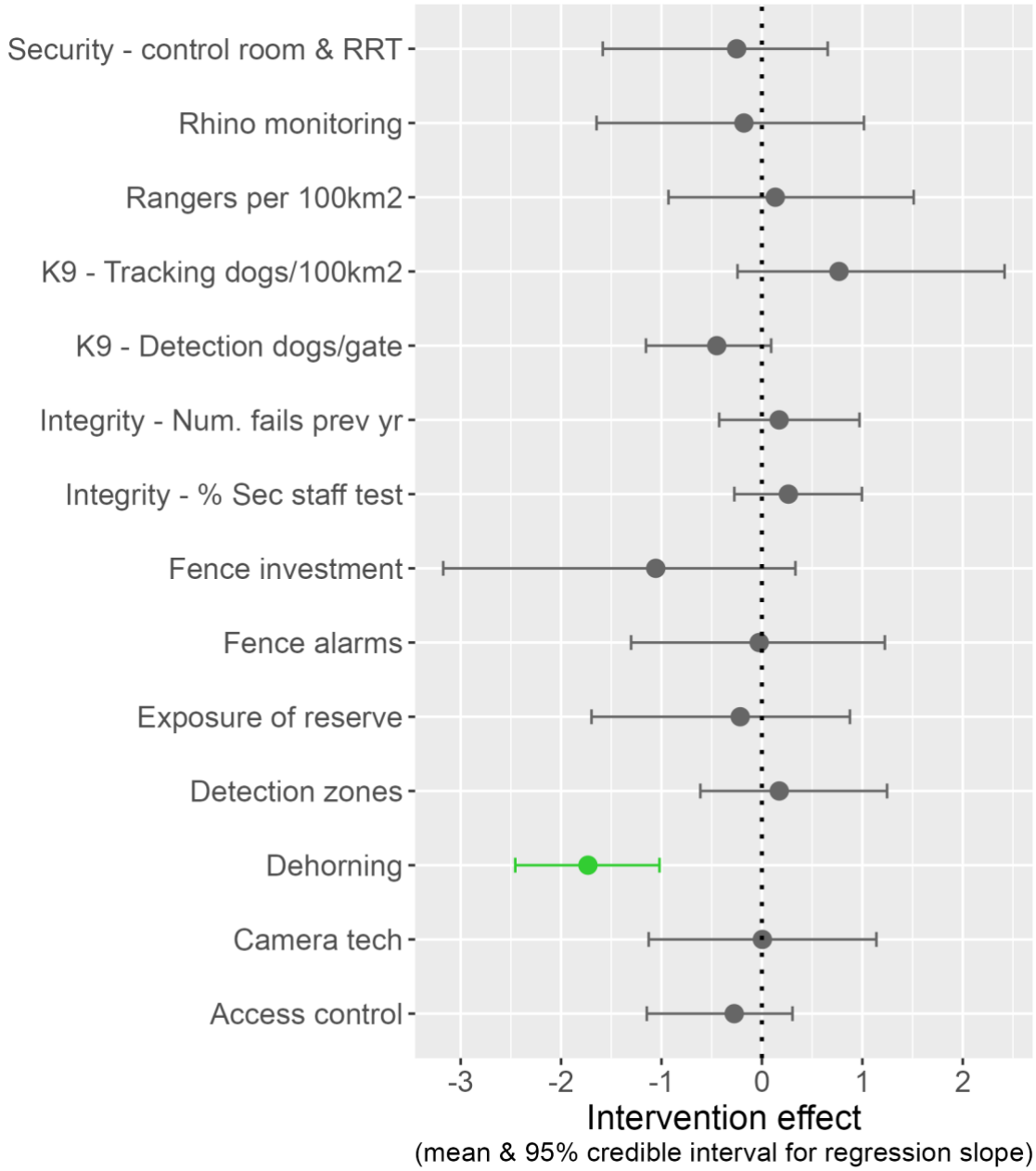


Figure S28. Supplementary model with population estimates corrected for possible under-estimation. Estimates were corrected upwards by a factor 1.245 following Kidwai et al. 2019 (see Supplementary text and ref 9). The estimated effect of each intervention on rhino poaching rates, based on statistical analysis of data across reserves and quarters (2017-2021). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

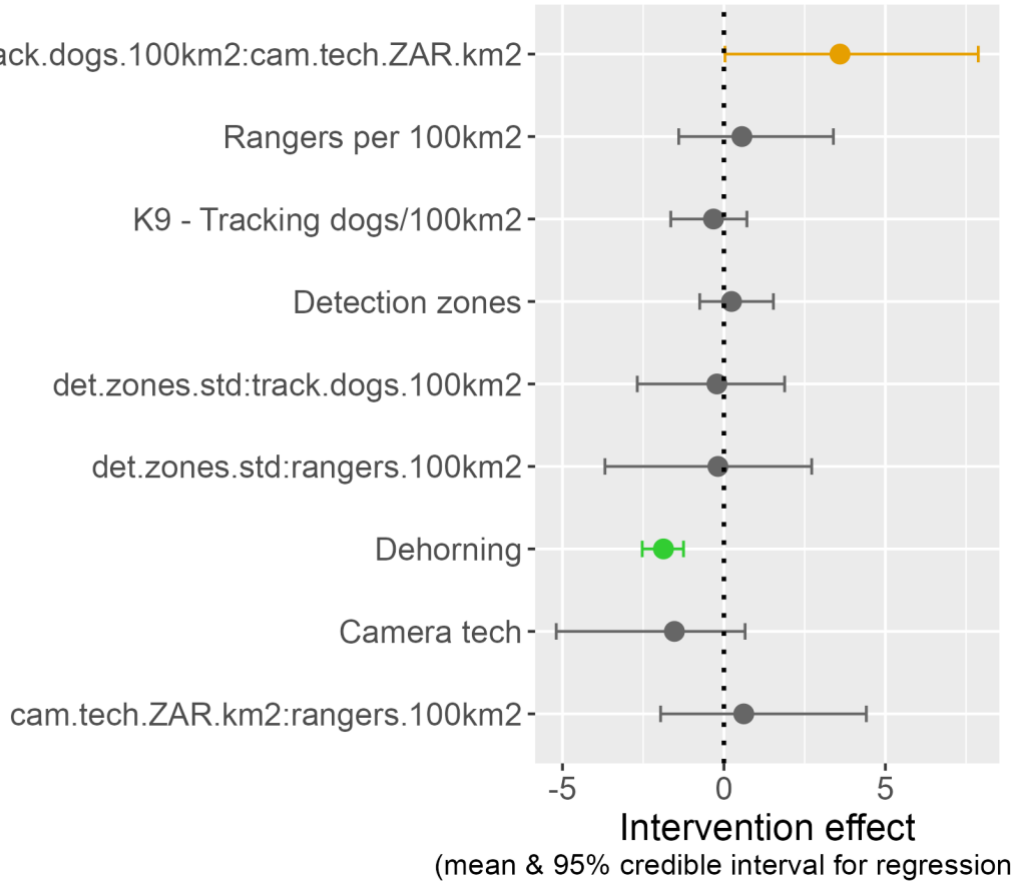


Figure S29. Supplementary model testing the effect on poaching rates of several key combinations of detect and react interventions (see fig. S1and materials and methods).Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

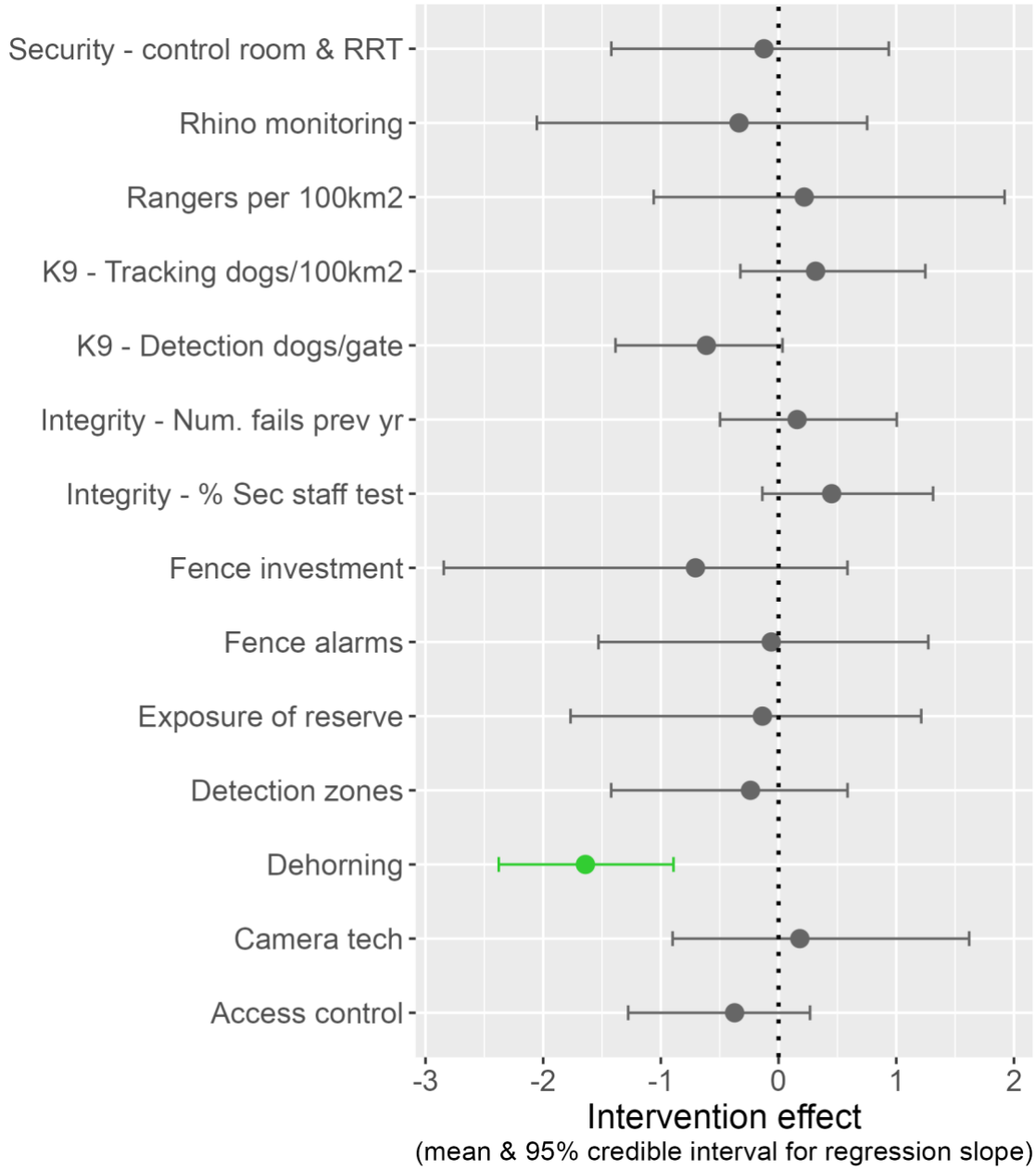


Figure S30. Supplementary model that tested for lagged effects of the detect interventions on poaching rates. The effect of all detect interventions on poaching rates were lagged by one quarter. The effect of a two-quarter lag was very similar (see materials and methods). Effects represent the regression coefficient for the relationship between each intervention variable and poaching levels. The intervention variable values are all scaled to vary between zero and 1, so effects are directly comparable among interventions.

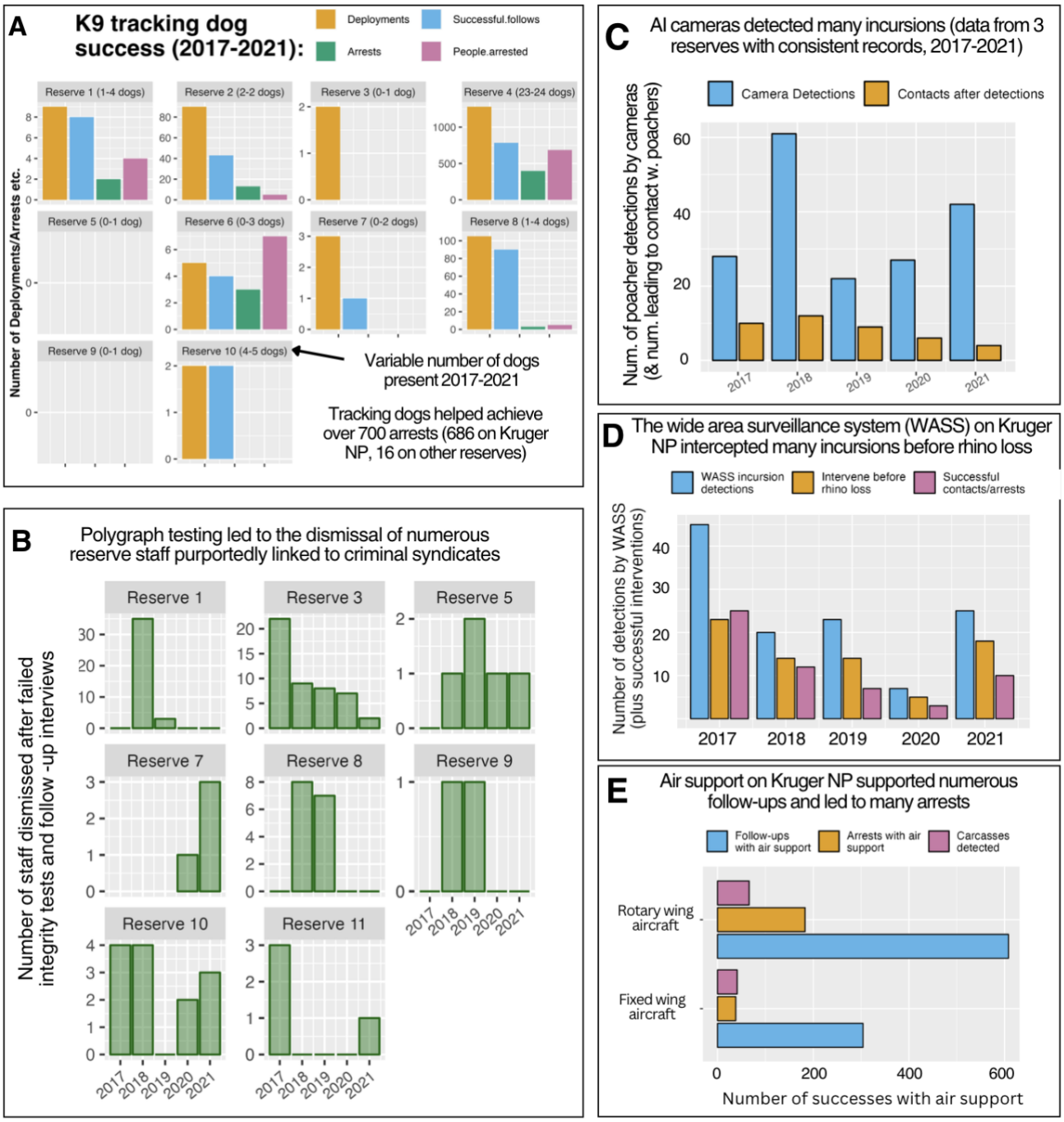


Figure S31. Alternative measures of interventions success. These measures provide evidence for success at intermediate steps along the hypothesised causal pathway for each intervention (see Fig. 2 main text and fig. S1), which the full analysis suggests rarely translated into the ultimate outcome of reduced poaching (Fig. 3 main text).