

## Policy analysis

# A demographic model to support an impact financing mechanism for black rhino metapopulations

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## A B S T R A C T

Payment-for-results mechanisms have the potential to increase funding for Critically Endangered species such as the black rhino (*Diceros bicornis*). Developing such financial mechanisms requires an understanding of the efficacy of conservation interventions, the potential conservation return on investment and an ability to rigorously measure the impact of interventions, such as change in abundance of live or poached animals. However, imperfect detection must be considered to derive robust estimates of these measures. Managing black rhino is often done at the metapopulation level (in distinct management units) where ecological and observational processes can differ substantially between populations.

We developed a multi-state capture-mark-resight model to estimate the abundance of live rhino and carcasses from annual historical observations. We used age, sex and management units as covariates. We used 25 years of monitoring data from two sections with contrasting rhino densities in Tsavo West National Park, Kenya as a test case. The model presented can be used to estimate abundances of rhino from historical data and provides a mechanism to measure changes across multiple management sections. We foresee this model being used as the basis for impact measurement of a rhino impact financing mechanism. The model can easily be modified for use in other species managed in a metapopulation framework.

## 1. Introduction

Payment-for-results mechanisms, in which there is a financial incentive for achieving predetermined objectives, have the potential to drive cost-effective and efficient biodiversity conservation (Gibbons et al., 2011; McDonald et al., 2018). Payment-for-results schemes in conservation are made difficult by monitoring and evaluation challenges, which weaken the value proposition. An inability to affect change or a seemingly weak relationship between investment and results makes investment into action unlikely (Gibbons et al., 2011). System-level indicators of success such as increased biodiversity, ecosystem services, or Essential Biodiversity Variables are fraught with practical and conceptual challenges around the appropriate metric,

scale, meaning and how to cost-effectively monitor their response to interventions. It can require significant resources to achieve the necessary repeatability, accuracy and precision required for robust monitoring and evaluation (Baker et al., 2010). Importantly, the levels of rigour needed to demonstrate impact for payment-for-results mechanisms are commonly higher than those for general conservation management, often requiring an increase in monitoring costs compared to operations pre-investment. This is because when payments are linked to financial investments, there are fiduciary responsibilities for investments to consider. This increase in expense and the effect on product viability is demonstrated in the implementation of many REDD (Reduction in Emissions and Deforestation) programs, where the monitoring and verification systems can be a cost trap (Köhl et al.,

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2020).

Single-species-focused impact mechanisms, such as the Wildlife Conservation Bond (WCB, formally the Rhino Impact Bond) (Aglionby, 2019; Jeffries et al., 2020) offer a promising avenue for promoting tangible and cost-effective conservation impact measurements due to the simplicity of the value proposition and cost-effectiveness of monitoring and evaluation. The WCB seeks to raise up-front capital from impact investors to fund strategic interventions over five years to achieve an agreed-upon impact on rhino abundance, measured as growth rate. Growth rate is the key performance indicator for the Theory of Change to grow African rhinos (Dave Balfour et al., 2019a) and has defined targets in many national black rhino management strategies (Amin et al., 2017; Knight et al., 2013).

The proposed target for the WCB is a set 5% compound annual growth rate over the 5-year investment period for entire metapopulation. There is potential for a sliding scale of returns up to this maximum target, which is subject to agreement between contracting parties. The metric requires a verifiable estimate of population abundance before the start of the investments and after 5 years of investment, as well as any man-made translocations of rhino. If this target is achieved, there is a guaranteed financial return to the investors for taking the risk.

Despite the single species focus of the financial mechanism, the WCB is geared to landscape conservation. Black Rhinos are sensitive to mismanagement and are highly persecuted, the WCB value proposition is that a growing black rhino population is an indicator of a large and well-managed protected area in which highly prized biodiversity elements are protected from overexploitation. We view black rhino in this context as an umbrella species, defined as “species with large area requirements, which if given sufficient protected habitat will bring many other species under protection” (Noss, 1990). The utility of umbrella species as a proxy for larger conservation success is widely recognized. Generally, species richness and abundance are greater in areas using an umbrella species as a conservation tool. However, context-specific consideration is required (Branton and Richardson, 2011; Roberge and Angelstam, 2004). An umbrella species should exhibit: a) well-known biology; b) large home range size; c) a high probability of population persistence; d) co-occurrence of additional species of conservation interest; e) management requirements that are beneficial to co-occurring species; f) be sensitive to human disturbance; and g) be relatively easy to monitor (Seddon and Leech, 2008).

The black rhino meets these requirements: a) the biological management of black rhinos is well understood with established best practice guidelines (Dave Balfour et al., 2019b); b) black rhinos are megaherbivores which can potentially occupy very large home ranges (2.5km<sup>2</sup> ->400 km<sup>2</sup> depending on the habitat) (Conway and Goodman, 1989; Hearn et al., 2000); c) black rhinos are the focal species of conservation for many protected areas, which ensures that resources are deployed to maintain their persistence; d) black rhino populations are almost exclusively conserved in large contiguous protected areas which have general biodiversity conservation mandates; e) management of black rhino populations requires ensuring high levels of security and often with managed water supply, which can directly benefit other species with similar requirements; and f) black rhinos are highly persecuted for their horn, are sensitive to land-use change and the majority of populations are monitored with well-established monitoring protocols (du Toit, 2006).

The success of the WCB is predicated on being able to estimate changes in population abundance accurately and precisely. Change estimation based on abundance, as opposed to the difference in survival and mortality rates, is important as it provides a metric of the scale of the impact, an important component of a financial mechanism. Also, intervention strategies and the ability to attribute impacts to the interventions requires information on the major drivers of population change. Information for security or biological management requires estimates of the number of animals poached vs naturally dying, their

densities and the age classes or sexes which are experiencing higher mortality rates than others, which are used as indicators for impending changes in growth rate (du Toit, 2006).

To date, statistical methods for abundance estimation of black rhinos have been unable to provide the rigour required for a financial product for two primary reasons:

First, imperfect detection of rhino or rhino carcasses is seldom considered. Trends in rhino populations have been variously estimated. Block counts are more common for population estimation of black rhino abundance where ID-based monitoring is not feasible (Brockett, 2002; Ferreira et al., 2011, 2017). Recently N mixture models have been used to estimate black rhino abundance (Kidwai et al., 2019). However, the bulk of black rhino populations, including all the sites selected for the WCB after the due diligence process (Jeffries et al., 2020) had entrenched ID based monitoring protocols. The black rhinos are rendered uniquely identifiable by their ear notch patterns (a combination of physical capture and cutting a unique pattern and naturally occurring tears), or in the case of dependent calves, association with their mothers (du Toit, 2006). The number of individuals/carcasses observed per observation window is used as a measure of abundance for rhinos or carcasses. Post-hoc adjustment of unobserved animals is not routine. Individuals not seen a long time, but for which there is no evidence of a carcass are presumed dead; a decision that is often subjective and inconsistent. Using these counts as true measures of abundance would assume that every individual, on every sampling occasion was detected. This would be very difficult to achieve given the prohibitive logistical costs. Using these counts to estimate trends, would assume that detection probability did not vary systematically over time. Black rhinos are cryptic and the detection of live individuals or carcasses will be influenced by heterogeneity in detection probability due to seasons, habitats, monitoring techniques, duration of surveys and size of reserves (Ferreira et al., 2018; Pledger et al., 2003). Disregarding imperfect and variable detection results in biased estimates of abundance, and therefore growth rate (Royle et al., 2005), which would bring the validity of the payments-for-results mechanism into question.

Second, despite the monitoring approaches being well suited to capture mark-resighting based abundance estimation, the previously used techniques that do incorporate detection probability are not easily extendable to multiple time points, cannot account for capture heterogeneity and assume that the population does not change over the data collection period (Emslie et al., 2005; Underhill and Fraser, 1989). This means that the models cannot account for changes in abundance as a function of birth, immigration, death and emigration, making the attribution of a mechanism to a change in abundance difficult. Moreover, these models do not estimate the quantity necessary for the WCB.

The challenges to robust impact measurement and effective biological management are clear; detection probability of live individuals and carcasses, as well as detection heterogeneity between populations, needs to be considered in models attempting to estimate black rhino abundance and growth rate. We address these issues by developing a multi-state capture-mark-resighting model to estimate abundance, growth rate, survival, and mortality (natural and by poaching) while explicitly accounting for imperfect detection. The model also incorporated data about translocations of rhinos into and out of populations as part of metapopulation management. Black rhinos are often managed as artificially created meta-populations (Amin et al., 2006, 2017), which vary from classic metapopulation theory (Elmhagen and Angerbjörn, 2001; Hanski, 1999; Olivier et al., 2009), as management investments are aimed at mimicking natural processes such as dispersal, but minimize population extinction and maximize persistence overall.

We estimated abundance by fitting the model to live-encounter and dead recovery data. We incorporated covariates of age, sex, sub-population, and time. We explored model performance and parameter identifiability using simulations. The model provides evidence of the efficacy of both biological management interventions and security interventions. Importantly our model explicitly acknowledged that

**Table 1**

State transition matrix for the multi-state model, indicating the transition from one state to another in time steps  $t$  and  $t + 1$ . (rows to columns) where  $s$  = survival probability, Intro = Introduction probability, tran is the probability of an individual being translocated out, gamma is a noise parameter, pp is the probability that mortality was due to poaching,  $r$  is the carcass recovery probability.

	Not entered	Alive in area	To Introduce	Recently killed poached	Recently killed other	Translocated out	Dead not found or long dead
Not entered	$(1-\text{gamma}[t])*(1-\text{intro}[t])$	$\text{gamma}[t]$	$\text{Intro}[t](1-\text{gamma}[t])$	0	0	0	0
Alive in area	0	$s[i,t] * (1-\text{tran}[t])$	0	$(1-s[i,t])*pp[t]*r$	$(1-s[i,t])*(1-pp[t])*r[i,t]$	$s[i,t] * \text{tran}[t]$	$(1-s[i,t])*pp[t]*(1-r[i,t]) + (1-s[i,t])*(1-pp[t])*(1-r[i,t])$
To introduce	0	1	0	0	0	0	0
Recently killed-Poached	0	0	0	0	0	0	1
Recently killed other	0	0	0	0	0	0	1
Translocated out	0	0	0	0	0	0	1
Dead not found or long dead	0	0	0	0	0	0	1

separate populations within a complex of protected areas may differ in their ecological state and detection process. Our model allowed us to take this variation into account when deriving demographic estimates of the separate management units (hereafter referred to as subpopulations).

To demonstrate the utility of the model as part of a payment-for-results mechanism we presented a retrospective analysis of a historic investment into rhino conservation. We derived the compound annual growth rate of the population over a 5-year window and compared it against a national target which defined success to demonstrate how such a payment-for-results mechanism can work.

**2. Materials and methods**

We used a multistate Jolly-Seber model, which allows us to estimate abundance in open populations (Dupuis and Schwarz, 2007). We implemented the model as a hierarchical, multi-state capture-mark-resighting model (Kéry and Schaub, 2011; Lebreton and Cefe, 2002; Pace III et al., 2017) and fitted the model to a combination of live-encounter and dead-recovery data. The live-encounter data consisted of sightings of marked individuals and the dead-recovery data consisted of records of fresh carcasses (found within a one-year sightings window) of marked individuals for which the cause of death (killed by poachers vs died from other causes) had been determined. Also, black rhinos may be managed in metapopulations through translocation of individuals into or out of a population, which we refer to as introductions or removals. We defined seven states,  $Z$ , for the model: State 1 = not yet entered the population; State 2 = alive and in the population; State 3 = to be introduced; State 4 = found freshly dead from poaching; State 5 = found freshly dead from other causes; State 6 = translocated out; and State 7 = no longer part of the population: long dead, freshly dead but not found, or translocated out in previous time step (absorbing state). Rhino populations are often closely managed and there is no natural emigration. In less closely managed populations, state 7 would include permanent emigration.

Alternative state definitions could be considered but Kery and Schaub (2012) showed that this choice leads to a stable implementation.

**Table 2**

Observation matrix defining the relationships between the observed states (columns) and the state process (rows), for each period  $t$ . Where  $p$  is the detection probability of an individual in state 2.

	Seen alive	Introduction	Recovered dead- Poached	Recovered dead other	Captured for trans- out	Neither seen or recovered
Not entered	0	0	0	0	0	1
Alive in area	$p[i,t]$	0	0	0	0	$1-p[i,t]$
To introduce	0	1	0	0	0	0
Recently killed-Poached	0	0	1	0	0	0
Recently killed other	0	0	0	1	0	0
Translocated out	0	0	0	0	1	0
Dead not found or long dead	0	0	0	0	0	1

The state-space model consists of a part describing the state at first encounter for each individual:

$$Z_{i,t} = fs_i$$

where  $fs_i$  is a vector with the true state of individual  $i$  at first encounter. The state-process is then assumed to follow a categorical distribution:

$$Z_{i,t+1} | Z_{i,t} \sim \text{categorical}(\sigma)$$

where  $\sigma$  is the state-transition matrix. The observation model links the true states to observed states,  $Y_{i,t}$ :

$$Y_{i,t} | Z_{i,t} \sim \text{categorical}(\omega)$$

where  $\omega$  is a matrix whose elements  $\omega_m$  describe the probabilities that an individual in state  $n$  is observed in state  $m$ .

Having defined the states as described above, our interest was in the probabilities of individuals transitioning between the states from one year to the next, i.e. the elements of  $\sigma$  (Table 1). For example, the probability of a rhino being killed by poachers is part of the probability that an individual in State 2 in year  $t$  transitions to State 4 by year  $t + 1$ , as well as part of the probability of the individual transitioning to state 7. Some transitions were impossible (e.g. transitioning from a dead state back to a live state) or certain (e.g. transition from a freshly dead state to the absorbing long-dead state) and these were set to 0 and 1, respectively.

Hierarchical models such as the one described here, distinguish between the true state process that describes how individuals' transition between states, and an observation process that describes how the actual observations relate to the true state. Given the definition of our states, the only uncertainty was that not all individuals that were alive were seen each year, i.e., an individual  $i$  in State 2 in year  $t$  was resighted with probability  $p_{i,t}$ . For the other states, there was no observation uncertainty, i.e., all other elements of  $\omega$  were either 0 or 1 (Table 2). The probability of finding a carcass was part of the state-transition model due to how we defined the states.

The transition probabilities into state 6 estimate the proportion of

animals that are translocated out of the population. There is no uncertainty about which individuals were translocated, reflected in the observation matrix where the probability of encountering an individual that is in state 6 is 1. However, the probability of moving to this state also depends on how many individuals are in the population, which needs to be estimated.

Technically the carcass abundance is not required to inform population growth rate and could be removed from the model. However, the measurement of the KPI is only part of the process in such a financial model. First, the poaching rate provides useful management information that mitigated investment risk. Second, to determine the risk of investment, a forecasting exercise was done which used various scenarios based on budgeted management intervention strategies. These strategies focus on security or biological management, as per the black rhino Theory of Change (Dave Balfour et al., 2019a, 2019b). We chose to use the same model structure to both predict outcomes and measure them, to avoid any arguments around differences in model bias.

### 2.1. Parameter estimation

To accommodate heterogeneity in survival rates, we modelled survival as:

$$\text{Logit}(\phi_{i,t}) = \beta_\phi + f(\text{Age}) + \beta_s * \text{Sex}_i + \text{Section}_{i,t} + \mu_i$$

where  $\beta_\phi$  is the intercept estimating the mean survival probability.

We modelled variation in survival accounting for age up to 15 years old, using regression splines with four knots,  $f(\text{Age})$  on the age of the animal when observed in the state, derived from known or estimated dates of birth (see Crainiceanu et al., 2005). Error in age classes for black rhinos is limited at the resolution of a year, due to age class monitoring being part of standard monitoring protocol and all known rhinos having a reported date of birth. There is difficulty in ageing adult animals of unknown origin, e.g. in some historical data, but these are assigned to adult age classes and will not affect model outputs.

The coefficient  $\beta_s$  estimates differences between males and females ( $\text{Sex}$  takes the value 1 for female, 0 for male and NA for unknown). If the sex is not known for all individuals we treated sex as a partially observed latent variable that follows a Bernoulli distribution:

$$\text{sex}_i \sim \text{Bern}(\pi)$$

where  $\pi$  is the probability of an individual of unknown sex to be female, assigned at the beginning for known animals with unknown sex and the augmented individuals. We must note that the unknown sex of a known black rhino is uncommon and for a short time while the calves are still very young.

Black rhino populations are often managed as discrete subpopulations within, or across protected areas. These subpopulations are fenced off from one another and animals cannot move between subpopulations unless translocated. The vital rates and detection processes are expected to vary between subpopulations, which we incorporated into the model.

$\text{Subpop}_{i,t}$  is an  $i \times t$  matrix of values between one and the total number of subpopulations, indicating which subpopulation each individual  $i$ , is during period  $t$ . Finally, we allowed for variation in survival over time by adding year as random effects  $\mu_t$ .

$$\mu_t \sim \text{Norm}(0, \sigma^{\text{st}})$$

where  $\sigma^{\text{st}}$  estimates the variance in logit survival among years.

The detection probability of live rhinos, across individuals and time ( $p_{i,t}$ ) is modelled as:

$$\text{Logit}(p_{i,t}) = \beta_p + f(\text{Age}) + \text{Subpop}_{i,t} + \mu_i + \mu_t$$

where  $\beta_p$  is the intercept of the linear model, estimating the mean detection probability,  $f(\text{Age})$  and  $\text{Subpop}_{i,t}$  are modelled the same as for

survival. Parameters  $\mu_i$  and  $\mu_t$ , are random effects for the individuals and year respectively.

$$\mu_i \sim \text{Norm}(0, \sigma^{\text{pi}})$$

$$\mu_t \sim \text{Norm}(0, \sigma^{\text{pt}})$$

The probability of finding carcasses is modelled with variation across time as:

$$\text{Logit}(r_{i,t}) = \beta_r + \text{Subpop}_{i,t} + \mu_r$$

where  $\beta_r$  is the intercept, reflecting the mean carcass recovery probability and  $\mu_r$  are year-specific random effects.

$$\mu_r \sim \text{Norm}(0, \sigma^{\text{rt}})$$

We note that carcasses are detected once, and there is only a single observation window to do so. Therefore, with long-lived species such as rhinos, under scenarios of low mortality, poor monitoring effectiveness, or with limited ability to link carcasses to individuals, there may be limited data to estimate  $\text{Logit}(r_{i,t})$ , varying by both subpopulation ( $\text{Subpop}_{i,t}$ ) and time ( $\mu_r$ ). In such cases, we removed the time-varying covariates to estimate the average recovery per subpopulation.

The proportion of carcasses attributable to poaching ( $K$ ), as opposed to natural causes, could vary across years:

$$\text{Logit}(k_t) = \beta_k + \mu_k$$

where  $\beta_k$  is the average proportion of carcasses attributed to poaching and  $\mu_k$  are year-specific random effects.

$$\mu_k \sim \text{Norm}(0, \sigma^{\text{kt}})$$

We assumed that all carcasses have the same detection probability irrespective of how the rhinos were killed. This assumption is not strictly true, occasionally poaching is detected through incursions or gunshots, which is not the case for deaths from natural causes. This assumption could be relaxed if there were sufficient mortalities. However, preliminary analyses of the model showed that the survival estimates were not sensitive to this assumption and that relatively large sample sizes of both types of carcasses are needed to reliably estimate separate detection probabilities.

To estimate population size, we augmented the observed capture histories by a large number of all-zero capture histories (Royle and Dorazio, 2012). We also augmented the entire data set by an initial occasion and assigned all individuals (real and augmented) to State 1 (not yet entered the population). Then, we estimated the probability of an individual entering the population (transition between State 1 and State 2),  $\gamma_t$ , allowing for unconstrained variation among the years. Population size was then estimated as the number of individuals in State 2 each year.

The multi-state model estimated the true state  $Z$  (States = 1–7) for all individuals each year. We summed the number of individuals in each of the states to derive estimates of Abundance ( $N$ ), Introductions ( $I$ ), Translocations out ( $T$ ), the number of mortalities from poaching ( $Mp$ ) and mortalities from natural causes ( $Mn$ ).

The model was fitted in JAGS v 4–8 (Plummer, 2017) called through R (R Core Team, 2018) using RStudio server (Rstudio Team, 2015). We used *jagsUI* (Kellner, 2015) for implementation, *MCMCVis* (Youngflesh, 2018) for verifying the model fit and the *ggplot2* (Wickham, 2011) package for visualization. The JAGS code is in supplementary material, full code package is available upon request.

Priors for parameters  $\beta_s$ ,  $\beta_p$ ,  $\beta_r$  were defined as normal (0, 0.001), truncated to  $\text{logit}(-10, 10)$  which are uninformative. For  $\beta_k$  we truncated the normal (0, 0.001) prior to be between  $\text{logit}(-3, 5)$  which means that we assume that there is at least a 1/20 chance that a rhino carcass will be found. Such a weakly informative prior was necessary to improve convergence due to the sparsity of dead recovery data. Live rhinos are



observed repeatedly, whereas carcasses are recovered once. In long-lived species in relatively small populations (<250) as we are assessing, there are few dead recovery data points from which to generate precise estimates. We used inverse gamma priors for the standard deviation of the random effects  $\mu$ ,  $\mu_i$ ,  $\mu_t$ ,  $\mu_r$ ,  $\mu_k$ ,  $\sim d\text{gamma}(0.001, 0.001)$ . Priors for sex followed a beta distribution  $(-5, 5)$ .

## 2.2. Evaluating model performance

To examine model precision, bias and overall utility, we created 125 artificial datasets each for 2 separate scenarios using a derivation of the simulation function developed by Kery and Shaub (2011). The simulation function generates known state and observation data from the same transition matrices as the model uses to estimate parameters, allowing one to test if the model can recover the truth from observed data. We replicate this process to generate a distribution of parameter estimates to better understand model precision and bias.

We fitted the model to each replicate of both scenarios and compared the distribution of model estimates, against the known input values. The model is relatively complex and computationally intensive and thereby costly to run numerous times. We were therefore restricted to two scenarios with 125 replicates to infer precision and bias from.

Scenario 1: The static process scenario was used to demonstrate that the model can recover the actual values for input parameters and state matrices, given an observation matrix. We simulated a metapopulation that was isolated into three subpopulations. Each subpopulation with its state and observation process that was static in time. We modelled the subpopulations as:

- Subpopulation 1: High survival rate, high monitoring effectiveness, high carcass recovery, even poaching probability.
- Subpopulation 2: Low survival rate, high monitoring effectiveness, high carcass recovery probability, even poaching probability.
- Subpopulation 3: High survival rate, low monitoring effectiveness, high carcass recovery probability, high poaching

Scenario 2: The Dynamic process scenario was used to demonstrate that the model can detect a change in state, i.e. impact we simulated a metapopulation that was isolated into 3 management sections/Subpopulation. Each Subpopulation was simulated with its different state and observation process that was dynamic in time.

- Subpopulation 1: A sudden poaching increase: Survival decreased suddenly after 5 years, and the probability of poaching increases. Resighting probability and carcass recovery probability remain constant.
- Section 2: A resource release: Survival increases, the other parameters remain constant.
- Section 3: An increase in monitoring effectiveness. The resighting probability increases, while all other parameters remain constant.

We believe that these scenarios provide realistic scenarios for which black rhino populations are likely to experience. Although there are two scenarios, the categorization into subpopulations means that the model is effectively estimating 6 sets of parameters.

For each iteration, we fitted the model in JAGS using 3 chains of 7000 iterations each with 2000 iterations for adaptation phase, 1000 for burn-in while thinning by 10 iterations. We tested convergence by checking that the *Rhat* value was <1.1 and that the effective sample size was sufficient for all parameters ( $n_{\text{eff}} > 40$ ). We estimated the standard deviation and standard error of  $s$ ,  $p$ ,  $r$ ,  $pp$  of the 125 iterations as measures of model precision. A detailed explanation of the simulation and outputs are available in the supplementary material.

## 2.3. Applied example

Tsavo West National Park (Tsavo West) in Kenya is an extensive landscape, managed by Kenya Wildlife Service (KWS) that historically had the highest natural rhino densities on record (Goddard, 1969). After rampant poaching decimated Kenya's black rhinos, the Ngulia Rhino Sanctuary (Ngulia) was established to protect the handful of remaining (Brett, 1990). Ngulia is a secured, fenced area preventing immigration and emigration of rhinos that has successfully protected a growing population over the last 34 years. Black rhinos are sensitive to density dependence. To increase available resources for rhinos while maintaining their security, KWS has expanded Ngulia periodically since its inception, of which the most recent expansion is the subject of this case study.

In 2008, significant investment was made into Tsavo-West as KWS expanded the Ngulia Rhino Sanctuary by 48%. Densities were further reduced as KWS translocated rhinos from the Ngulia Rhino Sanctuary into a 2000km<sup>2</sup> surrounding area, called the Intensive Protection Zone, combining these animals with a similar of founder rhinos from other Kenyan sanctuaries to create a new subpopulation.

We used this suite of interventions as a case study to demonstrate the utility of the model in determining if investors would have received a return under a payment-for-results mechanism.

### 2.3.1. Data collection and analysis

Monitoring quality has varied over the years, but KWS has maintained an individual-based monitoring program using relatively consistent methods, since inception. We compiled all monitoring data for both sub-populations from annual census records, ad hoc foot patrols, aerial patrols and introduction and removal records. We generated an annual capture history for all observed rhino between 1994 and 2018. We generated age covariates based on known dates of birth, or inferred to within a few months from age classes, and recorded sex which was known for all individuals. All rhino mortalities are reported by an experienced observer who has been trained to estimate carcass age from the state of decay. We used only those carcasses that were uniquely identifiable via ear notches or embedded tags. We acknowledge that unidentified carcasses could contribute information on mortality, but our model does not accommodate uncertainty in carcass identification. Modern DNA technology and radio-frequency identification tag implant protocols mean that carcasses are increasingly likely to be linked to an individual identity. We attributed every sighting to a subpopulation. We augmented the observed metapopulation by adding c. 50% of the number of observed animals in 2018. There were no records of animals in the IPZ before 2008. Therefore, we assigned the augmented individuals only to the Ngulia Rhino Sanctuary to avoid inflating the IPZ number erroneously. After modelling, we checked the posterior distribution of State 1 (unknown, unseen individuals) to ensure sufficient augmentation (viz. Kery and Schaub 2012). We fitted the model in JAGS using 100,000 iterations with 20,000 added for adaptation and 10,000 for burn-in, with three chains thinned by 100 iterations to reduce autocorrelation. We checked for chain-mixing visually using trace plots, ensured *Rhat* < 1.1 for all relevant parameters and that the effective sample size was large enough (range of  $n_{\text{eff}}$  values for all parameters was 131 to 2700).

### 2.3.2. Case study for payment-for-results

We use the net Compound Annual Growth Rate (net-CAGR) as the impact metric, which is an annualized measurement of the compound growth rate of the population, accounting for introductions and removals. We derived the abundance ( $N_t$ ) estimate for occasion  $t$ , from the  $Z_{I,t,j}$  matrix as the number of individuals ( $i$ ) in state 2 for each sample ( $j$ ) of the posterior distribution. We derived the posterior net-CAGR estimate as:

**Table 3**  
Table of the measures of precision and bias for both scenarios of the static and dynamic process.

	Truth	Mean Estimate	Median Estimate	Standard Deviation	Bias	Mean Squared Error
<b>Static process</b>						
s	0.953	0.962	0.962	0.007	0.000	0.000
p	0.850	0.889	0.889	0.012	0.002	0.002
r	0.900	0.911	0.917	0.012	0.002	0.002
pp	0.583	0.585	0.584	0.049	0.002	0.005
<b>Dynamic process</b>						
s	0.938	0.956	0.956	0.006	0.000	0.014
p	0.867	0.903	0.902	0.012	0.001	0.002
r	0.833	0.844	0.849	0.012	0.002	0.002
pp	0.517	0.617	0.627	0.046	0.012	0.005

$$net.CAGR_j = \left( \frac{N_{Tj} + \sum_{t=1}^T R_t - \sum_{t=1}^T I_t}{N_{0j}} \right)^{1/T} - 1$$

Where  $N_{Tj}$  was the estimated abundance at the end of the investment time  $T$ .  $N_{0j}$  was the abundance estimate at the start of the investment,  $\sum_{t=1}^T R_t$  was the total number of animals removed during the investment phase and  $\sum_{t=1}^T I_t$  was the total number of animals introduced into the metapopulation during the investment time. We note that the introductions and removals were completely known here and so did not vary across samples  $j$ .

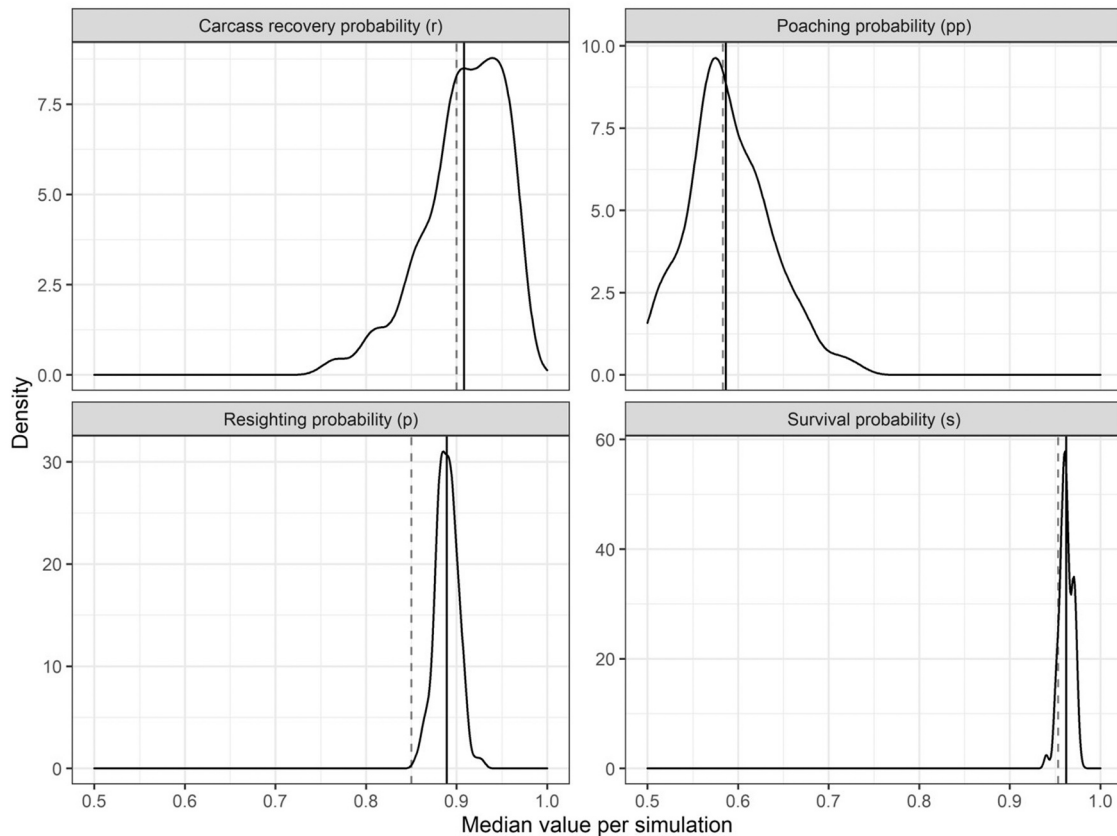
The Net-CAGR differs from the average net population growth rate but is a well-established financial metric and discussions with potential investors reflected a desire to use financial metrics. Investors are paid back based on a mutually agreed upon percentile of the CAGR value achieving the target. We set this at the 25th percentile for the case study.

There is a risk that there is insufficient precision in final estimates to assure impact is measurable, yet this is only realised after the duration of the WCB and the investment is spent. An option to mitigate this risk is to make any disbursement of funds to implementing agents contingent upon a specified value for the average resighting probability of rhinos being reached. The resighting probability of rhinos is directly linked to reduceable uncertainty in the model which can be addressed for the most part through effective monitoring. Such a contingent payment incentivized high levels of monitoring effectiveness and reduces investor risk.

For the case study, we assume that there is an investment in 2007 and the bond will pay the investors out if the management agency achieved a set 5% net-CAGR after five years with acceptance being the 25th percentile  $\geq 0.05$ . We also demonstrate the net-CAGR for five years pre-investment (2001–2006). In this example, we use an absolute 5% target to mirror management plans but could be negotiated relative to a baseline or modelled scenario. We hypothesise that disbursement is contingent upon agencies ensuring that the average detection probability of rhinos is greater than 0.75 annually.

### 3. Results

The model successfully recovered the true value of parameters  $s$ ,  $p$ ,  $pp$  and  $r$  (Table 3) for scenarios of the static process (Fig. 1) and dynamic process (Fig. 2). Our simulations showed little bias for either scenario in absolute terms and small MSE. On average the model overestimated the value of  $p$  by less than 0.03. We illustrated the outputs of a single iteration of the scenario with a time-varying process (Fig. 3) depicting how the model accounts for imperfect detection and recovers the truth, for both time-invariant and time-varying processes. We note that the observed number of individuals is considerably lower than the true



**Fig. 1.** Results for the simulation of a static process. Distributions of the median values of parameters for 125 iterations. Solid lines indicate the mean of the distribution, dashed lines indicate the truth based on the input values.

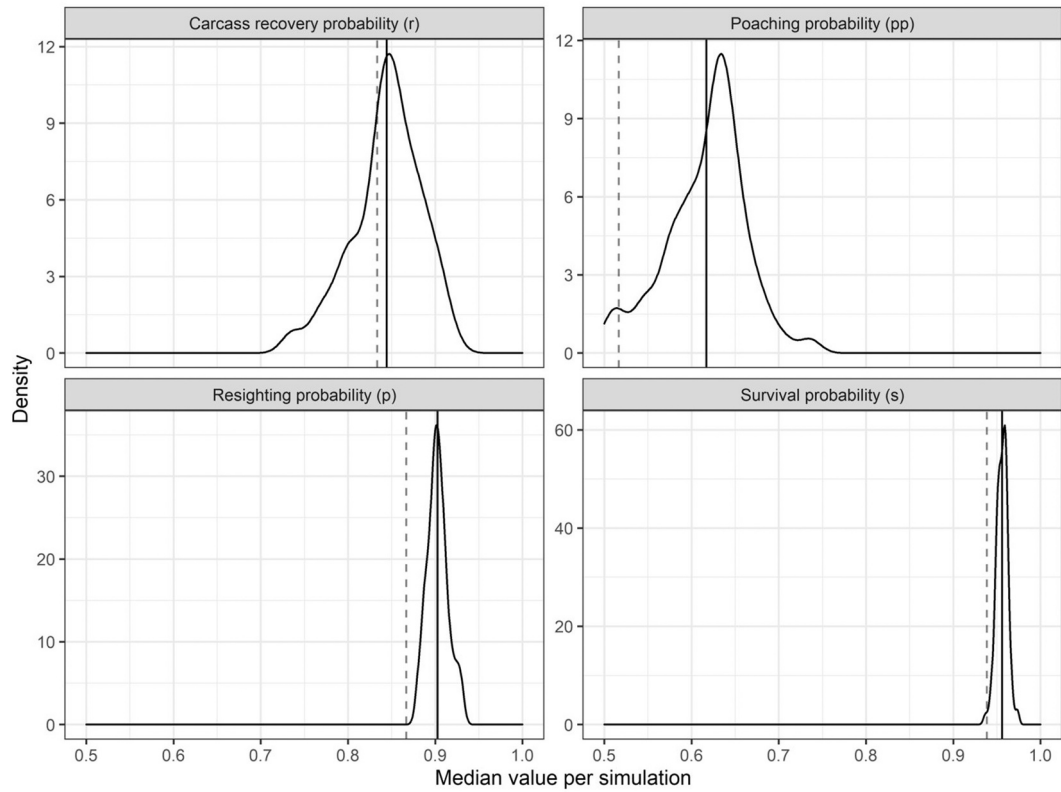


Fig. 2. Results for the simulation of a Dynamic process. Distributions of the median values of parameters for 125 iterations. Solid lines indicate the mean of the distribution, dashed lines indicate the truth based on the input values.

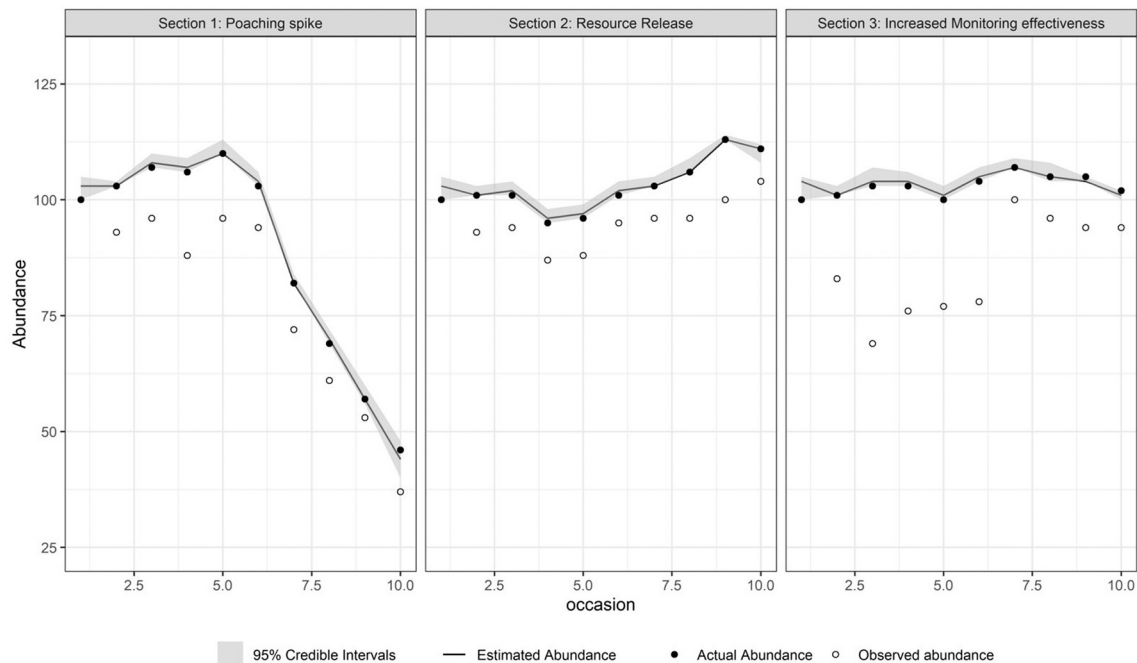
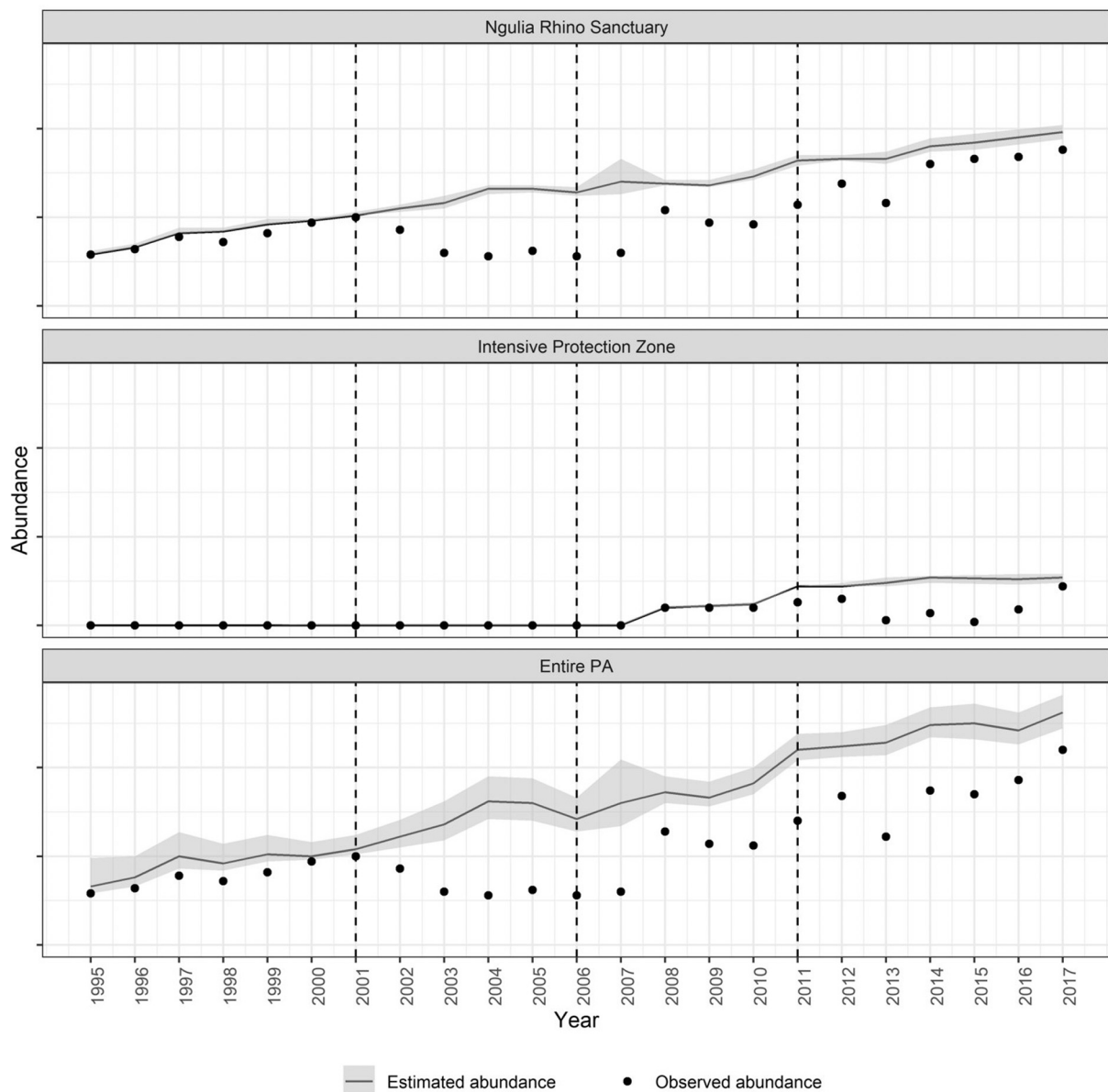


Fig. 3. Example of the abundance estimate of a single iteration from the model. Solid circles represent the truth, hollow circles represent the observed count, the black lines represent the estimate and the grey shading is the 95% CI.

number (A breakdown of simulations is in the supporting information).

Full estimates for the applied example are in the supporting information. Here we focus on the financial mechanism which is based on the derived estimate of abundance.

The observed number of rhinos fluctuated over the years in both the Intensive Protection Zone and Ngulia, which our model attributed to resighting probability rather than a change in abundance (Fig. 4). We did not show absolute numbers of rhino for security reasons.



**Fig. 4.** Abundance Estimates for Tsavo-West, stratified into the two subpopulations of Ngulia (top), the IPZ (middle) and the entire population (bottom). Solid circles indicate the total number of observed individuals during the year, the black line is the median value and grey shading is the 95% Credible Interval. Vertical dashed lines indicate the investment periods used. Actual abundance is not shown for security reasons, but the scales on the Y-axis are equivalent to one another.

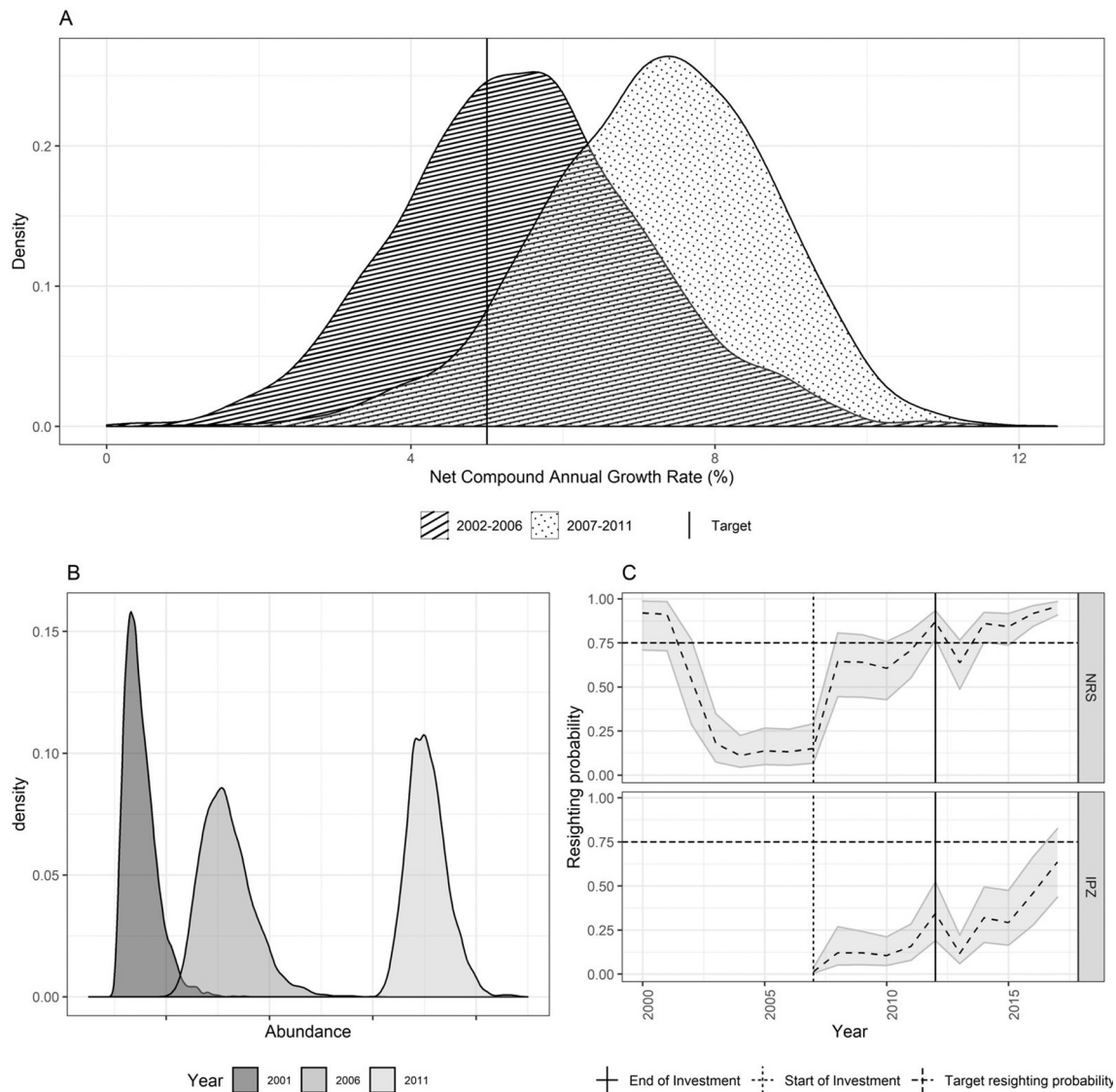
The median value of the net-CAGR estimates for the investment period, 2007–2011, was 0.073 (95% CI: 0.039–0.098) and the 25th percentile was 0.062. The median net-CAGR estimates for the pre-investment period was 0.054 (95% CI: 0.023–0.089) (Fig. 5A) and 25th percentile of 0.044 (Fig. 5B). Median carcass recovery rate during the investment period was 0.115 (95%CI: 0.055,0.201) for Ngulia and 0.005 (95%CI: 0,0.049) for the Intensive protection zone. The mean resighting probability for the investment period for the metapopulation was 0.24 (median: 0.12, 95% CI: 0,0.944), stratified as subpopulation it was 0.434 (median: 0.538,95%CI: 0.073, 0.773) for Ngulia and 0.079 (median: 0.077, 95%CI:0.005,0.225) for the IPZ (Fig. 5C). Based on the value proposition of a net-CAGR >0.050 the mechanism should have paid back investors plus a return. However, the failure to achieve minimum monitoring requirements would have caused the contingent payments to fail and an adaptive management process to ensue.

#### 4. Discussion

We have illustrated how our model can underpin a single species impact financing mechanism. We developed this model to specifically measure the impact of black rhino conservation interventions. We were able to account for uncertainties introduced by imperfect detection, behaviour, metapopulation management and natural variability in population growth. These data constraints are the norm rather than the exception, resulting in difficulties in the analyses of long-term datasets and precise estimation of impacts.

The model accounted for heterogeneity in detection probability, stratified ecological and observational processes, and imperfect knowledge. Such a model allows for the estimation of abundance in the face of uncertainty due to imperfect knowledge and can therefore be linked to a financial mechanism as the results are statistically defensible. Uncertainty can be reduced further through increasing monitoring effectiveness. Furthermore, the model is stratified by isolated subpopulations which allows any number of subpopulations to be combined into a single





**Fig. 5.** The Net CAGR estimates for the pre-investment (2002–2006) and investment (2007–2011) periods. The Main graphic (A) shows the distribution of net-CAGR values relative to the target of 5%. Plot B shows the abundance estimates for the T0 and T5 values used in the estimation of the CAGR, which are shown in the abundance figure (Fig. 4) as vertical lines. Plot C shows the median resighting probability through time, stratified by section, relative to the minimum required tar4get.

estimate, which allows for investment in a portfolio of rhino populations, thereby reducing the overall product risk.

Under both scenarios, the model recovered the input parameters. The bias in  $p$ , albeit small, does necessitate accommodation and we recommend that the WCB is conservative in the setting of contingent payments to ensure that even if there is a small overestimation of  $p$ , the true value is sufficiently high as ensuring sufficient statistical power to detect the change is imperative (Gerrodette, 1987). In cases where very small changes must be detected, uncertainty must be reduced where possible and high resighting and recovery rates are required.

#### 4.1.1. Tsavo west national park

The 2007 investment into Tsavo-West provided an informative case study. The observed rhino numbers showed both increases and decreases, while the abundance estimates show an almost monotonic increase in rhino abundance.

We attribute the uncertainty in abundance to the low resighting and

carcass recovery probability in the sampled periods and the subsequent uncertainty in abundance estimates. These results were not unexpected given the lack of identifiable carcasses in historical datasets due to periods of limited monitoring effectiveness, in particular in the Intensive Protection Zone which is a vast area with very low rhino densities, making monitoring difficult and very costly.

A challenge with using a multi-state model to estimate carcass recovery is that a carcass can only be detected once. The likelihood of an individual being alive is based on its individual capture history, but the detection probability of a carcass is limited by the number of carcasses that can be detected. We were unable to attribute certain carcasses to individuals, as the information was not recorded in historic data. This underrepresented the carcass recovery rate, and we could not stratify by section, and only provided a population-wide estimate that turned out to be imprecise. We see an opportunity for an extension of the model to incorporate information on the total number of carcasses found in an Integrated population model framework. For the financial model, this is unnecessary as increased monitoring and DNA technologies will allow for carcass matching.

In the hypothetical investment based on the Tsavo-West case study,

investors would be paid back at the site achieved the target of the 25th percentile of the net-CAGR being greater than 0.050. However, the drawdown of payments was contingent upon sites needing to meet a minimum resighting probability of 0.75. If the low detection probabilities were detected, the contingent payments contracted to in the financial mechanism would have compelled management agencies to adapt, to ensure the minimum monitoring requirements were met, thus reducing risk to investors. We used a minimum mean detection probability of 0.75 for the case study, the actual value must be negotiated and agreed in advance by the investors and the entities paying back the capital.

We suggest that before any investment, an analysis of current estimate precisions and expected impact be conducted to ensure that expected change can be detected. Our model provides a mechanism to do this using historic CMR type data and will identify where pre-investment funding can then be directed toward ensuring capabilities are built to sustain the required monitoring effectiveness. For the WCB, significant pre-investment funding has been directed toward ensuring monitoring effectiveness and building the monitoring and verification systems to provide auditable and verifiable impact. The ability to demonstrate this “Investment Readiness” has been vital in taking the fund to market.

The case study presents a large black rhino population, with high proportions of known individuals. In extending this model to larger populations with a lower proportion of marked individuals, the total amount of data available from a larger sample will likely provide more precise estimates. Only a few large black rhino populations do not have similar proportions of known individuals, but other species will differ. However, the WCB will need to ensure ongoing investment into monitoring and marking/notching activities to maintain precision. In the case of a population of unmarked individuals, the N-mixture model of [Kidwai et al. \(2019\)](#) is a promising avenue of research that could be adapted.

Although not highlighted, our model provided a framework for adaptive management. Our model can help save costs by targeting monitoring resources more efficiently. Parameters are estimated under a logit-regression framework which allows for the estimation of the effects of environmental and biological covariates on state and observation processes. This can provide insight into which drivers are likely to have the greatest effect on the impact metric, despite the uncertainty, and allows for rigorous due diligence of investment.

Our model can provide statistically rigorous estimates of the impact of conservation interventions which serves to improve investor confidence which and we hope to use to generate a single-species impact financing product. Despite the model being optimized for black rhino impact measurement, this model can be applied to other individually identifiable species such as lion (*Panthera leo*) and wild dog (*Lycaon pictus*), and species that are managed in a metapopulation approach. Hopefully, this will allow for the scaling of payment-for-results mechanisms into other species and bring much needed additional funding, and accountability to conservation.

#### CRedit authorship contribution statement

**Chris Barichiev:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Res Altwegg:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Dave Balfour:** Conceptualization, Writing – original draft. **Rob Brett:** Conceptualization, Writing – original draft. **Chris Gordon:** Conceptualization, Writing – original draft, Funding acquisition. **Dominic Henry:** Conceptualization, Methodology, Formal Analysis, Writing – original draft, Writing – review & editing. **Glen Jeffries:** Conceptualization, Writing – original draft. **Cedric Khayale:** Conceptualization, Investigation, Resources, Data curation, Writing – original draft, Funding acquisition. **Horris Wanyama:** Conceptualization, Investigation, Data curation, Writing –

original draft. **Oliver Withers:** Conceptualization, Project administration, Funding acquisition.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.biocon.2021.109073>.

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