How to Redirect Environmental Impact Assessments Towards Credible and Positive Predictions of Biodiversity Conservation

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Abstract

An Environmental Impact Assessment (EIA) may harbor deficiencies, and at worst, be intentionally misleading. A new protocol is proposed for the construction and vetting of an EIA that can improve the chances that the EIA's predictions of the effects that its project will have on biodiversity are credible. Three pieces of legislation to be passed by a project-hosting country are proposed that would operationalize this new protocol. The first of these pieces would raise EIA application fees in order to fund independent EIA reviews. The second would require the proponents of a project to write an EIA that contains a model-based prediction of the project's effect on local wildlife populations over a 10 or more years planning horizon. The third piece of legislation would require that this model-based EIA be reviewed by an independent panel of scientists. After reviewing the ways EIAs may be deficient and/or manipulated, this new protocol is illustrated by constructing a hypothetical EIA for the project of building a luxury safari lodge in Kenya. The impact on the local cheetah population caused by this project is assessed. This assessment begins by first, delineating a political-ecological model of the cheetah-hosting ecosystem that spans parts of Kenya and Tanzania. Then, a statistical fit is performed of selected model parameters to observations on both political actions and cheetah abundance. The credibility of this model is evaluated by computing its one-step-ahead prediction error rate. Having established the model's credibility, runs are made over a 10-year planning horizon. Model predictions indicate high risks of the extinction of local cheetah populations. This example highlights the importance of including trans-national regions when assessing a proposed project's impact on a wildlife population.

Keywords: environmental impact assessment, environmental law, political-ecological models, individual-based models, biodiversity conservation, cheetah extinction, prediction error rate

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Abbreviations:

CA: Consistency Analysis
EIA: Environmental Impact Assessment
EIS: Environmental Impact Statement
EMAT: Ecosystem Management Actions Taxonomy
IBM: Individual Based Model
IUCN: International Union for the Conservation of Nature
MPEMP: Most Practical Ecosystem Management Plan
MSHD: Minimum Simulated Hellinger Distance
MVP: Minimum Viable Population
NP: National Park
OGA: Overall Goal Attainment
RMSPE: Root Mean Squared Prediction Error
SA: Simulated Annealing
SA-MDAS: Simulated Annealing – Multiple Dimensions Ahead Search
SDE: Stochastic Differential Equation
STAR: Structured, Transparent, Accessible Reporting
TSCC: Triton Shared Computing Cluster

1 Introduction

An EIA is essentially about "futuring" or predicting the future state of an ecosystem given that a proposed project is implemented on its landscape (Duinker and Greig, 2007). An EIA's *planning horizon* is an interval having a specified start date and a specified end date (Newman et al., 2017). Potential impacts of the EIA's proposed project are forecast over this planning horizon.

The present article concerns EIAs written for proposed projects (hereafter, simply *projects*) that are forecast to impact the local survivability of some number of species. The intent of such an EIA is to show that the project will have a tolerably negative impact on these species, i.e., the EIA is written to identify the degree of harm the project may inflict on those species rather than being intended to show how the project may increase the chances of those species' survival.

Some of these species-impacting EIAs, however, may be deficient, or at worst manipulative. The present article reviews these deficiencies and manipulations. It then develops and illustrates a new way to construct an EIA that mitigates them.

1.1 EIA deficiencies and manipulations

The methodology that EIA authors use to compute future ecosystem states needs to be assessed as to its predictive performance. Examples of assessments whose predictive performance is assessed are given in Anifowose and Anifowose (2024) and Mohd Radzuan and Martin (2024). Addressing the widespread use of so-called "expert judgement" to forecast a project's environmental impacts, Retief et al. (2023) call for replacing expert judgements with statistical predictions as the latter can have credible measures of uncertainty applied to them.

Bigard et al. (2017) find several weakness in EIAs that are written to support projects in southern France. These weaknesses include no mention of alternate solutions to safeguarding at-risk species; no mention of project alternatives that avoid species impacts in the first place; no definition of the extent and location of the landscape that supports those species to be protected (called the *ecological network scale*); confusing definitions of avoidance, reduction, and offset methods for mitigating species impacts; and no mention of what wildlife monitoring and evaluation measures will be implemented should the project be approved.

Concerning deficiencies surrounding biodiversity conservation in particular, Agaba and Fischer (2026) find that only about a third of EIAs in Uganda fully implement biodiversity mitigation measures.

To help regulators flag deficient EIAs, Hughes et al. (2024) call for a scientific review of an EIA by scientists not affiliated with the project's proponents. This review would be completed before the EIA is accepted by the *permitting governmental authority* (PGA). But who will pay for this review?

EIAs can be manipulated by project proponents (Alert-Conservation, 2018; Little, 2019). Such manipulation can take several forms. The first is to ignore key aspects of the ecosystem's extant state. For instance, presence of one or more species might be omitted in an EIA in order to remove any question of their survival in the face of the project's predicted ecosystem impacts. A second form of manipulation is to avoid any discussion of the amount of uncertainty associated with an EIA's ecosystem state predictions (Tenny et al., 2006).

These deficiencies and manipulations of an EIA have led several authors to conclude that EIAs have failed to safeguard biodiversity. Instead, EIAs have all too often legitimized the destruction of habitat and the local extinction of prey species. For instance, in Brazil, many EIAs inaccurately assess current ecosystem states and under-predict the damage a project may inflict on a targeted ecosystem (Dias et al., 2022).

1.2 Political reactions to the project are ignored

The mechanics of using ecological models to predict species abundance under the scenario that an EIA's project is implemented has been understood for many years (Gontier et al., 2006). But most of these models do not assess the project's political feasibility. Failure to assess a project's political feasibility can result in the project triggering anthropogenic reactions that negatively affect the very species that the EIA claims will be viable over the planning horizon.

For instance, an EIA typically ignores potential reactions to its project from groups who may believe the project is harming them. Examples of such reactions include *retributive killing* of wildlife in Kenya (Fernandez et al., 2020) (see also (Hazzah et al., 2017)) as a reaction to forced evictions – and the shooting of wolves in the U.S. state of Wyoming to protest their forced reintroduction there (Koshmrl, 2023). Because of the ever-present influence of politics on projects that impact the environment, it can be argued that the model and computations used in an EIA to predict local species extinctions should include any anticipated political reactions.

1.3 A solution

One solution that would guard against many of these pitfalls while actively promoting the conservation of those species impacted by the project is to (a) construct a stochastic political-ecological model (Haas, 2026a) of the ecosystem under assessment; (b) using a political-ecological data set, statistically estimate the parameters of this model; and (c) using this statistically fitted model, compute predictions of ecosystem state at a planning horizon end date along with attendant measures of uncertainty.

This solution can be operationalized as follows.

1. Pass the following three pieces of legislation.

   Bill #1: *Be it resolved to increase the fee that a project proponent needs to pay in order to file an EIA with the PGA. These fees are collected into an* EIA Review Fund.

   Bill #2: *Be it resolved to require the following set of standards that an EIA needs to satisfy before it can be considered by the PGA.*

   (a) A planning horizon of 10 or more years is used for all predictions. This planning horizon's start date coincides with the proposed project's start date.

   (b) A peer-reviewed, published, stochastic model is used to predict abundance of each species impacted by the project.

(c) *Using data from the project's landscape, one-step-ahead prediction error rates are computed on each of the model's species-abundance output variables. All of these error rates are less than 40%.*

(d) *Each inventoried species has a computed extinction risk at the end of the planning horizon that is less than 10%.*

(e) *All computer code and data used to compute the EIA's ecosystem state predictions are placed in a free and publicly accessible location.*

Bill #3: *Be it resolved that every EIA is required to be reviewed by an independent scientific panel. This review will assess the credibility of the EIA's primary data, and all ecosystem state predictions computed by the EIA's authors. Further, the panel will conduct their own, separate species inventory on the project's landscape. The panel shall deliver a recommendation to the PGA to either accept reject the EIA. The panel's final report will be freely available to the public.*

2. For each EIA received, the PGA performs at least the first of the following tasks.

   Task #1: Check that the EIA meets Bill #2's five standards. An EIA that meets these standards is given the label "satisfies standards." Otherwise, do not consider the EIA further.

   Task #2: Send a standards-satisfying EIA out for independent scientific review. Upon receipt of a recommendation from this panel, pay reviewer honorariums out of the EIA Review Fund.

   Task #3: Taking into consideration the review panel's recommendation, decide to either issue permits for the EIA's project, or disallow the project to move forward.

Call the combination of the above three Bills and above three Tasks, the *EIA protocol*.

Notes:

1. This EIA protocol is new.

2. See Surtees (2019) for how laws are created in Canada; National Assembly of Kenya (2017) for how laws are created in Kenya; and EPA (2025) for how laws are created in the United States.

3. The fee in Bill #1 is set high enough to build an EIA review fund that can be used to compensate independent scientists who agree to review EIAs.

4. See Haas (2024a) for how to compute prediction error rates.

5. Extinction risks (Haas, 2026b) can be computed because Bill #2's standard (b) requires the species abundance model be stochastic.

6. The review panel uses the publicly available data as provided under Bill #2's standard (e) to check all predictions published in the EIA.

7. The review panel uses their own sampling methods to conduct their independent species inventory as mandated in Bill #3.

8. Bill #2's standard (d) assures that, up to prediction errors, all impacted species are sustainable over the planning horizon. Hence, following the present article's title, standard (d) turns the EIA into a credible statement of sustainability for all of these species.

1.4 Article layout

Following a literature review, a hypothetical EIA is constructed for a proposed luxury safari lodge in Kenya. This EIA illustrates how the set of standards described in Bill #2, above, would be implemented in the real world. The Results section exercises this EIA's political-ecological model to assess the cheetah's (*Acinonyx jubatus*) risk of local extinction at the end of a 10-year planning horizon whose start date coincides with the proposed first day of lodge construction. Shortcomings and extensions of the proposed EIA protocol are brought up in the Discussion section. Some conclusions that are supported by the article's presentation appear in the final section.

2 Literature Review of EIA Deficiencies and abuses

2.1 Basics

Chapter 1 of Bhateria et al. (2024) introduces EIAs while their chapters 2 through 8 provide a comprehensive, step-by-step guide to writing an EIA. EIAs come in several forms. For instance, there is a range of project impacts that different EIAs focus on. One type of impact that is receiving increasing coverage is a project's impact on climate change (Mayer, 2025). Impact categories are also referred to as *indicators* (RIVM, 2024).

Many EIAs focus on inorganic environmental impacts such as marine, air, and soil pollution – along with impacts on species richness. An early list of impact types is *Eco-Indicator 99* (Patsios et al., 2021). While describing an EIA written for a Brazilian agri-production project, these authors describe this list of impact categories as follows.

> "To calculate the EII, the Eco-Indicator 99 method was applied. Eco-indicator 99 is a damage-oriented method for LCA. More specifically, the methodology identifies three damage categories, based on which impact categories are classified (SimaPro, 2019):
>
> - Damage to Human Health: it expresses the number of years lost and number of years lived disabled, combined as Disability Adjusted Life Years (DALYs);
> - Damage to Ecosystem Quality: it expresses the loss of species over a specific area, under a given time period;
> - Damage to Resources: it expresses the additional energy that is required for future extractions of fossil fuels and minerals" (Patsios et al., 2021).

An EII is an *Environmental Impact Indicator*. See Dumont (2026) for the most recent version of the SimaPro software package. The present article's hypothetical EIA will consider only the "Damage to Ecosystem Quality" impact category mentioned above.

2.2 Articles concerning deficiencies

Janzen et al. (2025) sees a need to establish species abundance baselines in order to accurately assess an ecosystem's health in the face of different actions against it such as a natural disaster or the building of an EIA project.

> "For instance, a baseline on "healthy" species abundance for a given ecosystem (Wang et al., 2024) would be needed in order to assess how the measured biodiversity relates to the healthy ecosystem condition. Such baselines of the ecosystem conditions are key to address the practical limitations of integrating ecosystem health indicators into risk/vulnerability assessments linked to data scarcity or variability of ecosystems. Establishing such ecological baselines requires efforts but would support better understanding the dynamics of ecosystem health and service provision. It would also be essential for managing ecosystems for risk reduction and allow monitor and evaluate the effectiveness, in regard to the baseline condition" (Janzen et al., 2025).

These authors did not find accounts of such baselines being established in any of the articles they reviewed from their literature search.

The present article's hypothetical EIA below, implements this call for the use of baselines to describe ecosystem health by first, finding the minimum abundance needed for a species to avoid local extinction, second, statistically fitting a population dynamics model to abundance data, and then third, "integrating ecosystem health indicators into risk/vulnerability assessments" (Janzen et al., 2025) by using this statistically fitted model to predict the risk of the cheetahs' local extinction under the two scenarios of first, the EIA project being implemented, and then second, the EIA project not being implemented. The survivability baseline of the local cheetah population is expressed as the *minimum viable population* (MVP) size. For cheetah, this size is 11 to 14 individuals (Hilbers et al., 2017).

Note that an EIA is a form of "managing an ecosystem for risk reduction" (Janzen et al., 2025). Regarding the often overlooked monitoring plan once an EIA project is implemented, the use of the abundance indicator, being measurable, allows "monitor and evaluate the effectiveness, in regard to the baseline condition." (Janzen et al., 2025).

After studying many international EIAs, Singh et al. (2020) conclude as follows.

> "We argue that the credibility and accuracy of the EIA process could be improved by adopting more rigorous assessment methodologies and empowering regulators to enforce their use" (Singh et al., 2020).

This recommendation is essentially the same as the three pieces of legislation proposed above. These authors also find that (a) planning horizons are rarely long enough to capture long-term impacts, (b) few EIAs consider how cumulative impacts can interact, (c) mitigation measures lack transparent justification, and (d) professional judgement is overwhelmingly used to determine impact significance with little attendant justification or stakeholder input.

Current EIA standards do not mandate the creation of a mathematical model of future impacts and do not require any assessment of such a model's credibility and/or predictive performance (Sheth, 2026). This deficiency as been known for some time. For instance, Treweek (1996) calls for EIAs to use analytical procedures grounded in ecological science when assessing the relationships between organisms and their environment. This author also sees a need for EIAs to follow standardized survey protocols and be subject to formal requirements for monitoring ecological impacts.

Bojórquez-Tapia and García (1998) find that many EIAs in Mexico are based on inadequate science and note that

> "Results showed that, in general, the EISs tended to contain rather inadequate descriptions, and a biased and subjective assessment of impacts. The EIA reflected implicit values and failed to focus on the environmental conflicts likely to be generated by the projects" (Bojórquez-Tapia and García, 1998).

One such environmental conflict studied in the present article is the effect of retributive killing of wildlife.

EIA quality can also be slow to improve. For instance, Anifowose et al. (2016) do not find EIA quality improving between 1998 and 2008.

2.3 Articles concerning abuses

After studying several EIAs written for large projects across several countries, Laurance and Little (2018) call for every EIA to be freely available online in order to combat the rampant bribery and intentional omissions that plague many EIAs including those that these authors studied. This recommendation is also in agreement with the three pieces of legislation proposed above.

(Williams and Dupuy, 2017) delineate several corrupt practices that occur during the EIA process. Enríquez-de-Salamanca (2018) finds that bias and manipulation by stakeholders is common in the EIA process and concludes that biases need to be reduced but that manipulation needs to be stopped.

China has experienced several varieties of EIA fraud. As Runqiu (2024) notes,

> "Regulators have discovered a plethora of different fraudulent activities, including fabrication of data for EIA documents, forging of signatures, replacement of samples during environmental monitoring and interference with sampling investigations" (Runqiu, 2024).

3 Methods

A hypothetical EIA is written in support of a proposal to build a luxury safari lodge close to Tsavo West National Park (NP) in Kenya. This EIA's 10-year planning horizon stretches from the first day of lodge construction tentatively scheduled for February 1, 2027 to an end date of February 1, 2037.

The proposed location of the luxury safari lodge is just outside of the Park's boundary directly west of the Kitani Safari Camp (Figure 1). The Kitani Safari Camp is now called the *Severin Safari Camp* (Severin Safari Camp, 2026).

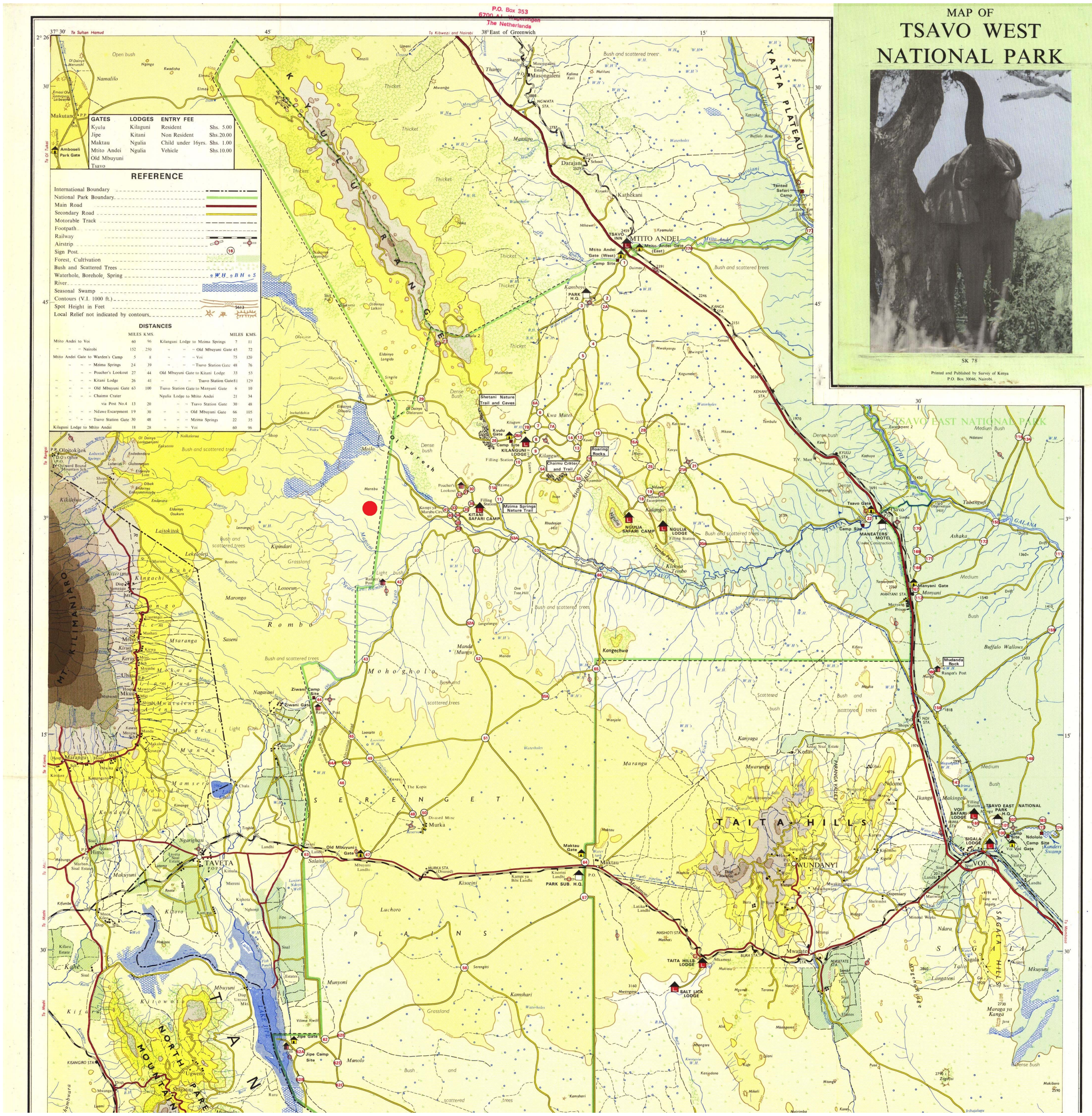

Figure 1: Map of Tsavo West NP, Kenya and environs (ESDAC, 1975). The proposed location of the luxury safari lodge is just outside of the Park's boundary directly west of the Kitani Safari Camp (red dot). The Kitani Safari Camp is now called the *Severin Safari Camp*.

One part of the EIA is an assessment of the impact of the proposed lodge (hereafter, simply *lodge*) on the cheetah population living within and close to Tsavo West NP. Call this population, the *local* cheetah population. The cheetah is listed as Vulnerable on the International Union for the Conservation of Nature (IUCN) Red list and as Endangered by the Namibian government Milloway (2025). Countries that host cheetah populations include Kenya and Tanzania Durant et al. (2022).

To support this assessment, a model is constructed of the political-ecological system that hosts this local cheetah population. This model consists of decision making submodels of several politically homogeneous groups (hereafter, simply *groups*) that affect the local cheetah population, and an ecosystem submodel of local cheetah population dynamics.

3.1 Cheetah-hosting political-ecological system submodels

Using the author's software package called **id** (see the Data Availability section, below), run-time input consists of a model input file that both defines the political-ecological model and runs it over a given interval. This run is accomplished with the command `idalone some_name.id` where `some_name.id` is the model input file name. This input file, in turn, lists the submodel files (.id files) and associated parameter value files (.par files). A unique pair of .id and .par files defines each group being modeled while a separate pair of .id and .par files defines the managed ecosystem.

An initial action from one of the group submodels is specified in the model's input file. Then, at each time step, each group submodel and the ecosystem submodel read actions directed against themselves from a bulletin board. Conditional on a read-in *input action*, a group submodel computes the expected value of *overall goal attainment* that they believe they will receive if they implement a particular action-target combination. After making this computation for all action-target combinations in their repertoire, they post to the bulletin board the combination that has the highest expected overall goal attainment. The Ecosystem Management Actions Taxonomy (EMAT) Haas (2024b) dictates what input actions a submodel recognizes and the contents of its repertoire of action-target combinations.

The ecosystem submodel reacts to actions directed against it by adjusting its output of cheetah and prey abundance across time. For instance, if at a particular time point during the simulation, this submodel reads in a poaching action that involves the shooting of a cheetah, it will immediately reduce cheetah abundance by some amount. Such killing is in addition to another threat to the cheetah's survival that this submodel recognizes: The capturing and selling of cheetah cubs for the illegal exotic pet market.

3.1.1 Group submodels

The political component of the model consists of decision making submodels for the following groups: The office of the president of Kenya; the Kenya Wildlife Service (KWS); Kenya rural residents living close to Tsavo West NP; and Kenya pastoralists using grazing grounds close to this Park (Mwangi, 2024). Rural residents are typically farmers (Johansson et al., 2025), and tourism operators (Callahan, 2026). The model also includes submodels of the president of Tanzania, the Tanzania Wildlife Management Authority (TAWA), Tanzania rural residents, and Tanzania pastoralists.

Within each country, the president submodel interacts with the wildlife authority, rural resident, and pastoralist submodels. Rural resident and pastoralist submodels interact with the wildlife authority submodel and with the ecosystem submodel.

3.1.2 Cheetah abundance submodel

The ecosystem submodel for cheetah abundance consists of first, a variable governed by a stochastic differential equation (SDE) that tracks the abundance of cheetah prey (Wells et al., 1998). Cheetah often prey on smaller herbivore ungulates such as Thomson's gazelle (*Gazella thomsoni*) (Fitzgibbon et al., 1990). This prey abundance variable in turn, is part of an individual-based approach to cheetah population dynamics that tracks these animals interacting with their prey, poaching pressures, and habitat type. In this *individual based model* (IBM), a living cheetah is a juvenile or adult if it is not a cub, i.e., is older than 18 months (78 weeks) (Cheetah Conservation Fund, 2026).

Both the IBM of cheetah population dynamics (called here the *cheetah abundance IBM*) and the prey abundance SDE model their populations stochastically. This synthetic predator-prey submodel extends a model described by Kimbrell and Holt (Kimbrell and Holt, 2005). Many of the submodel's parameter values are taken from Kelly et al. (1998) (Table 1).

Parameter	Value
Cheetah	
Female life expectancy	6.2
Male life expectancy	2.8
Age at maturity	1.42
Female sexual maturity	2.4
Interbirth interval	1.675
Herbivores	
Initial abundance (minor poaching)	2250
(moderate poaching)	4500
(severe poaching)	8750
Birth rate $-$ death rate (minor poaching)	-0.003
(moderate poaching)	-0.014
(severe poaching)	-0.017
White noise multiplier (minor poaching)	0.001
(moderate poaching)	0.001
(severe poaching)	0.001

Table 1: *Hypothesis values* (Haas and Ferreira, 2017) for parameters that define the ecosystem submodel. Cheetah abundance IBM values are based on those reported in Kelly et al. (1998). The temporal unit is *years*. Herbivore values drive submodel output of herbivore (prey) abundance to exhibit a negative trend through time that is influenced by the amount of herbivore poaching.

The ecological network scale of the cheetah population within and around Tsavo West NP includes parts of Tanzania and hence, Tanzania's Kilimanjaro region is included in the ecosystem submodel (Figure 2).

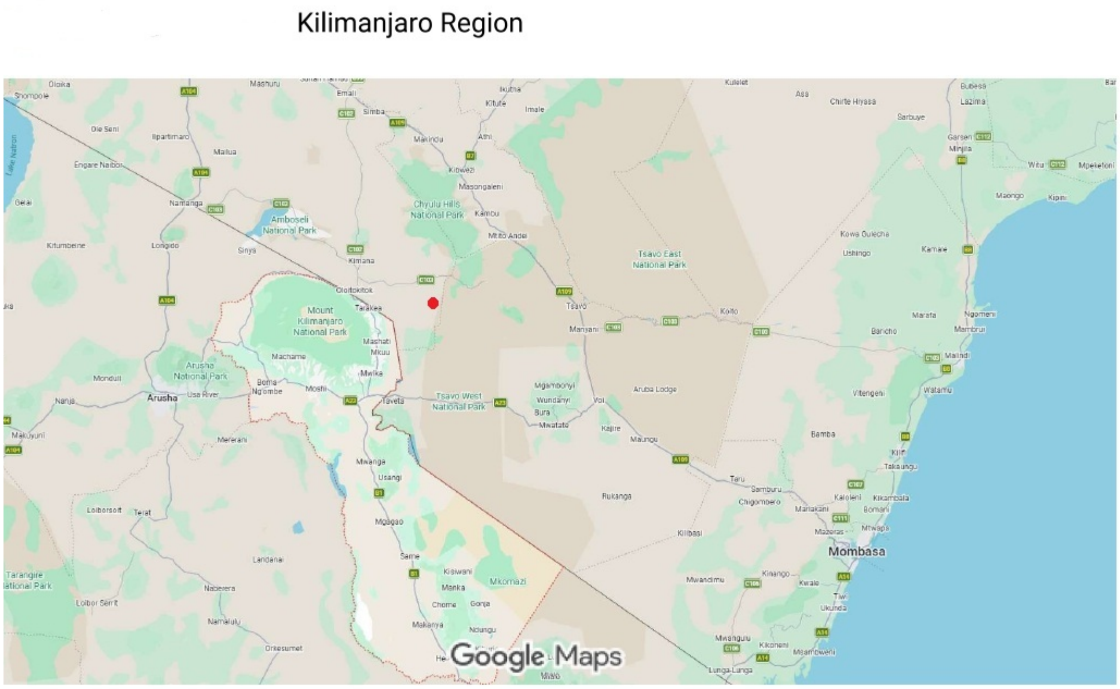

Figure 2: Map of Tsavo West NP, Kenya and the Kilimanjaro region of Tanzania (Google Maps, 2026). The red dot locates the site of the lodge.

Cheetah abundance IBM

Figure 3 displays the sequence of actions that the cheetah abundance IBM uses to update each individual cheetah's birth, prey intake, and death. Regions are viewed within this IBM as *patches*. A patch is an ecological concept of a contiguous area that can support a particular species (Proctor et al., 2025).

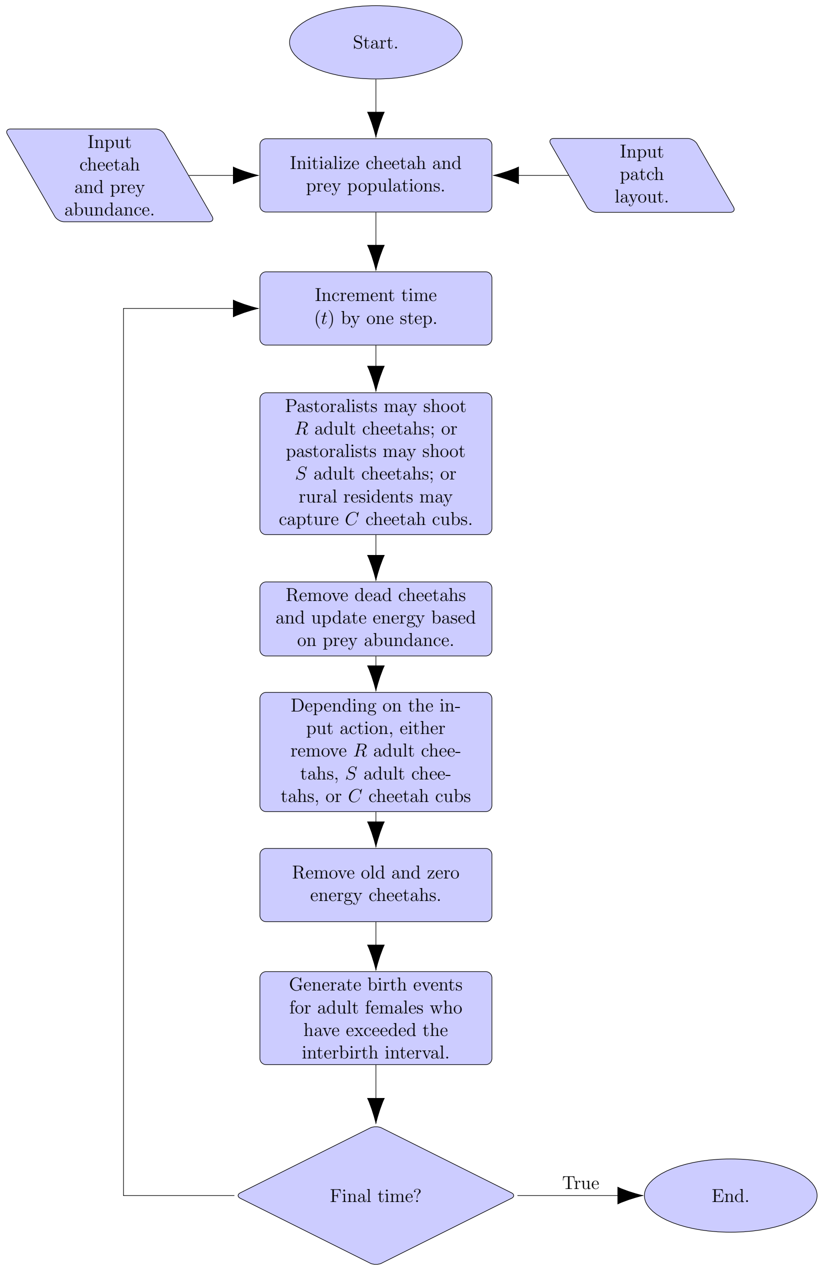

Figure 3: Flowchart of the cheetah abundance IBM.

This IBM tracks the age, gender, energetic budget, location, and status of each individual cheetah living and dying within a patch-partitioned landscape. It also tracks interactions of these cheetahs with their environment – namely prey, mates, poachers, and habitat.

The IBM executes the following schedule of actions each week.

1. Delete all cheetahs set to *dead* during the previous time step.
2. Find within-patch populations.
3. Increment each cheetah's age.
4. Up to a cheetah's mean energy budget (*meb*) or juvenile energy budget (*jeb*) value, update a cheetah's energy budget as follows.
   (a) Compute the *prey ratio*:

$$\texttt{vratio} = 0.01 \left[\frac{\texttt{prey}_t}{\boldsymbol{wfi} \times \texttt{nmindiv}_t + 1} - 1 \right] \tag{1}$$

   where $\boldsymbol{wfi}$ is a cheetah's weekly food intake, $\texttt{nmindiv}_t$ is the number of patch residents at time t, and $\texttt{prey}_t$ is the available prey within the patch at time t.

   (b) Compute the amount of energy change:

$$\texttt{ec} = \frac{2}{1 + \exp(-\texttt{vratio})} - 1. \tag{2}$$

   (c) Within each patch, if $\texttt{prey}_t < \boldsymbol{wfi} \times \texttt{nmindiv}_t$, do the following for each patch resident. First, sample once from V, a random variable uniformly distributed over the unit interval to obtain v. Then, if $v < 0.4$,

$$\texttt{energy}_t = \texttt{energy}_{t-1} + \texttt{ec}. \tag{3}$$

   Also, declare such a patch to be *food-deficient*.

   (d) If $\texttt{prey}_t > \boldsymbol{wfi} \times \texttt{nmindiv}_t$ then for each patch resident,

$$\texttt{energy}_t = \texttt{energy}_{t-1} + \texttt{ec}. \tag{4}$$

   (e) For each cheetah having $\texttt{energy}_t = 0$, draw a realization from V to obtain v. Set this cheetah to *dead* if $v < 0.1$.

5. Set to *dead*, any cheetahs having an age greater than *le*.

6. Following Haas and Ferreira (2017), simulate a food deficit effect on birth and maturation rates as follows.

   (a) Extend the interbirth interval by 50% for all females in a food deficient patch.

   (b) Extend the maturation age by 50% for all cheetahs in a food deficient patch.

7. Let R be the number of cheetahs shot by pastoralists seeking to protect their livestock, S be the number of cheetahs shot by Kenya pastoralists as retribution for being evicted from their grazing lands, and C be the number of cubs removed by rural residents for the exotic pet trade. Process these poaching actions as follows. Randomly select $R + S$ adult cheetahs and set them to *dead*. Also, randomly select C cheetah cubs and set them to *dead*.

   The region wherein a poaching action occurs is determined as follows.

   (a) *poach for protection*: Randomly select an unprotected region.

   (b) *poach to protest*: Randomly select a protected region.

   (c) *smuggle wildlife*: Randomly select an unprotected region rather than a protected region with probability 0.66.

8. For each mature female cheetah, create one newborn cheetah if:

   (a) Its $\texttt{time-since-last-birth}_t$ is greater than *interbirth*,

   (b) there is at least one male in the female's patch, and

   (c) the female's energy is greater than *meaneb*.

9. For each female not giving birth, set

$$\texttt{time-since-last-birth}_t = \texttt{time-since-last-birth}_{t-1} + 1. \tag{5}$$

10. Update patch membership by randomly moving cheetahs into different patches that possess nonzero prey abundance.

11. Update prey abundance in each patch. First, find the amount of new prey at this time point from the prey abundance SDE. Second, find the amount of left-over prey at this time point as

$$\texttt{preyleftover} = \texttt{prey}_t - \boldsymbol{wfi} \times \texttt{nmindiv}_t. \tag{6}$$

    Finally, sum these values of left over prey across the previous 36 weeks. If this sum is negative, reset it to zero.

Herbivore population SDE

The SDE for the abundance of small herbivores (cheetah prey) is:

$$\frac{dB_t}{dt} = \alpha_1 B_t (1 - B_t/\alpha_0) + \sigma dW_t \tag{7}$$

where α_0 is the habitat's herbivore carrying capacity, α_1 is the difference between herbivore birth and death rates, σ is the diffusion parameter, and W_t is a Wiener process.

The initial value is $B_0 = 0.6\alpha_0$. This model is a simplified version of the relationship given in Wells et al. (1998) derived by assuming that with probability 1.0, offspring will result from any union of a male herbivore and a female herbivore.

Converting a deterministic differential equation to a stochastic differential equation by adding a term that is the differential of a Wiener process is similar to how Manninen et al. (2006) modify a deterministic differential equation model of neuron operation in order to convert it to an SDE model.

3.1.3 Extinction probabilities and extinction risk computations

As described in Haas (2026b), extinction probability is computed by finding the fraction of the simulation's total number of realizations that give an abundance of less than 13 individuals at the planning horizon end date. An MVP size of 13 is in agreement with the range of 11 to 14 individuals given in Hilbers et al. (2017).

The formula for extinction risk at a future time point, t given in Haas and Ferreira (2016) is:

$$R(t) = L(t)P(\text{extinct at } t) \tag{8}$$

where the non-use loss due to extinction is $L(t) = (1 - 0.035)^t$ with 0.035 being the discount rate.

3.1.4 Modeling the impact of the lodge on cheetah abundance

Pastoralists kill cheetahs to stop them from preying their livestock (Jones et al., 2025). This behavior is referred to as *retaliatory killing.* And, as mentioned above, there is anecdotal evidence that pastoralists may engage in the killing of wildlife to protest their being forcibly evicted from their ancestral rangelands. Countries that have experienced such retributive killing of wildlife include Kenya (Fernandez et al., 2020) and Tanzania (Weldemichel, 2020). Indeed, several authors have advanced political and psychological theories to explain this behavior (Holmes, 2007; Fernandez et al., 2020).

In addition to retaliatory killing and retributive killing, cheetahs are threatened by a third anthropogenic threat: cheetah cub-capture. This form of *wildlife trafficking*

(Haas and Ferreira, 2017) involves seizing live cheetah cubs in their den while their mother is away hunting. The few cubs who survive transport, are sold to private parties who desire an exotic pet (Tricorache et al., 2021). Countries where these seizures occur include Kenya, Tanzania, and Uganda (Tricorache and Stiles, 2021).

To make room for the extensive grounds that this lodge will occupy, some number of Kenya pastoralists will be relocated. The political consequences of these relocations are represented in the model by having this group engage in retributive killing of cheetahs as their protest-response to being forcibly evicted from their ancestral rangelands due to the building and operation of the lodge. This cause and effect relationship among the model's groups is represented by fixing the KWS submodel's output action over the entire planning horizon at *evict residents from public lands* and having this action be recognized as an input action by the Kenya pastoralist submodel.

Note that the EIA's project or "cause" action is not the building of the luxury safari lodge, but rather is the needed first *political* step of evicting residents before the lodge can be built.

Under this input action, the Kenya pastoralist group perceives a threat to their goal of supporting their families due to their economic state being reduced as a consequence of their eviction. Because this group lacks the political power to stop such evictions, they turn to the political action of retributive killing of wildlife. Some of these retributively killed animals may be cheetahs.

This reaction by the Kenya pastoralist group is represented in the model as the hypothesis that retributive killing of cheetahs will occur when pastoralists are evicted from the grounds where the lodge will be located. This hypothesis is entered into the political-ecological model as part of the model's *hypothesis distribution* (Haas and Ferreira, 2017). Under this distribution, fixing the input action at *evict residents from public lands* generates the following causal chain within the Kenya pastoralist submodel:

`Input_Action`: *evict residents from public lands* →
Perceived loss of `Livestock_Resources` →
Perceived threat to the `Support_Family_Goal` →
`Output_Action`: *poach to protest* →
Perceived improvement to `Scenario_Livestock_Resources` →
Perceived improvement to `Scenario_Support_Family_Goal`.

This group determines that *poach to protest* is their optimal decision because they find the expected value of their `Overall Goal Attainment` (OGA) node is higher under this option than all other options even in the face of a risk that they will be arrested for poaching.

The cheetah abundance IBM models these three anthropogenic impacts on the local cheetah population as follows. If at any time point, a pastoralist group issues the action *poach for protection*, the IBM sets R randomly chosen adult cheetahs to *dead*. If at any time point, the Kenya pastoralist group issues the action *poach to protest*, the IBM sets S randomly chosen adult cheetahs to *dead*. Finally, if the cheetah abundance submodel receives the input action: *smuggle wildlife* issued by a rural resident submodel, it sets C randomly-selected cheetah cubs to *dead*. The variable R is a parameter of both pastoralist submodels, S is a parameter of the Kenya pastoralist submodel, and C is a parameter of both rural resident submodels.

Cheetah litters vary between one and six cubs (Cheetah Conservation Fund, 2026). Based on this reported range, the C parameter is fixed to a typical value, namely three cubs.

Tanzania pastoralists do not poach to protest because they do not perceive the Tanzania government as having anything to do with whether the lodge is permitted or not.

A region (spatial location) is needed for each model-generated poaching action. The data in Table 3 (below) is used to postulate that the chance of a *poach for cash* action (represented here as *smuggle wildlife*) on unprotected land is 0.66 – and 0.33 on protected land. A *poach for protection* action would typically be performed on unprotected land (grazing land) – whereas a *poach to protest* action happens only on protected land. These statements justify the rules listed in Section 3.1.2 for assigning a region to a poaching action.

Note that there are no submodel actions for rural residents or pastoralists shooting cheetah for their body parts. Hence, predictions of poaching intensity generated by this model are conservative.

3.1.5 Addressing the lack of data on retributive killings

Because the lodge has not been built at the time of the EIA's creation, there have not been any evictions around its site. This in-turn, means that there is no data on pastoralist cheetah poaching behavior after they have been forcibly evicted from their ancestral rangelands, i.e., there is no data on retributive killing events. In this case, the model can only be fitted to cheetah abundance data that is a result of cheetah poaching events that are not motivated by the perceived need for retribution due to being evicted. Indeed, a literature search failed to discover published data sets of the number of cheetahs killed by pastoralists who did so to protest their forced evictions. Due to this lack of data, the statistical estimation of S is challenging.

One answer to this challenge that is taken here is to run the statistically estimated model over the planning horizon at different values of S. The ensuing local extinction risks are then collected in a table of extinction risk by S. The PGA uses this table to first, select an S value that they believe to be the most credible, and then, second, decide if the associated patch-wise cheetah extinction risks are unacceptable. If they judge these risks to be unacceptable, they would not permit the lodge to be built.

In summary, by providing a range of possible local extinction risks, the EIA makes clear the consequences of having no data to support the statistical estimation of a key parameter in the EIA's political-ecological model.

4 Results

4.1 Data sets

Political-ecological actions were observed over the interval 2018 through 2026. Ecological output variables were also observed over this interval. Call this the *observed actions history interval*. An example of an ecological action is *elephants trample crops*.

4.1.1 Actions history

The raw HTML containing stories about human-wildlife interactions in Kenya and Tanzania have been downloaded from online news sources into the files listed in Table 2. In particular, this data contains cheetah poaching actions that have occurred within specific regions of Kenya and Tanzania.

Stories file name	Year(s)	Number of stories
ef19.txt	2019	9806
ef19-21a.txt	2019-2021	9953
ef19-21b.txt	2019-2021	8844
ef20211231.txt	2021	11623
ef20221231.txt	2022	30017
ef20230221.txt	2023	3016
ef20230529.txt	2023	2821
ef20231008.txt	2023	4605
ef20240111.txt	2024	2881
ef20240327.txt	2024	3173
ef20240609.txt	2024	3044
ef20240827.txt	2024	3508
ef20241112.txt	2024	3466
ef20250212.txt	2025	2391
ef20250315.txt	2025	1393
ef20250516.txt	2025	380
ef20250715.txt	2025	2405
ef20250906.txt	2025	2658
ef20251018.txt	2025	2424
ef20251202.txt	2025	2424
ef20260123.txt	2026	2969
ef20260321.txt	2026	2988
ef20260525.txt	2026	3324
ef20260710.txt	2026	2912

Table 2: Raw HTML of online stories about human-wildlife interactions in Kenya and Tanzania. These *stories files* cover the years 2018 through 2026.

The locations of these stories are from many parts of Kenya and Tanzania rather than exclusively from the region local to the lodge. The reasoning that leads to an action taken by a particular Kenya group is assumed to be independent of the location of that action. The reasoning that leads to an action taken by a particular Tanzania group is similarly assumed to be independent of action location. Hence, under these modeling assumptions, actions contained in the stories files of Table 2 may be used to fit the parameters of the group submodels of rural residents and pastoralists who live close to the lodge.

Action extraction

Table 2's stories files contain political-ecological actions that need to be matched to EMAT actions, and then extracted into an actions history data file. Such extraction is performed here with the author's *EMAT actions extractor* as implemented in the `parse_stories` relation of the **id** software package (Haas, 2026a) (see the Data Availability section, below). The EMAT actions extractor is compliant with the Structured, Transparent, Accessible Reporting (STAR) standard (Haas, 2024b). Applying this software to the stories files listed in Table 2 yields 105 actions over the period March 2018 through May 2026 (Table 3).

```
2018.26 kenrr sell_several_rhino_horns ecosys 1 Meru_National_Park
2018.48 kenrr smuggle_wildlife ecosys 2 Nairobi_National_Park Lake_Nakuru
2018.51 kenpres reach_agreement__ kenpres 2 Nakuru Maasai_Mara_Game_Reserve
2018.52 tanrr smuggle_wildlife ecosys 2 Arusha Maasai_Mara
2018.53 kenepa invest_in_tourism_infrastructure one,kenepa 2 Dar_es_Salaam Nairobi
2018.53 kenrr smuggle_wildlife ecosys 1 Nairobi
2018.53 kenepa translocate_animals ecosys 2 Tsavo_East_National_Park Nakuru_National_Park
2018.54 kenepa translocate_animals ecosys 1 Meru_National_Park
2018.56 kenrr offer_wildlife_products_for_purchase ecosys 2 Tsavo_East Tsavo_East_National_Park
2018.58 kenrr smuggle_wildlife ecosys 1 Nairobi
2018.64 kenrr poach_for_food ecosys 2 Dar_es_Salaam Nairobi
2018.67 tanrr smuggle_wildlife ecosys 1 Meru_National_Park
2018.68 kenepa positive_ecoreport one,kenpres 1 Meru_National_Park
2018.71 kenrr smuggle_wildlife ecosys 2 Entebbe Mombasa
2018.80 tanrr sell_several_rhino_horns ecosys 1 Meru_National_Park
2018.80 kenepa arrest_poaching_suspects ecosys 1 Tsavo_National_Park
2018.80 kenrr smuggle_wildlife ecosys 2 Tsavo_National_Park Nakuru
2018.80 kenepa experience_financial_shortfall ecosys 2 Kilimanjaro Dar_es_Salaam
2018.80 kenrr smuggle_wildlife ecosys 1 Lewa_Wildlife_Conservancy
2018.81 kenrr smuggle_wildlife ecosys 1 Nairobi
2018.83 kenrr sell_few_rhino_horns ecosys 2 Dar_es_Salaam Nairobi
2018.88 kenpas poach_for_protection ecosys 2 Dar_es_Salaam Tsavo_East_National_Park
2018.89 kenepa increase_wildlife_damage_control_measures ecosys 1 Dar_es_Salaam
2018.89 kenrr smuggle_wildlife ecosys 2 Maasai_Mara Mara_Conservancy
2019.02 kenrr sell_several_rhino_horns ecosys 1 Nairobi
2019.03 kenrr smuggle_wildlife ecosys 2 Dar_es_Salaam Nairobi
2019.12 tanrr smuggle_wildlife ecosys 1 Meru_National_Park
2019.13 kenepa rescue_wildlife ecosys 2 Murchison_Falls_National_Park Tooro-Semuliki_Wildlife_Reserve
2019.13 tanrr express_dissatisfaction_with_policy tanpres 1 Dar_es_Salaam
2019.14 kenrr smuggle_wildlife ecosys 2 Dar_es_Salaam Nairobi
2019.15 kenrr smuggle_wildlife ecosys 2 Tanga Coast
2019.16 kenrr degrade_forest_through_over-grazing_and_tree_removal ecosys 2 Nairobi Dar_es_Salaam
2019.19 kenrr sell_few_rhino_horns ecosys 2 Coast Eastern
2019.23 kenrr smuggle_wildlife ecosys 1 Meru_National_Park
2019.26 kenrr smuggle_wildlife two,kenpres,kenepa 1 Laikipia
2019.31 kenrr smuggle_wildlife ecosys 1 Meru_National_Park
          ...omitted lines...
2023.58 kenrr sponsor_poaching_raid ecosys 1 Meru_National_Park
2023.72 kenepa use_technology_to_find_wildlife_habitat ecosys 2 Narok Maasai_Mara_Game_Reserve
2023.83 kenrr smuggle_wildlife ecosys 2 Nairobi Nairobi_National_Park
2024.10 kenepa translocate_animals ecosys 2 Laikipia Nairobi_National_Park
2024.26 tanrr offer:_will_stop_poaching_for_livelihood tanpres 2 Dar_es_Salaam Arusha
2024.46 kenepa conduct_wildlife_abundance_survey ecosys 2 Maasai_Mara Lake_Nakuru_National_Park
2024.51 kenrr smuggle_wildlife ecosys 2 Kilimanjaro Amboseli
2025.17 kenpres shrink_in_trade_relations kenpres 1 Nairobi
2025.65 kenrr sell_several_rhino_horns ecosys 1 Nairobi
2025.66 kenepa translocate_animals ecosys 1 Nairobi
2025.94 kenepa translocate_animals ecosys 2 Eastern Taita_Taveta
2025.94 kenrr smuggle_wildlife ecosys 2 Eastern Taita_Taveta
2025.94 kenepa positive_ecoreport one,kenpres 1 Nairobi
2026.23 kenepa translocate_animals ecosys 1 Meru_National_Park
2026.46 tanrr smuggle_wildlife ecosys 2 Arusha Dar_es_Salaam
```

Table 3: Political-ecological actions extracted from online sources with the EMAT actions extractor. The columns are Date, Actor, Action, Target(s), and Location. See Haas (2026a), Appendix C for an assessment of the EMAT action extractor's accuracy.

4.1.2 Ecological data

A minimal political-ecological data set needed to estimate the model's parameters contains some number of cheetah poaching actions, and at least two observations on cheetah abundance taken at least a year apart. This minimal data set will support the estimation of the modeled effect of retaliatory and cub-capture poaching on the local cheetah population.

Observations on cheetah sightings or cheetah presence are typically collected by field ecologists running camera traps or observing cheetah spoor. Using these data-collection methods, the official report on the status of cheetah written by the International Union for the Conservation of Nature (IUCN) estimates 650 cheetahs in Tsavo West NP in the year 2022 (Durant et al., 2022).

Drawing from several publications, SafariFind (2026) reports estimates of cheetah abundance in several regions of Tanzania for the year 2026 (Table 4). The Kilimanjaro region and its Mkomazi NP are not included in this report.

Region	Area (km^2)	Abundance	Cheetah density	Status of the local cheetah population
Serengeti-Mara	30000	664	2.21	Declining
Ruaha-Rungwa	50886	166	0.33	Stable
Tarangire-Maasai Steppe	35000	100	0.29	Declining

Table 4: Estimates of cheetah abundance and density for the year 2026 in selected regions of Tanzania (SafariFind, 2026). Cheetah density is the number of cheetah per 100 km^2. The Serengeti-Mara protected area is from National Geographic (2026), the Ruaha-Rungwa area is from Tarimo et al. (2020), and the Tarangire-Maasai Steppe area is from Tanzania Travel Agent (2026).

In related work, Cheetah Conservation Initiative (2026) report cheetah density in protected areas to be approximately 2.5 individuals per 100 km^2 but note that outside these areas, densities can be as low as 0.2 individuals per 100 km^2

Based on these reports, the abundance estimates in Table 5 are computed using a density of 2.21 cheetahs per 100 km^2 for protected areas, and 0.33 for unprotected areas.

Patch ID	Country	Region	Area (km^2)	Cheetah abundance (2022, 2026)	Adjacent patches
1	Kenya	Unprotected area west of Tsavo West NP	10000**	20*, 20*	2
2	Kenya	Tsavo West NP	9065	650, 200*	1, 3
3	Tanzania	Kilimanjaro region outside of Mkomazi NP	10005	33*, 33*	2, 4
4	Tanzania	Mkomazi NP	3245	72*, 72*	3

Table 5: Contents of the local cheetah abundance input file, `cheetahpatches.dat`. Area values are taken from Mapy (2026), Kenya Biodiversity (2026), and Tanzania National Parks (2026) for Tsavo West NP, Kilimanjaro region, and Mkomazi NP, respectively. A "*" symbol indicates an estimate computed by multiplying area by density. A"**" symbol indicates a judgement-based value. Adjacencies are from Wikipedia (2025a), Masai Mara Travel (2025), and Wikipedia (2025b). Adjacency information is necessary to model cheetah movements across region boundaries.

Density-based estimates are used instead of actual observations because such data is not publicly available. For instance, although it is suspected that there is a small number of cheetahs in Tanzania's Kilimanjaro region – especially in Mkomazi NP (Mbise, 2024; African People & Wildlife, 2026), observations have either not been made or have not been published.

4.2 Parameter estimation

In order to provide starting values for the one-step-ahead prediction error rate computation (Haas, 2024a), the model's parameters are first estimated using all available data as follows.

4.2.1 Consistency Analysis objective function

The hypothesis distribution influences the results of the *consistency analysis* (CA) statistical estimation of a subset of the model's parameters. See Appendix S3 of Haas and Ferreira (2017) for the mathematical form of CA's objective function. To summarize, statistical estimates of the political-ecological model's parameters are computed under a frequentist approach, namely Minimum Simulated Hellinger Distance (MSHD) (Haas, 2024a). Abundance similarity (gs_{eco}) is measured by the negative of the average standardized residual absolute value where the residual is defined to be *(observed cheetah abundance - submodel-computed cheetah abundance)*.

The Simulated Annealing – Multiple Dimensions Ahead Search (SA-MDAS) algorithm described in Haas (2026a) is used to find a solution to the CA optimization problem. This computation is performed with a JAVA™ version of SA-MDAS running on the Triton Shared Cluster Computer (TSCC) (TSCC, 2025).

4.2.2 Parameters to be estimated

A subset of the model's parameters are estimated with CA. This subset consists of selected parameters that define the `Scenario_Livestock_Resource` variable in the Kenya pastoralist submodel. Parameters are selected for estimation if they are associated with the *poach for protection* action.

The `Scenario_Livestock_Resource` node is influenced by the decision option node, the node representing the current perceived state of the pastoralist group's livestock resource, and the node representing the current perception of how likely a group member will be arrested for poaching.

4.2.3 CA run and parameter estimates

Because the lodge is only at the proposal stage, no evictions have been carried out, and hence there has been no retributive killing of cheetah. Therefore, during the CA, the output action, *poach to protest* is set so that it drives low values of the `Scenario_Livestock_Resource` node. Doing so results in this action not being selected by any group submodel during the interval of observed political-ecological actions.

Trial runs exhibited an artificial two-week oscillation of cheetah abundance between protected and unprotected regions. This oscillation was stopped by modifying the cheetah abundance IBM so that cheetah did not move between regions.

Under these restrictions, a CA is performed using the constants in Table 1 and the data in Tables 2 and 5. The values of the above parameters are adjusted until the group submodels match as many observed actions (Table 3) as possible and the cheetah abundance submodel computes expected local cheetah abundance values that are similar to those of Table 5. Figure 4 displays this *consistent* model's output over the observed actions history interval.

Sample standard deviations of cheetah abundance realizations generated by the cheetah abundance submodel are about 10% of mean abundance for large mean values, and about 20% for small mean values.

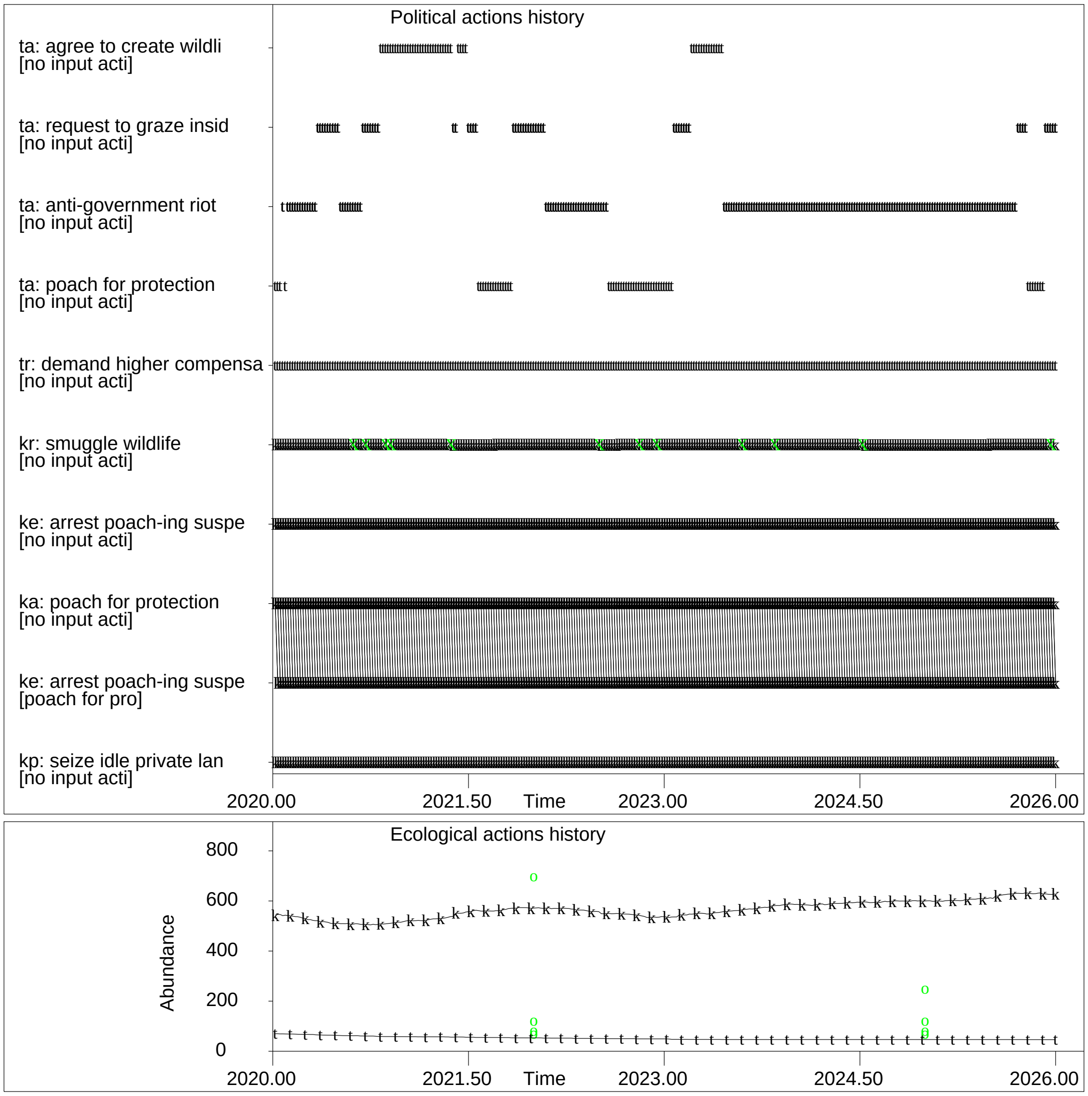

Figure 4: Actions history over the observed actions history interval. Actions and ecosystem responses are generated by the model using parameter values that have been statistically fitted via CA to the political-ecological data set of Section 4.1. The "X" symbol denotes an observed political action that is matched by the model. The "o" symbol denotes an observation on cheetah abundance. The "k"-symbol abundance curve denotes total mean cheetah abundance across the two modeled regions of Kenya while the "t"-symbol curve is total mean cheetah abundance across the two modeled regions of Tanzania.

This computation required 2.4 hours of wall clock time on a single TSCC compute node. The run increased the hypothesis distribution agreement value from -0.825604 to -0.288827 or a 65% increase. This was achieved while holding the fraction of matched actions to 0.6.

4.3 One-step-ahead error rates

Estimates of one-step-ahead prediction error rates can be computed when there are at least two observed actions, and at least two ecological variable observations taken at more than one time point.

The above model's one-step-ahead error rate is computed over the interval of 2018 through 2026 using 105 action observations, and eight observations on cheetah abundance. The model was refitted with CA using observations belonging to the interval 2018 to 2022, and then again, using observations from 2018 to 2024. These error rates are $\zeta = 0.335$, $\epsilon = 134.506$, and $\delta = 302.979$. The value of ζ is the rate of errors made by the group submodels when predicting actions, ϵ is the *root mean squared prediction error* (RMSPE) of the cheetah abundance variable in the cheetah abundance submodel, and δ is the RMSPE of this same variable when using naive forecasting to compute abundance predictions.

A naive predictor of a continuously-valued variable is to always use the most recent observation to predict the variable's value at a future time point. See Haas (2024a) for detailed developments of ζ, ϵ, and δ.

The number of possible output actions within each group submodel ranges from six to 25. The naive predictor of an action taken by a group is to choose an action randomly from a group's repertoire. Such a predictor has an error rate of $1 - 1/q$ where q is the number of actions in the group's actions repertoire. Hence, under the above model's set of group action repertoires, the error rate of using the naive predictor to make action predictions is at least $1 - 1/6 = 0.83$.

These diagnostics indicate that (a) the group submodels deliver action predictions that are superior to naive prediction, and (b) the cheetah abundance submodel delivers abundance predictions that are superior to those found using the naive predictor.

4.4 Local cheetah extinction risks

Runs of this statistically estimated political-ecological model are made under the two scenarios of first, the luxury safari lodge being built and run starting February 1, 2037 (along with needed evictions of Kenya rural residents and Kenya pastoralists); and second, all poaching of cheetah adults and cubs brought to zero in 2026 and held at that value over the planning horizon. The first scenario is represented in the model by fixing the output action of the KWS submodel at *evict residents from public lands* over the entire planning horizon. Predicted total local cheetah abundance over the planning horizon under the first of these scenarios is displayed in Figure 5. Kenya pastoralists target cheetah within national parks when they poach these animals to protest their being evicted from their ancestral rangelands to make room for the luxury safari lodge.

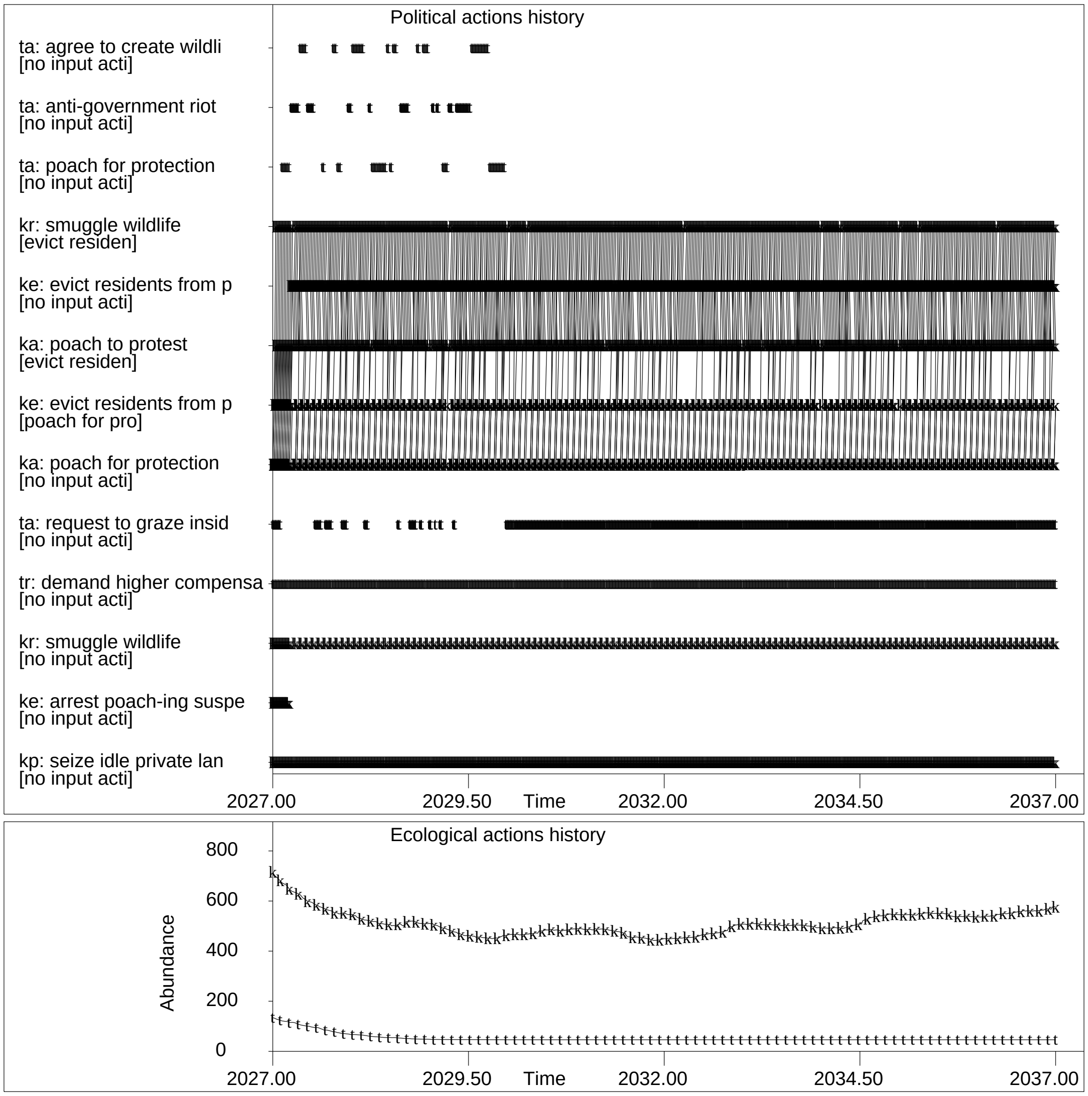

Figure 5: Predicted actions and per-country mean cheetah abundance over the EIA's planning horizon. The value of S is fixed at 1.0 for this run.

Table 6 shows the risks of the local cheetah population going extinct at the planning horizon end date as a function of the above two scenarios.

Region	Local extinction risk (probability)	
	Lodge	No poaching
West of Tsavo	0.836 (1.0)	0.836 (1.0)
Tsavo West NP	0.000 (0.0)	0.000 (0.0)
Kilimanjaro	0.836 (1.0)	0.836 (1.0)
Mkomazi NP	0.836 (1.0)	0.535 (0.640)

Table 6: Local extinction risks and local extinction probabilities on February 1, 2037 with the construction of the luxury safari lodge, and then, under zero poaching. The value of R, S, and C are held at 1.0, 1.0, and 3.0, respectively. Runs with $S > 1$ are not displayed because the resulting extinction risks are not different from the above.

4.5 Evaluation of EIA predictions

Under the values of $R = 1$, $S = 1$, and $C = 3$, the model predicts the local extinction of the cheetah population in three of the four patches. The only patch that does not exhibit local extinction is Tsavo West NP – mainly due to its large initial population of cheetah. The PGA would cite these EIA predictions to support their decision to not issue building permits for the proposed luxury safari lodge.

Poaching pressure on the local cheetah populations is so severe that to improve the survivability of local cheetah populations, all poaching would need be brought to zero in 2026 and continue at that value over the planning horizon.

5 Discussion

Many EIAs do not mention or assess alternate solutions to safeguarding an at-risk species (Bigard et al., 2017). If they did, they would become a special case of a Most Practical Ecosystem Management Plan (MPEMP) (Haas, 2026a) wherein the project is always a part of any proposed plan. This is because an MPEMP finds a combination of actions that, in-sum, form an ecosystem management plan that is both politically feasible and effective at sustaining an at-risk species.

As illustrated in the above example, the proposed EIA protocol works when there is sufficient data to statistically estimate selected parameters of both the group submodels and the ecosystem submodel. But acquiring these observations may be expensive or worse, not possible. For instance, the only publicly available data on cheetah abundance as shown in Table 5 is sparse. Such sparse and small data sets that often characterize those available for at-risk species can require advanced statistical methods and expensive computer resources before they can be used to statistically fit abundance model parameters. Here, CA running on a supercomputer was required to find parameter estimates. Other approaches to this challenge exist. For instance, (Sirén et al., 2018) use an approximate Bayesian method to statistically fit an IBM to sparse data in order to estimate the abundance of a wildlife population.

The present article's EIA protocol lacks a mechanism for stopping corrupt PGA officials from permitting a project whose EIA was rejected by the protocol's review panel. Such governmental corruption can occur because some projects, if implemented, can make the project's proponents large amounts of money – leading some project proponents to bribe corrupt PGA officials in order to secure project permits regardless of the review panel's recommendation.

Use of a formal corruption-prevention system such as the one developed by GIACC (2024) is the best way to avoid instances of corrupt PGA officials approving a project in-spite of its EIA having been rejected by the panel convened to review it. The only other alternative appears to be civil protest against a potentially harmful project (Laurance and Little, 2018).

6 Conclusions

The present article has proposed and illustrated a new way to write an EIA. The proposed protocol produces an EIA that is credible due to its use of a published model for species abundance predictions, publication of one-step-ahead prediction errors, and the scrutiny given it by an independent panel of scientists. Hence, through its literature review and example, the present article argues that the theory, mathematics, and technology all exist to support the recommendation that, when the necessary data can be acquired, EIA predictions of project impacts be based on predictions computed by statistically estimated models rather than those based on expert opinion (Retief et al., 2023).

Three pieces of legislation have also been described that, once made law within a particular governmental jurisdiction, would drive EIAs governed by that jurisdiction to adhere to this protocol. The present article has also shown that political reactions to a project can have significant negative impacts on at-risk species. In response to this relatively new environmental impact dimension, the example herein applies a political-ecological model to (a) understand the causal chain leading to such impacts, and (b) provide a model-based estimate of their severity.

In sum, an EIA that meets Bill #2's standard (d) describes a project that allows it to predict a credible and positive assessment for the local survival of those species impacted by that project. This is in contrast to several EIAs that, as shown in the literature review, have reported only poorly-justified or downright misleading assessments of such species' survival.

7 Conflicts of Interest

The author declares no competing interests.

8 Funding

This work received no funding support.

9 Data Availability

All source code and input files needed to run the hypothetical EIA described herein are contained in the four files `java_source.zip`, `scripts.zip`, `data.zip`, and `eia_cheetah.zip`. The first of these files contains all 87,620 lines of the toolkit's JAVA source code – namely the program **id**. The second file contains all needed Linux® shell scripts and Windows® batch files. The third and fourth files contain model definition files and all of the political-ecological data analyzed in the present article. These four files are freely available at either `www.profitablebiodiversity.com/software` or the Zenodo repository (see `https://about.zenodo.org/policies/`). Access Zenodo versions with the following digital object identifiers (DOIs):

10.5281/zenodo.19653266 (April 19, 2026 version) or
10.5281/zenodo.19653265 (all versions resolving to the latest).

10 Author Contributions Statement

T.C.H. developed the concept, wrote all code used in the article, collected all of the data, ran all of the computations, wrote the article's text, and reviewed the article.

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