Conservation Risks: When Will Rhinos be Extinct?

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***Abstract*—We develop a risk intelligence system for biodiversity enterprises. Such enterprises depend on a supply of endangered species for their revenue. Many of these enterprises, however, cannot purchase a supply of this resource and are largely unable to secure the resource against theft in the form of poaching. Because replacements are not available once a species becomes extinct, insurance products are not available to reduce the risk exposure of these enterprises to an extinction event. For many species, the dynamics of anthropogenic impacts driven by economic as well as noneconomic values of associated wildlife products along with their ecological stressors can help meaningfully predict extinction risks. We develop an agent/individual-based economic-ecological model that captures these effects and apply it to the case of South African rhinos. Our model uses observed rhino dynamics and poaching statistics. It seeks to predict rhino extinction under the present scenario. This scenario has no legal horn trade, but allows live African rhino trade and legal hunting. Present rhino populations are small and threatened by a rising onslaught of poaching. This present scenario and associated dynamics predicts continued decline in rhino population size with accelerated extinction risks of rhinos by 2036. Our model supports the computation of extinction risks at any future time point. This capability can be used to evaluate the effectiveness of proposed conservation strategies at reducing a species' extinction risk. Models used to compute risk predictions, however, need to be statistically estimated. We point out that statistically fitting such models to observations will involve massive numbers of observations on consumer behavior and time-stamped location observations on thousands of animals. Finally, we propose Big Data algorithms to perform such estimates and to interpret the fitted model's output.**

***Index Terms*—Agent-based economic models, ecological modeling, extinction risk, individual-based models (IBMs), wildlife trafficking.**

I. Introduction

A. Risk Management for Biodiversity Enterprises

WE CONSIDER how enterprises engaged in the biodiversity trade will develop risk intelligence in the future through application of "Big Data" techniques applied to computationally intensive risk models. We restrict ourselves to those enterprises engaged in the biodiversity trade in endangered animals. This service-oriented trade takes on several forms including: 1) the selling of guardianship services to governments and private firms so that they may in-turn claim nonuse value [1] of the endangered but protected species; 2) the selling of tourism activities centered around viewing such animals; 3) the selling of sustainable hunting opportunities of such animals; and 4) the selling of anxiety-reduction aids to private individuals who are concerned about the possible extinction of such animals. All of these services require the existence of a viable population of the endangered species being marketed. Thus, loss of such a population would permanently end the ability of these enterprises to trade in services associated with the now extinct species.

We consider one type of for-profit enterprise, and two types of nonprofit enterprises engaged in the legal global trade in biodiversity. The type of for-profit enterprise we consider is a private landowner who offers on-site viewing and/or hunting activities of a captive population of an endangered animal. The first type of nonprofit enterprise we consider is a government agency charged with protecting one or more endangered species within a government-owned plot of land, e.g., a national park so as to maintain their nonuse value. South African National Parks (SANParks), discussed in our case study below, is an example of such a nonprofit enterprise.

The second type of nonprofit we consider is a private, nonprofit organization with global reach chartered to promote biodiversity. Examples of such nonprofit enterprises include the World Wildlife Fund, and the Nature Conservancy. Armsworth *et al.* [2] reported that the combined assets of this type of enterprise in 2004 was $19.1 billion with annual revenues totaling $6.32 billion.

As an aside, most enterprises engaged in providing ecotourism services share the conundrum with most biodiversity enterprises of marketing ecological features (terrestrial and marine preserves, or endangered species) that they do not own and have no possibility of ever acquiring. This industry was estimated to have a market value of $473.6 billion in 2010 [3] and hence dwarfs the biodiversity industry.

Olson and Wu [4] reviewed a general supply chain risk framework originally developed by [5]. Table I gives the correspondence of each component of this framework to the case of a biodiversity enterprise managing its supply of an endangered animal. In particular, a high-priority performance outcome for these enterprises is the degree of biodiversity conservation of those endangered animals that have been targeted by particular projects funded by the enterprise [6].

We develop models and methods for computing the risk to these enterprises due to the extinction of a marketed endangered species. Such risk computations comprise step 8 of a process for managing supply chain risk first

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TABLE I
RISK FRAMEWORK APPLIED TO BIODIVERSITY ENTERPRISES

Number	Component	Biodiversity Enterprise Realization
1.	Risk context and drivers	Poaching, and habitat loss driving an animal to extinction
2.	Risk management influencers	Will of the enterprise to invest in extinction risk mitigation projects
3.	Decision makers	Decision making hierarchy within enterprises that vary seven orders of magnitude in size [2]
4.	Risk management responses	Repertoire of legal, political, and economic approaches to mitigating extinction risk but notably, no insurance option
5.	Performance outcomes	Future viability of the endangered animal's population

proposed by Cucchiella and Gastaldi [7] and later reviewed by Olson and Wu [4]. This step consists of risk assessment, estimation, and evaluation. Such estimation and evaluation is most precisely accomplished through the development of quantitative, stochastic models of future costs that can be used to compute a quantified measure of risk, namely expected cost.

Reference [4, Table I] lists several sources of external risks to a supply chain. One of these under the political system category is war, terrorism. A war or act of terrorism can interrupt the supply of a resource due to damage to the supplier or loss of resource stockpiles. We add the risk of resource theft to this risk category which in our case, is the illegal killing of individuals of an endangered animal in order to supply the black market with body parts from the poached animals.

Olson and Wu [4] discussed risk mitigation strategies including the purchase of insurance products to hedge against various insurable risks. A unique aspect of biodiversity resources is that there is no insurance option for mitigating the risk of a species extinction event.

Wu and Olson [8] presented three different approaches to computing risk (expected cost) of a supply chain. Wu and Olson [8] considered the case of a three-component chain: 1) several vendors (suppliers); 2) one retail enterprise whose risk is to be minimized; and 3) one to several customers. In our case study below, we consider a different supply chain: two suppliers of an endangered species, and the supply chain of theft off-take from these suppliers. This theft supply chain has two components: 1) the initial theft of animal products at the suppliers' resource warehouses (here, national parks or private ranches) and 2) the "consumers" of these stolen animal products. To minimize risk, biodiversity traders need to minimize the volume of animal products in this theft supply chain.

In practice, a biodiversity enterprise would run our model to compute species extinction risk at future time points under different business plans and market conditions, e.g., no change to current plans or conditions (the scenario we compute in our case study, below), or implementation of a species extinction risk mitigation strategy.

In this paper, we advocate the use of a stochastic economic-ecological simulator to compute supply chain risk to a biodiversity enterprise. This simulator is composed of an agent-based model (ABM) of the illegal off-take supply chain coupled to an individual-based model (IBM) of the endangered animal metapopulation residing within government-owned and private protected areas. The simulation step is performed by running a large number of Monte Carlo realizations across many threads of a multithreaded JAVA program running on each node of a cluster computer.

B. Using Big Data Techniques to Build and Interpret Economic-Ecological Simulator

The term Big Data is often thought to mean datasets so large that novel methods need to be developed to enable their analysis. For example, SAS Institute, Inc., sees Big Data has challenging analysts due to its volume, velocity, variety, variability, and complexity [9]. We argue here that in fact, complexity should be the focus of any definition of Big Data. Several prominent researchers in data analytics were queried by Dutcher [10] as to the definition of the term Big Data. Several of these researchers stressed that the complexity of the analysis needed to extract useful information from the data is more relevant to the term rather than the absolute size of the dataset being analyzed. For example, Jessica Kirkpatrick, Director of Data Science at InstaEDU states

> Big data refers to using complex datasets to drive focus, direction, and decision making within a company or organization. This is done by deriving actionable insights from the analysis of your organization's data.

And Amy Escobar, Data Scientist, 2U, Inc., states

> [Big data is] an opportunity to gain a more complex understanding of the relationships between different factors and to uncover previously undetected patterns in data by leveraging advances in the technical aspects of collecting, storing, and retrieving data along with innovative ideas and techniques for manipulating and analyzing data.

A third definition due to [11] that focuses on analytics is "data that you have not been able to extract new insights from yet."

Statistically fitting an economic-ecological model to observations will involve massive numbers of observations on consumer behavior and time-stamped location observations on thousands of animals. Hence, the size of the set of observations used to fit an economic-ecological model conforms to the traditional definition of Big Data. Our focus however, is on two more challenging problems—that of finding the estimates themselves, and interpreting the fitted model's output. Therefore, using the definition of Big Data that emphasizes the complexity of the dataset and the use of advanced methods for its analysis, we identify two areas within which Big Data can aid the development and use of ABMs/IBMs. These are: 1) statistically estimating the model's parameters and 2) visualization of, and relationship detection with the large output datasets generated by ABMs/IBMs.

One way to statistically estimate the parameters of a large ABM/IBM is to use a cluster of cluster computers to compute objective function values in order to optimize an objective function that measures the statistical fit of the model's output to observations. Specifically, we propose a multicluster computing architecture [12] consisting of a cluster grid controlled by a single processor that runs a parallel version of a nonlinear, constrained optimization algorithm, namely the classic Hooke and Jeeves coordinate search procedure [13, Appendix B]. As described below, this master processor assigns each cluster computer a vector of parameter values with which to compute the value of the statistical estimation objective function that in our case is a simulated likelihood. Each cluster computer runs the economic-ecological simulator to compute this objective function value. It is this set of trial parameter vector values that we are regarding here as Big Data within our statistical estimation context.

A biodiversity enterprise is particularly interested in temporal patterns of both illegal trade in endangered animal products, and endangered animal's abundance. Hence below, we also discuss how data mining techniques can provide interpretation and visualization of the high-dimensional time series output of the economic-ecological simulator.

C. Background

Rhinos are facing extinction risks [14], largely because rhino horn is of high value to Asian societies for several cultural reasons [15], [16, Ch. 14]. All rhino species' populations dramatically collapsed over the past century [17] with seven extant species and sub-species remaining [18]. Asian rhino species are holding on—barely [14], while some African species have recovered, most noticeable those with primary ranges in southern Africa [18]. Sustainable use proponents argue that recognition of most values of southern white rhinos (Ceratotherium simum simum) and to some extent southeastern (Diceros bicornis minor) and southwestern black rhino (D. b. bicornis) is the reason for recovery [19]. Unprecedented poaching [20] now places the continued recovery of these species at risk.

At present, no legal trade in rhino horn is allowed [21], but trade in live African rhinos, part of which feed the hunting industry [22] is legal. Rhinos also contribute significantly to ecotourism revenue [23] and has stimulated a vibrant wildlife industry in South Africa [24]. Asian demand is rising [25] and associates with the ebb and flow of economic well being of eastern countries [26]. In the short to medium term it is expected that Asian demand for rhino horn may increase [26], [25], introducing lengthy lag effects of demand reduction strategies. Rhino populations are relatively small and it is debatable whether the present conservation asset can provide for the demand of rhino horn [26] even if horn is harvested from live rhinos [28]. The present status quo is characterized by a rising onslaught of poaching on rhinos [20].

For further background on the economics of species extinction and rhino extinction in particular (see supplementary materials).

We develop an economic-ecological model of the interaction of poachers, their middlemen, legal traders, consumers, and the South African rhino population. We integrate an agent-based economics submodel with an individual-based rhino population model impacted by the actions of the economics submodel. To the best of our knowledge, our model is one of the first to achieve such integration. The stochasticity of our model allows us to compute species extinction risk as the expected value of a loss function where "loss" is defined to be the nonuse value of rhinos residing in a protected area [1].

This paper is structured as follows. In Section II, we describe our economic-ecological model of the illegal trade in rhino horn and its impact on the South African white rhino population. In Section III, we predict extinction risks over a 35 year horizon. In Section IV, we compare our model's output to data-based estimates of white rhino abundance and generate predictions of the coupled dynamics of rhino horn trade and rhino abundance. We discuss the implications of our results in Section V, and reach the conclusion in Section VI.

II. Economic-Ecological Model

Source code for the economic-ecological model (available at [31]) captures a model that consists of two interacting, stochastic submodels: 1) an ABM of competing traders modified from a model developed by Catullo [32] and 2) an IBM [33] of a wildlife population model inspired by one developed by Kostova *et al.* [34].

A. Applying Agent-Based Economic Models to Wildlife Trade

1) Products and Markets Modeled: We consider three products traded in three largely separate markets: 1) horn for Asian consumers; 2) live rhinos for the South African recreational hunter market; and 3) the international market for satisfying global anxiety about the future of biodiversity. We refer to the third market as the species extinction anxiety reduction (SEAR) market.

The last market is served by private firms and nongovernmental organizations (NGOs), hereafter referred to as simply SEAR traders. It is in the interest of SEAR traders to amplify and keep in the media the idea that the rhino is headed for extinction due to poaching. In other words, if rhinos cease to be endangered, the global feeling of anxiety toward the future of rhinos would be reduced thus reducing the demand for the service SEAR traders are selling (anxiety reduction). Crime syndicates pay a small sum [29] to poor, rural people who have limited economic opportunities [30] thus almost guaranteeing an illegal supply of rhino horn.

There are three consumer groups: 1) horn consumers in Asia; 2) donors to SEAR traders; and 3) recreational hunters of rhinos. There is little overlap between these groups. Legal and illegal traders would engage in direct competition if consumers of rhino horn were able to choose between illegal and legal horn.

It is important to note that in the present state of rules, legal rhino horn traders are only seeking to obtain permission to trade, but are not trading any rhino horn. See supplementary materials for a discussion of the possible impact legalization of rhino horn trade would have on demand and the behavior of illegal traders.

2) Economic Modeling With Interacting Agents: An agent-based economic model represents individual firms as agents and individual consumers as agents. During one step or cycle, each trader makes decisions about product resupply and product pricing that maximizes their individual utility. Also during this cycle, each consumer makes decisions about entering a market, and once entered, purchasing decisions that maximize their individual utility. Time is incremented, and another cycle is executed [35]–[37].

Building on Catullo [32], we construct an agent-based submodel of the international trade in rhino poaching goods across three markets. Our submodel contains a criminal network involved in illegal rhino horn trafficking, a firm involved in seeking to trade legally in horn, the effect of a meta-firm serving the international SEAR market, and the effect of a local, South African meta-firm serving the rhino hunting market.

Arthur [38] found that an agent-based economics model is able to distinguish among multiple equilibria: a feat that is difficult for models formed from the equilibrium solutions of systems of differential equations. The suspected existence of multiple equilibria in the dynamics of wildlife products trade [39] is possibly the central reason for the reluctance that nongovernment organizations and international convention secretariats such as Convention on International Trade in Endangered Species have toward the legalization of trade in wildlife products from endangered species. In essence, these agencies suspect multiple equilibria and have no assurance that reality will not settle into an equilibrium point of a species' extinction.

Arthur [38] also noted that agent-based economics models can model the effect that trader expectations can have on future product supply. An example of this in the present application is where illegal rhino horn traders expect to be undersold once legal horn trading is enacted—leading them to accelerate their poaching activities to maximize their profits before being forced out of the market [40].

In another review and critique of the literature advocating legal trade in wildlife products, Nadal and Aguayo [41] found many articles reaching the conclusion based on analyses of static models. The authors see this as inadequate as such models cannot shed light on how wildlife trade markets might unfold through time. Our agent-based submodel on the other hand, is a fully dynamic approach. The authors are also critical of the assumption of a downward sloping demand curve present in all pro-trade articles. Recent theoretical results, specifically the Sonnenschein–Mantel–Debreu theorems (see [41]) have shown that a market demand curve need not share any characteristics of an individual's demand curve. Hence, any theory that assumes aggregate behavior is a simple scaled function of individual behavior is theoretically invalid. Again, our agent-based submodel allows aggregate behavior to emerge from the interacting actions of many individual consumers.

B. Integrating Economic Behavior and Wildlife Dynamics

In our approach, an IBM [34] is employed to represent the South African rhino population as they are impacted through time by their birth process, natural death process, and the poaching process produced by the agent-based economics submodel of the legal and illegal traders.

In this model, the traders' submodel runs every 12 weeks and produces m, the number of rhinos to poach each week for the next 12 weeks. Then, the rhino IBM runs every week for 12 weeks. Each week, m mature rhinos are randomly selected and set to the value dead.

C. Traders as Agents

1) Rhino Horn Traders: In our economic submodel, there are two traders, one legal and one illegal. There are several levels of middlemen involved in the illegal rhino horn trade [42]. We model these as one meta-firm, i.e., we model the middlemen that directly purchase rhino horns from poachers up through the exporters as working for a single firm: the illegal trader. We argue that a criminal middleman has a restricted number of potential customers: other criminal middlemen or criminal exporters. Hence, the collection of middlemen up through the exporter acts more like a cooperative than a set of competing firms. Implicit profit sharing occurs as a middleman at one level will only be willing to purchase rhino horn from a lower level middleman if that price allows the middleman to make a profit. Ultimately, the ability of this cooperative to make a profit depends on the price demanded by poachers and the black market price that consumers are willing to pay. As long as the unit cost to this cooperative is lower than consumers' reserve price, the illegal trader will stay in the business of rhino horn trafficking—lowering or raising their black market price in response solely to the purchase decision making of consumers. Therefore, some estimate of an illegal trader's unit cost is needed.

In our economic submodel, the unit cost for acquiring and selling 1 kg of rhino horn by either trader is \$5000. For the illegal trader, this number is arrived at by considering that trader's costs as follows. First, the illegal trader needs to purchase a horn from a poacher. In [43, p. 21], the black market price for 1 kg of rhino horn is estimated to be between USD \$35 000 and \$60 000 with about 5% of that being used by the illegal trader to purchase the rhino horn from poachers. Using the lowest black market price, poachers are paid \$1750 for 1 kg of rhino horn. Next, the illegal trader needs to purchase a courier's airfare from Maputo, Mozambique to some city in Asia for \$2000. Finally, the illegal trader needs to pay the courier's fee of \$500 [44] per rhino horn or \$100/kg of rhino horn assuming an average rhino horn weighs about 5 kg [45]. Using these numbers, the trader has incurred a cost of \$3850 to bring 1 kg of rhino horn to an Asian market. Thus, a conservative unit cost is \$5000.

Traders are not allowed to engage in product "dumping," i.e., selling their rhino horns for less than their unit costs. Each week, traders always sell as many kilograms of rhino horns as there are consumers willing to purchase them. In other words, demand is insatiable [26].

Vietnamese rhino horn merchants usually have a number of rhino horns available for inspection [27]. This implies that: 1) there is no direct order placed by a customer before a rhino is poached and 2) illegal traders maintain a buffer stock (inventory) of rhino horn.

2) International SEAR Trade: Poaching frequency is a proxy for the amount of international anxiety about looming rhino extinction—a special case of species extinction anxiety defined in Section II-A1. Consumers wish to reduce their amount of this anxiety. Conservation-focused NGOs solicit donations by promising to help curb rhino poaching. In effect, these NGOs are selling anxiety-reduction aids [46]. An SEAR trader's revenue is driven by the demand for their product which in turn is driven by the amount of rhino poaching perceived by the international community. If the perceived amount of poaching lessens, an SEAR trader's revenue tends to lessen and vice versa. SEAR traders do indeed fund a portion of anti-poaching measures.

Therefore, if rhino poaching is reduced, external funds for anti-poaching measures are reduced. This effect is modeled in the agent-based submodel by weakly tying anti-poaching effectiveness to the number of rhinos poached per week (see Section II-C3, step 10). The economic submodel thus does not directly simulate SEAR trader transactions with their customers.

3) South African Trade in Rhino Hunting: The effect of recreational hunting of rhinos on private ranches (hereafter ranches) is modeled in the rhino abundance submodel (see Section II-D2, step 8). Economic transactions between these ranch owners and recreational hunters are not modeled in the economic submodel.

4) Submodel Operation: There are two basic goal functions in the following update rules. Collectively, these functions represent a firm's single goal of increasing its profits. These goal functions are updated through a reinforcement learning algorithm adapted to economic ABMs by L. Tesfatsion, an early advocate of economic ABMs [35]. Specifically, the price goal `q-response` and the production capacity goal, `c-response` are updated using price and production capacity experiences at the previous time point. Actual pricing and production capacity decisions are stochastic in order to represent as noise all effects on the firm's decision making not captured by the model.

1) *Compute the Expected New Price:* First compute the response to the price goal function

$$\mathtt{q\text{-}response}_{t-1} = \mathtt{price}_{t-1} \times \left[1 - \frac{\mathtt{capacity}_{t-1} - \mathtt{nmsold}_{t-1}}{\mathtt{capacity}_{t-1}}\right]. \quad (1)$$

To see "what the market will bear" (see [47])

$$\mathtt{q\text{-}response}_{t-1} = 1.01\mathtt{price}_{t-1} \quad (2)$$

if $\mathtt{capacity}_{t-1} = \mathtt{nmsold}_{t-1}$.

2) Compute the expected value of the new price

$$\mu_t = (1 - \mathtt{learn\text{-}rate})\mu_{t-1} + \mathtt{learn\text{-}rate} \times \mathtt{q\text{-}response}_{t-1}. \quad (3)$$

3) The new price is found by sampling once from a normal distribution with mean μ_t and a standard deviation of \$200.

4) The net revenue is

$$\mathtt{netrev}_t = \mathtt{nmsold}_{t-1}(\mathtt{price}_{t-1} - \mathtt{unit\text{-}cost}). \quad (4)$$

TABLE II
ASIAN CONTINENT POPULATION PROJECTIONS TAKEN FROM [49]

Year	Population Estimate/Prediction
2010	4,165,440,162
2020	4,581,523,062
2030	4,886,846,140
2040	5,080,418,644

5) The response to the production capacity goal function is

$$\mathtt{c\text{-}response}_t = \mathtt{netrev}_t - \mathtt{netrev}_{t-1}. \quad (5)$$

6) The production capacity decision constant is

$$\mathtt{q\text{-}prodcap}_t = (1 - \mathtt{learn\text{-}rate})\mathtt{q\text{-}prodcap}_{t-1} + \mathtt{learn\text{-}rate} \times \mathtt{c\text{-}response}_t. \quad (6)$$

7) The production capacity decision Binomial distribution probability is

$$p_c = \frac{\mathtt{q\text{-}prodcap}_t + \mathtt{maxnetrev}}{2 \times \mathtt{maxnetrev}}. \quad (7)$$

8) Production capacity is reduced, left unchanged, or increased according to the following rules. First, let D be a binomially distributed random variable with $n = 2$, and probability of success equal to p_c. Sample once from this distribution. If $d = 0$, $\mathtt{prodcap}_t = \mathtt{prodcap}_{t-1} - 1$. If $d = 1$, $\mathtt{prodcap}_t = \mathtt{prodcap}_{t-1}$. If $d = 2$, $\mathtt{prodcap}_t = \mathtt{prodcap}_{t-1} + 1$ up to this trader's maximum production capacity. Both traders have a maximum production capacity of 150 kg of rhino horns per week. Because the horns from an adult rhino weigh approximately 5 kg, this value represents 30 rhinos per week. In 2013, an average of 20 rhinos were poached per week across South Africa [48]. Hence, this maximum is ten rhinos above the 2013 weekly average.

9) Reduce the production capacity of the illegal trader in proportion to the effectiveness of anti-poaching operations as follows. Let N_p be binomially distributed with $n = \mathtt{prodcap}_t$ and probability of success equal to p_a. The probability p_a is set to a number close to 0.0 if anti-poaching operations are very effective at curbing poaching. Sample once from this binomial distribution to find n_p, the actual number of rhinos poached this week in spite of anti-poaching operations.

10) Model the effect of additional anti-poaching funds donated by SEAR traders by reducing n_p by 5% if n_p is greater than 25.

11) Model the effect of population growth on the Asian continent on the number of potential rhino horn consumers. Most consumers of rhino horn live on the Asian continent [25]. Table II contains population projections found in [49]. The initial consumer population is created as follows. To represent the assumption of insatiable demand at current (illegal) production levels, consumers are created as necessary to purchase all rhino horn poached under the maximum poaching rate of 30 rhinos per week across South Africa (20 in KNP, and 10 on the ranches).

Because each rhino horn weighs on average 5 kg, these numbers are multiplied by 5. Therefore, in the year 2014, the potential number of consumers is set to 300 (5×60). This value is increased in proportion to the entries in Table II to a maximum of 325 in the year 2033. For the case of a legal trading scheme operating in parallel to the illegal trade, this consumer pool is doubled. Because demand for rhino horn in the near future is predicted to be about four times current sales [26], doing so is well-within current demand forecasts. The supply of legally-traded rhino horn would be sourced from stockpiles and/or shavings from live rhinos. By a consumer we mean a group composed of a number of real-life individuals. Guilford [50] reported an individual purchase for \$2000 of rhino horn powder. At the per-kilogram prices mentioned above, this would be between 33 and 57 g of rhino horn. Other individuals may purchase other amounts of rhino horn. In our model however, one of our consumers always buys exactly 1 kg of rhino horn at each purchase event. Hence, one of our consumers represents approximately 18 to 30 real-life individuals. By doing so, we ignore the variability in the amount of purchased rhino horn and in-effect, lump approximately 18 to 30 real-life purchase events into one purchase event. Hence, our submodel's purchase event time series should be viewed as the aggregate behavior of groups of approximately 18 to 30 real-life individuals.

12) Consumer behaviors start with the decision to enter the rhino horn market or not. If there is a media campaign aimed at potential rhino horn consumers that delivers a message that rhino horn has no medicinal value, some of the potential consumers may decide to not try to purchase rhino horn. This media campaign effect is represented as follows. Let n_{pc} be the number of potential consumers each week. Let p_m be the effectiveness of a horn-is-not-medicine media campaign run in the country where the consumers live. If p_m is close to 1.0, the chance that a randomly chosen potential consumer will decide to buy rhino horn is close to zero. Let N_c be binomially distributed where there are n_{pc} trials, and the success probability is $1 - p_m$. Sample once from this distribution to find n_c, the number of consumers for that week who enter the market for rhino horn.
13) *Simulate Rhino Horn Purchases:* Each consumer buys one kilogram of rhino horn from the trader offering it at the lowest price as long as this price is below the consumer's reserve price of \$60 000 [20]. Because the illegal trader maintains a buffer stock of rhino horn, the number of kilograms of rhino horns the illegal trader sells each week need not equal five times the number of rhino horns poached the previous week.

See supplementary materials for further details of our economics submodel.

D. Individual-Based Model of the Rhino Meta-Population

An IBM of animal abundance is valid for any range size and number of animals when data structures and mapping functions are suitably developed [33, Ch. 4]. But a differential equation model of the animal's population dynamics (see [51]) may, depending on the assumptions that underlay its derivation, need relatively larger range sizes and initial abundance values for it to be a faithful representation of actual population dynamics. Within ranches, however, rhino abundance and range are often small.

An important characteristic of this habitat is that rhino are artificially restricted to anthropogenically-defined patches which in this case are those within the subregions of Kruger National Park (KNP) and ranches. An IBM can be developed to accurately represent the effects of these restrictions on the dynamics of the within-patch populations. The ability of IBMs to handle complex habitat-use conditions is one reason given by McLane *et al.* [52] for why IBMs should be used to model managed wildlife populations.

A spatially-explicit submodel of the South African rhino meta-population is built as opposed to a nonspatial, aggregated single population submodel for the following reasons.

1) Different tolerances for risk across ranch owners can be modeled. For example, a ranch owner might offer the opinion: "i will not keep rhinos, too risky."
2) Ranch-specific financial returns for keeping rhinos can be modeled.
3) Spatial effects on the amount of available forage can be modeled.
4) Spatially-heterogeneous anti-poaching effectiveness can be modeled.
5) Spatially-heterogeneous poaching pressure can be modeled.
6) Rhinos are highly territorial [53]. A spatially-explicit IBM is flexible enough to realistically capture all aspects of this behavior.

An IBM for the South African rhino meta-population is developed along the lines of the prairie vole (Microtus ochrogaster) IBM of Kostova *et al.* [34]. As with the prairie vole IBM of [34], the rhino IBM is stochastic in that one run over a time period will not necessarily produce the same history of abundance and dispersal as another run over the same time period. For this reason, many replications of the IBM over the same time period are needed so that at each time point, both expected value of abundance and extinction probability can be computed.

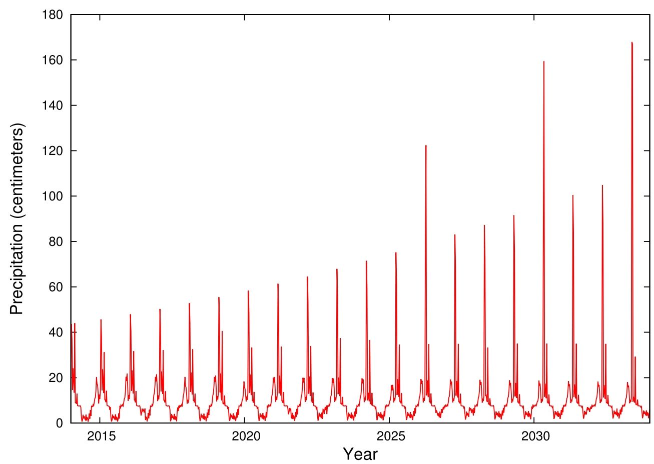
1) Rainfall Predictions and Available Vegetation: Rainfall predictions for KNP over the simulation interval (Fig. 1) are found by evaluating a mathematical model that has been statistically fitted to rainfall observations (see supplementary materials for how this is done).

Rainfall either observed or predicted is used as a scaled proxy of available vegetation. A scaling constant is selected so that approximately 25% of the population experiences a food deficit during the dry season [54].

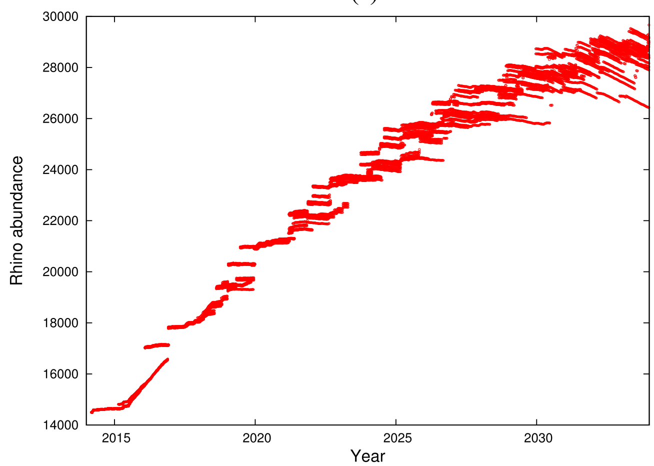
Specifically, a value of c is found such that

$$0.75 = \frac{c \times a \times v}{12000 \times \mathtt{wfi}} \tag{8}$$

where a is the area of KNP, v is unscaled available vegetation for week i set equal to the 0.91 quantile of the observed



(a)



(b)

Fig. 1. Top: predicted average rainfall in KNP per week in centimeters using the quasi-periodic rainfall model fitted to KNP rainfall data from 1903 to 2014. Average rainfall is a proxy for new vegetation. Bottom: predictions of rhino abundance (population size) assuming (a) zero poaching off-take and (b) ranch-based recreational hunting.

rainfall observations from 1910 to 2012, and 12 000 is the desired (target) value of rhino abundance in KNP. Week i's new vegetation per square kilometer is computed from the week i's rainfall with $\text{veg}_i = c \times r_i$ where $i = 1, \ldots, m$ and m is the number of weeks in the observation or prediction interval.

At any point in time, the available vegetation for a rhino's food supply is no more than 36 weeks old. To model this, the net vegetation in a week is set to the sum of the left-over vegetation from the past 36 weeks. This moving-window sum is initialized by setting the first week's net vegetation to four months of a representative value of weekly new vegetation. Specifically, the first week's available vegetation is set to 16 times the 0.99 quantile of the veg_i, $i = 1, \ldots, m$ values found from the observed rainfall series.

2) Submodel Operation: An IBM is an attractive model for an ecological system because "each individual is represented as a system of interacting components such as age, energetic budgets, location, status, etc., and these individuals interact with each other in ways depending on their own state and the state of the environment" [34]. Here, we model the age, gender, energetic budget, location, and status of each individual rhino living and dying in enclosed patches and hence also model interactions of these rhinos with their environment—namely seasonal fluctuations in food availability; and interactions with each other through the effects of their spatial density on their birth and mortality rates. Because Kostova *et al.* [34] give a series of update rules for a very similar situation involving voles, we use their rule set as a starting point for ours. The IBM executes the following schedule of actions each week.

1) Delete all rhinos set to dead during the previous time step.
2) Find within-patch populations.
3) Increment each rhino's age.
4) Up to a rhino's mean energy budget (meb) or juvenile energy budget (jeb) value, a rhino's energy budget is updated in the following manner.
   a) Compute the vegetation ratio
   $$\texttt{vratio} = 0.01\left[\frac{\texttt{netveg}_t}{\texttt{wfi} \times \texttt{nmindiv}_t + 1} - 1\right] \quad (9)$$
   where $\texttt{wfi}$ is a rhino's weekly food intake, $\texttt{nmindiv}_t$ is the number of patch residents at time t, and $\texttt{netveg}_t$ is the available vegetation within the patch at time t.
   b) Compute the amount of energy change
   $$\texttt{ec} = \frac{2}{1 + \exp(-\texttt{vratio})} - 1. \quad (10)$$
   c) If $\texttt{netveg}_t < \texttt{wfi} \times \texttt{nmindiv}_t$, 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 $v < 0.4$, $\texttt{energy}_t = \texttt{energy}_{t-1} + \texttt{ec}$.
   d) If $\texttt{netveg}_t > \texttt{wfi} \times \texttt{nmindiv}_t$ then for each patch resident, $\texttt{energy}_t = \texttt{energy}_{t-1} + \texttt{ec}$.
   e) For each rhino having $\texttt{energy}_t = 0$, draw a realization from V to obtain v. Set this rhino to dead if $v < 0.1$.
5) Set to dead, any rhinos having an age greater than *le*.
6) Simulate food deficit and animal density effects on birth and mortality rates (see supplementary materials for how this is modeled within our IBM).
7) Process Poaching Actions. From the economic submodel, read m, the number of rhinos that are to be poached for this week. Randomly select m mature rhinos and set them to dead.
8) Legal Hunting on Ranches. The hunting off-take from the ranch population is 50% of the oldest males annually. An "old male" is defined to be a male older than the 90th percentile of male ages on the ranch. Find these individuals as follows.
   a) Sort all male ages, and then locate the 90th percentile age.
   b) Form a group of males older than this threshold age. Say there are nm-old-males individuals in this group.
   c) If nm-old-males is positive, compute nmhunt, the number of individuals to hunt (kill) each

TABLE III
IBM PARAMETERS AND THEIR VALUES

Name	Notation	Units	Value	Source
Average Weekly Food Intake	*wfi*	kg	140	[62]
Life Expectancy	le	years	38	[55]
Maturation Age	ma	years	4	[63]
Maximum Energetic Budget	meb	weeks	5	after [34]
Mean Energetic Budget	*meaneb*	weeks	4	after [34]
Juvenile Energetic Budget	jeb	weeks	3	after [34]
Intercalving Interval	*intercalv*	years	2.5	[63]
Available Vegetation	$av(t)$	g/m2	(from Fig. 1)	see Sec. III.D.i

week with floor(0.5 × nm-old-males/52). Otherwise, set nmhunt to zero.

d) Randomly select nmhunt individuals from the old male group and kill them.

9) Sell Some Ranch-Kept Rhinos. This off-take is from all age classes and both genders. Each year, one-fourth of the exponential growth rate is removed from ranches. The exponential growth population model is $N_t = N_0 \exp(rt)$ where N_t is abundance at the end of the time interval, t (measured in years), N_0 is the initial population size, and r is the exponential growth rate. Then, for a given r, the selling off-take each week is $0.25r/52$.

10) For each mature female rhino, create one new rhino if: 1) its $\texttt{time-since-last-birth}_t$ is greater than intercalv; 2) some males are residents of the female's patch; and 3) the female's energy is greater than meaneb.

11) For each female not giving birth

$$\begin{aligned}&\texttt{time-since-last-birth}_t\\&\quad= \texttt{time-since-last-birth}_{t-1} + 1.\end{aligned} \tag{11}$$

12) Update patch membership by randomly moving rhinos into different patches within subregions that possess nonzero net vegetation.

13) Update the net vegetation of each patch. First, find the amount of new vegetation at this time point from the above set of vegetation predictions. Second, find the amount of left over vegetation at this time point as

$$\texttt{vegleftover} = \texttt{netveg}_t - \mathit{wfi} \times \texttt{nmindiv}_t. \tag{12}$$

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

3) Submodel Parameter Values: Table III gives the population dynamics parameters and their values used in the simulations. There are two subregions (KNP and ranches) each with four patches. The initial age distribution is gaussian with a mean of 7.5 years, and a standard deviation of three years truncated between one week old and the life expectancy of a rhino which here, is 38 years [55] (see Table III).

TABLE IV
ESTIMATED AND IBM-GENERATED ABUNDANCE

Time	Data-Based Abundance Estimate	Model-Based Expected Abundance
1998	2674	2706
1999	2938	3090
2000	2683	3401
2001	4552	3764
2002	4223	4217
2003	4765	4841
2004	5308	5465
2005	6974	5990
2006	8893	6704
2007	9119	7677
2008	11498	8601
2010	10621	10929
2012	10495	8453

III. COMPUTING THE RISK OF EXTINCTION

What is society's loss function as a function of the time at which a species becomes extinct? Denote this function with $L(t_e)$, where t_e is the time at which the species first becomes extinct. Note that $L(t) = 0$ for $t < t_e$. The loss due to the extinction of a species residing in a protected area can be approached through its nonuse value [1]. Nonuse value is the sum of the species' bequest value and existence value. Existence value is the value of knowing that a species exists, and bequest value is the value of conserving a species for future generations (see [56]). As nonuse value is unitless, we choose to define it over the unit interval. For those members of a species living in a protected area, there is usually no use value, e.g., harvesting the species for its economic value. Let $V(t)$ be the nonuse value of the species at time t. Note that $V(t) = 0$ for $t \geq t_e$. Let $L(t) = V(t - \epsilon)$ where ϵ is a small positive number.

Say that at $t = 0$, the nonuse value of the nonextinct species is V_0. Under the assumption that this value is constant across future time, $L(t_e) = V(t_e - \epsilon) = V_0$ for $t_e \geq \epsilon$. If however, future value is discounted (time discounting), $L(t_e) = V_0 D(t_e)$, where $D(t)$ is a discounting function. A standard approach to discounting the cost of extinction in the future is with an exponential discounting function, $D(t) = (1 - d)^t$ (see [57]). Setting $d = 0.035$ is not unusual.

A typical definition of risk used in environmental protection is the expected value of loss [58]. Mathematically, $R(t) = E[L(t)]$. Because $L(t)$ equals zero if the species is not extinct, and takes on a positive value otherwise

$$R(t) = L(t)P(t = t_e). \tag{13}$$

We use $V_0 = 1$, $d = 0.035$, and extinction probabilities computed from our economic-ecological model to compute local extinction risks over the period 2014 through 2045 (Fig. 2).

IV. MODEL OUTPUT

A. Submodel Output Compared to Survey Estimates

Ferreira [59] reported on estimates of KNP rhino abundance based on surveys conducted between 1998 and 2012. These surveys are conducted with aerial counts used as input to wildlife abundance estimators (see [60]). Table IV indicates

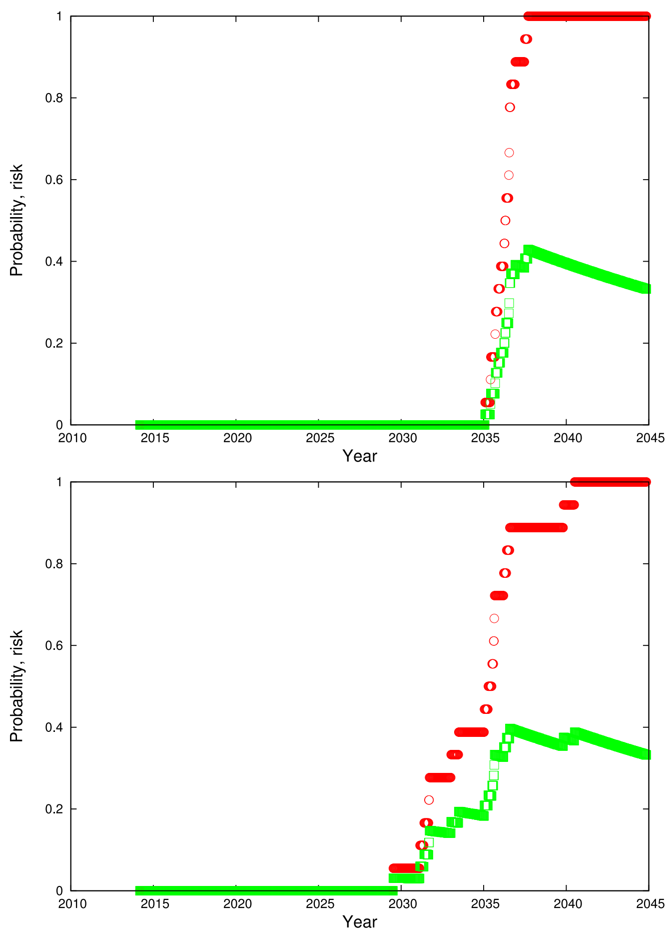


Fig. 2. Local extinction probability (circles) and local extinction risk (squares) under the status quo strategy. Top: KNP. Bottom: ranches.

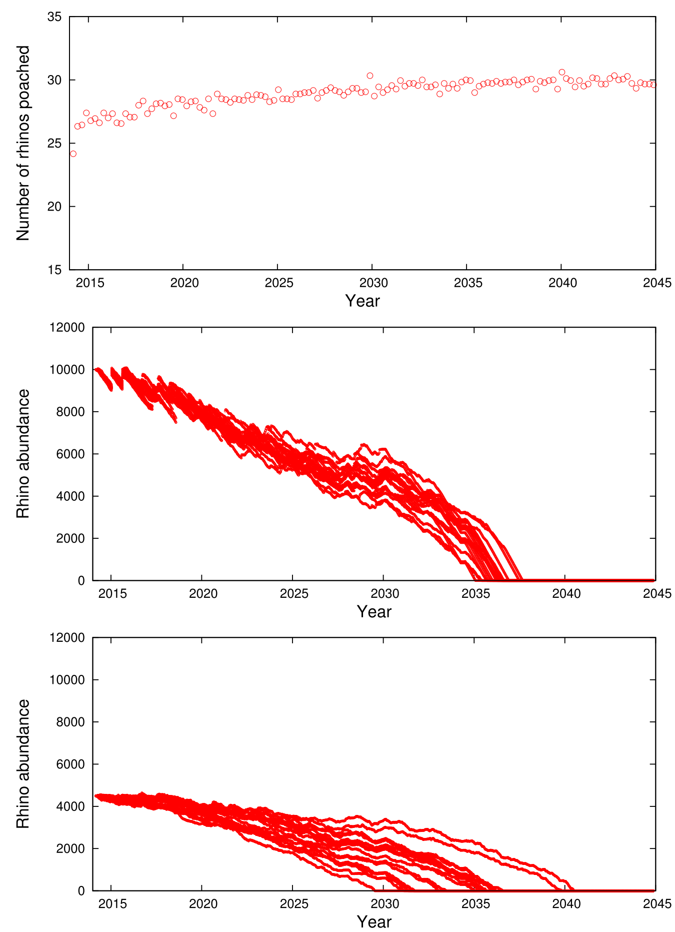


Fig. 3. Output of the economic-ecological model over the next 30 years assuming present management practices are unchanged (the status quo strategy). Top: total number of rhinos poached per week. Middle: predicted size of the KNP rhino population per week. Bottom: predicted total number of rhino on ranches.

a good fit of the IBM submodel to these estimates. Fig. 1 contains a prediction of rhino abundance over the period 2014 to 2033 under no poaching in either KNP or the ranches but with ranch-based recreational hunting. The 2014–2033 time period is the same over which the status quo strategy responses will be computed in Section IV-B. This plot indicates that with no poaching over this period, the South African rhino population is robust and increasing.

B. Simulating the Effects of the Present Rhino Management Strategy

The economic-ecological model may be used to predict rhino abundance and the behavior of the rhino horn market under different management strategies. One such strategy is that of continuing current management practices (current levels of anti-poaching enforcement, no changes to the current set of laws controlling trade in wildlife products and continued increases in demand for horn). Call this the status quo strategy. To assess the effects on future rhino abundance under this strategy, the model is run over a 30 year period: from January 1, 2014 through January 1, 2045. The 20 year period allows rhino population dynamics to react to management actions as this interval is approximately three rhino generations. Time series output from this run is plotted in Fig. 3. The present scenario predicts consistent decline of rhinos over the next 30 years in both KNP and ranches. And, because there is no competition, rhino horn purchases are executed at prices that are just below the consumers' reserve price (not shown). The illegal trader quickly reaches a steady state production level that is usually not far from the maximum number of rhinos that can be poached per week.

C. Extinction Risk

Under the status quo strategy, probabilities of local extinctions are zero until suddenly climbing around the year 2036 (Fig. 2) for both KNP and ranches rhino populations. Because of time discounting this delayed ramp-up of local extinction probabilities results in low, but increasing local extinction risks. Hence, with time discounting, sudden increases in local extinction probabilities that happen around 2036 results in extinction risks that are not alarming in the short to medium term. Because of this phenomenon, extinction risk with time discounting may not be the best information to present when attempting to motivate the public to support an increased focus on conservation. The trends in populations may serve as a better motivation in the short term.

V. Discussion

A. *Consequences of Model Output*

The onslaught on the world's wildlife resources [61] is a central theme in the international arena at present. All extant rhino species are threatened by poaching for their horn [64], [65]. Our modeling of southern white rhinos, the most numerous of the remaining extant species, suggest continuous declines if the present status quo remains for the next twenty years. We also predicted rapid increase in local extinction risks by 2036.

We acknowledge, however, that our predictions may carry some constraints. For instance, our white rhino IBM submodel derived parameters through comparison with observed trends in the southern white rhino population of KNP [54] as well as derived estimates for southern white rhinos living outside KNP in South Africa [64]. Our agent-based economic model uses proxies of poachers, middlemen, and consumers to tract anticipated effects of changes in demand for rhino horn in eastern countries [66]. Our retroactive model predictions, however, tract southern white rhino population estimates in KNP well from 1998 to 2012. We thus argue that these proxies serve as good substitutes of tracking economic dynamics to help predict scenario outcomes.

Under the present scenario, rhinos have an increased extinction risk by 2036. Who will safe them? The dichotomy of trade versus no-trade has distracted conservationists from considering sensible solutions. Integrated approaches [67] have been identified that manage the threat to rhinos in addition to enhancing rhino populations through ecological management [54]. The reality is that central to these strategic initiatives [67] is the involvement of transnational organized crime. The disruption of organized crime syndicates poses a key challenge to authorities, and should be of the highest priority.

Organized crime, however, exploits rural communities abutting protected areas [68]. These areas seldom offer economic opportunities other than those based on trading natural resources [69]. Communities living next to protected areas also carry the biggest opportunity costs inflicted by western conservation philosophy [70]. Some of those costs recently escalated when several resourced-based economic opportunities degraded such as those imposed by western and global north bans of hunting trophy imports [71]. These complex drivers thus place rural communities specifically at risk of being exploited by transnational organized crime focusing on rhino poaching. Authorities seeking to disrupt transnational organized crime also need to create economic opportunities for rural communities abutting protected areas.

One particular class of economic opportunity is that associated with wildlife products. It could include rhino-based initiatives. This is particularly attractive as it provides opportunities for authorities to develop economic options that do not fall in banking and betting on extinction strategies. Such initiatives can use dumping strategies [72] that predicts lower economic return, but persistence of rhinos and thus also many values associated with rhinos.

Our agent-based economic model allows incorporation of such scenarios that include complimentary initiatives as proposed in [67]. Predicting the outcomes of such inclusive scenarios can help inform decision makers and remove the inertia imposed by the banking and betting on extinction power struggle [72].

See supplementary materials for further implications suggested by the output of our model.

B. *Alternative Model*

We are aware of one other model that integrates rhino horn trade economics with a rhino population model [73]. These authors approximate the output from a matrix-based, age-class rhino population dynamics submodel with a generalized linear statistical submodel. This population dynamics submodel therefore, does not model age effects of individual rhinos nor density effects on birth and mortality rates as our IBM rhino population submodel does. Further, the highly variable availability of new vegetation and its effect on the rhino population is not modeled as is done within our IBM.

Although a submodel for the total number of poached rhinos per year is constructed, this submodel is not a maximum utility model of members of criminal syndicates running the illegal trade in rhino horn. Specifically, the potential profit by each member of the illegal supply chain from the poaching teams entering KNP and surrounding ranches, and the middlemen that fund the poaching raids, is not modeled. Our economic ABM, however, is easily extended to include utility-maximizing submodels of all members of wildlife trafficking criminal networks involved in the illegal trade in rhino horn. In [73], legal trade in: 1) live rhino hunting alone or 2) a possible future scenario of legal rhino hunting combined with legal rhino horn trade constitute the economic submodel realized as net present value formulas. There is no explicit submodel of Asian consumers other than an Asian continent total wealth effect within the poaching submodel. There is no submodel of the decision making of illegal horn traders nor of how Asian consumers would decide between legal and illegal rhino horn purchases. Therefore, this model has limited ability to assess what effect the legalization of rhino horn trade might have on the illegal trade in rhino horn. Our model, however, is constructed so that the effects that competition between legal and illegal traders has across the entire supply chain, from poaching event to a rhino horn purchase event in Asia can be factored-in when assessing what impact trade-legalization proposals might have on the rhino population.

C. *Big Data Techniques to Support the Estimation and Interpretation of Economic-Ecological Simulator*

1) Statistical Estimation on Cluster Computers: A biodiversity enterprise should not use risk predictions from an unreliable model to make significant business decisions. Statistically estimating the parameters of such a model is one step toward establishing its validity.

A realistic ABM of the illegal off-take supply chain involves at least a million Vietnamese and Chinese consumers [50]—and potentially more than that under different scenarios of legal trade in body parts of endangered animals. The IBM of the endangered animal metapopulation will typically contain about 15 000 individuals, e.g., rhinos, tigers, or elephants. Although under development (see [13]), the current version of our economic-ecological simulator does not contain actors such as the anti-poaching enforcement agencies nor an ABM of the population of potential and actual poachers. Once these other ABMs are incorporated, the economic-ecological simulator will be compute-bound if run on a single node and hence will need to be run on several nodes, i.e., a cluster computer. Specifically, each agent/individual-based submodel will be run on its own multiprocessor compute node and messages will be passed between nodes to achieve coupling of the models.

We briefly summarize our cluster computing version of the classic Hooke and Jeeves coordinate (dimension) search algorithm. For further details, see [13, Appendix B]. This algorithm, called multiple dimensions ahead search (MDAS) simultaneously searches the next M variables for a minimum as follows. Let K be the number of independent variables. For $M = 3$, exhaustively evaluate all possible visited locations for the next three dimensions in the inner "for" loop of the classic Hooke and Jeeves algorithm (see [13, Appendix B]). This requires $2 + (3 * 2) + (3 * 3 * 2) = 3^3 - 1 = 26$ parallel evaluations of the objective function. If an improvement is found at a particular set of dimensions, search these same three dimensions again to see if a further improvement can be had. Continue this way until these three dimensions do not yield an improvement. When this happens, move to the next three dimensions.

When there are at least 26 child processors available, this algorithm results in a six times speed-up over the worst-case of classic (sequential) Hooke and Jeeves search when K is a multiple of three. Note that the sequential version of the inner "for" loop will perform up to $2K$ function evaluations.

After the child processors return their function evaluation values, the master processor checks these values for a new minimum. If found, the master processor stores this new best solution. Therefore, the master processor performs this check every W seconds where W is the wall-clock time needed to compute the objective function on a single processor. This characteristic of the algorithm is important because it makes the algorithm robust to the loss of any part of the distributed computing system.

In general, to produce a $2M$ speed up over worst-case sequential Hooke and Jeeves, MDAS needs to be run on a cluster computer having $3^M - 1$ processors.

One run of our small economic-ecological simulator requires 3.2 min on a 3GHz personal computer. The parallel version of Hooke and Jeeves search provides at least a 20-fold speedup over the single processor version when 59 048 cluster computers are available to simultaneously receive 59 048 different trial parameter vectors from the master processor. It is well-known that the number of function evaluations needed to find a global minimum grows exponentially with the dimensionality of the search space (see [74]). Typically, functions with more than ten parameters are very expensive to optimize with standard algorithms (see [75]).

As delineated in [13, Chs. 6–7], our submodels of criminal network middlemen, and anti-poaching units will be realized as Bayesian networks. The number of parameters in such probabilistic networks is exponential in the number of network nodes. Hence, a fully developed economic-ecological model that includes submodels of poachers, middlemen, all consumers, and anti-poaching agencies will contain at least 100 parameters. One way to statistically estimate the parameters of such a model is to run the model under each trial parameter vector on a dedicated cluster computer. Then, to achieve at least a 20-fold increase in the runtime of the optimization algorithm, a cluster of 59 048 cluster computers is needed. To produce statistically estimated parameter values, the MDAS algorithm would minimize the negative of the simulated likelihood objective function.

But the most expedient way to reduce the computational expense of fitting an economic-ecological model to data is to reduce the dimensionality of the model itself. Because many of our submodels will be Bayesian networks, their dimensionality can be reduced using the family of tree-based local distributions developed in [76]. We see the conversion of our Bayesian network conditional probability tables to this family of local distributions as an immediate way to significantly reduce the dimensionality of our economic-ecological model.

The vertebrate immune system-inspired constrained optimization algorithm of [77] can be readily implemented on a cluster of cluster computers and addresses the problem of constraint violations in high dimensions. The algorithm evolves two populations of candidate solutions: one whose members are feasible solutions, and the other whose members are infeasible solutions. Because this algorithm performs a global search for feasible subregions in addition to a local function maximization search of the current feasible meta-region, it has the potential of requiring fewer cluster computers (one for each member of these two populations of candidate solutions) to achieve convergence than the MDAS algorithm, above as the latter does not explicitly search the infeasible meta-region for feasible subregions.

A swarm optimization algorithm based on pairwise competitions between particles is developed in [78]. This algorithm can be implemented on a cluster of cluster computers that share their high speed memory. Importantly, these authors prove convergence of their algorithm in the unconstrained case and show through experiment that it is resistant to premature convergence in high dimensions. To the extent that these desirable characteristics carry over to the constrained case, this swarm optimization algorithm may reduce the computational expense of our statistical estimation problem.

2) Observation Sets for Statistical Estimation Will be Massive: What is the nature of an ideal set of observations with which to compute these statistical parameter estimates? For the economic submodel, consumer purchase behavior is needed in the form of actual transactions with rhino horn retailers in Asia. Such observations would consist of the transaction's time and location along with the price paid and amount purchased. Social media could be one way to gather such data. Given the large number of consumers, this dataset alone would qualify as Big Data. Observations are also needed on the amount an individual poacher is paid for one rhino horn in addition to the amount paid by each middleman for rhino horn up through the wildlife trafficking criminal network's supply chain. In Section IV-A, we used SANParks rhino survey data to obtain a lumped observation of rhino abundance per year over several years. To be able to estimate parameters controlling rhino spatial dispersion and the probability of a successful poaching raid, however, an ongoing per-week spatio-temporal dataset on the whereabouts of each of the 15 000 rhino in KNP and ranches is needed. Again, this dataset alone would qualify as Big Data. Finally, spatio-temporal observations on poacher spoor (tracks) and poacher arrests/firefights is needed to estimate parameters defining the chance that a poaching raid is successful, results in an arrest, or results in a firefight.

3) Big Data Techniques for Interpreting Model Output: Procedures given in [79] support the discovery of reoccurring time series segments, motifs, and anomalies in multivariate time series datasets. A run of an economic-ecological simulator produces a large multivariate time series dataset if the analyst requests at every time point, output for every consumer in the consumer-trader ABM and every animal in the animal abundance IBM. Visualization of correlations and time-varying patterns between variables in such a dataset can be performed with a visualization system tied to a textual pattern matching query language as described in [80]. Lagged relationships between these variables (suggesting causality) can be discovered by an algorithm given in [81].

VI. Conclusion

We have shown how a biodiversity enterprise can manage their risks by predicting species extinction risks into the future under different scenarios of extinction mitigation strategies and projects. We have shown that the use of an ABM/IBM of the economic-ecological process within which a marketed species is embedded is an attractive approach to computing such risks. For a biodiversity enterprise, risks of species extinction events drive all of the firm's financial risks. Our model is realized as an agent-based economic submodel interacting with an individual-based ecological submodel.

As the rhino horn trafficking example shows, for model output to be reliable enough to inform decision makers in a biodiversity enterprise, a complex mix of economic and ecological processes needs to be accounted for. This is typically referred to as construct validity [13, Ch. 1]. A model enjoying some level of construct validity can then undergo a final test of its relevance to decision making, that of its ability to reproduce real-world observations, typically referred to as predictive validity [13, Ch. 1]. We have shown by example how the ecological submodel can be validated by comparing its output to data-based estimates of wildlife abundance. Predictive validity ideally takes into account parameter estimate uncertainty which in-turn, is typically found from a statistical estimate of all parameters in the model. This task is computationally expensive. We have outlined what sets of observations will be needed to do this, presented a Big Data algorithm to execute such a computation on a cluster of cluster computers, and have delineated how recent advances in visualization techniques can aid in interpreting the massive amounts of output such models generate.

An additional requirement of such modeling is required when applied to biodiversity management. Namely, to be effective, projects aimed at stemming an extinction event need to be implemented before extinction risks become large. Hence, extinction risk predictions need to be made available to decision makers many years prior to the potential extinction event. The model described in this paper provides one way to compute these forecasts.

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