The prevalence of documentation discrepancies in CITES (Convention on the International Trade in Endangered Species of Wild Fauna and Flora) trade data for Appendix I and II species exported out of Africa between the years 2003 and 2012.

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Abstract

The international trade in wildlife products is an extremely profitable industry, and is linked to many environmental, social, economic and political problems. The Convention on the International Trade of Endangered Species of Wild Fauna and Flora (CITES) is a non-self-executing multilateral treaty providing a framework for the international trade in wild animals and plants. Unfortunately, CITES wildlife trade data is not always accurate. Export and import trade records between nations rarely align and frequently contain data discrepancies**.**

This study analyzed CITES wildlife trade records for Appendix I and II species exported out of Africa between the years 2003 to 2012 to determine the frequency and types of discrepancies, and to identify nations and species particularly prone to record discrepancies. This study also attempted to profile countries with high and low documentation discrepancy rates based on annual precipitation, proportion of land covered by forest, length of coastline, GEF Benefits Index for Biodiversity, proportion of country designated as protected area, proportion of roads that are paved, number of international airplane departures, national population size, life expectancy, Gini Index, Gross Domestic Product, Mo Ibrahim Index of African Governance and unemployment rate.

During the ten-year study period 90% of trade records contained discrepancies. Overall, between the years 2003 and 2012 the discrepancy-rate increased significantly by 5.6%. Sixteen types of discrepancies were identified: quantity, Appendix, origin, purpose, source, term, unit, year, year and Appendix, year and origin, year and purpose, year and source, year and term, year and unit, missing an import quantity, and none. Records missing an import quantity were the most frequent type of discrepancy, occurring in 63% of all trade records.

All 50 African nations included in this study were involved in data discrepancies. The national average discrepancy-rate was 89.1% and the median was 91.2%. A total of 2337 species were traded during the ten-year period. These species had discrepancy-rates ranging from 0% to 100%, but the mean was 87.0%. There was a statistically significant positive correlation between national discrepancy-free rates and Global Environment Facility’s Index for Biodiversity scores, the number of international airplane departures, population sizes, and Gross Domestic Products. There was a statistically significant negative correlation between national discrepancy-free rates and Gini Index

scores. However, the overall high discrepancy rate (mean=89.1%) made it difficult to profile high and low discrepancy-rate countries.

Introduction

The international trade in wildlife products is an extremely profitable and rapidly growing industry. Though it is difficult to precisely measure the scale of the global wildlife trade (Oldfield 2014), estimates indicate hundreds of millions of animals, plants and their derivatives are harvested and shipped each year (Karesh *et al.* 2005, TRAFFIC 2008) to meet consumer demands (TRAFFIC 2015) of a growing human population (United Nations DESA 2014). Between the years 2005 and 2009, an annual average of 317,000 live birds, two million live reptiles and nearly 20,000 hunting trophies were legally shipped internationally (TRAFFIC 2008). This industry is so extensive that the exploitation and subsequent trade of wild species is considered one of the primary drivers of species population declines (Wilcove *et al.* 1998, Scanlon 2012), reduced ecosystem resilience (Bradley *et al.* 2012) and the introduction of alien species (Derraik and Phillips 2010).

The legal wildlife trade is worth an estimated USD $323 billion annually (Walley 2013). The clandestine nature of the illegal trade makes it difficult to measure and quantify; however, estimates range from USD $45 billion to $120 billion each year (Wyler and Sheikh 2013). In 2012 it was considered the fourth largest global illegal trade after narcotics, human beings and counterfeit products (WWF and Dalberg 2012).

Although the market is dominated by timber and fisheries products (WWF and Dalberg 2012, Wyler and Sheikh 2013), a demand also exists for medicinal goods, exotic pets and plants, as well as decorative and fashion items (TRAFFIC 2008). Consumers are willing to pay considerable amounts of money for many of these products. For example, a legal lion trophy hunt can cost USD $140,000 (Lindsey *et al.* 2012). On the black market in Thailand the wholesale value of raw elephant ivory can range from USD $300 to $1,000 per kilogram, depending on consumer demand and the quality and size of the ivory (Stiles 2009). In Vietnam, the street value of rhino horn can reach up to USD $65,000 per kilogram (UNOCD 2012). In general, the trading value for wildlife products increases as products progress through the trade continuum (Moreto and Lemieux 2014).

This has driven some wildlife products to become, kilogram-for-kilogram, more valuable than gold, diamonds and cocaine (Biggs *et al.* 2013).

In addition to threatening wild populations, the wildlife trade has been linked to a number of social, economic and political problems. For instance, the poaching of marine resources in South Africa has led to violent conflict between resource users as well as mistrust and corruption of authorities (Hauck and Sweijd 1999). Furthermore, the illegal harvesting of natural resources undermines policies and efforts that promote sustainable extraction, compromising the livelihoods of locals who depend upon natural resources for income and poverty alleviation (Duffy and St John 2013). Evidence also indicates that Al Shabab has illegally harvested and traded charcoal to fund its' actives (United Nations Security Council 2013).

With global demand for legal and illegal wildlife products increasing, a number of multilateral and regional agreements and institutions have been established to mitigate the devastating impacts of unsustainable wildlife exploitation. One such agreement, the Convention on the International Trade in Endangered Species of Wild Fauna and Flora (CITES), came into effect in 1975 and now has 180 members (referred to as Parties) (CITES 2014). CITES provides a legal framework for regulating the international trade in wild animals and plants. It is a non-self-executing multilateral treaty, meaning that although CITES is legally binding to all Parties, the Convention does not replace national laws. Each party must adopt its own domestic legislation to ensure that CITES is implemented at the national level (Saunders and Reeve 2014). Failing to do so may result in United Nations sanctions (Klemm 1993).

CITES regulated species are categorized into one of three Appendices (III, II and I) depending upon the level of protection required. Appendix III species are nationally protected in at least one member country which has sought the assistance of CITES to control the global trade of that species. Appendix II species are not threatened with extinction, but their trade is regulated to avoid exploitation that may threaten their survival in the wild. CITES minimum requirements state that Appendix III and Appendix II species may be traded internationally if the specimen is legally obtained and if all CITES export permits are in order. However, many nations have stricter domestic standards and require export *and* import permits for Appendix III and Appendix II species (Saunders and Reeve 2014). In accordance with CITES, Appendix I species are threatened with extinction and trade is only permitted in exceptional circumstances (such as scientific research and conservation efforts) with valid CITES export *and* import permits (CITES 2014).

To monitor the trade in CITES regulated species, Parties are required to submit annual reports summarizing import and export records. For each specimen traded, all of the following must be reported: taxonomy, CITES Appendix (III, II, I), year of shipment, exporting and importing nations, exported and imported quantities, as well as the country of origin of the specimen. Additionally, information on the purpose of the transaction (e.g. scientific, education, medical, etc.), the source of the specimen (e.g. wild, captivity, confiscated/seized, etc.), a description of the specimen traded (referred to as specimen "term," e.g. skins, tusks, wallet, etc.), and the unit of measurement associated with the quantity (e.g. grams, pairs, cans, etc.) must also be documented (CITES 2013).

Despite explicitly outlined reporting guidelines, many nations fail to adhere to these standards. Countries produce incomplete, inaccurate and inadequate reports, or they fail to submit reports timeously. CITES notes that common problems include reporting the number of export permits issued as the number of specimens physically traded (regardless of whether or not these values are equivalent), incorrectly documenting information about the source or purpose of the specimen, and using non-standard units to describe shipment quantities (CITES 2013).

The shortcomings of CITES data are concerning because CITES annual reports are one of the few means of monitoring the international trade of at-risk species (UNEP-WCMC 2004). In addition, enforcement personnel and conservationists are reluctant to make definitive conclusions about wildlife trade trends by analyzing CITES data. This study aims to address the limitations of CITES data by determining:

1. The prevalence of discrepancies in the data;
2. The main types of discrepancies that can be identified;
3. If patterns in export record quantity, discrepancy quantity and discrepancy-rate can be identified over time and between different countries;
4. If discrepancy-rates correlate with country-specific factors;
5. If certain species are more prone to export record discrepancies than others.

By identifying and understanding patterns in wildlife trade data discrepancies, this research will provide insight to CITES about how to improve its data collection methods. Specifically, it will reveal variables that are particularly prone to discrepancies and it will suggest ways to reduce them. This study will also provide border control agencies with information they need to increase monitoring efficiency. The findings in this study can help agents focus inspection efforts on shipments that are most likely to be incorrectly documented. This is particularly important because the high volume of wildlife products in trade makes it impossible for inspectors to examine every package crossing international borders.

Methods

1.1 Datasets

Fourteen datasets were used in this study. All datasets were downloaded in August of 2014. CITES trade data was used to explore trends in trade record discrepancies. The remaining 13 datasets were sourced from the World Bank, the Central Intelligence Agency and the Mo Ibrahim Foundation. Each of the thirteen datasets measured a different "country-specific factor," such as national population size, national life expectancy and national Gross Domestic Product. These datasets were analyzed to determine if trends in CITES trade record discrepancies correlated with any of the thirteen country-specific factors. This was done to gauge if any of the country-specific factors could serve as predictors as to whether or not a wildlife shipment record would contain documentation discrepancies.

1.1.1 CITES trade data

Understanding the complexity of CITES trade data is essential for addressing the objectives of this study. Upon receiving annual reports from all parties subject to the CITES agreement, the United Nations Environment Program — World Conservation Monitoring Center (UENP-WCMC) compiles the information into the CITES database. The database does not show individual specimens or shipments traded, but instead provides summed values. That is, all quantities traded are added together when their reported details are identical (CITES 2013).

Unfortunately, export and import trade records for a single shipment are rarely identical. As a result, many shipments contain *two incomplete* trade records in the CITES database (one produced by the exporting nation and one produced by the importing nation), instead of a single complete record. These incomplete records lack either a reported export quantity or a reported import quantity. A trade record missing an import quantity was submitted by the exporting nation, but the importing nation failed to submit an identical trade record (Table 1). A trade record missing an export quantity was submitted by the importing nation, but the exporting nation failed to submit an identical trade record.

Table 1: Examples of incomplete trade records. Row *A* shows a trade record missing an import quantity. Row *B* shows a trade record missing an export quantity The purpose code "S" indicates that the specimens were traded for scientific purposes. The source code "F" indicates that the specimens were born in captivity.

	Year	App	Species	Importer	Exporter	Origin	Import quant	Export quant	Term	Unit	Purpose	Source
A	2007	1	Loxodonta Africana	Germany	Algeria	Kenya	-	1	Ivory carving	Sets	S	F
B	2010	2	Strix varia	United States	Ghana	United States	2	-	Feather	Sets	S	F

The "Guide to using the CITES Trade Database" (CITES 2013) lists several reasons why export and import records fail to match. This occurs primarily when exporters and importers report different purposes (e.g. breeding, education, trophies, etc.), measurement units (e.g. grams, pairs, cans, etc.), terms (e.g. skins, tusks, wallet, etc.), years in which the trade occurred, or quantities of the specimens traded (Table 2). I propose ten additional reasons why export and import records fail to match. The first three are that exporting and importing nations report different CITES Appendices (I, II and III), countries of origin, or specimen sources (e.g. captivity, wild, seized specimens, etc.) (CITES 2013). Another reason is that a trade record is missing an import quantity. (Trade records missing an export quantity were not considered a discrepancy in this study. The following section explains the reasoning behind this.)

The remaining six reasons why export and import records may not match take into account the situation where shipments cross international boarders in subsequent years (in other words, a shipment exported from Country A at the end of a calendar year is only imported into Country B at

Table 2: A description of the sixteen discrepancy types tested in this study.

Type of record downloaded from CITES	Discrepancy	Description
Complete	None	No discrepancies were identified in the trade record.
	Quantity	Exporting and importing nations reported different quantities, but all other reported variable were identical.
Incomplete	Appendix Year Origin Purpose Source Term Unit Import quantity missing	Two incomplete trade records were downloaded from CITES. One was missing an export quantity and one was missing an import quantity. Their reported details were identical except for one variable. This variable is referred to as the discrepancy type.
Incomplete	Year & appendix Year & origin Year & purpose Year & source Year & term Year & unit	Two incomplete trade records were downloaded from CITES. One was missing an export quantity and one was missing an import quantity. Their reported details were identical except for two variables: shipment year plus a second variable. These variables are referred to as the discrepancy type.

the beginning of the following calendar year) may actually have two discrepancies – year *plus* another variable preventing export and import records from matching. Therefore, I developed the following additional discrepancy types: year and purpose, year and unit, year and term, year and source, year and Appendix, as well as year and origin. The assumption was made that any combination of "year" discrepancy could only exist if the import year occurred one year after the export year. This brings the total number of discrepancy types up to sixteen.

While the discrepancy types "taxonomic family" and "shipment year and quantity" likely did exist, I chose to exclude them from the study for several reasons. "Taxonomic family" discrepancies were omitted because I explored trends at the species level rather than at the family level. Also, during an initial examination of the data, no spelling mistakes in the family variable were identified, so it was presumed that they were not a major source of discrepancy. “Shipment year and quantity” discrepancies were omitted because I made the assumption that to identify a discrepancy the incomplete export record and the incomplete import record must refer to the same species, exporting nation, importing nation, *and* shipment quantity. Accordingly, the only way a quantity discrepancy could be identified was if a complete trade record downloaded from the database listed different values for exported and imported quantities.

Table 3 provides an example of a trade record with no discrepancies. In row *A* all variables (shipment year, Appendix, species, importing nation, exporting nation, origin, imported quantity, exported quantity, term, unit, purpose and source) are filled in and the reported import and export quantities match. This means the importing and exporting nations submitted identical trade records for *Panthera pardus* (Leopard) teeth in 2005. Table 3 also provides examples of trade records with discrepancies. Row *B* is an example of a quantity discrepancy. The reported import and export quantities do *not* match, indicating that somewhere in the reporting process a shipment quantity was incorrectly documented. Rows *C* and *D* illustrate a year discrepancy. The importer reported the shipment one year after the exporter, resulting in separate line items in the database. Rows *E* and *F* show a source discrepancy, rows *G* and *H* show a purpose discrepancy, and rows *I* and *J* show an Appendix discrepancy.

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Table 3: Fabricated CITES trade data illustrates correct and incorrect annual reporting. The purpose codes indicate the indented purpose of the specimens (S=scientific, T=commercial, P=personal, M=medical). The source codes indicate the reported source of the specimens (W=taken from the wild, O=pre-CITES specimen, F=born in captivity, I=confiscated or seized).

	Year	App	Species	Importer	Exporter	Origin	Import quant	Export quant	Term	Unit	Purpose	Source
A	2005	1	Panthera pardus	France	Djibouti	Unknown	65	65	Teeth	G	S	W
B	2003	2	Moschusosc hiferus	Hong Kong	Namibia	Russia	1.8	2	Musk	Kg	T	W
C	2007	1	Loxodonta Africana	Germany	Algeria	Unknown	-	1	Ivory carving	Sets	P	O
D	2008	1	Loxodonta Africana	Germany	Algeria	Unknown	1	-	Ivory carving	Sets	P	O
E	2003	2	Macaca fascicularis	France	Gabon	Mauritius	-	380	Live	Mg	M	W
F	2003	2	Macaca fascicularis	France	Gabon	Mauritius	380	-	Live	Mg	M	F
G	2010	2	Strix varia	United States	Ghana	United States	-	2	Feather	Sets	P	I
H	2010	2	Strix varia	United States	Ghana	United States	2	-	Feather	Sets	S	I
I	2008	2	Loxodonta Africana	United Kingdom	South Africa	Zambia	-	30	Skin pieces	Ft2	T	W
J	2008	1	Loxodonta Africana	United Kingdom	South Africa	Zambia	30	-	Skin pieces	Ft2	T	W

1.1.2 Country-specific factors

In addition to exploring trends in data discrepancies, this study determined if discrepancies correlate with thirteen country-specific factors (Table 4). Care was taken to incorporate statistics and indices. This was done because many indices are crafted using the same statistic(s). For example, multiple indices use Gross Domestic Product (GDP) as a variable factoring into the index. By limiting the number of indices used and by incorporating statistics, data redundancies were minimized and more comprehensive and straightforward results were developed.

Each of the thirteen country-specific factors was selected because of its ability to disclose information about a nations: available natural resources, commitment to conservation, accessibility to natural resources, population, life expectancy, wealth inequality, economic performance, and governance efficacy. The aim was to profile high and low discrepancy rate nations using the characteristics listed above. Available natural resources was represented by annual precipitation, proportion of land covered by forest, length of coastline, and GEF Benefits Index for Biodiversity. The proportion of territory designated as protected area measured commitment to conservation. Accessibility to natural resources was represented by proportion of paved roads and the number of international airplane departures. Gini Index score represented wealth inequality. Unemployment rate and Gross Domestic Product measured economic performance. The Mo Ibrahim Index of African Governance measured governance efficacy.

Table 4: The country-specific factors tested for correlations with trade record discrepancies.

Source	Country-specific factor	Description
World Bank Development Indicators	Annual precipitation	The long-term average depth (over space and time) of annual precipitation. Precipitation is measured in millimeters and includes liquid and solid water that falls from clouds.
	Global Environment Facility's (GEF) Benefits Index for Biodiversity score	An index of relative biodiversity potential for each country based on the species represented, their threat status, and the diversity of habitat types. Values range from 0=no biodiversity potential to 100=maximum biodiversity potential.
	Proportion of land covered by forest	Land under natural or planted tree stands at least 5 meters tall, excluding stands in agricultural production systems and trees in urban parks and gardens.
	Proportion of country designated as protected area (terrestrial and marine)	Totally or partially protected areas of at least 1,000 hectares that are designated by national authorities as scientific reserves with limited public access (i.e. national parks, natural monuments, nature reserves, wildlife sanctuaries, protected landscapes, and areas managed mainly for sustainable use). Also includes marine protected areas of intertidal or sub-tidal terrain and overlying water that have been reserved by law or other effective means to protect part or the entire enclosed environment. Sites protected under local or provincial law are excluded.
	Proportion of roads that are paved	Roads surfaced with crushed stone and hydrocarbon binder or bituminized agents, with concrete, or with cobblestones, as a percentage of all the country's roads, measured in length in kilometers.
	Number of international airplane departures	Domestic takeoffs and takeoffs abroad of air carriers registered in the country.
	National population size	Includes all residents regardless of legal status or citizenship – except refugees not permanently settled in the country of asylum. The values are midyear estimates.
	Life expectancy	The number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth was to stay the same throughout its life.
	Gini Index score	Measures the extent to which the distribution of income or consumption expenditure among individuals or households within an economy deviates from a perfectly equal destitution. A Gini index of 0 represents perfect equality, while a Gini index of 100 implies perfect inequality.
	Unemployment rate	The share of the labor force that is without work but available for and seeking employment. Definitions of labor force and unemployment differ by country.
	Gross Domestic Product (GDP)	GDP at purchaser's price is the sum of gross value added by all resident producers in the economy plus product taxes minus subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current US dollars during August 2015.
Central Intelligence Agency's World Fact Book	Length of coastline	The total length (in kilometers) of the boundary between the land (including islands) and the sea.
Mo Ibrahim Foundation	Mo Ibrahim Index of African Governance	Provides an assessment of the quality of governance in African countries in regards to the government's provision of political, social and economic goods that a citizen has the right to expect from his or her state. The index assesses progress under the categories of *Safety & Rule of Law, Participation & Human Rights, Sustainable Economic Opportunity and Human Development*. These categories are populated with data from 94 indicators from 32 sources.

1.2 Research approach

Carrying out this study involved four steps. I (1) identified incomplete trade records, (2) tested for discrepancies, (3) removed duplicate trade records, and (4) analyzed data. Each of these steps involved intricate processes that are described in detail in the following sections (Table 5).

1.2.1 Identifying incomplete trade records

International wildlife trade data was downloaded from the CITES database for all Appendix I and II listed species exported out of Africa between the years 2003 and 2012. The data was downloaded in August 2014. Export data was available for 50 African nations, producing 90204 shipment records over the ten-year period. The data was checked for spelling mistakes, but none were found. The dataset was immediately adapted by removing the "family" variable from each trade record. This was done because I chose to explore discrepancy trends at the species level rather than at the family level. Each trade record was placed into one of four categories (and documented on a separate excel sheet):

(1) Complete records – no discrepancies

(2) Complete records – quantity discrepancy

(3) Incomplete records – missing an import quantity

(4) Incomplete records – missing an export quantity

Trade records placed into category (1) "Complete records – no discrepancies" were entries that resembled row *A* in Table 3. All of the columns were filled in and the export and import quantities matched. Records placed into category (2) "Complete records – quantity discrepancy" were entries that resembled row *B*. All of the columns were filled in but the export and import quantities did *not* match. Records placed into category (3) "Incomplete records – missing an import quantity" were entries that resembled rows *C, E, G* and *I*. These records contained all required information *except* import quantity. Records placed into category (4) "Incomplete records – missing an export quantity" were entries that resembled rows *D, F, H* and *J*. These records contained all required information *except* export quantity.

Table 5: A summary of the procedures followed to conduct this study.

Identified incomplete trade records	1. Downloaded data from CITES database 2. Checked data for spelling mistakes 3. Removed family variable from dataset 4. Sorted trade records into one of four categories: a. Complete records – no discrepancies b. Complete records – quantity discrepancy c. Incomplete records – import quantity missing d. Incomplete records – export quantity missing
Tested for discrepancies	1. None 2. Appendix 3. Year 4. Origin 5. Source 6. Purpose 7. Term 8. Unit 9. Year & Appendix 10. Year & origin 11. Year & source 12. Year & purpose 13. Year & term 14. Year & unit 15. Missing an import quantity
Removed duplicate trade records	1. Removed records missing an export quantity 2. Sorted records into FINAL categories: a. Complete records – no discrepancies b. Complete records – quantity discrepancy c. Incomplete records – missing an import quantity d. Merged records
Analyzed data	1. Explored temporal and spatial patterns in export record quantity, discrepancy quantity and discrepancy-rate 2. Explored correlations between national discrepancy-rates and country-specific factors 3. Explored data discrepancy patterns among species

1.2.2 Testing for discrepancies

One of the primary objectives of this study was to see if two incomplete trade records (one missing an export quantity and one missing an import quantity) could be paired together to form a complete trade record *and* to determine what type of discrepancy had prevented them from matching identically. To test for discrepancies I used the *Merge* function in R Studio Statistical Computing and Graphic Software (R Studio 2013). The *Merge* function allows two datasets to be paired together if they share at least one common column. In this study, the *Merge* function was used to pair datasets that had all columns in common. The *Merge* function allowed me to pair together two trade records from separate datasheets if both trade records reported the same details.

1.2.2.1 Appendix discrepancies

The first discrepancy tested was the CITES Appendix category. The aim was to identify incomplete trade records that were identical *except* for their reported Appendix. To do this, I took records missing an import quantity and altered all of the Appendices. If a record was listed as Appendix II, I changed it to Appendix I, and vice versa. (Appendix III species were not included in the dataset). I uploaded these altered records into R Studio. Next, without making alterations, I uploaded the trade records missing an export quantity into R Studio. I used R Studio's *Merge* function to see if any incomplete records matched identically (considering the modified Appendices). If a *Merged* pair was identified, the records were placed onto a new datasheet titled "*Merged* records."

1.2.2.2 Year discrepancies

When testing for year discrepancies, the aim was to identify occasions when a shipment was imported (and recorded) the year after it was exported (and recorded). To do this, I took trade records missing an export quantity (presumably records submitted by importing nations) and I subtracted the shipment year by one. I uploaded these modified records into R Studio. Next, without making any alterations, I uploaded the trade records missing an import quantity (presumably records submitted by the exporting nation). Again, I used the *Merge* function to see if any incomplete trade records matched identically when the import years were altered.

1.2.2.3 Origin discrepancies

When testing for origin discrepancies the aim was to find incomplete trade records that likely referred to the same shipment(s), but only one nation specified an origin in the annual reports. This involved two steps. First, I took the trade records missing export quantities (submitted by the importing nations) and searched for all entries that listed the origin as “unknown” or “various,” or that left the column blank. I uploaded these records into R Studio, and I removed the origin column. Then, without making alterations, I took the trade records missing an import quantity (submitted by the exporting nations), uploaded them to R Studio, and removed the origin column. I used the *Merge* function to determine if any incomplete records matched identically when the origin columns were removed. This process was repeated a second time, however, instead of identifying import records that failed to specify an origin, I searched for incomplete export records that failed to specify an origin.

1.2.2.4 Source, purpose, term and unit discrepancies

Next I tested for source discrepancies. To do this, I removed the source column from all trade records that did not specify an export or import quantity. I uploaded these records into R Studio and used the *Merge* function to asses whether any incomplete records matched identically once the source variable was omitted. I followed the same procedure to test for purpose, term and unit discrepancies.

1.2.2.5 Combination discrepancies

To test for the remaining six discrepancy types (year and Appendix, year and origin, year and source, year and purpose, year and term, as well as year and unit) I used the same procedures described above *but* prior to conducting each *Merge* I subtracted the import year by one (just as I did to test for shipment year discrepancies).

Throughout this analysis, if R Studio identified multiple match combinations (i.e. if a record missing an export quantity matched with two records missing an import quantity), the first pair that R Studio identified was the one included in the “*Merged* records” datasheet. I did this to remain consistent and to eliminate sources of bias. Fortunately this happened on less than 10 occasions.

1.2.3 Removing duplicate records

Despite my efforts to match incomplete export records with their corresponding incomplete import records, 63347 records remained unmatched. This is equivalent to 72.8% of all trade records in the dataset. Due to the large number of incomplete records, I assumed the dataset still contained duplicate records that were separated by a discrepancy type for which I did not test. To eliminate the possibility of double counting shipments, I removed 23043 trade records that failed to specify an export quantity. Consequently, my final dataset included records in the following four categories:

(1) Complete records – no discrepancies

(2) Complete records – quantity discrepancy

(3) Incomplete trade records – missing an import quantity

(4) *Merged* records

1.2.4 Data analysis

After testing for each type of discrepancy and after removing records that failed to specify an export quantity, I explored temporal and spatial patterns in the data. I used the Mann-Kendall test to identify trends through time for the number of export records produced, the number of export records with discrepancies and the discrepancy-rate. I used Pearson's Correlation Coefficient test to identify correlations between: (1) the number of export records produced annually and the number of export records that contained discrepancies, and between (2) the number of export records produced annually and the discrepancy-rate. I also used Pearson's Rank Correlation Coefficient test to identify correlations between the number of export records produced by each nation and the national discrepancy-rates.

Next, I used R Studio to identify correlations between national discrepancy-free rates and country-specific factors. To do this, for each exporting nation I counted the number of export records that contained no discrepancies during the period 2003 to 2012. I used this value to calculate a ten-year "discrepancy-free rate" for each nation. These values were not normally distributed, so I transformed the data by taking the logs of the ten-year discrepancy-free rates, which were normally distributed. Then, for every exporting nation I took each country-specific factor and calculated the ten-year average. For example, I took South Africa's population size for each of the ten years and I calculated the mean population. I used Spearman's Rank Correlation Coefficient to determine if any mean country-specific factors correlated with the logs of the ten-year discrepancy-free rates. Only five factors correlated. I used combinations of these five factors to develop linear models in R Studio to predict if a wildlife trade record would contain discrepancies. Lastly, I created graphs and tables in Microsoft Excel to investigate trends in species data. Specifically, I explored species traded in comparatively high volumes and species associated with comparatively high discrepancy-rates.

Results

1.3 How prevalent are discrepancies in the data?

The data downloaded from the CITES database included trade records from 50 exporting African nations and 198 importing nations around the world. The data represented 2750 species. Of the 90204 records originally downloaded from the CITES database only 6542 (7.3%) were free from discrepancies (Table 6). After using the R Studio *Merge* function to match 3190 records missing an export quantity with 3190 records missing an import quantity, the size of the dataset was reduced to 87014 entries. After removing an additional 23043 trade records that lacked an export quantity the dataset was reduced to 63969 entries. Only 6542 (10.2%) of these records were free from discrepancies.

Table 6: Frequency and rate of occurrence (%) of each category of trade record before and after R Studio *Merging*, and after removing records without an export quantity.

	Type of trade record		Frequency	Rate of occurrence (%)	Total
Before R Studio Merging (original data downloaded from CITES)	Complete	No discrepancies	6,542	7.25	90,204
	Complete	Quantity discrepancy	13,937	15.45	
	Incomplete	Missing an import quantity	43,492	48.22	
	Incomplete	Missing an export quantity	26,233	29.08	
After R Studio Merging	Complete	No discrepancies	6,542	7.52	87,014
	Complete	Quantity discrepancy	13,937	16.02	
	Complete	Merged pairs	3,190	3.67	
	Incomplete	Missing an import quantity	40,302	46.32	
	Incomplete	Missing an export quantity	23,043	26.48	
After removing records without an export quantity (final dataset)	Complete	No discrepancies	6,542	10.23	63,969
	Complete	Quantity discrepancy	13,937	21.79	
	Complete	Merged pairs	3,190	4.99	
	Incomplete	Missing an import quantity	40,300	63.00	

1.4 What are the main types of discrepancies that can be identified?

All discrepancy types investigated in this study were present in the data. “Missing an import quantity” was the most prevalent, occurring in 13937 (63.0%) export records (Table 7). Quantity discrepancies were the second most prevalent. Combined, the discrepancy types “missing an import quantity” and “quantity” accounted for nearly 85% of discrepancies.

Table 7: The frequency and rate of occurrence (%) of each type of discrepancy during the period 2003-2012.

Discrepancy type	Frequency	Rate of occurrence (%)
Quantity	13,937	21.79
Appendix	70	0.11
Origin	193	0.3
Purpose	703	1.10
Source	316	0.49
Term	790	1.23
Unit	69	0.11
Year	492	0.77
Year & Appendix	28	0.04
Year & origin	34	0.05
Year & purpose	177	0.28
Year & source	63	0.10
Year & term	251	0.39
Year & unit	3	0.00
Missing an import quantity	40,301	63.00
None	6,542	10.23
Total	63,969	100.00

1.5 Can patterns in export record quantity, discrepancy quantity and discrepancy-rate be identified over time?

In the year 2003, a total of 6360 export records were documented. In the year 2012, a total of 6759 export records were documented. While this is a slight increase, the trend over time was not statistically significant ($t = 0.422$, $p = 0.1074$). In the year 2003 there were 5529 export records with discrepancies. In the year 2012 there were 6252 export records with discrepancies. This is a statistically significant increase of 11.6% ($t = 0.511$, $p = 0.04$). The year 2003 had the lowest discrepancy-rate at 86.9% (Table 8), while the year 2012 had the highest discrepancy-rate at 92.5%. The 5.6% increase in discrepancy-rate was found to be statistically significant ($t = 4.68$, $p = 0.002$).

Table 8: The rates of CITES trade record discrepancies for Appendix I and II species exported out of Africa during the years 2003-2012.

Export year	Discrepancy-rate (%)
2003	86.93
2004	89.01
2005	88.57
2006	88.51
2007	87.81
2008	89.05
2009	90.59
2010	91.02
2011	92.43
2012	92.50
10-year average	89.77

Between the years 2003 and 2012, there was a statistically significant positive correlation between the number of export records produced annually and the number of trade records that contained discrepancies ($R^2 = 0.9831$, $p = 0.0001$) (Figure 1). There was also a statistically significant positive correlation between the number of export records produced annually and the discrepancy-rate ($R^2 = 0.6875$, $p = 0.0280$).

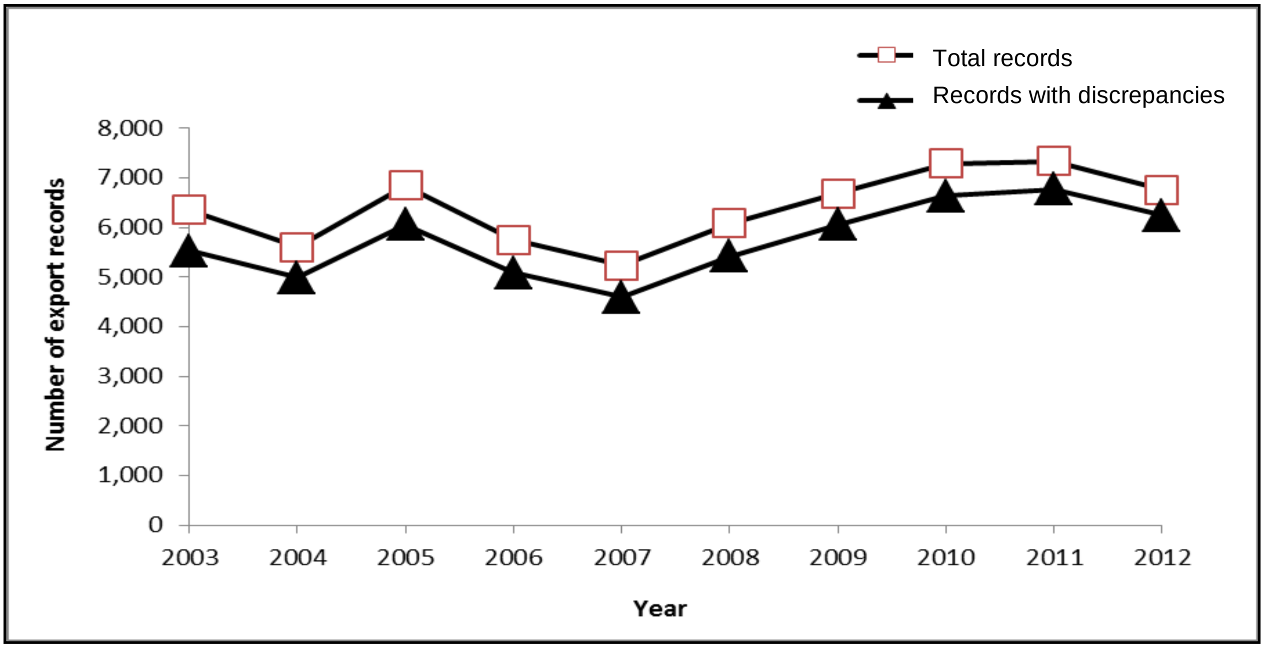


Figure 1: The change in the number of total export records and records with discrepancies in the CITES database for 50 African nations over the period 2003-2012.

1.6 Can patterns in export record quantity, discrepancy quantity and discrepancy-rate be identified between different countries?

The number of export records produced by each nation during the period 2003-2012 ranged from one to 31305. South Africa had the greatest number of records, accounting for nearly half of all export records in the dataset (Table 9). Including South Africa, only ten nations (Madagascar, Namibia, Zimbabwe, Tanzania, Ghana, Mozambique, Zambia, Mauritius, and Togo) had more than 1000 export records. Combined, these nations accounted for 88.4% of all export records and 88.5% of records with discrepancies. The mean number of trade records produced was 1279.4 and the median was 187.5. Excluding South Africa, the mean decreased by 47.9% to 666.6 and the median decreased by 4.5% to 179.0.

Every country produced trade records with discrepancies. The count of records with discrepancies ranged from one (Sao Tome and Principe) to 28461 (South Africa). The mean number of trade records with discrepancies was 1148.54 per nation and the median was 176.5. When excluding South Africa from the dataset, the mean decreased by 49.5% to 591.1 and the median decreased by 10.5% to 158.0.

Table 9: Summary of CITES export records for 50 African nations for the period 2003-2012.

Exporting nation	Total number of trade records	Trade records with discrepancies	Discrepancy-rate (%)
Algeria	35	26	74.29
Benin	515	479	93.01
Botswana	309	280	90.61
Burkina Faso	87	83	95.40
Burundi	32	21	65.63
Cameroon	735	661	89.93
Cape Verde	11	11	100.00
Central African Republic	223	221	99.10
Chad	64	64	100.00
Comoros	11	11	100.00
Dem. Rep. Congo	671	615	91.65
Egypt	179	158	88.27
Equatorial Guinea	24	23	95.83
Eritrea	4	4	100.00
Ethiopia	139	91	65.47
Gabon	197	186	94.42
Gambia	12	11	91.67
Ghana	1,791	1,529	85.37
Guinea	252	206	81.75
Guinea-Bissau	23	23	100.00
Ivory Coast	196	177	90.31
Kenya	559	505	90.34
Liberia	31	25	80.65
Libya	69	66	95.65
Madagascar	7,140	6,309	88.36
Malawi	105	76	72.38
Mali	482	437	90.66
Mauritius	1,068	914	85.58
Mayotte	118	38	32.20
Morocco	221	199	90.05
Mozambique	1,627	1,512	92.93
Namibia	4,221	3,758	89.03
Niger	167	147	88.02
Nigeria	13	12	92.31
Rep. Congo	91	84	92.31
Reunion	27	27	100.00
Rwanda	42	39	92.86
Sao Tome & Principe	1	1	100.00
Senegal	485	454	93.61
Seychelles	214	197	92.06
Sierra Leone	32	29	90.63
South Africa	31,305	28,461	90.92
Sudan	353	323	91.50
Swaziland	60	55	91.67
Tanzania	3,120	2,607	83.56
Togo	1,033	976	94.48
Tunisia	134	119	88.81
Uganda	477	417	87.42
Zambia	1,570	1,442	91.85
Zimbabwe	3,694	3,318	89.82
Total	**63,969**	**57,427**	**89.77**

Since every nation produced at least one export record with a discrepancy, no nation had a 0% discrepancy-rate. The lowest discrepancy-rate was 32.2% (Mayotte) and seven nations had a 100% discrepancy-rate (Cape Verde, Chad, Comoros, Eritrea, Guinea-Bissau, Reunion and Sao Tome and Principe). In fact Mayotte was the only nation with a discrepancy-rate below 60%. A majority of nations (64%) had discrepancy-rates greater than 90%. The mean discrepancy-rate was 89.05% and the median was 91.21%.

There was no significant relationship between the number of export records a nation produced and a nation's discrepancy-rate ($r = 0.0188$, $p = 0.90$) (Figure 2). It should be noted that Figure 2 excludes data for South Africa, which was determined to be an outlier due to its comparatively high volume of export records and discrepancies.

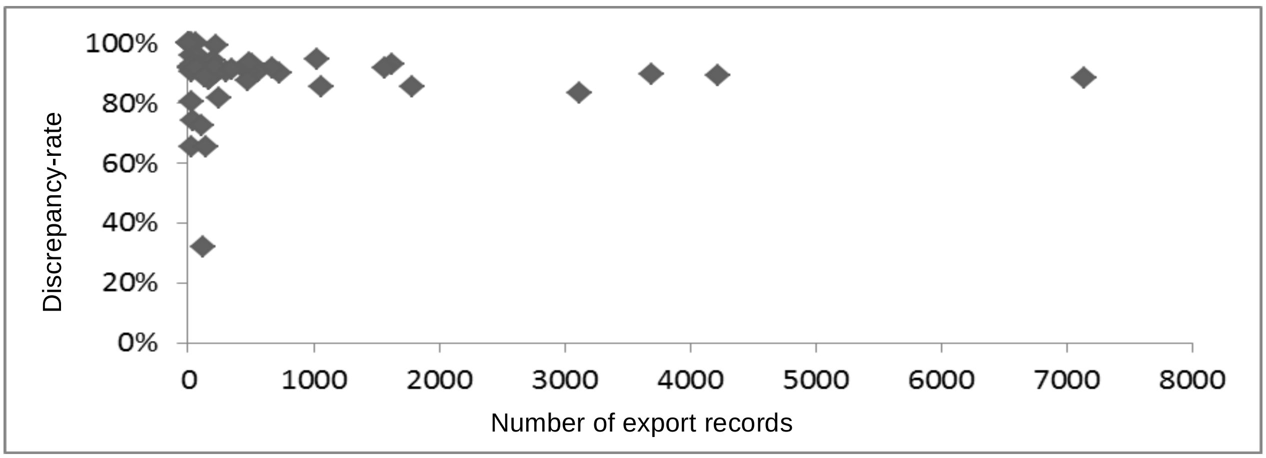


Figure 2: The relationship between a country's total number of export records during the period 2003-2012 (x-axis) and its discrepancy-rate for the same period (y-axis).

Although South Africa was responsible for fewer than 50% of all export records, South Africa was responsible for a disproportionately high number of Appendix, origin and purpose discrepancies. South Africa produced 67% of the Appendix discrepancies, 68% of the origin discrepancies, and 57% of the purpose discrepancies (Table 10). Similarly, Madagascar was responsible for just 11% of all export records but produced 67% of the unit discrepancies.

Table 10: Export summary for the ten African exporters with the most trade records between the years 2003-2012.

	Export Records	Records with discrepancies	Discrepancy-rate	Discrepancy type								
				Quantity	App.	Origin	Purpose	Source	Term	Unit	Year	Missing an import quantity
				(Frequency) (Percent of total %)								
South Africa	31,305 49	28,461 50	91 -	5,165 37	66 67	155 68	500 57	186 49	544 52	5 7	542 52	21,641 54
Madagascar	7,140 11	6,309 11	88 -	1,549 11	2 2	2 1	86 10	37 10	32 3	48 67	80 8	4,508 11
Namibia	4,221 7	3,758 7	89 -	1,022 7	6 6	6 3	77 9	41 11	143 14	3 4	103 10	2,411 6
Zimbabwe	3,694 6	3,318 6	90 -	915 7	9 9	5 2	76 9	6 2	103 10	6 8	66 6	2,176 5
Tanzania	3,120 5	2,607 5	84 -	1,361 10	- -	1 <1	27 3	13 3	51 5	- -	64 6	1,117 3
Ghana	1,791 3	1,529 3	85 -	745 5	- -	20 9	2 <1	11 3	1 <1	1 1	6 1	745 2
Mozambique	1,627 3	1,512 3	93 -	418 3	7 7	1 <1	4 <1	2 1	66 6	- -	36 3	995 2
Zambia	1,570 2	1,442 3	92 -	458 3	3 3	5 2	10 1	11 3	22 2	1 1	44 4	905 2
Mauritius	1,068 2	914 2	86 -	316 2	1 1	3 1	11 1	3 1	5 <1	3 4	7 1	570 1
Togo	1,033 2	976 2	94 -	405 3	- -	1 <1	2 <1	5 1	- -	- -	7 1	557 1
Full dataset	63,969 100	57,427 90	90 -	13,037 22	98 <1	227 <1	880 1	379 1	1,041 2	72 <1	1,048 2	40,301 63

1.7 Do discrepancy-rates correlate with country-specific factors?

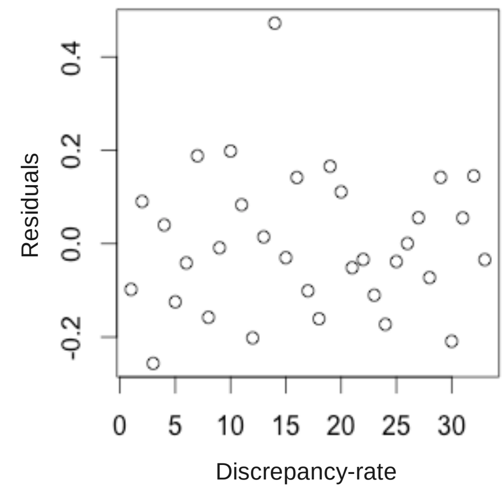
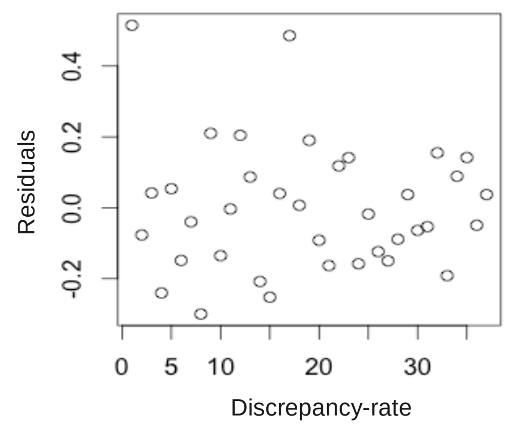
Out of the thirteen country-specific factors explored, only five had a statistically significant correlation with the logs of the discrepancy-free rates (Table 8). The five factors that did correlate were used to create linear models in R Studio (Table 11).

Table 11: The thirteen country-specific factors that were tested for correlations with the logs of the 10-year discrepancy-free rates.

Country-specific factor	Spearman's Rank Correlation Coefficient	P-value
Average annual precipitation	0.0026	0.9859
Global Environment Facility's Index for Biodiversity score	0.3178	0.0277
Proportion of land covered by forests	-0.2079	0.1562
Proportion of country designated as protected area (terrestrial and marine)	0.0166	0.9107
Proportion of roads that are paved	0.1642	0.3612
Length of coastline	0.0194	0.8957
Number of international airplane departures	0.3164	0.0467
Mo Ibrahim Index of African Governance	0.1829	0.2185
National population size	0.4767	0.0006
Life expectancy	0.0422	0.7758
Gini Index score	-0.4040	0.0080
Unemployment rate	-0.1745	0.4041
Gross Domestic Product (GDP)	0.3393	0.0204

In Model 1, three out of the four explanatory variables had statistically significant non-zero coefficients: population ($p = 0.069$), international airplane departures ($p = 0.013$), and GDP ($p = 0.015$) (Table 12). Although Gini Index score ($p = 0.350$) did not have a significant correlation in this model, its inclusion allowed for an adjusted R-squared value of 0.1884, which was the highest out of all models. In Model 2, all three explanatory variables had statistically significant non-zero coefficients. While this model did have a slightly lower adjusted R-squared value (0.1329) than the previous model (0.1884), it was the most parsimonious model.

Table 12: Two linear models that may effectively predict if a wildlife shipment record contains discrepancies.

	Explanatory variables	Coefficient Estimated	Coefficient Standard error	P-value	Residuals
Model 1	Population size	2.46E-09	1.30E-09	0.069	
	Gini Index score	-3.46E-03	3.64E-03	0.350	
	International airplane departures (count)	6.19E-06	2.33E-06	0.013	
	GDP	-3.92E12	1.51E-12	0.015	
Model 2	Population size	3.09E-09	1.33E-09	0.026	
	International airplane departures (count)	5.73E-06	2.64E-06	0.037	
	GDP	-3.52E-12	1.61E-12	0.036	

1.8 Are certain species more prone to export record discrepancies than others?

Over the ten-year period 2337 species were exported out of Africa (Table 13). These species had between one and 4530 export records. The mean number of export records was 27.3 and the median was 3.0. These species had discrepancy-rates ranging from 0% to 100%. The mean species discrepancy-rate was 87% and the median was 100%. A total of 110 species had a 0% discrepancy-rate. However, none of these species had more than three trade records. By comparison, 1273 species had a 100% discrepancy-rate, and these species had between one and 58 trade records. Only species with less than 19 trade records had a discrepancy-rate below 50%. A significant positive correlation was found between the number of export records produced for a species, and species discrepancy-rates ($p = 0.020$) (Figure 3).

Table 13: The number of species that fell into each discrepancy-rate bracket for the time period 2003-2012.

Discrepancy-rate (%)	Frequency
0.00	110
0.01-9.99	0
10.00-19.99	0
20.00-29.99	9
30.00-39.99	16
40.00-49.99	7
50.00-59.99	91
60.00-69.99	86
70.00-79.99	138
80.00-89.99	328
90.00-99.99	279
100.00	1,273
Total number of species = 2,337	
Mean discrepancy-rate = 87%, Median discrepancy-rate = 100%	

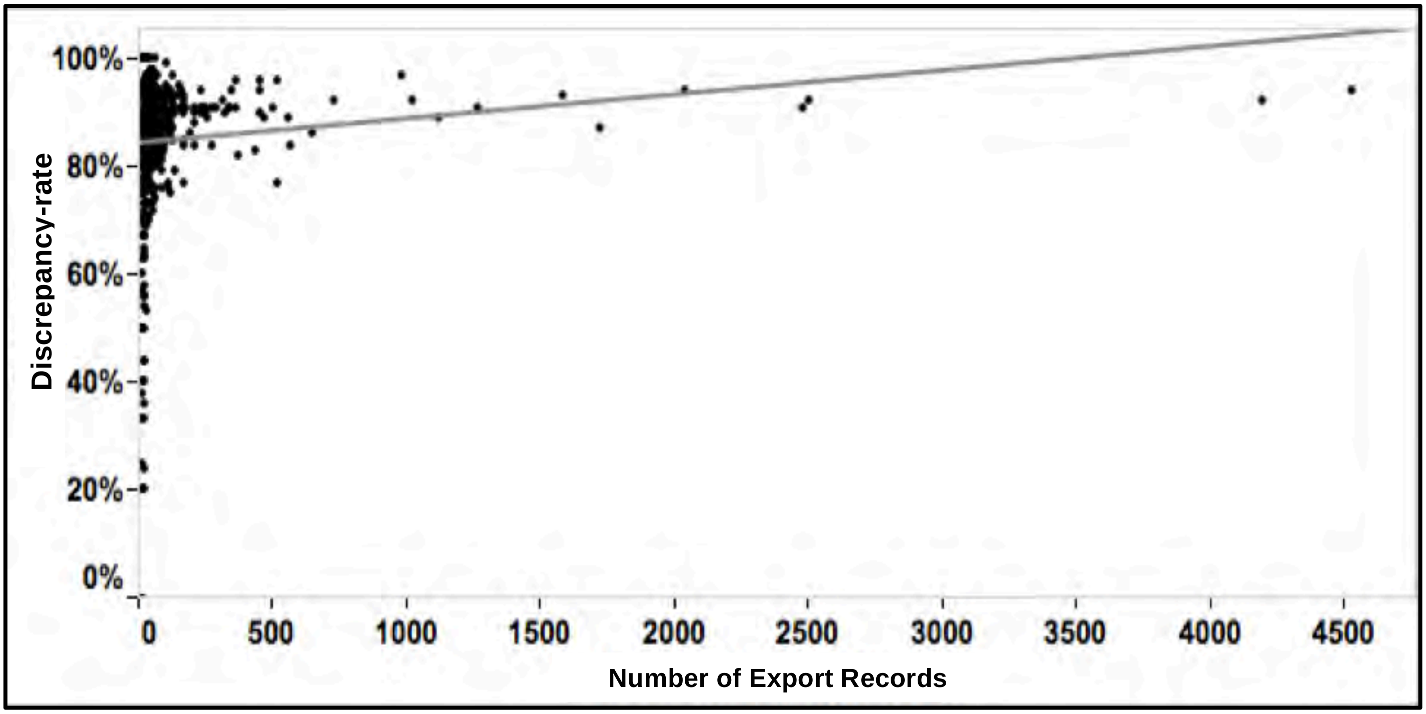


Figure 3: The relationship between the number of export records and the discrepancy-rate for species exported out of Africa between 2003-2012.

A total of 322 Appendix I species were exported out of Africa. These species had a mean discrepancy-rate of 90.8%. By comparison, 2015 Appendix II species were exported out of Africa. These species had a mean discrepancy-rate of 86.4 – 4% lower than the average discrepancy-rate for Appendix I species.

The five species with the most export records also had discrepancy-rates above the mean (Table 14). These species were *Loxodonta Africana* (African elephant), *Crocodylus niloticus* (Nile crocodile), *Panthera leo* (African lion), *Hippopotamus amphibious* (Common hippopotamus) and *Equus zebra hartmannae* (Hartmann's mountain zebra). Although African elephants made up just 7% of all export records, they were responsible for 56% of Appendix discrepancies. Similarly, while Nile crocodiles accounted for only 7% of export records, they were responsible for nearly 20% of unit discrepancies. Despite being one of the most frequently traded species, Hartmann's mountain zebra were only exported from two countries (Namibia and South Africa). The other top-five species were exported from at least 24 African nations.

Table 14: Summary of trade record accuracy for the species with the most export records. For each species the table contains two rows of data. The top row shows the total count of export records, the count of records with discrepancies, the discrepancy-rate, and the frequency of each type of discrepancy. The second row (referred to as percent of total) expresses the above value as a percent. For example, *Loxodonta Africana* (African elephant) is responsible for 4530 export records, which happens to be 7% of all export records in the dataset, and *Crocodylus niloticus* (Nile crocodile) is responsible for fourteen unit discrepancies, which happens to be 19% of all unit discrepancies in the dataset.

				Discrepancy type								
	Export records	Records with discrepancies	Discrepancy -rate	Quantity	Appendix	Origin	Purpose	Source	Term	Unit	Year	Import quantity missing
				(Frequency) (Percent of total - %)								
Loxondonta Africana	4,530 7	4,268 7	94 -	925 7	55 56	19 8	56 6	13 3	154 15	1 1	134 13	3,018 7
Crocodylus niloticus	4,194 7	3,871 7	92 -	940 7	3 3	15 7	33 4	29 8	92 9	14 19	88 8	2,711 7
Panthera leo	2,504 4	2,293 4	92 -	447 3	2 2	14 6	67 8	24 6	78 7	2 3	52 5	1,641 4
Hippopoamus amphibious	2,475 4	2,255 4	91 -	566 4	0 0	17 7	21 2	4 1	94 9	0 0	54 5	1,531 4
Equus zebra hartmannae	2,041 3	1,919 3	6 -	470 3	0 0	10 4	27 3	8 2	46 4	1 1	37 4	1,345 3
Dataset totals	63,969 100	57,427 10	10 -	13,937 22	98 0	227 0	880 1	379 1	1041 2	72 0	1,048 2	40,301 63

Discussion

By exploring CITES trade data for shipments exported out of Africa during the period 2003 to 2012, this study successfully determined:

1. The prevalence of discrepancies in the data;
2. The main types of discrepancies that can be identified;
3. If patterns in export record quantity, discrepancy quantity and discrepancy-rate can be identified over time and between different countries;
4. If discrepancy-rates correlate with country-specific factors; and
5. If certain species are more prone to trade record discrepancies than others.

Documentation discrepancies occurred in 90% of Africa's export records between the years 2003 and 2012. These findings quantify the inaccuracy of CITES trade data and confirm the need to improve international wildlife trade monitoring systems. While previous studies have commented on the prevalence of gaps in CITES trade data (Blundell and Rodan 2003, Sonricker Hansen *et al.* 2012), this is the most comprehensive study in terms of understanding the types of data discrepancies and their patterns.

Although 16 discrepancy types were tested and identified, it is possible that additional types of untested discrepancies did exist in the data. Examples of untested discrepancies include variable combinations that were not tested (such as "source and term" or "purpose and unit") or mismatches in reported taxon. For example, Foster *et al.* (2014) and Green and Hendry (1999) confirmed that incorrectly recording the taxon was a major source of discrepancy in international wildlife trade data. Testing and identifying additional discrepancy types could be a useful follow-up study and would produce even more thorough and in-depth information on how to improve CITES data collection system.

In addition to identifying and quantifying data discrepancies, this study revealed patterns in export record quantity, discrepancy quantity and discrepancy-rate over time. The total number of CITES export records did not increase significantly between the period 2003-2012, but the data did reveal a slight upwards trend in the number of export records over time. This is not unexpected considering the global population grew during this time (United States Census Bureau 2013), with an expected corresponding increase in demand for wildlife products. This finding is supported by Smith *et al.* (2009) that noted an increase in wildlife trade records during the study period 2000-2006.

During the years 2003 to 2012, the number of export records with discrepancies increased significantly by more than 13%. One would expect the number of records with discrepancies to increase in sync with the total number of export records. However, the number of records with discrepancies did *not increase proportionally* to the total number of export records. The discrepancy-rate rose between 2003 and 2012 by 5.6%. This is concerning because joining CITES is a national (and international) commitment to conserving at-risk species (U.S Fish and Wildlife Service 2014). Inherent to this commitment should be that nations adequately monitor the trade of these species (CITES 2014). Unfortunately, not only does a 92.5% discrepancy-rate in 2012 indicate that the wildlife trade was *not* sufficiently regulated in 2012, but the increase in discrepancy-rate between 2003 and 2012 suggests that the trade was monitored *less* efficiently in 2012 than it was in 2003.

While my results did not identify any clear patterns in export record quantity, discrepancy quantity or discrepancy-rate between different countries, two things were apparent: (1) some nations produced more total export records *and* more records with discrepancies than other nations, and (2) all nations (with the exception of Mayotte) had high discrepancy-rates. International trade intensity varies among countries (Knack and Azfar 2003), and it is reasonable for nations with more total export records to also have more records with discrepancies. Interestingly, though, all nations in this study had high discrepancy-rates, regardless of the number of export records they produced and regardless of the values of their country-specific factors. This makes it difficult to profile high and low discrepancy-rate nations using the country-specific factors because, overall, all shipments have a high chance of containing documentation discrepancies.

The strongest positive correlating factor was national population size; indicating nations with larger populations are more likely to have accurate wildlife trade data. Mayotte, however, had one of the smallest populations (Population Reference Bureau 2013), but the most accurate CITES trade data. Fortunately, nations with higher GEF Index for Biodiversity scores and nations with more international airplane departures are more likely to correctly document wildlife trade records. This is encouraging because nations with higher GEF Index for Biodiversity scores have high levels of biodiversity and, presumably, an abundance of natural resources. The fact that these nations are more likely to correctly document wildlife shipments means the natural resources from these nations are less likely to be illegally harvested and traded internationally. Similarly, it is encouraging that nations with more international airplane departures are likely to correctly document wildlife trade shipments. This is encouraging because nations with more international airplane departures have more opportunities to be involved in the international wildlife trade. It is reassuring to know that countries with more opportunities to ship wildlife products have an increased likelihood to document these shipments correctly. While it is difficult to conclude why nations with high GEF Index for Biodiversity scores and nations with more international airplane departures are more likely to correctly document wildlife trade shipments, we can hypothesize it is because these nations have more experience (or practice) monitoring and documenting the legal wildlife trade. A follow-up study testing the correlation between country-specific factors and the number of specimens traded would confirm or reject this hypothesis.

Arguably, one of the most worrying findings is the relationship between Gini Index score and the log of the error-free rates. As Gini Index score increase (representing higher levels of wealth inequality), the rate of discrepancy also increases. Essentially, this indicates nations with greater wealth and income inequality are more likely to incorrectly document wildlife shipments. It is difficult to say why this is, but perhaps nations with greater levels of wealth inequality are particularly prone to corruption and crime. However this is merely speculation and would benefit from a follow up study.

Further exploration of the relationships between discrepancy-free rates and country-specific factors is necessary to fully understand the predictive ability of country-specific factors. As the quality of CITES data improves, more variation in national discrepancy-rates will emerge. This will facilitate the discovery of country-specific factors with stronger correlations with the discrepancy-free rates. These stronger correlations will develop more accurate predictive models to guide wildlife shipment inspection efforts. Models such as these may also enable the findings from this study (and follow-up studies) to be applied to geographic areas outside of Africa. For instance, a follow-up study may indicate whether national population size, number of international airplane departures and GDP effectively predict the accuracy of wildlife shipments from *every* continent, not just Africa.

The fifth and final research question asked if certain species were more prone to trade record discrepancies than others. Overall, species with more export records had higher discrepancy-rates than species with fewer export records. Also, despite the stringent regulations governing the trade of CITES Appendix I species, the average Appendix I discrepancy-rate was 4% higher than the average Appendix II discrepancy-rate. Future research should explore this phenomenon in greater depth to determine which types of discrepancies are most common for Appendix I and Appendix II species. Gathering this information may shed light on to the actions needed to reduce data inaccuracies.

These results which summarize the inaccuracy of CITES trade records provide a platform to guide effective, positive changes in international wildlife trade monitoring systems. Based on the results of this study, it is recommended that the CITES Secretariat explore ways to improve annual reporting. For example, CITES could organize workshops to clarify annual reporting guidelines or CITES could alter its data collection system to reduce discrepancies. One way CITES can alter its data collection system is by assigning unique identification numbers to each wildlife shipment in trade. This would enable CITES to pair import and export trade records for a single shipment, and it would enable CITES to recognize which discrepancy type(s) prevented the records from matching up identically. Another way CITES can alter its data collection system is by requiring shipments to document the exporting *and* importing year. This would eliminate year discrepancies. Finally, CITES can consider implementing a multiple-choice system for certain variables, such as "unit." This would reduce discrepancies that arise from using non-standard measurement units.

The wildlife trade is an enormous industry that impacts the livelihood and wellbeing of people around the world (Nijman 2010). Unfortunately, the wildlife trade can sometimes be a very destructive industry, devastating habitats (Daraik and Phillips 2010 and Bradley *et al.* 2012) and causing irreversible species population declines (Wilcove *et al.* 1998 and Scanlon 2012). During current times of unprecedented human population growth, natural resource exploitation and globalization, it is imperative to safeguard our planet's remaining natural assets. The current system for monitoring the international trade of these natural assets is not adequate and will yield little information to guide conservation decisions. Fortunately, understanding the extent and types of trade record discrepancies is the first step to improving in the international wildlife trade data collection system, which will facilitate informed and effective conservation decisions.

Acknowledgements

I would like to thank my advisors, Timm Hoffman and Markus Burgener, for their constant guidance and support through this project. I would also like to thank my friend and statistical advisor, Phil Chodrow. I'm not sure what I would have done without him! Another giant thank you my diligent editors, Jean Holmes, Alicia Russo and Robert Russo. And one last thank you to Jenna Bowker for submitting my project.

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