



INSTITUTE FOR DEFENSE ANALYSES

**Data Requirements to Assess
Department of Defense (DOD)
Investments in Law Enforcement
in Southwest Asia**

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Executive Summary

Background

The objective of this task, sponsored by the Deputy Assistant Secretary of Defense for Counternarcotics and Global Threats (CN>), was to improve the effectiveness of the Counternarcotics Police of Afghanistan (CNPA). In addition, the Institute for Defense Analyses (IDA) supported the United States Central Command's (CENTCOM's) Counternarcotics Program in the Interagency Action Group (IAG), and received additional requirements from CENTCOM. CENTCOM sought data to drive resourcing decisions, i.e., to identify functional areas where the United States Government (USG) should concentrate CN resources. Finally, multiple counternarcotics program goals would be achieved through the Defense Intelligence Agency's (DIA's) effort to develop data collection and validation procedures for Southwest Asia (SWA) that are consistent with the Western Hemisphere's Consolidated Counterdrug Database (CCDB) process. Accordingly, IDA's efforts were directed toward supporting this DIA effort and creating a CCDB-East.

To support CCDB-East development, IDA analyzed drug seizure event data from the United Nations Office of Drugs and Crime (UNODC) and data extracts used by DIA to assess their quality and utility for this purpose. IDA studied and observed the existing process for collecting, validating, and analyzing cocaine data in the Western Hemisphere and how it could be applied in SWA. Finally, IDA devised techniques that would allow analysts to derive useful information from limited data sets. This document presents these techniques and shows how they can be employed in SWA to assist the USG in measuring the success of CENTCOM's CN programs.

Findings and Recommendations

The following findings and recommendations highlight how understanding patterns in drug data enables better analysis.

1. Finding: Raw, not averaged, data are necessary for more accurate analyses.

Raw data, i.e., individual values collected from the field, are necessary to accurately calculate the sample means, data distributions, and medians used for statistical analyses. Depending on the sample size, there can be significant divergence between means and median values. For certain applications, the sample mean will be much higher than the sample median. Moreover, the sample mean is highly erratic while medians can better

reveal true trends. Thus interpretations based on a sample mean may lead to erroneous conclusions. Moreover, raw data are better for making comparisons to *power law* distributions,¹ providing some sense of statistical variation, and offering more support for trend analysis.

Recommendation: Entries in the CCDB-East should be in the form of raw event data, not averaged estimates (i.e., sample mean and sample median).

2. Finding: It is essential to maintain the integrity of separate data sets.

Combining two or more data sets obscures the time-dependent information contained within the data and renders it unusable for validation purposes.

Recommendation: Analyses of the data contained in the CCDB-East should maintain the integrity of separate data sets.

3. Finding: Systematized data collection methods yield more reliable information.

Coordinated data collection and information sharing efforts across civilian and military government agencies that have some role to play in the counternarcotics mission yield a more robust data set that can be used to inform policy and extract other useful information.

Recommendation: Formal coordination of the data collection processes should be implemented among the interagency and multinational partners.

4. Finding: Event data should be categorized by confidence levels before analysis.

Confidence levels are assigned by assessing the reliability of each event based on multiple sources of corroborating data. This allows analysts to use data in different ways, including as a validation tool for other data sources.

Recommendation: The CCDB-East should have a system for assigning and vetting event data confidence levels.

5. Finding: Event data may be validated using independent variables that are known to indirectly corroborate event data.

Comparing separate but related independent variables, such as price or user rates, reveal similarities as well as inconsistencies that reflect the quality of the data and potential anomalies that require further examination. For example, changes in seizure rates may also be reflected in changes in prices or consumption.

¹ A power law is a distribution where rates change as the size of events and risk levels grows. This concept is examined in detail in this document.

Recommendation: Data in the CCDB-East should be compared with independent data sets that provide some validation potential.

6. Finding: Event data may be validated using time series plots.

Comparing different variables over time allows analysts to identify reinforcing trends and anomalies, and compels analysts to account for differences in interpretations of causal factors.

Recommendation: Data in the CCDB-East should be compared with independent data sets that provide some validation potential.

7. Finding: Event data may be validated by comparing it with the underlying functional distributions (power laws).

Because many sets of drug data, especially observed counts for specific sizes of events, follow similar functional distributions, data sets can be compared with each other for consistency. When data sets diverge from the expected distribution, one can reasonably infer that the data set may be incomplete, contaminated, or suffer from some other fundamental shortcoming.

Recommendation: Administrators of the CCDB-East should ensure the thorough technical validation of all event-level data to maximize the utility of limited data sets.

Recommendation: CCDB-East administrators and data collectors should agree on minimal reporting thresholds that accurately sample the universe of drug trafficking events.

8. Finding: CENTCOM should extract surrogate data where incomplete data sets exist.

New analytic methods can be used to extract additional data from existing data sets providing the potential for insight into otherwise unknown aspects of the drug trade. For these methods to work, small trafficking events down to one kilogram (kg) must be collected.

Recommendation: CENTCOM should extract surrogate data where incomplete data sets exist.

9. Finding: Better event data can support CENTCOM's programs by mitigating some of the challenges associated with data limitations.

Various interagency stakeholders have identified specific data gaps where additional information could be extremely helpful, such as the location of stockpiles, processing labs, routes, and the supply of precursor chemicals. These data, however, have limited

availability. Moreover, USG data collection efforts are neither coordinated nor systematic, resulting in incomplete data sets that may not accurately reflect drug trafficking in SWA. The techniques presented in this document offer ways to validate existing data, fill in missing data, and extract supplemental insights.

Recommendation: See all recommendations associated with findings 1–8.

10. Finding: CENTCOM can improve its knowledge of its adversaries, how they resource themselves, and how they operate based on perceived risk.

This finding regarding criminals’ tolerance for risk-taking offers opportunities for the USG to tailor its counternarcotics activities. By creating a sufficient level of risk that deters traffickers, the USG can make progress towards achieving its objectives and maximizing its returns on counternarcotics investments.

Recommendation: See all recommendations associated with findings 1–8.

An Analytic Breakthrough

In executing this task, IDA made a breakthrough in its broader analysis of criminal systems. Decades of research on the cocaine market, this research on opiates in SWA, and research on the behavior of insurgents in Iraq have suggested that irregular adversaries, including insurgents, drug traffickers, and other criminal enterprises, all exhibit similarly-structured rates (or time intervals between events) of risk-taking.

While many will take small risks for small returns because the perceived risk is low, only a few take very big risks for large returns. For example, small drug seizures of amounts less than one kilogram are far more frequent than seizures of a ton. Similarly, more traffickers sell smaller amounts more frequently than very large amounts. Likewise, more users buy small amounts more often than users who buy large amounts. In other words, the rate of criminal behavior (i.e., the interval between events) is faster for smaller risks and slower for larger risks. This observation is central to the principle known as *equal risks for equal returns* and to the associated power law distributions where rates change as the size of events and risk levels grows. This behavior appears to be a fundamental signature of irregular gangs, insurgents, traffickers, and any other small illicit organization avoiding detection by a state. Because these rates are linked to each other, analysts may be able to derive significant amounts of information from limited data sets.

The research presented in this document and its appendices suggest that this risk-taking behavior is ubiquitous and applies not only to global criminal activities, but also to insurgent forces—many of which are funded through the drug trade.² Further analysis of

² For more detail on analysis of combat data, see Appendix C, “Analysis of Combat Data.”

the limited data is required to confirm this hypothesis, but assuming it is correct, it could assist the U.S. military in identifying the conditions under which it must operate (and the risks it must impose upon insurgents) for U.S. forces to gain the advantage in irregular wars. In other words, it could improve the U.S. military's knowledge of its adversaries and how they operate based on perceived risk.

The implication for the USG is that it might be able to determine—with far better accuracy—the actual scope of certain aspects of the drug and irregular warfare systems. With more accurate data, policy makers could begin to pinpoint with better precision when certain government policies and interventions begin to work.

Contents

1.	Introduction	1
A.	Objectives	1
B.	Methodology	2
C.	Document Outline	7
2.	Research Findings	9
A.	What Data Are Necessary?	9
B.	What Processes Are Necessary?	17
C.	What Analytical Capabilities Are Necessary?	28
D.	How Can Better Event Data be Used to Support U.S. Central Command's Programs?	29
3.	Recommendations	33
4.	Conclusions	37

Appendices

A.	Models and Simulations	A-1
B.	Analysis of the Cocaine Market	B-1
C.	Analysis of Combat Data	C-1
D.	Illustrations	D-1
E.	References	E-1
F.	Abbreviations	F-1

1. Introduction

This chapter explains the objectives and methodology the Institute for Defense Analyses (IDA) used to conduct this study, describes how IDA used data provided by the United Nations Office on Drugs and Crime (UNODC) and provides an outline of the document's organization.

A. Objectives

This research was carried out in support of the Office of the Deputy Assistant Secretary of Defense (DASD) for Counternarcotics and Global Threats (CN>). The ultimate objective of the DASD-sponsored effort is to improve the effectiveness of the Counternarcotics Police of Afghanistan (CNPA).

The United States Central Command (CENTCOM) was also pursuing improvement in data quality and use in connection with the CENTCOM Counternarcotics Program. In particular, CENTCOM sought better data to drive its resourcing decisions, i.e., to determine the functional areas to concentrate its CN resources (e.g., border enhancements or intelligence-sharing efforts, interdiction or eradication, training, equipping, or infrastructure support, etc.). Moreover, CENTCOM was focused on the global nature of opiate trafficking. Although more than 90% of opiates are produced in CENTCOM's area of responsibility (AOR), they cross several Combatant Command (COCOM) boundaries en route to their final destination. Thus, the methods developed to answer these questions needed to be holistic so that the principles can be applied by any COCOM.

Simultaneously, the Defense Intelligence Agency (DIA) was engaged in an effort to develop an opiate module within the Consolidated Counterdrug Database (CCDB). As part of this effort, DIA is preparing for data collection and validation procedures consistent with the existing CCDB process and contained within that database infrastructure.¹

DIA looks for event-level, seizure data with basic descriptive details including date, location, drug type, amount, destination, description of where it was seized, the force/organization that claimed the seizure, operation type/name, and if available, a

¹ The CCDB is a repository of Western Hemisphere cocaine event data from drug movements and seizures. It captures the details of these drug-related events and supports both Interagency Assessment of Cocaine Movement (IACM) and Performance Assessment Review (PAR) data requirements. For more information, see the CCDB User Guide.

narrative of the seizure. DIA is seeking this level of detail for reports from Afghanistan, Turkey, Iran, Pakistan, India, Russia, as well as African and European countries as a secondary requirement. Unlike the UNODC, which collects regional drug data in a systematized fashion, early DIA collection efforts have not had the benefit of regional data and have had to rely largely on data from existing databases that are not designed to acquire and house drug data. DIA plans to use these reports to ensure the event data within the opiate module of the CCDB (hereafter referred to as “CCDB-East”) is not duplicative and to de-conflict/combine seizures that are reported or claimed by more than one unit. The CCDB-East calls this practice “validation” although it is quite different from the technical process of validation.²

Ultimately, the DIA effort to create a “CCDB-East” became the common focus for the improvement of the data collection and analysis capabilities essential to the counternarcotics efforts of the United States and the CNPA. IDA’s efforts were directed toward supporting development of the CCDB-East. IDA’s task was to identify the characteristics that would make the data most useful for a technical analysis. To that end, IDA formulated the following research questions to drive this study:

- What data are necessary for the CCDB-East?
- What processes are necessary for the CCDB-East?
- What analytical capabilities are necessary for the CCDB-East?
- How can (better) event data be used to support CENTCOM’s CN programs?

B. Methodology

IDA employed a multi-faceted approach to this research utilizing qualitative and quantitative methods. Analysts conducted research along three distinct, but mutually reinforcing, lines of inquiry:

1. Examine and assess current data collection, validation, and analysis efforts in the Western Hemisphere (WH) by observing the CCDB process, techniques, and use of collected data

² Unlike the current validation process, which reviews the content of various reports to avoid duplication, IDA emphasizes technical validation of event data to ensure different sources of data “tell the same story” and that drug volumes, flow, consumption, or other estimates of the drug system are reliable and accurate.

2. Examine and assess existing data collection, validation, and analysis efforts in Southwest Asia (SWA) by interviewing United States Government (USG) departments and agencies that have a role in drug data collection in the region³
3. Devise advanced statistical techniques that address some of the challenges identified in the first two phases and illustrate how they may be used to support CENTCOM's counternarcotics programs

The first two lines of inquiry were presented in previously published IDA documents.⁴ This document addresses the third and most analytically challenging line of inquiry. IDA developed advanced statistical techniques and tested those techniques using the UNODC database of Afghan and Central Asian seizures and extracts from the DIA's Significant Activities (SIGACT) reports contained in the Combined Information Data Network Exchange (CIDNE) database.

1. The Use of United Nations (UN) Data

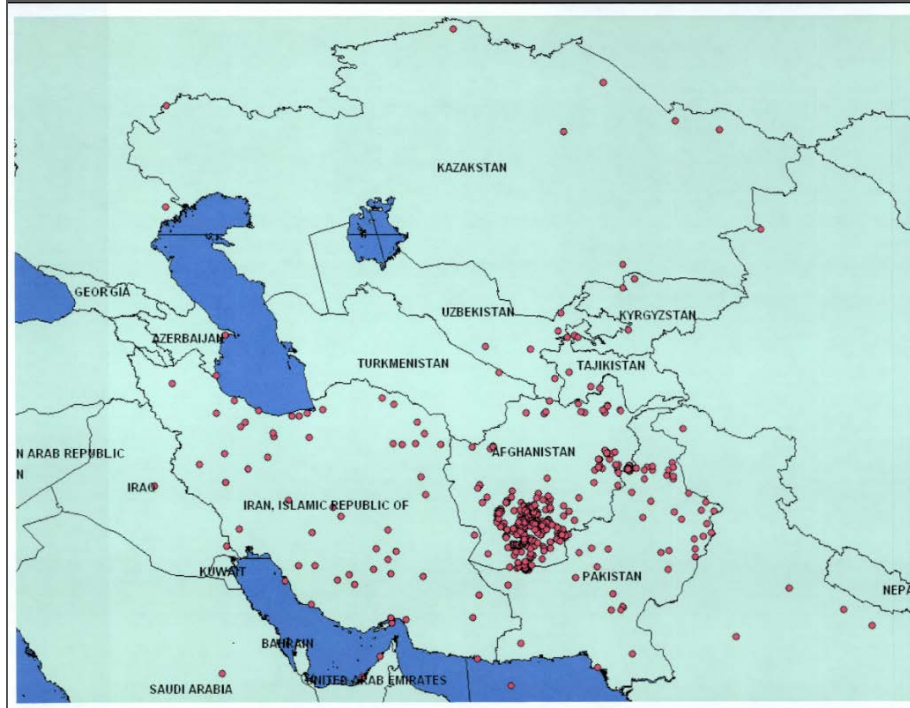
Because UN data has been systematically and methodically collected over time, it represents the most comprehensive database of seizure events in the region (though it is still only as accurate as each member state's contribution). UN data has the additional benefit of having been collected around Afghanistan, including in Iran (where the largest number of seizures are made). IDA compared data from all other sources to the UN data. Since this comparison of other data sources to UN data is central to the analytic methodology used in this document, a discussion of that data is provided here. The UN data has proven in the past to have significant utility when compared to highly detailed USG data previously gathered and much of it unknown to UN researchers.

Figure 1 shows the physical distribution of the 9,416 seizures of opiates (opium, morphine, and heroin) in and around Afghanistan that were analyzed during this research.⁵ These seizures have several properties: quantity, time, and location. Usually seizures are reported in one of two ways: events in time (where a seizure is an event) or quantities in time (where quantity is the mass or weight of opiates seized).

³ Barry D. Crane, Ashley-Louise N. Bybee, Andrew Cseko, Andrea S. Pongo, and Zachary S. Rabold, *Phase II Findings: Leveraging Lessons Learned to Inform Southwest Asia Counter-Drug Efforts*, IDA Document D-4324, Draft Final (Alexandria, VA: Institute for Defense Analyses, May 2011).

⁴ Ibid. and Crane et al., *Developing a Strategy*.

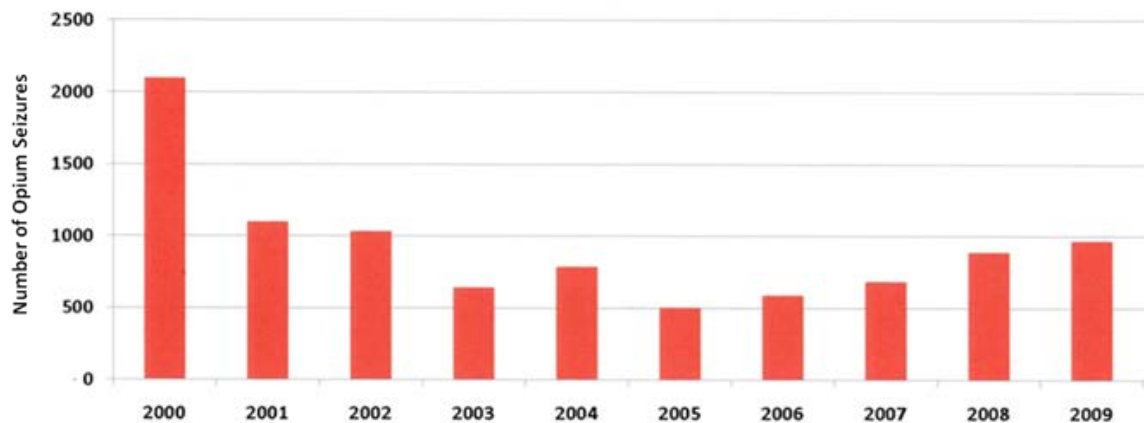
⁵ This figure contains only preliminary data for 2010.



Source: UNODC and USG data

Figure 1. Physical Distribution of One or More Events Where Opium, Morphine or Heroin Were Seized, 2000–2010

Figure 2 shows the time distribution of the seizures. The rate of these events, partitioned by different quantity bins (for example the number of seizures in the amount of 1–10 kilograms (kgs) per unit of time) is a stable indicator of risk-taking activity within the narcotics market. This insight is what led IDA technical staff—in collaboration with UNODC research analysts and a representative from CENTCOM—to conclude in December 2010 that *the distribution of the rate of drug seizure sizes (e.g., kg seized /event/unit time) can be used to determine the validity of data describing other aspects (e.g., price) of the drug market system*. This fundamental feature of the drug trade significantly improves IDA’s analyses of the limited data available in SWA.



Source: UNODC and USG data

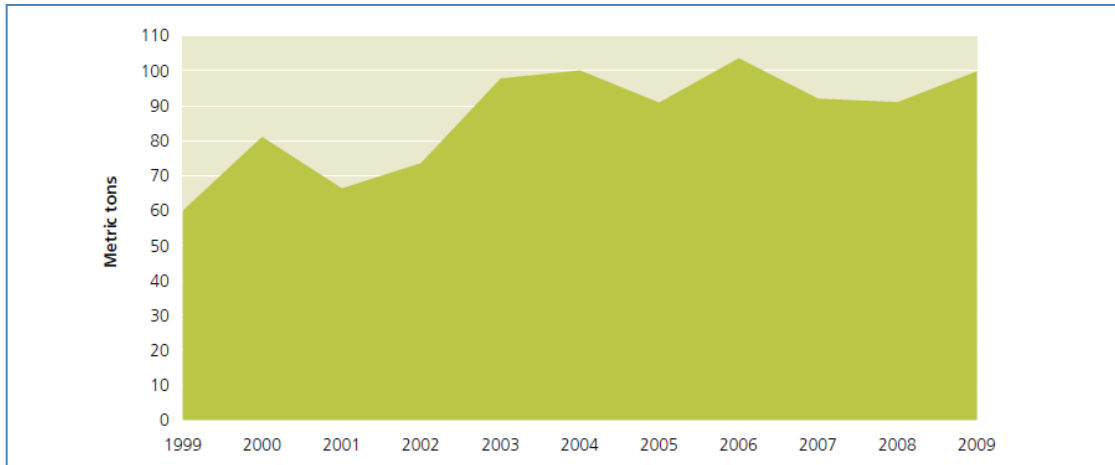
Figure 2. Temporal Distribution of Events Analyzed, 2000–2009

Figures 3 through 6 (extracted from the *2011 UNODC World Drug Report*) illustrate global opiate seizures. The regions inside the red circle show the data that IDA analyzed for this task. Figure 3 shows the global seizures of heroin and morphine and Figure 4 shows the totals for those seizures in metric tons through 2009.



Source: UNODC, *World Drug Report, 2011*, 62

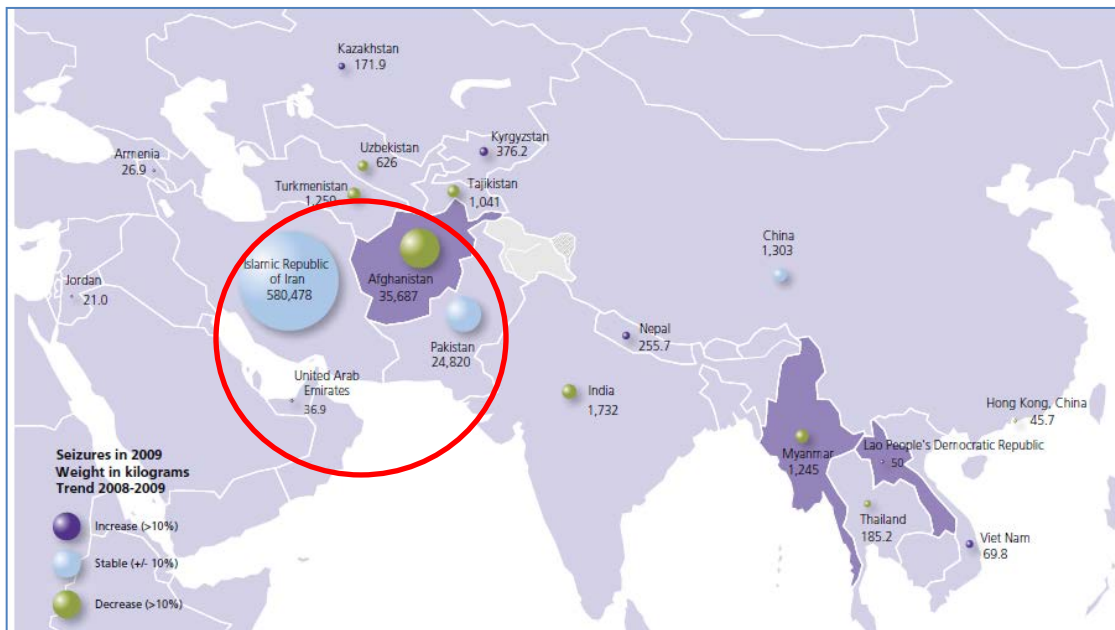
Figure 3. Physical Distribution of Heroin and Morphine Data Analyzed from Map 10, “Seizures of Heroin and Morphine, 2009 (Countries and Territories Reporting Seizures of More than 10 kg)”



Source: UNODC, *World Drug Report, 2011*, 63

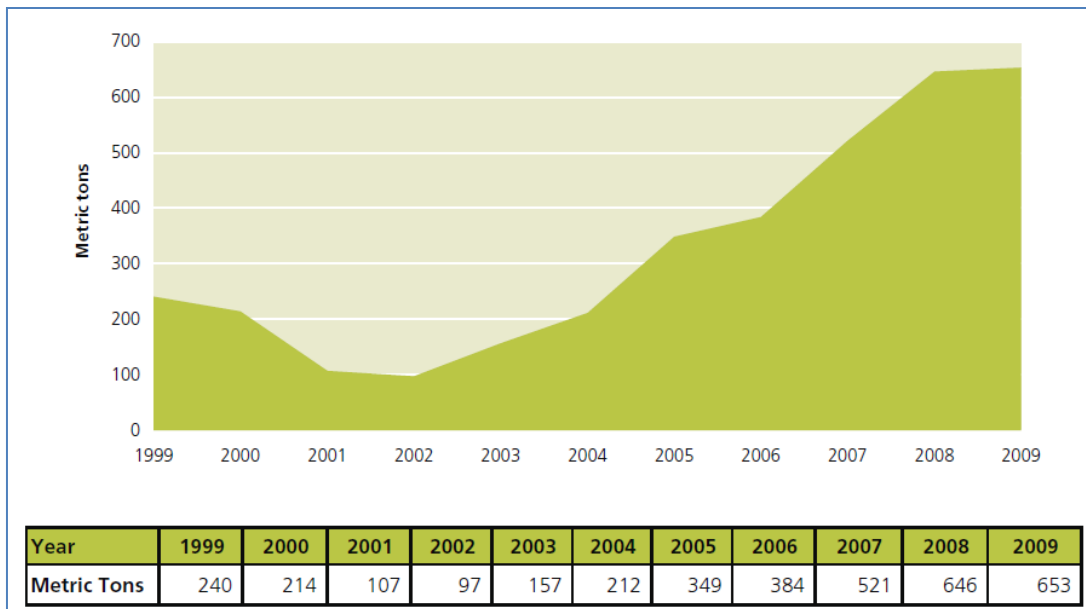
Figure 4. Temporal Distribution of Heroin and Morphine Data Analyzed from Figure 29, “Global Seizures of Heroin and Morphine: 1999-2009”

Figure 5 shows the physical distribution of global seizures of opium and Figure 6 shows the totals for those seizures in metric tons through 2009.



Source: UNODC, *World Drug Report, 2011*, 65

Figure 5. Physical Distribution of Opium Data Analyzed from Map 11, “Opium Seizures in Asia, 2009”



Source: UNODC, *World Drug Report, 2011*, 64

Figure 6. Temporal Distribution of Opium Data Analyzed from Figure 30, “Global Seizures of Opium: 1999-2009”⁶

C. Document Outline

Portions of this study are predicated on decades of previous IDA research focused on the cocaine market in the WH.⁷ This research provided many of the foundational principles upon which this study was built. This document synthesizes that research with the findings from this study to formulate recommendations for SWA. Chapter 2 of this document is organized in line with the research questions presented on page 3. Section A of Chapter 2 presents findings about data that should be contained in a CCDB-East and some of the challenges associated with that data. Section B of Chapter 2 describes the processes and statistical techniques that are necessary for the proper interpretation of that data. Section C of Chapter 2 presents the analytical capabilities that a CCDB-East should have in order to best assist users. Section D describes how a database can be used to support CENTCOM’s CN programs. Chapter 3 offers recommendations and Chapter 4 presents conclusions.

⁶ IDA analyses used more than 95% of about 400–600 metric tons of opium seized per year.

⁷ See Appendix B, “Analysis of the Cocaine Market.”

2. Research Findings

A. What Data Are Necessary?

IDA's task was to identify the characteristics that would make the data most useful for a technical analysis. For this aspect of the task, IDA did not examine the specific fields that would be necessary in the CCDB-East. This is a function already being performed by DIA.

1. Raw, not averaged, data are necessary for more accurate analyses.

Previous IDA research has shown that *power law* distributions (where many events occur at small values and few events occur at large values, and there is a consistent pattern that systematically relates incidence rates to changes in value sizes) characterize many components of the illicit drug trade. The adherence of drug data, including quantities seized, consumption, and the price of a given volume,⁸ to these known statistical distributions has one critical implication for interpreting the data: the use of the mean (average) as an estimate of any power law-like distribution may be extremely misleading—both for summarizing a single data set and for characterizing trends exhibited by multiple data sets over time. Medians, on the other hand, offer a more accurate and stable representation of the entire system of analytic products.⁹ Unfortunately, most reporting to policy makers typically comes in the form of monthly averages (i.e., means), which can misrepresent the facts.

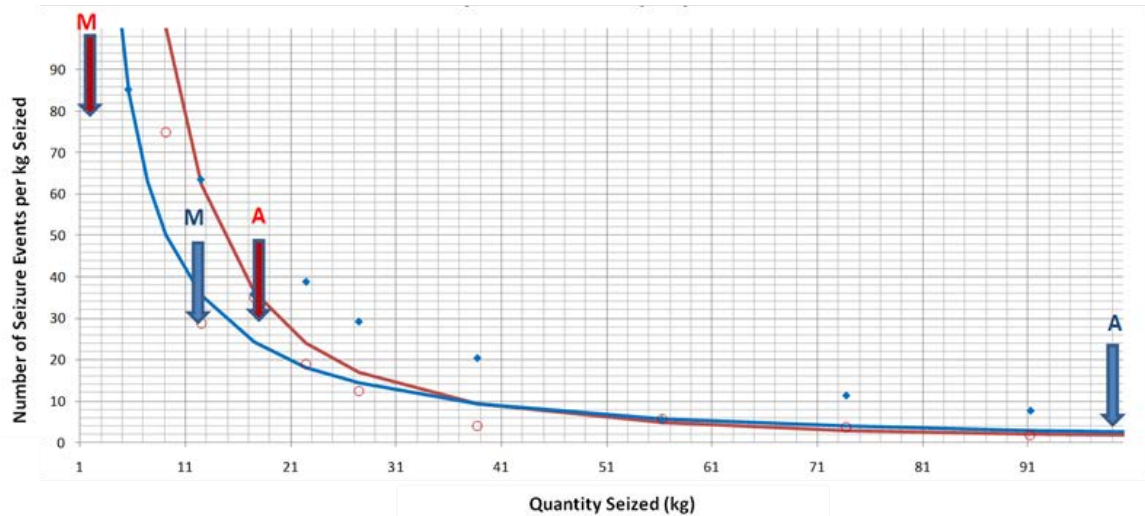
Depending on the sample size, the divergence between the mean and median can be quite large.¹⁰ Figure 7 shows a typical comparison between means and medians using UN seizure data, which produces a highly asymmetric and skewed distribution. The M

⁸ See Appendix A, “Models and Simulations,” and Appendix B, “Analysis of the Cocaine Market,” for more detail.

⁹ Barry D. Crane, A. Rex Rivolo, and Gary C. Comfort, *An Empirical Examination of Counterdrug Interdiction Program Effectiveness*, IDA Paper P-3219 (Alexandria, VA: Institute for Defense Analyses, 1997). The first arguments are presented that for unknown (especially power law-like) distributions only the medians might converge. Previous engineering research of a similar technical problem when analyzing the signal-to-noise and detection performance of over-the-horizon radars were well characterized by median statistical representations. Testing these analyses over ten years confirm the practical use of these techniques.

¹⁰ For a more detailed description of the inflationary effects of a statistical mean and the use of the median value, see Appendix A, “Models and Simulations.”

(medians) and A (averages/mean) are shown for actual heroin and opium data (in red and blue respectively), with each median being substantially less than its average/mean counterpart for lower quantities seized.



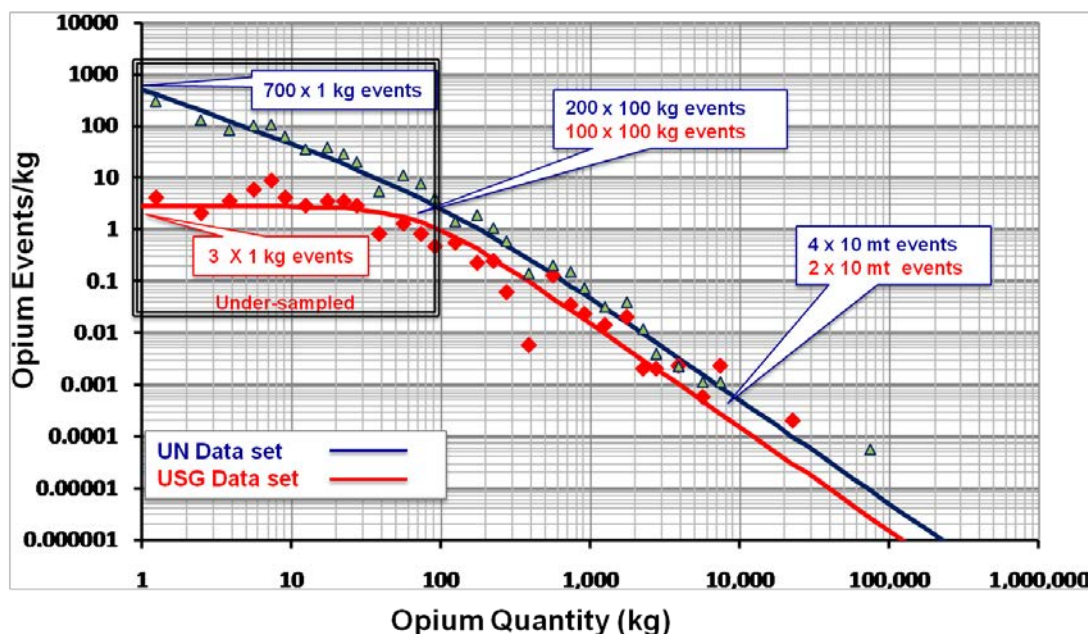
Source: UNODC

Note: M=median. A=average (mean). Heroin=red. Opium=blue

Figure 7. A Small Sample of UNODC Heroin and Opium Seizures Showing Overall Averages and Medians for All UNODC Data

Figure 8 illustrates the significantly different distributions between the UN's opium¹¹ event data (2,606 total events collected between 2000 and 2010) and the USG's *chance* data (295 total events collected between 2008 and 2010). Chance data refers to drug seizures made during a military operation that was not planned or intended to be a CN operation. Due to limited collection assets, capabilities, or systematic data collection procedures, most USG event data falls into this category. Logarithmic-scaled axes (log of the events and the log of the quantities) are used to show the extraordinary range of all data quantities and the stability of the seizure distributions.

¹¹ Opium data was used over heroin data due to its greater sensitivity to enforcement actions. See Thomas Pietschman, "Price-setting Behaviour in the Heroin Market," *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004): 105.



Note: mt=metric tons and kg=kilograms. The box displays the region where USG event data is significantly under-sampled. The flag boxes show typical number of events at each quantity.

Figure 8. A Comparison of UN Opium and USG Event Data and Underlying Distribution

A sampling bias causes the difference in these distributions. UN data is collected in a systematic fashion, resulting in a proportionate number of events collected at both the low and high ends of the distribution curve. On the other hand, USG chance data significantly under samples the low end of the distribution curve (small events) because arbitrary reporting thresholds are too high to capture the majority of small seizure events. This is why the two curves are consistent with each other for seizures greater than 100 kg while there is significant deviation for events less than 100 kg (see the box in Figure 8). In other words, the UN consistently has two times as many events recorded for events larger than 100 kg while it has approximately 230 times as many events recorded for 1 kg events (see call-out boxes in Figure 8).

The medians and means depicted in Table 1 can be calculated based on these data. Both the USG median and mean overestimate trafficking and are about 3.5 times larger than the associated estimate derived from the more complete UN data set.¹²

¹² Incidentally, the average cocaine seizure value taken from CCDB data is about 20 times the median cocaine seizure value.

Table 1. Gross Descriptors of UN and USG Data

	Total (mt)	Average (kg)	Median (kg)
UN Data	278	99	12
USG Data	105	350	40

The events/kilogram format also allows analysts to examine the *rate* of trafficking of various quantities. Figure 8 illustrates that high-risk events (involving larger quantities) occur at a slower rate while low-risk events (involving smaller quantities) occur at a much faster rate. This is consistent with the principle of *equal risks for equal returns* which is described in more detail under research finding 4. However, this generally accepted principle is not observed in the highlighted portion of the USG data (for small seizures of less than 100 kg), providing further evidence that USG data under samples small, low-risk events.

The implications of this finding are multi-fold. As it is currently collected, USG data cannot be used to calculate accurate flow estimates, including averages and medians, due to the bias that results from the USG’s unsystematic collection procedures. This sampling bias also affects USG estimates for other important characteristics of the drug trade, such as quantities trafficked or surrogate prices. Monthly averages derived from current USG data, such as those typically reported to policy makers, likely contain errors and may be misleading (e.g., overestimating enemy capabilities and making it difficult to accurately assess trends). Furthermore, the sample average will vary dramatically over time. Tracking sample averages over regularly spaced time periods can obscure real trends and even—in the short term—create a false appearance of a trend. Even with the sampling bias, more stable and operationally useful analytic descriptions of drug data can be achieved using the median value for the sample.

Due to the operational environment in SWA, where there are limited personnel, platforms, and assets available for drug event data collection, it is unrealistic to expect to collect a large sample size of opiate data. In lieu of a very large sample (data set) for SWA opiates, analysts must ensure that they overcome some of the challenges associated with small sample sizes. To compound the challenge of limited data, small numbers of seizure events (which are very common) over short time intervals can be under-represented in a sample (for example, because of an arbitrary reporting threshold that is too high to capture the majority of small seizure events). Under these circumstances, using the larger derived mean value from these small samples to estimate a typical value for a drug seizure is likely to result in a grossly inflated estimate.

2. It is essential to maintain the integrity of separate data sets.

In order to compare and validate data sets accurately, the data sets themselves must reflect systematic data collection procedures that are applied consistently over time. IDA

technical experts found that when data sources are combined into a single data set, there are invariably differences in the raw data that distort the time-dependent information—particularly when the criteria for data inclusion changes, making relative measurements difficult. For example, combining UN and USG seizure event databases eliminates the potential for analysts to calculate estimates and/or extract valuable insights from the UN’s systematically collected data.

The following example shows opium cultivation and production estimates from USG (specifically the Central Intelligence Agency, (CIA)) and UN (UNODC, *World Drug Report, 2011*) data. By comparing these two independent data sets, it is possible to estimate what may be termed the “measurement error.” This measurement error is actually the difference between the two data sets that may occur as a result of different collection methodologies or biases inherent to the data collection process. Tracking the measurement error is a useful way to determine the underlying accuracy of the data sets, i.e., if differences in measurement are consistent over time, then one can place higher confidence in the accuracy of the data. It is, of course, possible that both data sets may have inherent errors in measurement. However, these differences in measurement are inconsequential if both data sets display the same trends. Determining that two data sets are consistent with each other, i.e., they “tell the same story,” is a valuable validation technique. Ultimately the most valuable insights are derived from analyzing the overall trends of the data.

Figure 9 compares USG and UN cultivation estimates, including a “best fit to the data” curve for each data series. Using this presentation, one can visually observe the measurement error, or difference in measurement, which is the difference between the dotted lines. In this example there is a measurement difference of approximately +/- 25,000 hectares before 2005 and approximately +/- 5,000 hectares since 2005.¹³ The converging data points since 2005 reflect recent improvements in estimates.

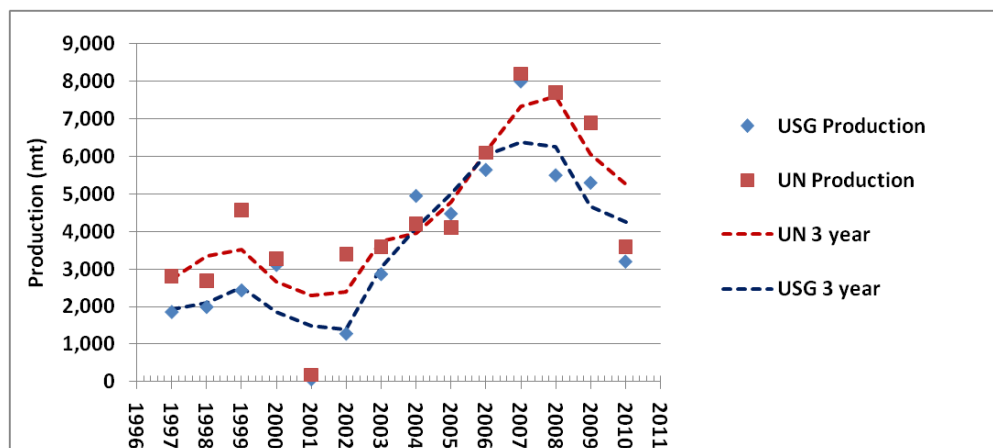
¹³ After 2004, significant efforts were made to discuss technical means for generating cultivation estimates. These most likely reduced the measurement error.



Source: USG crop estimate, and UNODC, *World Drug Report, 2011*

Figure 9. Estimates of Afghan Opium Cultivation (hectares)

Similarly, Figure 10 compares production estimates since 1996. These estimates may vary slightly due to differences in cultivation and yield. An approximate measurement error (or difference) of +/- 1000 metric tons (mt) exists prior to 2004. Estimates appear to be very close during the 2004–2006 time frame, but they diverged again after 2006. The main reason for these variations in measurements is ongoing disagreement over the calculation of production levels based on cultivation and the yields of opium gum per hectare.

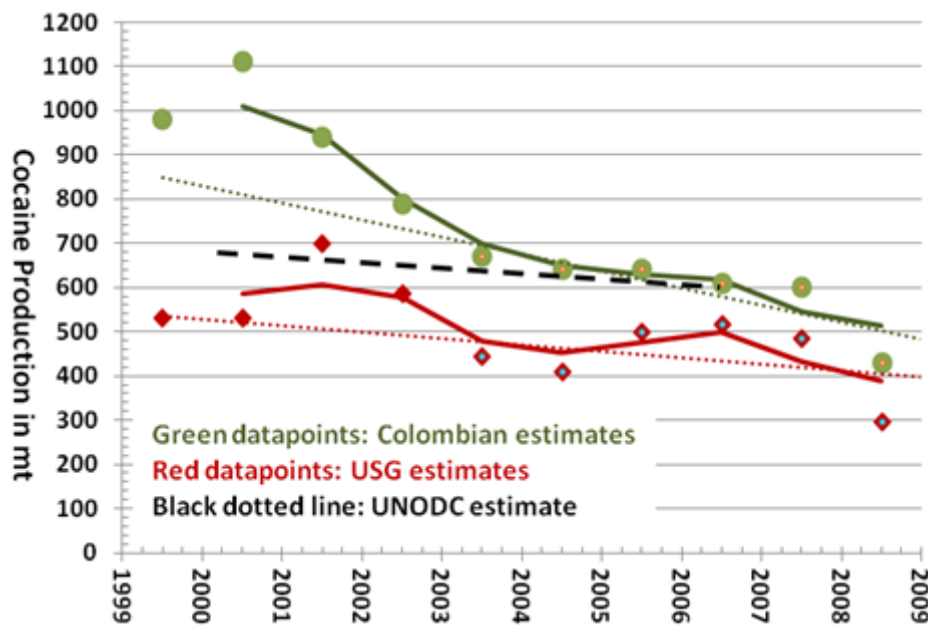


Source: USG crop estimate, and UNODC, *World Drug Report, 2011*

Figure 10. Estimates of Afghan Opium Production (Metric Ton)

While this example highlights the importance of maintaining the integrity of separate data sets so that each may be checked for consistency (i.e., validated), the following example using cocaine data illustrates the danger of combining different time series data. Figure 11 depicts two sets of cocaine production estimates over a common

time span. The green data points plot the estimates of the Colombian National Police (CNP) (generated by the Integrated Crops Monitoring System, known by its Colombian acronym SIMCI). The red data points plot the USG estimates. The two data sets used different data collection and analysis approaches, but individually their methodologies were applied consistently over time and yielded the same general trends, thus validating each other. Therefore, while their respective absolute estimates vary—with the USG always reporting lower annual values—each set of results portrays the same general declining trend in cocaine production. The dotted black line shows the UNODC estimates of Colombian cocaine production which combines USG and SIMCI data.



Source: Data provided by the Colombian National Police (CNP) and the USG

Figure 11. Colombian Cocaine Production: Separate Time Series

The UN used the USG data until 2004 and then switched to SIMCI data when that program matured. As a result, the UNODC representation of the data shows a relatively steady level of cocaine production prior to 2008.

The UN combined data set display implied that Colombian production control was ineffective, since according to the UNODC representation of the data, production was not affected by the counternarcotics campaign. Prior to 2003 the UN varied the ratio of attributing values from USG and UN estimates in production and cultivation in order to yield a single value for production. In some cases the UN used USG production values applied to UN cultivation figures. Combining these values made it appear that there was no change in production, though in reality production control was effective as evidenced by the two distinct and separate data sets provided by the U.S. and Colombian governments. This example illustrates the importance of examining independent data sets

separately to validate each other and corroborate conclusions. It also illustrates the danger of consolidating disparate data sets prior to analysis.

Whereas the Afghan opium example (Figures 9 and 10) shows both absolute values and trends that are similar, the Columbian cocaine data (Figure 11) shows trends that are similar, but absolute numbers that are not. This suggests a much larger measurement error and as such, the two Columbian cocaine data sets should not be combined, as the ability to measure quality and absolute numbers is lost.

CCDB data collection procedures for cocaine have continuously evolved since the inception of the Interagency Assessment of Cocaine Movement (IACM) in 1991. The CCDB, however, never formally incorporated many of the other independent data sources (UN, Colombian, Mexican, and U.S. Drug Enforcement Administration (DEA) data) needed to validate and assist in interpreting the CCDB data sets. More importantly, there has been no concerted effort to ensure systematic data collection, nor to control changes over time in the assignment of confidence levels to the CCDB data. For example, while the IACM includes confirmed drug seizures, it also includes events relating to unconfirmed reports of drug movements. Unconfirmed reports may be vague and even speculative, generating large period-to-period reporting variances in IACM data. The rules for assigning confidence levels to those data can be changed year-to-year making it hard to compare confidence levels over time. Assignment of high confidence to reports of one type (e.g., estimated shipping volumes) in one year and low confidence to the same type of data in the next year inhibits use of the data in temporal analyses.

IDA finds that an effective, event-driven database must insure the integrity of its separate data inputs by accounting for differences in collection methodology, measurements, etc., for each data set. The data collection methodology must be consistent within any given data set. Changing data sources, contributors, or other important collection features will affect the way events are characterized, measured, or otherwise recorded. Comparison across independent data sets allows the analyst to detect these changes. The difficulty for the CCDB-East is the lack of independent data sets with which to perform this validation.

3. Systematized data collection methods yield more reliable information.

Based on lessons learned from decades of operations in the WH, effective CN data collection and information sharing requires interagency participation and active, effective coordination. Coordination insures that needed and relevant information is being shared with analysts who seek it. There are several entities currently collecting drug data in Afghanistan, including the U.S. military, the DEA, and international partners in the International Security Assistance Force (ISAF). Although only the DEA is formally tasked with a CN mission, about 90% of drug event reporting used by DIA comes from military sources. IDA researchers also learned that ISAF personnel are making numerous

chance drug seizures during operations, but much of this data may not be provided to the U.S. CN community and its allies for security reasons. Similarly, U.S. Customs and Border Protection and U.S. Immigration and Customs Enforcement personnel have been collecting data on precursor chemicals—information that is eagerly sought by the rest of the CN community, but that remains unavailable to them because of a lack of coordination.¹⁴

Coordination of data collection can also facilitate the use of technical guidance to inform collection procedures. For example, this document emphasizes the importance of using lower reporting thresholds (1 kg versus 100 kg) that more accurately reflect the rate of market activity, since smaller quantities of drugs are most frequently trafficked in SWA. Consistently applied collection and reporting guidance also helps to systematize drug data collection by requiring that specific fields of information be included (for example, seizure geo-coordinates or event confidence levels).

It is difficult but possible to coordinate contributions of drug data from law enforcement (LE), military, and allied personnel in Afghanistan. Voluntary cooperation will be easier if a system is established to automatically ‘push’ data from interagency partners to a centralized database, rather than having database administrators ‘pull’ information from each partner, especially since partners will not always be aware of the specific data potentially available from other partners.

Current U.S. drug data collection efforts in SWA are still nascent and coordination of data collection is very important due to limited assets, platforms, personnel, and capabilities available in the region. If military resources are scaled back, reporting will be even more limited. However, even limited data may still be useful for analyses if it can be validated and a determination made regarding its quality.

B. What Processes Are Necessary?

In order to interpret data correctly, it is essential that the data be of the highest confidence and that they have been validated to ensure their accuracy. The following processes must be applied to ensure the quality of the data contained in the CCDB-East.

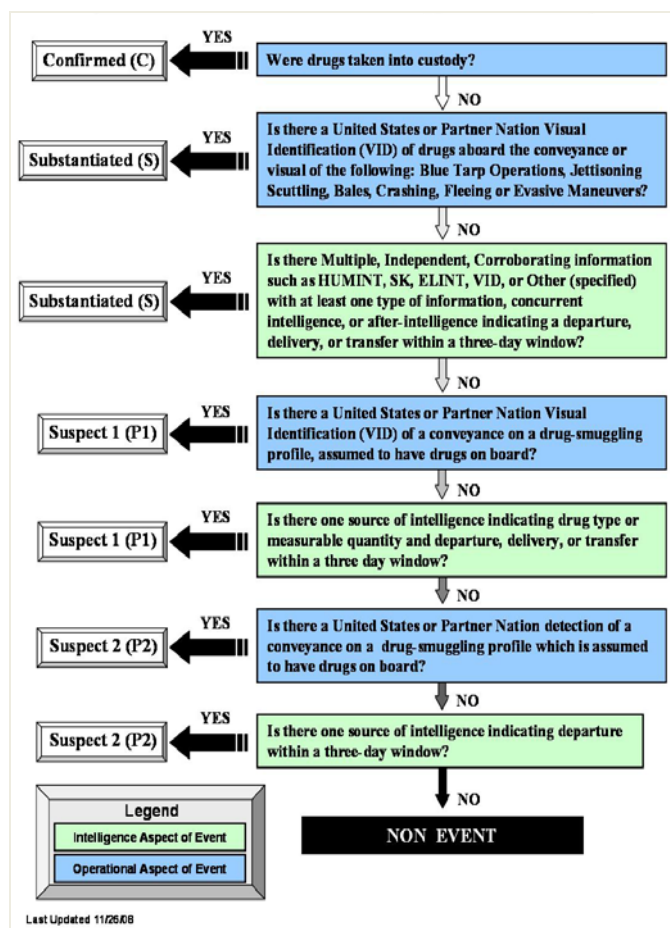
1. Event data should be categorized by confidence levels before analysis.

In observing the CCDB process, IDA found that one of its greatest strengths is its deliberative process to vet the assigned confidence levels of data in the database. Events are categorized into one of four confidence levels (previous iterations of the confidence-assigning process had three categories of confidence levels). Physical seizures are rated at

¹⁴ For more detail, see Crane et al., *Phase II Findings: Leveraging Lessons Learned to Inform Southwest Asia Counter-Drug Efforts*.

the highest level of confidence and are categorized as “Confirmed” or “C.” Events that cannot be confirmed by physical evidence, but have been either visibly observed or described by multiple, independent, and corroborating sources are categorized as “Substantiated” or “S.” Lastly suspected events assumed to involve illicit drugs—such as open-source press reports or single intelligence reports—in the CCDB are rated at the “Suspect” or, more recently, “1P” or “2P” levels of confidence (with 1P indicating a higher level of confidence than 2P). Earlier representations of the confidence levels had only one category for the “P” data contained in what is now 1P and 2P data.¹⁵ Figure 12 illustrates this confidence-ranking process.

¹⁵ Early analysis of P data suggested that it was only accurate about 5% to 10% of the time based upon quantitative comparisons. This type of analysis does not occur today.

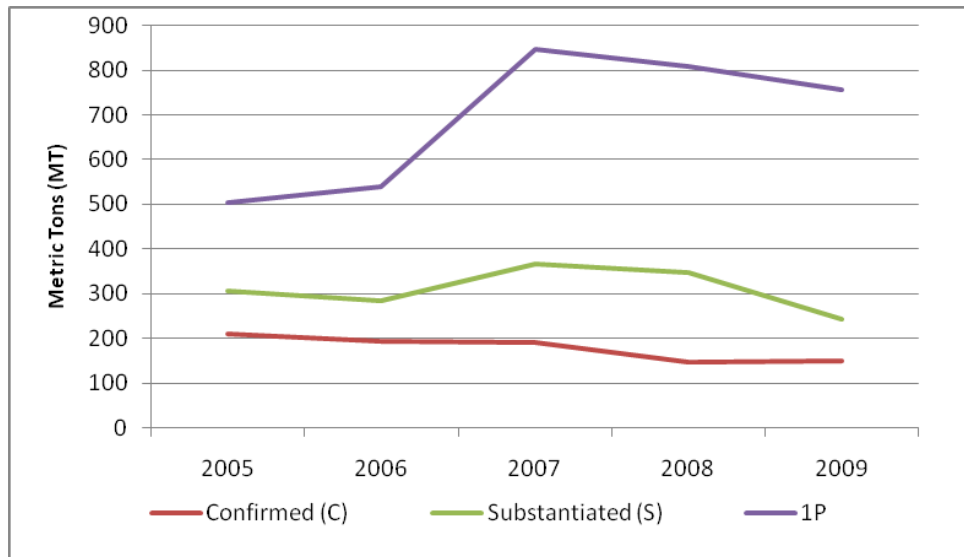


Source: CCDB User's Guide, Work in Progress, June 2010, 19¹⁶

Figure 12. CCDB Confidence Ranking Flow Chart

IDA finds that this practice of designating confidence levels is critical, since the use of P-level data, in some analyses, can drastically skew results and lead to erroneous conclusions. For example, Figure 13 shows reported cocaine movements based on Confirmed and Substantiated data (in red and green respectively) compared with the reported cocaine movement based on low-confidence P-level data (in purple).

¹⁶ The 1P and 2P data illustrated here are referred to collectively as "P data" in subsequent sections.



Source: IACM, 2010

Figure 13. Reported Cocaine Movements by Confidence Level

A significant discrepancy emerges from this chart, with the P data, and to a certain extent the S data, differing from the C data (particularly in the 2006–2007 and 2008–2009 time frames). Given this discrepancy, IDA recommends testing the P data as part of the validation process. This chapter presents several proven validation techniques to determine whether P data are consistent with other, higher-confidence data. If the P data is found to be inconsistent with other data sources (such as price or purity) then the unexplained behavior of the data should cast doubt on its utility for policy analysis. Ultimately its inclusion in official estimates, as it is currently presented in the quarterly IACM, may have the effect of inflating the total estimated quantity of cocaine movements and overestimating enemy capabilities.

Nevertheless, capturing P-level data in the CCDB is still a valuable practice that should be continued. Moreover, particular attention should be paid to P data that may be “promoted” to higher confidence levels when new data becomes available. Including all data, ranging from the most reliable to the least, allows analysts to use the data many ways. For example, some agencies rely on the highest quality data to drive resourcing decisions—including the allocation of their assets—but still value low-confidence data for context and for understanding the potential scope of trafficking activity. The ability to extract data of different confidence types for different analyses is a great strength of the CCDB.

2. Event data may be validated using time series plots.

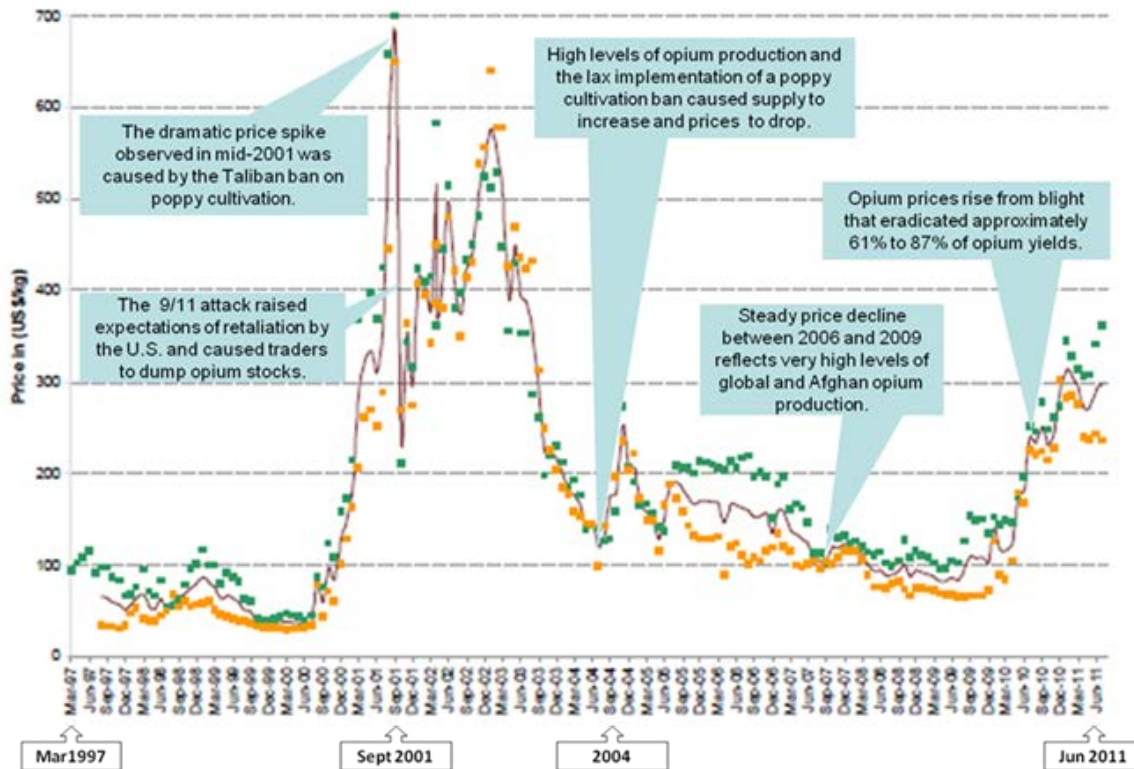
Time series plots are important validation tools to understand the drug market as a system because they allow analysts to compare different variables over time. When

linked together, time series comparisons show analysts how complex systems behave and respond to the CN campaign or other changes in the system's environment.¹⁷

For example, Figure 14 illustrates opium prices reported by traders in Kandahar and Nangarhar, Afghanistan between March 1997 and June 2011. In this case, the time series data show that opium prices are highly responsive to external shocks to the drug trafficking system and also to expectations of future supply. The dramatic price spike observed in mid-2001 was caused by the Taliban ban on poppy cultivation. Immediately following the September 11 attacks on the United States, Afghan traders dumped stocks of opium in expectation of retaliatory attacks. The drop-off shown during 2004 was caused by high levels of opium production and the lax implementation of a poppy cultivation ban previously announced by the Karzai government.¹⁸ As a result, supply increased and prices quickly dropped.

¹⁷ Ibid.

¹⁸ Pietschman, "Price-setting Behaviour," 119.



Source: UNODC *Opium Survey 2011*, 74

Note: Vertical axis: price of dry opium (\$/kg); horizontal axis: quarterly—1997–2011

Figure 14. Opium Prices Reported by Traders in Kandahar (Green) and Nangarhar (Orange)
Vertical

The steady but moderate price decline between 2006 and 2009 reflects very high levels of global and Afghan opium production at that time. The chart shows a turnaround in average prices in 2010 caused by a serious drop-off in opium supply resulting from a blight that eradicated approximately 61% to 87% of opium yields in disease-affected fields. Even though the same approximate number of hectares of poppy was cultivated in 2010 as in 2009, the blight—in addition to the effects of frost and drought—contributed to the ongoing increase in Afghan opium prices.¹⁹

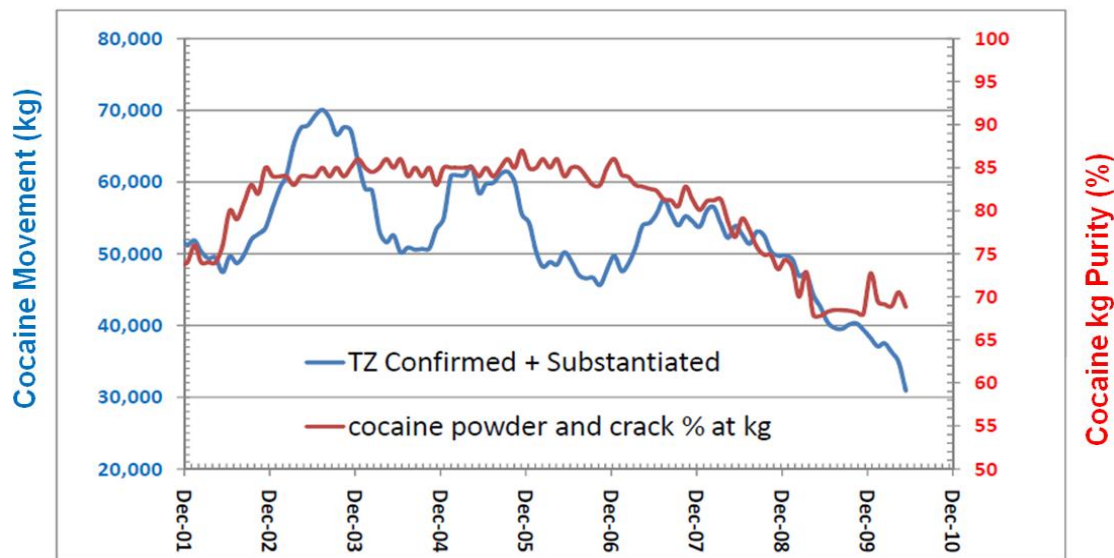
3. Event data may be validated using independent variables that are known to indirectly corroborate event data.

Validating drug event data by testing them against independent variables, such as price or purity, is a second useful technique. Since purity levels are known to correlate with actual flow estimates, purity levels over time should move consistently with estimates of flow. If not, this could reflect poor quality data, or have a more significant

¹⁹ UNODC, *Afghanistan Opium Survey 2010, Summary Findings*, September 2010, 2, 16, 22.

implication, such as the diversion of drugs or other developments that should be investigated further.

Figure 15 shows a comparison between the volume of U.S. cocaine movement (using only ‘Confirmed’ and ‘Substantiated’ data from the CCDB) and the general purity of cocaine (measured by the DEA). The blue line shows the higher confidence movements of cocaine while the red line shows the mean purity of the 1 kg seizures contained within a particular time interval (i.e., the quality of product being seized, either cocaine base or powder).



Source: CCDB and STRIDE databases

Note: TZ=Transit Zone

Figure 15. Cocaine Movement (as Reported by the CCDB) and Purity (as Measured by the DEA in the STRIDE Database) 2001–2010

This graph shows how, in general, purity levels track with the volume of cocaine being moved, assuming constant demand.²⁰ Interestingly, because this graph uses C and S data for movement—and demonstrates their validity by comparing them with purity data—one can infer inconsistencies in P-level data (see Figure 13, Reported Cocaine Movements by Confidence Level). Because 1P and 2P data (previously referred to as simply P data) are not consistent with C data (particularly between 2006 and 2008 where P data indicates an increasing trend while the C data indicates a declining trend) one could hypothesize that that P-level data does not generate an accurate depiction of cocaine movement. Moreover, as Figure 15 shows, purity levels in the 2008 time frame

²⁰ Spikes in the blue line correspond with various CN operations when additional seizures were made.

do not corroborate the P data, providing further evidence that P data are not accurate representations of real cocaine movements.

Purity is a valuable independent variable to use, not only because the DEA collects hard and reliable data on it (as opposed to estimates), but also because it facilitates a better description of seizures beyond quantities of unknown quality. Through its System to Retrieve Information from Drug Evidence (STRIDE) database, the DEA captures purity levels, prices, and other market data collected in the continental U.S. (CONUS) when undercover agents pose as consumers and/or resellers of illicit substances and purchase drugs. Thus, STRIDE is a particularly useful data source to validate CCDB data because it provides an additional independent variable.

4. Event data may be validated by comparing it with the underlying functional distributions (power laws).

IDA's research has identified one critical feature shared by most components of a drug system—their behavior is consistent with established statistical patterns known as power laws. A power law-like function is a mathematical relationship between two values where the frequency of an event (e.g., a drug seizure) varies as a power of an attribute of the event (e.g., the size of the drug seizure). That is to say, the frequency of drug trafficking events for smaller quantities of a drug is higher than the frequency of events for large quantities. While this is inherently intuitive, the “power” of power laws are that they capture, in a systematic way, the rate at which these incidences decrease over a great range. The slope that is generated when original scales are changed to log-log is a valuable finding for each data set.²¹

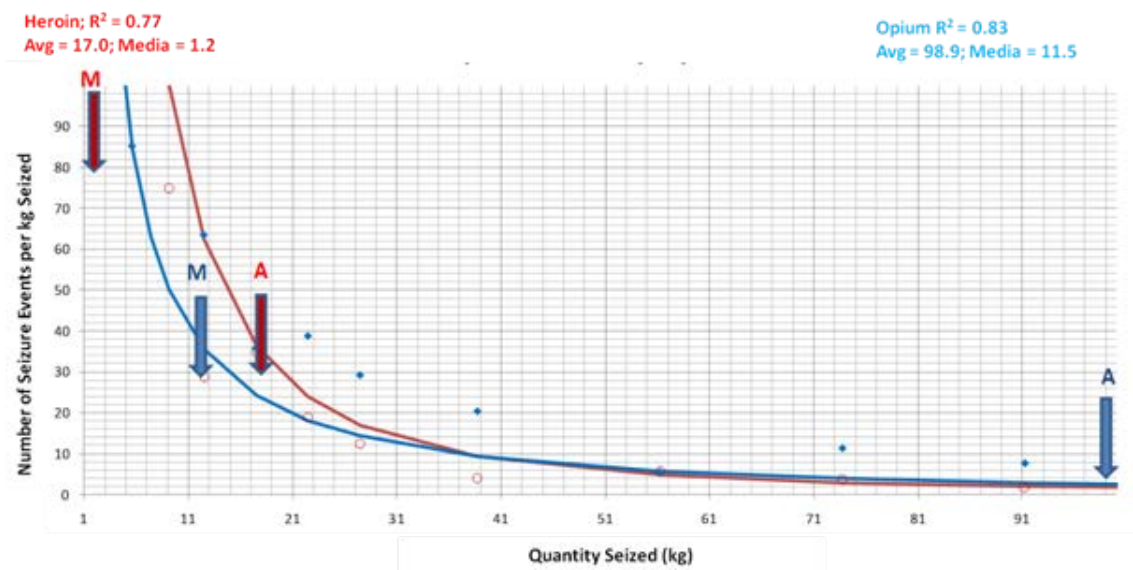
IDA analysts have established that these unambiguous distributions, or power laws, provide useful insights into illicit drug markets. They are ubiquitous across most types of drug data: transaction sizes, user rates, price ratios, time intervals between seizure events, and the likelihood that criminals will traffic drugs given a certain perceived likelihood of arrest.²² Further, the more rigorous the data collection procedures, the more likely the data set will follow the expected pattern. As such, power laws provide a valuable baseline against which to compare actual event data. Because the distribution of drug data is so consistent with power laws, event data inconsistent with a power law formulation could indicate potentially suspect or revealing information, such as a new trafficking behavior, missing information, or a flawed collection procedure. These types of anomalies should prompt analysts to conduct further research in order to account for these deviations.

²¹ The UNODC Director requested that IDA brief UNODC analysts on these emerging techniques in order to potentially improve the *World Drug Report*.

²² For more detail see Appendix B, “Analysis of the Cocaine Market.”

The use of power law distributions to validate opiate data was discussed during technical meetings among IDA staff, UN researchers, and the government sponsor. IDA presented analyses that showed that the UN's systematically collected data follow the functional distribution, whereas non-systematically collected data (e.g., chance data currently collected by the USG) do not.²³ This process of comparing a limited sample of data with a power law serves as an independent check of the quality of the data and, therefore, a valuable validation method.

Figures 16 and 17, based on UN data, illustrate the applicability and utility of power law representations. This is a small subset of the UN data, excerpted to show the means and medians.



Source: UNODC

Figure 16. Number of Binned Seizure Events per kg for Heroin and Opium and Corresponding Averages and Medians

Presenting the data in a graph makes it easier to visualize the statistical distribution of these seizures. In Figure 16, the seizure size data are partitioned into quantity bins (e.g., Bin = 1 to 50 kg), with the middle of each bin represented by a point in the graph. The total number of seizures recorded for each bin is divided by the nominal size (in kilograms) associated with that bin, and the resultant pairs of values (i.e., size and normalized counts) constitute the points displayed in the figure. Both the averages/means (A) and the medians (M) are shown. The order of magnitude between averages and medians shows a highly asymmetric distribution. The opium average of about 100 kg

²³ There also appears to be significant under sampling of the smaller values, which results in a distorted distribution.

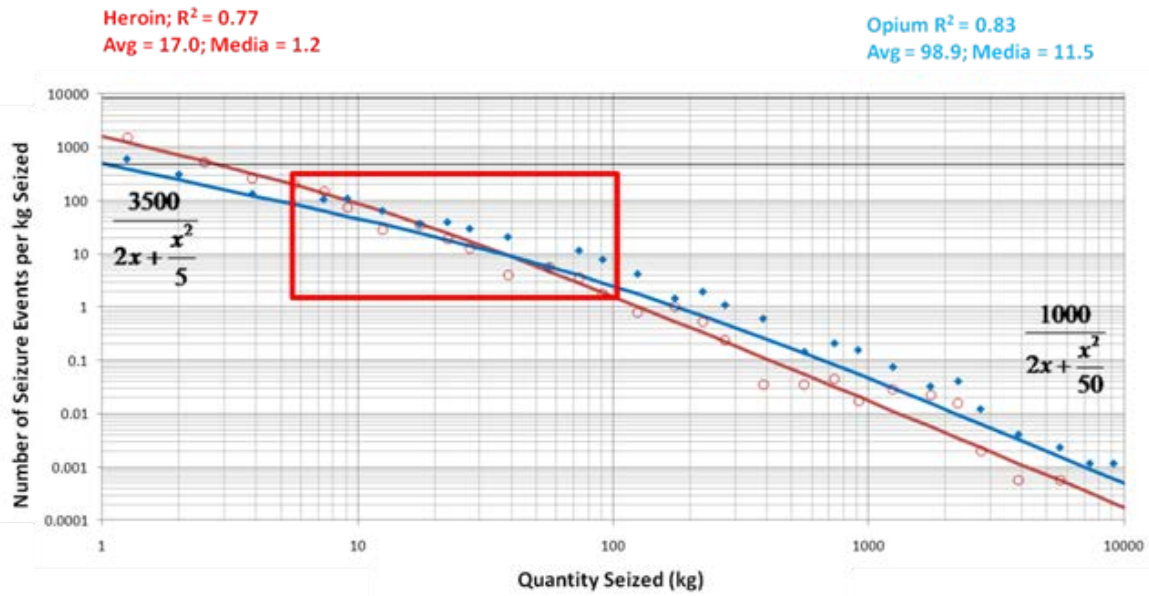
shows that a few very large seizures drive the average with most events involving smaller seizure quantities. Because the data are displayed on ordinal scales, the graph omits the many more extreme data points. The opium data scale maximum range is to 100 kg, where the underlying data set contains at least one reported seizure of about 10,000 kg.

When the sample averages and medians are as divergent as they are in Figure 17, interpreting and extrapolating the data to describe the seizure distribution would be ill-advised as it is almost always erroneous.²⁴ Fitting the data to a continuous power law function is illustrative of the remarkably robust and stable nature of these distributions (and the difficulties in evaluating them).²⁵

Figure 17 represents the same data set using logarithmic-scaled axes (log of the numbers versus the log of the quantities) to better visualize all of the data. The data are displayed in color-coded bins, with heroin containing approximately 128 events/kg per bin in red, and opium containing approximately 56 events/kg per bin in blue. The red box shows the same partial set of the data that was displayed in Figure 16. It shows a very few large seizures (one seizure of 10,000 kg is displayed on the vertical-axis as 0.0001), and several thousand small events (of 1 kg quantities.). The equations shown indicate similar power law structures (exponent of X^{-2} for the highest power in each denominator) for both opium and heroin seizures over a 10 year period and a vast range of data.

²⁴ This concept is explained in detail and put in context in Appendix A, “Models and Simulations.”

²⁵ It should be noted that the Y axis in Figure 18 (numbers of events per kilogram) has a large range of eight orders of magnitudes (10^8) while the X axis (quantity) has a range of four orders of magnitude (10^4).



Source: UNODC, 2011

Figure 17. UN Analyzed Heroin and Opium Binned Seizures (2000–2009)

This representation of the seizure data is illustrative and consistent with the equal risks for equal returns principle—that the data represent thousands of small traffickers moving small loads and getting smaller rewards while there are only a few traffickers moving large loads with potentially high rewards. However, ad hoc or open source reporting often (and in some cases intentionally limited reporting to limit the documentation burden) under-represents smaller quantities (1–100 kg) by many fold which distorts this distribution (as in Figure 8). As a result, it is harder to extract new information, such as a surrogate for price or other valuable information derived from seizures.

In response to IDA’s presentation of these emerging techniques, UN researchers have suggested that this distribution function be used to “fill in” the missing data from limited data sets to make better estimates from seizures of actual quantities. They concur that smaller quantities are likely under-reported, thus anchoring the distribution function at the high end.

IDA finds that the analysis generated by the CCDB-East will be of the highest possible quality if rigorous data validation techniques are applied. IDA asked statisticians in the UNODC’s Studies and Threat Analysis Section within the Policy Analysis and Research Branch to peer review this technique using power laws. In consultation with CENTCOM, the analysts agreed on the utility of these techniques and expressed interest in their continued application to SWA.

C. What Analytical Capabilities Are Necessary?

Because of the illicit nature of drug trafficking and the high-risk operational environment in SWA, it is not realistic to expect that large and highly detailed sets of drug event data can always be collected. Nonetheless, because there are established quantitative relationships among the different components of the illicit narcotics system, data it is not feasible to collect (e.g., opium prices) can be inferred from data that have been collected or observed (e.g., seizure quantities in a particular time period). The accuracy and utility of these techniques for generating “surrogate” data have been tested and validated in analyses of the Western Hemisphere illicit drug markets. Surrogate data are useful when they are extracted from systemically collected data sets that contain actual observations (not merely averages within a period) and that sample the entire relevant range (e.g., high volume and low volume shipments). Current USG data in SWA do not meet this criterion.

Figure 18 can be employed to illustrate the utility of surrogate data. The IDA study team used reports of opium seizures in specific periods (months) to estimate the opium price during that same period. The blue circles represent IDA’s estimated price—the surrogate data set. The IDA team then fitted a curve to those data points, generating the dark blue line in the figure. The red line records the average dry opium price reported by the UNODC. The UN’s use of average prices masks the variability in dry opium prices, which can be seen in the price estimates IDA generated from seizure data. The UN and the IDA lines are, however, highly correlated with nearly identical slopes. The surrogate data (price estimates generated from seizure reports) could be further validated by comparison to other characteristics of the drug market, which have established power-law mathematical relationships to one another.

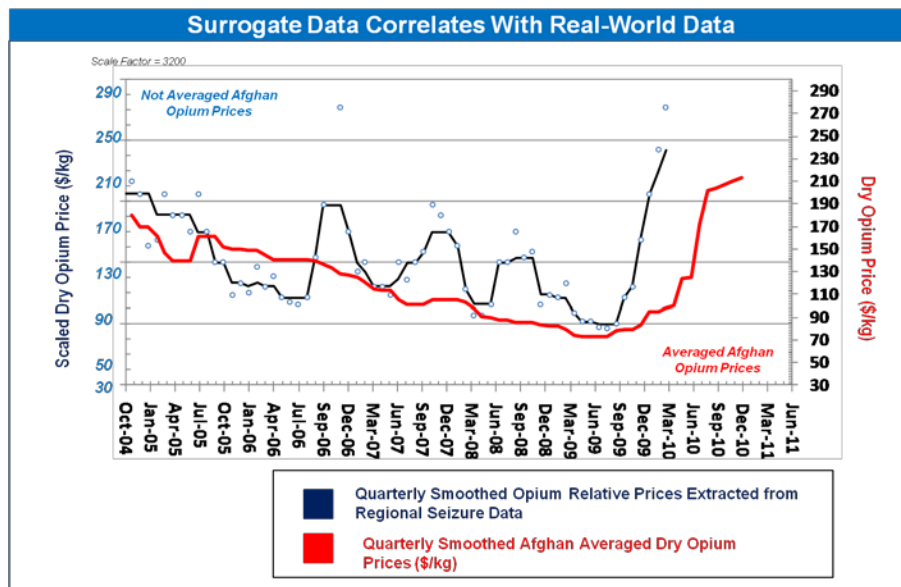


Figure 18. Surrogate Opium Price versus Real Opium Price

D. How Can Better Event Data be Used to Support U.S. Central Command's Programs?

1. Better event data can support CENTCOM's programs by mitigating some of the challenges associated with data limitations.

As demonstrated in the previous chapters, the major shortcoming associated with SWA opiate data is that it is extremely limited due to collection efforts that are neither methodical nor coordinated. Recognizing the added challenge of collecting accurate data on an inherently secretive and illicit market, the USG must rely on incomplete data sets for its analyses. The statistical techniques presented in this document offer a way to mitigate the impact of these data gaps by correcting erroneous assumptions, filling in numbers or events where data is missing, and extracting useful, but otherwise unknown, information from limited data sets. As a result, CENTCOM can now determine, with far greater accuracy, the actual scope of the heroin and opium trades in its and neighboring AORs. With more accurate data, CENTCOM can pinpoint with better precision when certain government policies and interventions actually begin to work.

For example, throughout the course of this study various interagency stakeholders identified specific data gaps where additional information could be extremely helpful. With additional research and testing, the techniques presented in this document can likely be used to provide insight into the following aspects of the opium and heroin trades:

a. Existence of stockpiles and the effect on prices

Based on the proven power law distributions of drug data, IDA researchers hypothesize that the sizes of opium stockpiles are overestimated. Currently existing stockpile estimates are calculated by subtracting missing amounts from the entire amount of opiates.²⁶ However, it is likely that many analysts used averaged samples to calculate the missing amounts. As demonstrated in this document, using averages rather than medians has the effect of significantly inflating the value being measured. In this case, the following could be overestimated: production (cultivation), seizures, or consumption rates. Ongoing price fluctuations in Afghan, Asian, and world markets for opium appear to confirm the finding that there are not large stockpiles of opium available to cushion price movements, and that there likely are not large or coordinated trafficking organizations that would draw on any existing stockpiles.

b. Precursor chemicals

It may be possible to extract information about drug purity from limited drug event data collected in SWA using the analytic methods presented here. Although Afghan personnel and DEA personnel in Afghanistan collect some information about drug purity, limited drug testing infrastructure and ongoing security issues make this data rare. Data on drug purity could indirectly provide information about the supply of precursor chemicals reaching Afghanistan and what affect counter-measures may have on availability.

c. Locations of drug labs

It is plausible that tracking price-like surrogate data extracted from limited seizure data could contribute to a better understanding of the location of drug labs. This is based on the assumption that the price changes as drugs move from production labs in SWA to their final destination in European markets. The surrogate data could not support a capacity to precisely target specific locations, but it could provide insight into the amount of production in a given region or where, in a general sense, numerous labs might exist.²⁷

²⁶ The UNODC estimates missing amounts by comparing flow volumes with consumption rates. The difference indicates the existence of stockpiles.

²⁷ Incidentally, the effectiveness of attacking drug labs depends on the threshold of effects, i.e., destroying enough labs to make an impact. Two IDA papers describe deterrence in detail: Barry D. Crane, *Deterrence Effects of Operation Frontier Shield*, IDA Paper P-3460 (Alexandria, VA: Institute for Defense Analyses, March 1999) and Robert W. Anthony, Barry D. Crane, Stephen F. Hanson, *Deterrence Effects of Peru's Force-down/Shoot-down Policy*, IDA Paper P-3472, (Alexandria, VA: Institute for Defense Analyses, April, 2000) Using the methods presented in this document, policy makers could plan and assess a campaign to eliminate drug labs in a given region, versus the current operational trial and error method.

d. Quantities and physical locations of seizures

Traditional methods of data analysis have not accounted for the inherent tendency to overestimate quantities extrapolated from small data samples. There is a wide difference between an average, or mean, value for seizure size, and the median. The methods presented here can provide more accurate analyses of drug quantities and can extract more value from drug data to characterize individual data sets and trends exhibited by time-sequenced data collections.

e. Intermediate drug prices within Afghanistan

The analytic methods used to extract additional information from drug data lead to better descriptions of the drug market than traditional methods. For example, this document demonstrates that Afghan drug prices appear correlated to price-like surrogate data for drugs in SWA. Better knowledge of intermediate prices can help analysts map and explain trafficking behavior in the Afghan market and evaluate the effectiveness of CN efforts.

2. CENTCOM can improve its knowledge of its adversaries, how they resource themselves, and how they operate based on perceived risk.

More fundamentally, IDA's research has suggested a fundamental finding regarding criminals' tolerance for risk-taking. Past IDA research demonstrated that drug traffickers, insurgents, and terrorists form similar organizational structures—loosely-connected webs of small, specialized cells, etc.²⁸ Illicit networks form organizational structures that allow them to operate asymmetrically and clandestinely against enemies of overwhelming size and resources. Key to the illicit network structure is the number of so-called “trusted agents” employed by the organization. If the organization employs too many, it is vulnerable to infiltration and enemy action. If it employs too few, operations will be difficult or impossible to execute.

IDA research indicates that most components of illicit drug networks assume risk at a similar rate. Similarly, IDA observed that this relationship holds for all levels of a drug market, from wholesaler to street-level dealer and among different geographic regions in the world.²⁹ Illicit trafficking organizations will take small risks for small returns because the perceived risk is low. Only a few take very big risks for large returns, because the perceived risk is very high. This risk-taking behavior is otherwise known as equal risks for equal returns. For example, small seizures of less than 1 kg amounts are far more frequent than seizures of a ton. Similarly, more traffickers traffic smaller amounts more

²⁸ R. Anthony and A. Fries, “Empirical Modelling of Narcotics Trafficking from Farm Gate to Street,” *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004): 7–8.

²⁹ *Ibid.*, 16.

frequently than very large amounts. Likewise, more users buy smaller amounts more often than users who buy large amounts. In other words, the rate of criminal behavior (i.e., the interval between events) is faster for smaller risks and slower for larger risks.

This distribution of rates appears to be a fundamental signature of irregular gangs, insurgents, traffickers, and any other illicit organizations avoiding detection by a state. Because these rates are linked across networks, analysts are able to construct drug market indices from the data. Time intervals between drug trafficking events (e.g., two-month intervals between one ton shipments) are observed to be a stable analytic indicator. Changes in the rate of trafficking incidents are consistent with changing levels of market activity. There can be many reasons for changes in market activity, such as bad crop yields, supply-chain disruptions, or increased LE seizures on the supply side or decreased drug consumption on the demand side. To resolve causal ambiguities, additional (demand side) data, such as positive drug testing rates, should be used to corroborate hypotheses developed from seizure data. In the underlying analytical products supporting formal UN publications, this process has been used repeatedly for the last ten years, but not in USG products since 2004.

The research presented in this document suggests that this risk-taking behavior is ubiquitous and applies not only to global criminal activities but also to insurgent forces—many of which are funded through the drug trade. This fact can assist CENTCOM in designing and evaluating counterinsurgency (COIN) strategies. Moreover, the methods presented here will foster greater efficiencies by making it possible for CENTCOM to: (1) improve the accuracy of drug data without expanding existing programs, (2) shorten the reaction time of U.S. government entities to changes in a drug market, and (3) measure and analyze the effects of CN programs.

3. Recommendations

1. Entries in the CCDB-East should be in the distribution of raw event data, not averaged estimates.

In order to apply the analytic methods described in this study, analysts must have access to raw, event-level data sets. Averaged values for any measurements of drug activity over a period of time (for example, average seizure size, average number of seizures made, average amount of drugs used in the past month, etc.) do not have the degree of granularity needed to model the drug market. The process of calculating an average value for a set of data hides critical information needed for understanding the system. It is important to also evaluate the median and compare it to the average, and even more important to examine the actual distribution of data.

2. Analysis from data contained in the CCDB-East should maintain the integrity of separate data sets.

While consolidated data sets may list the total number of events, they cannot show patterns in the seizure data or support detailed analysis of events. This is true because data sources that are combined into a single data set will distort the time-dependent information contained in each data point. There will invariably be differences in the collection methodologies of the two distinct data sets and losing critical time-dependent information will make relative measurements difficult. For this reason, it is critical that the CCDB-East and different data sources not be combined into one data set. If they are, then it must be possible to differentiate between each data source and compare and analyze them separately. Comparing different data sets allows analysts to see if they exhibit the same patterns using time series and non-CCDB data validation sets.

3. Formal coordination of the data collection processes should be implemented among the interagency and multinational partners.

Voluntary data collection and information sharing should be encouraged at all levels. An example would be making collection tools (e.g., drug testing equipment) available to personnel in return for data submissions. Collection procedures should be efficient and easy to follow. Care must be taken to ensure that interagency partners are not required to repeatedly enter the same data into multiple databases, which discourages voluntary compliance. Formal coordination of data collection among the interagency

partners will facilitate identifying data requirements, data sharing, and the systematic use of analytic methods to improve data quality, which improves efficiency and reduces costs.

4. CCDB-East should have a system for assigning and vetting event data confidence levels.

As the CCDB-East evolves, it will become critical to ensure that a process similar to the one that exists for the current CCDB, is in place for assigning and vetting confidence levels for each entry into the database. Considering the sporadic nature of data collection in SWA, where the vast majority of reports will likely be rated a “P” with only a few “C” and “S” reports, this function will be even more important.

5. Data in the CCDB-East should be compared with independent data sets that provide some validation potential.

Sufficient independent event data of high enough quality to generate dependable analyses and corroboration is not currently being collected by the USG, nor is it easy to collect, in SWA. Although additional, independent data to validate CCDB-East data are sparse, some data collected by the UNODC, such as consumption statistics, can be used for this purpose. As a result, IDA finds that data from the CCDB-East should be compared with additional independent data sources (such as price and consumption, which the *UNODC World Drug Report* attempts to assimilate) as well as any other event databases in the region, to provide context for the event data and some validation potential.³⁰ Where validation with independent data is impossible or insufficient, then validation using power laws may be used to test newly acquired data. This technique is described in the next recommendation.

6. Administrators of the CCDB-East should ensure the thorough technical validation of all event-level data to maximize the utility of limited data sets.

Event data contained in the CCDB-East must be validated for accuracy. This validation process is different from the existing process, which validates for consistency across event reporting, even when events may not be confirmed or substantiated. There are several advanced analytical methods that can be applied to event data to assess its quality, including analysis of comparable and independent time series data sets to see whether patterns exist (therefore increasing confidence in the data’s quality) or comparison with independent data sources, such as price and purity, to see whether they “tell the same story.” Power law distributions can serve as valuable tools to validate new

³⁰ Purity data would ideally provide an additional data source for validation purposes, but currently very little is known about the purity levels of SWA opiates. There are, however, proposals for the UN to fund several laboratories in the future to measure drug quality and purity.

and existing repositories of drug data, thus improving the quality of the data used to extract information. Because low-confidence data, including open-source data, are problematic, the use of analytic methods to correct for inaccuracies or bias can improve the overall understanding of the drug system. Power laws provide a way to independently check for missing data, new market conditions, or changes in collection procedures (when collection procedures are changed without recalibrating the data analysis, the data can no longer provide consistent relative results). Preliminary testing of the new statistical techniques presented here demonstrate a proof of principle, but additional testing is needed to standardize the methodology and make it fully operational. That said, the use of power laws over the last 15 years has resulted in more accurate estimates of trafficking conditions and the detection of hidden trafficking patterns. It has also allowed policy makers to assess the impact of government interventions, such as the demise of air and surface trafficking conveyances in the WH and the impact of the surge in Iraq.

7. CCDB-East administrators and data collectors should agree on minimal reporting thresholds that accurately sample the universe of drug trafficking events.

CCDB-East administrators and data collectors should agree on minimal reporting thresholds that accurately sample the universe of drug trafficking events. For example, if the majority of seizures of a given drug are in the range of one and five kilograms, reporting thresholds must be low enough to capture this information. Limiting data collection to seizures of hundreds of kilograms prevents the extraction of more detailed information.

8. CENTCOM should extract surrogate data where incomplete data sets exist.

Extracting and using surrogate or inferred data—calculated from directly observable data and used where the data desired for analysis does not exist—in lieu of incomplete data sets is a valuable method to make better estimates of the drug system. Moreover, this analytical technique can reveal previously unknown information. Although this analytical method works for systematically-collected UN data, surrogate data cannot be derived from the chance data that is currently contained in the CCDB-East. As such, the CCDB-East should exploit UN data to the fullest extent while systematic data collection procedures are established.

4. Conclusions

During the course of this research, IDA examined issues related to data availability, collection, and analysis for opiates in SWA. Researchers first studied the CCDB and observed the associated process for evaluating seizure events in the WH. This provided the context for understanding USG drug data collection efforts in SWA. Next, technical experts examined drug event databases shared by the UNODC and the DIA to learn how analyses of drug data can be improved, particularly in SWA, especially in Afghanistan where there is limited data collection capacity.

A critical observation from this study is the starkly different operating environment for CN programs in SWA when compared to those in the WH. U.S. forces do not have the Detection and Monitoring (D&M) assets, capabilities or collection platforms in SWA that have accrued over decades in the WH. A more fundamental challenge is that very little reliable information about drug seizures is available. The U.S. military and ISAF personnel currently operating in Afghanistan have limited involvement in CN operations—mainly providing security to Afghan and U.S. law enforcement personnel who perform CN functions. Although the DEA and vetted Afghan units are actively performing CN missions, their ability to carry out robust and thorough data collection is constrained by limited resources (personnel and equipment) and even more by the high-risk security environment in Afghanistan.

As a result, the majority of event data reported by the U.S. military and allied partners originates from chance seizures.³¹ These data are used to generate estimates of regional drug trafficking activity. IDA research suggests that the standard interpretation of USG data significantly overestimates the threat. Moreover, the use of averages (rather than medians) creates large errors that make it difficult to assess the success of USG interventions. One way to mitigate this challenge is to place more emphasis on opium data (versus heroin data) which is proven to be a better indicator due to its greater sensitivity to enforcement actions.³² In addition, the USG could benefit greatly from analytic methods that add value to existing drug data. As troop levels draw down and these reporting streams decline, these analytic methods will become even more important

³¹ As stated above, *chance* drug seizures refer to drug seizures made during a military operation that was not planned or intended to be a CN operation.

³² See Pietschman, “Price-setting Behaviour,” 105.

to understand and implement. The ability to extract valuable information from limited sets of drug data without assigning additional personnel or other assets to create more robust data collection efforts is critically important in the context of the resource-constrained operating environment in SWA. Streamlining CN operations could develop more efficient strategies and programs that can be effectively measured and analyzed.

This task was built on many of the foundational principles provided by decades of previous IDA research focused on the cocaine market in the WH, specifically the consistent patterns of drug trafficking behavior that result in power law distributions.³³ A power law distribution of drug event data can be observed for numerous characteristics of a drug market, including trafficker behavior (equal risks for equal returns), size of drug seizures, and quantity of drugs used, among other things. But until now researchers had not yet explored the applicability of this pattern to opiate data in SWA.

Most importantly, IDA has developed techniques for extracting valuable information from limited data sets, such as estimates of price data where actual data does not exist. This value is known as a price-like surrogate and when compared to real-world opium price data collected by the UN, IDA observed consistency in overall trends, thus validating the use of the surrogate. These analytic methods are evolving techniques and will benefit from additional testing, but initial results seem to indicate that a systematically collected set of seizure data can, in some circumstances, be used to derive a price-like surrogate value for drug prices—a highly valuable piece of information for measuring drug market trends in Afghanistan. For example, a price-like surrogate may help analysts identify regions where drug supply seems high (and price low), potentially indicating the presence of drug labs or possibly stockpiles. Analysts may also use the data to discern previously unknown trafficking routes, where drug prices rise as drugs are passed from buyers to sellers from the source zone to consumer markets. A similar approach (requiring additional study and testing) may enable analysts to extract information about drug purity from event data (test results using cocaine data suggest this is possible) and thus derive knowledge about the availability of precursor chemicals.

In order to maximize the utility of CN data, the USG must adopt the following measures:

- Use raw (not averaged) data sets and keep data sources separate
 - Construct distributions based on events per kilogram versus summarized quantities
 - Calculate rates of trafficking by parsing the larger distribution into smaller desired time blocks

³³ See Appendix B, “Analysis of the Cocaine Market.”

- Employ systematized data collection methods and ensure data is collected across the spectrum of event sizes (small as well as large events)
 - Compare USG with UN data (or data proven to be consistent with the underlying functional power law distribution) to determine an estimate of measurement error
 - Use the comparison to provide a basis for estimating corrections for the USG data
 - Develop a correction protocol for USG data that overcomes the bias associated with under-sampling small seizures missing from chance data
- Categorize event data by confidence levels and validate it using time series plots, comparison with independent variables, and underlying power law functional distributions

If adopted, these new analytic methods being developed by IDA researchers could provide cost savings to Department of Defense (DOD) by making it possible to extract otherwise unavailable but valuable information from existing data and to validate available data sets. When the analytic method becomes fully operational, it will be possible to “do more with less” without committing additional resources to data collection efforts.

Appendix A

Models and Simulations

Terrorist and Criminal Behaviors Learned from Countering Drug Systems

Since the mid-1990s the Institute for Defense Analyses (IDA) has conducted research on irregular adversaries: criminal drug enterprises (producers, cultivators, traffickers, dealers, and users) and, more recently, insurgents, terrorists, and their sympathizers. The basic characteristic of these organizations is that they are small groups engaging a larger and more powerful state or group that is attempting to eliminate their illicit behaviors through enforcement actions. IDA research has focused on advanced statistical methods to quantify and ultimately test these behaviors, and has found that consistent patterns of behavior characterized by *power laws* can allow analysts to estimate the consequences of enforcement actions and other aspects of the drug system (to include supply, demand, consumption, and volumes of drugs trafficked, among others).

One of the fundamental principles of these analyses is that the risk traffickers and criminals are willing to take is proportional to their expected return. This is known as the *equal risk for equal returns* principle.¹ Moreover, if these groups try to organize into a larger organization, then the capture of one individual may lead to an action against all. If the group is too small, then it is not very competitive with other similar organizations. As a result, the size of a criminal organization most often depends on the severity of the enforcement penalty, which is, in turn, a factor of the commodity type (the more dangerous and valuable the commodity, the greater the risk in trafficking that commodity).² A second observation regarding irregular organizations is that size of an organization appears to be inversely proportional to the risks taken and effective actions taken against the organization depend on risk dependent thresholds.³ Below the threshold

¹ These concepts and observations were first made to the UNODC on Afghanistan as UN personnel left Afghanistan after the attacks of September 11th, 2001: A. Rex Rivolo, "Structural Dynamics of the Cocaine Market," IDA Joint Meeting with UNODC, September 20, 2001, Vienna.

² Thomas Pietschmann, "Price-setting Behaviour in the Heroin Market," *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004):106.

³ Risk dependent thresholds were observed when the small adversary units parse risk, the more severe the risk, the lower the threshold and the smaller the organizational core. Thresholds were determined from repeated observations of criminal, trafficking, and combat activities.

the organization slowly improves its ability to evade detection, above the threshold there is rapid decline. This behavior was also observed to be true for insurgent networks (where the combat insurgent groups were relatively small because the kinetic penalty is severe) and for their larger support networks (where the enforcement penalty for arrest and criminal conviction is less severe).⁴ Finally, it was observed that the organizational structures developed to mitigate risk were almost universal⁵ and ubiquitous in nature.

This equal risks for equal returns principle means that power laws—i.e., that more criminals take smaller risk for smaller return while a few take larger risks for larger returns—exist in many aspects of the drug trade and insurgent behavior. This analytical observation has many practical applications that are critical for policy makers and operational commanders: revising drug stockpile estimates to realistic levels, calculating more accurate flow and use estimates, determining successful operational outcomes, and most importantly, making terrorist denial and deception tactics to avoid detection far more difficult. In particular, when irregular forces and drug traffickers are deterred the effect has been observed to be inversely proportional to the intervention technique.

The mass distribution of an illicit substance among market participants is observed to follow a power law-like distribution with smaller events occurring more frequently than larger events.⁶ In licit economies distributions of wealth obey similar power laws, such as the median prices of homes.⁷ Correspondingly, indicators of wealth in both research and popular publications have exclusively relied on percentiles such the fiftieth percentile, also known as median, or upper and lower first, fifth or tenth, etc. as wealth distribution descriptors, as opposed to the mean or average. It is understood that the mean has little descriptive value for these situations because the means of most power law distributions do not converge, even with very large sample sizes.⁸ As a consequence, if different subsets of a power law-distributed population are selected (e.g., monthly compilations), the calculated sample mean for each subset will likely differ greatly.

⁴ Observed and demonstrated by A. Rex Rivolo, as a member of a special advisory team to the Third U.S. Corps, Iraq, during surge operations after reviewing published papers by Professor Neil F. Johnson.

⁵ A. Rex Rivolo, “Structural Dynamics of the Cocaine Market,” IDA Joint Meeting with UNODC, September 20, 2001, Vienna.

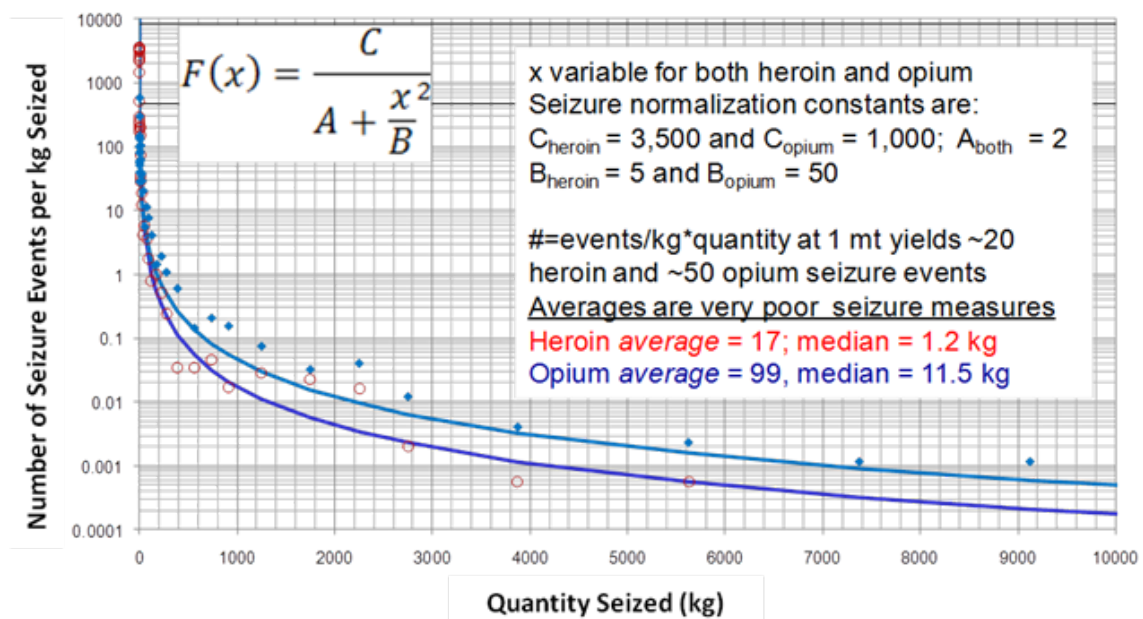
⁶ Cauchy-like is a more technically accurate description of this distribution, but for understandability the more commonly understood power law analytic distribution is used.

⁷ This feature is also characterized as following a Pareto power law distribution.

⁸ The mean is non-convergent for power law distributions with a power law exponent (shape parameter) of less than two. For shape parameter values between two and three, although theoretically convergent, it does so very slowly. A large number of sample points are required to achieve even modest convergence.

This appendix examines the analytical difficulties of interpreting the power law-like data that underpins the behavior of drug traffickers, terrorists, and insurgents in order to process it into valuable information. Estimating informative quantities from these distributions requires more than using simple averages and sums. Sampling small portions of the data may produce randomly varying averages that are very poor estimators. Averages, small summed quantities, and other important attributes cannot be simply computed without recognizing the extreme nature of these asymmetric distributions. Averages may be many times greater than medians, which are convergent statistics. Small samples of asymmetric distributions will produce highly variable estimates that tend to skew reported results in favor of the traffickers, insurgents, or criminals.

Figure A-1 shows the functional distributions of systematically and carefully collected United Nations (UN) opium and heroin data binned into equal-sized collections of 100 data points. The presentation was sized to include both the averages and medians, but not all the data was included since many larger values are further out on the horizontal axis. Averages were repeatedly observed in many cases to be very poor representations of useful information from the data because the averages are heavily influenced by a very few large seizure events. Medians are more accurate since these values represent the fiftieth percentile and do not overestimate the typical quantities seized.



Source: UNODC

Figure A-1. Number of Seizure Events per kg of Opium and Heroin

The opium and heroin data generate very robust and stable power law models (distribution or functional shape distribution x^{-2}). Knowing the stable model distributions allows extraction of more valuable information than monthly averages that would be better described by the distribution function. This is an important use of the data because it allows analysts to accomplish several objectives. First, they can validate and test newly acquired data. A new data source, such as a new UN reporting country, can reveal previously hidden patterns of trafficking or reveal changes in risk-taking and drug trafficking organizational operations. Secondly, analysts can test the effectiveness of operations with updated data. Trafficking that is declining very slowly is observed⁹ to be below the threshold in seizures, arrests, or kinetic interventions, while rapid drops in seizures suggest that an above the threshold, efficient, and effective enforcement operation may be taking place. Moreover, operations can be tested on a small-scale and at reasonable costs to determine whether a policy or tactic works. Lastly, analysts can improve their ability to measure the success of operations. Monthly averages will tend to exaggerate enemy or trafficking performance. Once more accurate estimates are made, policy makers can measure enemy performance with greater accuracy. These models guided Western Hemisphere operations to defeat cocaine trafficking by reducing user testing rates more than 80% and supply availability by 75%.

Figure A-2 compares the UN data collected over ten years ending in 2010 with the United States Government (USG) data on heroin and opium. It illustrates the significant difference between the UN's opium¹⁰ event data (2,606 total events) and the USG's *chance* data (295 total events). Chance data refers to drug seizures made during a military operation that was not planned or intended to be a CN operation. Due to limited collection assets, capabilities, or systematic data collection procedures and only three years of collection ending in 2010, most USG event data falls into this category. Logarithmic-scaled axes are used (log of the events and the log of the quantities) to show the extraordinary range of all data quantities and the stability of the seizure distributions. (It should be noted that the log-log display enables the display across an enormous value range while continuing to make visible the concentration of data at one end of the scale.)

⁹ Barry D. Crane, *Deterrence Effects of Operation Frontier Shield*, IDA Paper P-3460 (Alexandria VA: Institute for Defense Analyses, 1997).

¹⁰ Opium data was used over heroin data due to its greater sensitivity to enforcement actions. See Pietschman, "Price-setting Behaviour," 105.

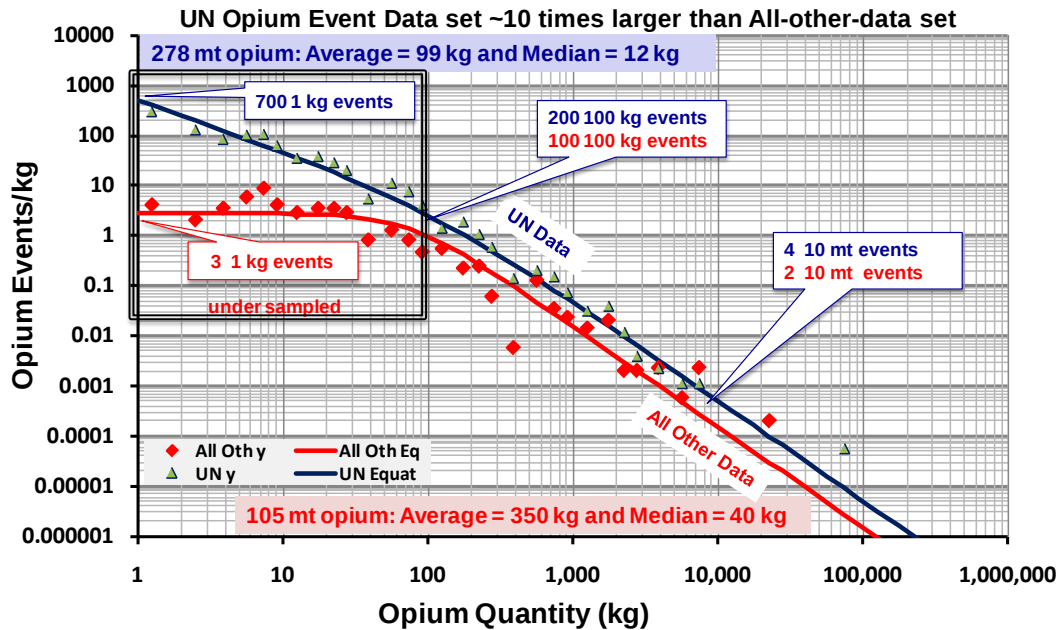


Figure A-2. A Comparison of UN Opium and USG Event Data

Different distributions stemming from different collection methodologies have critical implications for the calculated averages and medians, and result in a sampling bias. Because UN data is collected in a systematic fashion, a proportionate number of events are collected at both the low and high ends of the distribution curve. In contrast, USG chance data significantly under samples the low end of the distribution curve (small events). This is why the two curves are consistent with each other for seizures greater than 100 kg but there is significant deviation for events less than 100 kg (see the box in Figure A-2). In other words, the UN data consistently shows two times as many events recorded for events larger than 100 kg while it has approximately 230 times as many events recorded for 1 kg events. (see call-out boxes in Figure A-2).

Figure A-3 shows how the known power law distribution derived from the UN data set can be used as a validation tool to assess the value of USG data in evaluating investments. The dashed line shows the approximate trajectory that USG data *should* follow before it can be used to assess the performance of Department of Defense (DOD) investments.

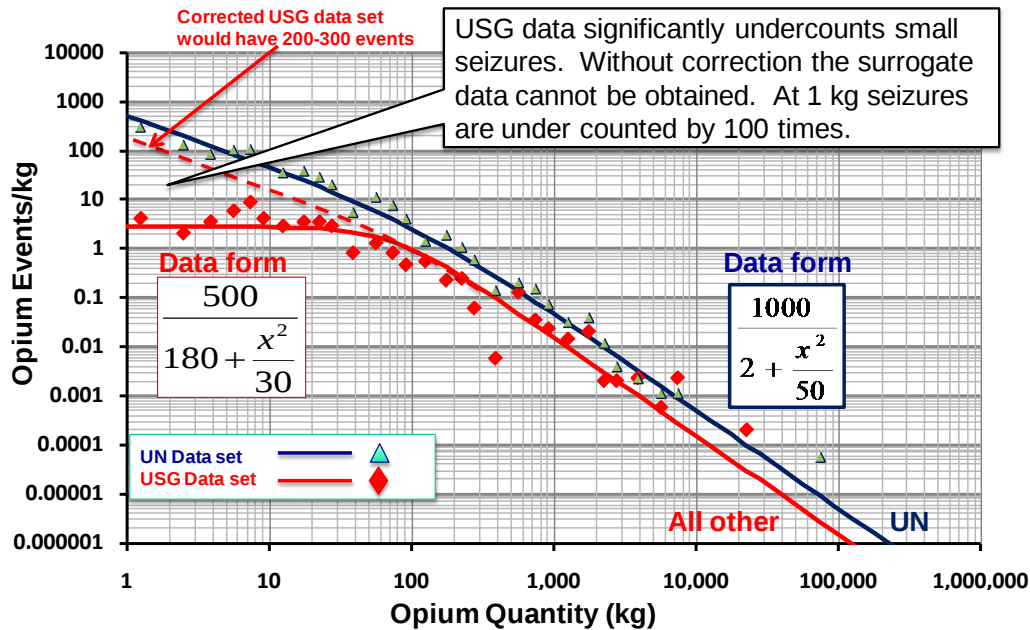


Figure A-3. Correcting USG Data

This format also allows analysts to examine the rates of seizures or trafficking of various quantities. Figure A-3 illustrates that high-risk events (involving larger quantities) occur at a slower rate while low risk events (involving smaller quantities) occur at a much faster rate. This is consistent with the principle of equal risks for equal returns. However, this is only observable from the UN data, providing further evidence that USG data under samples small, low-risk events.

Constructing Surrogate Data from Well Behaved Power Law Data

Surrogate price data can be extracted from the UN's seizure data because it appropriately samples all seizure sizes. USG data does not include the majority of small seizure events, thus invalidating this technique. Ultimately, surrogate price data provides the relative changes between two values, therefore a scaling factor needs to be applied to anchor it to a realistic price. New analytic methods can be applied to well behaved data that sufficiently sample the entire range of seizure quantities. IDA has tested and validated this process with USG cocaine data. However, when this method was applied to the Southwest Asia (SWA) data (from both the UN and USG), only the UN data yielded accurate results that could be used as surrogate data.

Preliminary technical analysis of UN data for SWA opium seizures supports the finding that surrogate price-like data are approximate representations of real-world price data. Figure A-3 demonstrates why only UN surrogate data for estimating SWA opium price, extracted from seizure data, basically correlates with real Afghan opium prices. (regional and Afghan prices would be expected to move in tandem over time.) The

surrogate data could also be validated by comparing them to other characteristics of the drug market (for example, earlier 2000–2003 regional price data reported by the UN also verified the surrogate process) to see that they conform to the expected power law distributions of drug data.

Difficulties in Representing Sequential Monthly Small Samples

In order to create and test statistical techniques that will assist analysts in extracting valuable information from these data sets, one must first understand the nature of this data. Although this data almost universally exhibits features consistent with power laws (similar to heroin and opium data), the sampling methods used may have significant implications when calculating estimates. For example, although monthly averages are commonly used, they are highly variable, which makes it difficult to transform the data into useful information.

Using the Median Over the Mean¹¹

Conventional analyses of average monthly seizures of illicit substances by law enforcement (LE) agencies generally consider the total weight of the seizures over a fixed period of time. Variations over different times were assumed to result from changes in production, trafficking rate, and market conditions. Analysis of seizure data shows that the sum of seized quantities over a sampling period is a metric that is a poorly converging indicator of the illicit drug economy. The use of the median significantly decreases the variation and improves estimates of relative changes in seizure rates. The median is a better converging metric.

A very large number of seizures (perhaps as many as half) may be required to improve estimates to within 10% of actual values or, in some cases, they may remain non-convergent. No accurate estimate may be possible in some cases even with large quantities of seizures within the evaluation period. In many irregular war and trafficking situations, the database is highly unlikely to contain more than a small fraction of the true data. If so, the techniques presented here may be the only way to make a useful estimate.

Many of these analyses are non-intuitive because most common analyses use a finite sample of a larger population derived from a sub-period of time (monthly average) that assumes that the sampled average and quantity describe some (known or reasonably inferred) portion of the true trafficked quantities. A quickly converging metric of the

¹¹ Annex A, B, and C of R. Anthony and A. Fries, “Empirical Modelling of Narcotics Trafficking from Farm Gate to Street,” in *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2, (2004) show different methods of analyzing and obtaining valid market information when the distributions are as asymmetric and heavy tailed as these. The construction of a median index by using randomized percentiles appears to be superior to most other techniques.

illicit drug sample economy can be shown to consist of the total *count* of seizures within the same fixed time intervals.¹² Monte Carlo simulations¹³ were conducted to demonstrate that this metric achieves significant precision within hundreds of samples (versus thousands). The simulation uses a known distribution to calibrate the analyses, but uses estimates from the randomly extracted data to show the approximate estimation error from small samples of the distribution. Small samples create additional analysis problems by overestimating the true values of these asymmetric distributions.

In order to more easily visualize and understand the underlying, bounded, distribution, a Monte Carlo simulation was applied to test different sampled percentages. Random draws consisting of 2,500 samples each were summed to form a plot that shows the distribution as nearly normal in shape with a distribution mode near 10,000. Subsequent simulations were repeated with different sample sizes (e.g., 250 for 10% or 25 for 1%) to assess the effect of small samples. After the different percentages were obtained, each sample was scaled to a size comparable to the original distribution in order to more clearly show the sampling effect.

Figure A-4 shows how the average (the red arrow, computed from the raw sample of the Monte Carlo simulation) steadily increases as the sample size decreases. In this series of charts, the blue line is the median, i.e., where there are an equal number of events on either side of the middle value (fiftieth percentile). The red arrow is the sample average and the peak is the mode.¹⁴ Comparing the top and bottom simulations (representing a 100% and 1% sample size, respectively) shows how divergent the two means are and, therefore, why the use of averages is not a good estimator of the system (all are the same scale).

¹² In Barry D. Crane, A. Rex Rivolo, and Gary C. Comfort, *An Empirical Examination of Counterdrug Interdiction Program Effectiveness*, IDA Paper P-3219 (Alexandria, VA: Institute for Defense Analyses, 1997), the detailed construction of a median index is described to maximize the extracted information content from difficult data.

¹³ A Monte Carlo simulation is a type of computational simulation that relies on repeated random sampling to compute results.

¹⁴ Crane, Rivolo, and Comfort, *An Empirical Examination*. This paper was the first to document how in unknown (especially power law-like) distributions only the medians might converge. Testing these analyses over ten years confirms the practical use of these techniques.

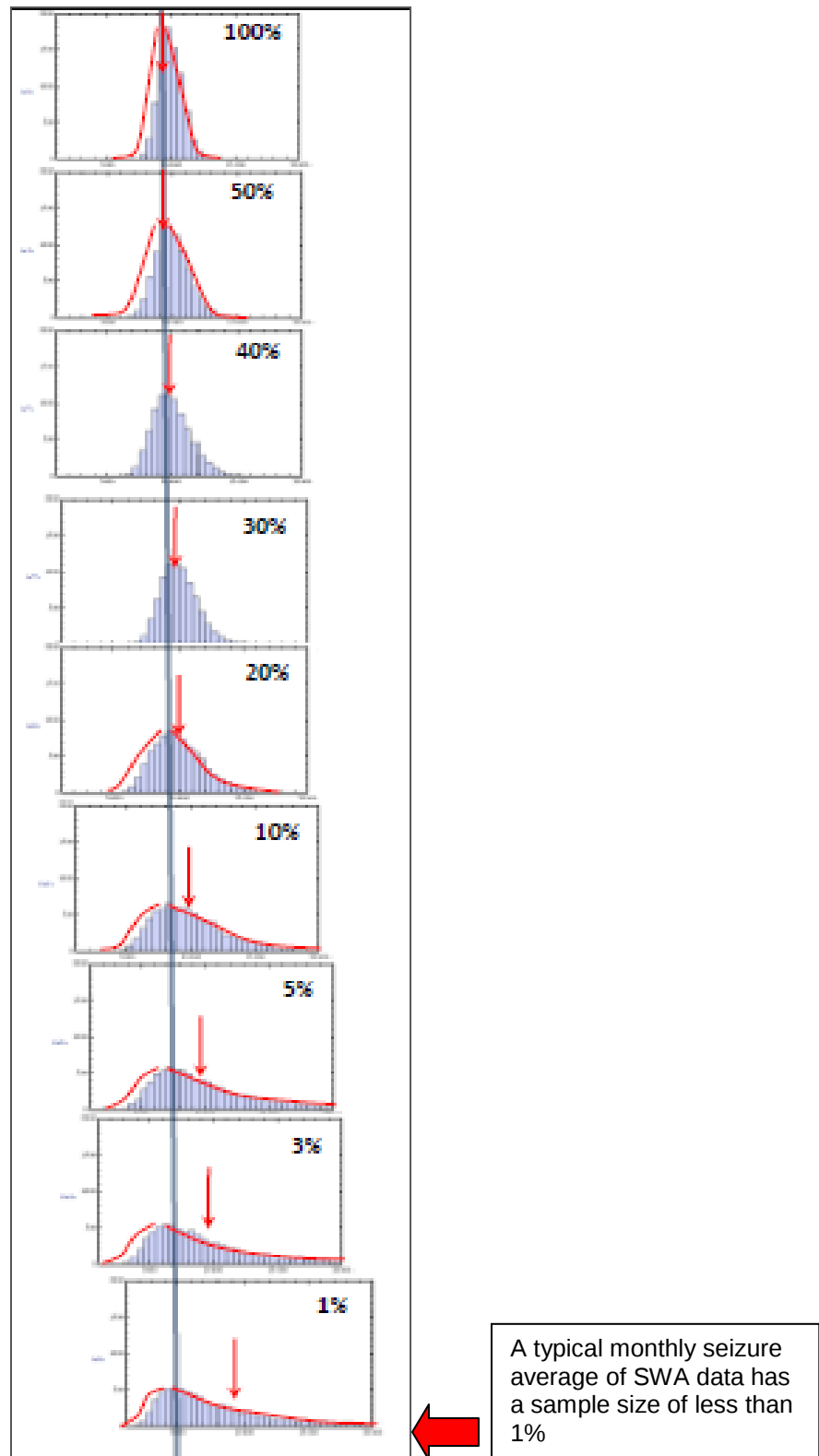


Figure A-4. Monte Carlo Simulations of Progressively Smaller Sample Sizes and the Corresponding Overestimation of Averages

Figure A-5 uses actual operational data from attacks on an Iraqi airbase to show that IDA techniques have a much broader application than drug data (a more detailed explanation is presented in Appendix C). It shows that averages (100 attack events—blue dots) appear not to converge when the number of attacks decline to small values (where the largest differences occur) of the total distribution and the intervals between attacks grow larger from a successful defense. When the number of attacks declined by approximately 75%, the average difference grew as the sampling became smaller; and it is obvious that the random variation of average attack intervals is unpredictable from negative excursions of -30% to positive excursions greater than +150%.

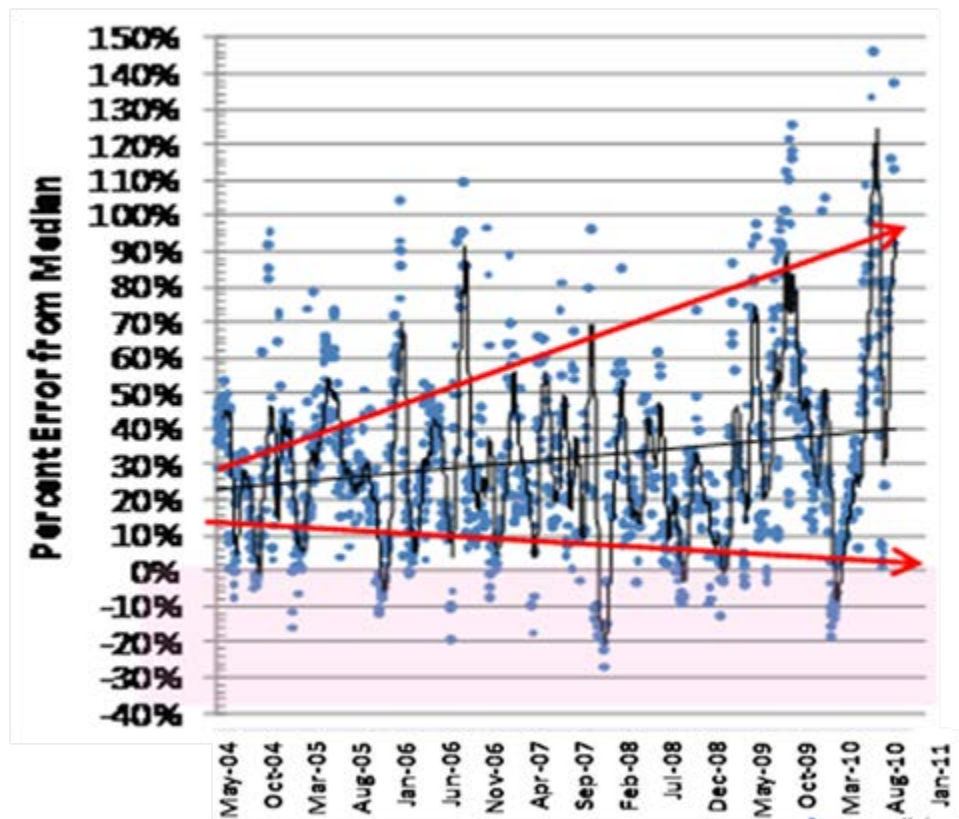


Figure A-5. Random Average Fluctuations in Attack Intervals over Five Years with Increasing Differences as illustrated by the Red Arrows

This example shows how the use of averages is unpredictable and does not help Commanders assess when their interventions are successful. The median is a much more precise and practical estimate to help determine when tactics are effective. As in Iraq, this concept can be applied to sparse SWA data to determine the success of very large DOD investments in security.

Impact of Threshold Effects in Evaluating Performance

Besides determining the analytical power law distributions, it is also necessary to determine thresholds for effective actions. The thresholds have been observed repeatedly with respect to insurgents and traffickers. Figure A-6 shows typical characteristics of traffickers or insurgents learning from insufficient interventions. When critical thresholds are reached, insurgent and trafficking activities decline abruptly.¹⁵ Threshold determination from real data requires estimation of unknown parameters. Although this process is demonstrated in the analysis of the battle for Iraq, the study uses various well known drug data and other activities to illustrate the underlying principles.¹⁶ Since irregular adversaries learn from USG operations, they can improve their methods—in economics this is known as a “progress curve.” Deterrence is vitally important because it greatly improves the efficiency of intervention operations. Panama Express and Joint Interagency Task Force South operations achieved a four-fold improvement in performance with no additional resources or costs. Figure A-6 provides a simple illustration of progress and deterrence.

¹⁵ Drug trafficking declines were observed from the above threshold operations: in air trafficking in Peru and the Caribbean Sea, the decline of go-fast trafficking through the Caribbean, the defense of Puerto Rico, and finally, the 70% decline in cocaine flow through Mexico are all examples. In combat operations, detailed tactical deterrence was observed at checkpoints, in many different specific counter tactics, in the defense at Joint Base Balad, and in overall insurgent activities in Iraq.

¹⁶ Joseph A. Milner and Barry D. Crane, *Integrated Defense: Lessons Learned from Joint Base Balad*, IDA Document NS D-4372 (Alexandria, VA: Institute for Defense Analyses, August 2011).

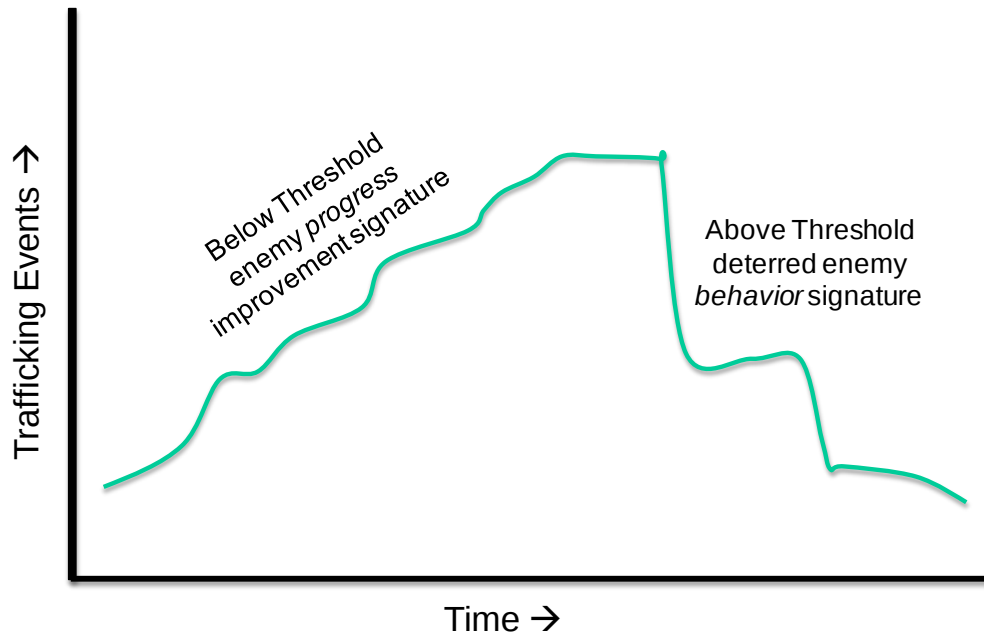


Figure A-6. Typical Observed Behavior of the Onset of Deterrence from “Enemy/Trafficker” Operations

The implication of this research is that counter-trafficking operations should be conducted with sufficient enforcement actions to modify insurgents’ and traffickers’ behaviors by exceeding the risk return curves, i.e., to *deter* them.¹⁷ This effect is determined by thresholds: below the threshold the adversary learns from enforcement operations, above the threshold some begin to be deterred.

The following discussion of deterrence is paraphrased from original IDA research that is still valid.¹⁸ When irregular forces and traffickers are deterred, they are repeatedly observed to respond inversely to an intervention (power law exponent -1) making analyses difficult. The functions described here were derived directly from observations alone and not any network theory, game theory, or other kind of underlying process.

IDA has performed extensive research since the mid-1990s on deterrence and its impact on operational effectiveness.¹⁹ This includes the Rockwell interviews of captured

¹⁷ Classified risk-return curves for enemy combatants define their ranges of observed acceptable risks. These analyses techniques are general in nature, widely known, and apply to a large set of irregular conflicts. See R. Anthony, “A Calibrated Model of the Psychology of Deterrence,” *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004).

¹⁸ Robert W. Anthony, Barry D. Crane, and Stephen F. Hanson, *Deterrence Effects from Peru’s Force-down/Shoot-down Policy*, IDA Paper P-3472 (Alexandria, VA: Institute for Defense Analyses, April 2000), 20–32.

¹⁹ Ibid., Appendix A. Also see R. Anthony, “A Calibrated Model of the Psychology of Deterrence,” *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004).

smugglers, which were remarkably useful for determining the underlying mathematical distribution of the “willingness to traffic” function. A single power law exponent was found to represent all seven sets of conditions (from the three categories: lethal force, arrests with conviction, and material loss) for evaluating deterrence:

1. Material Loss to Capture
2. Capture to Prison
3. Prison to Loss of Life
4. Self Caught (individuals view of risk)
5. Associate Caught (effect of an individual's colleague being caught)
6. Self Imprisoned
7. Associate Imprisoned

Above the threshold, where W is the willingness to smuggle or commit the act from the probability of interdiction (P_I) and the threshold denoted by $P_{\min}$ and the following condition describes this:

$$W(P_I) = \begin{cases} \left(\frac{P_I}{P_{\min}} \right)^{-1.03 \pm 0.07} & \text{for } P_I \geq P_{\min} \\ 1.0 & \text{for } P_I \leq P_{\min} \end{cases}$$

The values $P_{\min}$ describe the thresholds for three approximate sets of risk conditions:

Kinetic operations: 2% to 5%, nominally 3%

Arrest operations: 5% to 13%, nominally 8%

Property seizure/loss operations: 13% to 30%, nominally 24%²⁰

The following equation depicts the willingness to smuggle. One interesting observation is that there are similar thresholds observed in the analyses of combat data (see Appendix C). A second observation is the fraction that is not deterred, as shown in the term $P_{\min}^{1.029}$ as undeterred²¹ and dependent on the intervention risks.

²⁰ Ibid., Appendix A.

²¹ There are cases where some fraction of criminals, even if they know they are going to be caught, commit the crime, especially when their families are threatened or some other factor outweighs the penalty for getting caught.

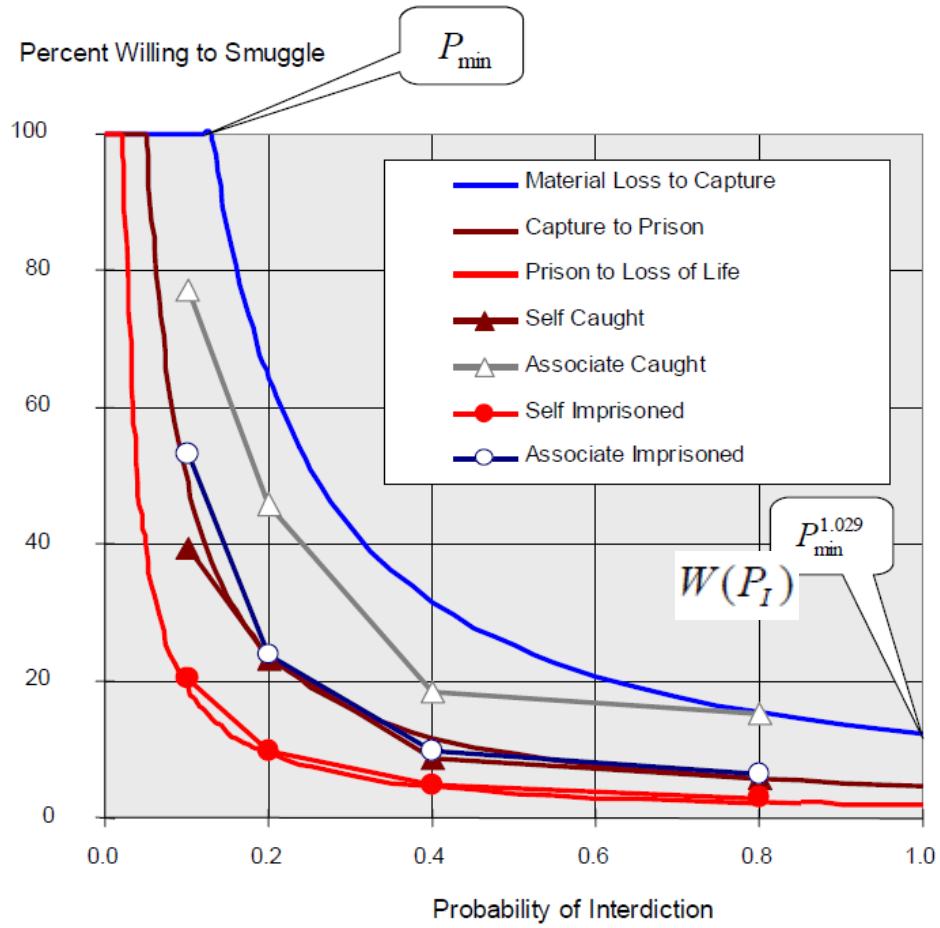


Figure A-7. Willingness to Smuggle $[W(PI)]^{22}$

From the willingness function, the deterrence function, i.e., the probability of thwarting (= deterrence + interdiction) can be easily derived as:

$$P_t = 1 - (1 - P_I) \cdot W(P_I).$$

$$P_t = 1 - (1 - P_I) \cdot \left(\frac{P_I}{P_{\min}} \right)^{-1.03 \pm 0.07} \quad \text{for } P_I \geq P_{\min}$$

$$= 1 - (1 - P_I) \quad \text{for } P_I \leq P_{\min}$$

The threshold conditions describe a *non-linear break point* and the transition to a power law with an exponent of -1. All deterrence conditions that have been observed seem to obey the power law and the difficult mathematics needed to analyze this

²² Ibid.

situation. This condition reinforces the argument against using averages rather than medians in sampling strategies to assess performance or in attempting to quantify the system. Figure A-8 shows the deterrence function as a graph:

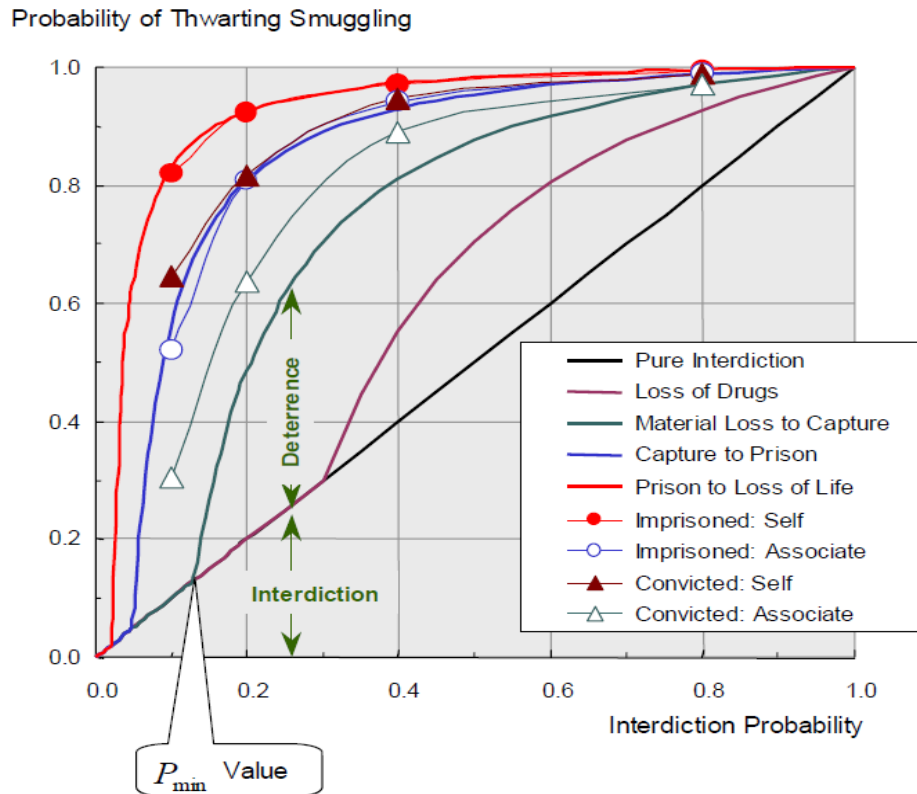


Figure A-8. Deterrence Graphical Formulation (Power Law Exponent = -1)²³

The many conditions shown in Figure A-8 essentially breakdown into loss of life, arrest with conviction, and material loss. The ranges of these effects are also shown in Figure A-8. In summary, this view, developed in the 1990s, was repeatedly tested and is useful in planning operations, efficiently using resources, and assessing outcomes.

Figure A-8 illustrates the probability of thwarting drug smuggling (otherwise known as deterrence, measured on the y axis) that can be expected for any given level of interdiction resources (x axis). The lower the probability of interdiction, the more severe the action that must be taken by LE to achieve deterrence. In other words, given a very low level of interdiction resources, a government may need to use lethal force to prevent the movement of drugs. Or, the government can commit a great deal more assets and make many more arrests to have the same deterrent effect. From the trafficker's

²³ Ibid.

perspective, the use of lethal force (personal death and associate death) has the greatest deterrent effect, followed by risk of arrest (personal and associate), and then loss of drugs and equipment.

The text below quantifies this deterrence effect mathematically for deterrence efforts in Peru.²⁴

- *Lethal Force* ($P_{\min} \leq 0.02$): With the threat of lethal force, traffickers begin to quit challenging the interdictors when $P_{\min}$ reaches about 2%. Much below this threshold, however, traffickers are willing to accept the risks as a cost of doing business.
- *Personal Imprisonment* ($0.02 \leq P_{\min} \leq 0.05$): If experienced traffickers anticipate a severe sentence whenever they are captured, they will begin to be significantly deterred in this range of interdiction probabilities.
- *Capture and Imprisonment of an Associate* ($0.05 \leq P_{\min} \leq 0.13$): Those who have not experienced prison life may be more difficult to deter and require thresholds in the range from 5 to 13%.
- *Loss of Boat or Aircraft* ($0.13 \leq P_{\min} \leq 0.3$): This zone of interdiction threat includes loss of the drugs as well.
- *Loss of Drugs* ($0.3 \leq P_{\min} \leq 1$): Interviews with inmates and observed avoidance behavior when threatened with interdiction indicate another zone of loss of drugs.

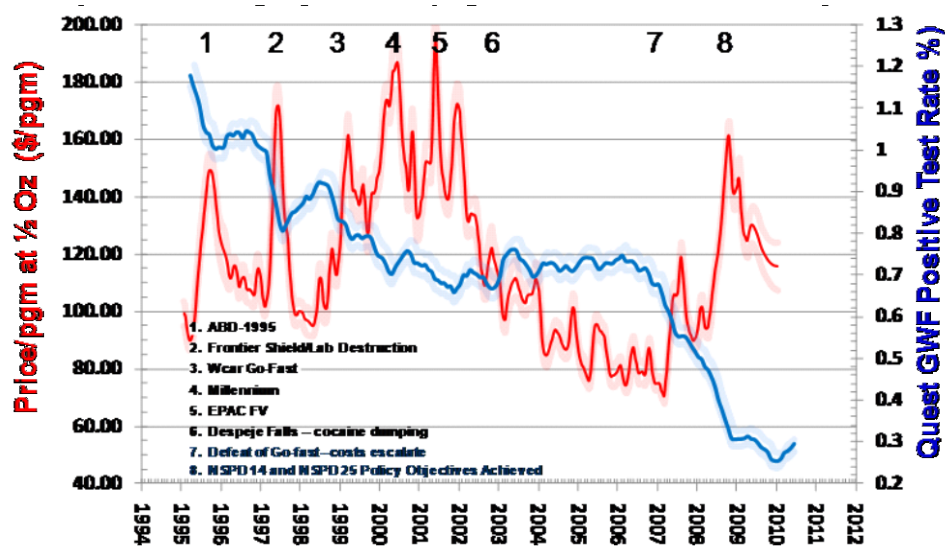
Many operations were conducted utilizing tactics and strategies developed from this deterrence concept and the underlying power law. Median estimates, versus average estimates, routinely aided in understanding the degree of success attained by individual counter-cocaine operations and trends exhibited across a series of operations. Threshold conditions ($P_{\min}$) are shown in Figure A-7 and Figure A-8. Deterrence effects have also been used to affect consumption.

Figure A-9 illustrates the empirical relationship between price and user rates. This analysis was mandated by several Presidential Directives that sought to control the cocaine epidemic by driving up cocaine prices to decrease consumption. The eight red spikes indicating price increases were a result of repeatedly-tested deterrence actions that reduced supply. Drops in positive cocaine testing rates confirmed this reduction in supply. More importantly, this figure illustrates that consistent and repeated supply attacks significantly altered the recovery of user demand as measured by positive test rates.²⁵ One of the most critical observations is the elasticity and relationships between

²⁴ Anthony, Crane, and Hanson, *Deterrence Effects from Peru's Force-down/Shoot-down Policy*, 20–32.

²⁵ Crane, Rivolo, and Comfort, *An Empirical Examination*.

supply (price changes) and demand (positive test rates) power laws. The user testing rates drop when prices rise, but when prices recover, user testing rates recover initially at a slow rate, and after repeated attacks hardly recover at all. This critical observation is the basis for estimating the time necessary for allied forces to conduct effective major operations to gain the initiative against cocaine trafficking—euphemistically called “getting inside the enemy’s response loop.”



Note: pgm=pure gram, GWF=general workforce, and Oz=ounce. Numbers indicate the peak of identified operation.

Figure A-9. The Relationship Between Cocaine Price and Positive Test Rates (Demand)²⁶

This deterrence formulation clearly explained how power law type data can be transformed into valuable information and how repeated analytical applications lead to strategic, theater-wide effects.

²⁶ Test rates data is provided by the Quest Corporation which tests the general workforce employees (600,000/year). Price data is from the System to Retrieve Drug Evidence (STRIDE) database which constructs a price index.

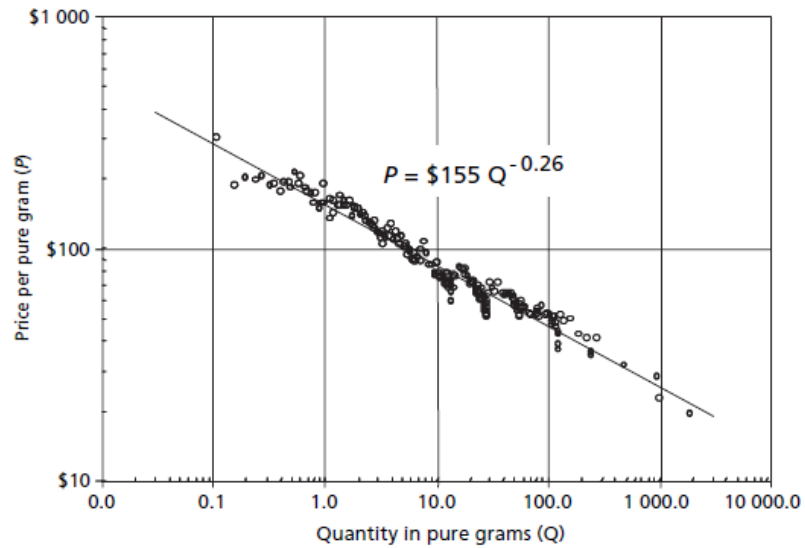
Appendix B

Analysis of the Cocaine Market

The Institute for Defense Analyses' (IDA) initial research on *power laws* pertained to the cocaine market in the Western Hemisphere. This appendix contains examples of how power laws applied to most aspects of the cocaine system, such as assuming market risk and consumption. Having demonstrated that the cocaine system exhibits behavior consistent with power laws, it is logical to assume that the opium and heroin market data and consumption will also follow the same distribution. IDA's analysis suggests that these functional distributions characterize not only the cocaine market, but the heroin, marijuana, methamphetamine, and methylenedioxymethamphetamine (MDMA) markets as well. Because of the pervasive and ubiquitous nature of drug data distributions, IDA's research findings from the Western Hemisphere can be applied to Southwest Asia (SWA) heroin and opium markets. IDA Document D-4324, *Phase II Findings: Leveraging Lessons Learned to Inform Southwest Asia Counter-Drug Efforts*¹ provides further evidence that SWA heroin and opium will also exhibit the power laws presented in this appendix.

In the cocaine market, power laws effectively characterize the behaviors of users, buyers, and sellers of drugs who assume market risk. More criminals sell smaller amounts since it is much less risky than selling larger quantities. IDA asserts that similar conditions likely exist for SWA heroin and opium markets. Preliminary tests of SWA data confirm this assertion. Figure B-1 shows price per pure gram versus quantity purchased in then-year dollars in the 1990s.

¹ Barry D. Crane, Ashley-Louise N. Bybee, Andrew Cseko, Andrea S. Pongo, and Zachary S. Rabold, *Phase II Findings: Leveraging Lessons Learned to Inform Southwest Asia Counter-Drug Efforts*, IDA Document D-4324 (Alexandria, VA: Institute for Defense Analyses, May 2011).



Source: System To Retrieve Information from Drug Evidence (STRIDE) database.

Figure B-1. Cocaine Purchase Quantity Relationships²

Figure B-2 illustrates that this same characteristic exists for all drugs, including cocaine, heroin, methamphetamine, marijuana, and MDMA. In other words, they all have a similar price discount behavior. This is consistent with the underlying organizational structure of criminal networks selling illegal substances.³

² See R. Anthony and A. Fries, "Empirical Modelling of Narcotics trafficking from Farm Gate to Street," *UNODC Bulletin on Narcotics: Illicit Drug Markets* LVI, nos. 1 and 2 (2004): 11, Figure III, for a more complete description of these data.

³ Ibid.

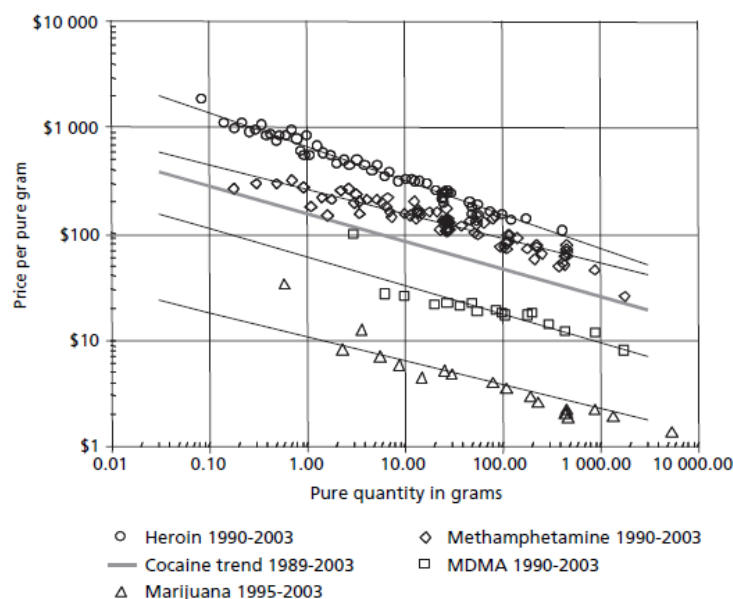


Figure B-2. All U.S. Drugs and Purchase Quantity Relationships⁴

The data presented in Figure B-2 supports the assertion that these drugs have the same price-amount percentage markup because the underlying organizational structure exhibits the same risk mitigation tendency. Similar organizational structures exist in SWA and subsequent analysis of SWA data can be expected to reveal comparable power law depictions. Since many of the organizations do not know or even communicate with each other, this observed behavior is consistent with a fundamental underlying principle of risk-taking: *equal risks for equal returns*.

The power law characterizing the *entire* cocaine market is a powerful insight and applies to the entire trafficking system, from cultivation in the source zone, to laboratory production of cocaine hydrochloride (HCl), to final retail distribution in user markets, as presented in Figure B-3.

⁴ Ibid., 12, Figure IV for a more complete description of these data.

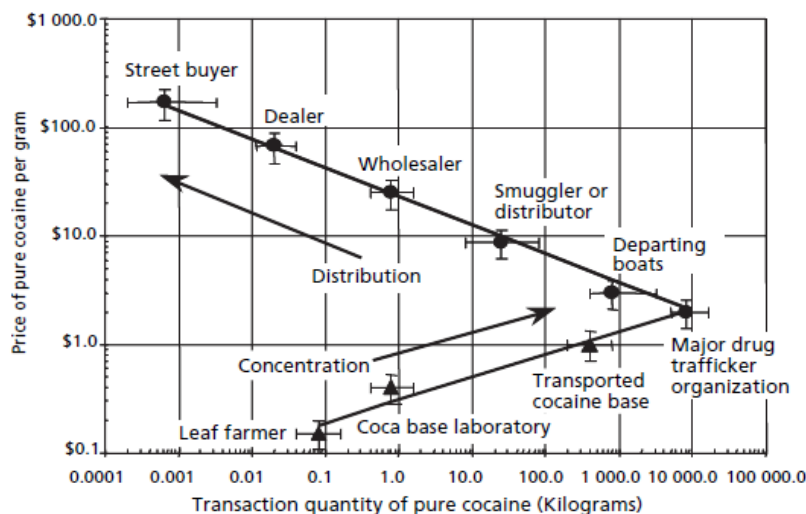
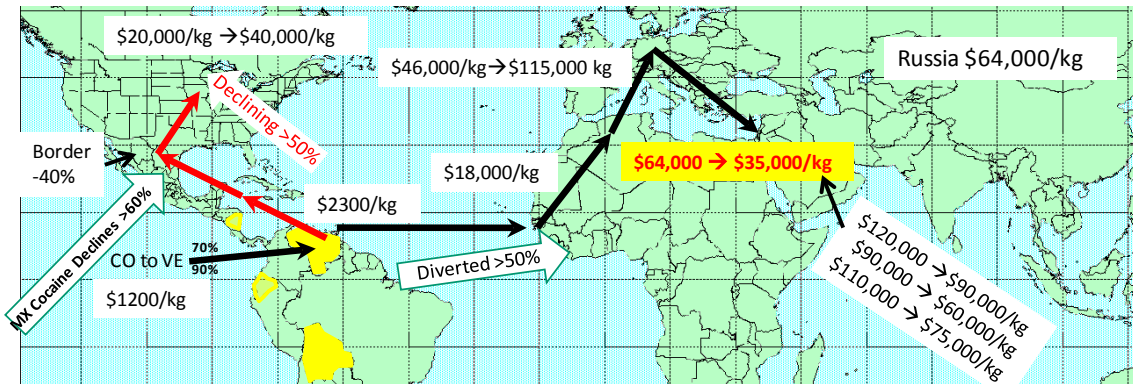


Figure B-3. Price Quantity Trends for Consolidation and Distribution⁵

This vertical trafficking system typically imposes a price markup of about 2.5 times per stage as the different organizations parse risk for each stage of trafficking. Ultimately all elements of this vertical trafficking system—from coca farmers to the casual user—follow this power law and thus the euphemism, consistent from “leaf to street,” applies.

Using this power law structure, analysts subsequently tested United Nations global cocaine price data and found several anomalous features in the data. Recognizing that power laws are observed to apply in *all* aspects of the drug trafficking system, this prompted analysts to question unexplained fluctuations in the data, such as where declining prices (indicating a substantial supply) emerged in unexpected places. The power law representation of markups, shown in Figure B-3, held for global markets, but if the mark ups suddenly change, then these prices show hidden or covert trafficking or bad data. Multiple checks of other related data, such as consumption, confirm changes. Figure B-4 shows how these price relationships, in a steady-state cocaine market observed in 2007, suddenly change when they did not follow the same mark up structure. Other data confirm these dramatic changes. Deviations from the steady-state conditions reveal previously unknown patterns of trafficking—particularly the declines in prices in the region around Syria.

⁵ Ibid., 16, Figure V.

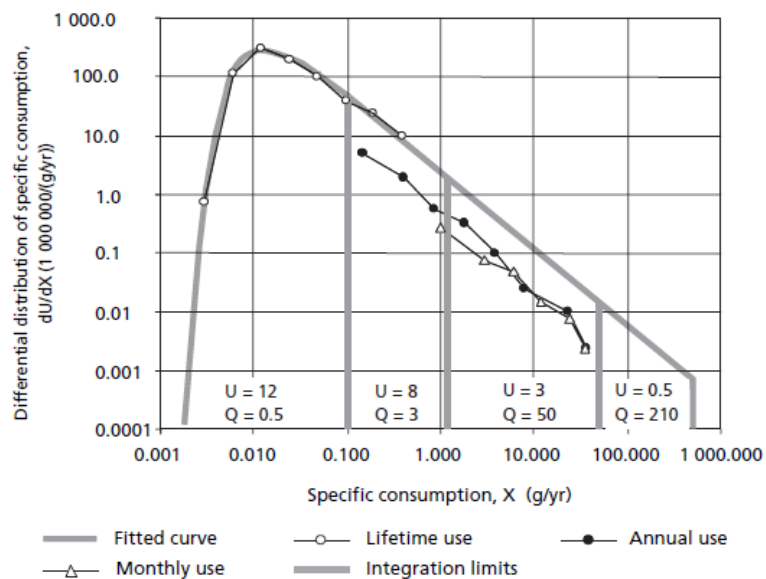


Data Source: UNODC Delta Database provided by the research section in 2008

Figure B-4. The UN Reported Global Price Network with Highlighted Changes

This anomaly allowed analysts to uncover previously unknown trafficking patterns. This information also aided in uncovering and targeting these new supply routes and has resulted in arrests, extraditions, and trials.

Drug use (demand) is also characterized by a power law, since heavy drug users take more risks than light drug users. The relative consumption of heavy users (about 20% of total users and monthly or perhaps weekly use) is about 80% of the total quantity of drugs, while light users (about 80% of total users who are perhaps annual or just lifetime users) consume about 20% of the total quantity of drugs. This is a classic example of a power law and is known as the “80-20 rule” in the statistical literature. Figure B-5 illustrates this consumer behavior.



Source: United States National Household Survey on Drug Abuse, 1990-1994.

Figure B-5. Power Law Describing Differential Rate of Cocaine Use⁶

⁶ Ibid., 5, Figure I.

Appendix C

Analysis of Combat Data

Analyses of the attacks on the Joint Iraqi Airbase Balad provide a simple demonstration of the complexities of *power laws* and of the fact that the monthly average is not a good indicator of change for assessing the success of deterrence operations.¹ Using drug data analyses techniques and understanding the underlying organization of the attackers on Joint Base Balad was helpful for analyzing when the attacks began to be deterred. What was learned regarding drug criminal behavior could be used to understand how well the base was defended.

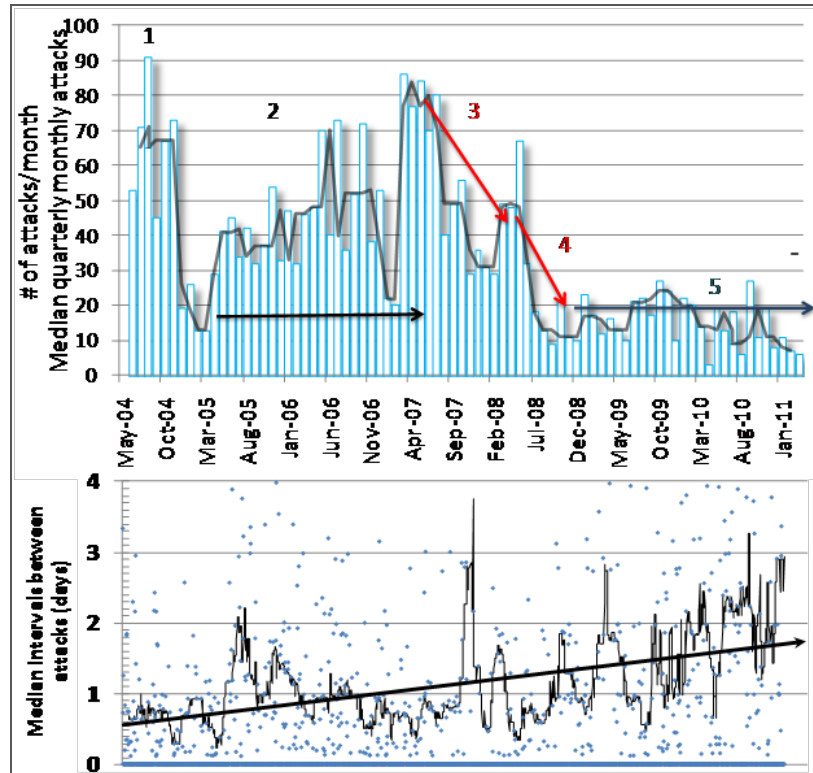
A power law also applies to anti-Iraqi insurgent and coalition forces' willingness to incur casualties in combat and indirect attacks on installations.² This application may assist analysts in identifying the likelihood of a future event occurring, but cannot predict the exact timing of an event.

These observations and hypotheses have been used to uncover more detailed behaviors of insurgent combat groups in both Iraq and Afghanistan. Analyses of the attack on Joint Base Balad in Iraq demonstrate all of the power law analysis characteristics.³ Figure C-1 shows the *median* number of monthly attacks (top diagram) and the median intervals between attacks (bottom diagram). It also shows the large errors that result from using monthly averages, and why averages are problematic in assessing the success of operations.

¹ For more detail see Barry D. Crane, A. Rex Rivolo, and Gary C. Comfort, *An Empirical Examination of Counterdrug Interdiction Program Effectiveness*, IDA Paper P-3219 (Alexandria, VA: Institute for Defense Analyses, 1997). Other techniques for examining these power law situations are described in *UNODC Bulletin on Narcotics: Illicit Drugs*, 2004, Chapters 1 and 2.

² Data are available in classified combat reporting.

³ Joseph A. Milner, Barry D. Crane, *Integrated Defense: Lessons Learned from Joint Base Balad*, IDA Document NS D-4372 (Alexandria, VA: Institute for Defense Analyses, August 2011).

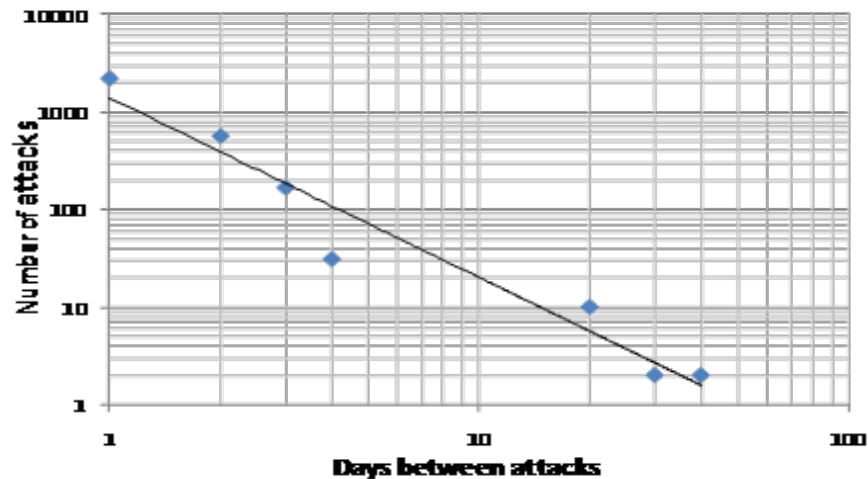


Note: Each blue dot is an attack interval while the line is a median monthly average

Figure C-1. Median Number of Monthly Attacks (top) and the Median Intervals Between Attacks (bottom)⁴

Figure C-2 shows that the time intervals (days) between attacks also follow an approximate power law [$Number=450*[Days]^{-1.087}$] with an exponent of -1.087. Interestingly, this exponent is almost identical to the one derived from an analysis of the rate of cocaine trafficking, reflecting similar behaviors of traffickers with regard to risk-taking.

⁴ Ibid., 39.



Note: Blue dots are the number of attacks per attack interval in days (1, 2, 3, 4, 20, 30, and 40)

Figure C-2. Relationship Between the Number and Rate of Attacks (since 2006)⁵

When the power law shape exponent is near -1, as it is in this case, averages are a very poor measure of effectiveness. Figure C-3 demonstrates the ineffectiveness of using averages to describe the interval data (described earlier, but added for clarification here). The average shows random fluctuations of growing magnitude making it difficult to determine any effectiveness at all.⁶ The average percent error is a result of comparing the average to a stable indicator, such as the median. In nonconvergent systems, using different starting points reveals a completely different set of error results with no correlation to previous values.

⁵ Ibid., 41.

⁶ COL Joseph Milner, as senior security group commander, confirmed this difficulty in 2007. His analyses confirmed the operational assessment of the commander. The typical security group data analyses made it very difficult to observe success. See NSD-4372 waiting publishing at Air University. Used with permission of COL Milner.

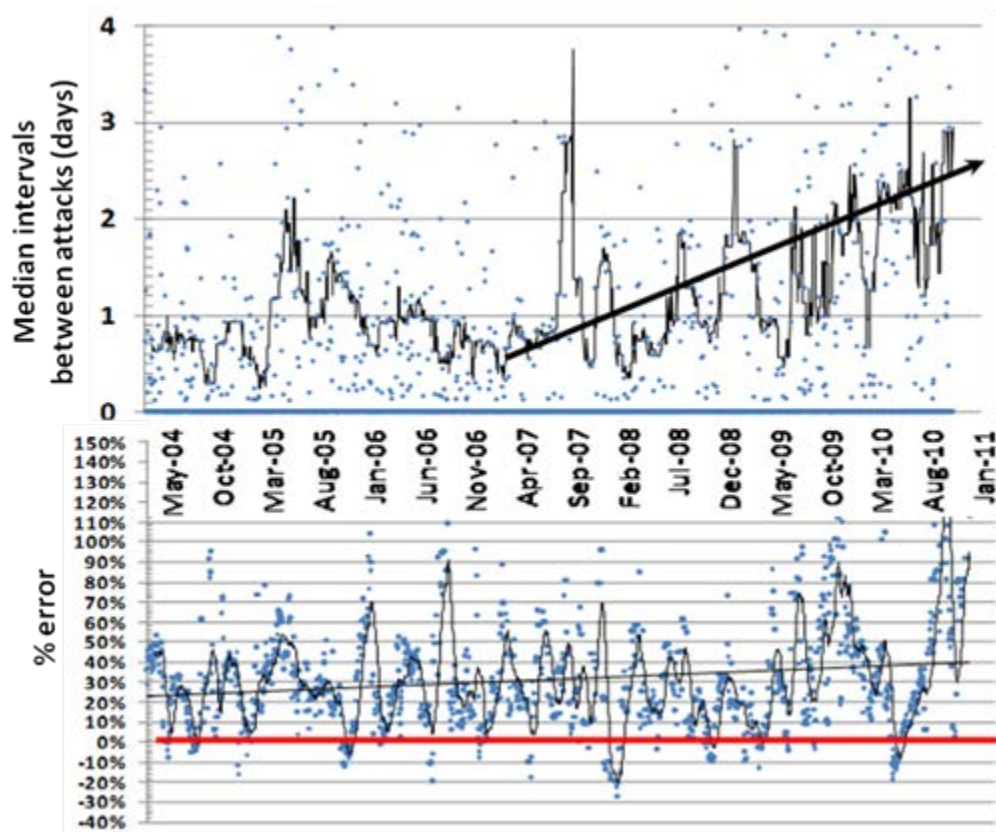


Figure C-3. Median (top) Time Interval and Increasingly Random Nature of Mean (error in %)⁷

⁷ Ibid.

Appendix D

Illustrations

Figures

Figure 1. Physical Distribution of One or More Events Where Opium, Morphine or Heroin Were Seized, 2000–2010	4
Figure 2. Temporal Distribution of Events Analyzed, 2000–2009.....	5
Figure 3. Physical Distribution of Heroin and Morphine Data Analyzed from Map 10, “Seizures of Heroin and Morphine, 2009 (Countries and Territories Reporting Seizures of More than 10 kg)”	5
Figure 4. Temporal Distribution of Heroin and Morphine Data Analyzed from Figure 29, “Global Seizures of Heroin and Morphine: 1999-2009”	6
Figure 5. Physical Distribution of Opium Data Analyzed from Map 11, “Opium Seizures in Asia, 2009”	6
Figure 6. Temporal Distribution of Opium Data Analyzed from Figure 30, “Global Seizures of Opium: 1999-2009”	7
Figure 7. A Small Sample of UNODC Heroin and Opium Seizures Showing Overall Averages and Medians for All UNODC Data	10
Figure 8. A Comparison of UN Opium and USG Event Data and Underlying Distribution	11
Figure 9. Estimates of Afghan Opium Cultivation (hectares)	14
Figure 10. Estimates of Afghan Opium Production (Metric Ton).....	14
Figure 11. Colombian Cocaine Production: Separate Time Series.....	15
Figure 12. CCDB Confidence Ranking Flow Chart	19
Figure 13. Reported Cocaine Movements by Confidence Level.....	20
Figure 14. Opium Prices Reported by Traders in Kandahar (Green) and Nangarhar (Orange) Vertical	22
Figure 15. Cocaine Movement (as Reported by the CCDB) and Purity (as Measured by the DEA in the STRIDE Database) 2001–2010	23
Figure 16. Number of Binned Seizure Events per kg for Heroin and Opium and Corresponding Averages and Medians	25
Figure 17. UN Analyzed Heroin and Opium Binned Seizures (2000–2009)	27
Figure 18. Surrogate Opium Price versus Real Opium Price	29

Tables

Table 1. Gross Descriptors of UN and USG Data	12
---	----

Appendix Figures

Figure A-1. Number of Seizure Events per kg of Opium and Heroin	A-3
Figure A-2. A Comparison of UN Opium and USG Event Data.....	A-5
Figure A-3. Correcting USG Data	A-6
Figure A-4. Monte Carlo Simulations of Progressively Smaller Sample Sizes and the Corresponding Overestimation of Averages.....	A-9
Figure A-5. Random Average Fluctuations in Attack Intervals over Five Years with Increasing Differences as illustrated by the Red Arrows	A-10
Figure A-6. Typical Observed Behavior of the Onset of Deterrence from “Enemy/Trafficker” Operations.....	A-12
Figure A-7. Willingness to Smuggle [W(PI)].....	A-14
Figure A-8. Deterrence Graphical Formulation (Power Law Exponent = -1).....	A-15
Figure A-9. The Relationship Between Cocaine Price and Positive Test Rates (Demand)	A-17
Figure B-1. Cocaine Purchase Quantity Relationships.....	B-2
Figure B-2. All U.S. Drugs and Purchase Quantity Relationships	B-3
Figure B-3. Price Quantity Trends for Consolidation and Distribution.....	B-4
Figure B-4. The UN Reported Global Price Network with Highlighted Changes	B-5
Figure B-5. Power Law Describing Differential Rate of Cocaine Use.....	B-6
Figure C-1. Median Number of Monthly Attacks (top) and the Median Intervals Between Attacks (bottom)	C-2
Figure C-2. Relationship Between the Number and Rate of Attacks (since 2006)	C-3
Figure C-3. Median (top) Time Interval and Increasingly Random Nature of Mean (error in %).....	C-4

Appendix E

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Appendix F

Abbreviations

AOR	Area of Responsibility
CN>	Counternarcotics and Global Threat
CCDB	Consolidated Counterdrug Database
CCDB-E	Consolidated Counterdrug Database-East
CENTCOM	United States Central Command
CIA	Central Intelligence Agency
CIDNE	Combined Information Data Network Exchange
CN	Counternarcotics
CNP	Colombian National Police
CNPA	Counternarcotics Police of Afghanistan
COCOM	Combatant Command
COIN	Counterinsurgency
CONUS	Continental United States
D&M	Detection and Monitoring
DASD	Deputy Assistant Secretary of Defense
DEA	Drug Enforcement Administration
DIA	Defense Intelligence Agency
DOD	Department of Defense
FOUO	For Official Use Only
g/yr	Grams per year
GWF	General Workforce
HC1	Cocaine Hydrochloride
IACM	Interagency Assessment of Cocaine Movement
IAG	Interagency Group
IDA	Institute for Defense Analyses
ISAF	International Security Assistance Force
kg	kilogram
LE	Law Enforcement
MDMA	methylenedioxymethamphetamine
mt	Metric Tons
Oz	Ounce
PAR	Performance Assessment Review
PGM	Pure Gram
SIGACT	Significant Activities
SIMCI	Sistema Integrado de Monitoreo de Cultivos Ilícitos (Integrated Crops Monitoring System)
STRIDE	System To Retrieve Information from Drug Evidence
SWA	Southwest Asia

TZ	Transit Zone
UN	United Nations
UNODC	United Nations Office on Drugs and Crime
USG	United States Government
WH	Western Hemisphere

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