Chapter 22 Solving the Wrong Resource Assessment Problems Precisely



Donald A. Singer

Abstract Samples are often taken to test whether they came from a specific population. These tests are performed at some level of significance (α). Even when the hypothesis is correct, we risk rejecting it in α percent of the cases—a Type I error. We also risk accepting it when it is not correct—a Type II error at β probability. In resource assessments much of the work is balancing these two kinds of errors. Remarkable advances in the last 40 years in mathematics, statistics, and computer sciences provide extremely powerful tools to solve many mineral resource problems. It is seldom recognized that perhaps the largest error—a third type—is solving the wrong problem. Most such errors are a result of the mismatch between information provided and information needed. Grade and tonnage or contained models can contain doubly counted deposits reported at different map scales with different names resulting in seriously flawed analyses because the studied population does not represent the target population of mineral resources. Among examples from mineral resource assessments are providing point estimates of quantities of recoverable materials that exist in Earth's crust. What decision is possible with that information? Without conditioning such estimates with grades, mineralogy, remoteness, and their associated uncertainties, costs cannot be considered, and possible availability of the resources to society cannot be evaluated. Examples include confusing mineral occurrences with rare economically desirable deposits. Another example is researching how to find the exposed deposits in an area that is already well explored whereas any undiscovered deposits are likely to be covered. Some ways to avoid some of these type III errors are presented. Errors of solving the wrong mineral resource problem can make a study's value negative.

Keywords Quantitative resource assessment • Decision analysis Uncertainty • Lognormal

D. A. Singer (⋈)

22.1 Introduction

Howard Raiffa (1968, p. 264) noted that statistics students learn the importance of constantly balancing making an error of the first kind (that is, rejecting the null hypothesis when it is true) and an error of the second kind, that is, accepting the null hypothesis when it is false (Fig. 22.1). Raiffa thought it was John Tukey who suggested that practitioners all too often make errors of a third kind: of solving the wrong problem. Raiffa nominated a candidate for the error of the fourth kind: solving the right problem too late. John Tukey believed that it was better to find an approximate answer to the right question, than the exact answer to the wrong question, which can always be made precise. More recently, Mitroff and Silvers (2009) focused mostly on social questions where type III errors occurred and provided many examples of developing good answers to the wrong questions (type III error). Unfortunately concerns of Raiffa, Tukey, Mitroff, Silvers, and others are appropriate for mineral resource assessments. And the concerns should not be limited to classical statistics.

Supply of minerals to society is dependent not only on the total amount of mineral material but also on quality or concentrations, spatial distributions or how scattered the material is, whether it has been found, whether it is remote from infrastructure, and a whole host of other issues such as government policies, production technologies, and market structures. Decision-makers, whether concerned about development of a technology, development of a region, exploration, or land management, are faced with the dilemma of obtaining new information, or allowing or encouraging others to obtain it, and the possible benefits and costs of development if mineral deposits of value are discovered. Decisions about exploration for these resources and their possible development require awareness of various kinds and the import of errors that can be made by analysts in their studies.

A type I error is the rejection of the null hypothesis when it is true. In some fields a type I error is called a false positive. The risk of this error is α , the level of significance. A type II error is the acceptance of the null hypothesis when it is false, also known as a false negative error. The probability of making a Type II error, β ,

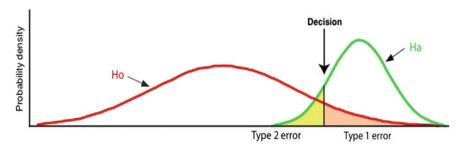


Fig. 22.1 Type I error is the rejection of the null hypothesis (Ho) when it is true. The risk of this is α , the level of significance. Type II error is the acceptance of the null hypothesis when it is false

depends on the alternative value and its distribution. The most important question of the analyst and decision-maker should be: Are we solving the right problem? It is the need to consider this source of error in mineral resource studies that is the focus of this chapter. Common to many of the errors of solving the wrong problem is a mismatch of the studied population and the population that is central to the decisions—this topic is presented first. Next, effects of mismatches of populations to some mineral resource assessments are discussed. Possible ways to avoid some of these type III errors are finally presented.

22.2 Target Population

Type III errors are fundamental and should be considered before errors of types I and II. Type III errors stem from improper definition of the problem and therefore are not strictly a statistical issue, but one of critical thinking. It does no good to minimize the expected costs of type I and type II errors if the wrong problem is being solved. In mineral resource assessments, careless problem definition is the primary source of type III errors. For almost all resource assessment problems, the fundamental sample is the mineral deposit.

The idea of a mineral resource involves both geologic and economic aspects and because knowledge about the earth and future economic conditions is limited, should recognize uncertainty. Mineral deposits are the geologic entities containing resources. Mineral deposits and their contents are the fundamental target populations that are estimated. So what is a mineral deposit? Mineral deposits are defined as mineral occurrences of sufficient size and grade that they might, under favorable circumstances, be economic.

A map of some volcanogenic massive sulfide deposits from Northern Japan is used to clarify our understanding of what is a deposit (Fig. 22.2). From this plot one can see that some of the deposits are just a few meters apart from each other. Grade and tonnages are available for 23 of these named deposits from the western part of the Hokuroku district, Japan (Ohmoto and Takahashi 1983). It is important that if a different map scale were used, this part of the district might have three or four named deposits with grades and tonnages. This well-studied district has more detailed maps than many other volcanogenic massive sulfide districts around the world. If one gathered all available data on the names and grades and tonnages of volcanogenic massive sulfide deposits and built grade and tonnage or contained metal models, the models would contain metals double counted from deposits reported at different map scales and from the same deposits with different names due to grouping. To have a consistent sampling unit that can be applied in statistical analysis and in assessments of undiscovered deposits it is necessary to have spatial rules to help define a deposit. In addition, mine names and deposit names do not always match, mine names sometimes change over time, and district and deposits can be reported with different names and numbers. For example, careless data gathering might contain the grades and tonnage of the total Sudbury Ni-Cu District

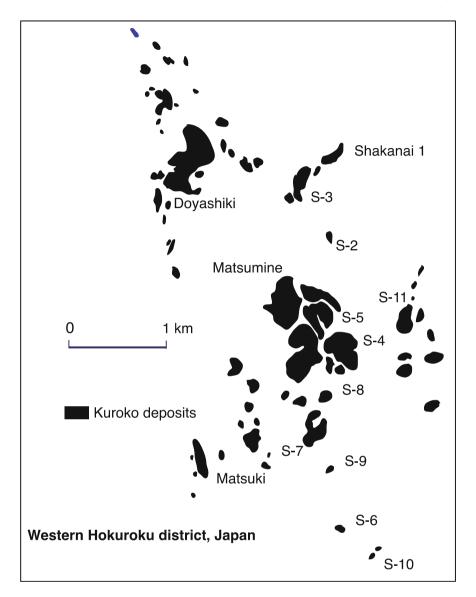


Fig. 22.2 Kuroko volcanogenic massive sulfide deposits of the western part of the Hokuroku district in Northern Japan (after Ohmoto and Takahashi 1983)

in Canada and also contain grades and tonnages of the many mines thus double counting and generating biased metal statistics and frequency distributions of questionable value. There are databases in which spatial rules for combining adjacent deposits have been consistently applied and multiple names have been eliminated (e.g., Mosier et al. 2009). Compilations that use the above sources combined with other sources of data on, for example, volcanic-hosted massive sulfide deposits very likely contain deposits and prospects counted twice (e.g., Patiño-Douce 2016), resulting in statistical analyses that are seriously flawed because the studied population does not represent the target population of mineral resources. Operational rules defining deposits need to account for these map scale effects and for the fact that some deposits have multiple names, mines and separate reported tonnages (Singer 2017).

Mineral occurrences or prospects which are the focus of prospectivity analysis do not qualify as economic mineral deposits because they are typically quite small and incompletely explored. Because number of undiscovered deposits estimates must be defined in a way that is linked to the grade-tonnage or contained metal models, estimates of number of deposits made using models based on such flawed grade-tonnage models must also be a mismatch with the target population.

22.3 Examples of Mismatches in Assessments

Solving the wrong problem due to mismatches of the target population with the studied or estimated population abound in mineral resource assessments. Examples of mismatches include issues of not understanding where the undiscovered resources might exist and estimating something other than mineral deposits that might be economic to mine (De Young and Singer 1981).

In one example, five or more epithermal gold vein deposits were estimated at the 90% level but no grade-and-tonnage model was provided, so the estimated deposits could be any size (Singer and Menzie 2010). To provide critical information to decision-makers, a grade-and-tonnage or contained metal model is key, and the estimated number of deposits that might exist must be from the linked grade-and-tonnage frequency distributions. Estimates of number of undiscovered deposits are completely arbitrary unless tied to a grade-and-tonnage or contained metal model that has been defined in a consistent operational manner.

In an unpublished study, four geoscientists made subjective probabilistic estimates of the number of undiscovered hot-spring mercury deposits in a 1:250,000 scale quadrangle in Alaska. They made independent estimates at the 90th, 50th, and 10th percentiles (Table 22.1). The 10th percentile, for example, is the number of deposits for which there is at least a 10% chance of that number of deposits or more exist.

It was pointed out to participant D that because the number of deposit estimates must be consistent with the grade and tonnage model, his estimates imply that there is more undiscovered mercury in this quadrangle than has been found in the world

Participant	A	В	C	D	
90% chance of at least	1	1	2	9,000	Deposits
50% chance of at least	3	2	4	10,000	Deposits
10% chance of at least	6	6	7	11.000	Deposits

Table 22.1 Independent estimates by four scientists of the number of undiscovered hot-spring Hg deposits in a quadrangle in Alaska

in this deposit type. He responded that he was estimating wisps of cinnabar, not deposits consistent with the grade and tonnage model. In this case, the population considered by participant D did not match the target population. Using a variety of different guidelines such as deposit densities (Singer 2008) for estimates of the number of undiscovered deposits provides a useful crosscheck of assumptions that may have been relied upon and discourages mismatches between target and estimated populations. In these examples of errors in estimating the number of undiscovered deposits, the key is the difference between the understanding of what was being estimated and the population of interest.

In Harris's landmark study (1965), multiple discriminate analysis was used to predict value of mineral production—among the best predictors was geologic cover with a negative value. In a study by Singer (1971), multiple regression was used to predict mineral production and again, cover with a negative value was an important variable. Unlike in petroleum exploration, minerals exploration under cover is a developing technology. Most commonly, mineral exploration under cover results from trying to extend known deposits, that is, additions to reserves. More difficult discovery and higher costs relative to exposed deposits, tend to reduce interest in covered areas. Covered areas tend to be poorly explored and, consequently, deposits under cover tend to be underreported.

In situations where resource assessments are made based on local information, the possibility of solving the wrong problem is high. For example, if the mapped geology were used to predict where and how many undiscovered orogenic gold deposits might in the Bendigo Zone of Victoria Australia, one would conclude that deposits are clustered in space and gold deposits are related to older rocks and covered areas would be worst place to look (Fig. 22.3). Even if we use some modern tools like weights of evidence or neural networks, we would predict no undiscovered deposits under cover. Yet, because geology permissive for the gold deposits is known under cover, and exposed permissive geology is thoroughly explored, most experts would recommend exploration under cover (Lisitin et al. 2007).

Each of these examples demonstrates mismatches of the target population and the studied population. Type III errors in these cases could produce useless or, even worse, misleading assessments.

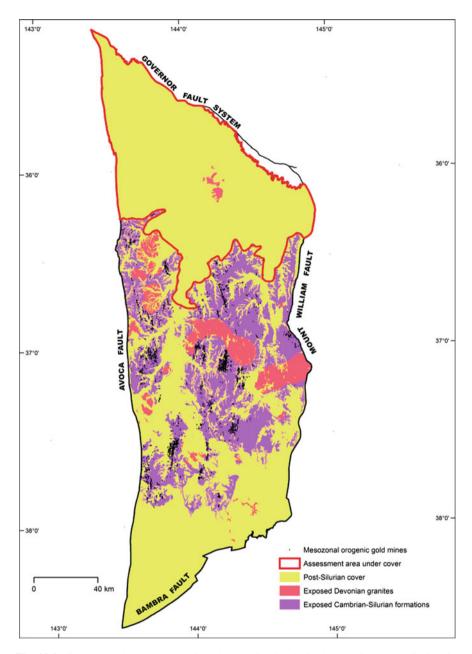


Fig. 22.3 Geology and known orogenic gold deposits (black) in the Bendigo Zone of Victoria, Australia (modified after Lisitsin et al. 2007)

22.4 How to Correct Type III Errors

The problems of mineral resource assessment can only be solved if they are formulated in a way consistent with the decision-maker's language and understanding of the problem. The questions need to be asked: Why perform an assessment? Who is the study being done for and what are the problems they are trying to resolve?

We start with the question of what kinds of issues decision makers are trying to resolve and what types and forms of information would aid in resolving these issues. Unfortunately, the decision-maker may not be available for the needed insight or may not be able to clearly state the information needs. Because the primary purpose of the kinds of assessments recommended here is to help decision-makers determine consequences of economic and policy decisions about tracts of land, regions, countries, or the earth, it is critical that the assessments be unbiased. For example, if the question concerns the long-term supply of a metal, the data used should not contain biased information such as grades and tonnages on multiple versions of the same deposits. These situations require care in compiling data and using sources that report locations, other names of deposits and names of deposits that have been combined with the primary deposit to meet spatial combination rules. A reliable source (e.g., Mosier et al. 2009) has specific information about locations, rules used to combine deposits and specific names that were combined for each deposit. These kinds of data provide a reliable basis for testing statistical distributions of metals in mineral deposits such as the lognormal distribution (Singer 2013).

It is important to recognize that success of assessments depends on the assessments following an integrated approach. This means that no part of the models and methods of estimation have any meaning in isolation. For instance, estimates of number of undiscovered deposits are completely arbitrary unless tied to a grade and tonnage or contained metal model. The goal should be to make explicit the factors that can affect a mineral-related decision so that the decision-maker can clearly see what are the possible consequences of decisions (Singer and Menzie 2010).

To avoid situations where occurrences are the basis of information used to discriminate barren areas from the economic deposits sought, it is necessary to construct models based on the economic deposits sought. Mineral deposit models can be based on data gathered from well-explored deposits of each type from around the world. This would allow the determination of how commonly different attributes and combinations of attributes occur. Quantifying mineral deposit attributes is the necessary and sufficient next step in statistically classifying known deposits by type. Quantified deposit attributes also can provide a firm foundation to identify which observations on geologic and other maps should be effective in delineation of tracts and perhaps identifying sites for detailed exploration. The kind of digital models advocated here would require the recording of both absolute time units and the relative time units of spatially related mineral deposits, rocks, geochemistry, geophysics, and tectonics. The scale of the observations is critical to proper application of such models. This is required to properly apply the models in

new geologic settings. Information in these models about the attributes associated with known deposits is necessary but not sufficient to discriminate barren from mineralized environments; quantifying the attributes of barren environments also is necessary for this task. Such digital models could be the foundation for identifying the discriminating functions that could remove many type III errors in assessments.

The exploration department of a major zinc producer found it essential to document a robust decision-making process to maintain internal and investor support (Penney et al. 2004). Zinc deposits from around the world were classed by type, grade, and tonnage models developed for each, cost filters were applied to each, and tracts around the world were delineated where the types could occur (Penney et al. 2004). This study was designed to aid the exploration decision-makers plan the search for economic deposits. Their process was the same as that recommended in three-part assessments (Singer and Menzie 2010), with the exception that they ranked or scored tracts rather than estimating the number of undiscovered deposits.

22.5 Conclusions

Errors of solving the wrong mineral resource problem can make a study's value negative. Type III errors, solving the wrong problem, can be avoided by using care in matching the information needed to solve the decision-maker's problem with information provided in the study. In some cases, we know how to solve the wrong problem but not the real one. It is not uncommon to get rewarded for publishing an answer—not THE answer. With some care and critical thinking in the planning stages, it is possible to provide information useful to decision-makers and to be rewarded for a publication.

References

DeYoung JH Jr, Singer DA (1981) Physical factors that could restrict mineral supply. In: Skinner BJ (ed) 75th anniversary volume. Economic geology, pp 939–954

Harris DP (1965) An application of multivariate statistical analysis to mineral exploration. PhD dissertation, The Pennsylvania State University, 265 pp

Lisitsin V, Olshina A, Moore DH, Willman CE (2007) Assessment of undiscovered mesozonal orogenic gold endowment under cover in the northern part of the Bendigo Zone. GeoScience Victoria Gold Undercover Report 2, Department of Primary Industries, 98 pp. www.dpi.vic. gov.au/minpet/store

Mitroff II, Silvers A (2009) Dirty rotten strategies—how we trick ourselves and others into solving the wrong problems precisely. Stanford University Press, Stanford, 232 pp

Mosier DL, Berger VI, Singer DA (2009) Volcanogenic massive sulfide deposits of the world—database and grade and tonnage models. U.S. Geological Survey Open-file Report 2009-1034. http://pubs.usgs.gov/of/2009/1034/

Ohmoto H, Takahashi T (1983) Submarine calderas and Kuroko genesis. In: Omoto H, Skinner BJ (eds) The Kuroko and related volcanogenic massive sulfide deposits. Econ Geol Monogr 5:38–54

- Patiño-Douce AE (2016) Metallic mineral resources in the twenty first century. II. Constraints on future supply. Nat Resour Res 25(1):97–124
- Penney SR, Allen RM, Harrisson S, Lees TC, Murphy FC, Norman AR, Roberts PA (2004) A global-scale exploration risk analysis technique to determine the best mineral belts for exploration. Trans Inst Min Metall Sect B. Appl Earth Sci 113:B183–B196
- Raiffa H (1968) Decision analysis—introductory lectures on choices under uncertainty. Random House, New York, 309 pp
- Singer DA (1971) Multivariate statistical analysis of the unit regional value of mineral resources. Unpublished PhD thesis, The Pennsylvania State University, 210 pp
- Singer DA (2017) Future copper resources. Ore Depos Rev 86:271–278. http://dx.doi.org/10.1016/ j.oregeorev.2017.02.022
- Singer DA (2008) Mineral deposit densities for estimating mineral resources. Math Geosci 40(1):33–46
- Singer DA (2013) The lognormal distribution of metal resources in mineral deposits. Ore Geol Rev 55:80–86. http://dx.doi.org/10.1016/j.oregeorev.2013.04.009
- Singer DA, Menzie WD (2010) Quantitative mineral resource assessments—an integrated approach. Oxford University Press, New York, 219 pp

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