Estimating an upper limit for primary copper supply using empirically derived mineral resource-to-production rate relationships

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Abstract

A theoretical upper limit for the annual primary supply rate of copper is estimated under the overoptimistic assumption that all known mineral deposits can be mined simultaneously. Factors for mineral resource and reserve-to-production relationships – often referred to as Taylor's rule – were derived for specific deposit types and mining methods based on data for existing mining operations. These were used to estimate potential production rates with uncertainty bounds for the remaining set of known deposits that are not currently being mined. A Monte-Carlo analysis was performed and the 90% confidence intervals for the upper limit of primary supply were determined. For the deposits (n = 407) with defined mineral reserves in 2015 (649 Mt Cu) this was found to be 22-27 Mt Cu/year. For the broader set of deposits (n = 2296) with resource estimates in 2015 (3,054 Mt Cu) this was found to be 59-69 Mt Cu/year. Published scenarios indicate that annual primary copper demand may reach the upper primary supply limit derived from mineral reserves by the middle of this century, but not the upper limit derived from identified mineral resources. This suggests that successful conversion of mineral resources to reserves and subsequent mine development may be able to bridge potential supply-demand gaps. Further analysis of factors not considered by this study such as social and environmental considerations and the availability of labour, equipment, energy and capital into the sector may provide further insight into the upper limits of primary copper supply.

Keywords

resource; reserve; production rate; throughput; production capacity; mining

Statements and Declarations

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Not applicable

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Not applicable

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Data sets generated during this study are available from the corresponding author on reasonable request.

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Authors' Contributions
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resource; reserve; production rate; supply rate; mining; copper

1. Introduction

Over a decade ago, Gerst (2009) published an upper bounding scenario for primary (i.e. mined) copper demand, finding that by 2100 the in-use stock of copper may be as large as contemporaneous estimates of identified mineral resources. This upper bound was not intended to represent a likely outcome, as it specifically excluded important factors such as recycling, but rather it was meant as "an exploration of the bounds of possible technological outcomes" (Gerst, 2009). Before and since then, a myriad of studies has modelled strong growth in primary copper demand towards the middle of the 21st century in response to continued socio-economic development and the deployment of technologies required to electrify and decarbonise the global economy (e.g. Watari et al., 2020; 2021; 2022; Dominish et al., 2019; Klose and Pauliuk, 2023; Schipper et al., 2018; IEA, 2024). Emerging from these studies and the public discourse surrounding them are growing concerns regarding society's ability to meet long-term copper demand with primary supply from the mining sector, even with enhanced supply from secondary sources and recycling (Elshkaki et al., 2018; Hunt et al., 2021).

These concerns have emerged despite the majority of these studies not actually assessing primary material supply constraints in detail (Singer et al., 2017; Watari et al., 2021).[1] To the extent that such constraints are considered, typically it is just through comparison of cumulative primary demand over time against static estimates of mineral reserves or resources (Hunt et al., 2021). Yet this approach is regarded by many scholars to have limited utility for understanding long-term supply potential due to uncertainties associated with future exploration, technology development and the relationship between mineral reserve/resource definitions and prevailing economic conditions (Tilton and Lagos, 2007; West, 2020; Wellmer, 2022). These factors combine to create price and economic feedback cycles that mean that any likely impending mineral scarcity has often historically been overcome through additional investment in exploration, mine development, demand reductions, material substitutions, product substitutions and technology development (Wellmer and Dalheimer, 2012; Tilton et al., 2018). Existing studies have also given only limited consideration to annual supply rates that are actually achievable based upon defined mineral reserves and resources. Studies that assess future supply rates often use highly aggregated estimates derived from methods such as fitting Hubbert curves to historic production and estimates of ultimately recoverable resources, despite the shortcomings of these types of approaches (Meinert et al., 2016; Tilton, 2018; Riondet et al., 2023). More sophisticated, but often still aggregated approaches using systems dynamics modelling are also being used for these purposes (see Watari et al., 2021). Deposit scale estimates of achievable production capacity have rarely been incorporated into scenario models, although some examples do exist (e.g. Kushnir and Sandén, 2012; Guj and Schodde, 2025) and we note that new scenario modelling approaches have been developed to incorporate this more explicitly (Northey et al., 2023).

To provide a thematic continuation from the work of Gerst (2009), we estimate the upper limits of annual primary supply of copper using the overoptimistic assumption that all known mineral deposits can be exploited simultaneously. This upper estimate is found by relating the estimated mineral reserve and/or resource of each deposit to the annual mine production rates that they can support – using empirically derived factors for a power law relationship ($P=aR^b$) that is often known as *Taylor's rule* (Taylor, 1977; Long,

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[1] In a review of 70 studies of long-term scenario analysis of metal supply and demand, Watari et al. (2021) found that only 27 explicitly addressed physical availability. Of these 27, 17 simply considered projected demand in relation to reserve or resource estimates, while only 10 modelled supply using either the Hubbert curve model, scheduling models, systems dynamics models, linear programming models or predator-prey models.

2009; Wellmer and Drobe, 2019). The derived upper limits for primary supply provide the basis to conduct a sanity check on published scenarios for long-term primary copper demand – raising important questions regarding future sustainable development, the material requirements of technology deployment and the need for continued mineral exploration and possible material substitution.

2. Methods

2.1. Approach for Estimating an Upper Limit for Primary Metal Supply Rates

A multi-stage process was used to estimate the upper limit of annual primary supply for copper. The main steps in this process were:

1. Collation of datasets for copper mineral resources, reserves and mine production and classification

2. Classification of existing mines into open pit (OP), underground (UG) or both open pit and underground (OP-UG) mine types.

3. Derivation of regression factors for power-law resource or reserve-to-production relationships (i.e. Taylor's rule; $P={}_{a}R^{b}$) on both an ore basis[2] and a contained metal basis for each deposit type and mine type combination.

4. Estimation of production rates, including uncertainty bounds, for all deposits not currently being mined.

5. Estimation of the upper limit for annual primary supply based on a Monte-Carlo analysis of the sum of observed production rates at existing mines and those derived for deposits not currently being mined.

6. Determination of the minimum and maximum number of mines required to reach a given annual supply rate.

The upper primary supply limits were then compared to several primary demand scenarios from the literature.

2.2. Data Preparation

A published dataset for globally identified copper deposits was used as the basis of this study (Mudd and Jowitt, 2018). This dataset contains a mixture of the reported mineral reserves, mineral resources, metal grades, contained metal tonnages and deposit type classifications of 2,301 deposits for the year 2015. Mineral resources estimates within the dataset are inclusive of reserves when these have been defined (and reported) for a given deposit. Estimated contained copper within the mineral resources and mineral reserves in this dataset amount to 3,034.7 Mt Cu and 640.9 Mt Cu, respectively. This represents a minimum estimate of total copper in known resources and reserves given that reporting is incomplete as a result of some resources and reserves being held by private or government entities or by differences in reporting standards

[2] Noting that under the CRISCRO International Reporting Template (CRISCRO, 2024), the term "ore" should only be used in reference to a mineral reserve estimate due to connotations of economic feasibility and should not be used for describing a mineral resource. However, in the context of this article it is assumed that all identified mineral resources would be economic to mine and so a broader, more colloquial definition of the term "ore" is used to also refer to mineralised material forming a mineral resource estimate.

and requirements for different countries, meaning that some known reserves and resources are unreported or have no publicly available data. Building on this published dataset, we classified individual deposits within these datasets based upon whether they were being actively exploited by a mining operation in 2015 and have used compiled estimates of annual ore production and annual metal production in 2015 for each deposit in the dataset. These production statistics are primarily based on a mixture of mining industry technical and financial corporate reporting, industry association reporting, as well government reports and databases. We have assigned a primary mining method (open pit and/or underground) for each mine being exploited and cross-validated these where possible using a combination of industry corporate and technical reporting, satellite imagery and web-based searches and data sources such miningdataonline.com. We also initially sought to sub-classify underground mining methods but decided against this once we identified that a significant number of underground mines utilise multiple mining methods (e.g. stoping, caving, etc.) that become difficult to quantitatively resolve due to data limitations. Instead, the influence of differing underground mining methods is captured implicitly as part of our uncertainty analysis. A summary of the classified datasets is provided in Table 1. This includes annual copper production statistics for 189 copper mines constituting ~12.5 Mt Cu production in 2015, which represents ~65% of the estimated 19.3 Mt Cu of global mine production in 2015 (BGS, 2025). These data include mines that produce Cu as a main product as well as those that produce Cu as a co- or by-product of one or more main products (e.g. gold, molybdenum, nickel). This co-production was not explicitly considered as part of this analysis.

2.3. Empirically deriving factors for mineral resource or reserve-to-production rate relationships

Equation 1 shows a simple power law relationship that can be used to predict mineral production rates (P; *mass.time*$^{-1}$) based upon a deposit's given mineral resource or mineral reserve estimate (R; *mass*). This is sometimes referred to as *Taylor's Rule* in the minerals industry, after the original study on the issue by Taylor (1977). The empirical calibration factors *a* and *b* have previously been fitted for this relationship by other authors (Long, 2009; Wellmer and Drobe, 2019) and been shown to have sufficient predictive capacity for use when determining likely ranges of production capacity for mine feasibility studies. Achieved mine production rates are observed to generally increase as deposit size increases, albeit in a non-linear way due to physical, operating and economic constraints that can be quite variable across mine sites.

Equation 1: $\boldsymbol{P = a \cdot R^b}$

The calibration factors available in the literature have some limitations in terms of suitability for the research presented in this paper. Literature values have often been derived using datasets that include multiple datapoints for individual mines in cases where they have undergone expansion to higher production rates and larger defined reserves throughout their mine life, which may introduce some bias into the datasets. These literature values are almost always derived based on estimated mineral reserves rather than mineral resources (Long, 2009; Taylor, 1986; Wellmer and Drobe, 2019), whereas for most identified deposits we only have mineral resource estimates. The literature values discussed here are also often derived by excluding mines using block caving from underground mine datasets and instead grouping these with open pit mines when deriving calibration factors (Long, 2009). In subsequent studies we plan to use these relationships as part of modelling to understand potential land-use change impacts associated with mining, where the distinction between open pit and underground mining and different deposit types is critically important. For these reasons we decided to derive new calibration factors more directly suited to our purpose using the datasets described previously in Section 2.2. As part of this, our calibration factors produce supply capacities in units of tonnes ore per year or tonnes recovered copper per year, whereas most factors presented in the literature are derived for units of tonnes per day. We view this as a more appropriate presentation, as we are working with annual production data and so resolving to achieved hourly production rates would require additional assumptions for mine operating periods or utilisation.

The *a* and *b* calibration factors for the relationship in Equation 1 were derived to relate: (1) a mineral resource estimate (inclusive of reserves when available) to annual production, and (2) a mineral reserve estimate to annual production. This was done through regression analysis of $\log_{10}$ transformed data for every deposit type and mining method combination on both ore and contained metal bases. Explanatory variables were calculated for the regression data including the coefficient of determination (R^2), the standard error of the slope (*SE*), the geometric standard deviation (*SD*) and the probability of the null hypothesis (p). Regression factors derived for some deposit type and mine type combinations were excluded from use in the subsequent analysis, as they were derived from an insufficient sample size ($n<=3$) or were not statistically significant ($p>0.05$).

2.4. Estimating Upper Primary Supply Limits via Monte Carlo Simulation

The upper supply limit is defined on the assumption that all known deposits can be mined simultaneously and so is the sum of estimated production rates (P) for all deposits (d) (Equation 2). There is considerable uncertainty associated with estimating the production capacity of individual deposits and the observed values follow a log-normal distribution. As log-normal distributions are positively skewed the simple summation of Taylor's rule derived production capacities for all deposits without considering uncertainty would be biased to underestimate total upper supply capacity. For this reason, Monte-Carlo analysis of Equation 2, considering the uncertainty of estimated production rate for each deposit, was performed 2000 times and weonly present results for the full range of calculated upper primary supply limits.

Equation 2: $\boldsymbol{Upper\ Supply\ Limit = \sum_d P_d}$

For each simulation of the Monte-Carlo analysis, where the production rate deposit in 2015 was known, this this original production rate was used. To estimate the production capacity of all other deposits without a known production rate, Equation 1 is first applied to determine a mean estimate for each deposit (d). This was incorporated into a log-normal probability distribution function (Equation 3) to stochastically estimate production rates for each deposit, also using the geometric standard deviations derived from the regression analysis. Deposit type specific factors were used in cases where there was a high likelihood of statistical significance for the derived factors (p value < 0.05). In other cases, the factors derived for the set of all copper mines was used.

Upper supply limits derived from the set of deposits with mineral reserve estimates and the set of deposits with mineral resource estimates were estimated on both a metal and an ore tonnage basis.

Equation 3: $P_d = f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-aR_d{}^b}{\sigma}\right)^2}$

3. Results and Discussion

3.1. Derived mineral resource and reserve-to-production rate factors

Figure 1 shows the derived regression factors for the set of all mines for which production data was available in 2015. Additional figures are available in the electronic supporting information for all mine and deposit type combinations (see Supplementary Figures 1 to 45).

The regression factors derived for mineral resource and reserve to production rate relationships are shown in Table 2. Statistically significant ($p<0.05$) relationships were derived for a number of deposit types including porphyry, iron oxide copper-gold (IOCG), magmatic sulphide, skarn, sediment-hosted and volcanic massive sulphide (VMS) deposits as well as for open pit and underground mines across the full set of copper deposits. However, for specific mine type and deposit type combinations, many of the derived regression relationships were found to not be statistically significant (e.g. open pit mining of magmatic sulphide deposits), potentially in part due to small sample sizes.

Copper mines vary considerably in their scale of production. For open pit mines, the observed annual supply rate range from 185 kt – 184 Mt ore/year and 400 – 828,400 t Cu/year, with mineral reserves ranging from 1.3 Mt – 8.6 Gt ore and 1 kt – 50.6 Mt Cu and mineral resources ranging from 7.4 Mt– 19 Gt ore and 84.5 kt – 104 Mt Cu. In comparison, underground mines have observed annual supply rates that range from 17 kt–59 Mt ore/year and 100 t – 471 kt Cu/year, mineral reserves that range from 289 kt– 1.7 Gt ore and 1 kt – 15 Mt Cu, and mineral resources that range from 289 kt – 21.7 Gt ore and 1.6 kt – 99 Mt Cu. Deposits with defined reserves above ~83 Mt ore or resources above ~140 Mt ore were more often mined via open pit methods than underground. The dataset contained some outliers, such as several medium-to-high tonnage deposits with very low annual copper supply rates. Factors contributing to this are varied, but include some mines being in their initial stage of production ramp up and also some mines primarily target other commodities, where copper is being extracted from low copper grade ore as a co- or by-product of another commodity. Despite the presence of these outliers, sample sizes were generally large enough that most regressions had a good statistical fit.

Regressions performed using reserves data typically resulted in a higher coefficient of determination (R^2) and a lower geometric standard deviation (SD), although there are exceptions for some deposit type and mine type combinations. This is notable as previous studies have relied on mineral reserve estimates when deriving similar regression factors, including the two most relevant studies by Taylor (1977) and Long (2009). Long (2009) in particular provided updated factors for copper deposits on a metric tonnes per day basis based on data for 94 open pit (and block caving) and 31 underground mines (with high geographical bias towards Australia and the Americas).

Definitions for mineral reserves and resources have varied across jurisdictions and through time, but in general mineral reserves have a higher degree of economic and/or geologic certainty and an associated higher likelihood to be economically recoverable (i.e., the essential definition of a reserve). Mineral reserve estimates are also influenced by modifying factors to better incorporate aspects of the economic and technical feasibility of ore extraction, which can be highly tailored and site specific (Jowitt and McNulty, 2021). There is increasing conformance of mineral reserve and resource reporting terminology across jurisdictions as a result of initiatives such as those by CRISCRO (2024). Wellmer and Drobe (2019) noted that mining projects in China and Russia had smaller installed production capacity than predictions based on Long (2009)'s regression factors, suggesting that one reason could be due to differences in mineral reserve reporting standards. The deposit data used by this study includes both reporting code and non-code compliant mineral resource estimates (Mudd and Jowitt, 2018) and so these types of biases and uncertainties may be embedded in the dataset.

3.2. Upper Supply Limits based on Monte Carlo Simulation

The derived upper primary supply limits for copper resources are shown in Figure 3 and in Supplementary Figure 51. For the set of deposits with mineral reserve estimates the 90% confidence interval for the upper primary supply limit is estimated to be 22-27 Mt Cu/year and 4.6-6.0 Gt ore/year. In comparison, for the set of deposits with mineral resource estimates the 90% confidence interval for the upper primary supply limit is 59-69 Mt Cu/year and 12-15 Gt ore/year.

These derived upper primary supply limits can be compared with published scenarios for primary copper demand, which may provide some indication of their potential feasibility. Increasingly, scenarios for future mineral production and commodity demand are incorporating defined scenario frameworks, such as the shared socio-economic pathways (SSP) that were developed for understanding socio-economic transitions and climate mitigation pathways (O'Neill et al., 2017). Some scenarios for primary copper demand have been evaluated for SSPs, for instance Klose and Pauliuk (2023) modelled primary copper demand for SSP2 under both business-as-usual and a resource efficiency scenario. The results of their study are also shown in Figure 3, demonstrating that although primary copper demand has the potential to exceed the upper primary supply limit of identified reserves by 2050, there is also strong potential for implementation of resource efficiency strategies to constrain primary demand growth below this. Likewise, scenarios from Schipper et al. (2018) assuming high copper recycling rates (90%) do not exceed the potential upper annual supply limit of currently identified copper reserves under SSPs 1 to 4, although by mid-century this could be exceeded under SSP5. Scenarios produced by the International Energy Agency for primary copper demand in 2040 also do not exceed the potential upper supply limits of deposits with reserves (IEA, 2024).

Increasingly, scenario modelling approaches are attempting to understand required rates of future mine development and the extent to which mineral resources can support mineral supply rates into the future. For instance, the recently developed PEMMSS model (Northey et al., 2023) has been designed to utilise the resource-production relationship when evaluating the likely achievable rate of production from known deposits and potential future discoveries. Other recent modelling approaches are also providing new insights into how mineral supply rates may be influenced by price (and vice versa) (Ryter et al., 2024). There are multiple economic feedbacks and price signals that regulate the supply, demand and availability of mineral resources through changes to cut-off grades and the economic feasibility of resource exploration, development, mine expansion, mineral co-production and demand side responses (Wellmer and Dalheimer, 2012; Tilton et al., 2018). Systems dynamics models incorporating some of these feedback mechanisms have been developed for the copper sector and have been used to develop scenarios for future copper supply (Sverdrup et al., 2014). We note that scenario modelling approaches considering identified copper resources as a fixed stock without consideration for further resource discovery or expansion will inevitably produce results depicting a looming peak in annual primary copper supply. On this basis, scenarios of Northey et al. (2014) and Sverdrup et al. (2014) produced peak primary copper supply of 25.3-27.5 Mt Cu/year and ~21 Mt Cu/year, respectively. The results of these studies are within the range of upper primary supply limit of copper reserves identified in 2015, but well below the upper primary supply limits estimated from identified copper resources in 2015. The underlying assumptions and model design used in these types of studies should be carefully considered when interpreting scenario results. Our perspective is that the significant inherent uncertainty associated with any scenario modelling of both the timing and magnitude of peak primary copper supply should be emphasised when communicating study results. These should also be considered alongside the ongoing, healthy debate in the literature regarding the case for both economic-techno-optimism and fixed stock pessimism in relation to future copper supply (Gordon et al., 2006; Tilton and Lagos, 2007; Gordon et al., 2007; Kerr et al., 2014; Meinert et al., 2016; Singer, 2017; Tilton et al., 2018; Jowitt et al., 2020; Guj and Schodde, 2025).

There may also be significant potential for improvements to material efficiency and end-of-life management of materials to dramatically reduce the long-term need for primary material supply. Dominish et al. (2019) identified the need for implementation of strategies to slow and narrow material flows through the economy. In addition, Watari et al. (2022) identified that application of a proportional carbon budget to the copper sector would require suppression of long-term primary copper demand. Examples of how primary demand growth could be suppressed include activities that extend the lifetime of products, improve collection rates for end-of-life products and scrap, improve recovery and recycling efficiencies at all stages of production systems, as well as change societal expectations regarding acceptable rates of material consumption and consumerism (Dominish et al., 2019; Klose and Pauliuk, 2023; Watari et al., 2022). Beyond stock dynamics, copper market dynamics may also heavily influence secondary supply over the long-term and development of markets specifically for copper scrap could be a mechanism to influence this (Ryter et al., 2022). The combination of these types of measures may constrain growth in primary copper demand, hopefully to within any fundamental primary supply limits.

3.3. Implications for the Future

The feasibility of some long-term demand scenarios for copper should be considered. The results of this analysis suggest that both strong implementation of circular economy strategies (including copper demand reduction, reuse and recycling) and also continued investment in mineral exploration to identify additional mineral resources will both be required to bridge the gap between the future supply and demand of copper.

In the absence of a publicly accessible concrete mine plan, Taylor’s rule provides an empirical estimate of the likely lifetime and rate of production for a given deposit. As such, it is particularly useful in the early stages of mine development, and is frequently employed during the scoping and prefeasibility stages. For example, Taylor’s rule is incorporated into the procedures for estimation of mineral deposit value that have been developed and applied by the former US Bureau of Mines and the USGS (eg. Camm, 1991; Long and Singer, 2001; Camm and Stebbins, 2020). Even prior to the planning stage of a project, Taylor’s rule has been used to winnow-down potential development options or even highlight new exploration targets. Singer *et al.* (1998) illustrated how estimates of mine costs derived using Taylor’s rule, combined with projected revenues from those projects may be used to categorize deposits as uneconomic, marginal or economic from an estimate of orebody tonnage. Walsh and others (Walsh et al., 2020; Haynes et al., 2020) later applied Taylor’s-rule informed cost models as part of mapping the “Economic Fairways” for exploration projects (i.e. regions favoured for mineral project development based on factors governing their relative economic viability). Mine cost modelling based on these approaches have had reasonable predictive capacity and anecdotally have seen meaningful use and adoption by industry. Improving the availability and accuracy of models and relationships for predicting production capacity have a variety of potential uses in these fields of study and analysis, so we encourage further work to update these relationships for a broader set of commodities, deposit types, mine types and regions. Long (2009) provides some useful examples including analysis of how regression factors have changed across decades, differences between commodities and mine types, and how additional explanatory factors, such as ore grades or mine expansion, can further explain observed data and refine the derived relationships.

Attempts to understand the upper primary supply limit from identified resources for other commodities may also help inform discussions regarding the feasibility of future technology roll-out scenarios and the material intensive based strategies for decarbonisation and environmental impact mitigation. We expect that this form of analysis would lead to different discussions when compared to traditional assessments of resource depletion that have tended to focus on total material stocks available to society or cumulative extraction through time. As part of this, there may be potential to better understand hard production limits for mineral co-product and by-product commodities, which have been poorly assessed to date and for which there is now only emerging reasonable approaches for global mineral resource or reserve estimation (McNulty and Jowitt, 2021; Werner et al., 2017; Werner et al., 2023; Greffe et al., 2024). Frenzel et al. (2015) also previously estimated the by-product supply potential of gallium, germanium and indium based on supply capacity of existing copper and zinc mines, providing a useful proof of concept that we suggest could be extended to also consider supply capacity estimates for undeveloped deposits.

3.4. Limitations and Caveats

We recommend caution when interpreting the results of this study and we emphasise that they only provide an upper bound on potential annual supply from copper resources and reserves identified in 2015. There is also uncertainty and biases that are embedded in the datasets relied on for the analysis. For instance, the derived factors for Taylor's rule implicitly assume a static relationship between orebody size and production rate. However, it is widely recognized that the rule must be regularly updated to account for changing technology and economic factors (Long and Singer, 2001). Ideal rates of production will shift over the multidecadal lifetime of many mines. Similarly, an orebody's nominal size will fluctuate over its lifetime, as changing circumstances render grades previously considered uneconomic, economic and vice versa. As mining will often commence before a deposit has been fully explored and delineated there can be considerable re-evaluation or expansion of defined reserves and resources through the life of a mine (Meinert et al., 2016; Jowitt et al., 2020), which has implications for the economically optimal rate of production (Wellmer et al., 2008). Price fluctuations, changing cost drivers and geologic uncertainty can all lead to change of mine plans in both positive and negative ways (Wellmer and Dalheimer, 2012) and techniques such as real options analysis can be used to identify opportunities for counter-intuitive optimisation decisions, such as increasing ore throughput to process operations to maximise short-term production and revenues at the expense of life-of-mine recovery (Yap et al., 2013).

Given these types of confounding factors and uncertainties, it should be emphasised that Taylor's rule only gives a rough approximation of potential production rates for any individual deposit. More precise quantifications are made during advanced feasibility, engineering design and mine planning processes where information on deposit geomorphology, block modelling, mining methods, equipment selection and metallurgical process design is combined to establish anticipated production schedules. Anticipated production rates in turn often differ from achieved production rates due to the realities of mine operation such as differences in modelled and achieved equipment cycle times, equipment breakage and unplanned maintenance, unexpected rock and ore characteristics, and process performance (Berkhimer, 2011; Sinclair and Blackwell, 2004). There can also be potential for ore dilution and recovery difficulties, which can result in varying copper losses to waste rock dumps and tailings through the life of a mine that affects achieved production rates. Copper ore mineralogy also greatly influences the production technology employed and the potential for bottlenecks at different stages of the process. Copper oxide ores tend to be shallower and more likely mined via open pit (although not always) and are heap leached for subsequent solvent extraction-electrowinning. In contrast, copper sulphide ores tend to be located deeper than often near-surface oxide mineralisation, can be mined via either open pit or underground methods, and are typically processed to produce flotation concentrates. Many deposits also have mixed ore types (e.g. oxide caps overlaying deeper sulphide sections), which necessarily results in changing processing requirements and performance through the mine life.

The dataset of copper deposits used (Mudd and Jowitt, 2018) also has limitations that should be recognised. For instance, some datapoints represent aggregations between satellite deposits, or distinct ore zones for individual resource projects. The achievable production rate from a set of production deposits with a given aggregate mineral resource may differ when compared to if this resource was contained within a single contiguous deposit. The data quality of the reserve and resource estimates for individual deposits will also vary considerably, particularly for deposits in regions where there is less strict adherence to formal reserve/resource reporting codes (e.g. JORC, NI43-101, etc.) or for regions where mineral deposits are controlled by private entities or subsidies or by government-controlled entities without formal reporting requirements. In addition, the deposits contained in the datasets represent mines at different points in their mine life, meaning that a variable portion of the deposits in these datasets will have already been mined, leading in turn to a variable and unquantified reduction in the associated resource or reserve. There is also uncertainty regarding the extent of completion of exploration of individual mineral deposits within datasets, which is likely to be a significant factor given the nature of mineral resource and reserve reporting that necessarily and significantly under-reports contained metal amounts relative to the true extent of mineralized systems (Jowitt et al., 2020; Jowitt and McNulty, 2021). Many reserve / resource estimates remain 'open' in multiple dimensions as a result of this code-based requirement for under-reporting of total endowments that are not quantified in sufficient detail to be reported as resources. It is also unclear which individual deposits or what proportion of the deposits within these datasets could have resource sizes that may grow in responses to reduction in cut-off grades associated with altered economics and increased market prices for copper (or indeed for associated other products such as co- and by-product metals) in the future. Furthermore, although the dataset is extensive it is by no means complete since public reporting of reserves-resources for many countries remains inadequate (meaning the dataset represents an underestimate of global copper reserves/resources). In short, there is considerable unquantified uncertainty embedded in all aspects of this analysis that should be communicated alongside the quantified results of this study.

4. Conclusions

Concerns over society's ability to maintain and grow primary copper supply are well founded. There are real-world constraints to continued growth of mineral extraction rates that must be recognised. The ability to grow future primary copper supply will ultimately depend on several factors that go beyond the defined size of existing mineral resources, including the availability of capital, labour, infrastructure, machinery and expertise plus the social-licence of the sector. The complex inter-play between copper prices, cut-off grades, resource and reserve definitions, efficiencies of scale, geologic and economic uncertainties, variable process configurations and technologies, and the willingness to invest in exploration activities are all key long-term determinants of future availability. These are difficult to comprehensively assess due to practical data limitations and model deficiencies.

Our study ignored these complex factors and relationships and instead answered a simpler question. What is an upper limit for primary copper supply, assuming that all known deposits can be exploited simultaneously at rates comparable to those observed at existing copper projects with comparable defined mineral reserves and resources? The 90% confidence interval of this theoretical upper supply limit was found to be 22-27 Mt Cu/year for the set of deposits with reserve estimates and 59-69 Mt Cu/year for the set of deposits with resource estimates. Recent annual primary production and scenarios for future copper demand in 2040 and 2050 extend firmly into the range of the upper supply limit of reserves that were known in 2015, however are well below the upper supply limit from known resources in 2015. This suggests that annual production could grow further into the future if continued exploration, demand and price signals were in place to allow conversion of known resources into reserves and then mine production.

This study did not consider analysis of the so-called 'ultimate' copper resource accessible to society or the potential to grow primary supply from non-conventional, unidentified or undefined mineral resources. The past ten years of copper exploration has also not been considered due to the age of the resource dataset used. The study also does not include or consider secondary copper supply potential and how that may change in response to in-use stock, scrap recovery and urban mining dynamics overtime. Although these have not been assessed, we view that there may be strong long-term benefits for actions to improve resource efficiency at all stages of the copper life cycle and to enact strategies to avoid any unnecessary primary demand increases. A range of strategies can be employed in this regard (Dominish et al., 2018; Klose and Pauliuk, 2023). This may help to preserve the accessibility of mineral resources for future generations and to constrain resource exploitation to a rate that would ensure that environmental and social safeguards can be put in place alongside extractive operations.

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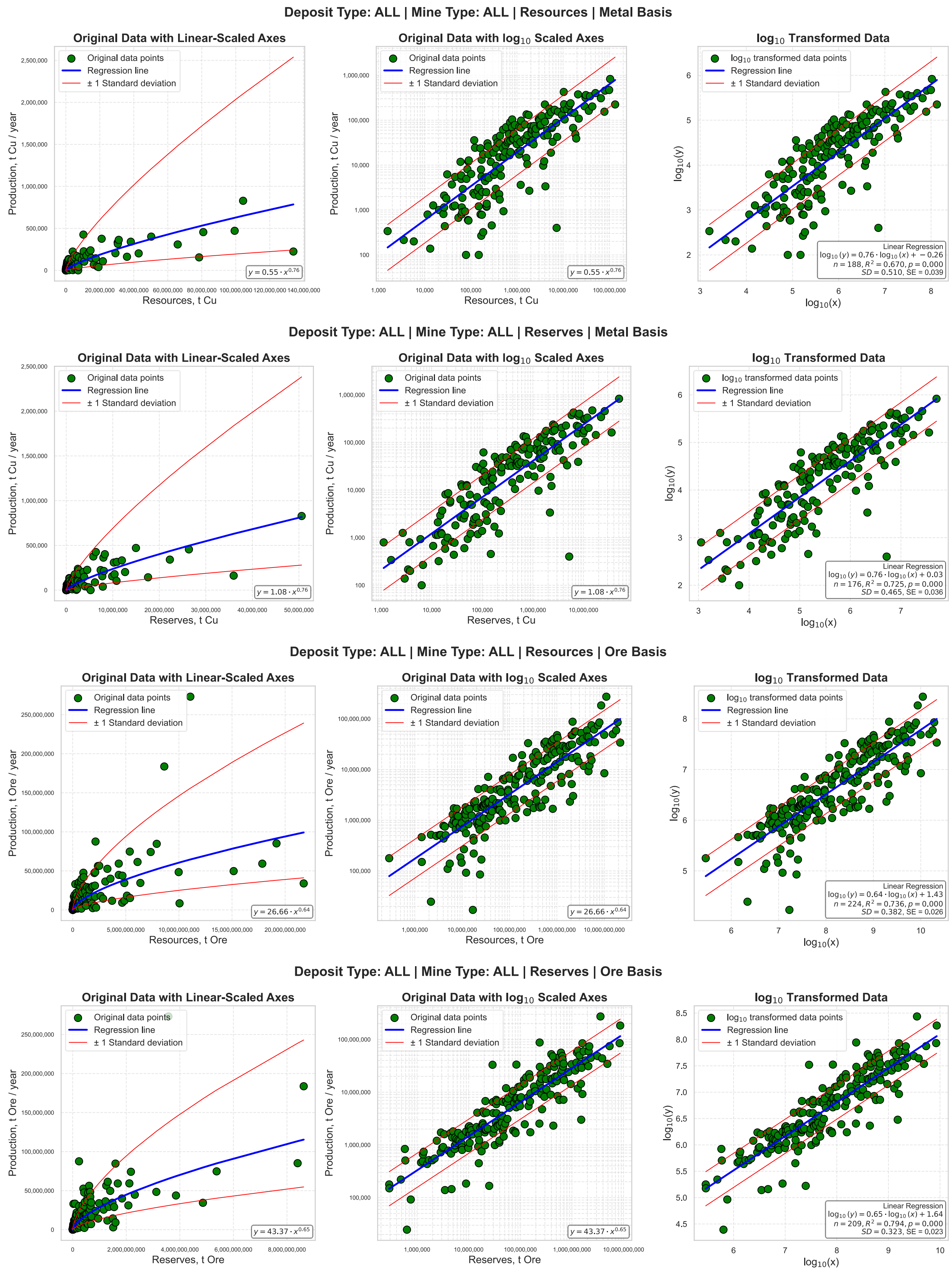

Figure 1: Original and log10 transformed data for copper mine production rates and reserves or resources for the year 2015, shown on both a copper and ore tonnage basis. Linear regressions were performed on the $\log_{10}$ transformed data. See electronic supplementary information for regression graphs for all copper deposit types and mine types combinations (Supplementary Figure 1 to 45).

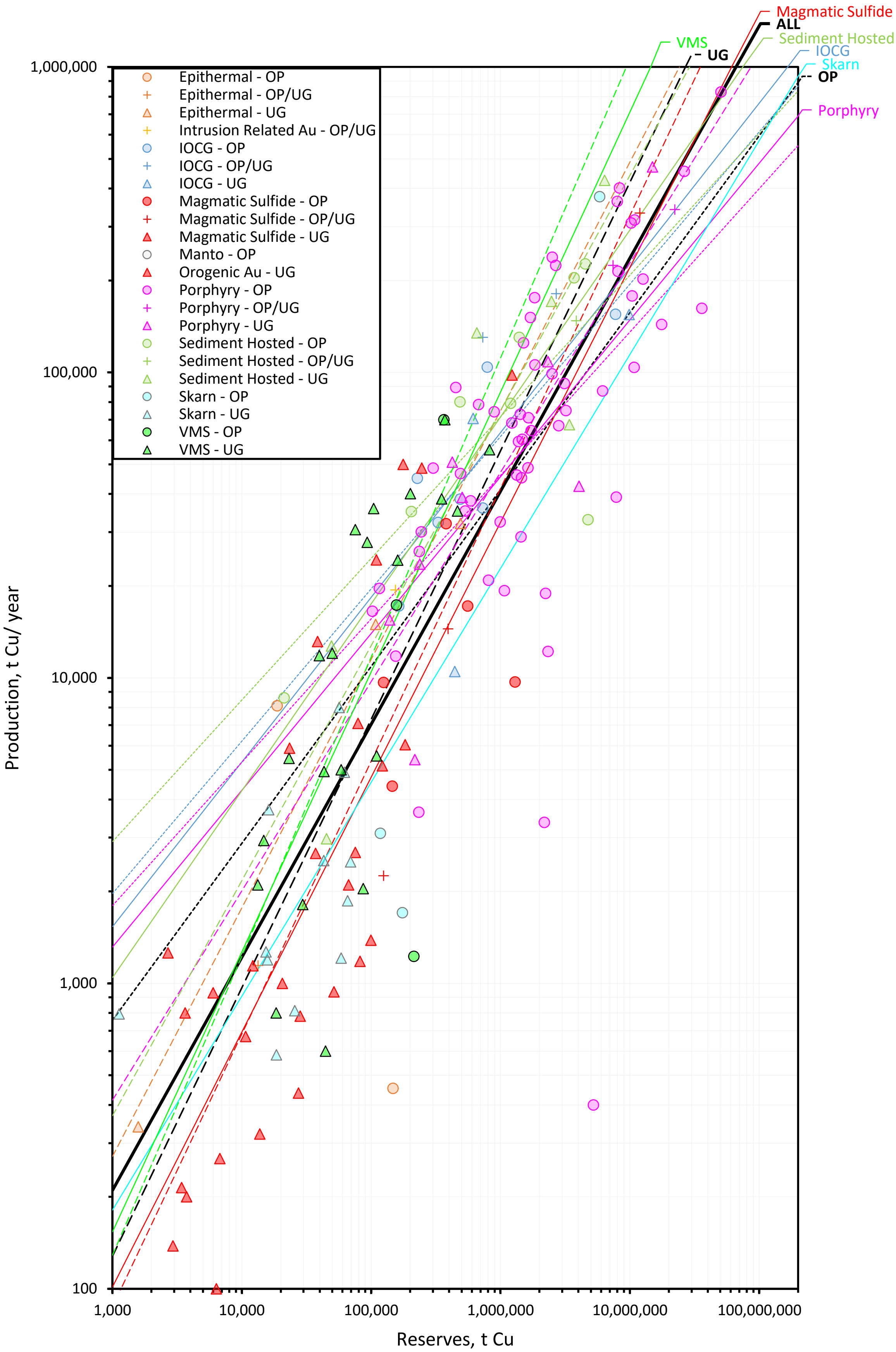

Figure 2: Derived copper production rate to contained copper reserve relationships for copper mine types and deposit types in the year 2015. Lines represent power-law regressions coloured according to deposit type, with short-dash lines indicating open pit mines, long-dash lines indicating underground mines and solid lines representing the relationship for all mines in the deposit type category. Only statistically significant ($p<0.05$) relationships are shown. See electronic supplementary information for equivalent plots on a resource and an ore basis (Supplementary Figures 48 to 51).

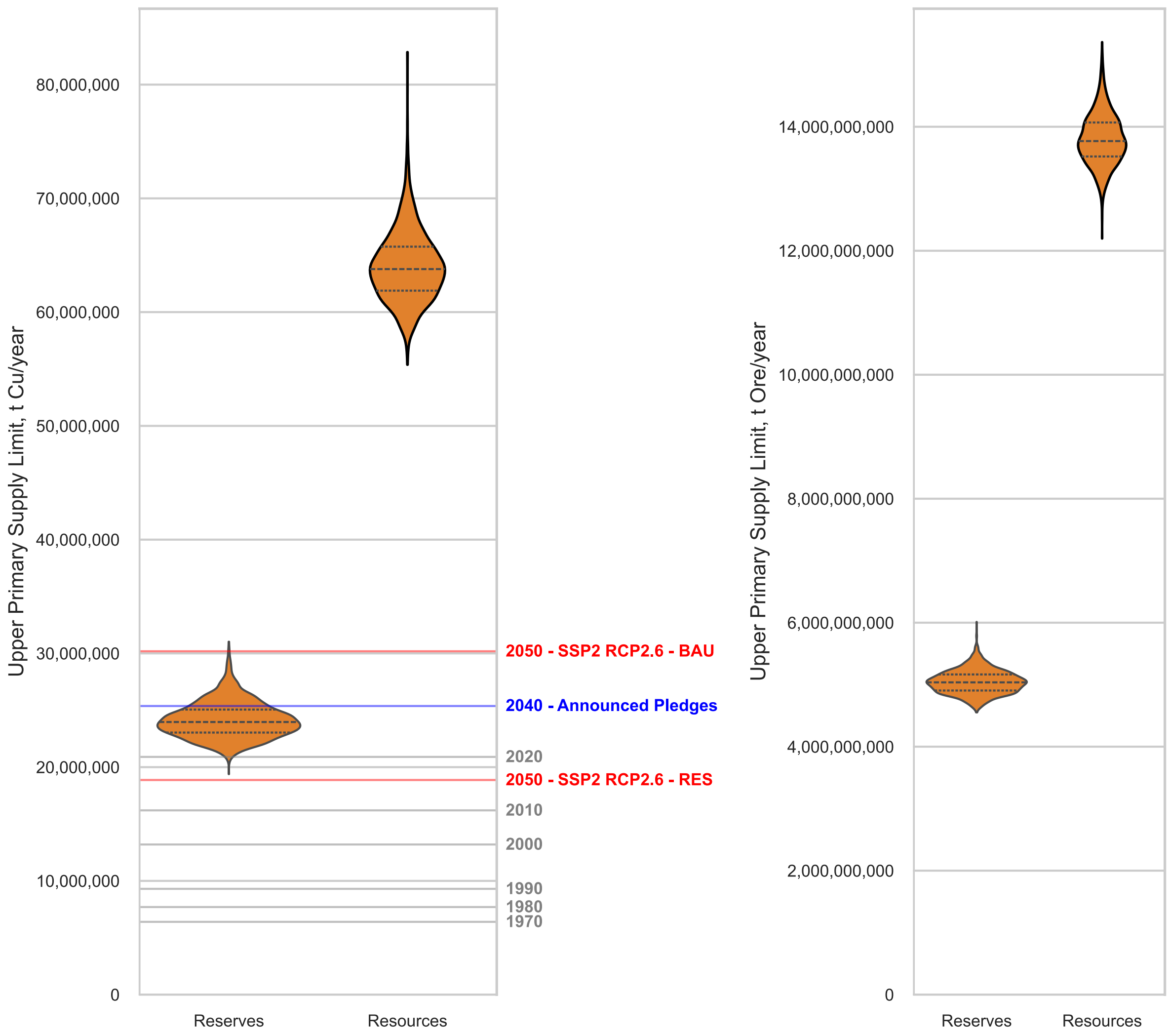

Figure 3: Monte Carlo simulation (n=2000) of the upper primary supply limit for the sets of copper deposits with reserve estimates and resource estimates. Interquartile ranges are shown by dotted lines. Horizontal lines indicate historic copper mine production (BGS, 2025) and projected primary copper demand under the IEAs' Announced Pledges Scenario (IEA, 2024) and Klose and Pauliuk (2023)'s Business as Usual (BAU) and with Resource Efficiency Strategies (RES) scenarios for the second shared socio-economic pathway (SSP2 RCP2.6).

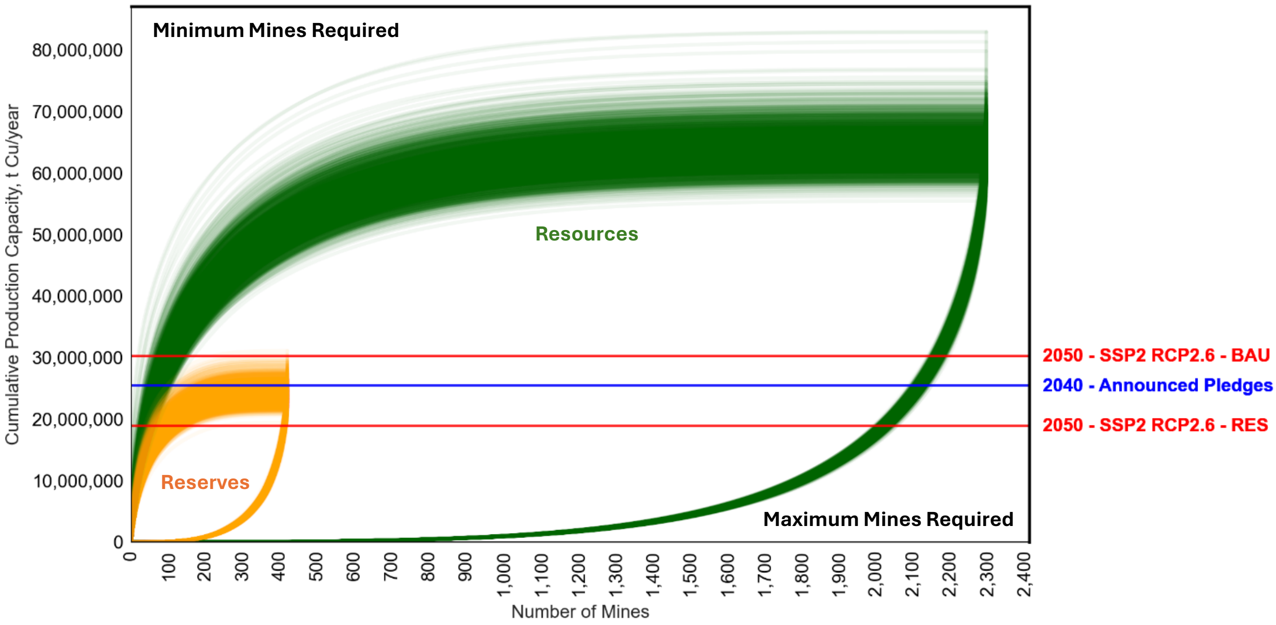

Figure 4: Monte Carlo simulation (n=2000) results for the minimum and maximum number of mines required to reach a given production capacity from the sets of deposits with reserve and resource estimates. Horizontal lines indicate projected primary copper demand under the IEAs' Announced Pledges Scenario (IEA, 2024) and Klose and Pauliuk (2023)'s Business as Usual (BAU) and with Resource Efficiency Strategies (RES) scenarios for the second shared socio-economic pathway (SSP2 RCP2.6).

Table 1: Data for copper mines in 2015 where both a resource or reserve estimate and the production rate was available. Resource estimates shown are inclusive of reserves.

		Metal Basis						Ore Basis					
Deposit Type	Mine Type	No.	Resources t Cu	Production t Cu/year	No.	Reserves t Cu	Production t Cu/year	No.	Resources kt Ore	Production kt Ore/year	No.	Reserves kt Ore	Production kt Ore/year
ALL	ALL	188	1,274,478,975	12,455,886	176	421,927,682	12,160,836	224	279,895,589	3,202,335	209	95,450,774	3,158,361
ALL	OP	89	778,103,781	8,445,001	83	318,508,989	8,185,524	89	160,230,426	1,930,447	83	67,913,119	1,893,508
ALL	OP-UG	10	226,995,031	1,394,187	10	49,585,691	1,394,187	10	31,265,825	198,332	10	5,047,265	198,332
ALL	UG	89	269,380,163	2,616,698	83	53,833,002	2,581,125	89	47,581,940	339,165	83	7,064,588	333,123
ALL	Unknown	-	-	-	-	-	-	36	40,817,399	734,391	33	15,425,801	733,399
Epithermal	ALL	7	2,862,365	63,414	7	815,911	63,414	11	579,870	9,148	9	208,687	8,667
Epithermal	OP	2	369,153	8,554	2	166,347	8,554	2	330,835	2,398	2	157,762	2,398
Epithermal	OP-UG	1	26,460	1,143	1	13,350	1,143	1	8,820	747	1	4,450	747
Epithermal	UG	4	2,466,752	53,717	4	636,214	53,717	4	167,973	3,944	4	32,124	3,944
Epithermal	Unknown	-	-	-	-	-	-	4	72,242	2,059	2	14,350	1,578
Intrusion-Related Au	ALL	1	559,044	19,399	1	153,785	19,399	1	360,437	22,055	1	149,000	22,055
Intrusion-Related Au	OP	-	-	-	-	-	-	-	-	-	-	-	-
Intrusion-Related Au	OP-UG	1	559,044	19,399	1	153,785	19,399	1	360,437	22,055	1	149,000	22,055
Intrusion-Related Au	UG	-	-	-	-	-	-	-	-	-	-	-	-
Intrusion-Related Au	Unknown	-	-	-	-	-	-	-	-	-	-	-	-
IOCG	ALL	12	100,923,773	975,176	12	24,837,313	975,176	13	13,313,967	141,089	13	2,757,866	141,089
IOCG	OP	7	12,867,880	428,001	7	10,476,196	428,001	7	2,112,293	82,385	7	1,603,953	82,385
IOCG	OP-UG	2	6,816,868	311,345	2	3,430,252	311,345	2	905,289	40,722	2	528,183	40,722
IOCG	UG	3	81,239,025	235,830	3	10,930,865	235,830	3	10,290,220	17,144	3	625,150	17,144
IOCG	Unknown	-	-	-	-	-	-	1	6,165	838	1	580	838
Magmatic Sulphide	ALL	36	46,001,001	657,119	35	17,495,688	650,898	36	14,791,588	140,527	35	4,039,872	139,235
Magmatic Sulphide	OP	5	5,761,370	72,988	5	2,501,208	72,988	5	4,468,279	35,143	5	1,686,176	35,143
Magmatic Sulphide	OP-UG	3	32,522,139	349,158	3	12,473,954	349,158	3	3,500,679	36,110	3	1,165,132	36,110
Magmatic Sulphide	UG	28	7,717,492	234,973	27	2,520,526	228,752	28	6,822,629	69,273	27	1,188,564	67,981
Magmatic Sulphide	Unknown	-	-	-	-	-	-	-	-	-	-	-	-
Manto	ALL	1	988,920	29,400	-	-	-	2	67,738	3,033	1	3,056	879
Manto	OP	1	988,920	29,400	-	-	-	1	60,300	2,154	-	-	-
Manto	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-
Manto	UG	-	-	-	-	-	-	-	-	-	-	-	-
Manto	Unknown	-	-	-	-	-	-	1	7,438	879	1	3,056	879
Orogenic Au	ALL	2	685,944	48,798	2	249,430	48,798	4	139,436	6,188	4	41,910	6,188
Orogenic Au	OP	-	-	-	-	-	-	-	-	-	-	-	-
Orogenic Au	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-
Orogenic Au	UG	2	685,944	48,798	2	249,430	48,798	2	14,098	1,120	2	6,437	1,120
Orogenic Au	Unknown	-	-	-	-	-	-	2	125,338	5,068	2	35,473	5,068
Porphyry	ALL	67	980,984,285	7,867,151	65	334,784,374	7,731,243	80	237,982,280	2,561,427	78	83,545,165	2,532,972
Porphyry	OP	57	675,936,857	6,545,308	55	282,240,840	6,409,400	57	145,210,754	1,655,779	55	61,628,011	1,627,324
Porphyry	OP-UG	2	172,121,400	565,369	2	29,663,000	565,369	2	26,083,000	93,243	2	3,102,000	93,243
Porphyry	UG	8	132,926,028	756,474	8	22,880,534	756,474	8	27,038,554	119,307	8	3,736,243	119,307
Porphyry	Unknown	-	-	-	-	-	-	13	39,649,972	693,099	13	15,078,910	693,099
Sediment Hosted	ALL	19	109,624,901	1,839,343	15	33,117,486	1,759,526	21	8,766,927	179,980	17	3,401,509	172,793
Sediment Hosted	OP	10	59,038,773	872,144	8	16,271,958	796,921	10	5,460,605	85,087	8	2,113,004	80,723
Sediment Hosted	OP-UG	1	14,949,120	147,773	1	3,851,350	147,773	1	407,600	5,455	1	98,500	5,455
Sediment Hosted	UG	8	35,637,008	819,426	6	12,994,178	814,832	8	2,156,022	73,164	6	1,012,105	70,340
Sediment Hosted	Unknown	-	-	-	-	-	-	2	742,700	16,275	2	177,900	16,275
Skarn	ALL	16	22,863,496	434,211	15	6,565,615	410,447	18	2,873,772	81,700	17	877,250	79,900
Skarn	OP	3	21,641,050	381,099	3	6,117,660	381,099	3	2,485,622	59,746	3	685,912	59,746
Skarn	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-
Skarn	UG	13	1,222,446	53,112	12	447,955	29,348	13	352,737	20,202	12	182,469	18,402
Skarn	Unknown	-	-	-	-	-	-	2	35,413	1,751	2	8,869	1,751
VMS	ALL	27	8,985,246	521,875	24	3,908,080	501,935	38	1,019,575	57,190	34	426,459	54,585
VMS	OP	4	1,499,778	107,507	3	734,780	88,561	4	101,737	7,756	3	38,300	5,789
VMS	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-
VMS	UG	23	7,485,468	414,368	21	3,173,300	413,374	23	739,707	35,012	21	281,496	34,885
VMS	Unknown	-	-	-	-	-	-	11	178,131	14,422	10	106,663	13,911

Table 2: Power law ($P=aR^b$) regression factors and explanatory statistics for copper deposit types and mining methods. Refer to the electronic supplementary information for regressions conducted on an ore basis (Supplementary Table S2) and for plots of each regression (Supplementary Figures 1 to 45).

		Metal Basis													
		Resources (incl. reserves)							Reserves						
Deposit Type	**Mine Type**	**a**	**b**	**No.**	**R^2**	**p**	**SD**	**SE**	**a**	**b**	**No.**	**R^2**	**p**	**SD**	**SE**
ALL	**ALL**	**0.555**	**0.757**	**188**	**0.670**	**0.000**	**0.510**	**0.039**	**1.080**	**0.763**	**176**	**0.725**	**0.000**	**0.465**	**0.036**
ALL	OP	4.858	0.618	89	0.466	0.000	0.465	0.071	13.854	0.579	83	0.401	0.000	0.500	0.079
ALL	OP-UG	0.732	0.737	10	0.807	0.000	0.379	0.127	0.447	0.836	10	0.883	0.000	0.296	0.108
ALL	UG	0.404	0.772	89	0.587	0.000	0.548	0.069	0.295	0.879	83	0.766	0.000	0.413	0.054
ALL	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Epithermal	**ALL**	**4.896**	**0.567**	**7**	**0.526**	**0.065**	**0.492**	**0.241**	**6.897**	**0.585**	**7**	**0.383**	0.138	**0.561**	**0.332**
Epithermal	OP	$4x10^{15}$	-2.373	2	1.000	0.000	0.000	0.000	$7.41x10^9$	-1.395	2	1.000	0.000	0.000	0.000
Epithermal	OP-UG	-	-	1	-	-	-	-	-	-	1	-	-	-	-
Epithermal	UG	3.054	0.650	4	0.995	0.002	0.052	0.032	0.981	0.814	4	0.985	0.008	0.092	0.071
Epithermal	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intrusion-Related Au	**ALL**	-	-	**1**	-	-	-	-	-	-	**1**	-	-	-	-
Intrusion-Related Au	OP	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intrusion-Related Au	OP-UG	-	-	1	-	-	-	-	-	-	1	-	-	-	-
Intrusion-Related Au	UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intrusion-Related Au	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
IOCG	**ALL**	**290.799**	**0.368**	**12**	**0.366**	**0.037**	**0.307**	**0.153**	**36.938**	**0.539**	**12**	**0.568**	**0.005**	**0.253**	**0.149**
IOCG	OP	54.932	0.490	7	0.547	0.057	0.201	0.199	62.797	0.499	7	0.727	0.015	0.156	0.137
IOCG	OP-UG	1329.388	0.318	2	1.000	0.000	0.000	0.000	4374.662	0.251	2	1.000	0.000	0.000	0.000
IOCG	UG	114.059	0.391	3	0.439	0.539	0.367	0.442	5.837	0.638	3	0.619	0.424	0.303	0.501
IOCG	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Magmatic Sulphide	**ALL**	**0.335**	**0.744**	**36**	**0.487**	**0.00**	**0.565**	**0.131**	**0.318**	**0.834**	**35**	**0.728**	**0.000**	**0.416**	**0.089**
Magmatic Sulphide	OP	2751.336	0.109	5	0.029	0.785	0.283	0.364	321.009	0.283	5	0.138	0.538	0.266	0.408
Magmatic Sulphide	OP-UG	0.001	1.146	3	0.996	0.042	0.059	0.075	0.013	1.054	3	0.982	0.085	0.119	0.142
Magmatic Sulphide	UG	0.967	0.645	28	0.303	0.002	0.597	0.192	0.183	0.893	27	0.626	0.000	0.441	0.138
Magmatic Sulphide	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Manto	**ALL**	-	-	**1**	-	-	-	-	-	-	-	-	-	-	-
Manto	OP	-	-	1	-	-	-	-	-	-	-	-	-	-	-
Manto	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Manto	UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Manto	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Orogenic Au	**ALL**	**0.000**	**1.493**	**2**	**1.000**	**0.000**	**0.000**	**0.000**	**0.004**	**1.323**	**2**	**1.000**	**0.000**	**0.000**	**0.000**
Orogenic Au	OP	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Orogenic Au	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Orogenic Au	UG	0.000	1.493	2	1.000	0.000	0.000	0.000	0.004	1.323	2	1.000	0.000	0.000	0.000
Orogenic Au	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Porphyry	**ALL**	**15.466**	**0.541**	**67**	**0.429**	**0.000**	**0.435**	**0.078**	**37.857**	**0.513**	**65**	**0.352**	**0.000**	**0.458**	**0.088**
Porphyry	OP	18.327	0.531	57	0.346	0.000	0.464	0.099	70.022	0.469	55	0.276	0.000	0.481	0.105
Porphyry	OP-UG	$1.17x10^8$	-0.334	2	1.000	0.000	0.000	0.000	546.519	0.380	2	1.000	0.000	0.000	0.000
Porphyry	UG	6.730	0.591	8	0.888	0.000	0.180	0.086	3.642	0.685	8	0.731	0.007	0.280	0.170
Porphyry	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Sediment Hosted	**ALL**	**0.613**	**0.771**	**19**	**0.745**	**0.000**	**0.345**	**0.109**	**15.242**	**0.612**	**15**	**0.720**	**0.000**	**0.304**	**0.106**
Sediment Hosted	OP	3.652	0.654	10	0.710	0.002	0.237	0.148	118.417	0.464	8	0.623	0.020	0.273	0.147
Sediment Hosted	OP-UG	-	-	1	-	-	-	-	-	-	1	-	-	-	-
Sediment Hosted	UG	0.221	0.843	8	0.736	0.006	0.446	0.206	1.805	0.770	6	0.820	0.013	0.310	0.180
Sediment Hosted	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Skarn	**ALL**	**0.545**	**0.743**	**16**	**0.643**	**0.000**	**0.400**	**0.148**	**1.433**	**0.700**	**15**	**0.657**	**0.000**	**0.380**	**0.140**
Skarn	OP	0.004	1.082	3	0.911	0.193	0.314	0.339	0.000	1.352	3	0.963	0.123	0.201	0.264
Skarn	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Skarn	UG	5.079	0.547	13	0.259	0.076	0.376	0.279	49.350	0.354	12	0.266	0.086	0.284	0.186
Skarn	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-
VMS	**ALL**	**0.042**	**1.001**	**27**	**0.425**	**0.000**	**0.552**	**0.233**	**0.273**	**0.917**	**24**	**0.503**	**0.000**	**0.445**	**0.194**
VMS	OP	0.000	1.788	4	0.459	0.323	0.469	1.373	0.000	2.313	3	0.230	0.681	0.639	4.230
VMS	OP-UG	-	-	-	-	-	-	-	-	-	-	-	-	-	-
VMS	UG	0.060	0.971	23	0.421	0.001	0.560	0.249	0.149	0.979	21	0.612	0.000	0.383	0.179
VMS	Unknown	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Notes:
Mine Types – OP (Open Pit), OP-UG (Open Pit and Underground), UG (Underground)
(tonnes Cu per year) = a(tonnes Cu)^b
a – regression coefficient
b – regression coefficient
No. – Sample Size
R^2 – Coefficient of determination
p – Probability that observed data, or more extreme data, would occur if the null hypothesis were true
SD – Geometric standard deviation of the residual (predicted production minus actual production)
SE – Standard error of the slope
Red text indicates relationships that are not statistically significant (p>0.05) or that have insufficient sample size (No. <=3).

Table 3: Monte Carlo simulation (n=2000) of the upper primary supply limit for the sets of copper deposits with reserve and resource estimates. Results rounded to two significant figures. Resources are inclusive of reserves.

Metal Basis			**Upper Primary Supply Limit, Mt Cu/year**						
	No.	**Mt Cu**	**min**	**5th**	**25th**	**median**	**75th**	**95th**	**max**
Deposits with Reserves	407	649	19	22	23	24	25	27	31
Deposits with Resources	2,296	3,054	55	59	62	64	66	69	83
Ore Basis			**Upper Primary Supply Limit, Mt Ore/year**						
	No.	**Mt Ore**	**min**	**5th**	**25th**	**median**	**75th**	**95th**	**max**
Deposits with Reserves	407	130,557	4,600	4,700	4,900	5,000	5,200	5,400	6,000
Deposits with Resources	2,296	671,615	12,000	13,200	13,500	14,000	14,000	15,000	15,000