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Global-scale remote sensing of mine areas and analysis of factors explaining their extent

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ABSTRACT

Mines are composed of features like open cut pits, water storage ponds, milling infrastructure, waste rock dumps, and tailings storage facilities that are often associated with impacts to surrounding areas. The size and location of mine features can be determined from satellite imagery, but to date a systematic analysis of these features across commodities and countries has not been conducted. We created detailed maps of 295 mines producing copper, gold, silver, platinum group elements, molybdenum, lead-zinc, nickel, uranium or diamonds, representing the dominant share of global production of these commodities. The mapping entailed the delineation and classification of 3,736 open pits, waste rock dumps, water ponds, tailings storage facilities, heap leach pads, milling infrastructure and other features, totalling ~3,633 km². Collectively, our maps highlight that mine areas can be highly heterogeneous in composition and diverse in form, reflecting variations in underlying geology, commodities produced, topography and mining methods. Our study therefore emphasises that distinguishing between specific mine features in satellite imagery may foster more refined assessments of mine-related impacts. We also compiled detailed annual data on the operational characteristics of 129 mines to show via regression analysis that the sum area of a mine's features is mainly explained by its cumulative production volume (cross-validated R² of 0.73). This suggests that the extent of future mine areas can be estimated with reasonable certainty based on expected total production volume. Our research may inform environmental impact assessments of new mining proposals, or provide land use data for life cycle analyses of mined products.

1. Introduction

Thousands of landscapes around the world are affected by mining, with social, economic and environmental impacts experienced in surrounding areas (Sonter et al., 2014; Bebbington et al., 2018). Land cover changes due to mining are often distinguishable in satellite imagery, and indeed many studies have used remote sensing techniques to assess mining impacts (see Werner et al., 2019). These studies often focus on the issues and impacts of individual sites or regions, and while this knowledge is clearly important, the outputs of such studies are highly context-specific. This means that a review of past research on mining land uses provides a limited basis for understanding impacts of other mining areas that are yet to be studied. Iwatsuki et al. (2018) and Murguía and Bringlezu (2016) are among the very few studies that have

sought to benchmark mine areas (i.e., relate mine areas to operational variables), and to make comparisons across multiple regions or commodities. Other studies examining the impacts of mining at a global scale typically consider the mine as a point location in relation to an impact overlay (e.g. Northey et al., 2017), which does not involve the estimation of the size of mine areas. A deeper understanding of the factors that govern the size of mine areas may help decision makers to gauge the impacts of newly proposed projects (e.g. for environmental impact assessments) or to assess the land use implications of mined products (e.g. with life cycle assessments).

In addition to assessing the size of mine areas, there is a need to better understand their spatial form and composition (Sonter et al., 2018). That is, to distinguish between the different components of a mine that can create appreciably different impacts. Many studies do not

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Fig. 1. Mines mapped and analysed in this study. Circle = site features mapped. Square = site features mapped and detailed production history compiled. Symbol colours reflect the primary commodities: Cu/Cu-Au/Cu-Co/Cu-Mo (red, $N = 109$), Pb-Zn (light blue, $N = 11$), Pb-Zn-Cu (dark blue, $N = 46$), Au/Au-Ag/Au-Cu (yellow, $N = 63$), PGEs (grey, $N = 17$), Ni laterite and Ni sulphide (purple, $N = 23$), diamonds (white, $N = 15$), U (green, $N = 11$).

make such a distinction, essentially treating all cleared land equally, regardless of whether it is occupied by tailings, waste rock, infrastructure or otherwise (e.g. Swenson et al., 2011; Asner et al., 2013). Separating and understanding the spatial characteristics of such features may contribute to a more refined understanding of the distinct environmental, social and economic risks each of these features may present. As growing demand for both food and mineral resources generates competition for land between agriculture, biodiversity conservation, mining and many other land uses, it is becoming increasingly important to assess the land demands of current and future mining developments.

To begin to address each of these issues, the main aims of our study were twofold: 1) to produce detailed maps of a representative sample of current larger-scale (formal, not artisanal) mines worldwide, and 2) to determine if generalisations can be made about mine areas based on factors that influence their extent. To better understand the spatial composition of mine areas, we delineated the area occupied by the open cut pits, tailings storage facilities (TSFs), waste rock dumps (WRDs), infrastructure areas and water storage ponds of 295 mines across 43 countries using publicly available Google Earth imagery. These mines represent the dominant share of global production of copper (Cu), gold (Au), silver (Ag), platinum group element (PGE), molybdenum (Mo), lead-zinc (Pb-Zn), nickel (Ni), uranium (U) and diamonds. We used these maps to analyse areas of mine features across countries and commodities, and to discuss challenges arising in the spatial analysis of mines. Following this, we collated complete annual datasets on the operational characteristics of 129 of these mines to examine what factors influence the extent of mine features, using multiple regression analysis. In the following sections, we outline our methods and results of mapping and statistical analysis, and draw conclusions toward a better understanding of land use in the mining industry.

2. Methods

2.1. Selection of commodities and mining sites

For comparative analysis, it is necessary to select commodities that are mined via similar methods. In this study, we focussed on commodities primarily produced via underground or open-cut mines, with flotation or heap leach circuits. We also considered which commodities are subject to relatively consistent and detailed reporting of production by mining companies, such that annual production data could be compiled for a globally representative sample of sites. To this end, we performed a review of government and industry periodicals, mining

company annual and quarterly reports, company websites, technical reports, scientific monographs and other published literature, and compiled a list of mines reporting production of Cu, Mo, Pb-Zn, Ni, PGE's, Au, U and diamonds in 2015 (a baseline for which annual reports from mining companies are consistently available). From this list, we identified sites whose location could be determined, and which were covered by recent Google Earth imagery that was sufficiently clear to allow delineation and classification of individual features. Location data for the selected mines and deposits were obtained from online literature review. In some cases, only qualitative descriptions were available (e.g. distance from the nearest town) in which case visual inspection of satellite imagery from Google Earth was employed, cross-referencing with known photographs or descriptions of the mine (where available from company reports or websites) to verify the correct coordinates. In other cases, coordinate data were available from online databases such as the Australian Mines Atlas. We excluded sites where multiple mines are co-located and have features that are highly interspersed, such that it was not feasible to determine which features belonged to each mine. Following these criteria, 295 sites were appropriate for mapping. These mines represent approximately 72–76% of global mine production of Cu in 2015, plus 44–48% of Mo, 56–69% of Au, 33–51% of Ag, 44–50% of Ni, 100% of hard rock mined U, 89–90% of PGEs, and 91% of diamonds. These relatively large ranges highlight that global commodity production estimates are generally subject to high uncertainty, and discrepancies exist between reports of global production by the USGS (2018) and BGS (Brown et al., 2019). A summary map of sites analysed and mapped in this study is presented in Fig. 1.

2.2. Site mapping

We geo-referenced, delineated and classified various features of mines that are 1) related to the scale of the mine's production, and 2) consistently present across countries and commodities, and therefore relevant for comparative analysis. We focussed primarily on open pits, infrastructure areas within the mining site, WRDs, water storage ponds and TSFs. Where present, we delineated additional features including heap leach pads, quarries, and riverine tailings disposal areas. Features were manually delineated through visual inspection, using polygon tools in Google Earth Pro. To delineate and classify areas, we considered aspects such as colour (e.g. exposed rock, waste materials or tailings being distinct from undisturbed soil or vegetation), texture (e.g. evidence of sediment flow in tailings disposal areas or smooth engineered surfaces of WRDs), composition (considering whether the

location of a feature made practical sense within the layout of a mine), topography (e.g. using topographical visualisations to see which areas sit above or below natural contours to draw boundaries between excavated and deposited areas), light (e.g. using shadows to identify pit areas or engineered rock surfaces), and overall form (e.g. recognising whole features as milling process infrastructure). We examined multiple images over time to verify the appropriate classifications for areas up until the date of the primary image used. We classified revegetated or backfilled areas according to the materials present (e.g. waste rock or tailings), regardless of overlying vegetation, in order to get the most accurate estimate of areas related to mine production. Revegetated areas, backfilled pits, or pits subsequently used for water storage were identified using the historical imagery as well as company reports. We only delineated infrastructure areas that were clearly related to mine operations. In cases where mines operated close to built-up areas, this process entailed distinguishing milling infrastructure (e.g. areas with certain features like tanks, conveyor belts or pipelines that make milling infrastructure areas quite distinct from other forms of infrastructure) from surrounding buildings. We excluded other secondary infrastructure, such as what exists in nearby towns, which may be economically attributable to a mine, but is otherwise not directly associated with mining operations. For mines located in arid or semi-arid areas, the water that we observed in ponds exist in engineered features that have reasonably strict boundaries. For mines in our dataset located in wet regions, or those that may expect cyclic flooding or storm events, we distinguish between temporary flooding and permanent water storage ponds and tailings storage facilities. Here, only features related to direct water use or storage are considered. In some cases, the processes of delineation and classification were supported by examination of historical imagery and company reporting. An example of our method of delineation in progress is shown in Fig. 2, where we show the partial demarcation of a tailings disposal area at the Padcal Cu mine, Philippines.

Fig. 3 shows an example of a whole mine site (Reefton, New Zealand) before and after mapping, with areas of specific mining features categorised and delineated. The extent to which individual

Fig. 2. Example of the delineation in progress of a tailings storage area by visual inspection, visualized for the Padcal Cu mine, Philippines. Red areas indicate the boundary being drawn in progress. The grey/white areas show apparent features of tailings deposition. The adjacent surface water to the south is included in this tailings disposal area. Light blue areas depict areas delineated (Google Earth image date 15 April 2017; approx. location 16° 14' 26.16" N, 120° 40' 12.07" E).

features can be distinguished in our method is generally high, as exemplified by Fig. 3 showing a clear distinction between the TSF and surrounding WRD areas. In some cases, areas were given multiple classifications, for example where a pit void was determined to have since been used as a water storage pond. Similarly, to account for some temporal changes in areas (for example as a result of backfilling or revegetation), we examined historical imagery to verify the appropriate classifications for areas up until the date of the primary image used.

All maps were cross-checked by at least one other author, drawing upon over 40 years of cumulative research experience on mining, and past visits to several hundred mine sites, including some of those assessed in this study. Additional literature or images (e.g. company websites, aerial photographs, technical reports, or Landsat imagery) were consulted to verify features that were unclear to all authors after initial cross-checking. If features remained uncertain after cross-checking and verification, they were marked accordingly in map data files, whereby we distinguished three types of uncertainty: i) classification uncertainty (e.g. whether an area should be classified as TSF or WRD), ii) delineation uncertainty (reflecting difficulties in determining where one feature ends and another begins) and iii) uncertainty related to image quality (e.g. low-resolution data, images of multiple dates cutting across mine features, or no cloud-free images available beyond a certain date).

2.3. Compilation of additional site characteristics

We performed additional reviews of company reporting to determine if a complete annual production history could be compiled for each mine in terms of metals produced and ore milled, from establishment up until the date of the satellite image assessed. This process resulted in detailed production histories compiled for 129 of the mines mapped (see Fig. 1, and refer to supplementary section V for full datasets), plus majority or near-complete production histories for 11 sites. For each site, information was collected on factors that might influence the extent of the mine's features. We focused on variables that are related to the scale of production or are otherwise clearly important considerations in the engineering of mine features, such that they are likely to significantly influence the extent of the mine's major features (e.g. topography). An additional criterion was data availability, i.e., whether variables could be quantified across our whole dataset. Information collected included: project mine configuration (i.e. the extent that the site is operating as open-cut or underground), mill configuration (e.g. combination of flotation, smelting, refining, heap leaching or hydrometallurgy taking place on site), quantities of ore milled up until the date of the satellite image used for mapping (calculated as the sum across annual reports), average ore grades of primary and by-product commodities, quantities of metals produced in terms of concentrates and total metal, reported or calculated production of tailings (dry basis, noting that the extent to which dewatering occurs at each site is not always reported) and waste rock, and average monetary value of the metals contained in both resources and products (\$USD per tonne of ore). Assuming that mountainous terrains might restrict the ability of mine operators to spread features over larger areas, we also determined the elevation (m amsl) and slope (degrees) of each site, based on the 30 arc-seconds resolution (~ 1 km) GLOBE elevation dataset (Hastings et al., 1999). As we required average terrain estimates across broader mine areas, we established circular zones with a radius of 20 cells around the coordinates of each site and calculated the mean elevation (m amsl) and slope (degrees) within the zone using ArcMAP version 10.3.1. Collectively, the variables collected represent key operational and situational characteristics of mines that are expected to influence the extent of mining area features. However, we acknowledge that additional factors, such as the technical capacities of mine operators, workforce availability, distance to key infrastructure or other socioeconomic or environmental factors may also influence the extent of mine features. Such aspects were excluded in this study due to sporadic

Fig. 3. Remote sensing image (left) and map (right) of features of the Reefton gold mine, New Zealand (Google Earth Image Date 27 Dec 2015). TSF = tailings storage facility, WRD = waste rock dump area, Pit = Open cut pit area. Note that where there is a pit area that is subsequently used as a pond, an area is classified as both. Infiltration or temporary flooding is not considered in our pond area classifications. .

data availability across commodities and countries, but are important avenues for future study. We expand upon our hypotheses for including our explanatory variables, and outline our analysis of cross-correlation between explanatory variables in the supplementary information (Section IV).

2.4. Regression analysis

We analysed possible relationships between mining feature extent and the potential explanatory variables using multiple regression analyses. Prior to the regression analysis, we assessed the correlations among the explanatory variables in order to check for collinearity and found high bivariate correlations (Spearman's $\rho > 0.8$) between production, waste rock and tailings, as well as between production value and grade value (Table S3). Because bivariate correlations may miss out on more subtle forms of collinearity in a dataset, we removed redundant variables based on variance inflation factors (VIFs), which reflect the correlation of a variable with all other explanatory variables in the set (Field, 2005). We removed the variable with the highest VIFs one after the other until all VIFs were below 5 (Zuur et al., 2009; see Table S4 for details). This left us with the following explanatory variables: production duration (years), cumulative production (Mt ore milled), waste rock volume (Mt), proportion of open cut (%), elevation (m amsl), slope (degrees) and contained value in production (US\$/t). Of these, we removed waste rock volume because of the large number of missing values, which would significantly reduce the dataset we could use for the regression modelling. We $\log_{10}$ -transformed the remaining continuous predictor variables to reduce the positive skew, except for the proportion of open cut. We then fitted linear mixed effect models with country and commodity as crossed random intercept terms to account for possible systematic differences among countries and commodities. We included six response variables: total mine extent (measured as the sum of the delineated areas of the different features) and the extent of five specific features, i.e., open pits, waste rock dumps,

tailings storage facilities, milling infrastructure and ponds (all in km^2). Heap leach pad areas were not modelled using multiple regression due to a limited sample size, but are examined in supplementary section IV. To prevent overfitting, we first tested the most parsimonious random effects structure based on the full fixed effects models. Using the selected random effects structure, we then selected the fixed effect variables according to an information-theoretic approach, i.e., we fitted all possible combinations of variables to identify the most parsimonious set (Burnham and Anderson, 2002). We performed the random and fixed effects variable selection based on the Bayesian Information Criterion (BIC). Finally, we performed a 5-fold cross-validation to assess the predictive power of the selected models and we assessed the importance of the selected explanatory variables. Variable importance was quantified by refitting each model using randomized values for the explanatory variable of concern, calculating Pearson's correlation coefficient between the predictions of the model based on original and randomized data, and quantifying variable importance as 1 minus the correlation (Thuiller et al., 2016). We performed the multiple regression modelling in the R environment (R Core Team, 2017), including the lme4 package (version 1.1–12) for the mixed effect modelling (Bates et al., 2014) and the glmulti package (version 1.0–7) for the fixed effects selection (Calcagno and de Mazancourt, 2010).

3. Results

3.1. . Mapped areas

The mines analysed in this study revealed considerable diversity in their extent and configurations. Fig. 4 shows a sample of mapped sites that collectively highlight the range of environments in which mining takes place, and show how the arrangement of features around a mine can be influenced by the distribution of ore and surrounding topography. The remaining 289 maps are provided as georeferenced, dated and annotated shapefiles in the supplementary materials, which can be

Fig. 4. Sample of the 295 sites mapped in this study, including (a) Chiquicamata, Ministro Hales and Radomiro Tomic, Chile (Cu, 2017); (b) Koniambo, New Caledonia (Ni, 2015); (c) Bajo de la Alumbrera, Argentina (Cu, 2013); (d) Lihir, PNG (Au, 2014); (e) Murrin Murrin, Australia (Ni, 2013); (f) Mogalakwena, South Africa (PGEs, 2017). Green = WRD, light blue = TSF, dark blue = water storage pond, orange = milling and processing infrastructure areas, purple = open cut pits, dark red = heap leach pads. The full suite of sites, along with site-specific production, configuration, ore grades, location and calculated area data are provided as electronic supplementary files (GIS and spreadsheet form).

viewed using Google Earth or other GIS software. Of the 295 sites mapped, only 25 (~8.5%) contained at least one feature associated with one of three kinds of uncertainty (delineation, classification and image quality; see Table S1 for an overview). The average proportion of areas affected within these 25 sites was 9.2%.

We found that WRDs typically comprise the greatest proportion of a mine site's area (~15–51%), followed by HLPs (~7–60% where present), TSFs (~11–30%), pits (~8–42% where present), milling infrastructure (~6–16%) and waste storage ponds (~0.3–3%), although this can also be highly variable between sites. In general, we found larger pit, waste rock, milling infrastructure and tailings areas for Cu mines than for Pb–Zn, Ni or Au mines (Fig. 5), reflecting differences in scale of production (see supplementary section V). However, we note that our sample of mines span multiple orders of magnitude in terms of both production and feature areas, and the variability of areas among mines of a particular commodity can be high.

3.2. Multiple regressions to predict mine areas

The most parsimonious regression models accounted for ~40–75% of the variability in extent of the different mining features (based on adjusted R^2) and the predictive power (cross-validated R^2) was nearly similar, except in the case of water storage ponds (adjusted $R^2=0.13$; cross-validated $R^2=0.21$, Table 1). Residual plots revealed no deviations from the assumptions of homoscedasticity and linear relationships (Fig. S7). Cumulative production tonnage was the strongest

determinant of the extent of most of the features, including the total mine extent (Fig. 6). The proportion of open-cut mining was a more important explanatory variable only for pit areas, as might be expected. Product value was a significant explanatory variable for infrastructure extent, but not for the extent of the other features. Cumulative mining duration was significant in explaining total mine extent as well as TSF, WRD and infrastructure extent. The relationships with duration were negative, suggesting that newer mines operate at a larger scale than older sites. The topographic variables (slope and elevation) generally did not play an important role in explaining mine extent, although areas with higher average slope tended to lead to reduced areas for tailings storage facilities. Finally, the random intercept terms were not retained in the most parsimonious models, indicating that there are no systematic differences in the area of different mining features between countries and between commodities.

4. Discussion and Conclusions

4.1. On the spatial composition and mapping of mine areas

From the mapping and visualisation of mine features from 295 sites in 43 countries, we identified that 1) mine areas are highly heterogeneous in composition, which is important as their constituent features pose intrinsically different risks, and 2) mine areas are also highly diverse in spatial configuration, showing a range of different arrangements reflecting differences in orebody distribution, topography, and

Fig. 5. Summary of primary mine feature areas quantified in this study, depicting interquartile ranges, and maximum/minimum whiskers. All values are in km².

Table 1

Regression coefficients, goodness of fit and sample size of the selected regression models for total mine size and the size of each of five specific features. Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

	Response variables Total area	Pit area	TSF area	WRD area	Infra area	Pond area
Coefficients (± SE)						
Production volume (Mt)	0.61 (± 0.06)***	0.50 (± 0.07)***	0.73 (± 0.08)***	0.53 (± 0.08)***	0.53 (± 0.07)***	0.35 (± 0.10)***
Duration (yr)	-0.30 (± 0.11)*	NA	-0.44 (± 0.15)**	-0.47 (± 0.15)**	-0.54 (± 0.13)***	NA
Open cut (%)	0.003 (± 0.001)***	0.01 (± 0.001)***	NA	0.005 (± 0.001)***	NA	NA
Elevation (m amsl)	NA	NA	NA	NA	NA	NA
Slope (degrees)	-0.13 (± 0.05)*	NA	-0.30 (± 0.08)***	NA	NA	NA
Production value (US\$/t)	NA	NA	NA	NA	0.23 (± 0.06)***	NA
Intercept	-0.06 (± 0.11)	-1.75 (± 0.18)***	-0.51 (± 0.16)**	-0.19 (± 0.15)	-0.96 (± 0.18)***	-1.55 (± 0.18)***
Goodness of fit						
Adjusted R ²	0.74	0.60	0.51	0.61	0.39	0.13
Cross-validated R ²	0.73 (± 0.02)	0.62 (± 0.02)	0.49 (± 0.07)	0.60 (± 0.01)	0.39 (± 0.02)	0.21 (± 0.02)
Sample size	87	72	80	87	87	79

Fig. 6. Importance of five explanatory variables for a) total mine extent, b) pit area, c) TSF area, d) WRD area, e) infrastructure area and f) pond area, whereby the sign of the importance value reflects the direction of the relationship.

mining methods. Our results emphasise that mine areas are not homogeneous, despite their common classification as a single “mine area” category in past remote sensing studies (see Werner et al., 2019). In addition to the features we classified, mines may be composed of a number of additional features, e.g. roads, natural vegetation or conservation areas, staff accommodation and offices. Further, each mining feature type could likely be split into sub-categories, for example to reflect differences in the composition of waste materials, or to specify different types of infrastructure or vegetation. This diversity of features within mine areas has long influenced the management and understanding of risks at mine sites. For example, abandoned coal pit areas in Kalimantan, Indonesia, have led to a number of drownings due to filling with rainwater, and proximity to local villages (Gokkon, 2019). Studies like Hu et al. (2017) have analysed TSF location and areas with respect to local topography to examine failure risks. Similarly, studies like Hasani et al. (2017) have used geostatistics to study WRDs and indicate risks of acid mine drainage. Our maps may complement such studies by contributing an understanding of the typical proportion and extent of various mine features within open-cut and underground mines producing commodities via flotation or heap leaching circuits. However, more work is required to spatially link remotely sensed mine feature

areas to the impacts derived from these features, as is done more broadly for mine-induced deforestation in studies like Sonter et al. (2017).

Underlying geology strongly determines what commodities are present, the scale of their production, and the methods of their extraction and processing. For example, Cu mines are largely represented by porphyry copper type deposits, and Cu-Pb-Zn mines are largely represented by volcanic massive sulphide (VMS) deposits. VMS deposits tend to be higher grade and lower tonnage than porphyry copper deposits (Mudd and Jowitt, 2018). Accordingly, we observe that mine areas are on average smaller for Cu-Pb-Zn mines than for Cu mines (Fig. 5).

Our maps demonstrate a range of spatial forms among commodities using similar mining methods and comparable features. This reflects variation in geology, in that the size and number of pits (or absence of pits) reflect the depth and spread of ore. The nature and formation of this ore determines what commodities are present, which in turn determine processing methods. Accordingly, we observed heap leach pads only for Cu, Au, Ni laterite and U among the mines studied. As the distribution of commodities is a result of the described geologic features, which are not or hardly reflected by country borders, our regressions show that using commodity or country as explanatory variables for the extent of mine features is not viable. For each commodity, it should also be noted that there are scales we have not considered. While multiple orders of magnitude (in terms of both mine production volumes and mine areas) are represented in this study (see the range of values in Fig. 5), we exclude informal or artisanal operations. This is partially because our ability to distinguish between individual mining features from remote sensing imagery diminishes as the scale of operation becomes smaller. Informal mines are also not required to publicly report production, meaning that we could not develop regressions for these sites. Small-scale operations may also use different methods (particularly for alluvial gold mines) such that they could not be compared to our sample of mines. Asner et al. (2013) analyse informal mining areas for the Peruvian Amazon, showing that informal mines can be highly dispersed over large areas, unlike the generally more clustered features observed in our sample. More work is needed to refine our understanding of the links between commodities produced, scale of production and mine areas, particularly as our scope includes a limited selection of comparable commodities.

Our analyses and results may apply to some additional commodities using flotation or heap leaching, based on underground or open cut mine configurations. However, comparative analyses of mine areas for other commodities may require further examination. For example, commodities like bauxite and lithium are produced from deposits with entirely different spatial configurations (Fig. 7). Bauxite deposits such as at the Huntly bauxite mine (Fig. 7, left) are typically shallow, and hence mined with comparatively little overburden, such that areas of

Fig. 7. (left) Huntly bauxite mine, Western Australia (Google Earth image date 12 Dec 2018) (right) Soquimich lithium mine, Salar de Atacama, Chile (Google Earth image date 8 Feb 2017).

extraction and waste rock deposition are much more difficult to separate. These low strip ratio sites also tend to occupy vast areas (in this case, the extraction areas depicted in light yellow to brown hues total nearly 120 km²). On the right, Fig. 7 depicts a lithium mine developed on salt flats of the Atacama Desert, Chile. Here, lithium is produced via a series of evaporation ponds, which are not comparable in form or function to any of the features analysed in this study.

We did not find that the country in which a mine operates is statistically significant in determining the size of mine areas. However, we do note differences in average mine extent between countries, which may reflect the distribution of various mineral deposit types, or among-country differences in regulation and practices. For example, while total WRD areas may not differ, single dumped truckloads of waste rock (e.g. at the Etoile Cu mine in DRC, see supplementary Fig. S9) are visible in some countries, while only highly engineered (compacted and stacked) WRDs are seen in others. Similarly, we observe riverine tailings disposal at sites like Ok Tedi, Papua New Guinea and Grasberg, Indonesia, where lenient environmental regulations permit these practices (Mudd et al., 2013). The Lihir gold mine in Papua New Guinea, shown in Fig. 4(d) has WRD areas that are directly dumped alongside and into the adjacent bay, and no TSF areas could be delineated due to marine tailings disposal. Such practices would be highly unusual for many other countries, and highlight that environmental regulations, which can vary substantially between countries, can translate to distinct differences in the spatial form and composition of mine areas.

4.2. On the factors influencing mine area extent

While our mapping highlighted diversity within and between mines, our study also aimed to determine whether there are generalisations that can be made about mine areas, such that they are predictable, or such that reasonable inferences from some mine sites can be made about others. Our regression analyses employed six variables (slope, elevation, percentage of production derived from open cut mining, product value [\$USD per tonne], years of operation and cumulative production volumes) which were thought to influence the extent of different mine features. We had expected that tailings mass would most strongly relate to tailings area, similar with waste rock volumes and waste rock dumps, and heap leach production and heap leach pads (these comparisons are provided in supplementary section III for reference). Yet each of these factors correlate strongly with total production volume, which itself was determined to be the most influential

explanatory variable. These results are potentially useful for predicting the extent of currently undeveloped mines, given that the explanatory variables we have identified can largely be determined prior to a mine's development. Average slope and elevation can be determined from existing terrain datasets. Product value, cumulative production and years of production can all be estimated from a deposit's reported economic resources, assuming the extent to which these resources are ultimately mined. The mine configuration (open cut percentage) depends on a number of factors including the deposit's depth, surrounding topography, and a mine operator's technical capabilities. This variable is not as easily predetermined, but could be explored further in various development scenarios. To be clear, the application of these explanatory variables on undeveloped sites would not implicitly consider the likelihood of a deposit being developed into a mine, only the potential extent of the mine area if it were developed.

In Section 2.3, we noted that there are additional factors likely affecting the extent of mine areas that we have not explored due to data availability, but which nonetheless might improve the accuracy of the estimates. Mine leases (concession boundaries) present a regulatory context that can strongly influence patterns of land use change due to mining (Sonter et al., 2017). Mines developed adjacent to water bodies (e.g. Lihir, PNG, or Cowal, Australia) are often constrained by these water bodies, or must undertake considerable engineering measures in response to these constraints (e.g. dewatering to prevent infiltration of pits). Similarly, the location of a mine in relation to dwellings or protected areas can also constrain the expansion of mines (e.g. in Kalgoorlie, Australia). These factors could not be quantitatively addressed in our study due to data limitations, but are worthy of further consideration to develop additional understanding of the spatial dynamics of mine areas. Some additional variables (e.g. strip ratio, $N = 72$) are recorded in the supplementary information, but despite collecting these data, our regressions are only based on variables that could be determined for all sites with complete production histories. The regressions we develop are therefore optimised for useability (on the basis of data likely being available for a given deposit or mine), versus prediction accuracy.

4.3. Additional uncertainties and considerations for future work

This study does not directly delineate areas of impact derived from mining, or total land use changes due to mining. Estimating areas affected by pollution, groundwater depletion, habitat fragmentation and deforestation is of clear importance, but outside the scope of this study.

We provide data to disaggregate mine areas into some of their constituent features (in this case, those related directly to mine production), each of which represent a source of impacts. In addition, we have examined the drivers behind the size and composition of mine areas. Additional zones of exploration and road infrastructure can have noticeable environmental impacts; however, some features are either not clearly visible in satellite imagery or difficult to attribute to a mine itself. Without appropriate historical imagery at a site, or in-depth knowledge of the drivers behind infrastructure development in an area, it can be difficult to attribute roads or the development of other supporting infrastructure to a specific mine. Indeed, secondary or tertiary land use changes (such as the development of railroad and ports to ship mined products) are rarely accounted for in GIS- and remote sensing-based studies of mining (Werner et al., 2019).

Our method differs substantially from many past remote sensing studies like Sonter et al. (2017); Asner et al. (2013) or DeWitt et al. (2017), which use image classification algorithms to distinguish between disturbed and natural features in landscapes. Automated image classification is arguably less sensitive to human error, yet still requires some degree of user classification of which features exist as a consequence of mining. This method is also limited in its capacity to distinguish between specific features of a mine (which are frequently quite similar in appearance to their surroundings and to one another) as we do here. We determined that image classification software could not distinguish individual mine features to the extent required for this study, particularly as mine features can vary considerably in appearance between mine sites. However, there remain a number of uncertainties of our manual approach that are addressed in detail in the supplementary information (Sections I and II).

Each year, new deposits are discovered, new mines develop and old mines expand, become decommissioned or are abandoned, suggesting a need for ongoing spatial research on mining and its impacts. While we have analysed the extent of mine features during various stages of production, the land use changes brought about by mining occur before, during and after operation, and can extend well beyond a mine site in numerous and complex ways (see Sonter et al., 2014). As such, there is scope to revise and update our study as new images become available, to better explore changes in mine features over time. A preliminary analysis of these changes is provided in the supplementary materials (Section III). More research is also necessary to comparatively analyse post-mining landscapes (Kivinen et al., 2017), e.g. measuring the effectiveness of rehabilitation measures across countries or commodities. In addition, increased coverage of other commodities, e.g. coal and iron ore, would be an important future contribution, given their typical large scales of production and likely significant impacts. The extent to which the regressions developed in this study would translate to these contexts needs to be investigated.

In many countries, new mine approvals are often contingent on the provision of mine plans that provide considerably more detail on land use than what can be estimated from regressions. Given this, we envisage our study providing information towards much earlier stages of impact assessment. For example, during the granting of new exploration or extraction licenses, decision makers or communities may draw upon our estimates of the potential extent and composition of mine areas, based on the likely amount of mineral resources in a region. Another potential application is in life cycle analyses or ecological footprint studies, which often require estimates of the land-use impacts of mined products (e.g. areas affected per kg product). As agriculture, protected areas, mining and many other land uses increasingly compete for land, it is becoming ever more important to measure and model the extent of current and future mines. Key to this will be to better understand what factors drive the extent and spatial configuration of mine areas, and to ensure that the information needed to study these factors is readily available.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.gloenvcha.2019.102007](https://doi.org/10.1016/j.gloenvcha.2019.102007).

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