nature portfolio

Peer Review File

Mapping Global Resource Driven Nature Loss in the Mining Sector from 2001 to 2022

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This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
The authors have combined a very large number of datasets and methods to address a critical issue that will be of great interest to the journal's readership. The paper is broadly well written and shows much skill in certain areas. If successfully executed, this paper could attract significant attention in the field.

However, I did have a number of major methodological concerns that I feel must be addressed at length before publication is possible. In a marked up PDF I explain these further. Certain methdological choices were troubling to me, and the effects of uncertainty arising from these choices were not measured or visualised.

Furthermore, there are some rather obvious errors in the results. There are some locations of which I am familiar where the authors' classification schemes have suggested certain types of mining that simply isn't there. Given these issues with the methods, which I primarily focussed my review on, I did not feel it appropriate to read into the results and discussion in too much detail, because I feel those need to be addressed first.

My sense is that the underlying work needs a significant rework, but given the article's importance, and the authors capabilities, the work should not be entirely disregarded. I would personally suggest resubmission.

Reviewer #2

(Remarks to the Author)

This paper explores the highly relevant and practical topic of the impact of different mineral mining activities on global deforestation and biodiversity loss. By integrating remote sensing, machine learning, and cloud computing methods, the study conducts on a global scale, commodity - level classification of approximately 40,000 mining areas and quantifies the environmental impacts of 20 types of minerals, thus possessing significant significance and innovation. Its research background is clear, linking the contradiction between the demand for minerals driven by the clean energy transition and environmental risks. The methodology is innovative, employing a stratified random forest combined with ASTER spectral indices for the classification of mining areas. The data scale is large and the coverage is wide, making the research results of global significance. The results have important reference value for policy practice, especially in relation to the EU Deforestation Regulation (EUDR) and the Taskforce on Nature - related Financial Disclosures (TNFD). However, there are also some shortcomings: the representativeness of the data is limited, the classification accuracy of some mineral species (such as copper and gold) is relatively low, and the uncertainty is not fully reflected in the interpretation of the results; some charts and tables are overly complex or redundant, affecting readability; the discussion on policy application is rather general, lacking more operational suggestions. The following are specific comments:
(1) Line 1, P6: The total amount of forest loss caused by the mining industry is approximately 14,619 km² (2001–2022). This conclusion is quite prominent, and it would be more convincing if a numerical comparison with existing studies is made.
(2) Line 17, P14: Reliance on a small number of labeled polygons (1,941, accounting for less than 5%) leads to potential bias. This may result in an underestimation of small - and medium - sized or artisanal mining areas. The proportion of large - scale industrial mines is too high, and the impact of this bias on the results should be discussed more explicitly. The classification uncertainty should be reflected in the description of the results.
(3) Lines 10 - 12, P16: The SMOTE and undersampling methods may bring the risk of overfitting, which needs further

discussion.
(4) Figure 1a, P4: A uniformly fixed vertical axis scale may be misleading. It is recommended to adopt an adaptive scale or an alternative visualization method.
(5) P4 - 5, 8 - 9: In the results section, figures are presented first followed by text, which is inconvenient for reading. It is suggested that the charts be placed after the first text paragraph that mentions them.
(6) P11 - 13: In the discussion, the connection between the results and policy frameworks (EUDR, TNFD) has been established, but the suggestions are too general. Specific operational suggestions for enterprises and government levels should be added. Although the research limitations are acknowledged, the emphasis is insufficient. For example, indirect impacts (such as transportation and infrastructure) are not included, and it should be clearly pointed out that this may lead to an underestimation of the overall footprint of the mining industry.
(7) P13 - 17: The methodology section is placed at the end of the main text. Unless it is the unified format of the journal, it is recommended to place the data and methodology section between the Introduction and the Results sections to ensure logical coherence.
(8) There is a lack of an independent conclusion section. It is recommended to add one to summarize the research contributions and highlight future research directions.
(9) P18 - 26: The references are comprehensive, including the latest studies (2023–2024). However, policy and regulatory documents (such as relevant EU regulations and TNFD official reports) should be directly cited. The formats of some references are inconsistent, lacking the place of publication or volume and page numbers (e.g., References 1, 2, 9, 21, 59, 71, 72, etc.), which need to be standardized.
(10) There are a large number of charts in the appendix. It is recommended to streamline them and retain only the key ones.

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
I am really pleased with the level of improvement with this manuscript. The authors have addressed each comment in considerable detail, and have signitifantly improved the results, and the way they are presented. I was initially concerned about what I thought were some obvious errors that might require too much work to address, but the authors have gracefully taken the comments and used them to conduct a considerable amount of additional work. This is very commendable. I am happy for the article to proceed to publication.

Dear Editor and Reviewers,

We thank you for the thoughtful and constructive comments on our manuscript. The reviewers' concerns centred on whether

(1) the spatial datasets and commodity assignments were sufficiently accurate,
(2) the classification framework reliably captured real-world mining activities, and
(3) the resulting estimates of nature loss were supported by robust validation and transparent methodological explanation.

In revising the manuscript, we have substantially strengthened each of these aspects. Specifically, we

(1) refined the spatial matching procedure to ensure one-to-one correspondence between mining polygons and verified commodity points and incorporated additional polygon and open-pit datasets;
(2) updated the hierarchical random forest classification structure, training-sample construction, and spectral extraction, including the integration of HISUI hyperspectral imagery; and
(3) implemented a comprehensive validation and uncertainty framework, including external validation, stratified random-sampling validation, and Monte Carlo–based propagation of classification uncertainty to the key environmental metrics (deforestation and Extinction Risk Index), accompanied by clearer presentations of limitations and policy implications.

We have also revised figure styles and reorganised the Supplementary Information (SI) to improve clarity and traceability. We believe these revisions thoroughly address all reviewer comments and have substantially enhanced the rigour, transparency, and robustness of the study.

All revisions made in response to reviewer comments are highlighted in **yellow** for clarity. For sections that underwent substantial revisions (Sections 2, 3, and 5), the section headings are highlighted to indicate major updates, including model refinements and corresponding changes to results. We appreciate the opportunity to revise our manuscript and hope it now meets the standards for publication in *Nature Communications*.

Sincerely,

Kanemoto and co-authors

Point-by-point Response to Reviewers' Comments

Reviewer 1

1. (Abstract) "due to the clean energy transition", or "for clean energy"

Response 1:

We thank the reviewer for the suggestion. We have adopted the reviewer's recommended phrasing and revised the sentence to read: "Global mineral extraction is expected to surge due to the growing demand for clean energy." Please refer to the updated **Abstract** of the revised manuscript.

2. (Abstract) This is debatable. Yes it's common, but at same time, the extent of undocumented areas is equally high - https://www.nature.com/articles/d41586-023-04090-3

So while I agree there's a gap in assessing commodity level impacts, it's not a unique gap.

Response 2:

We appreciate the reviewer's thoughtful comment and have revised the statement to provide clearer context on the extent of undocumented areas. The sentence now reads:

"While mining is critical to modern society, its environmental impacts, though increasingly studied, remain undocumented for half of the world's mining areas and are rarely analysed at the commodity level." Please refer to the updated **Abstract** of the revised manuscript.

3. (Line 5, P2) You already introduced threats to biodiversity in the previous paragraph. Address the repetition in this section.

Response 3:

We thank the reviewer for this observation. While biodiversity impacts were discussed in the preceding paragraph, that section focused primarily on local and regional studies. We have retained "biodiversity threats" here to maintain consistency and to emphasise that recent research has begun to reveal these impacts at the global scale. The sentence has been revised to clarify this distinction and to improve the transition from local to global perspectives. The part now read:

"… and biodiversity threats. These global assessments extend the understanding of mining's impacts beyond site-level case studies, revealing cumulative and transboundary patterns of environmental change. Such insights have been facilitated…" Please refer to the updated text in **Line 5–8 on Page 2** of the revised manuscript.

4. (Line 5, P5) I would suggest to change the colour scale, because I don't think the low to high colour grading is not visually intuitive. I could suggest a more consistent "cool to warm" colour scale, or otherwise adopt a single colour gradient.

Response 4:

Thank you very much for the helpful suggestion. The colour scale has been revised to a single-colour gradient to more intuitively reflect the transition from low to high values. Please see the updated **Figure 2 (Page 8)** of the revised manuscript.

5. (Line 5, P5) It should be noted that levels of deforestation do not necessarily correlate with areas of greatest impacts to biodiversity. In Western Australia, for example, certain desert landscapes are highly biodiverse, and support richer ecosystems than, for example, a timber plantation that might appear as "forest" in satellite data. This could be noted as an uncertainty in interpreting these results.

Response 5:

Yes, levels of deforestation do not necessarily correlate with areas of greatest impact on biodiversity, which is why this study applied different datasets to measure them. Tree loss data were obtained from Global Forest Watch, while biodiversity impacts were derived from the Red List of extinction. As shown in the lithium maps (Figures 2 and 4), lithium triangle in Chile exhibits low deforestation but high biodiversity impact (ERI). This reflects that these areas naturally have limited tree cover, yet brine mining causes habitat fragmentation and pollution that still threaten biodiversity. Specifically, the Andean mountain cat (*Leopardus jacobita*, Endangered) and the Andean flamingo (*Phoenicoparrus andinus*, Vulnerable), identified by the IUCN as threatened by mining-related seepage, occur in these areas. This illustrates an uncertainty in interpreting deforestation as a proxy for biodiversity impact, as deforestation data alone may underestimate impacts in ecosystems where vegetation is sparse but ecological sensitivity is high.

At the same time, it is important to acknowledge the limitations of the Global Forest Watch dataset, used in this study to quantify deforestation, which cannot distinguish between natural forests and plantations (Tropek *et al.,* 2014). Consequently, areas showing high deforestation on our maps may correspond to plantation harvesting rather than loss of natural forests, and therefore may not represent equivalent impacts on biodiversity

These clarifications have been added to the main text; please refer to **Lines 5–20 on Page 11** of the revised manuscript.

6. (Figure 4, P9) Some of these maps don't make sense to me. There are no lithium mines in Victoria, Australia. Why do I see a dark cell shaded there? At best, there is exploration taking place. I wonder if the source data for exploration areas has been assigned to polygons in error.

   I'm concerned that there are other errors for locations where I'm not as familiar.

   Response 6:

   We thank the reviewer for this insightful comment. We acknowledge that some identified mining polygons may correspond to exploration or pre-operational areas rather than active, large-scale mining. Because our approach relies on satellite-derived data, certain polygons may represent exploration sites, indications of mineralisation, or nearby industrial activities (e.g. refineries or processing facilities) with similar spectral characteristics. We also recognise that some misassignments may exist in the source polygons, as full site-level validation is not feasible globally, and that a proportion of misclassifications may arise from the model itself due to spectral similarity.

   To address these issues, in this revision, we have refined and expanded the dataset by incorporating additional mining polygons provided by Tang and Werner (2023). We then intersected all polygons from the union of Maus *et al.* (2022) and Tang and Werner (2023) with verified commodity data points from USGS, S&P (SNL), Jasansky *et al.* (2023) and Franks *et al.* (2021). Only polygons that completely contained at least one data point were retained. To prevent bias in the training dataset, we further restricted the selection to polygons containing exactly one intersected point, ensuring that each training polygon corresponded uniquely to a single verified mining site.

Second, recognising that each training polygon may largely comprise waste rock dumps (WRDs) and tailings storage facilities (TSFs), we refined the extraction of spectral information to better represent the minerals exposed in open-pit areas. Specifically, we used the identified open-pit locations from the Global dataset mapping land use and land cover across more than 80 000 mining areas (Cheng *et al.*, 2025), which was derived using digital elevation model (DEM) differences from TanDEM-X and Sentinel-2 spectral imagery combined with machine-learning approaches. This allowed us to obtain more representative spectral signatures from active extraction zones rather than waste or storage areas.

Third, instead of relying solely on the ASTER satellite data as in the previous version, this revision additionally incorporates the latest HISUI (Hyperspectral Imager Suite) dataset. HISUI provides 185 spectral bands, offering substantially greater spectral detail and allowing for more precise identification of mineralogical features. While we continued to apply the same mineral indices developed by Geoscience Australia (2004) for consistency and comparability, we expanded the analysis by incorporating the additional spectral bands available from HISUI to improve the discrimination of mineral signatures. Although HISUI does not yet provide full global coverage, it currently encompasses approximately 68 % of the mining polygons in our dataset; for regions outside its coverage, ASTER data were retained.

Furthermore, after classification, we first conducted external validation using independent mine datasets. We then used the stratified random-sampling confusion matrix to evaluate model accuracy and quantify classification uncertainty. Because many minor commodity classes had small sample sizes in the random sampling, we aggregated these (Pb, Cr, Mn, Mo, Ni, Sn, W, Ti, Li, PGE, U and Other metals) into a single "Rare metals" group for statistical stability. Using this aggregated confusion matrix, we applied a Monte Carlo (MC) resampling procedure to generate confidence intervals (CIs) for the accuracy metrics, including overall accuracy (OA) and commodity-specific producer's accuracy (PA) and user's accuracy (UA). These CIs quantify the uncertainty in the accuracy estimates and provide a statistically grounded indication of the reliability of the classification.

In addition to the accuracy assessment, we also quantified how classification uncertainty propagates to the key environmental metrics used in our analysis. Using the same random-sampling confusion matrix, we generated MC CIs for commodity-level deforestation areas and ERI values and compared them with the results derived from the predicted classes for the full dataset. For deforestation (**Figure 1c**), most commodities fall within the MC intervals, and the three commodities outside the bounds (Gold, Rare metals and Coal) differ from the nearest CI bound by only 141 km², 111 km² and 252 km², corresponding to 2.8%, 10.8% and 4.6% of their total mapped deforestation areas. For ERI (**Figure 3b**), the predicted-class ERI values generally align with the MC intervals, with a few commodities (Zinc, Silver, Aluminium and Coal) lying very close to the CI boundaries (differences of about 0.001–0.01) and a larger deviation only for Other non-metals (0.019), which reflects the heterogeneity of this group (all non-metallic sites except coal). The overall commodity rankings are preserved in both metrics. Together, these results show that the deforestation and ERI metrics derived from the predicted classes are robust to reasonable levels of classification uncertainty.

We have revised the Methodology (**Section 5; Pages 15)** to describe the incorporation of datasets from Tang and Werner (2023), Cheng *et al*. (2025), and HISUI (**also noted in Lines 1–7 on Page 3**), along with the corresponding data-processing procedures. For classification validation and uncertainty assessment, **Section S8 of SI Part 1** now presents both the external validation and the stratified random-sampling validation with the associated uncertainty estimates. Related text has also been added to the **captions of Figures 1c and 3b (Pages 5 and 10)**, **Lines 18–31 on Page 6 to Line 1 on Page 7**, **Lines 17–28 on Page 9**, and **Lines 9–27 on Page 20** of the revised manuscript.

7. (Line 8, P13) I am very concerned with the statement in S6: "A spatial join was performed to integrate these point datasets with Maus et al's polygons, linking point data to polygons where spatial overlap was detected. In cases where multiple points were associated with a single polygon, the most frequently represented commodity was assigned, and where no clear majority existed, a commodity was randomly selected. "

   It is a known problem that the areas outlined in Maus et al, and Tang & Werner do not align on a 1:1 basis with the points in the SNL (S&P) database.

   Sometimes there will be no points for a polygon, and sometimes there will be multiple points. Assigning a random commodity does not seem justified, and will certainly skew your results. At the very least, the effect of this uncertainty should be reflected in the way your results are presented.

Many of your results relating commodities to forest loss and other factors are presented in km2 or in percentages, but no ranges are given, when this form of uncertainty alone leads to the expectation that your results have larger uncertainty ranges.

It is also a problem that one point in SNL represents a mine, and that mine may have dozens of polygons associated with it. In remote regions where only 1 mine operates, it is easy to associate surrounding polygons to the point, but in mining regions with dense activity, it becomes a task to choose which polygons belong to which point. Analyses from our group show that this is very difficult to do without site-specific information around mine boundaries. 0

How did you overcome this uncertainty? I assume certain spatial rules were applied, but these rules come with uncertainties that I do not see quantified or visualised in your results.

There is a need for MUCH greater detail on how this step was performed, and how sensitive your results are to the idea that commodities might be misclassified.

Response 7:

We thank the reviewer for this important comment and for highlighting the potential uncertainty introduced by linking point-based commodity data to polygon-based mining footprints. As detailed in the **response to Comment #6** and the revised **Methodology** section, we have removed the previous random assignment procedure and implemented a stricter spatial-matching rule that retains only polygons fully containing a single verified commodity point. This substantially reduces spatial-join ambiguity and ensures a one-to-one correspondence between polygons and verified sites. Please refer to the updated text in **Lines 12–19 on Page 16 and Lines 1–7 on Page 17** of the revised manuscript.

While this stricter rule greatly limits spatial-matching uncertainty, minor discrepancies across datasets may still occur. To evaluate how such uncertainties affect the final commodity assignments, we implemented a two-part validation and uncertainty framework (**Section S8 of SI Part 1**). First, external validation was conducted using independent mine datasets (Iron and Coal Mine Trackers and Northey *et al.*, 2017). Second, a stratified random-sampling validation was conducted, from which an aggregated confusion matrix was derived, where Pb, Cr, Mn, Mo, Ni, Sn, W, Ti, Li, PGE, U and Other metals were combined into a single 'Rare metals' group for statistical stability. A MC resampling procedure was applied to this matrix to generate confidence intervals for OA and for commodity-specific PA and UA. These intervals quantify the uncertainty in the accuracy estimates and indicate the sensitivity of the mapped commodity assignments to potential misclassification, including uncertainty related to polygon–point matching.

We also quantified how classification uncertainty propagates to the two key environmental metrics used in this study. Using the same confusion matrix, we generated MC CIs for commodity-level deforestation areas and ERI values and compared them with the results derived from the predicted classes for the full dataset. For deforestation (**Figure 1c**), most commodities fall within the intervals, and the three commodities outside the bounds (Gold, Rare metals and Coal) differ from the nearest interval by only 141 km² (2.8%), Rare metals by 111 km² (10.8%) and Coal by 252 km² (4.6%), respectively, with the commodity ranking unchanged. For ERI (**Figure 3b**), the predicted-class ERI values generally align with the intervals, with a few commodities lying very close to the boundaries (Zinc, Silver, Aluminium and Coal differ from the nearest bound by about 0.001–0.01) and one larger deviation for Other non-metals (0.019), which reflects the heterogeneity of this group (all non-metallic sites except coal). These results show that the deforestation and ERI outcomes derived from the predicted classes are robust to reasonable levels of classification uncertainty, including uncertainty related to polygon–point matching.

The corresponding validation results and uncertainty assessment are reported in **Table S8.3 of SI Part 1.** Related text has also been added to the **captions of Figures 1c and 3b (Pages 5 and 10)**, **Lines 18–31 on Page 6 to Line 1 on Page 7**, **Lines 17–28 on Page 9**, and **Lines 9–27 on Page 20** of the revised manuscript.

8. (Line 9–10, P13) Does this mean that underground mining operations are excluded from your dataset? If so, what does this mean about the representativeness of your study? It would be valuable to see what % of global production of represented in your results.

Response 8:

Thank you for raising this important point. Indeed, our dataset focuses on surface-visible mining operations (primarily open-pit and other surface excavation methods) because these are more reliably detectable via satellite imagery. We recognise that underground mining operations, which often have minimal surface expression, are largely excluded from our mapping.

For context, existing industry analysis (Martino *et al.*, 2021), though excluding China and the

Middle East, represents the most comprehensive assessment currently available. It indicates that underground hard-rock mines account for about 40 % of global operations but contribute only 12 % of run-of-mine production, suggesting that surface mining dominates and that this study remains broadly representative. Nonetheless, we acknowledge that the exclusion of underground mines means that the results do not capture all global extraction activities.

We have now added the clarifying sentences to the **Discussion section;** please refer to **Lines 28–30 on Page 14** and **Lines 1–4 on Page 15** of the revised manuscript.

9. (Line 9–10, P15) I don't understand this number at all. Maus et al 2022 only have 44,929 polygons in their entire dataset. How can this possibly correspond to that many open pits?

Response 9:

Thank you for the comment, and I apologise for the misunderstanding. The number reported in this revised version refers to the number of open-pit pixels (15m), not the number of mining polygons in Maus *et al*. (2022) or Tang and Werner (2023). Each mining polygon may contain multiple open-pit areas, and each open pit is represented by many pixels. In the previous version, we identified open-pit areas using a grid-based approach. In this revision, we have instead used the dataset from Cheng *et al.* (2025), which directly identifies open-pit locations based on TanDEM-X elevation differences and Sentinel-2 spectral imagery through a machine-learning framework. Because the dataset is pixel-based, the total number of open-pit pixels substantially exceeds the number of polygons, as it represents the pixel-level extent of extraction zones rather than the number of individual mines or polygons. We have clarified this point to avoid confusion; please refer to **Lines 22–29 on Page 17** of the revised manuscript.

10. (Line 10–13, P15) While I trust that the authors have tried to employ an objective approach to classifying the polygons, I do not believe this result is at all accurate.

    97% of all mine polygons cannot be classified as open pits. The vast majority of mine footprints are made up of waste rock dumps (WRDs) and tailings storage facilities (TSFs).

A typical breakdown of a mine footprint we would expect would be something like 30–50% WRD, 25–50% tailings dams, and around 25% for milling facilities, leaching ponds and open pits, combined. I have serious concerns for your classification model if it recognises so many polygons as pits. It is simply not consistent with the anatomy of the world's mines, and so I have major concerns about the underlying methodology of this step.

Response 10:

We sincerely apologise for the misunderstanding. As clarified in our response to **Comment #9**, the previously reported 97% refers to the total proportion of mining polygons containing open-pit pixels, rather than 97% of mine footprints being physically open pits. After updating the datasets and refining the method in this revision, 50,093 polygons were found to contain open-pit pixels, covering an area of 112,980 km² (representing mining areas that include all mining-related land uses). These open-pit polygons account for approximately 61% of all 81,614 polygons and 95% of the total mining area (118,935 km²) derived from the union of the Maus *et al*. (2022) and Tang and Werner (2023) datasets. Please refer to **Lines 22–29 on Page 17** of the revised manuscript.

It is important to emphasise that these polygons typically include a combination of land-use types such as waste-rock dumps (WRDs), tailings dams, facilities, and vegetation, where only a portion of each polygon is classified as open pit. The term "open-pit polygons" therefore refers to polygons containing open-pit land-use pixels rather than polygons entirely covered by open pits.

11. (Line 16–17, P15) For mining regions where multiple mines operate in close proximity, this approach may incorrectly assign polygons between operations. How do you quantify the effect of this uncertainty?

Response 11:

Thank you for the valuable comment. We acknowledge that polygons located in dense mining regions could be incorrectly assigned between adjacent operations. To minimise this source of uncertainty, we refined the spatial matching threshold from 3000 m to 2000 m in this revision. The 2,000 m threshold was determined by analysing cumulative coverage and marginal increases in polygon connections and covered area at 500 m intervals, identifying where the growth began to level off **(S6 of SI Part 1)**. The incremental gains in both polygon count and covered area fall below 5% only after 2,000 m, indicating diminishing returns. Therefore, 2 km was selected as the optimal threshold, effectively capturing most relevant connections while limiting spatial spillover. Please refer to the updated text in **Lines 3–8 on Page 18** of the revised manuscript, as well as **Section S6 of SI Part 1**, which presents the cumulative proportion of polygons linked under varying distance thresholds.

12. (Line 19, P16) A cursory glance of the commodity distribution figures in supplementary section S2 suggests that your accuracies should not necessarily be classified as strong.

    95% sounds reasonable, but misclassifying 19% of mines for a commodity does not sound strong to me.

    I also see some rather egregious errors that I feel have not been addressed appropriately.

    If I look at lithium, for example, there are some parts of the world that are simply inexplicable to me. There are only 6-7 lithium mines in Australia. All of them are in Western Australia and the Northern Territory, yet your map shows lithium locations across all states. You also show two locations in New Zealand, which certainly doesn't mine lithium.

    If I look at Bauxite, there are also only 7 or so bauxite mines in Australia, and once again you show locations in states that don't host them.

    Given the errors associated with this small sample of which I am familiar, I am sure there are many other examples of such errors across all the maps. This is a major concern as these errors will propagate to your assessment of associated biodiversity risks.

Response 12:

We thank the reviewer for this thoughtful and detailed comment. We acknowledge that local discrepancies remain inevitable in global-scale classification, yet the updated workflow has demonstrably improved both spectral and spatial precision. As noted in the responses to earlier comments, the previous version of the dataset has been substantially revised by (1) integrating additional verified mining polygons from Tang and Werner (2023), (2) improving the spectral extraction procedure using open-pit data from Cheng *et al.* (2025), (3) incorporating HISUI hyperspectral imagery, and (4) implementing validation and uncertainty assessment to measure accuracies and quantify classification uncertainty and its propagation into key environmental metrics. Together, these steps substantially reduced potential misassignments and improved the spatial and spectral reliability of the classification results.

For (4) specifically, to evaluate the robustness of the updated maps, we conducted three independent validation exercises:

(1) **External data validation**. The mapped commodities were validated against independent datasets, including the Iron Ore Mine Tracker, Coal Mine Tracker, and point-location datasets for copper, lead-zinc, and nickel compiled by Northey *et al*. (2017). Agreement between our classified polygons and these references was high, with point-level accuracies of 74–77 % and areal (footprint) accuracies of 75–88 % across major commodities (iron, coal, copper-lead-zinc, and nickel) **(Table S8.1)**.

(2) **Stratified random-sampling validation.** To complement the external validation and evaluate potential systematic bias, we implemented a stratified random-sampling design (418 polygons) with proportional representation of both major and minor commodities. Verification was performed using Google Earth imagery, supported by auxiliary sources such as Google Maps, Street View, OpenStreetMap, and other publicly available datasets. Because many of the rare-metal commodities had small sample sizes in the random sampling, these classes (Pb, Cr, Mn, Mo, Ni, Sn, W, Ti, Li, PGE, U, and Other metals) were aggregated into a single 'Rare metals' group. Table S8.3 presents the aggregated confusion matrix for the nine resulting commodity groups (Fe, Cu, Zn, Au, Ag, Al, Rare metals, Coal, and Other non-metals), together with the resulting overall accuracy (OA) of 77% and the commodity-specific producer's accuracy (PA) and user's accuracy (UA). We then applied 10,000 Monte Carlo resamplings to this confusion matrix to derive 95% confidence intervals for OA, PA, and UA. These intervals quantify the uncertainty in the accuracy estimates and indicate the sensitivity of the mapped commodity assignments to potential misclassification **(Table S8.3)**.

(3) **Propagation of classification uncertainty into key environmental metrics.** In addition to the accuracy assessment, we quantified how classification uncertainty propagates to the two environmental metrics central to our analysis: commodity-level deforestation areas and the ERI. Using the same random-sampling confusion matrix, we generated MC CIs for both metrics and

compared them with the values derived from the predicted classes for the full dataset. For deforestation (**Figure 1c**), most commodities fall within the CIs, and the few that fall outside show only small deviations relative to their total deforestation magnitudes: Gold differs by 141 km^2 (2.8%), Rare metals by 111 km^2 (10.8%) and Coal by 252 km^2 (4.6%). The overall ordering of commodities is also preserved. For ERI (**Figure 3b**), the predicted-class ERI values generally align with the intervals, with a few commodities lying very close to the CI boundaries (Zinc, Silver, Aluminium and Coal differ from the nearest bound by about 0.001–0.01) and one larger difference for Other non-metals (0.019), which reflects the heterogeneity of this group (all non-metallic sites except coal). Together, these results show that the deforestation and ERI outcomes derived from the predicted classes are robust to reasonable levels of classification uncertainty.

Collectively, these external and random-sampling validations demonstrate that, despite some local-scale uncertainties, the updated classification performs consistently and robustly at the global scale. The observed overall accuracies are comparable to leading global mapping products, such as ESA WorldCover (~75-77%) and NASA MODIS MCD12Q1 (73.6%), and fall within the expected range for complex, multi-class global mapping tasks. This level of performance is considered acceptable for analyses of global-scale patterns such as deforestation and biodiversity risk. The validation methods, datasets, and results have been added; please refer to **Section S8 of SI Part 1**. Related text has also been added to the **captions of Figures 1c and 3b (Pages 5 and 10)**, **Lines 18–31 on Page 6 to Line 1 on Page 7**, **Lines 17–28 on Page 9**, and **Lines 9–27 on Page 20** of the revised manuscript.

Reviewer 2

1. (Figure la, P4) A uniformly fixed vertical axis scale may be misleading. It is recommended to adopt an adaptive scale or an alternative visualization method.

   Response 1:

   Thank you very much for the comment. We chose to keep a fixed y-axis scale across all commodities to allow direct comparison of deforestation magnitudes. We also tested logarithmic and square-root transformations, but these distorted values for commodities with low deforestation, making comparisons less interpretable. However, we recognise that the stacked colour representation of biome shares is not ideal for commodities with smaller deforestation areas. To address this, the original stacked areas have been replaced with line plots, and the biome shares are now presented as bars on the right of each line plot. The y-axes remain fixed to the same range across all plots to facilitate comparison among commodities. **Please see Figure 1a (Page 5)** of the revised manuscript.

2. (P4–5, 8–9) In the results section, figures are presented first followed by text, which is inconvenient for reading. It is suggested that the charts be placed after the first text paragraph that mentions them.

   Response 2:

   Thank you for the suggestion. The figures in the Results section have been repositioned to appear after the first text paragraph that introduces and discusses them, improving readability and logical flow. **Please refer to Pages 4 and 9 for the new arrangement.**

3. (Line 1, P6) The total amount of forest loss caused by the mining industry is approximately 14,619 km2 (2001–2022). This conclusion is quite prominent, and it would be more convincing if a numerical comparison with existing studies is made.

   Response 3:

   We thank the reviewer for this constructive suggestion. Our global deforestation estimate (~16,000 km^2, 2001–2022) is slightly higher than the ~14,000 km^2 reported by Stanimirova *et al.* (2024). This difference reflects our longer temporal coverage and the use of gross tree-cover loss without applying a >30 % canopy-cover threshold, which ensures the inclusion of all forested biomes, whereas the previous study focused primarily on humid tropical regions. Regional analyses such as Giljum *et al*. (2022), which estimated ~3,264 km^2 of deforestation across tropical regions, focus exclusively on industrial mining and are therefore not directly comparable due to their limited spatial and sectoral scope. Importantly, our study provides the first global, commodity-level quantification of mining-related forest loss and biodiversity risk, offering a more detailed and policy-relevant understanding of sector-specific environmental impacts. This clarification has been incorporated into the revised manuscript **(Lines 2–6, Page 13)**.

4. (P11–13) In the discussion, the connection between the results and policy frameworks (EUDR, TNFD) has been established, but the suggestions are too general. Specific operational suggestions for enterprises and government levels should be added. Although the research limitations are acknowledged, the emphasis is insufficient. For example, indirect impacts (such as transportation and infrastructure) are not included, and it should be clearly pointed out that this may lead to an underestimation of the overall footprint of the mining industry.

   Response 4:

   Thank you for the valuable comment. Specific operational suggestions for both enterprises and government levels have been added as recommended.

   "To operationalise these insights, governments could incorporate the derived nature loss indices into environmental due diligence, certification, and procurement frameworks, prioritising high-risk commodity–region combinations such as gold, coal, aluminium (bauxite), nickel–cobalt, and copper extraction in rainforest areas. Even when companies do not have mine-level traceability, they can use these spatially explicit indices to estimate the potential biodiversity and forest loss impacts associated with sourcing specific commodities from particular countries or regions. This enables enterprises to benchmark the relative impacts of their sourcing portfolios against global averages and to prioritise risk mitigation accordingly. Furthermore, enterprises could integrate these datasets into supply chain traceability and disclosure systems, adopting supplier screening protocols that flag sourcing areas overlapping with high-biodiversity zones." Please refer to **Lines 17–27 on Page 13** of the revised manuscript.

   "In addition, financial institutions and investors could leverage these datasets to evaluate their exposure to biodiversity-related risks within mining portfolios and align investment strategies with TNFD-aligned nature-risk disclosure requirements." Please refer to **Lines 6–9 on Page 14** of the revised manuscript.

   We appreciate the reviewer's comment. The exclusion of indirect impacts, such as transportation corridors, infrastructure development, and other land-use changes, was already acknowledged and discussed in the previous version. To improve clarity, we have slightly revised the text to explicitly state that this omission may lead to an underestimation of the overall mining footprint. **Please see Lines 5–12 on Page 15 of the revised manuscript.**

5. (P11–13) There is a lack of an independent conclusion section. It is recommended to add one to summarize the research contributions and highlight future research directions.

   Response 5:

   Thank you for the comment. According to the formatting guidelines of *Nature Communications*, the journal typically does not include a separate Conclusion section. However, we have added a concise concluding paragraph at the end of the Discussion to summarise the key findings and outline future research directions. It reads as follows:

   "Despite its limitations, this study offers a global, commodity-level assessment of mining-induced deforestation and biodiversity risk. From 2001 to 2022, mining activities caused ~16,000 km² of forest loss, about two-thirds of which occurred in tropical and subtropical regions. Nearly half of this loss was associated with gold, coal, aluminium, nickel–cobalt, and copper extraction concentrated in the Amazon, Southeast Asian, and Congo Basin rainforests. Biodiversity risks, however, vary regionally and do not necessarily scale with deforestation extent. These findings provide practical guidance for managing nature-related risks in mineral supply chains and support frameworks such as the EUDR and TNFD through commodity-specific insights. Future work should consider temporal mining dynamics, underground operations, and indirect land-use effects to advance nature-positive resource governance." Please refer to Lines **14–24 on Page 15** of the revised manuscript.

6. (P13–17) The methodology section is placed at the end of the main text. Unless it is the unified format of the journal, it is recommended to place the data and methodology section between the Introduction and the Results sections to ensure logical coherence.

   Response 6:

We thank the reviewer for the comment. However, in accordance with *Nature Communications'* formatting requirements, the Methods section is placed after the main text (i.e. following the Discussion and before the References). Therefore, we have **retained the current structure** to comply with the journal's standard format.

7. (Line 17, P14) Reliance on a small number of labeled polygons (1,941, accounting for less than 5%) leads to potential bias. This may result in an underestimation of small- and medium- sized or artisanal mining areas. The proportion of large-scale industrial mines is too high, and the impact of this bias on the results should be discussed more explicitly. The classification uncertainty should be reflected in the description of the results.

Response 7:

We thank the reviewer for this thoughtful comment. Classification in this study was performed on a pixel basis using spectral information, so the physical size of mining polygons does not directly influence predictions. However, smaller or artisanal sites can exhibit more heterogeneous or mixed spectral signals, and their underrepresentation among labelled polygons could introduce minor bias. To mitigate this during model development, we applied SMOTE to balance the training data (the potential overfitting risk associated with SMOTE was addressed by reporting the out-of-bag accuracy; please see the **response to Comment #8** for details).

After model training, we evaluated classification performance through two complementary validation procedures presented in **Section S8 of SI Part 1.** External validation compared the mapped commodities with independent datasets, including the Iron Ore Mine Tracker, Coal Mine Tracker, and point-location datasets for copper, lead–zinc, and nickel from Northey *et al.* (2017). Agreement between our mapped polygons and these reference datasets was high, with point-level accuracies of 74–77% and areal (footprint) accuracies of 75–88% across the major commodities (**Table S8.1**).

To further evaluate potential systematic bias, we conducted a stratified random-sampling validation consisting of 418 polygons proportionally allocated across commodity groups. Verification was performed primarily through Google Earth imagery, supported by Google Maps, Street View, OpenStreetMap, and other publicly available sources. Because several rare-metal commodities had small sample sizes, these classes (Pb, Cr, Mn, Mo, Ni, Sn, W, Ti, Li, PGE, U, and Other metals) were aggregated into a single "Rare metals" group. **Table S8.3** presents the aggregated confusion matrix for the nine resulting commodity groups (Fe, Cu, Zn, Au, Ag, Al, Rare metals, Coal, and Other non-metals). Using the confusion matrix from **Table S8.3**, we then applied 10,000 Monte Carlo (MC) resamplings to derive 95% confidence intervals for overall accuracy (OA; 77%), commodity-specific producer's accuracy (PA), and user's accuracy (UA). These intervals quantify the uncertainty in the accuracy estimates and indicate the sensitivity of the mapped commodity assignments to potential misclassification. The procedure is fully described in **Section S8 of SI Part 1.**

In addition to the accuracy assessment, we also quantified how classification uncertainty propagates to the two key environmental metrics used in our analysis: commodity-level deforestation areas and the Extinction Risk Index (ERI). Using the same random-sampling confusion matrix, we generated Monte Carlo confidence intervals (CIs) for both metrics and compared these intervals with the values derived from the predicted classes for the full dataset. For deforestation (**Figure 1c)**, most commodities fall within their MC intervals, and the three commodities outside the bounds (Gold, Rare metals and Coal) differ from the nearest CI limit by only 141 km^2 (2.8%), 111 km^2 (10.8%) and 252 km^2 (4.6%) relative to their total mapped deforestation areas, with the commodity ranking unchanged. For ERI (**Figure 3b**), the predicted-class ERI values generally align with the MC intervals, with several commodities lying very close to the CI boundaries (Zinc, Silver, Aluminium and Coal differ by only about 0.001–0.01) and one larger deviation only for Other non-metals (0.019), which reflects the heterogeneity of this group (all non-metallic sites except coal). Together, these results show that the deforestation and ERI outcomes derived from the predicted classes are robust to reasonable levels of classification uncertainty.

Collectively, the SMOTE-balanced model, the external validation, the stratified random-sampling validation, and the MC–based uncertainty assessment demonstrate that, despite inevitable local-scale uncertainties, the classification performs consistently and robustly at the global scale. The resulting accuracy levels are comparable to leading global mapping products such as ESA WorldCover (~75–77%) and NASA MODIS MCD12Q1 (73.6%). Related text has also been added to the **captions of Figures 1c and 3b (Pages 5 and 10)**, **Lines 18–31 on Page 6 to Line 1 on Page 7**, **Lines 17–28 on Page 9**, and **Lines 9–27 on Page 20** of the revised manuscript.

8. (Lines 10–12, P16) The SMOTE and undersampling methods may bring the risk of overfitting,

which needs further discussion.

Response 8:

We appreciate the reviewer's insightful comment. To address the potential risk of overfitting associated with the use of SMOTE and undersampling, we report both out-of-bag accuracy (OOB Acc) and balanced accuracy (OOB Bal) for the training and test sets to evaluate model generalisation **(Tables S7.2 and S7.3 of SI part 1).** Across all models, the differences between OOB and test accuracies were below 0.025, which is well within the ~0.05 overestimation typically observed in random forests, indicating no substantial overfitting (Janitza & Hornung, 2018). Please see **Line 30 on Page 19 and Lines 1–4 on Page 20** of the revised manuscript.

9. (P18–26) The references are comprehensive, including the latest studies (2023–2024). However, policy and regulatory documents (such as relevant EU regulations and TNFD official reports) should be directly cited. The formats of some references are inconsistent, lacking the place of publication or volume and page numbers (e.g., References 1, 2, 9, 21, 59, 71, 72, etc.), which need to be standardized.

Response 9:

We thank the reviewer for this helpful comment. The relevant policy and regulatory documents, including the EU Deforestation Regulation (EUDR), the Carbon Border Adjustment Mechanism (CBAM), the Taskforce on Nature-related Financial Disclosures (TNFD), the International Council on Mining and Metals (ICMM), and the Initiative for Responsible Mining Assurance (IRMA), have now been directly cited in both the main text and the reference list. Furthermore, all references have been standardised in accordance with the *Nature Communications* reference style. We have added the corresponding citations and clarifications. Please refer to **Lines 16–17 on Page 3**, **Line 11 on Page 13, Lines 16 and 19 on Page 14,** and the **Reference section** of the revised manuscript.

10. There are a large number of charts in the appendix. It is recommended to streamline them and retain only the key ones.

Response 10:

We thank the reviewer for this helpful suggestion. All maps previously included in SI Part 1 have been removed to streamline the supplementary materials. **The mining area maps have been reorganised and moved to SI Part 2, the deforestation ratio maps to SI Part 3, and the ERI (Extinction Risk Index) maps to SI Part 4.**

Point-by-point Response to Reviewers' Comments

Reviewer #1 (Remarks to the Author):

I am really pleased with the level of improvement with this manuscript. The authors have addressed each comment in considerable detail, and have signitifantly improved the results, and the way they are presented. I was initially concerned about what I thought were some obvious errors that might require too much work to address, but the authors have gracefully taken the comments and used them to conduct a considerable amount of additional work. This is very commendable. I am happy for the article to proceed to publication.

Response

We thank the reviewer for the positive evaluation and for recognising the improvements made in the revised manuscript.