











Uncontrolled Illegal Mining and *Garimpo* in the Brazilian Amazon

Received: 22 April 2024

Accepted: 1 November 2024

Published online: 13 November 2024

 Check for updates

Luiz Cortinhas Ferreira Neto ^{1,2}✉, Cesar Guerreiro Diniz ^{1,3,4}✉, Raian Vargas Maretto ⁵, Claudio Persello ⁵, Maria Luize Silva Pinheiro ¹, Marcia C. Castro ⁴, Luis Waldyr Rodrigues Sadeck^{1,6}, Alexandre Fernandes Filho⁷, Julia Cansado ¹, Arlesson Antonio de Almeida Souza^{1,6}, Jeremias Pinto Feitosa⁶, Diogo Corrêa Santos^{3,8}, Marcos Adami ⁷, Pedro Walfir M. Souza-Filho ^{3,8}, Alfred Stein ⁵, Andre Biehl⁹ & Aldebaro Klautau²

Mining has played an important role in the economies of South American countries. Although industrial mining prevails in most countries, the expansion of *garimpo* activity has increased substantially. Recently, Brazil exhibited two moments of *garimpo* dominance over industrial mining: 1989–1997 and 2019–2022. While industrial mining sites occupied ~ 360 km² in 1985 but increased to 1800 km² in 2022, a 5-fold increase, *garimpo* mining area increased by ~ 1200%, from ~ 218 km² in 1985 to ~ 2627 km² in 2022. More than 91% of this activity is concentrated in the Amazon. Where almost 40% of the sites are five years old or younger, this proportion increases to 62% within Indigenous lands (ILs). Regarding the legal aspect, at least 77% of the 2022 extraction sites showed explicit signs of illegality. Particular attention must be given to the Kayapo, Munduruku, and Yanomami ILs. Together, they concentrate over 90% of the *garimpo* across ILs.

Mining entails the extraction of economically valuable minerals or other geological materials from the Earth's crust. This activity plays a pivotal role in the economies of South American nations and remains important to this day^{1,2}. Similar to many other countries, Brazil has embraced the economic potential of the industrial mining sector. However, there has been a notable increase in the occurrence of a specific type of mineral extraction method, traditionally referred to as artisanal small-scale mining (ASM) and denoted hereinafter as *garimpo*, which primarily encompasses illegal activities^{3–5} and is fueled by the latest surge in gold prices⁶.

Many *garimpo* sites, particularly (but not exclusively) those where gold is extracted, exhibit activities that are not only harmful to human

health due to the use of mercury (Hg) in the gold amalgamation process but also leave behind a disastrous trail of ecosystem service depletion, especially in the Amazon, where, in addition to deforestation and forest degradation, *garimpo* notably disrupts fishing, hunting, and freshwater availability^{7–11}. Within this context, it is common for municipalities adjacent to mining regions to exhibit high deforestation rates, elevated methyl mercury (MeHg) concentrations in inhabitants and fauna, low human development index (HDI) values, and increased suspended sediment discharge into river courses and their surroundings^{12–14}.

Mineral extraction is an economic activity safeguarded by the federal constitution of almost all pan-Amazonian countries¹⁵. However,

¹Solved - Solutions in Geoinformation, Belem, PA, Brazil. ²Federal University of Para, UFPA, Technology Institute, PPGE, Belem, PA, Brazil. ³Federal University of Para, UFPA, Geoscience Institute, PPGG, Belem, PA, Brazil. ⁴Harvard TH Chan School of Public Health, Harvard, Boston, MA, USA. ⁵University of Twente, UT, Department of Earth Observation Science, Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Enschede, The Netherlands. ⁶National Institute for Space Research, INPE, Amazon Regional Center, Belém, PA, Brazil. ⁷National Institute for Space Research, INPE, São José do Campos, SP, Brazil. ⁸Vale Research Institute, ITV, Belem, PA, Brazil. ⁹Princeton University, Department of Computer Science, Princeton, NJ, USA.

✉ e-mail: luiz.cortinhas@solved.eco.br; cesar.diniz@solved.eco.br

illegal mining activities, in general, are characterized by the invasion of protected areas (indigenous lands (ILs) and conservation units (CUs) – in Brazil, protected areas are referred to as CUs), a lack of formal mining documentation and environmental licensing, the improper disposal of chemical contaminants, the illegal acquisition and use of mercury, the absence of environmental recovery plans, the existence of a parallel market for mineral assets, adverse effects on population health (e.g., malaria, intestinal infections, and chronic conditions due to mercury exposure), and social disruption of local communities and indigenous people^{16–18}. In Brazil, any mining activity within the limits of ILs, fully protected CUs, and some of sustainable use constitutes an unrestricted illegal activity¹⁹. Law No. 9.985²⁰, which institutes the National System of Conservation Units (SNUC), states that inside fully protected CUs and CUs of sustainable use, designated as extractive reserves (RESEXs) and private natural heritage reserves (RPPNs), mining of any kind is strictly prohibited, either *garimpo* or industrial mining.

Despite crucial efforts to map mining footprints globally^{21,22}, knowledge gaps must still be resolved regarding distinguishing extraction patterns derived from more comprehensive time series data, whether at industrial mining or *garimpo* sites. The analysis proposed here addresses extensive spatiotemporal mining mapping (spanning four decades) on a nearly continental scale (the entire territory of Brazil) while simultaneously distinguishing two distinct extraction types. The use of extensive Landsat-derived (30 m resolution) time series data is essential for obtaining a more precise spatial and temporal understanding of the development of mining in Brazil, especially in the Brazilian Amazon. An in-depth understanding of the evolution of mining in time and space supports more accurate identification of the ILs, CUs, and inhabitant groups most impacted by this activity.

The spatialization of such land use provides a better understanding of Brazil's evolution of industrial mining and *garimpo*. Specifically, this geospatial dataset supports scientific developments in diverse cross-related areas, such as assisting in the estimation of the financial loss inherent to illegal mining^{19,23}, spatial and temporal correlation analyzes between mining expansion and increases in methyl mercury levels in the trophic chain²⁴ and consequent human mercury exposure²⁵, creation and calibration of epidemiological models regarding the spread of mosquito-related diseases²⁶, changes in the physical-chemical¹² and biological characteristics of water courses surrounding mining operations²⁷, and associated morphometric changes due to excessive silting of river courses²⁸.

Therefore, using a deep learning-based classifier and cloud computing infrastructure, we mapped the evolution of mineral extraction in Brazil from 1985 to 2022. Here, we tracked industrial mining and *garimpo* extraction sites in time and space to determine the distribution, predominance, age, and signs of illegality associated with the detected Brazilian *garimpo* sites. Furthermore, we discussed the suitability of the classic ASM terminology, as it no longer reflects reality. All the data produced here have already been transferred to the Map-Biomass initiative—as part of our multi-institutional scientific agreement (Solved/UFGA/MapBiomass)—and are publicly available for download within its Collection 8^{29,30}.

Results

Mining area Evolution: industrial mining and Garimpo

The extent of Brazilian surface mining was monitored systematically and continuously, producing maps and annual statistics from 1985 to 2022. Moreover, the data produced allow the classification of two distinct mining extraction patterns: *garimpo* (generally referred to as ASM) and industrial mining (Fig. 1). These data provide a better understanding of the dynamics of mining extraction in Brazil, paving the way toward a greater comprehension of its social-environmental impacts and updating the status of this economic activity through 38 years of data.

In terms of extraction patterns, Brazil has exhibited a mostly industrial mining exploitation profile for almost four decades. However, the recent pattern of mining extraction has changed, and the area occupied by *garimpo* activities in 2022 was already 1.46 times larger than that used for industrial extraction. Over nearly four decades, Brazil exhibited two distinct periods when the *garimpo* extraction area exceeded the industrial extraction area, from 1989–1997 and 2020–2022 (Fig. 1C).

At the beginning of the time series, in 1985, the area occupied by industrial mining operations reached approximately 360 km², while the area occupied by *garimpo* extraction operations reached approximately 220 km². In addition to the reversal of industrial mining dominance from 2020 to 2022, there was a notable acceleration in *garimpo* expansion. Such extraction notably increased in space, dominating northern Brazil, mainly in Pará, Mato Grosso, Rondônia, and Amazonas. Moreover, industrial activity was concentrated in the southeastern region of Brazil, especially in Minas Gerais (Fig. 1).

In 2022, the *garimpo* extraction area reached 2630 km², 12 times larger than that in 1985, an increase of nearly 1200%. In addition to this increase, in 2022, 91.75% (2410 km²) of the *garimpo* area occurred within the Amazon biome boundary (Fig. 1). Importantly, the area associated with industrial mining also increased in Brazil, but more gradually and at a much lower intensity than that in the most recent years of the time series. In 1985, the industrial mining area reached 360 km² but increased to 1800 km² in 2022, representing a 5-fold increase.

Nevertheless, the rate of increase in recent years is the most alarming aspect of this growth. In the last four years of the series, namely, from 2019–2022, there was almost no relevant expansion of the industrial mining area, which increased from 1730 km² in 2019 to 1800 km² in 2022, an absolute increase of approximately 4%. In contrast, if stability is a recent hallmark of industrial extraction, the exact opposite applies to the *garimpo* extraction area. From 2019 to 2022, the *garimpo* extraction area increased from 1720 km² in 2018 to 2670 km² in 2022—an absolute increase of 55%. Furthermore, in the last year of the series, namely, from 2021 to 2022, the *garimpo* extraction area increased by 350 km², rising from 2280 to 2630 km².

The state of Pará is centrally relevant to the expansion observed in Amazonia. The state of Pará contains four of the five largest municipalities in Brazil in terms of *garimpo* extension. Notably, Itaituba (710 km²), Jacareacanga (195 km²), São Feliz do Xingu (101 km²), and Ourilandia do Norte (91 km²) jointly constitute 41.7% of the national *garimpo* area, with an area of 1097 km². In third place, the only municipality outside Pará is Peixoto de Azevedo, in Mato Grosso (MT), with 126 km² of *garimpo* activities in 2022.

Signs of illegality and temporal persistence of garimpo sites

Recently, *garimpo* activity has spread throughout the Amazon. Initially concentrated in the southern region of Pará and in the northern parts of the states of Mato Grosso and Rondônia (Fig. 1), *garimpo* extraction has reached the border of neighboring countries (French Guiana, Venezuela, and Colombia), the interior of fully protected CUs, CUs of sustainable use, natural heritage reserves (RPPNs), extractive reserves (RESEXs) and ILs, as shown in Fig. 2 and Supplementary Material S.5. In 2022, 780 km² of *garimpo* extension occurred within CUs, while 250 km² occurred within ILs, although its distribution, in both cases, was not homogeneous. When ranked by extension, five CUs accounted for 85.5% of the total *garimpo* area: APA do Tapajós (environmental protection area - APA), FLONA do Amaná (national forest - FLONA), ESEC Juami-Japura (ecological station - ESEC), FLONA do Crepori, and PARNA do Rio Novo (national park - PARNA). Similarly, signs of *garimpo* activity were not evenly distributed across Brazil's ILs. The Kayapo, Mundurucu, and Yanomami ILs accounted for more than 90% of the total *garimpo* extraction area within indigenous territories (Fig. 2C).

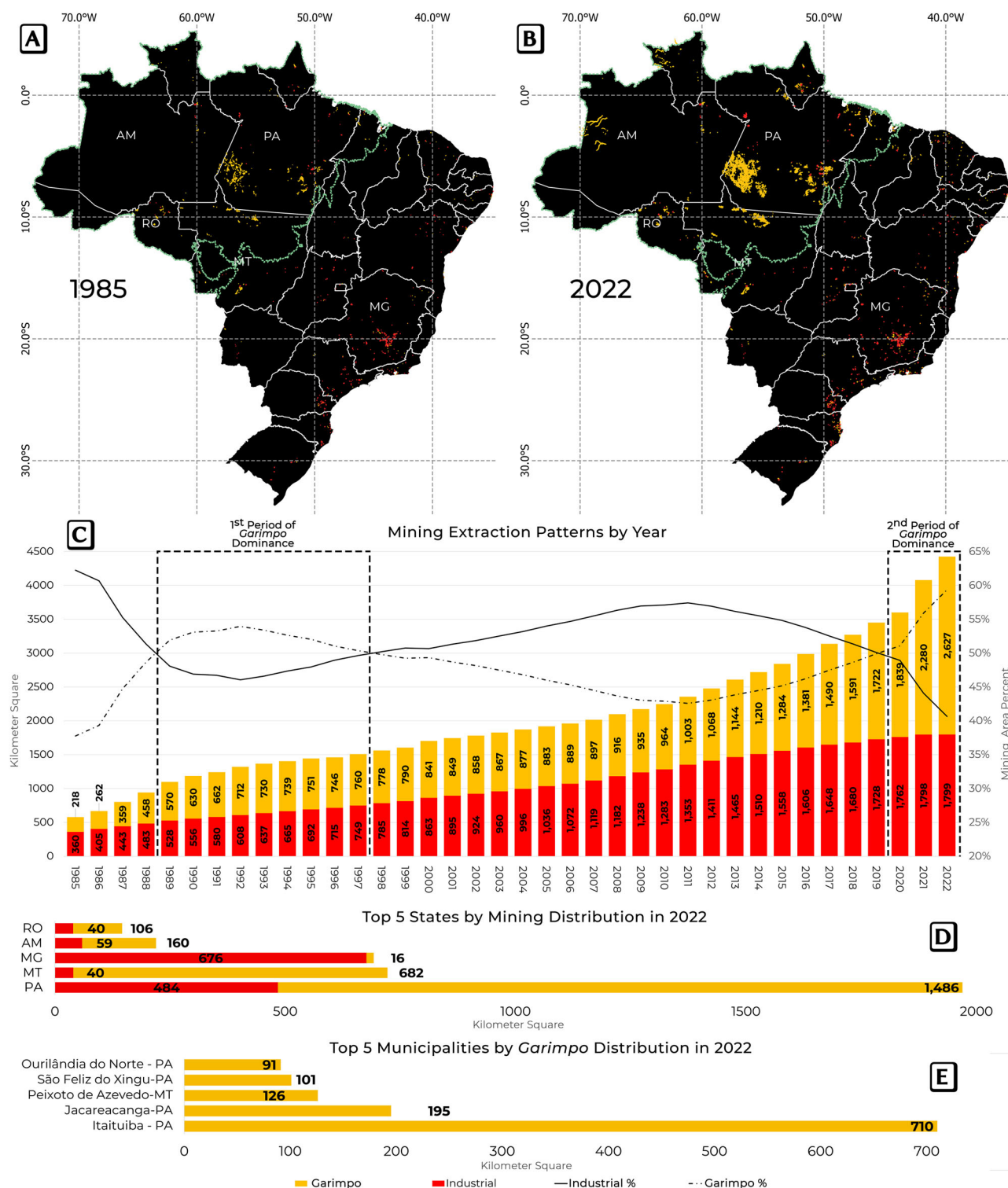


Fig. 1 | Spatial-temporal distribution of mining extraction patterns in Brazil. **A** Spatial distribution in 1985. **B** Spatial distribution in 2022. **C** The total area of mining extraction patterns per type per year. **D** Top 5 states by mining distribution in 2022. **E** Top 5 municipalities by *garimpo* distribution in 2022. In every section, yellow denotes *garimpo*, while red denotes industrial mining. The abbreviations

RO, AM, MG, MT, and PA denote the states of Rondônia, Amazonas, Minas Gerais, Mato Grosso, and Pará, respectively. The Amazon biome delimitation is represented by a light green boundary in maps A and B. The states and Amazonian delineations were downloaded from the IBGE.

In 2022, at least 15% (390 km²) of the *garimpo* mining area, as shown in Fig. 2D, occurred within regions with restrictions set in place to limit this activity. Mineral extraction activity of any type is constitutionally prohibited within ILs, fully protected CUs, RPPNs, and RESEXs. Furthermore, proportional to the area detected over the last

decade (2013–2022), the expansion of *garimpo* within both ILs and CUs was 462% greater in 2022 than in 2013. Within ILs alone, the *garimpo* area in 2022 was 625% larger than that in 2013, an absolute gain of 210 km², jumping from 40 to 250 km². Within CUs, the *garimpo* mining area was 300% larger in 2022 than in 2013, with an absolute gain of

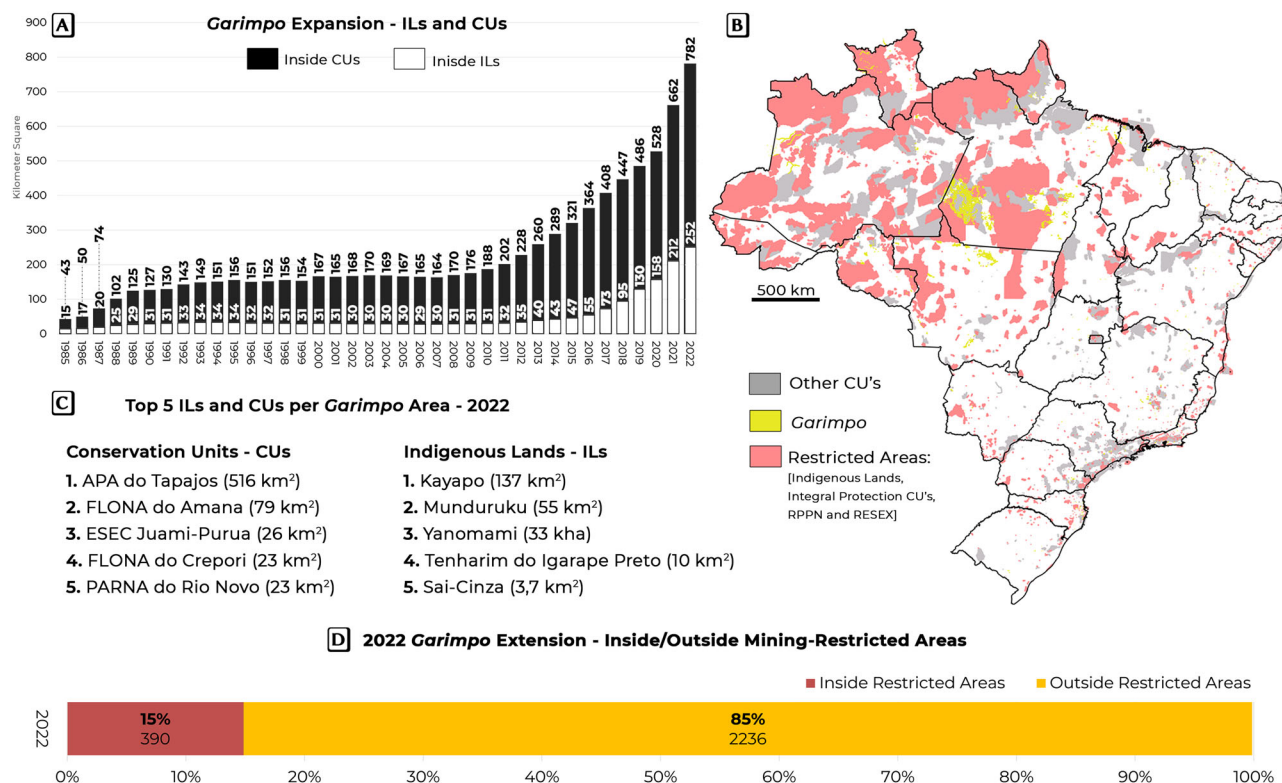


Fig. 2 | Garimpo sites in restricted areas. A Garimpo area in indigenous lands and conservation units per year. **B** Spatial distribution of the garimpo area in 2022. On the map, gray denotes the location of the conservation units. Red denotes the location of indigenous lands. Yellow denotes the garimpo sites. **C** The top 5 ILs and

CUs per garimpo area in 2022. **D** The bar graph shows the absolute and percent values inside and outside mining-restricted areas. In the graph, yellow denotes garimpo extension outside restricted areas, while dark red denotes mining sites within restricted areas (indigenous lands, fully protected CUs, RPPNs, and RESEXs).

520 km², jumping from 260 to 780 km². Combined, the mining expansion on ILs and CUs reached 730 km² in one decade. Cross-referencing garimpo locations with the national bases of mining-restricted regions is a simple way to verify spatial illegality. However, spatial violations are not the most common sign of illegality. A mining operation may exhibit signs of illegality even when it is not located within a restricted region. One way to verify this is by using the SIGMINE platform. Developed and updated by the Brazilian National Mining Agency (ANM), this platform provides the location and details of active mining processes throughout Brazil. The SIGMINE platform adds an essential degree of transparency to ANM information, allowing public verification of formal records of mineral extraction in Brazil. Even if registered in the SIGMINE platform as a formal holder of a garimpo permit (PLG) or a mining concession (CL), the absence of a preexisting environmental license issued by an official Brazilian environmental institute (Brazilian Institute of Environment and Renewable Natural Resources—IBAMA—or the State Secretary of the Environment—SEMA—and in the case of Para state, the Municipal Secretary of the Environment—SEMA)) may also categorize operators as engaging in illegal activity. In this sense, all detected garimpo sites were classified as either showing explicit signs of illegality or no explicit signs of illegality, relying exclusively on the garimpo extraction site position versus the geolocation and license type recorded on the SIGMINE platform (Fig. 3A). A more in-depth verification of environmental licensing, guaranteeing the preexistence of an environmental authorization for each SIGMINE-registered plot, could not be conducted, as no centralized or digital database allows public access to all environmental licenses issued for mining activities.

In 2022, considering the 2630 km² of garimpo mined area, 77% (2024 km²) exhibited explicit signs of illegality, 58% (1522 km²) was not associated with the appropriate mining permit (PLG or CL), 4.2%

(112.27 km²) occurred outside SIGMINE boundaries, and 15% (390 km²) occurred within restricted areas (ILs, fully protected CUs, RPPNs and RESEXs). Notably, the analysis considered every mining license currently available in SIGMINE as an a priori holder of an environmental license. Thus, some extraction sites, despite falling within the category of showing no explicit signs of illegality, may still be environmentally irregular but could not be further assessed. Nonetheless, even assuming that every SIGMINE plot exhibited appropriate environmental conformity, only 23% of the garimpo area in Brazil did not show explicit signs of illegality.

Regarding temporal persistence, the Amazonian garimpo explosion is unequivocally very recent; 41% (980 km²) of the exploited area in the Brazilian Amazon is less than five years old. In terms of size, the area occupied by very young sites is equivalent to the extent of Los Angeles, the United States, or Rio de Janeiro, Brazil. The recent increase in activity within ILs or CUs is even worse. Mining sites less than five years old account for 62.3% (157 km²) of the total mining area within ILs. Within CUs, the conditions are similar, and 42.8% (334 km²) of the mining area is five years old or younger. If the timeframe refers to mines that have existed for up to 10 years, the conditions worsen. More than 58% (1408 km²) of the mines in the Brazilian Amazon were opened between 2012 and 2022. Within ILs, the proportion of mining areas opened within the last 10 years, namely, 2012–2022, is approximately 84.2% (212 km²) of the total illegal mining area. In CUs, mines that are 10 years old or younger account for 66.8% (552 km²) of the total mining area.

Error assessment analysis

In this study, a two-stage stratified random sampling approach was used to assess the accuracy of the artificial intelligence (AI)-based model, categorizing 52,320 samples based on a human/visual interpretation as belonging to the mining or non-mining category.

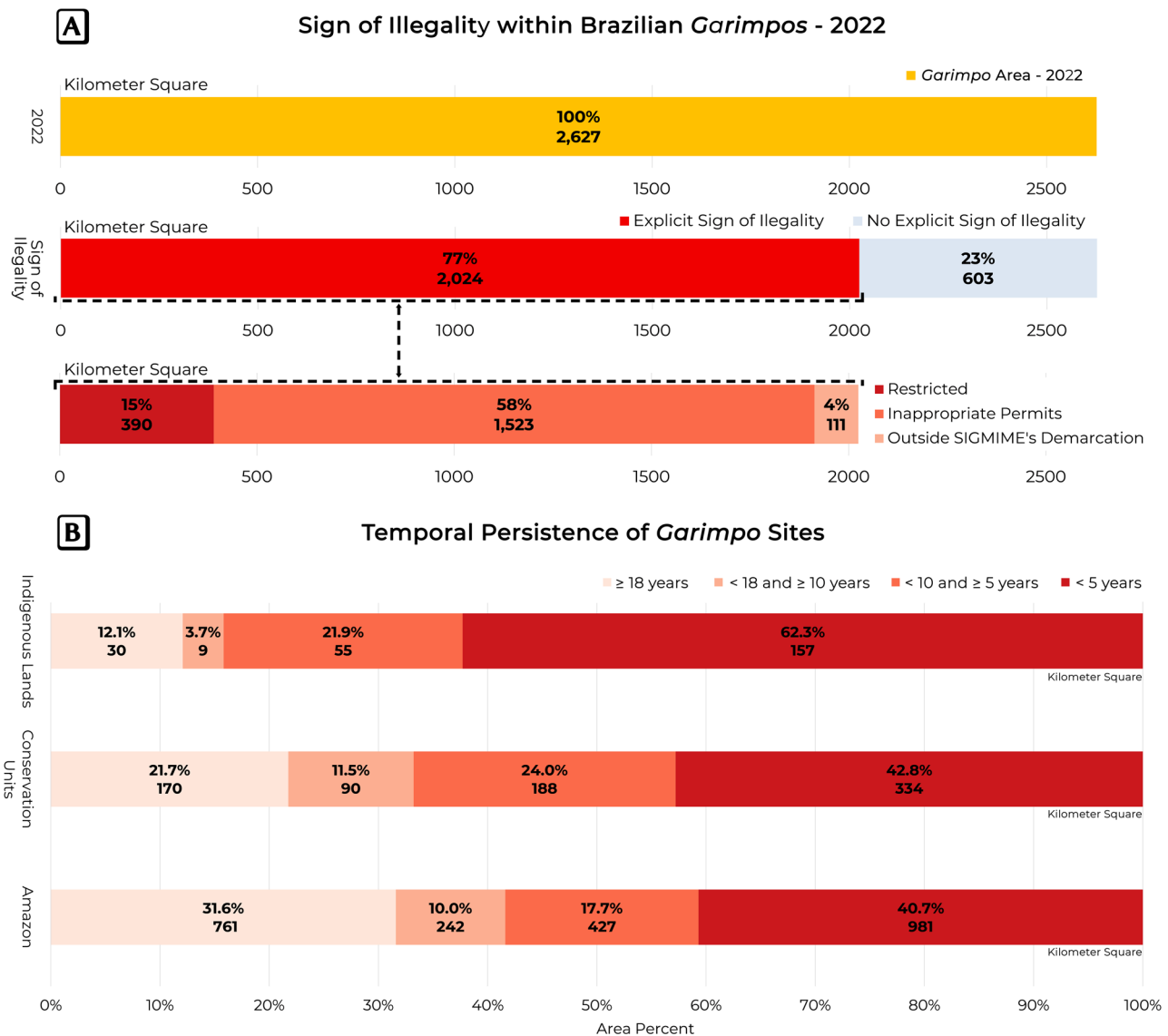


Fig. 3 | Illegality and timing of *garimpo* activities. A Signs of illegality and nature of *garimpo* in 2022. At the top, the yellow bar denotes the total area in 2022. In the middle, the area is visualized according to signs of illegality and is classified as showing explicit signs of illegality or no explicit sign of illegality. At the bottom, the nature of illegality is provided, as are three distinct signs of illegality: occurring inside restricted areas, exhibiting inappropriate permits, and occurring outside the

SIGMIME demarcation. **B** Temporal persistence of *garimpo* sites. The bar graphs show the proportion of the detected *garimpo* area as a function of its age [time]. The ages of the extraction sites within indigenous lands, conservation units, and the Brazilian Amazon are shown from top to bottom. The tonal variations (red) indicate age ≥ 18 years, < 18 and ≥ 10 years, < 10 and ≥ 5 years, or < 5 years. The redder the tone is, the younger the mining area.

Furthermore, the adopted strategy was weighted by a per grid-per-area approach (the proportion of the classes within the 62.5-km² grid), as provided in S.1 in the Supplementary Material. Nevertheless, mining is a statistically rare land use within the Brazilian context, given the size of the country. Thus, the reported error analysis must always account for this nature.

Traditionally, the overall accuracy (OA) metric is derived using a single error matrix generated over a specific period and by aggregating a complete set of validation samples to illustrate the amount of agreement or disagreement between the reference and categorized pixels. However, without a finer spatial constraint to account for the mining class rarity, the OA metric would be statistically inflated to the point where a nonlocally constrained method would quickly yield OA levels greater than 99% while statistically inflating the producer and consumer accuracy (PA and CA, respectively) metrics. Table 1 shows the annual OA metric and mining and non-mining PA and CA metrics [PA(Mi), CA(Mi), and PA(N-Mi), CA(N-Mi), respectively].

In Fig. 4, the per grid-per-area weighted approach demonstrated that in 2022, every grid exhibited an OA value greater than 97% throughout Brazil's territory. Moreover, most grids exhibited PA(Mi) and CA(Mi) values greater than 90%. Of the 182 possible grids, PA(Mi) was greater than 90% in 164 (90%) of the grids, while CA(Mi) was greater than 90% in 144 (79%) of the grids. In most evaluated years, the PA(Mi) rate was above 70%, except for the three years with the highest age, namely, 1985, 1990, and 1995, where the PA(Mi) value was approximately 65% (Table 1). Moreover, Fig. 4 shows how statistical inflation or deflation of the error metrics significantly affects the map accuracy (in particular, but not exclusively, the OA metric). If non-weighted/nonlocally constrained methods were used to assess rare, non-homogeneously distributed events, the local variation in error metrics would not be possible to capture.

Therefore, regardless of which error metrics are displayed, the ability to locally diagnose such inaccuracies is far greater than the mere presentation of simply inflated or deflated global metrics. A per-grid-

Table 1 | Aggregated annual error metrics and confidence intervals

Year	OA	PA(Mi)	CA(Mi)	PA(N-Mi)	CA(N-Mi)
2022	99.85 (± 0.33)	91.42 (± 6.18)	91.95 (± 19.61)	99.93 (± 0.006)	99.92 (± 0.33)
2020	99.92 (± 0.33)	90.32 (± 7.67)	91.57 (± 21.83)	99.99 (± 0.005)	99.92 (± 0.33)
2015	99.74 (± 0.58)	75.37 (± 7.06)	91.25 (± 21.19)	99.99 (± 0.004)	99.75 (± 0.60)
2010	99.70 (± 0.59)	77.95 (± 4.66)	91.67 (± 17.81)	99.99 (± 0.005)	99.70 (± 0.63)
2005	99.66 (± 0.64)	73.09 (± 4.93)	91.36 (± 18.44)	99.99 (± 0.004)	99.66 (± 0.67)
2000	99.64 (± 0.64)	70.12 (± 4.93)	90.56 (± 23.37)	99.99 (± 0.005)	99.65 (± 0.68)
1995	99.59 (± 0.58)	64.40 (± 2.94)	92.74 (± 21.08)	99.99 (± 0.003)	99.59 (± 0.72)
1990	99.64 (± 0.58)	66.08 (± 4.18)	93.41 (± 21.58)	99.99 (± 0.003)	99.64 (± 0.68)
1985	99.70 (± 0.43)	69.45 (± 2.16)	93.60 (± 15.85)	99.99 (± 0.001)	99.70 (± 0.61)

The columns provide distinct error assessment metrics: overall accuracy (OA), mining producer accuracy (PA(Mi)), non-mining producer accuracy (PA(N-Mi)), mining consumer accuracy (CA(Mi)), and non-mining consumer accuracy (CA(N-Mi)). All values were calculated based on a per grid-per-area weighted approach.

per-area weighted approach was applied to evaluate nine distinct years of the time series. Notably, the local distribution of each annual error metric is available in the Supplementary Material section, S.2 and S.3. The high accuracy rates obtained by this extensive error analysis confirm the general effectiveness and precision of the adopted AI-based method while indicating that regional training improvements remain necessary.

Discussion

In 5 years, from 2018–2022, 40% (1063 km²) of the *garimpo* sites detected in Brazil started and developed, as shown in Figs. 1, 4. Within ILs, where mining restrictions apply, this rate was even higher, with 62% (157 km²) of the mining area being five years old or younger. Notably, *garimpo* essentially occurs in the Amazon. More than 91% (2410 km²) of such extraction patterns occur in that biome (Fig. 1), and 41% (981 km²) of such sites are five years old or younger (Fig. 3) and expanding rapidly (Figs. 2, 3).

In academic parlance, we classified *garimpo* as ASM or artisanal small-scale gold mining (ASGM). However, in 2022 alone, the *garimpo* area increased by 341 km² and surpassed the industrial mining area by 848 km² (an industrial mining area of 1779 km² and a *garimpo* area of 2627 km²). In the same year, within the Kaypó IL, where mining activity of any kind is restricted, a single *garimpo* conglomerate covered an area of 50 km², reaching linear extensions of 20 km (Fig. 5). Thus, the small-scale concept no longer applies since such lengths and areas cannot represent small-scale measures. Likewise, there is nothing artisanal associated with the workforce size and transportation volume of several tons of sediments excavated via the use of dozens, sometimes hundreds, of backhoe loaders and hydraulic diggers, which are often combined with the use of helicopters, clandestine landing strips, and dredging ferries^{31–35}, to increase production and flow capacity of the Amazonian *garimpos*. Such sizes and expanding velocities are incompatible with the alleged artisanal and small-scale concept.

Additionally, almost 77% (2030 km²) of the sites detected in 2022 showed explicit signs of illegality. The use of inappropriate mining licenses, any but not a *Garimpo* Permit (PLG) or a Mining Concession (CL), constituted 57.8% (1520 km²) of the illegality signs, while the invasion of mining restricted areas (ILs and CUs, as defined by Law No. 9.985²⁰) responded to 15.2% (399 km²), and other 4.2%, (111.27 km²) were lacking mining licenses of any kind (as implemented outside of SIGMINE’s demarcations). Several factors contribute to this scenario.

First, a centralized and digital database is necessary to ensure public access to environmental licenses issued in favor of individuals or *garimpo* cooperatives. The lack of transparency in environmental licensing prevents accurate assessment of the levels of documentary legality, which could render the observed proportion of activities considered to present no explicit sign of illegality to levels that are even smaller than the reported 23% (603 km²).

Second, the state of Pará (PA), which alone accounts for 56% of the total activity (Fig. 1), is the only state where the environmental licensing of mining operations has been transferred to the municipal level. In 2015, the state delegated this role to municipal entities through Resolution No. 120/2015³⁶ of the State Council for the Environment (COEMA-PA), which classified mining operations up to 500 hectares as “small-scale activities with local environmental impacts.” In response to the COEMA Resolution, the Federal Public Ministry (MPF) stated through Recommendation No. 01/2023³⁷ that a city hall shall not grant environmental licensing for *garimpo* activities since the environmental damage associated with such far outweighs the concept of local activity-related impacts. While a final decision revoking *garimpo* licensing at municipal level has not yet been issued, four of the five municipalities with the largest *garimpo* areas occur in the state of Pará: Itaituba, PA (710 km²); Jacareacanga, PA (200 km²); Peixoto de Azevedo, MT (130 km²); São Felix do Xingu, PA (100 km²); and Ourilândia do Norte, PA (91 km²).

Third, there is a lack of processes to mitigate the impacts of *garimpo*, and efforts to rehabilitate the mining sites are even less common. In this sense, the widespread use of mercury (Hg) in the Amazon poses far-reaching human health and ecological concerns. This is particularly alarming given that Brazil is not a mercury-producing country, and owing to its character, both Hg import and use are controlled—an indication of fraudulent mercury acquisition^{38,39}. Globally, Hg release from tailings and vaporized mercury is estimated to exceed 1000 tons yearly⁴⁰. Once available as an organic compound, methyl mercury (MeHg) can easily enter the aquatic food chain^{12,41–43}. In this sense, riverine communities in the Amazon biome are particularly vulnerable to MeHg since they mostly rely on fish as their primary protein source^{12,44}. Amazonian populations have demonstrated critical neuropathological symptoms associated with mercury exposure, particularly cognitive^{45,46}, vision^{47–50}, motor^{45,46,51,52}, somatosensory^{45,48,53}, and emotional deficits⁵¹. Specifically, in pediatric populations, mercury poisoning is associated with neurodevelopmental and motor deficits, including delayed milestone achievements, language problems, and low mental and psychomotor scores^{54–56}.

Way before long-term chronic exposure, food security and hunger were acute short-term conditions among indigenous and riverine populations. The environmental depletion of ecosystem services triggered by *garimpo* operations causes notable disruptions in fishing, hunting, and freshwater availability. Consequently, once-abundant resources have become scarce and unsuitable for human consumption. Prevented from eating and properly hydrating, indigenous and riverine communities, especially newborns and children, experience malnutrition, dehydration, and anemia^{9–11,25,57,58}, subsequently, even if infant mortality does not increase^{10,11}, these communities will suffer long-term problems related to cognitive^{45,46}, motor^{45,46,51,52}, visual^{47–50} and neurological deficits^{45,48,51,53}.

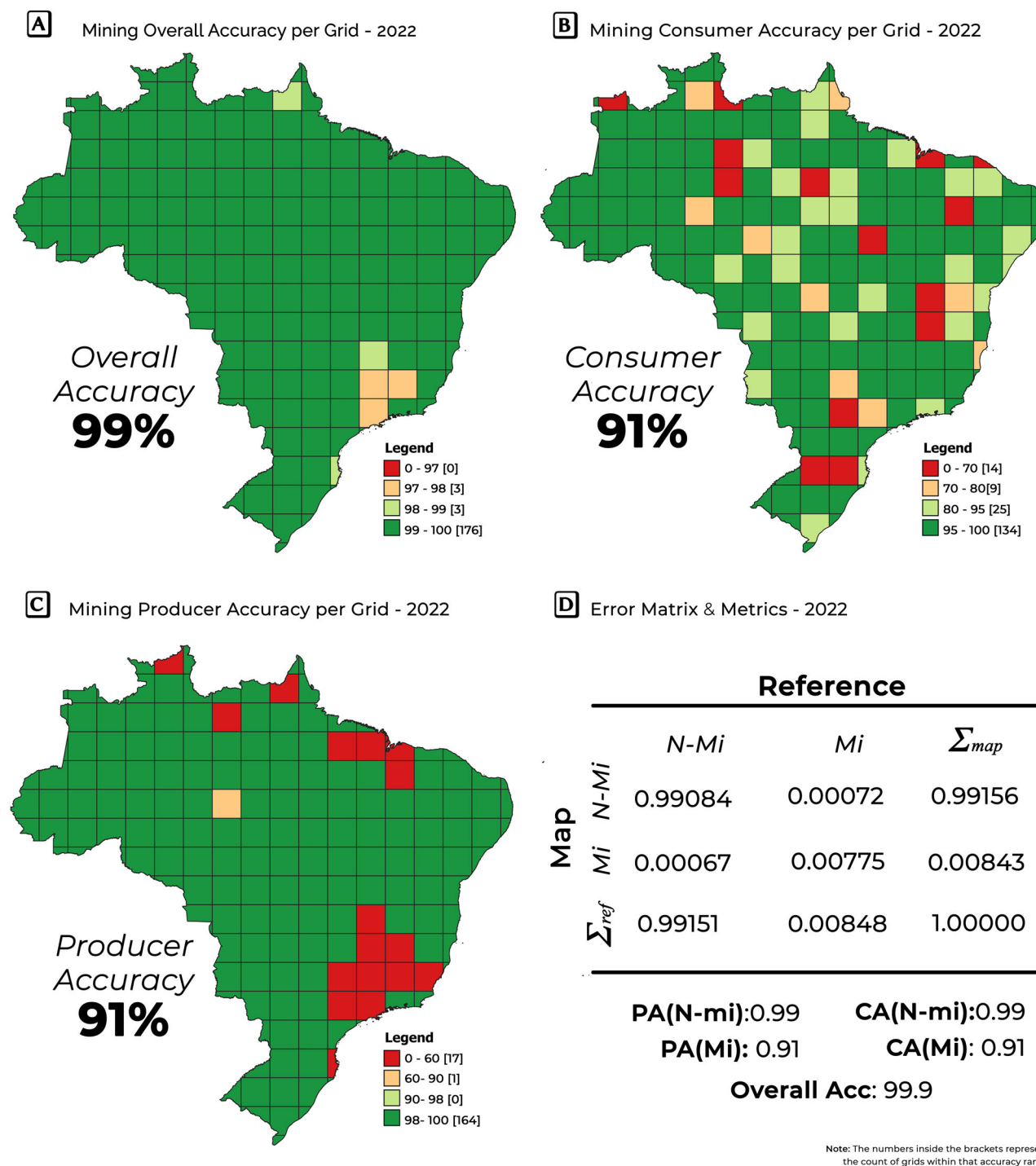
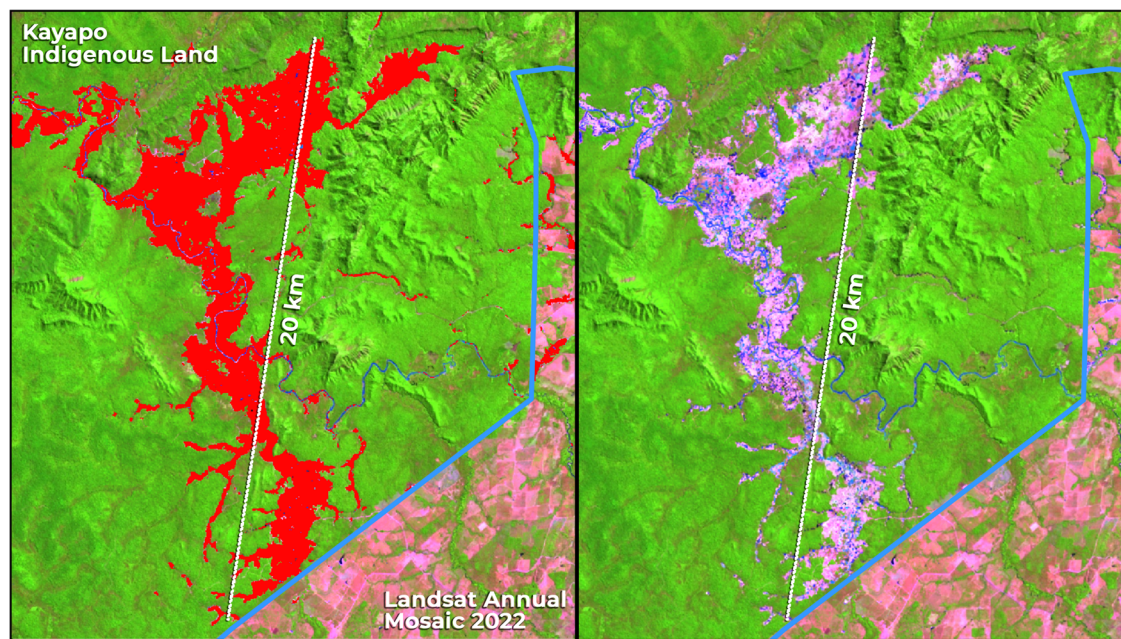


Fig. 4 | Error matrix and locally distributed accuracy metrics for 2022. The accuracy assessment approach was weighted by the area of each category/class according to the 250 × 250 km grid (62,500 km²). A total of 182 grids were regularly

distributed throughout Brazil. The metrics for 2022 revealed an OA value of 99% (A), a CA(Mi) value of 91% (B), and a PA(Mi) value of 91% (C). Error matrix and associated metrics (D).

In all territorial sections analyzed, whether within restricted areas (ILs, fully protected UCs, RESEXs, and RPPNs) or outside, the *garimpo* mining area substantially increased over the years. Nevertheless, the progression of the increase in recent years is worrisome. From 2018 to 2022, the *garimpo* mining area expanded by nearly 1000 km², representing a short-term expansion of 60% within only five years (Fig. 1). The recent expansion is also reflected inside ILs and CUs. In the past decade, for ILs combined with CUs, the *garimpo* area was 440% larger in 2022 than in 2018 (Fig. 2). Within ILs alone, the area in 2022 was 250% larger than that in 2018, which ranged from 100 to 250 km²

(Fig. 2). Within CUs, the extraction extent was 190% greater in 2022 than in 2018, expanding from 410 to 780 km² (Fig. 2). Overall, the increase within ILs and CUs reached 520 km² in just five years. This fast and spatially persistent expansion, inside and outside mining-restricted areas, either ILs or CUs, indicates Brazil's lack of control of illegal mining in the Amazon. Notably, ILs and CUs are the territorial units facing an urgent need of assistance^{59,60}. While there are 48 CUs with *garimpo* extraction signals, only five CUs account for 85.5% of the total *garimpo* area within such units: APA do Tapajós, FLONA do Amana, ESEC Juami-Japura, FLONA do Crepori, and PARNA do Rio



Garimpo Legislation and Expansion inside ILs

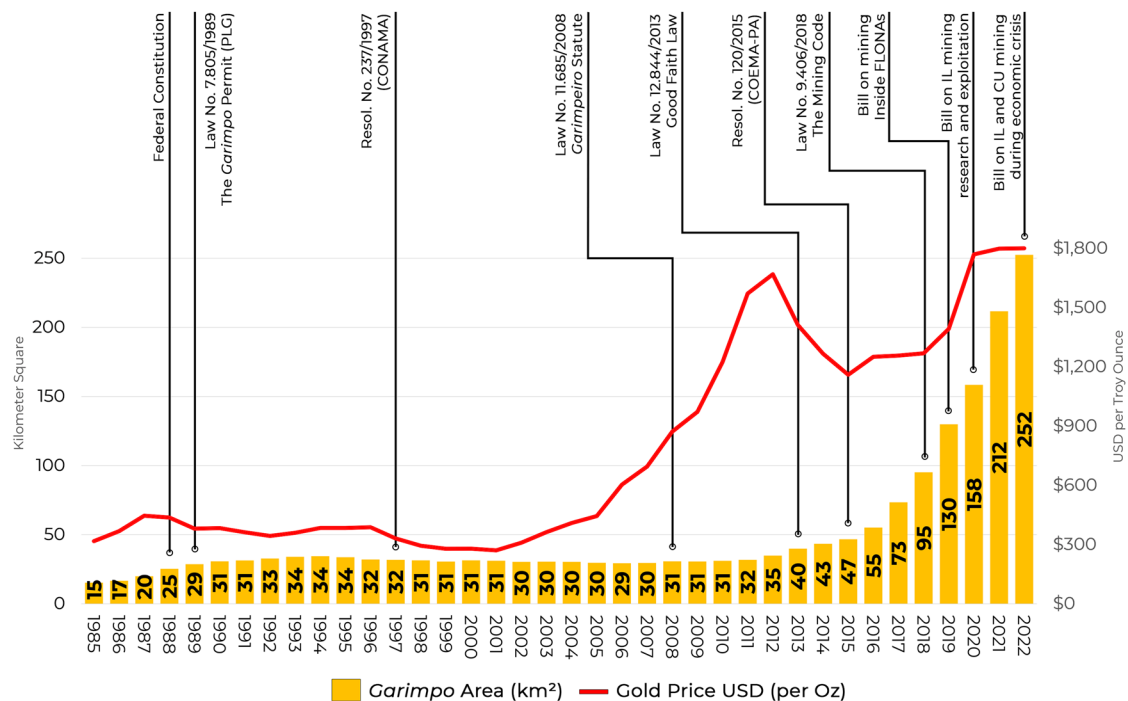


Fig. 5 | Garimpo legislation and expansion inside indigenous lands. In the upper right corner, a Landsat 8 annual mosaic from 2022 is shown. In the top left, a Kayapo *garimpo* conglomerate, highlighted in red, extends for more than 20 km. At the bottom, the yellow bars show the evolution of Amazonian extraction within indigenous lands from 1985–2022, expressed in km². The red line denotes the

annual volatility of international gold prices, expressed in USD per troy ounce (World Gold Council). Each black line denotes the year a specific law, resolution, or bill was ratified, directly impacting the recent *garimpo* spread in the Brazilian Amazon. The annual composites are derived from the Landsat 8, Collection 2, Tier 1, TOA dataset, which is courtesy of the U.S. Geological Survey.

Novo. Similarly, 22 ILs with signs of *garimpo* activity were detected. However, three ILs alone—Kayapo, Munduruku, and Yanomami—accounted for more than 90% of the total mining area in such protected regions (Fig. 2).

Since 2000, the international gold market has shown signs of persistent growth. Concurrently, changes in the Brazilian legislation facilitated the expansion of *garimpo*⁶¹. In 2008, Law No. 11.685/2008⁶² created the *Garimpeiro* Statute, differentiating *garimpo* from industrial mining, considering the former small-scale technology and able to be

practiced individually or collectively through cooperatives. This law, based once more on the small-scale argument, deregulated *garimpo* operators from the necessity of presenting a mining research authorization (an ANM authorization anterior to the mine opening, which aims to demonstrate the economic and environmental viability of the proposed operation). Today, this regulatory mechanism applies only to industrial mining sites, contrary to the ordinances formally expressed in CONAMA Resolution No. 237/1997⁶³. Furthermore, in 2013, Law No. 12.844/2013⁶⁴ expanded mining deregulation by

presuming those legal entities buying and selling gold act in good faith. From a legal perspective, the good faith law allowed the presumption of legality of mining documents, which in turn excluded routine inspection of their legitimacy and veracity. Ten years later, on May 5, 2023, the Federal Supreme Court overturned the validity of such a law.

In 2019, 2020, and 2022, three bills emerged, which are still awaiting a definitive decision but demonstrate that the deregulation of *garimpo* activity is still active in a part of the Brazilian political body seeking to further expand the permissibility of Amazonian mining. Bills No. 5822/2019⁶⁵, 191/2020⁶⁶, and 571/2022⁶⁷ could provide the possibility of mining ventures to be implemented inside national forests (FLONA), establish conditions for the research and exploitation of mineral resources and hydrocarbons in ILs, and enable the President of the Republic to release mineral extraction in any area of the country in times of economic crisis, including IL and CUs.

An enormous number of validation samples supported the statistical findings reported here. There were more than 52 thousand human-validated samples, distributed over nine different years of the time series (from 1985 to 2022), in which reasonably favorable error metrics, considering the rare characteristic of the class of interest, were systematically achieved (OA > 98%, PA > 65%, and CA > 90%). In turn, omission errors were more abundant than commission errors, which is a positive aspect from a map user perspective, as it reveals that every mention of a mining site on the map generally matches the reality of the Earth's surface. However, as a social-environmental indicator, some mining is still undetected, exacerbating this disastrous scenario's seriousness. Nevertheless, the high accuracy rates obtained in this extensive error analysis confirm the general effectiveness and suitability of the adopted AI-based method while indicating that local training improvements remain necessary, particularly considering the first three years of the time series, namely, 1985, 1990, and 1995. In turn, error metrics cannot serve as quality guarantees. Error/accuracy metrics are mechanisms for finding, understanding, and fixing a categorical unconformity, whether in time or space, thus supporting the future production of better versions of Earth's surface representations. Due to the rare nature of the target of interest (considering Brazil's continental scale), without the local spatialization and weighted approaches applied here, the error metrics would be quickly inflated or deflated and thus miss the central usage concept as an analytical tool that allows a better fit between the cartographic representation and reality. The error analysis allowed us to locally reduce spatial and temporal inconsistencies, which will be publicly available within Collection 9 of the MapBiomias initiative.

The technical characteristics of the adopted methodology limit its detection capability and analytical accomplishments. In this sense, the current Brazilian structural architecture and remote sensing-related technicalities constrain our research. Structurally, as it is impractical to obtain environmental licenses, it was acknowledged that all mining licensing present in SIGMINE platform also includes prior environmental licensing. This condition may need to be further verified. Nevertheless, this task is insurmountable as the country still needs to establish a public and centralized database of environmental licenses. From a spatial perspective, as in any remote sensing-based analysis, the earth's surface reality may differ from its cartographic categorization. Our results were based on Landsat data (30 m), so undetected sites are undoubtedly smaller than the Landsat detection resolution, pointing to larger mining areas than reported here. On the other hand, some commission errors still exist, as reported by the Error Assessment section. Finally, there are latent illegalities within *garimpo* activities that are not spatial nor documented and, therefore, are outside the scope of our method, such as the quantification of the irregular use of mercury and arsenic in the amalgamation of gold and other metals, the verification of the associated labor conditions, the economic and logistical relationships between *garimpo* and drug trafficking

activities, and the mechanism by which vast amounts of illegal gold are sold and bought on the formal national and international markets (gold laundering).

Methods

Reference data and study area

Brazil, especially the Brazilian Amazon, is associated with many publicly available datasets, ranging from geological surveys and change detection platforms to deforestation early warning systems. Thus, data availability is highly diverse in scale, type, and timeframe. Spatially explicit data may exhibit varying resolutions, with a varying degree of human intervention, for scientific or journalistic use. Despite these variations, a notable set of spatial references for *garimpo* and industrial mining sites can be acquired or inferred. The reference dataset adopted here resulted from aggregating data from multiple sources^{22,68–74}.

The research encompasses all of Brazil's territory. Due to its size, the region was divided into a grid of 100 × 100 km cells, i.e., 10,000-km² grids. As a result, if reference sample data existed in a given position, the corresponding cell was activated. These cells limited the execution of a deep learning U-Net-based algorithm⁷⁵, which only operates within active grid cells. Figure 6 shows the distribution of all 535 cells.

Image Processing

Data processing and analysis were performed in a cloud computing environment combining the use of the Google Earth Engine (GEE) platform and the TensorFlow framework (Fig. 5). All raster data and subproducts were obtained from USGS Landsat Collection 2 Tier 1 top of atmosphere (TOA) data, including Level-1 precision terrain (L1TP) data^{76–78}.

For each year, Landsat Collection 2, Tier 1, TOA data ranging from the 1st of January to the 31st of December were used to obtain annual cloud-free composites. In the cloud/shadow removal routine, the quality assessment (QA) band and the GEE median reducer are combined to eliminate too-bright or too-dark values (e.g., clouds and shadows, respectively), and the median of the pixel value in each band over time was determined^{79,80}. Subsequently, the annual median mosaics were subset to the area that comprises the 535 searching grids, excluding areas where mining sites are not expected to exist (e.g., open water bodies/ocean). Next, the training dataset was generated. The U-Net-based supervised approach relies on human-labeled data as training samples, categorized as mining (Mi) or non-mining (N-Mi) samples. Guided by the reference dataset, the mining and non-mining samples were visually delineated. Importantly, the U-Net classifier does not differentiate between *garimpo* or industrial patterns. The distinction between these two patterns is a human-dependent task performed by visual interpretation as part of a post classification process (Supplementary Material S.4).

Once the sample acquisition task is finished, the U-Net-based classifier is run, resulting in a prefiltered classification product. The classified data were entered into the GEE, where spatial-temporal filtering and visual inspection were performed. This phase was employed to correct misclassified data and ensure the necessity of acquiring (or not) more training samples. Table 2 provides the U-Net algorithm hyperparameters.

Due to the pixel-based classification method and the extended temporal series, a chain of post classification filters was implemented. In a long time series of severely cloud-affected regions, such as Brazilian tropical forests, no-data values are expected to persist in the annual median composites. In this filter, no-data values (gaps) are theoretically not allowed and are replaced by the temporally nearest valid class pixel^{80,81}. If no future valid position is available in this procedure, the no-data value is then replaced by its previous valid class. Up to three prior years can be used to replace persistent no-data positions. Therefore, gaps should only exist if a given pixel has been

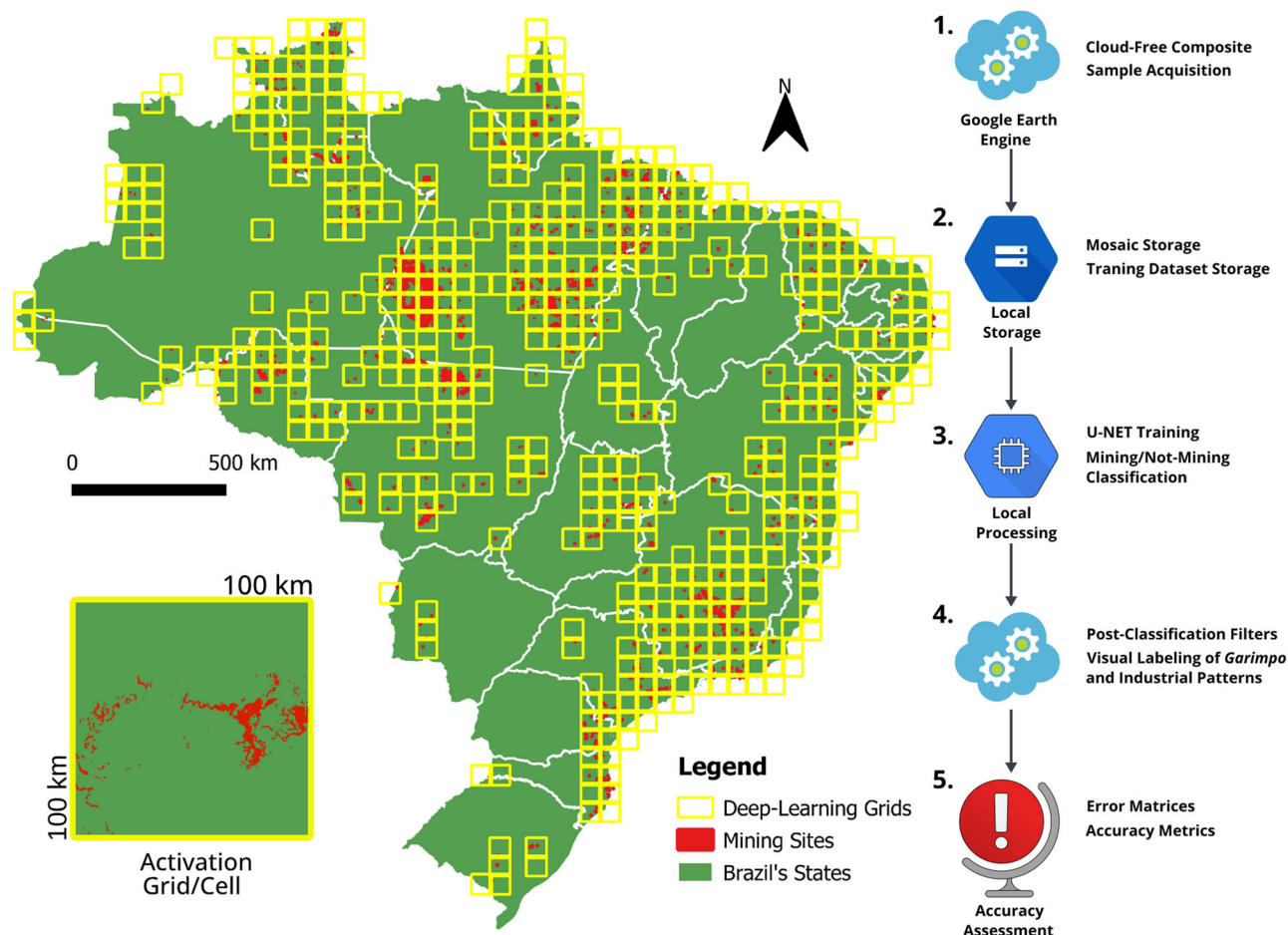


Fig. 6 | Activation grids and processing flowchart. In the map, 535 search grids were activated according to the existence of a mining reference sample. In yellow, the squares function as U-Net search grids. The mining site references are marked in red. The white lines denote the official boundaries of Brazilian states. The right side shows the mining detection Earth Engine–TensorFlow pipeline. The pipeline is structured in 5 steps. First, the GEE generates cloud-free composites and creates

the initial training dataset. Second, mosaics and training data are downloaded and stored locally. Third, patchwise training and classification are initiated. Fourth, the classified product is spatiotemporally filtered. The filtered product is visually and statistically inspected. Multiple iterations are executed until a satisfactory spatial and temporal quality is achieved. Fifth, the accuracy assessment is performed.

permanently classified as a no-data pixel throughout the entire temporal domain.

After gap filling, a temporal filter was applied. The temporal filter involves the use of sequential classifications in a three-year unidirectional moving window for identifying temporally nonpermitted transitions. Based on a single generic rule, the temporal filter aims to inspect the central position in three consecutive years (ternary). If the extremities of the ternary are identical but the center position is not,

the central pixel is then reclassified to match its temporal neighbor class^{80,81}.

Finally, a spatial filter was applied. This filter aims to locate connected neighbor pixels (based on a 3×3 square kernel) if they share the same pixel value. This spatial postprocessing aims to remove disconnected/isolated pixels (*salt and pepper effect*) classified as mining (M) pixels. This filter needs at least ten connected pixels to reach the minimum connection value. Consequently, the minimum mapping unit is directly affected by the spatial filter applied, which was defined as 10 pixels (~ 1 ha).

Table 2 | Classifier attributes and classification parameters

Parameters	Values
Classifier	U-Net
Tile-Size	256 × 256 pixels
Optimizer	Nadam
Learning-Rate	0.01
Decay Rate	0.1
Samples	35,000 (17,500–1985, 17,500–2022)
Attributes	Swir1, Nir1, Red, modified normalized difference water index (MNDWI) ⁸⁸ , normalized difference vegetation index (NDVI) ⁸⁹ , and normalized difference soil index (NDSI) ⁹⁰
Classes	2 (mining and non-mining)

In total, six (6) distinct attributes were used.

Protected areas and mining activity: Indigenous lands (ILs), Conservation Units (CUs), mining permits (PLGs), and mining concessions (CLs)

Protected areas, in Brazil referred to as CUs, are instruments created to safeguard the integrity of ecosystems and associated environmental services, such as soil conservation, biodiversity preservation, watershed protection, nutrient recycling, and thermal balance. Creating and implementing protected areas also contribute to ensuring the right of permanence and the culture of previously existing traditional populations and indigenous peoples⁸². Constitutionally, by several legal mechanisms, mining activity within the limits of ILs and fully protected CUs constitutes an unrestricted illegal activity¹⁹. Additionally, Law No. 9.985²⁰, which institutes the National System of Conservation Units

Table 3 | Spatially restricted protected areas

Spatially Restricted Areas		
Fully Protected CUs (All)	CUs of Sustainable Use	Indigenous Lands (All)
Ecological Stations (ESEC)	Extractive Reserves (RESEXs)	All
Biological Reserve (REBIO)	Private Natural Heritage Reserves (RPPNs)	—
National Parks (PARNA)	—	—
Natural Monuments (MONAT)	—	—
Wildlife Refuges (RVS)	—	—

All mining sites geographically established within fully protected CUs, ILs, or CUs of sustainable use, designated as extractive reserves (RESEXs) and private natural heritage reserves (RPPNs), constitute undeniable violations of the Federal Constitution.

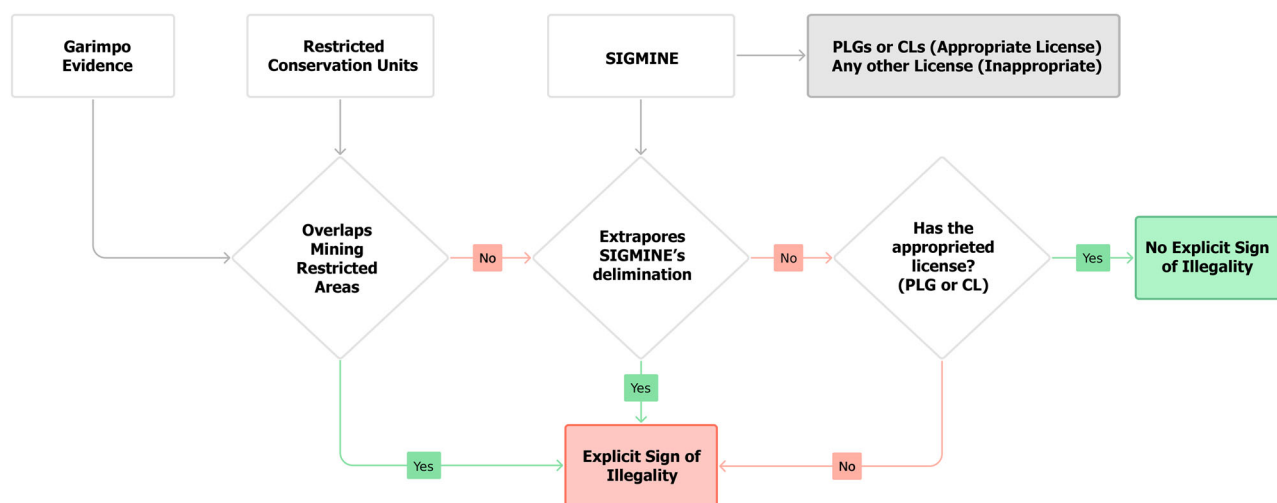


Fig. 7 | Flowchart demonstrating the data sources, analytical phases, and criteria for categorizing an ore extraction site as showing explicit signs of illegality or no explicit sign of illegality. Among all possible operational licenses or

licensing phases within the ANM's SIGMINE platform, PLGs and CLs are considered *garimpo*-appropriated permits. In contrast, any other license type or phase is regarded as inappropriate.

(SNUC), stated that in all the fully protected CUs and CUs of sustainable use, designated as extractive reserves (RESEXs) and private natural heritage reserves (RPPNs), mining of any kind is strictly prohibited, either *garimpo* or industrial mining. Thus, mining is prohibited within the areas of ecological stations (ESEC), extractive reserves (RESEXs), biological reserves (REBIO), private natural heritage reserves (RPPNs), national parks (PARNA), natural monuments (MONAT), and wildlife refuges (RVS). All mining extraction operations geographically established in the areas described above are undeniably in violation of the Brazilian Federal Constitution, as indicated in Table 3 and Supplementary Material S.5. Nevertheless, even those mines that are outside restricted regions can also be considered illegal if they operate without proper environmental licenses and proper mining permits, either *garimpo* permits (PLGs) or mining concessions (CLs).

According to Decree No. 227/1967⁸³, a mining concession (CL) is a mineral exploitation regime designed for exploiting minerals on an industrial scale. The issuance of a CL is always preceded by a mineral research request and its subsequent research authorization, which are necessary phases of ANM licensing procedures seeking to determine the economic and environmental viability of the proposed mining operation. This concession regime requires proper environmental licensing. In contrast, the *garimpo* permit (PLG) regime, established by Law No. 7.805/1989⁸⁴, is the most suitable exploitation regime for individual Brazilian citizens (*garimpeiros*) or *garimpo* cooperatives. Individual permits are limited to 50 hectares, whereas cooperative permits are limited to 10,000 hectares. Gold, diamond,

cassiterite, columbite, tantalite, and wolframite are legally recognized as mineable substances in alluvial, eluvial, and colluvial deposits. Different substances are subject to mining extraction in various forms, but only with a prior license from the National Mining Agency (ANM), as stated by Law No. 7.805/1989⁸⁴. This use regime is excluded from the mineral research request but is also subject to the crucial requirement of proper environmental licensing, to be issued by the appropriate environmental instance. Thus, no mineral exploration mechanism in Brazil is exempt from previous environmental licensing.

Thus, a sequence of spatial operations and license/permit verifications was employed to identify possible signs of illegality among the *garimpo* sites in Brazil, in which a set of spatial operations was executed (Fig. 7), to determine whether the mining site showed explicit signs of illegality or if no explicit sign of illegality was found.

The mining evidence produced here was cross-referenced with the official spatial boundaries of CUs (Ministry of Environment–MMA) and ILs (National Foundation of Indigenous People–FUNAI) and the demarcation processes for mineral extraction licenses (National Mining Agency–ANM; SIGMINE platform). The signs of legality or illegality attributed to each detected mining site were derived from analyzing these spatial relationships. Acquired in November 2023, the SIGMINE dataset was divided per license type, and all personal information was removed from the resulting analysis.

Explicit signs of illegality were considered any mining activity that occurs 1) within mining-restricted areas (ILs, fully protected CUs, extractive reserves, and private natural heritage reserves), 2) outside

the delimitations provided in the SIGMINE platform, and 3) within the delimiting geometries of SIGMINE but without the appropriate licensing permit, either PLG or CL. In contrast, any mining sites that 1) occur outside mining-restricted areas may show no explicit signs of illegality if 2) they occur within the SIGMINE-delimited geometries and 3) they exhibit the appropriate licensing regime, either PLG or CL.

Even though Brazil is a global reference in the production and use of geospatial data to control, survey, and manage several internal aspects of its territory, it is not feasible to confirm the legality or illegality of a given mining site exclusively through the aforementioned spatial analysis. Thus, the categories of probable irregularities adopted here include explicit signs of illegality and no explicit signs of illegality.

Most of this incapacity stems from the lack of a national and centralized system of environmental licenses to safeguard Brazil's native natural conditions and prevent their unnatural suppression. The environmental licensing of a mining extraction activity can involve any of the three levels of public organization: federal, state, or municipal. Each level operates through its individual executing bodies, which are still to be integrated. Moreover, these bodies rarely, if ever, offer the option of digital consultation for their environmental processes.

At the federal level, the responsibility for issuing and advertising mining licenses is reserved for the Brazilian Institute of the Environment and Renewable Resources—IBAMA. If inside a CU, the license may be issued by the Chico Mendes Institute for Biodiversity Conservation—ICMBio. At the state level, the state environmental secretariats (SEMAs) are responsible for this task. Brazil has one environmental secretariat, or a relative environment instance, for each of its 26 states, as well as one specific to the federal district. Finally, all 144 Para state municipalities are authorized to issue and publish environmental authorizations at the municipal level. This contradictory condition was put in place in 2015 through resolution No. 120/2015³⁶ issued by the State Council for the Environment (COEMA-PA), which allegedly categorized *garimpo* operations up to 500 hectares as “small-scale operations with local environmental impacts.” Regretfully, within this complex and multilayered administrative framework, no central database is integrated among the different organizational levels and is accessible to the public via digital means, granting transparency to the environmental licensing of mining operations.

Error assessment and area estimation

Despite the traditional importance and economic relevance of mining in Brazil, this extraction activity is considered a statistically rare land-use pattern due to the vast geographical area. Consequently, the training and error assessment sampling design must consider the infrequent distribution of mining sites across the country. If dependent upon a simple, randomly stratified approach, omission errors could significantly impact the map accuracy. Thus, to avoid this scenario, a two-stage stratified random sampling approach was used to constrain (weight) the impact of possible omission errors on a pre-existing grid cell. A mesh of grids was created over Brazil, encompassing 250 km × 250 km cells, for a total of 182 cells. Importantly, the error assessment grid is independent of the U-Net activation grid shown in Fig. 6 and Supplementary Material S.1.

The double-stage stratification approach considers that the existence of the grid, by itself, demands a simple and random distribution of a given number of samples per grid, even when a specific cell shows no sign of mining pixels. The second branch of the dual stratification structure considers the area proportions of mining and non-mining strata. Here, the area of each class serves as a weighting factor that forces the distribution of varying samples within each of the two possible classes, whether mining or non-mining. In this way, 52,320 samples were distributed throughout the Brazilian territory, S.1 Supplementary Material.

The mathematical model that governs the number of mining and non-mining samples to be distributed per grid can be described as follows:

$$N = \left(\frac{\sum_i W_i S_i}{S(\hat{O})} \right)^2$$

where $S(\hat{O})$ is the admitted standard error of the estimated OA, which is set to 0.005 in our case, W_i is the mapped area proportion of class i , and S_i is the standard deviation of stratum i ⁸⁵. Summation was performed over the different classes.

Once calculated and distributed, this layer of samples was manually validated. In this step, three specialists visually interpreted the same orbital inputs to which the contextual classification algorithm was subjected. In addition to Landsat data, human evaluators can access higher-resolution images from Google and Planet (when spatially and temporarily available) as inputs to facilitate decision-making. During the validation routine, human interpreters choose only two categorical options for each sample point/pixel: a) mining (Mi) and b) non-mining (N-Mi). In addition to categorical labels, it was possible to report technical difficulties that prevented visual interpretation: a) clouds or shadows, b) no data, c) edge/border pixels, and d) isolated pixel clusters.

In the case of possible divergence between human interpretations, the golden rule (majority decision) was used as a final decision strategy. Once finished, each validated sample was cross-compared with its corresponding annual map, and an error matrix was computed. The following error metrics were extracted from the generated contingency tables: overall accuracy (OA) and per-class PA [PA(Mi) and [PA(N-Mi)] and CA [CA(Mi) and CA(N-Mi)] measures^{86,87}.

It is essential to mention that the error analysis stage focused on evaluating the classifier's effectiveness, trained to identify mining areas, regardless of whether they are industrial mining or *garimpo* sites. Thus, the error evaluation process involved two stages of stratified random sample design based on the binary probability density function, allocating samples to the mining (Mi) and non-mining (N-Mi) classes. Furthermore, it considered the cost and effort of assessing the accuracy of a cartographic product on a continental and multi-temporal scale of rare events such as mining. As a result, the binary assessment path was chosen, limited by the output of U-Net used in labeling the Landsat pixels.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The classifier outputs, high resolution figures and other ancillary files are all available in the informed GitLab repository. Please visit <https://gitlab.com/luizcf14/brazil-mining>.

Code availability

The backbone code of the article is available in a Git-lab repository. Please visit <https://gitlab.com/luizcf14/brazil-mining>.

References

1. Cypher, J. M. South America's commodities boom: developmental opportunity or path dependent reversion? *Can. J. Dev. Stud. / Rev. canadienne d. études du d. développement* **30**, 635–662 (2010).
2. Paiva, P. H. de A. & Bacha, C. J. C. The gross domestic product (GDP) shares of the agriculture sector and the hydrocarbon and mining sector in the countries of South America between 1960 and 2014. *CEPAL Review* (2019).

3. Machado, I. F. & de M. Figueirôa, S. F. 500 years of mining in Brazil: a brief review. *Resour. Policy* **27**, 9–24 (2001).
4. Bruno, D. E. et al. Artisanal and small-scale gold mining, meandering tropical rivers, and geological heritage: evidence from Brazil and Indonesia. *Sci. Total Environ.* **715**, 136907 (2020).
5. Fritz, M., McQuilken, J., Collins, N. & Weldegiorgis, F. *Global Trends in Artisanal and Small-Scale Mining (ASM): A Review of Key Numbers and Issues*. (International Institute for Sustainable Development Winnipeg, MB, Canada, 2018).
6. Gautam, R., Kim, Y., Topal, E. & Hitch, M. Correlation between COVID-19 cases and gold price fluctuation. *Int. J. Min., Reclam. Environ.* **36**, 574–586 (2022).
7. Lobo, F. D. L., Souza-Filho, P. W. M., Novo, E. M. L. d. M., Carlos, F. M. & Barbosa, C. C. F. Mapping Mining Areas in the Brazilian Amazon Using MSI/Sentinel-2 Imagery (2017). *Remote. Sens.* **10**, 1178 (2018).
8. Crespo-Lopez, M. E. et al. Mercury: what can we learn from the Amazon? *Environ. Int.* **146**, 106223 (2021).
9. Macklin, M. G. et al. Impacts of metal mining on river systems: a global assessment. *Science* **381**, 1345–1350 (2023).
10. Watts, J. Health emergency over Brazil's Yanomami people. *Lancet* **401**, 631 (2023).
11. Da Luz Scherf, E. & Viana da Silva, M. V. Brazil's Yanomami health disaster: addressing the public health emergency requires advancing criminal accountability. *Front. Public Health* **11**, 1166167 (2023).
12. Telmer, K., Costa, M., Simões Angélica, R., Araujo, E. S. & Maurice, Y. The source and fate of sediment and mercury in the Tapajós River, Pará, Brazilian Amazon: Ground- and space-based evidence. *J. Environ. Manag.* **81**, 101–113 (2006).
13. Berzas Nevado, J. J. et al. Mercury in the Tapajós River basin, Brazilian Amazon: a review. *Environ. Int.* **36**, 593–608 (2010).
14. Dethier, E. N. et al. A global rise in alluvial mining increases sediment load in tropical rivers. *Nature* **620**, 787–793 (2023).
15. Marques, F. & Guzman, E. R. Mining in Latin America: an overview of mining law in Argentina, Brazil, Chile, and Peru. trends and main challenges. McCarthy Tétrault http://mccarthy.ca/pubs/MINING_LAW_Latin_America-McCarthy-Tetrault-2017.pdf (2017).
16. Urkidi, L. & Walter, M. Dimensions of environmental justice in anti-gold mining movements in Latin America. *Geoforum* **42**, 683–695 (2011).
17. Helwege, A. Challenges with resolving mining conflicts in Latin America. *Extractive Industries Soc.* **2**, 73–84 (2015).
18. Haslam, P. A. & Ary Tanimoune, N. The determinants of social conflict in the Latin American mining sector: new evidence with quantitative data. *World Dev.* **78**, 401–419 (2016).
19. MPF. *Mineração Ilegal de Ouro Na Amazônia: Marcos Jurídicos e Questões Controversas*. 4ª Câmara de Coordenação e Revisão do Ministério Público Federal. Série Manuais de Atuação, **7** (2020).
20. Congresso Nacional. *Lei No. 9.985/2000: Regulamenta o Art. 225, § 1o, Incisos I, II, III e VII Da Constituição Federal, Institui o Sistema Nacional de Unidades de Conservação Da Natureza e Dá Outras Providências*. (2000).
21. Tang, L. & Werner, T. T. Global mining footprint mapped from high-resolution satellite imagery. *Commun. Earth Environ.* **4**, 134 (2023).
22. Maus, V. et al. An update on global mining land use. *Sci. Data* **9**, 433 (2022).
23. Manzolli, B. et al. Legalidade da Produção de Ouro no Brasil. IGC/UFMG (2021).
24. Swenson, J. J., Carter, C. E., Domec, J.-C. & Delgado, C. I. Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports. *PLOS ONE* **6**, e18875 (2011).
25. Vega, C. M., Orellana, J. D. Y., Oliveira, M. W., Hacon, S. S. & Basta, P. C. Human mercury exposure in Yanomami Indigenous villages from the Brazilian Amazon. *Int. J. Environ. Res. Public Health* **15**, 1051 (2018).
26. Castro, M. C. & Peterka, C. Malaria is increasing in Indigenous and artisanal mining areas in the Brazilian Amazon. *Nat. Med.* **29**, 762–764 (2023).
27. Lobo, F. L., Costa, M. P. F. & Novo, E. M. L. M. Time-series analysis of landsat-MSS/TM/OLI images over Amazonian waters impacted by gold mining activities. *Remote Sens. Environ.* **157**, 170–184 (2015).
28. Lobo, F. D., Costa, M., Novo, E. M. & Telmer, K. Distribution of artisanal and small-scale gold mining in the tapajós river basin (Brazilian Amazon) over the past 40 years and relationship with water siltation. *Remote Sens.* **8**, 579 (2016).
29. MapBiomass. Projeto MapBiomass – Coleção 8 da Série Anual de Mapas de Cobertura e Uso da Terra do Brasil. Entre (1985 e 2022). [<https://www.mapbiomas.org/>] acessado em [26/06/2023]. (2023).
30. Souza, C. M. et al. Reconstructing three decades of land use and land cover changes in Brazilian biomes with Landsat archive and earth engine. *Remote Sensing* **12**, 2735 (2020).
31. MapBiomass. Mapeamento das Pistas de Pousio e Garimpo na Amazônia. (2023).
32. Basso, G. Ibama: garimpo ilegal perde R\$ 1 bilhão em máquinas com operações na Amazônia. *Reporter Brasil* (2023).
33. IBAMA. Governo federal anuncia presença permanente e investimentos de R\$ 1,2 bi na TI Yanomami. <https://www.gov.br/ibama/pt-br/assuntos/noticias/2024/governo-federal-anuncia-presenca-permanente-e-investimentos-de-r-1-2-bi-na-ti-yanomami> (2024).
34. Andreoni, M., Miglioni, B., Robles, P. & Lu, D. The illegal airstrips bringing toxic mining to Brazil's indigenous land. *The New York Times* (2022).
35. Diniz, C. et al. Nota Técnica sobre Garimpo no Rio Madeira. (2021).
36. COEMA. *Resol. No. 120/2015: Dispõe Sobre as Atividades de Impacto Ambiental Local, de Competência Dos Municípios, e dá Outras Providências*. (2015).
37. MPF. *Recom. No 01/2023: Recomendação Para Que Não Se Admita o Licenciamento Ambiental Municipal Para Empreendimentos de Garimpo Considerando-Se a Regionalidade Dos Impactos*. (2023).
38. INSTITUTO ESCOLHAS. Where does so much mercury come from? São Paulo, Brasil (2024).
39. Gonzales, O. C. The Business of mercury in Bolivia: a study about the commercialization of mercury for gold mining in Bolivia. LA LIBRE Editorial Project, Cochabamba, Bolivia. (2020).
40. Seccatore, J., Veiga, M., Origliasso, C., Marin, T. & De Tomi, G. An estimation of the artisanal small-scale production of gold in the world. *Sci. Total Environ.* **496**, 662–667 (2014).
41. Passos, C. J. S. et al. Daily mercury intake in fish-eating populations in the Brazilian Amazon. *J. Expo. Sci. Environ. Epidemiol.* **18**, 76–87 (2008).
42. Gimenes, T. C., Penteado, J. O., dos Santos, M. & da Silva Júnior, F. M. R. Methylmercury in Fish from the Amazon Region—a Review Focused on Eating Habits. *Water, Air, & Soil Pollution* **232**, 199 (2021).
43. Hacon, SdeS. et al. Mercury exposure through fish consumption in traditional communities in the Brazilian Northern Amazon. *Int. J. Environ. Res. Public Health* **17**, 5269 (2020).
44. Begossi, A. et al. Fish consumption on the Amazon: a review of biodiversity, hydropower and food security issues. *Braz. J. Biol.* **79**, 345–357 (2019).
45. Peplow, D. & Augustine, S. Neurological abnormalities in a mercury exposed population among indigenous Wayana in Southeast Suriname. *Environ. Sci.: Process. Impacts* **16**, 2415–2422 (2014).
46. Harada, M. et al. Mercury pollution in the Tapajós River basin, Amazon. *Environ. Int.* **27**, 285–290 (2001).
47. Lacerda, E. M. D. C. B. et al. Comparison of visual functions of two Amazonian populations: possible consequences of different mercury exposure. *Front. Neurosci.* **13**, 1428 (2020).
48. Benefice, E., Luna-Monroy, S. & Lopez-Rodríguez, R. Fishing activity, health characteristics and mercury exposure of Amerindian

- women living alongside the Beni River (Amazonian Bolivia). *Int. J. Hyg. Environ. Health* **213**, 458–464 (2010).
49. Fillion, M. et al. Neurotoxic sequelae of mercury exposure: an intervention and follow-up study in the Brazilian Amazon. *EcoHealth* **8**, 210–222 (2011).
 50. Fillion, M. et al. Visual acuity in fish consumers of the Brazilian Amazon: risks and benefits from local diet. *Public Health Nutr.* **14**, 2236–2244 (2011).
 51. Costa Junior, J. M. F. et al. Manifestações emocionais e motoras de ribeirinhos expostos ao mercúrio na Amazônia. *Rev. Brasileira de Epidemiologia* **20**, 212–224 (2017).
 52. Dolbec, J., Mergler, D., Sousa Passos, C.-J., Sousa de Moraes, S. & Lebel, J. Methylmercury exposure affects motor performance of a riverine population of the Tapajós river, Brazilian Amazon. *Int. Arch. Occup. Environ. Health* **73**, 195–203 (2000).
 53. Khoury, E. D. T. et al. Manifestações neurológicas em ribeirinhos de áreas expostas ao mercúrio na Amazônia brasileira. *Cad. Saúde. Pública* **29**, 2307–2318 (2013).
 54. Chevrier, C. et al. Qualitative assessment of visuospatial errors in mercury-exposed Amazonian children. *NeuroToxicology* **30**, 37–46 (2009).
 55. Santos-Lima, C. D. et al. Neuropsychological effects of mercury exposure in children and adolescents of the Amazon Region, Brazil. *NeuroToxicology* **79**, 48–57 (2020).
 56. Reuben, A. et al. Elevated hair mercury levels are associated with neurodevelopmental deficits in children living near artisanal and small-scale gold mining in Peru. *GeoHealth* **4**, e2019GH000222 (2020).
 57. Aska, B., Franks, D. M., Stringer, M. & Sonter, L. J. Biodiversity conservation threatened by global mining wastes. *Nat. Sustain.* <https://doi.org/10.1038/s41893-023-01251-0> (2023).
 58. Montaña, C. G., Liverpool, E., Taphorn, D. C. & Schalk, C. M. The cost of gold: Mercury contamination of fishes in a Neotropical river food web. *Neotrop. ichthyol.* **19**, e200155 (2021).
 59. Silva-Junior, C. H. L. et al. Brazilian Amazon indigenous territories under deforestation pressure. *Sci. Rep.* **13**, 5851 (2023).
 60. Qin, Y. et al. Forest conservation in Indigenous territories and protected areas in the Brazilian Amazon. *Nat. Sustainability* **6**, 295–305 (2023).
 61. Fellows, M. et al. Scars of Mining in Indigenous Lands of the Brazilian Amazon. (2024).
 62. Congresso Nacional. *Lei No. 11.685/2008: Institui o Estatuto Do Garimpeiro*. (2008).
 63. CONAMA. *Resol. No. 237/1997: Dispõe Sobre a Revisão e Complementação Dos Procedimentos e Critérios Utilizados Para o Licenciamento Ambiental*. (1997).
 64. Congresso Nacional. *Lei No. 12.844/2013: Regula a Compra, Venda e Transporte de Ouro e Dá Outras Providências*. (2013).
 65. Mauro, E. *PL No. 5822/2019: Acrescenta Redação à Lei No 9.985, de 18 de Julho de 2000, Para Viabilizar o Licenciamento Ambiental de Lavras Garimpeiras de Pequeno Porte Em Unidades de Conservação de Uso Sustentável Do Tipo Floresta Nacional*. (2019).
 66. Poder Executivo. *PL No. 191/2020: Regulamenta o § 1º Do Art. 176 e o § 3º Do Art. 231 Da Constituição Para Estabelecer as Condições Específicas Para a Realização Da Pesquisa e Da Lavra de Recursos Minerais e Hidrocarbonetos e Para o Aproveitamento de Recursos Hídricos Para Geração de Energia Elétrica Em Terras Indígenas e Institui a Indenização Pela Restrição Do Usufruto de Terras Indígenas*. (2020).
 67. Medeiros, J. *PL No. 571/2022: Acrescenta o Art. 82-A Ao Decreto-Lei Nº 227, de 28 de Fevereiro de 1967, “Código de Minas”, Para Criar Condições Especiais Ao Exercício de Atividade Minerária Em Caso de Interesse à Soberania Nacional, Assim Declarado Pelo Presidente da República*. (2022).
 68. Diniz, C. G. et al. DETER-B: The New Amazon Near Real-Time Deforestation Detection System. *IEEE J. Sel. Top. Appl. Earth Observations Remote Sens.* **8**, 3619–3628 (2015).
 69. MapBiomas Alerta. Projeto MapBiomas Alerta - Sistema de Validação e Refinamento de Alertas de Desmatamento com Imagens de Alta Resolução: [<https://alerta.mapbiomas.org/>] acessado em [26/06/2023]. 2023 (2023).
 70. RAISG. Rede Amazônia de Informação Socioambiental Georreferenciada - RAISG: [<https://www.raisg.org/>] acessado em [26/06/2023] (2023).
 71. ISA. Instituto Socioambiental - ISA: [<https://www.socioambiental.org/>] acessado em [26/06/2023]. (2023).
 72. CPRM. Sistema de Geociências do Serviço Geológico do Brasil - CPRM - GeoSGB: [<https://geoportal.cprm.gov.br/>] acessado em [26/06/2023] (2023).
 73. Ahkbrasilien. Mapa da Mineração Brasileira - Câmara de Comercio e Industria Brasil-Alemanha: [www.ahkbrasilien.com.br/projetos/mineracao/mapa-da-mineracao-brasileira/] acessado em [26/06/2023] (2023).
 74. AMW. Amazon Mining Watch: [<https://amazonminingwatch.org/>] acessado em [26/06/2023] (2023).
 75. Ronneberger, O., Fischer, P. & Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation. *CoRR* abs/1505.0, (2015).
 76. USGS. *LANDSAT Collection 1 Level 1 Product Definition*. (Earth Resources Observation and Science (EROS) Center, 2017).
 77. Storey, J., Choate, M. & Lee, K. Landsat 8 operational land imager on-orbit geometric calibration and performance. *Remote Sens.* **6**, 11127–11152 (2014).
 78. Teillet, P. M. et al. Radiometric cross-calibration of the Landsat-7 ETM+ and Landsat-5 TM sensors based on tandem data sets. *Remote Sens. Environ.* **78**, 39–54 (2001).
 79. Gorelick, N. et al. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **202**, 18–27 (2017).
 80. Diniz, C. et al. Brazilian Mangrove Status: Three Decades of Satellite Data Analysis. *Remote Sens.* **11**, 808 (2019).
 81. Diniz, C. et al. A Large-Scale Deep-Learning Approach for Multi-Temporal Aqua and Salt-Culture Mapping. *Remote Sens.* **13**, 1415 (2021).
 82. Veríssimo, A., Rolla, A., Vedoveto, M. & Futada, S. de M. Áreas Protegidas na Amazônia Brasileira: avanços e desafios. Imazon/ Instituto Socioambiental (2011).
 83. Presidência da República. *Del No. 227/1967: Dá Nova Redação Ao Decreto-Lei Nº 1.985, de 29 de Janeiro de 1940. (Código de Minas)*. (1967).
 84. Congresso Nacional. *Lei No. 7.805/1989: Altera o Decreto-Lei Nº 227, de 28 de Fevereiro de 1967, Cria o Regime de Permissão de Lavra Garimpeira, Extingue o Regime de Matrícula, e Dá Outras Providências*. (1989).
 85. Cochran, W. G. *Sampling Techniques*. (John Wiley & Sons, 1977).
 86. Pontius, R. G. & Millones, M. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *Int. J. Remote Sens.* **32**, 4407–4429 (2011).
 87. Pontius, R. G. & Santacruz, A. Quantity, exchange, and shift components of difference in a square contingency table. *Int. J. Remote Sens.* **35**, 7543–7554 (2014).
 88. Xu, H. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Int. J. Remote Sens.* **27**, 3025–3033 (2006).
 89. Tucker, C. J. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* **8**, 127–150 (1979).
 90. Rogers, A. S. & Kearney, M. S. Reducing signature variability in unmixing coastal marsh Thematic Mapper scenes using spectral indices. *Int. J. Remote Sens.* **25**, 2317–2335 (2004).

Acknowledgements

The authors thank the Brazilian National Council for Scientific and Technological Development (CNPq) and Harvard University as partial funders of this research. The Junior Post-Doc Funding (PDJ-152722/2022-O), the CNPq Research Productivity grant (309045/2023-1), and the Harvard Data Science Initiative (HDSI) were essential for the financial support of some of the authors. We acknowledge the Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, for the long-term hosting of the authors as a counterpart of a scientific cooperation agreement. The authors also thank the MapBiomass Network and the GEE team. Together, the GEE and MapBiomass initiative constitute the structural foundation of this study.

Author contributions

Conceptualization, C.G.D., L.C.F.N. and P.W.M.S.-F.; methodology, C.G.D. and L.C.F.N.; software development, L.C.F.N., and M.L.P.; sampling design, L.C.F.N. and M.A.; validation, L.W.R.S., A.F.F., J.C., A.A.A.S., J.P.F., D.C.S.; formal analysis, C.G.D., L.C.F.N. and M.A.; investigation, C.G.D. and L.C.F.N.; resources, C.G.D., L.C.F.N., M.C.C. and P.W.M.S.-F.; data curation, C.G.D., L.C.F.N. and M.A.; writing—original draft preparation, C.G.D. and L.C.F.N.; writing—review and editing, C.G.D., R.V.M., C.P., M.C.C., M.A., J.C., P.W.M.S.-F., A.S., A.B. and A.K.; visualization, C.G.D., L.W.R.S. and J.C.; supervision, A.K., C.P., R.V.M. and M.C.C.; project administration, C.G.D. and L.C.F.N.; funding acquisition, C.G.D., L.C.F.N., P.W.M.S.-F. and M.C.C.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41467-024-54220-2>.

Correspondence and requests for materials should be addressed to Luiz Cortinhas Ferreira Neto or Cesar Guerreiro Diniz.

Peer review information *Nature Communications* thanks Luis Enrique Sánchez and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. A peer review file is available.

Reprints and permissions information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2024