International Journal of Applied Earth Observations and Geoinformation 112 (2022) 102873

Contents lists available at ScienceDirect

International Journal of Applied Earth Observations and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Recent expansion of artisanal gold mining along the Bandama River (Côte d'Ivoire)

Ndeye Marame Ngom[a,c,*], Modou Mbaye[b,c], David Baratoux[d,e], Lenka Baratoux[d,e], Kouassi Ernest Ahoussi[e], Jean Kan Kouame[f], Gayane Faye[c], El Hadji Sow[a]

[a] Département de Géologie, Université Cheikh Anta Diop de Dakar (UCAD), Dakar, Sénégal
[b] Institut Sénégalais de Recherches Agricole (ISRA), Centre d'étude régional pour l'amélioration de l'adaptation à la sécheresse (CERAAS), Sénégal
[c] Laboratoire de Télédétection Appliquée (LTA), Institut des Sciences de la Terre, Université Cheikh Anta Diop de Dakar (UCAD), Dakar, Sénégal
[d] Géosciences Environnement Toulouse, Université de Toulouse, CNRS & IRD, 14, Avenue Edouard Belin, 31 400 Toulouse, France
[e] UFR Sciences de la Terre et des Ressources Minières (STRM), Université Félix Houphouët-Boigny, Abidjan, Côte d'Ivoire
[f] Centre Universitaire de Recherche et d'Applications en Télédétection (CURAT), Université Félix Houphouët-Boigny, Abidjan, Côte d'Ivoire

ARTICLE INFO

Keywords:
Artisanal and small-scale gold mining
Sentinel-2
Google Earth Engine
Bandama river
Surface changes

ABSTRACT

Recent development of small-scale gold mining activities in Côte d'Ivoire is a serious threat to the environment because of deforestation, soil scrapping, pit mining, over-use of water resources and pollution of surface and ground waters by mercury, cyanides, and acids. The challenge for the governance of this activity is to resolve the tension between the desired development of a small-scale mining activity, which may benefit the local and national economy, and the impacts of this activity on the environment. The regulation of the exploration and exploitation of mining sites and the promotion of best practices was part of the National program for the rationalization of gold-panning in Côte d'Ivoire. The capacity of the government to monitor the expansion of numerous mining sites disseminated all over the country is one of the key aspects for successful implementation of these policies. This study explores the potential value of computer-assisted mapping of artisanal mining sites based on Sentinel-2 imagery. The detection method, using artificial intelligence and training data sets generated during field campaigns, was inspired from a previous experience in Senegal. It was applied to a region of about 600 km^2 in Central Côte d'Ivoire. Annual maps of areas affected by the mining activities were produced for the period 2018 – 2021. The areas affected by artisanal mining activities expanded from 3.39 km^2 to 8.80 km^2 in December 2021, corresponding to an average growth rate of 0.24 km^2/month. The temporal and spatial resolution of the Sentinel satellite imagery proved to be useful to map and quantify the expansion rate of artisanal mining sites in Côte d'Ivoire. Recommendations are made for the integration of these tools into plans for the development of small-scale mining activities in Côte d'Ivoire that would be more respectful of the environment and societies.

1. Introduction

In West Africa, the gold mining sector has seen an intense development during the last three decades, propelled by the rise of gold prices. Gold is extracted at various scales, from small artisanal or semi-industrial mining sites, exploited by nationals or migrant workers from neighboring countries, to large permits exploited by mining companies. Large-scale mining is a concession-based mining activity authorized by the government and considered as legal. On the other hand, most of artisanal and small-scale gold mining (ASGM) is considered as an informal and/or illegal activity due to lack of effective regulation. ASGM uses low-tech, labor intensive mineral processing and extraction (Hilson et al., 2017). It requires a combination of deforestation, soil scrapping, pit mining, use of water and chemicals products used to recover the precious metal, such as mercury, cyanides, and acids (Macháček, 2020; World Health Organization, 2017; Hentschel, Hruschka, and Priester, 2003; Gibb and O'Leary, 2014; Miserendino et al., 2013; Kinyondo and Huggins, 2021). These processes generate negative impacts on the environment and human health. Populations working in the mining areas and also living around the mining areas are directly concerned by these impacts (Niane et al., 2019; Boudou et al., 2006; Ako et al., 2014; Bamba et al., 2013; Weinhouse et al., 2021;

* Corresponding author.
E-mail address: ndeyemarame.ngom@ucad.edu.sn (N.M. Ngom).

https://doi.org/10.1016/j.jag.2022.102873
Received 18 June 2021; Received in revised form 8 June 2022; Accepted 15 June 2022
Available online 27 June 2022
1569-8432/

Nyanza et al., 2019, 2021). In spite of these negative impacts, ASGM has the capacity to generate employment and income in rural areas and to enhance the standard of living (MacDonald, 2006). The socio-economic importance of artisanal mining characterizes it as a poverty driven activity (Hilson 2009; 2008; Schwartz et al., 2021; Isung et al., 2021; Ofosu et al., 2020).

In Sub-Saharan Africa, some governments have understood this economic importance and have tried to reorganize and regulate this activity. Thus, many laws and policy framework aimed at reforming, reorganizing and legalizing the ASGM sector have been introduced in countries such as Senegal (IGF, 2016), Ghana (Graphic, 2018), Côte d'Ivoire (Sauerwein, 2017), Niger (Hilson, 2011) and Congo (Singo and Seguin, 2018). However, many of these laws are poorly enforced and as a results of this, informal mining remains and expands in many countries (Ngom et al., 2020). A major challenge for the regulation of the artisanal mining sector is the constantly evolving nature of this activity, driven by the discoveries of new mining sites and the abandonment of less profitable sites. First, the temporality of the artisanal mining activity appears to be somehow incompatible with, for instance, the frozen definition of authorized mining corridors, whose limits do not evolve regularly with the findings of viable ore deposits. Second, the spatial dispersion of mining sites precludes a ground-based monitoring of these activities on a regular basis. The government has therefore severe difficulties to determine if and when activities take place outside of these corridors. In this context, and considering previous experiences in west Africa and South America (Ngom et al., 2022), it is justified to explore the potential value space-based technologies to map in "real-time" the expansion of artisanal mining sites in Côte d'Ivoire.

In this study, the recent expansion of ASGM in the area of Marahoué along the Bandama River in Côte d'Ivoire is analyzed during the 2018 – 2021 period of time using Sentinel-2 images. Our mapping approach is based on an artificial intelligence (AI) method. The data processing pipeline is implemented on the Google Earth Engine (GEE), following the development made for the study in Senegal (Ngom et al., 2020). The main objective of this study is to document the recent expansion of artisanal mining on a section of the Bandama river. Given the lack of information about ASGM in this region, and its suspected recent expansion, the present study aims at filling existing gaps. Testing our approach in Senegal and Côte d'Ivoire may also offer validation in a wide range of climatic contexts, covering the Sahelian to tropical climatic zones. If validated, this approach may then be applied more widely to other areas affected by ASGM in West Africa.

2. Remote sensing observations of ASGM: Previous study and strategic choices for this study

Over the last two decades, remote sensing imaging capabilities of satellites orbiting the Earth has prompted the monitoring of artisanal mining activity from space (see the bibliographic synthesis of Ngom et al., 2022). Taking advantage of the public access of satellite data disseminated by agencies such as the United States Geological Survey (USGS), and the European Space Agency (ESA), researchers have developed approaches to detect, map, monitor and analyze the expansion with time of artisanal and small-scale mining in different regions of the world. These advances have enabled the governments of several countries to reduce the lack of information on the spatial and temporal characteristics of gold mining sites, including Brazil (Lobo, 2015; Lobo et al., 2018), French Guyana (Gond and Brognoly, 2005), Myanmar (LaJeunesse Connette et al., 2016), and Ghana (Forkuor et al., 2020; Snapir et al., 2017). The use of remote sensing data also provides a better assessment and understanding of the environmental consequences of ASGM such as deforestation (Adamek et al., 2020; Barenblitt et al., 2021; Caballero Espejo et al., 2018; Swenson et al., 2011), land degradation (Liman et al., 2021; Lobo et al., 2016; Souza-Filho et al., 2021; Telmer and Stapper 2007), acid mine drainage (Mielke et al., 2014; Seifi et al., 2019), and water pollution (Gallay et al., 2018; Lobo, 2015; Lobo et al., 2018). The main challenge for mapping and monitoring ASGM from satellite data is the fact that neither dedicated data nor universal method are available. The general principles are similar everywhere on Earth. The fundamental working hypothesis is that mining sites has physical properties (generally optical) that are distinct from other types of land use. However, the details of the approaches may differ from one study area to another and depend on the type of data (e.g., characteristics of spectral channels for multi-spectral optical data). The methodological optimization often focuses on the choice of relevant combinations of properties (spectral indices or spectral bands), on the construction of time series, and on the consideration of the climatic context, vegetation cover, and diversity of land use of the area of study.

The objective of automated or computer-assisted detection of mining sites is to produce maps of ASGM from remote sensing data, in areas that are not easily accessible, without the need to repeatedly validate the outlines of each mining site in the field. From the remote-sensing viewpoint, an ASGM site is defined as a continuous region that shares specific and distinct optical properties, as a consequence of gold exploration or extraction. The modification of optical properties with respect to unperturbed areas may result from one or several activities among those found on mining sites, including deforestation, removal and physical mixing or superficial layers of soil, regolith, crushing and processing of rocks (including use of chemical, and cyanidation areas), accumulation and weathering of mining waste. Considering this definition, the climate, the evolution of vegetated areas with seasons, the size and the typical extent of ASGM sites might influence the choice of the data (spectral bands, spectral, spatial and temporal resolutions) and mapping method (classification algorithms).

The spatial resolution of the images is an important factor considering the commonly small dimension of mining sites in West Africa. ASGM sites have indeed generally small footprints that may be only tens of meters long, especially during the early stages of development. In this case, a higher resolution (=< 10 m) than Landsat data (most often used for site mapping in the past) is needed to map them. In addition, in case of mining sites located in tropical area or the rainiest region, the availability of cloud-free optical images area is not warranted. Furthermore, the most frequent optical signatures of ASGM are the consequences of mine waste and scraping of soil, and these signatures may be produced by other land uses such as habitations, and areas exploited for agriculture or agroforestry. The similarities of the spectral response may lead to misclassification (Isidro et al., 2017; Lobo et al., 2018; Boakye et al., 2020). Considering these difficulties, the use of data with a high frequency of revisit, high spatial resolution and rich spectral characteristics is critical to overcome the problems of frequent cloud cover, small extent of ASGM areas and possible spectral similarity between different land use and land cover types. In particular, we have shown in Senegal that different types of land use may potentially show different temporalities, which could help to distinguish them at certain periods of the year, even if they show similar spectral properties at other times of the year (Ngom et al., 2020). Taking into account these different factors, the multi-spectral (visible and near-infrared) Sentinel-2 data with a resolution of 10 m/pixel, appears to be a suitable choice, which is also justified by the success of recent mapping gold mining sites conducted in Senegal and Brazil with these data (Ngom et al., 2020; Lobo et al., 2018). With regard to the data processing, we will explore the value of spectral indices in addition to spectral bands and machine learning methods such as Support Vector Machine (SVM), object-oriented or decision tree, which are expected to produce satisfactory

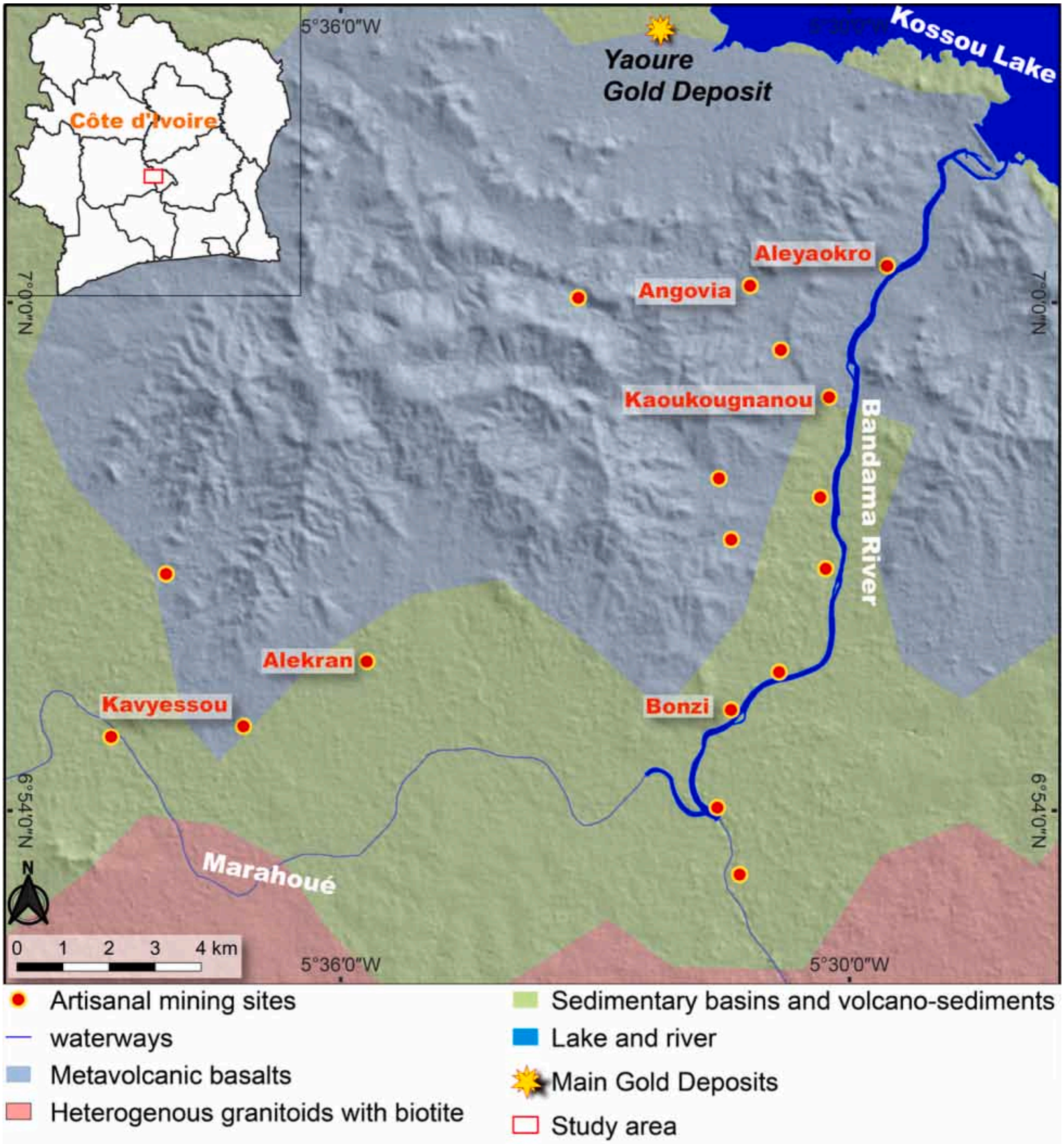

Fig. 1. Geological setting of the study area, overlayed on a shaded relief image built from the SRTM 1′ Digital Elevation Model.

classification of mining areas (Nyamekye et al., 2021).

As for the processing aspects, we chose to use the Google Earth Engine Platform. Thanks to the data catalogue, that is continuously updated, end-users have access to a wide range of geospatial data from earth observation satellites and aerial imaging systems in optical and non-optical wavelengths, as well as environmental variables, weather and climate forecasting and hindcasting, land cover, topographic and socio-economic data sets. Furthermore, the GEE platform provides innovative data processing algorithms which help researchers to improve their capability to analyze and interpret Earth observation data. The platform is also aimed to facilitate the dissemination of their results making them accessible to other researchers or, in this case, to people in charge of management of the mining sectors in government to support management decisions, irrespective of the country of residence (Kumar and Mutanga 2018). Users can produce systematic data products or deploy interactive applications backed by Earth Engine's resources (Gorelick et al., 2017).

3. Formalizing artisanal gold mining in Côte d'Ivoire

As many countries in West Africa, Côte d'Ivoire has also embarked on the process of formalizing artisanal gold mining sector. It is in this context that the National Plan of Rationalization of Gold-panning, (PNRO standing for "*Plan National de Rationalisation de l'Orpaillage*" *in*

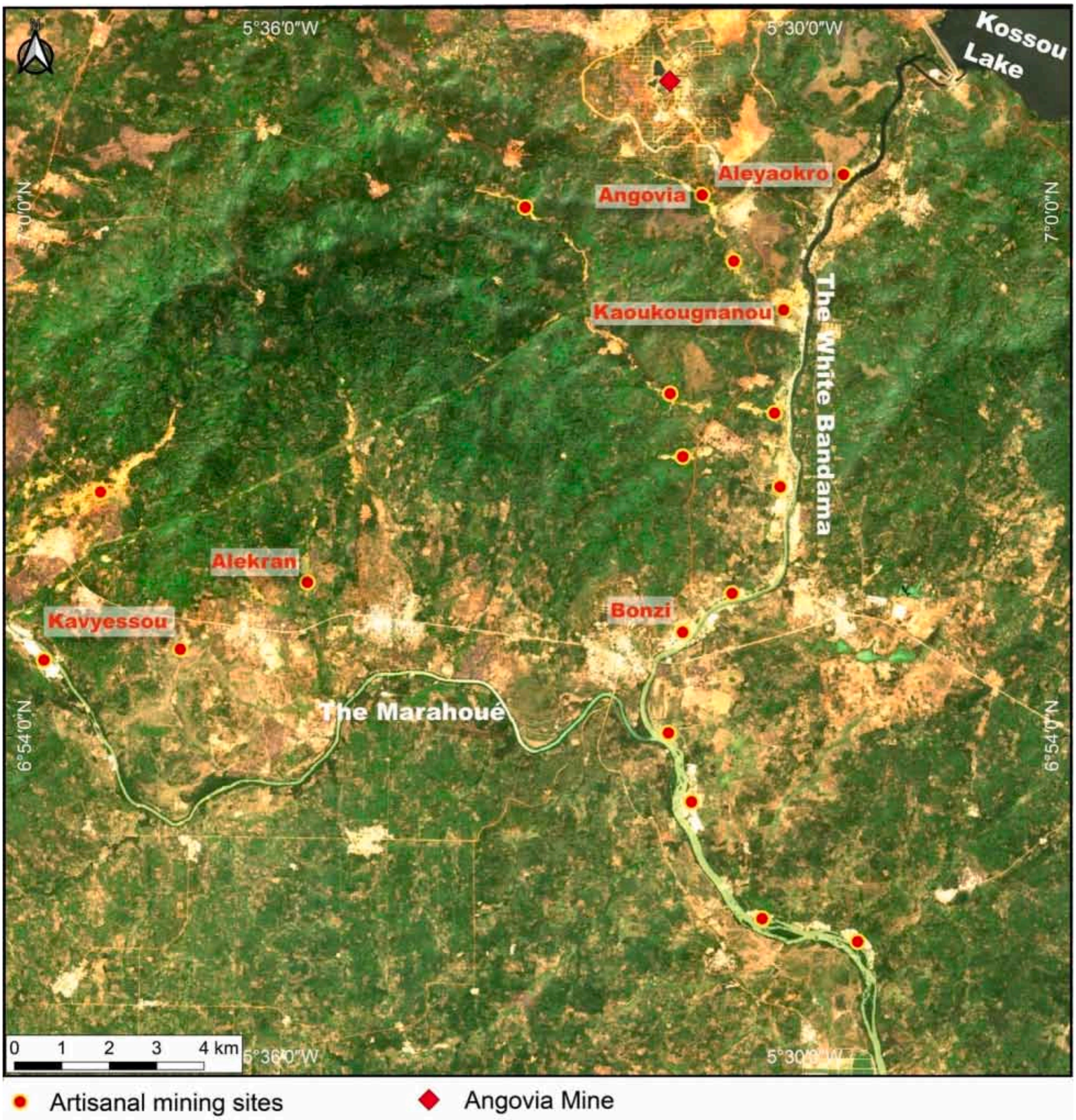

Fig. 2. Extract of the Sentinel-2B scene of 13 January 2020 covering the study area. The image is a color-composite for natural color, R = band 4, G = band 3, B = band 2. The localization of artisanal mining sites visited during the field work in 2018 are indicated in a red font. The Sentinel-2 data was extracted and downloaded via the Google Earth Engine cloud.

French language), was elaborated in 2013 in Côte d'Ivoire (MIM, 2014). The *PNRO* was initially a three-year plan (2013–2016). Its general objective was to restrict the activities of the gold diggers in legal perimeters and to teach them how to use more environmentally friendly techniques. In details, the *PNRO* had the objectives to map at a given time all the artisanal mining sites of the country (phase 1–2), to classify them and decide those that will be permanently or temporarily closed and those that may continue to operate legally (phase 3). The *PNRO* had also the objectives to train artisanal miners with best practices (phase 4) and it was planned to mobilize relevant administrative service to handle the negative impact on the environment (phase 5) (Van Bockstael, 2019; Sauerwein, 2020). In order to avoid the opening of new illegal mining sites or the illegal re-opening of close mining sites, the implementation of a monitoring system was anticipated as one of the perspectives of the *PNRO*. The first activities carried out were the identification of 258 artisanal mining sites, of which 158 were in the northern and central

Fig. 3. Artisanal mining sites visited during the field work. (a & b) women washing ore in Kaoukougnanou, (c) semi-industrial exploration in Angovia, (d) exploitation of duricrust levels rich in gold in Kavyessou, (e) extraction well, (f) the brown color of the water of the Bandama river illustrating its important sediment load.

regions and 100 in the east of the country (MIM, 2014). In 2015, 150 mining sites were cleared and closed. Then artisanal mining permits were issued. Several artisanal miners have been arrested and chemical substances seized. While the program was aimed to end in 2016, the implementation of the process is still ongoing and considered to be ineffective. Authorizations have been handed out, but no geologically viable gold-mining corridors have been identified. About 185 illegal gold-mining sites were still operating in 2017, 142 of which are former recolonized sites and 47, new sites which opened in 2016 (Sauerwein, 2017). Very quickly in 2017, this number grew to over 650 illegal sites (FES, 2018). The number of sites is still growing given the evolution of artisanal mining activity in recent years in this country and the government is increasingly lacking information on the location and spatial distribution of sites. Today, this activity is informally known in 24 of the 31 regions in the country and is concentrated in the North and the Southwestern areas of Yaouré, Hire and Gaminia (Martin et al., 2017).

4. Study area

The Bandama River is an important part of the river system of Côte d'Ivoire. It extends from North to South over a length of 1 050 km and the basin of the river has a surface area of 97 500 km^2. The river has three main tributaries: the Marahoué, commonly named the red Bandama, the N'zi, and the white Bandama (Soro et al., 2017). The study area covers 610 km^2 along the Bandama River. It is located at the south of the Kossou Lake.

The climatic context of the study area is that of ecological zone 2 of Côte d'Ivoire (MINESUDD, 2014). This zone is characterized by a humid tropical climate (also called "*climat Baouléen*") which makes the transition between the subtropical climate and the subequatorial climate. This climate is close to the sub-equatorial climate because of its abundant rainfall. The average annual rainfall varies between 1200 mm and 1600 mm. The dominant winds are the southwestern winds during the monsoon (April – November) and the northeastern winds during the harmattan (January – March). Maximum daily temperatures vary between 22°C and 32°C throughout the year.

The study area is located around the Yaouré gold deposit in the area known as the "Bouaflé greenstone belt" in central Côte d'Ivoire. The gold deposit is hosted by Paleoproterozoic Birimian basaltic rocks with intrusions of granodiorite (Fig. 1).

The Angovia mine (Fig. 2) is currently extracting ore from the Yaouré gold deposit. In the vicinity of the Angovia mine are many small artisanal mines located on the bank of the Bandama River. The most known artisanal mining sites are Aleyaokro, Kaoukougnanou, Kavyessou, Bonzi, Alekran and Angovia (named after the villages) (Figs. 1 & 2). The study area encompasses several small villages. The main economic activities of these communities are agriculture, fishing, and artisanal gold mining.

These 6 sites were visited during a field campaign organized in November 2018. The exploitation involves extraction and washing ore on site (Fig. 3). According to field observations, gold is found in the form of nuggets in quantities that can be significant in certain areas. The exploitation is most often limited to the superficial levels of the river banks that's form fluvio-deltaic formations which consists of sandstone, conglomerate, and argillite. There are rarely areas with wells. In the rare cases where the ore is extracted from wells, these do not reach great depths because of the upwelling of water. These observations lead us to characterize them as alluvial sites. Further to the west, at Bouaflé and Kavyessou, duricrust levels, also rich in gold, are found. This lateritic zone covers much of the area immediately surrounding the Yaouré deposits and consists of transported and *in-situ* regolith material covering saprolite (Abbott et al., 2017). (Fig. 3-d)

Table 1
Spectral indices, their acronyms, and the mathematical expressions used to compute them from Sentinel-2 bands.

Index	Formulas
Normalized Difference Vegetation Index (NDVI)	$\frac{B8-B4}{B8+B4}$
Normalized Difference Water Index (NDWIa)	$\frac{B8-B11}{B8+B11}$
Normalized Difference Water Index (NDWIb)	$\frac{B3-B8}{B3+B8}$
Brightness Index (BIa)	$\sqrt{B4^2+B3^2}$
Brightness Index (BIb)	$\sqrt{B4^2+B3^2+B8^2}$
Color Index (CI)	$\frac{B4-B3}{B4+B3}$
Redness Index (RI)	$\frac{B4^2}{B3^2}$
Normalized Difference Build-up Index (NDBI)	$\frac{B11-B8}{B11+B8}$
Bare Soil Index (BSI)	$\frac{(B11+B4)-(B8+B2)}{(B11+B4)+(B8+B2)}$
Normalized Built-up Area Index (NBAI)	$\frac{(B12-B8)/(B2)}{(B12+B8)/(B2)}$
Band Ration for Built-up Area (BRBA)	$\frac{B3}{B8}$

These artisanal gold mining sites are frequented by the inhabitants of about twenty villages in the study area (Fig. 2). Referenced points (by GPS measurement) and georeferenced photos (photos associated with geographic coordinates) were taken during the field work. GPS points served first as recognition of mining site on satellites imagery and are used as learning and validation points for our classification algorithm. Georeferenced photos improved understanding of optical properties of ASGM sites on satellite images.

5. Method

As explained and justified in the section 2, Sentinel-2 data and the Google Earth Engine platform are used in this study. The Sentinel-2 data in Level-2A format (atmospherically corrected) were downloaded from the Scihub website (https://scihub.copernicus.eu/). Sen2cor was used for computing atmospheric correction and produce the level-2A data, as described in the Sentinel-2 users Handbook (ESA, 2015). It is a processor for Sentinel-2 Level-2A product generation and formatting provided by ESA/Sentinel mission; it performs the atmospheric, terrain and cirrus correction from Top-Of-Atmosphere Level-1C input data. Sen2Cor creates Bottom-Of-Atmosphere, optionally terrain- and cirrus corrected reflectance images; this algorithm creates in addition an Aerosol Optical Thickness (AOT) band, a Water Vapor band (WV), a Scene Classification Maps and a Quality Indicators map for cloud and snow probabilities. The Level-2A data are available on the study area since the end of 2018, whereas the data are still in Level-1C format for the previous period (2015–2017). The southern part of Côte d'Ivoire being one of the rainiest regions in West Africa, the cloud cover is a major obstacle to the use of optical imagery. With the high temporal repetitiveness of the data acquisition the probability of having images with minimal cloud cover is better. Applying a selection script on this database based on criteria of date (2018–2021), cloud percentage (less than 5%) study area boundaries, and band selection (all bands without B01, B09 and B10 generally used for atmospheric correction), we obtained 2 Sentinel-2 granules for 2018, 15 for 2019, 7 for 2020 and 8 for 2021. Three images separated by approximately 12 months, and therefore acquired at the same period of year, were used for the analysis of the evolution of mining sites in the study area.

The approach used here is inspired by the work of Ngom et al. (2020). In the previous study, the evolution over time of the spectral properties of artisanal mining sites in Senegal were studied using a Sentinel-2 image time series. In this study, due to important cloud coverage over most of the year, it is not possible to build time series of spectral properties to define the best season for mapping artisanal mining sites, as in Senegal. However, the availability of a few cloud-free images may be already considered as a definitive asset of Sentinel-2, with respect to previous imaging satellites. For instance, over the same period of time (2018 to 2021), only 6 almost cloud-free Landsat images would have been available, and at lower resolution (30 m/pixel). Furthermore, it is of note that there are less changes in the vegetation cover in this tropical climate (Osborne et al., 2004), in comparison with East Senegal, which has a more marked rainy and dry seasons. The question of defining the best season for mapping is less critical in Côte d'Ivoire than in Senegal, and the answer is more straightforward: it's the time for which cloud coverage is minimal. The analysis of the satellite data is achieved here in four steps:

a) **Integration of field data and definition of training samples.** GPS points collected during field work were integrated (loaded) as an asset in the GEE platform. These points are used for the site identification. On the basis of field observations, GPS points and Google Earth Imagery, the study area was divided into 5 types of land use: vegetation, settlements (urban), bare soil, water and artisanal mining sites. A set of samples or region of interest (ROI) comprising the different land use types was produced. A fraction of the GPS points collected during field work serves as a training sample for IA-based classification and the remaining fraction is used for validation
b) **Band sets definitions.** This step includes selection of the imaging bands, calculation of spectral indices, and spectral analysis, in preparation for the classification algorithm.

A series of spectral indices was calculated to better explore the benefits of the spectral richness of the Sentinel-2 data. These indices are sensitive to vegetation (Normalized Difference Vegetation Index (NDVI)), soil moisture (Normalized Difference Water Index (NDWI)), soil coloring and brightness (Color Index (CI), Redness Index (RI), Brightness Index (BI)), the presence of bare soils (Bare soil Index (BSI)), and the presence of builds (Normalized Difference Buildup Index (NDBI) and the Normalized Build-up Area Index (NBAI)). In the Table 1 are presented the equations used to generate these indices.

The spectral values on the bands and indices for each ROI for each type of land use were extracted. The data were then statistically analyzed using the average value and standard deviation. To evaluate the relevance of band indices for the detection of artisanal mining site, the spectral properties of different land use, which can be potentially confused and misclassified are examined. Then, the most appropriate bands and indices for classification were determined by using the SEaTH (Separability and Threshold) algorithm. This step consists in estimating the probability of distribution for each class and to calculate the separability between two classes of land use. As in the study of Ngom et al. (2020) the Bhattacharyya distance was computed for each class. This distance is defined for two classes by the Eq. (1).

$$B=\frac{1}{8}(m_1-m_2)^2\frac{2}{\sigma_1^2+\sigma_2^2}+\frac{1}{2}ln\left[\frac{\sigma_1^2+\sigma_2^2}{2\sigma_1^2\sigma_2^2}\right] \quad (1)$$

m_1 and m_2 are the respective average values of the chosen characteristic for each class (reflectance value of bands and index values), σ_1 and σ_2 are the corresponding standard deviations for each class. The Bhattacharyya distance is generally used to assess separability of land-cover classes and to prioritize features that most contribute to the discrimination among the land-cover classes of interest (Herold et al., 2003). Considering the fact that the range of B falls in half-closed interval $[0,\infty]$, it is possible to transform this range into a closed interval [0, 2] by using a simple transformation of B into a Jeffries Matusita (J) distance (Eq. (2)) (Adam et al., 2016).

$$J=2\left(1-e^{-B}\right) \quad (2)$$

A value of J near 2 indicates complete separability between the two

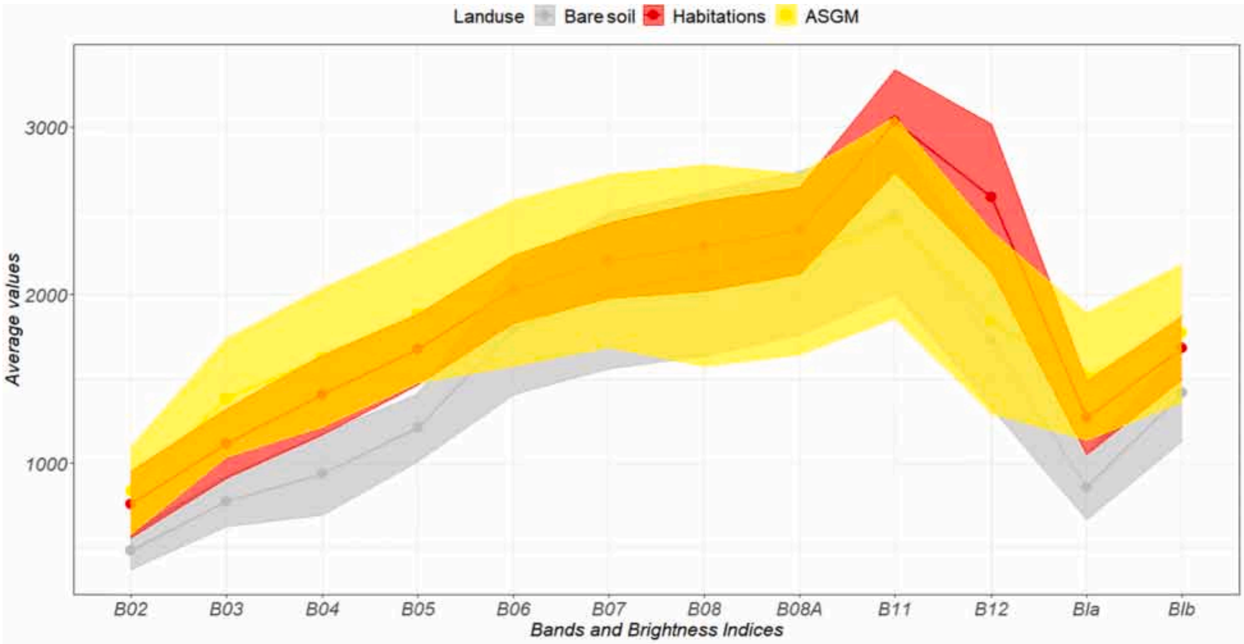

Fig. 4. Average and standard deviation of Sentinel-2 spectral bands and Brightness indices of ASGM, habitations and bare soil.

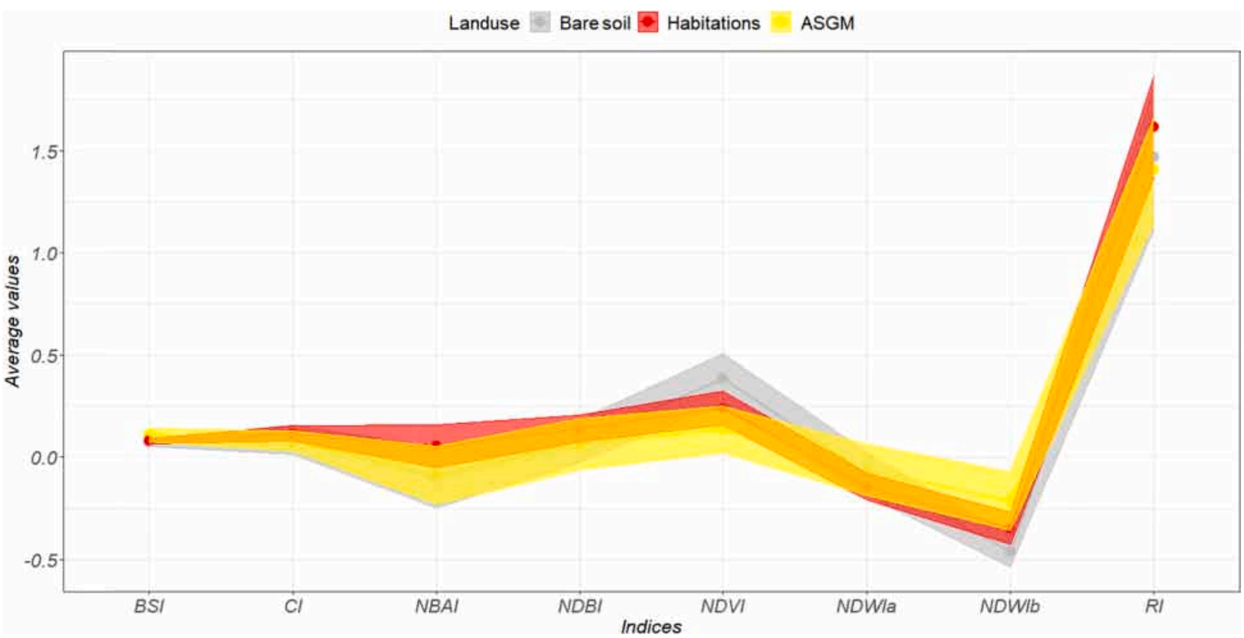

Fig. 5. Average and standard deviation of indices of ASGM, habitations and bare soil.

classes and a value near 0 indicates that classes are not separable. The main result of this step is the definition of the most relevant bands and indices for the detection of ASGM with the minimum confusion possible. These bands and indices are used as input data for the classification (Carleer and Wolff, 2006).

c) **Image classification and accuracy assessment.** The Support Vector Machine (SVM), a machine-learning approach, is used in this study. The SVM is one of the most widely used machine learning methods in remote sensing due to the high capacity in image recognition (Bruzzone et al., 2006; Foody and Mathur, 2004; Mantero et al., 2005). It is a non-parametric supervised classifier based on statistical learning theory and adapted in case where a limited amount of reference data is often provided. The SVM learns from the training dataset and attempts to generalize and make a correct prediction on new datasets. The SVM algorithm is already implemented in the Google Earth Engine platform. Google Earth Engine proposes a library of SVM named LibSVM that helps users to perform their classification using different parameters. For this study we have varied the parameters of the SVM in order to have the most accurate

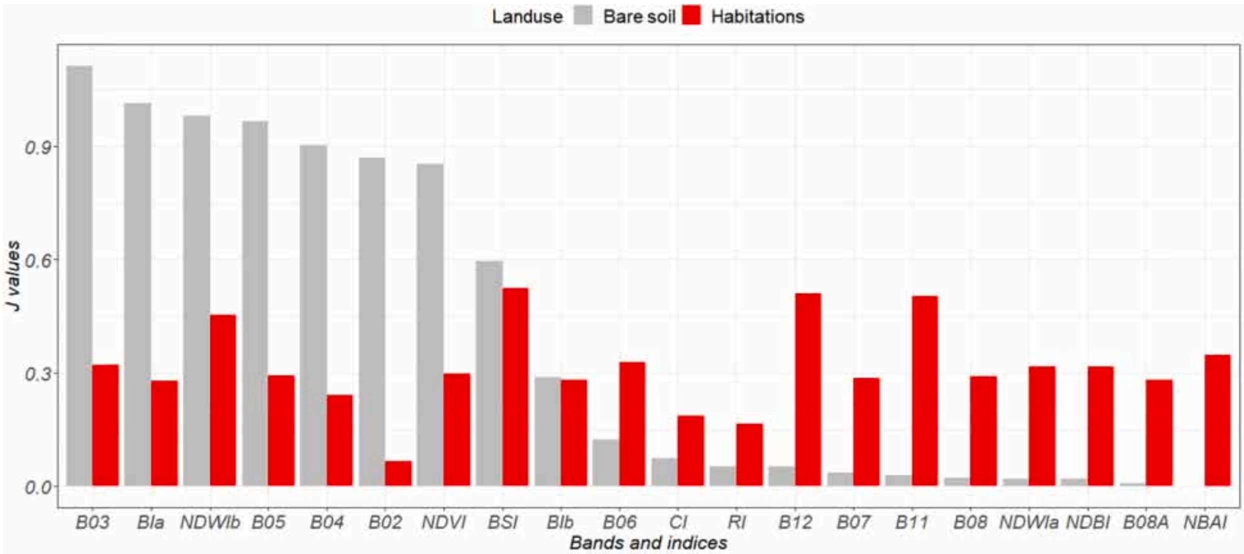

Fig. 6. Separability measurements between the ASGM site versus bare soil and urban, estimated for all spectral bands and spectral indices for the image of December 2018. The bars are ordered by decreasing values of J (Jeffries-Matusita distance) and therefore the following bands are retained for classification: B02, B03, B04, B05, B11, B12, BSI, NDVI, BIa and NDWIb).

result possible. The final parameter used are: kernel = Radial Basis Function (RBF), C (cost) = 100 and $y = 1$. The Cost parameter C is the price for misclassified samples in the training set. This parameter is important to minimize classification errors. It allows to make a compromise between training errors and the complexity of the model. Large values of C help to minimize the training errors and lead to behavior similar to that of the hard-margin SVM (Kuhn and Johnson, 2013). The free parameter, y, influences the variance. If y is high the variance is low and vice versa. (Kranjčić et al., 2019). SVM classifier is applied on each image and validated by ground truth samples. Using the confusion matrix, an accuracy assessment (Kappa index) was performed. This confusion matrix includes commission and omission error based on validated samples. Commission's errors are defined as pixels, which have been classified as belonging to a given class while they are not and errors of omission refer to pixels that were left out (or omitted) from the correct class in the classified map (Lewis and Brown, 2001).

The final classification is therefore based on the use of the set of training samples defined on the study area. 70% of the samples were randomly selected for the training and the rest (30%) for validation. Bands and indices with high values of separability served as band sets for the classification. The classifier model developed with the training data acquired in 2018 is applied to Sentinel-2 image of 2019 and 2021.

d) **Map to map comparison to assess the recent expansion of ASGM.** The raster result of the classification is exported on Google Drive. Note that none of the voluminous data sets are downloaded at any time of the process, and the download to local storage is limited to the raster containing the classification (total size: 517 Kb). This approach clearly puts local computing requirements at an affordable level, even if generalization to mapping at a national scale is considered. For each year, the result of the classification was exported in a tiff format into a Google Drive. Once exported, this file is opened in QGIS and the map is edited manually. The step of manual edition consists of an extraction for each result (2018, 2019 and 2021) of the ASGM class using the module raster calculator of QGIS, transformation of raster into polygons and vector editing to eliminate misclassification of mining areas. For the vector editing in the villages, we assume that artisanal mining does not take place within the villages/habitations. A mask has been applied on the villages and the pixels contained in the villages classified as belonging to the gold panning class have not been taken into account. Concerning bare soil, the confusions concern a small number of pixels that have been classified as belonging to the mining class. These pixels can be either sites in early stages of exploration or errors. Based on size criteria and Google earth imagery we have chosen to eliminate them. After vector editing, the surface exploited in the study area has been calculated for each year using the field calculator of QGIS and a map-to-map comparison is achieved to document the extension of mining sites.

6. Results

6.1. Spectral properties of artisanal mining sites

Figs. 4 and 5 show the average and standard deviation of the spectrum (reflectance values for each band) and spectral indices for ASGM, bare soil and habitations (urban areas). Standard deviations are used to create envelopes of average curves. The curves are superimposed on bands and indices where there is a possibility of class confusion. For each of these figures, the x-axis corresponds to the Sentinel-2 bands and indices and the y-axis to the reflectance/spectral index values. These graphs show that the ASGM class is essentially distinguished from the bare soil class by its higher reflectance values in the visible domain (B02, B03, B04 and B05), and by the brightness and NDWI indices. This distinction is also possible using the Normalized Difference Vegetation Index (NDVI) which has lower values. On the other hand, the distinction between the ASGM class and habitations class is difficult, with only B11 and B12, which are the mid-infrared bands, showing a higher reflectance

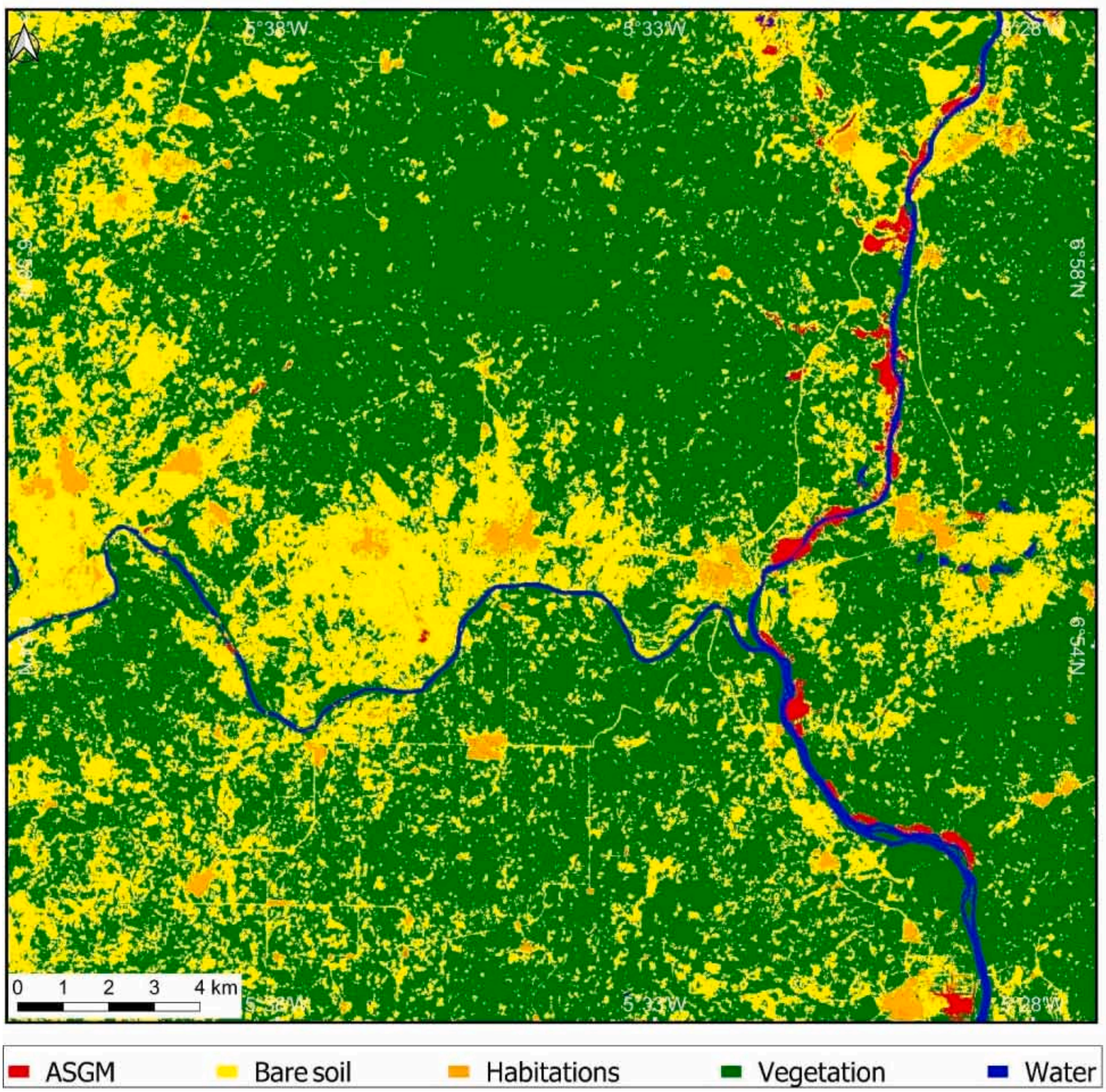

Fig. 7. Results of classification derived by the application of the SVM on selected spectral bands in indices on Sentinel-2 granule of December 2018.

value for habitations than for ASGM. This is because these bands are very sensitive to the presence of urban areas and are often used to differentiate them from other areas (Lefebvre et al; 2016). Fig. 6 presents the results of the calculation of separability measures between the ASGM class and the bare soil and habitations and confirm these results. All spectral bands and indices were included in this analysis and are represented on the *x* axis. The *y* axis represents the value of J. The top ten bands with high value of J were used for the classification (B02, B03, B04, B05, B11, B12, BSI, NDVI, BIa and NDWIb).

6.2. Map of ASGM area in 2018

For each image, the same sets of bands are used. The classification is achieved using the SVM with parameter as explained in section 3.3.c. By using the training sample designed for validation, an overall accuracy of 94% is found for December 2018 s (Kappa = 0.92). Fig. 7 is a map which presents the result of classification applied on an extract of Sentinel-2 granule covering the study area in December 2018, before vector editing. For the years 2019 and 2021 the results are presented in Appendices 1 and 2. The confusion matrix table constructed with validation data is presented in Appendix 3.

Misclassified pixels have been observed in the villages (habitations)

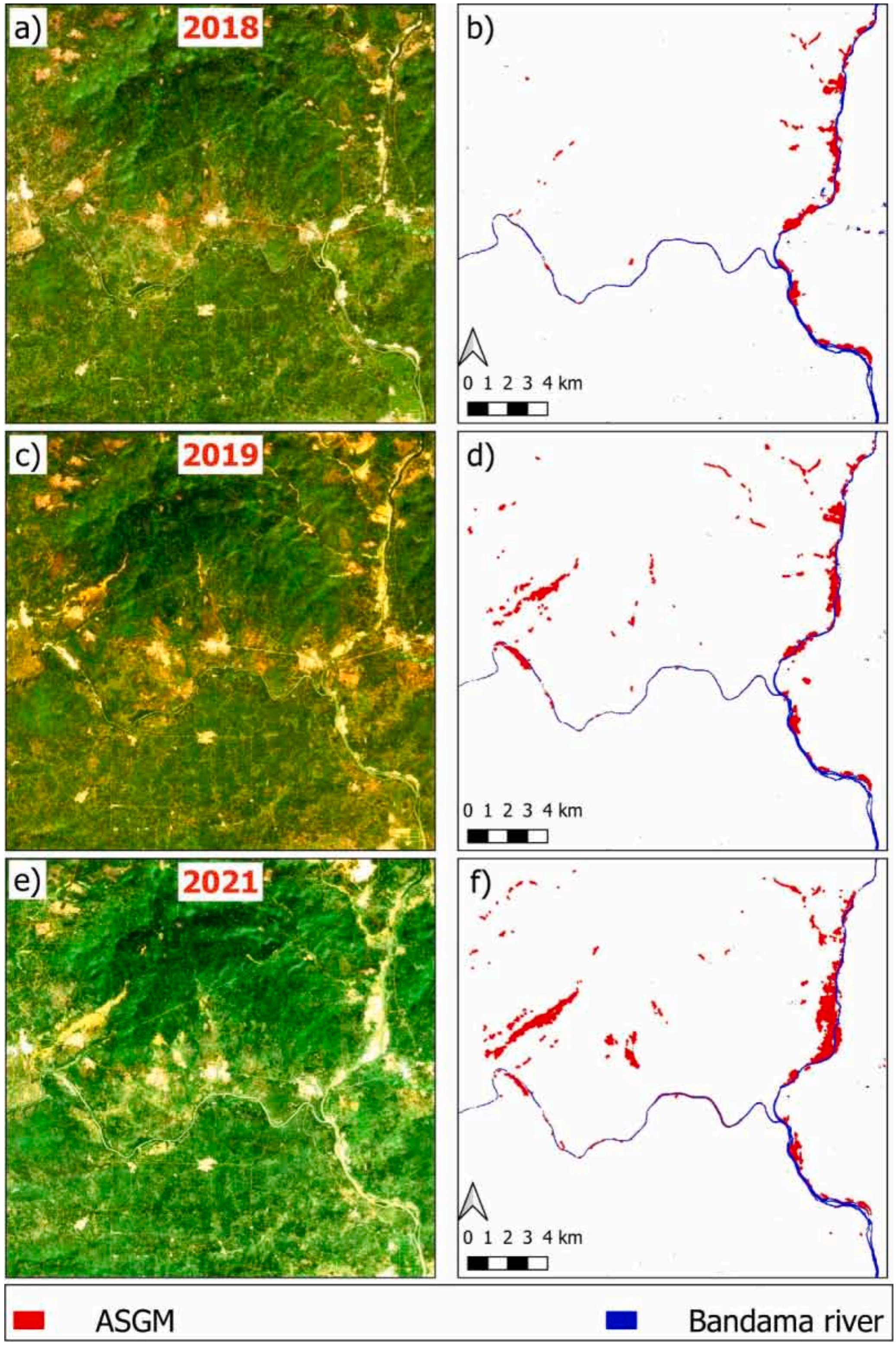

Fig. 8. Illustration of expansion of ASGM between December 2018 to December2021; a, c and e are respectively Sentinel-2 images acquired at December 2018, December 2019 and December 2021. Figures b, d and f represent detected and mapped artisanal mining area, respectively.

Table 2
Mining area in km^2 mapped with Sentinel-2 images acquired in the period of 2018 to 2021 in the study area.

Date	December 2018	December 2019	January 2021
Mining area in km^2	3.39	5.16	8.80

and some bare soil. This result confirms the spectral profile and separability analyses which showed the possibility of confusion between artisanal gold mining class, habitation and bare soil. After this step, the total area occupied by artisanal gold mining is calculated.

6.3. Expansion of ASGM

Once we have applied and validated the approach on the 2018 data (the year for which we have ground observations), the 2019 and 2021 data were processed in a similar way. It is then possible to explore the changes and expansion of the mining site from the comparison of the mapping results. Fig. 8 shows the result of the mapping of the recent extension of ASGM along a section of the Bandama River derived from three Sentinel-2 images acquired at December 2018 (a), December 2019 (c) and December 2021 (e). The detected and mapped mining areas for each year are presented in Fig. 8 b, d and f, respectively. Table 2 shows the total mining area calculated for each year in the study area. According to Table 2, the total area exploited by artisanal gold mining for the year 2018 is 3.39 km^2 and increases to 516 km^2 for 2019, and 8.80 km^2 for 2021. These surfaces correspond to 0.55%, 0.84% and 1.44% of the area that have been processes by the classification algorithm (which corresponds to 0.2% of the surface area of Côte d'Ivoire). These figures show that this activity has more than tripled in three years and corresponds to a growth rate of 0.24 km^2/month. This expansion is much more marked in the western part of the study area, specifically in the villages of Kouassi Perita, Alekran and Kavyessou (see Appendix 3).

7. Discussion

7.1. Factors of expansion of artisanal gold mining in Côte d'Ivoire

This expansion of artisanal gold mining in Côte d'Ivoire is due to several economic, political and social factors. On the economic level, the main factor is the current rise of gold prices, stimulated by strong demand. Between 2000 and 2021, the price of an ounce of gold rose from $280 to $1,800, an increase of over 600%. This increase has led to the development of artisanal gold mining in many rural areas of Côte d'Ivoire, and in neighboring countries (Abass Saley et al., 2021). Indeed, due to great poverty, many communities practice this activity, which is much more lucrative than agriculture. This is accentuated by the ease of selling gold quickly (mostly) on the spot, unlike agricultural products (cocoa and coffee) which may be unsold due to lack of buyers. On the political level, the issue of mining in several countries has revealed that in most producing countries, populations do not benefit from the dividends of industrial mining. This encourages the development of clandestine activities in the rural areas where the resource is available (Soko, 2019). In addition, the development of gold mining can be explained by the lack of effective regulation despite the government's efforts under the PNRO and the long administrative procedures that can discourage gold miners to enter the legal system (FES, 2018).

7.2. An approach designed for low/middle income countries – advantage, risks and limitations

Considering that until now, the only available geographical information on artisanal mining is a map of localization of ASGM based on a census realized in 2016, this study opens the paths to address the lack of information related to the continuous growth of artisanal mining in Côte d'Ivoire. In this research, a cost-effective method in terms of time and resources is proposed for identification and analysis of the expansion of ASGM in Côte d'Ivoire. This methodology of detection and mapping is based on Ngom et al. (2020), and has been developed, at first, for Senegal. This approach is adapted for countries with a broad range of levels of economic development, as it relies on publicly available data (Sentinel-2), open access software (R and QGIS), and a cloud computing platform (GEE). Downloading and processing Sentinel-2 data that would take a long time and require fast internet connections, very large storage capacity and efficient computational power is now made easier by using GEE. Artisanal gold mining takes place in 24 of the 31 regions of Côte d'Ivoire, which corresponds to an area covered by about 30 Sentinel-2 tiles. The volume of data to be processed (if we consider that the volume of each Sentinel-2 tile can measure 800 MB) may reach 24 GB for one date. Considering that the application of the model developed for the study area lasts about 30 s, the extrapolation to entire Côte d'Ivoire would take about 4 h of computation time, but much more time would be required for final manual vector editing. The efforts to reduce the time necessary for vector editing should be a priority, but this step cannot be entirely suppressed. The use of commercial software for data processing is avoided by the cloud computing GEE, though it is admitted that any change in the condition of utilization of the platform may affect the end-users, including potentially at the governmental level. However, the Is the case with any commercial platform of software and it is therefore a risk that is not specific to the GEE platform.

7.3. Comparison Côte d'Ivoire – Senegal

The first difference that arises is the use of time series and the definition of the ideal period for site identification and mapping in Senegal, which is not possible and relevant in Côte d'Ivoire. In Côte d'Ivoire the cloud cover is significant throughout the year and there are few images with a cloud cover rate of $<10\%$. The only period with the fewest clouds is between December and January. The separability analysis has shown the relevance of the brightness index for the detection of artisanal mining sites; however, it should be noted that the most relevant spectral bands and indices may change from one study area to another.

Despite the low J values found, the SVM is able to classify the different types of land use. This can be explained with the PCA results presented in Appendix 4. These results show that it is possible to minimize the confusions between habitations, ASGM and bare soil classes. Concerning the classification errors that have been noted in Senegal (Ngom et al., 2020), the results are more precise in this study. The detection of artisanal gold mining sites in Côte d'Ivoire remains less difficult than in Senegal, where it is often confused with bare soils. In Côte d'Ivoire, the presence of dense vegetation throughout the year makes it easier to detect a landcover change.

7.4. Perspectives of this study: A possible contribution for the regulation of artisanal and small-scale gold mining in cote d'Ivoire

This study demonstrates the capacity of spatial data for monitoring artisanal mining activity in Côte d'Ivoire. Although the area covered in this study represents only 0.2% of the area of Côte d'Ivoire, it is important to emphasize that the method can be applied semi-automatically on a regional scale. Field campaigns in other sites are to be considered. It is important to note that additional training data will be needed to feed the model in order to make the result more accurate.

Of the 2,300,000,000 FCFA budget that was allocated to the PNRO, a large portion was earmarked for the survey of gold panning sites (MIM, 2014). Regular (annual) update of the location and extent of ASGM site could be achieved with reduced costs based on the initial inventory. This way, the country could maintain and share with the different actors of the mining sector a database on gold panning as done for the mining industry with the Mining Cadastre Portal of Côte d'Ivoire (https://portals.landfolio.com/CoteDIvoire/FR/).

8. Conclusion

This article presents an AI method based applied to Sentinel-2 data for the detection and mapping the extent of artisanal mining site along the Bandama River in Côte d'Ivoire. The proposed approach takes advantage of the regular availability of new images (5 days) provided by Sentinel-2a and 2b, which increases the chance of having optical images with a minimum of cloud cover in Côte d'Ivoire. This availability of images makes it possible to follow the yearly evolution of the gold mining sites but also the opening of new areas of exploitation. The analysis of Sentinel-2 data shows that the areas affected by artisanal mining activities expanded from 3.39 km^2 to 8.80 km^2 between December 2018 and December 2021, corresponding to an average growth rate of 0.24 km^2/month. This study could represent a contribution to the policies on artisanal gold mining to the extent since regulation requires regular monitoring of mining sites and objective documents on the impacts on the environment. This approach may represent an affordable alternative for regular updating of gold panning expansion as envisaged in the PNRO, given that the activity is evolving very rapidly, hence the need for governments to implement such tools. This method may also allow the exploration of gold panning sites in regions or areas that are difficult to access, such as the northern part of Côte d'Ivoire and in particular its borders with Burkina Faso and Mali. This approach is also based on public data and open access software, and shall promote the sharing of knowledge and information between all the actors involved.

Declaration of Competing Interest

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

Appendix A

(see Fig. A1)

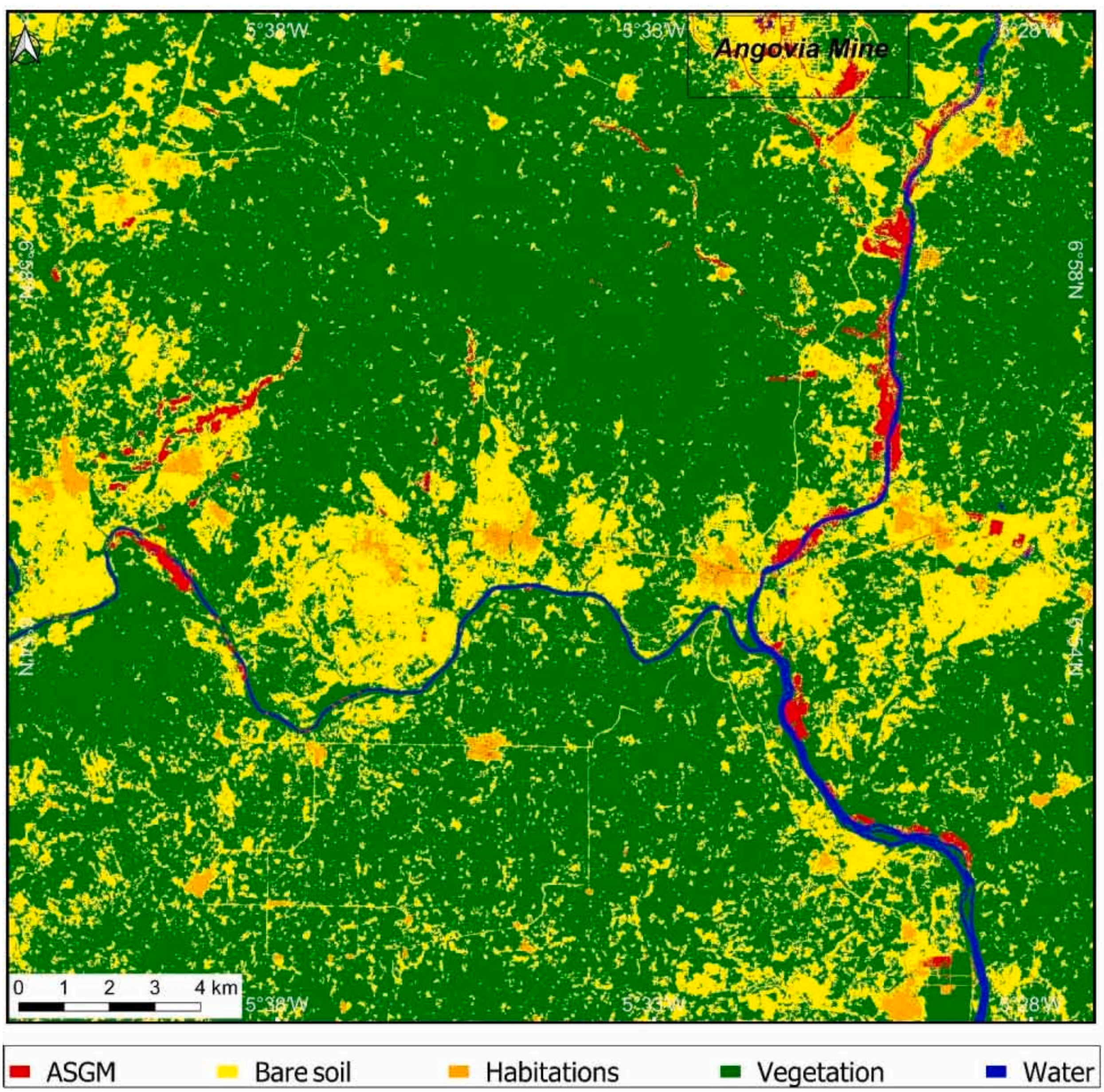

Fig. A1. Results of classification derived by the application of the SVM on selected spectral bands in indices on Sentinel-2 granule of December 2019.

Appendix B

(see Fig. A2)

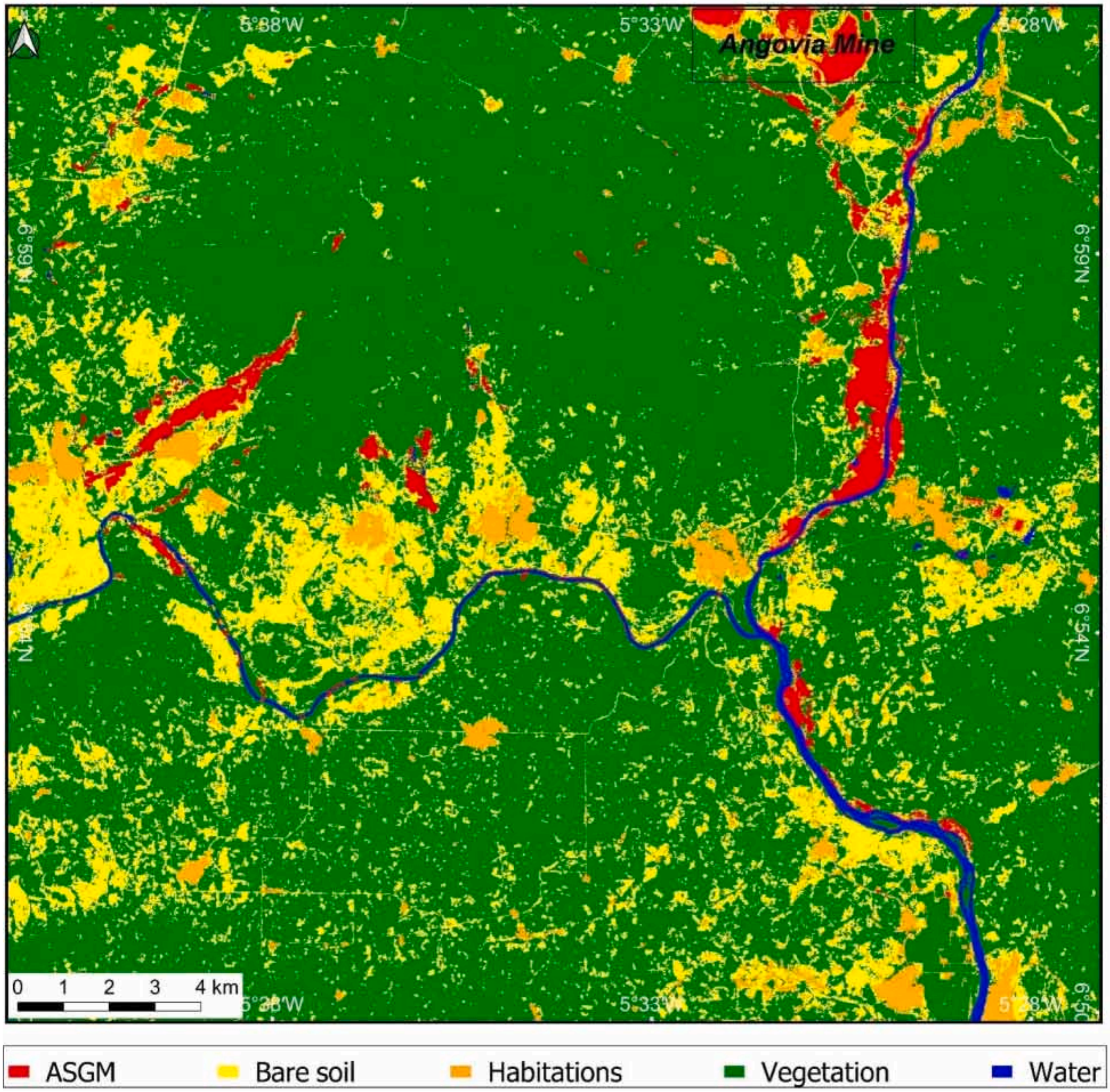

Fig. A2. Results of classification derived by the application of the SVM on selected spectral bands in indices on Sentinel-2 granule of January 2021.

Appendix C

(see Table A1)

Table A1
Confusion matrix according to validation data.

		Reference Data					
		ASGM	Vegetation	Water	Urban	Bare soil	Total
Classified	ASGM	87	0	0	3	5	95
	Vegetation	0	59	0	0	0	59
	Water	0	1	44	0	0	45
	Urban	0	0	0	76	0	76
	Bare soil	0	2	0	8	34	44
	Total	87	62	44	87	39	319

Appendix D

(see Fig. A3)

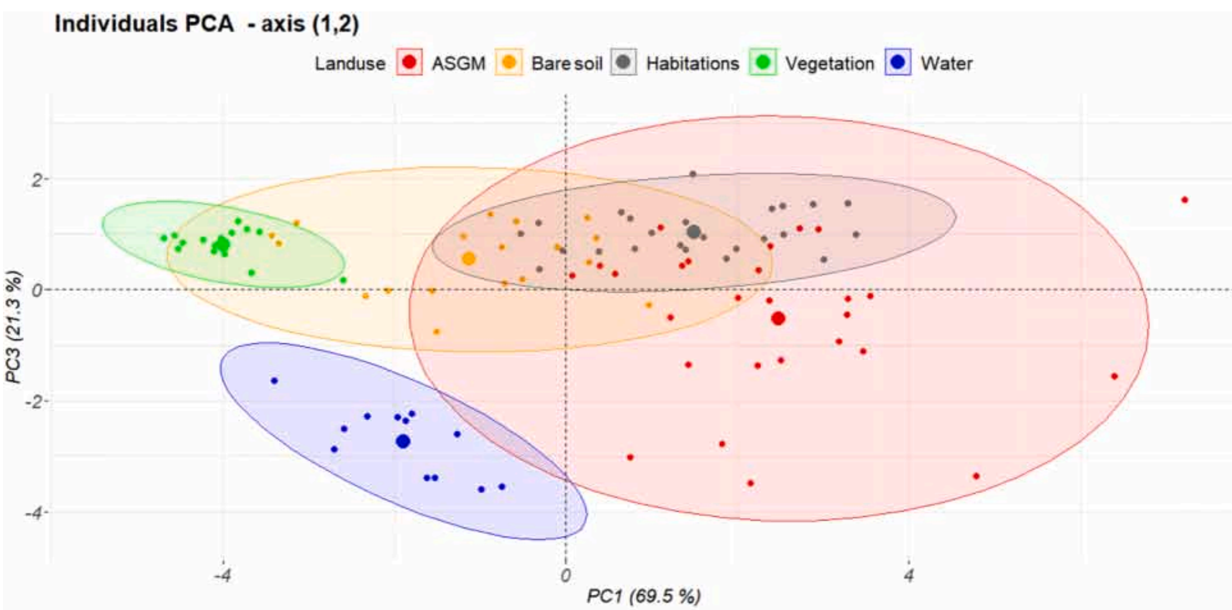

Fig. A3. Results of the PCA (observations projected on the PC1–PC2 planes). Numbers in brackets on the x and y labels are the variance for each PCA axis. Concentration ellipses are drawn based on the average and 2 standard deviations of the projected values in the principal axes of the ellipse.

References

Abass Saley, A., Baratoux, D., Baratoux, L., Ahoussi, K.E., Yao, K.A., Kouamé, K.J., 2021. Evolution of the Koma Bangou Gold Panning Site (Niger) from 1984 to 2020 Using Landsat Imagery. Earth Space Sci. 8 (11) https://doi.org/10.1029/2021EA001879.

Abbott, Jonathon, Joe McDiarmid, David Morgan, David Gordon, Paul Thompson, and Gary Brabham. 2017. Perseus Mining Limited Technical Report Yaouré Gold Project Côte d'Ivoire, 294.

Adam, H.E., Csaplovics, E., Elhaja, M.E., 2016. A comparison of pixel-based and object-based approaches for land use land cover classification in semi-arid Areas, Sudan. IOP Conf. Ser.: Earth Environ. Sci. 37 (June), 012061 https://doi.org/10.1088/1755-1315/37/1/012061.

Adamek, Katarzyna, Michał Lupa, and Mateusz Zawadzki. 2020. Remote Sensing Techniques for Tracking Changes Caused by Illegal Gold Mining in Madre de Dios, Peru. Miscellanea Geographica 0 (0): 000010247820200028. https://doi.org/10.2478/mgrsd-2020-0028.

Miserendino, A., Rebecca, B.A., Bergquist, S.E., Adler, J.R., Guimarães, D., Lees, P.S.J., Wilmer Niquen, P., Velasquez-López, C., Veiga, M.M., 2013. Challenges to Measuring, Monitoring, and Addressing the Cumulative Impacts of Artisanal and Small-Scale Gold Mining in Ecuador. Resour. Policy 38 (4), 713–722. https://doi.org/10.1016/j.resourpol.2013.03.007.

Ako, T.A., Onoduku, U.S., Adamu, I.A., Ali, S.E., Mamodu, A., Ibrahim, A.T., 2014. Environmental Impact of Artisanal Gold Mining in Luku, Minna, Niger State, North Central Nigeria. J. Geosci. Geomatics 2 (1), 28–37. https://doi.org/10.12691/jgg-2-1-5.

Bamba, Ousmane, Souleymane Pelede, Aboubakar Sako, Nicolas Kagambega, Mariette Y W Miningou. 2013. "IMPACT DE L'ARTISANAT MINIER SUR LES SOLS D'UN ENVIRONNEMENT AGRICOLE AMENAGE AU BURKINA FASO" 13: 12.

Barenblitt, Abigail, Amanda Payton, David Lagomasino, Lola Fatoyinbo, Kofi Asare, Kenneth Aidoo, Hugo Pigott, et al. 2021. The Large Footprint of Small-Scale Artisanal Gold Mining in Ghana. Sci. Total Environ. 781 (August): 146644. https://doi.org/10.1016/j.scitotenv.2021.146644.

Boakye, E., Anyemedu, F.O.K., Quaye-Ballard, J.A., Donkor, E.A., 2020. Spatio-Temporal Analysis of Land Use/Cover Changes in the Pra River Basin, Ghana. Appl. Geomat. 12 (1), 83–93. https://doi.org/10.1007/s12518-019-00278-3.

Boudou, A., Dominique, Y., Cordier, S., Frery, N., 2006. "Les Chercheurs d'or et La Pollution Par Le Mercure En Guyane Française: Conséquences Environnementales et Sanitaires. Environnement, Risques Santé 5 (n° 3), 14.

Bruzzone, L., Chi, M., Marconcini, M., 2006. A Novel Transductive SVM for Semisupervised Classification of Remote-Sensing Images. IEEE Trans. Geosci. Remote Sens. 44 (11), 3363–3373. https://doi.org/10.1109/TGRS.2006.877950.

Espejo, C., Jorge, M.M., Román-Dañobeytia, F., Ascorra, C., Fernandez, L., Silman, M., 2018. Deforestation and Forest Degradation Due to Gold Mining in the Peruvian Amazon: A 34-Year Perspective. Remote Sensing 10 (12), 1903. https://doi.org/10.3390/rs10121903.

Carleer, A.P., Wolff, E., 2006. Urban Land Cover Multi-level Region-based Classification of VHR Data by Selecting Relevant Features. Int. J. Remote Sens. 27 (6), 1035–1051. https://doi.org/10.1080/01431160500297956.

ESA. 2015. "ESA Standard Document," no. 1: 64.

Fes, 2018. La Gouvernance Locale Dans La Lutte Contre l'orpaillage Clandestin En Côte d'Ivoire. Regard Jeune, Analyses Politiques sur la Cote d'Ivoire https://library.fes.de/pdf-files/bueros/elfenbeinkueste/14575/2018-01.pdf.
Foody, G.M., Mathur, A., 2004. Toward Intelligent Training of Supervised Image Classifications: Directing Training Data Acquisition for SVM Classification. Remote Sens. Environ. 93 (1–2), 107–117. https://doi.org/10.1016/j.rse.2004.06.017.
Forkuor, G., Ullmann, T., Griesbeck, M., 2020. Mapping and Monitoring Small-Scale Mining Activities in Ghana Using Sentinel-1 Time Series (2015–2019). Remote Sensing 12 (6), 911. https://doi.org/10.3390/rs12060911.
Gallay, M., Martinez, J.-M., Allo, S., Mora, A., Cochonneau, G., Gardel, A., Doudou, J.-C., Sarrazin, M., Chow-Toun, F., Laraque, A., 2018. Impact of land degradation from mining activities on the sediment fluxes in two large rivers of French Guiana. Land Degrad. Dev. 29 (12), 4323–4336. https://doi.org/10.1002/ldr.3150.
Gibb, H., O'Leary, K.G., 2014. Mercury exposure and health impacts among individuals in the artisanal and small-scale gold mining community: a comprehensive review. Environ. Health Perspect. 122 (7), 667–672. https://doi.org/10.1289/ehp.1307864.
Gond, V., Brognoly, C., 2005. Télédétection et aménagement du territoire : localisation et identification des sites d'orpaillage en Guyane française. Bois et Forêts des tropiques 286 (4), 5–13.
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202 (December), 18–27. https://doi.org/10.1016/j.rse.2017.06.031.
Graphic D. 2018. New Policy Framework on Small-Scale Mining out on Friday - Graphic Online, 14. https://www.graphic.com.gh/news/general-news/ghana-news-govt-to-announce-new-policy-framework-on-small-scale-mining-friday.html.
Hentschel, T., Hruschka, F., Priester, M., 2003. Artisanal and Small-Scale Mining: Challenges and Opportunities. WBCSD, London: IIED.
Herold, M., Gardner, M.E., Roberts, D.A., 2003. Spectral Resolution Requirements for Mapping Urban Areas. IEEE Trans. Geosci. Remote Sens. 41 (9), 1907–1919. https://doi.org/10.1109/TGRS.2003.815238.
Hilson, G., 2008. 'A Load Too Heavy': Critical Reflections on the Child Labor Problem in Africa's Small-Scale Mining Sector. Children Youth Services Review 30 (11), 1233–1245. https://doi.org/10.1016/j.childyouth.2008.03.008.
Hilson, G., 2009. Small-scale mining, poverty and economic development in sub-saharan africa: an overview. Resour. Policy 34 (1–2), 1–5. https://doi.org/10.1016/j.resourpol.2008.12.001.
Hilson, G., 2011. Artisanal mining, smallholder farming and livelihood diversification in rural sub-Saharan Africa: an introduction: Artisanal Mining in Rural Sub-Saharan Africa. J. Int. Dev. 23 (8), 1031–1041. https://doi.org/10.1002/jid.1829.
Hilson, G., Hilson, A., Maconachie, R., McQuilken, J., Goumandakoye, H., 2017. Artisanal and Small-Scale Mining (ASM) in Sub-Saharan Africa: Re-Conceptualizing Formalization and 'Illegal' Activity. Geoforum 83 (July), 80–90. https://doi.org/10.1016/j.geoforum.2017.05.004.
IGF. 2016. Senegal Mining Policy Framework Assessment." ntergovernmental Forum on Mining, Minerals, Metals and Sustainable Development (IGF. https://www.iisd.org/system/files/publications/senegal-mining-policy-framework-assessment-en.pdf?q=sites/default/files/publications/senegal-mining-policy-framework-assessment-en.pdf.
Isidro, C.M., McIntyre, N., Lechner, A.M., Callow, I., 2017. Applicability of Earth Observation for Identifying Small-Scale Mining Footprints in a Wet Tropical Region. Remote Sensing 9 (9), 945. https://doi.org/10.3390/rs9090945.
Isung, C.B., Salifu, Y., Agana, T.A., 2021. The Socio-Economic Implications of Artisanal and Small-Scale Mining on Mining Communities in Northern Ghana. OALib 08 (03), 1–17. https://doi.org/10.4236/oalib.1107010.
Kinyondo, A., Huggins, C., 2021. State-led efforts to reduce environmental impacts of artisanal and small-scale mining in tanzania: implications for fulfilment of the sustainable development goals. Environ. Sci. Policy 120 (June), 157–164. https://doi.org/10.1016/j.envsci.2021.02.017.
Kranjčić, N., Medak, D., Župan, R., Rezo, M., 2019. Support vector machine accuracy assessment for extracting green urban areas in towns. Remote Sensing 11 (6), 655. https://doi.org/10.3390/rs11060655.
Kuhn, Max, Kjell Johnson. 2013. Applied Predictive Modeling. New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-6849-3.
Kumar, L., Mutanga, O., 2018. Google Earth Engine Applications Since Inception: Usage, Trends, and Potential. Remote Sensing 10 (10), 1509. https://doi.org/10.3390/rs10101509.
Connette, LaJeunesse, Katherine, G.C., Bernd, A., Phyo, P., Aung, K., Tun, Y.e., Thein, Z., Horning, N., Leimgruber, P., Songer, M., 2016. Assessment of mining extent and expansion in Myanmar based on freely-available satellite imagery. Remote Sensing 8 (11), 912. https://doi.org/10.3390/rs8110912.
Lefebvre, A., Sannier, C., Corpetti, T., 2016. Monitoring Urban Areas with Sentinel-2A Data: Application to the Update of the Copernicus High Resolution Layer Imperviousness Degree. Remote Sensing 8 (7), 606. https://doi.org/10.3390/rs8070606.
Lewis, H.G., Brown, M., 2001. A Generalized Confusion Matrix for Assessing Area Estimates from Remotely Sensed Data. Int. J. Remote Sens. 22 (16), 3223–3235. https://doi.org/10.1080/01431160152558332.
Liman, H., Obaje, N., Aliyu, A.S., Nwaerema, P., 2021. Impact evaluation of artisanal and small-scale mining on land use land cover: implication for sustainable mining environment in Niger State, Nigeria. J. Earth Sci. Geotech. Eng. https://doi.org/10.47260/jesge/01133.
Lobo, Felipe. 2015. Spatial and Temporal Analysis of Water Siltation Caused by Artisanal Small-Scale Gold Mining in the Tapajós Water Basin, Brazilian Amazon: An Optics and Remote Sensing Approach. Ph.D., University of Victoria. https://doi.org/10.13140/RG.2.1.4455.6247.
Lobo, F., Costa, M., Novo, E., Telmer, K., 2016. 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 Sensing 8 (July), 579. https://doi.org/10.3390/rs8070579.
Lobo, Felipe de Lucia, Evlyn Márcia Leão de Moraes Novo, Claudio Clemente Faria Barbosa, and Vitor Hugo Fernandes de Vasconcelos. 2018. "Monitoring Water Siltation Caused by Small-Scale Gold Mining in Amazonian Rivers Using Multi-Satellite Images. Limnology - Some New Aspects of Inland Water Ecology, November. https://doi.org/10.5772/intechopen.79725.
MacDonald, Karen. 2006. Artisanal and Small-Scale Mining in West Africa: Achieving Sustainable Development through Environmental and Human Rights Law. In: Small-Scale Mining, Rural Subsistence and Poverty in West Africa, edited by Gavin Hilson, Chapter 7:75–101. Rugby, Warwickshire, United Kingdom: Practical Action Publishing. https://doi.org/10.3362/9781780445939.
Machácek, Jan. 2020. Alluvial Artisanal and Small-Scale Mining in A River Stream—Rutsiro Case Study (Rwanda). 24. https://doi.org/10.3390/f11070762.
Mantero, P., Moser, G., Serpico, S.B., 2005. Partially Supervised Classification of Remote Sensing Images through SVM-Based Probability Density Estimation. IEEE Trans. Geosci. Remote Sens. 43 (3), 559–570. https://doi.org/10.1109/TGRS.2004.842022.
Martin, Alan, Hélène Helbig de Balzac, and Partnership Africa Canada. 2017. L'Eldorado ouest-africain: cartographie du commerce illicite de l'or en Côte d'Ivoire, au Mali et au Burkina Faso. Ottawa: Partenariat Afrique Canada.
Mielke, C., Boesche, N., Rogass, C., Kaufmann, H., Gauert, C., de Wit, M., 2014. Spaceborne Mine Waste Mineralogy Monitoring in South Africa, Applications for Modern Push-Broom Missions: Hyperion/OLI and EnMAP/Sentinel-2. Remote Sensing 6 (8), 6790–6816. https://doi.org/10.3390/rs6086790.
MIM. 2014. "Programme Rationalisation de l'Orpaillage." Ministere de l'Industrie et des Mines, Cote d'Ivoire. http://mines.gouv.ci/wp-content/themes/Newsmag/doc/programme_rationalisation_or.pdf.
MINESUDD. 2014. Strtégie Nationale de Lutte Contre Les Changements Climatiques. https://chm.cbd.int/api/v2013/documents/02BD4D5F-376D-457C-0F61-4370D0BCE50E/attachments/207104/STRATEGIE_NATIONALE_CHANGEMENT_CLIMATIQUE.pdf.
Ngom, N.M., Mbaye, M., Baratoux, D., Baratoux, L., Catry, T., Dessay, N., Faye, G., Sow, E.H., Delaitre, E., 2020. Mapping Artisanal and Small-Scale Gold Mining in Senegal Using Sentinel 2 Data. GeoHealth 4 (12). https://doi.org/10.1029/2020GH000310.
Ngom, Ndeye, Marame, David Baratoux, Anne Dessertine, Abdoulatif Abass Saley, Lenka Baratoux, Gayane Faye, Alphonse Yao Kouakou, and Jean Kouamé Kan. 2022. Artisanal Exploitation of Mineral Resources: Remote Sensing Observations of Environmental Consequences, Social and Ethical Aspects. Surveys Geophys. Revision Special Volume "Global change in Afrique.".
Niane, B., Guedron, S., Feder, F., Legros, S., Ngom, P.M., Moritz, R., 2019. Impact of recent artisanal small-scale gold mining in senegal: mercury and methylmercury contamination of terrestrial and aquatic ecosystems. Sci. Total Environ. 669 (March), 32. https://doi.org/10.1016/j.scitotenv.2019.03.108.
Nyamekye, C., Ghansah, B., Agyapong, E., Kwofie, S., 2021. Mapping Changes in Artisanal and Small-Scale Mining (ASM) Landscape Using Machine and Deep Learning Algorithms. - a Proxy Evaluation of the 2017 Ban on ASM in Ghana. Environ. Challenges 3 (April), 100053. https://doi.org/10.1016/j.envc.2021.100053.
Nyanza, E.C., Bernier, F.P., Manyama, M., Hatfield, J., Martin, J.W., Dewey, D., 2019. Maternal Exposure to Arsenic and Mercury in Small-Scale Gold Mining Areas of Northern Tanzania. Environ. Res. 173 (June), 432–442. https://doi.org/10.1016/j.envres.2019.03.031.
Nyanza, E.C., Bernier, F.P., Martin, J.W., Manyama, M., Hatfield, J., Dewey, D., 2021. Effects of prenatal exposure and co-exposure to metallic or metalloid elements on early infant neurodevelopmental outcomes in areas with small-scale gold mining activities in Northern Tanzania. Environ. Int. 149 (April), 106104 https://doi.org/10.1016/j.envint.2020.106104.
Ofosu, G., Dittmann, A., Sarpong, D., Botchie, D., 2020. Socio-economic and environmental implications of artisanal and small-scale mining (ASM) on agriculture and livelihoods. Environ. Sci. Policy 106 (April), 210–220. https://doi.org/10.1016/j.envsci.2020.02.005.
Osborne, T.M., Lawrence, D.M., Slingo, J.M., Challinor, A.J., Wheeler, T.R., 2004. Influence of Vegetation on the Local Climate and Hydrology in the Tropics: Sensitivity to Soil Parameters. Clim. Dyn. 23 (1), 45–61. https://doi.org/10.1007/s00382-004-0421-1.
Sauerwein, Titus. 2017. Formalizing Artisanal and Small-Scale Gold Mining; A Case Study of Côte d'Ivoire. https://studenttheses.universiteitleiden.nl/handle/1887/52587.
Sauerwein, T., 2020. Gold Mining and Development in Côte d'Ivoire: Trajectories, Opportunities and Oversights. Land Use Policy 91 (February), 104323. https://doi.org/10.1016/j.landusepol.2019.104323.
Schwartz, F.W., Lee, S., Darrah, T.H., 2021. A Review of the Scope of Artisanal and Small-Scale Mining Worldwide, Poverty, and the Associated Health Impacts. GeoHealth 5 (1). https://doi.org/10.1029/2020GH000325.
Seifi, A., Hosseinjanizadeh, M., Ranjbar, H., Honarmand, M., 2019. Identification of Acid Mine Drainage Potential Using Sentinel 2a Imagery and Field Data. Mine Water Environ. 38 (4), 707–717. https://doi.org/10.1007/s10230-019-00632-2.
Singo, P., Seguin, K., 2018. Best Practices: Formalization and Due Diligence in Artisanal and Small-Scale Mining. Best Practices 24.
Snapir, B., Simms, D.M., Waine, T.W., 2017. Mapping the Expansion of Galamsey Gold Mines in the Cocoa Growing Area of Ghana Using Optical Remote Sensing. Int. J.

Appl. Earth Obs. Geoinf. 58 (June), 225–233. https://doi.org/10.1016/j.jag.2017.02.009.

Soko, C., 2019. L' économie minière de l'orpaillage artisanal dans les sociétés post-conflit : jeux des acteurs et enjeux de développement et de coopération internationale. Étude de cas en Côte d'Ivoire. Revue Organisations & territoires 28 (1), 61–79. https://doi.org/10.1522/revueot.v28n1.1023.

Soro, G., Yao, A., Kouame, Y., Bi, T., 2017. Climate Change and Its Impacts on Water Resources in the Bandama Basin, Côte D'ivoire. Hydrology 4 (1), 18. https://doi.org/10.3390/hydrology4010018.

Souza-Filho, P.W.M., Lobo, F., Cavalcante, R., Mota, J.A., Nascimento, W., Santos, D.C., Novo, E., Barbosa, C.C.F., Siqueira, J.O., 2021. Land-Use Intensity of Official Mineral Extraction in the Amazon Region: Linking Economic and Spatial Data. Land Degrad. Dev. 32 (4), 1706–1717.

Swenson, Jennifer J., Catherine E. Carter, Jean-Christophe Domec, and Cesar I. Delgado. 2011. "Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports." Edited by Guy J-P. Schumann. PLoS One 6 (4): e18875. https://doi.org/10.1371/journal.pone.0018875.

Telmer, Kevin, and Daniel Stapper. 2007. "UNIDO PROJECT EG/GLO/01/G34 FINAL REPORT," 49.

Van Bockstael, Steven. 2019. Land Grabbing 'from below'? Illicit Artisanal Gold Mining and Access to Land in Post-Conflict Côte d'Ivoire. Land Use Policy 81 (February): 904–14. https://doi.org/10.1016/j.landusepol.2018.04.045.

Weinhouse, C., Gallis, J.A., Ortiz, E., Berky, A.J., Morales, A.M., Diringer, S.E., Harrington, J., Bullins, P., Rogers, L., Hare-Grogg, J., Hsu-Kim, H., Pan, W.K., 2021. A Population-Based Mercury Exposure Assessment near an Artisanal and Small-Scale Gold Mining Site in the Peruvian Amazon. J. Eposure Sci. Environ. Epidemiol. 31 (1), 126–136.

World Health Organization. 2017. Environmental and occupational health hazards associated with artisanal and small-scale gold mining. https://apps.who.int/iris/bitstream/handle/10665/247195/9789241510271-eng.pdf?sequence=1&ua=1.