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ISSN 2183-0843

Working Paper No 2201

March 2022

NOVAFRICA Working Paper

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Artisanal mining in Africa*

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Current version: March 3, 2022– [click HERE for updated version](#)

Abstract

The livelihoods of 130 to 270 million people depend on artisanal and small-scale mining (ASM), a labor-intensive method of mineral extraction. Based on geological mapping and gold price variations in a yearly panel of 10,628 fine-grained cells, we provide the first estimation of the environmental and wealth impacts of the main form of ASM, gold ASM, throughout the African continent. We first demonstrate that artisanal mining leads to tropical deforestation and vegetation degradation. We find that the historical increase in the gold price accounts for 20 percent of the total deforestation in the gold-prone tropical regions in Africa. Second, we contrast these negative environmental impacts with the positive economic effects of ASM, which increases nighttime light emissions and households wealth. Last, we show how droughts magnify the effects of ASM, suggesting that mining may be a way for households to diversify their livelihoods when agricultural incomes fall short. These results are policy relevant: a one standard deviation increase in artisanal gold mining revenues increases wealth by 2% of a standard deviation, an effect larger than the effect of drought alone on wealth.

JEL Codes: O13, O55, Q32, Q56.

Keywords: artisanal mining, drought, gold, natural resources.

*We thank Alex Armand, Andrew Foster, Thomas Fujiwara, Craig McIntosh, Nathalie Monnet, Jean-Philippe Platteau, Ariane Salem, and seminar participants in Nova SBE and the University of Alicante for their helpful comments. We thank Alex Armand, Nicolas Berman and Frits Steenhuisen for sharing their codes or data with us. Victoire Girard acknowledges funding by the Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722) and POR Norte. Teresa Molina-Millán acknowledges financial support from Generalitat Valenciana through the plan GenT program (CDEIGENT/2020/016).

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1 Introduction

Artisanal and small-scale mining (ASM) provides livelihoods to 2 to 3% of the world’s population (World Bank, 2020). In Africa alone, 60 million people depend of this labor-intensive way to extract minerals (World Bank, 2019).¹ Artisanal gold mining, the main employer in the ASM sector, extracts a fifth of the global gold supply (Hilson, 2016; IGF, 2018). The miners extract the ground from deep underground tunnels or wide surface holes before separating the gold from the rest, often using chemicals. The activity destroys soils, forests and fields, and is estimated to be the main source of anthropogenic mercury emissions (Caballero Espejo et al., 2018; Pacyna et al., 2016). However, despite the scale of the activity and its potential consequences, we still know little about the causal impacts of ASM.

This paper provides the first quantitative evidence of the environmental effects of ASM throughout the African continent, of its concomitant economic effects, and discusses the possibility that households turn to ASM as an adaptation strategy to droughts. We focus on artisanal gold mining as it is the main employer in the artisanal mining sector in Africa.² The key challenge is to assess the existence and extent of artisanal and small-scale gold mining activities. ASM is a largely informal sector and, as often with informal activities, we face a paucity of data (World Bank, 2019). To overcome this challenge, we transpose to the study of mining the notion of suitability largely used for crops since Nunn and Qian (2011).

Our identification strategy relies on a spatial and a temporal source of variation in ASM activities, both of which are exogenous to households’ actions. For spatial variation, we exploit the fact that artisanal gold mining requires geologically suitable locations. All the gold-suitable locations will not constantly host ASM, however, if gold ASM is to take place, it will be most successful within these locations. We isolate the features of these locations from Thieblemont and BRGM (2016)’s comprehensive mapping of Africa’s geology, and establish that 18 percent of the total surface of Africa is suitable for gold ASM. The temporal variation comes from changes in the international price of gold over time. The potential revenues from artisanal gold mining directly depend on the international price of gold, and miners are price takers on this market which they

¹“When combining ASM’s direct labor figure with its indirect one—at least a further 134 million and perhaps as many as 269 million people depending on the multiplier used are supported in service and downstream industries” (World Bank, 2020), while, “By region, sub-Saharan Africa is home to one of the largest numbers of artisanal and small-scale miners in the world, close to an estimated 10 million, with at least a further 60 million people who derive a livelihood or are supported by its activities in associated industries.” (World Bank, 2019).

²Hilson (2016); Tyschen J. (2019) and Table A-1. Artisanal diamond and gems mining in contrast – the second source of artisanal employment – concerns a much smaller number of people, has important heterogeneities in quality and does not have an unique market (Bergenstock, Maskulka et al., 2001). Unlike gold which is usually processed to reach the unified standards of purity, diamonds and gems heavily differ in their quality when extracted from the ground, leading to many sub-markets by quality.

closely follow (Alvarez, Coué, and Patrick, 2016; Balme and Lanzano, 2013; Sánchez De La Sierra, 2020).³ Our rich set of fixed effects accounts for any unobserved heterogeneity that is cell specific or time and country specific – such as gold suitability, macroeconomic shocks to the gold price, or any change in the legal status of ASM in a country. We document the within-gold area panel variation in each outcome steaming from exogenous changes in the international gold price. Furthermore, to isolate the effects of artisanal gold mining, we explicitly and separately account for income shocks in agriculture, industrial mining (including industrial gold mining) and climatic shocks.

We combine satellite imagery, household surveys, and geological data, in a yearly Africa-wide panel. We isolate gold-suitable bedrocks and intersect the location of these gold bedrocks with the PRIO-Grid cells – a worldwide standardized grid of 0.5×0.5 degrees cells, or 55×55 kilometers at the Equator – which are our main unit of analysis. The full data for the African continent covers over 10,000 fine-grained cells between 1992-2019. The extent of the years coverage varies depending on the outcome of interest.

Results shows that artisanal gold mining significantly degrades its surrounding environment. We first consider tropical deforestation. Tropical deforestation is a prime area of policy concern given forests’ environmental services (Hansen et al., 2013; Curtis et al., 2018). We find that the historical increase in the gold price accounts for 20 percent of the total deforestation in the gold-prone tropical regions in Africa. This effect is independent from the opening or closing of industrial gold mines, or other local shocks such as droughts or a surge in agricultural prices. Alternatively, we can look at vegetation health as measured by the Normalized Difference Vegetation Index (NDVI, retrieved from [Didan, na](#)). The NDVI captures any variations taking place in a heterogeneous setting of baseline levels of vegetation (including sparse wild vegetation, crops, etc.), complementing the deforestation data. We find that ASM significantly lowers vegetation health.

Recognizing these environmental damages, we question whether ASM provides economic benefits, a controversial issue.⁴ We analyze the impact of ASM on two complementary economic outcomes: nighttime light emissions, and household wealth (for which we switch to a household level analysis).⁵ Nighttime lights inform us about continent-wide yearly changes in local economic activities stemming from households, firms, or states. In contrast, measures of household wealth are available only for the 31 (out of 54)

³An estimated 2 millions people were active in the African ASM sector in 1999, in 20 years this number has been multiplied by five (World Bank, 2019). Over the same period, the gold price was multiplied by four. The same increase has been observed worldwide, where the number of people directly involved in the activity is estimated to have increased from 13 million in 1999 to 40.5 million in 2017, and many more through linkages (IGF, 2018; World Bank, 2020).

⁴A wide-spread view being that “artisanal mining, [in] many rural areas may cause severe environmental and health risks, conflict and generally few economic benefits.” (Cust and Poelhekke, 2015), studies suggest that artisanal mining may have a positive link with both conflicts and economic outcomes (e.g. World Bank, 2019; Bazillier and Girard, 2020; Rigterink, 2020; World Bank, 2020).

⁵Bruederle and Hodler (2018) discuss the overlap between both data.

African countries covered by the Demographic and Health Surveys (DHS), but have the interest of focusing exclusively on local inhabitants. We find a positive and significant effect of ASM on both measures. The estimated effects are larger than the effects of an increase of comparable magnitude for prices in agriculture, or of avoiding a drought. Using data on the economic activity of the respondent and their spouse in the DHS, we also confirm that gold suitability increases the likelihood of being involved in extractive activities. Although the DHS data on economic activities is limited, this set of results establishes for the first time the link between gold suitable locations and household income continent-wide. Overall, the results highlight the tradeoff between economic development and environmental conservation.

Finally, we analyze whether ASM allows households to diversify their sources of livelihoods. As extreme weather events are expected to become more common with global warming the adaptation of farming strategies became an area of concern (Bryan et al., 2013). However, given the low barriers to entry, smallholder farmers may also turn to ASM for supplementary income during periods of adverse weather conditions (Hilson, 2016), provided that they can access mineral deposits. Results confirm that ASM acts as an important livelihood diversification strategy in periods of drought. During a drought, deforestation appears to be more likely to happen in gold suitable cells, in which we also observe a statistically significant increase in night-light emissions.

These results contribute to four main strands of the literature. First, in light of the large debate about how economic development affect the environment (reviewed in Jayachandran, 2022), this paper establishes the relevance of ASM across the African continent. ASM appears to be both an important driver of economic development, but also a major driver of deforestation and environmental degradation. As climate change increases pressure on agricultural households in Africa (Collier, Conway, and Venables, 2008), researchers and policy stakeholders need more than ever to get a clear vision of the role ASM may play as a source of livelihood (Hilson and Maconachie, 2020), and with which associated environmental or societal costs.

We also contribute to the growing literature on the economic drivers of tropical deforestation by dragging attention to the role of artisanal mines. This literature focuses on the impacts of agricultural expansion (e.g. Angelsen, 1999; DeFries et al., 2010; Doggart et al., 2020; Faria and Almeida, 2016; Berman et al., 2021), sometimes extending to the question of industrial mining or urbanization (Curtis et al., 2018). Artisanal mining, like agriculture, is widespread in the continent, and is a source of local income fluctuating with international prices. However, while sustainable agriculture may take place, forest may slowly (re)grow in former fields, or some agriculture may happen below the canopy, sustainable mining is an oxymoron. We document economically and politically significant

impacts of ASM on deforestation in Africa.⁶

These results may be of concern for the literature on livelihoods diversification in front of climate shocks. We are expected to face an increase in the number or intensity of weather shocks with global warming (Trenberth et al., 2014). In light of such shocks, a recent literature shows that agricultural households may adjust their farming activity or resort to migration (e.g. Bryan et al., 2013; Fisher et al., 2015; Carleton and Hsiang, 2016; Cattaneo and Peri, 2016; Ali and Erenstein, 2017; Mueller et al., 2020).⁷ We show that yet an alternative option is to turn to artisanal mining. ASM may be the most rational choice for each individual as mining areas do see an increase in nighttime light emissions during droughts. However, unlike adaptation through alternative agricultural practices or migration, mining raises concerns of a vicious circle. Mining, by increasing deforestation, risks to increase future droughts (Bagley et al., 2014), leading to more mining and deforestation.

Lastly, we contribute to the scarce literature on artisanal mining by providing a novel methodology and data. Recent works use satellite data to proxy for outcomes that we cannot otherwise measure directly or immediately, such as illegal logging (Alix-Garcia, Sims, and Yañez-Pagans, 2015) or real-time conflict destruction (Mueller et al., 2021). We draw attention to the potential of geological data. Compared to alternative ASM measures – namely administrative registers, field surveys, or machine learning over fine grain maps (Bazillier and Girard, 2020; Sánchez De La Sierra, 2020; Romero and Saavedra, 2016; Ngom et al., 2020) – geological suitability provides a cost-efficient and quasi-experimental source of variation, available at a large spatial scale, which we make available for the research and policy communities.

The remainder of the article starts with a description of the context of artisanal mining activities and the operationalization of our measure of this activity. The following section presents our identification strategy, before presenting the empirical results in terms of ASM impacts, and ASM potential as a source of livelihood diversification strategy. The last section concludes.

2 Artisanal gold mining : context and measure

The first challenge to assess the impact of artisanal gold mining is to know where and when it is taking place. This section describes how we overcome this challenge.

⁶The magnitude of these impacts aligns with the magnitudes of impacts suggested in (Caballero Espejo et al., 2018) for the mining area of Madre de Dios in the Peruvian Amazon.

⁷According to the World Bank’s World Development Indicators, this sector has always employed more than 50% of the population in Sub-Saharan Africa since 1998. Global warming poses a threat to the livelihoods of these households.

2.1 Artisanal gold mining location

Artisanal gold mining requires the presence of gold in the ground or rivers. The geological formation of the African continent is such that primary and alluvial gold deposits are found almost exclusively in Archean domains and Proterozoic orogens, almost always associated with large crustal-scale shear zones, and are mainly of the orogenic gold type (Goldfarb, Groves, and Gardoll, 2001). Most of the gold suitable zones are associated with greenstone belts, meaning sedimentary, volcano-sedimentary and volcanic formations metamorphosed in the faces of green schist during various orogenic events (Frost-Killian et al., 2016; Markwitz, Hein, and Miller, 2016; Robertson and Peters, 2016; Henckel et al., 2016). These types of mineralization are also well known in Archean cratons (Congo craton, Kenema-Man craton, Tanzanian craton), in the Eburnean Paleoproterozoic domains (Birimian in West Africa, Ubendian Orogenic belt in Tanzania, Limpopo belt in Zimbabwe and South Africa) and finally in the Panafrican mobile belts (Nubian belt, the Damara belt in Namibia and the trans-Saharan mobile belt in the Hoggar) (Kirk et al., 2002; Gabert, 1990; Goldfarb et al., 2017; Masurel et al., 2019). Gold mineralization associated with the most recent panafrican orogenic cycle presents more varied typologies than those associated with the Archean and Paleoproterozoic due to different orogenic dynamics and a large amount of re-mobilized older rocks (Kpeou et al., 2020; Fagbohun et al., 2020; Bjerkgard et al., 2009; Elsamani, Almuslem, and Tokhi, 2001). More rarely, secondary occurrences, of the placer and paleo placer type, can be located at the edge of intracratonic and coastal sedimentary basins Neoproterozoic to present. We present a more complete characterization of the gold mineralization in the continent in the Appendix section A-6.2.

We build upon this geological necessity to assess where artisanal mining may take place. We exploit the most recent mapping of the contours, age and chemical composition of the African geological bedrocks (Thieblemont and BRGM, 2016). In Figure A-1 panel (a) we isolate the geological stratas that correspond to geological ages prone to gold mineralization. In panel (b) we isolate the lithologies prone to hosting gold. A bedrock needs to meet both the strata and the lithology criteria to be suitable for gold ASM. Figure A-1(a) shows where these bedrocks are located. 18% of the surface of the continent is suitable for artisanal gold mining.

2.2 Artisanal gold mining timing

The number of people involved in artisanal gold mining, and the revenues they get, evolves in time. We exploit the fact that this evolution depends on the level of the international gold price and that artisanal miners are price-takers on the international gold market.

Prices in local gold markets are highly correlated with the international price (Balme and Lanzano, 2013; Sánchez De La Sierra, 2020). Artisanal miners follow the international

gold market through news or cell-phones and local buyers pay gold diggers a percentage – typically above 83% for places with available data – of the world gold price (Alvarez, Coué, and Patrick, 2016). As a result, a high international gold price may increase ASM both at the intensive and extensive margin. Put differently, when the gold price is high, ASM workers may put more effort or new workers may join.

In the last 20 years, the international price of gold increased more than fourfold, fueling public and private interest in ASM. The estimated number of people directly involved in the activity increased from 13 million in 1999 to 40.5 million in 2017, and many more through linkages (IGF, 2018).

A push factor may be also be at play next to the role of the pulling gold price: droughts. According to the World Bank’s World Development Indicators, the agricultural sector has employed more than 50% of the population in Sub-Saharan Africa since 1998. Since a large share of the agricultural sector is rain-fed, droughts and other adverse weather events put livelihoods at risk and push households towards other economic activities (Gueye, 2001; Hilson and Garforth, 2012). The final section of this paper investigates the heterogeneous impacts of droughts on gold and non-gold sites (Section 5).

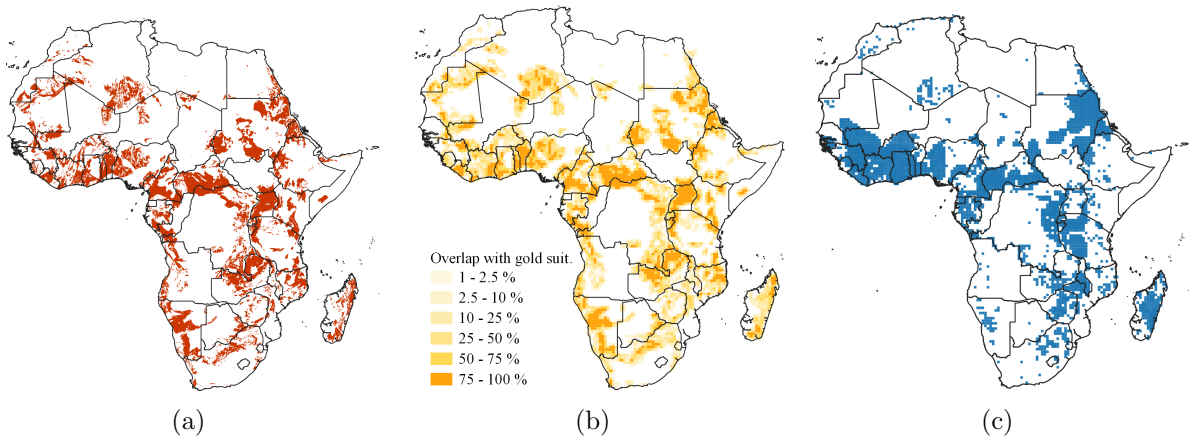
2.3 Measuring artisanal gold mining

Knowing where ASM may take place and the revenues it generates, we define the first continent-wide measure of ASM activities which varies in place and time. We multiply the international gold price by the variable capturing whether the geology of each site is suitable for ASM. We account for variations in the potential revenues of ASM activities through the international gold price. We consider a price index (base 1 in 2013) with one year lag to households to adjust their activities. We illustrate the performance of alternative ways to account for price variations in Table A-2.

We define geological suitability as the share of the fine-grained PRIO-Grid cell which overlaps with ASM suitable bedrocks: the variable takes continuous values between 0 (for non suitable cells) and 1 (for cells which entirely overlap with gold-suitable bedrocks). The African continent is divided in more than 10,000 PRIO-Grid cells, a standardized fine grain grid of 0.5×0.5 degrees cells (about 55×55 kilometers at the Equator) (Tollefsen, Strand, and Buhaug, 2012).⁸ Figure 1(b) shows the share of each cell that is suitable for ASM, this share allows us to keep a maximum amount of information from the raw bedrock-level data presented in Figure 1(a). About 42% of the PRIO-Grid cells in Africa have some overlap with an ASM-suitable bedrock.

⁸The information on bedrock suitability for ASM presented in Figure A-2 can be exploited at various levels of aggregation, such as the overlap with agro-climatic zones, rivers, or households dwellings, etc., depending on future research questions. The widely used PRIO-Grid cells are particularly well suited for our objective, which is to precisely measure the evolution of local outcomes – such as vegetation cover or wealth – while keeping a large-scale coverage.

Figure 1: Geological suitability, known ASM and other gold hints



Notes: (a) Map of the geological bedrocks suitable for artisanal gold mining in Africa. (b) Prevalence of bedrock geology suitable for gold mining at the PRIO-Grid cell level (55×55 kilometers at the Equator). (c) Known incidence of gold and of artisanal gold mining at the PRIO-Grid cell level. The map shows: (i) cells with at least one of the 9,617 manual records made by the BRGM exploration geologists when they witness gold incidence during their field work; (ii) gold records from the GOLDATA source included in the PRIO-Grid database (Balestri, 2015); (iii) administrative records of ASM obtained from the Ministry of Mines in Burkina Faso in 2015; (iv) survey records of ASM made by the IPIS in sub-regions of the Central African Republic (2019), Democratic Republic of Congo (2019), Tanzania (2019) and Zimbabwe (2018,2019); and, (v) cells with mercury emissions due to ASM estimated to be superior or equal to 3kg per area of 0.05×0.05 degrees within that cell (Steenhuisen and Wilson, 2019); which are represented separately in Figure A-2.

We confirm the high correlation between cells geological suitability to artisanal gold mining and other known records of the activity. We favor the geological measure over known records as each record is likely to be incomplete, many focusing on a sub part of the continent (as is clear from Figure A-2), and some are endogenous (the choice of study sites, or of performing an administrative registration, may stem from policy or economic interests). We combine all records into the most comprehensive measure possible, a dummy taking value one in a cell whenever at least one record of ASM or gold exists in that cell (represented in Figure 1(c)). The correlation between the dummy for all these records and our baseline measure of cells' geological suitability is 37% (p-value below 0.01). Figure A-2 and Table A-2 detail this correlation for alternative data sources and data curation approaches.

3 Identification strategy

The purpose of our empirical strategy is to estimate how artisanal gold mining affects environmental and wealth outcomes. In order to address causality, we focus on exogenous variations in the economic value of potential artisanal mines. As the value of the gold increases, the revenues of mining a gold deposit increases, increasing the likelihood that mining takes place, and the subsequent environmental and wealth impacts. To abstract

from other local determinants and guarantee exogeneity, we exploit the variations in the world prices of gold. At the cell level, the first specification we consider is the following:

$$Y_{ct} = \alpha_1 + \alpha_2 \text{ gold suitable}_c \times \text{gold price}_{t-1} + FE_c + FE_{t \times Country} + \varepsilon_{ct} \quad (1)$$

Where Y_{ct} is the environmental or wealth outcome of interest, i.e., deforestation share, vegetation health (NDVI), or nighttime lights emission, in cell c , and year t (we present the estimation for the household-level outcome below). The dependent variables are presented in the next section as we discuss results. The rest of the data we use is presented in detail in section [A-6.1](#). All variables descriptive statistics appear in [Table A-3](#).

The variable $\text{gold suitable}_c \times \text{gold price}_{t-1}$ is our measure of artisanal mining activities, it is the interaction of the proportion of the surface of the cell c which is gold suitable with the value of the world gold price with a one year lag (in $t - 1$), as described in the previous section.

The cell fixed effects FE_c account both for the main effect of the cell being suitable for gold ASM, and for any other local features, such as a cell's remoteness, exposure to climatic variability, etc. $FE_{t \times Country}$ account for any time varying change at the country such as changes in institutions, changes in environmental policy or the legal status of ASM. These fixed effects also account for any year specific feature such as a price shock in the international commodity price market. We cluster standard errors at the cell level. We also assess in [Table A-8](#) the robustness of our results to resorting to standard errors accounting for spatial and temporal correlation in error terms ([Conley, 1999](#); [Hsiang, Meng, and Cane, 2011](#); [Collela et al., 2018](#)).

For each cell, our first set of baseline results rest on the within-cell panel variation coming from exogenous changes in the international gold price, accounting for a rich set of time-varying, country-specific, unobserved heterogeneity.

We need to keep in mind that with this approach, our estimates will provide a lower-bound approximation of the true effects of ASM. Indeed, not every location above the ASM bedrocks will host an active artisanal mine during every year with a high gold price. Hence, our analysis will consider some non-treated places (places without mining) as treated (with mining). Conversely, a secondary artisanal mine may lie outside the bedrocks (for example because a river carried some ore away), or may continue in operation during periods of lower gold price. Hence, some treated places will be considered non-treated. Put differently, the noise in the measurement of ASM corresponds to a mutual contamination of the treatment and control samples, that will lead to an attenuation bias when measuring the impact of ASM.⁹

⁹To get a sense of the magnitude of the approximation on the spatial dimension, we can levy in-

Our second set of baseline results extends equation 1 to account for time-varying cell-level factors which might be correlated with variations in the international gold price, such as industrial gold exploitation, agricultural prices or weather conditions. To control for time-varying weather conditions we include the average Standardized Precipitation and Evapotranspiration Index (SPEI) during the first three months of PRIO cell’s rainy season (similar to Harari and Ferrara, 2018). Everything else equal, higher rain will increase the SPEI. As ASM can be replaced by industrial mining (Bazillier and Girard, 2020; Stoop and Verpoorten, 2020), we include an interaction between an indicator variable equal to one if the cell has a record of hosting an industrial mine, and the annual price of that industrial mineral (as in Berman et al., 2017). We investigate in more detail the potential role of industrial gold mines in section 4.4.¹⁰ Finally, we include a control variable on cell’s crop suitability which consists on the interaction between each cell’s most suitable crop multiplied by its’ international price. This measure is similar to that used in McGuirk and Burke (2020), except that like Nunn and Qian (2011) we use the suitability for the crop rather than the actual main crop – suitability is more exogenous to local actions, and best mirrors for crops the approach of gold suitability. Each variable is described in more detail in the Appendix (section A-6.1). We consider variations to the specification of these control variables in our sensitivity analysis (section 4.4).

Alternatively, to assess the causal relation between ASM and outcomes at the household level, we estimate the following equation:

$$Y_{ict} = \alpha_1 + \alpha_2 \text{gold suitable}_c \times \text{gold price}_{t-1} + \beta' X_{it} + FE_c + FE_{t \times Country} + \varepsilon_{ct} \quad (2)$$

Where Y_{ict} is the outcome of interest, i.e., DHS household wealth factor or probability that any household member works in the extractive sector, for household i in cell c , and year t . X_{it} is a vector of household controls including a dummy for residence in rural area, the age and its square (for the respondent and her partner), the level of education (9 categories, for the respondent and her partner), the household size, and a dummy for the month of the interview. The remainder of the equation and controls is similar to that discussed above for the cell-level outcomes.

formation from Burkina Faso. Burkina Faso offers a country-wide administrative record of artisanal gold mines as well as detailed surveys of households consumption. Administrative records are prone to an upward bias as they takes time and money, raising concerns that the smallest artisanal mines may not be registered. Still, when available, administrative records overlap remarkably well with geological suitability as shown in Bazillier and Girard (2020). Moreover, Bazillier and Girard (2020) report similar impacts on households consumption when using the administrative or geological suitability measures of artisanal mines presence. The attenuation bias of using the geological suitability for ASM appears to be about 30% of the upper bound effects of ASM as measured through administrative registers.

¹⁰338 cells, that is, less than 2% of the sample, host an industrial gold mine at some point in time.

4 The environmental and wealth impacts of artisanal mining

4.1 Environmental impacts

We consider two dimensions of ASM impacts on the environment: impacts on deforestation, and on plant health. ASM intensification means that (i) wild vegetation and forest or agricultural fields are replaced and/or polluted by mines or miners settlements, and (ii) households may abandon their fields if they switch from agriculture to mining. These negative effects on vegetation health may be attenuated when ASM is used as a productive complement to agriculture (Hilson and Maconachie, 2020). We document the net environmental impact of ASM.

Deforestation. Our first outcome of interest is deforestation in the tropics. Tropical forests are under scrutiny as they provide key environmental services, but 17% of tropical moist forests have disappeared since 1990 (Angelsen, 2010; Vancutsem et al., 2021). We resort to the deforestation data of Hansen et al. (2013), curated for cell level analysis by Berman et al. (2021)¹¹. We consider as a forest any pixel with more than 25% of forest cover and restrict attention to cells in the tropics (Berman et al., 2021; Burgess et al., 2012). Our measure of deforestation is the yearly number of deforested pixels of a cell, divided by the number of forested pixel in that cell in the year 2000 – it takes value 0 if the cell has no forest in year 2000. The variable ranges from 0 (no deforestation) to 1 (all the forest existing in the year 2000 has disappeared).

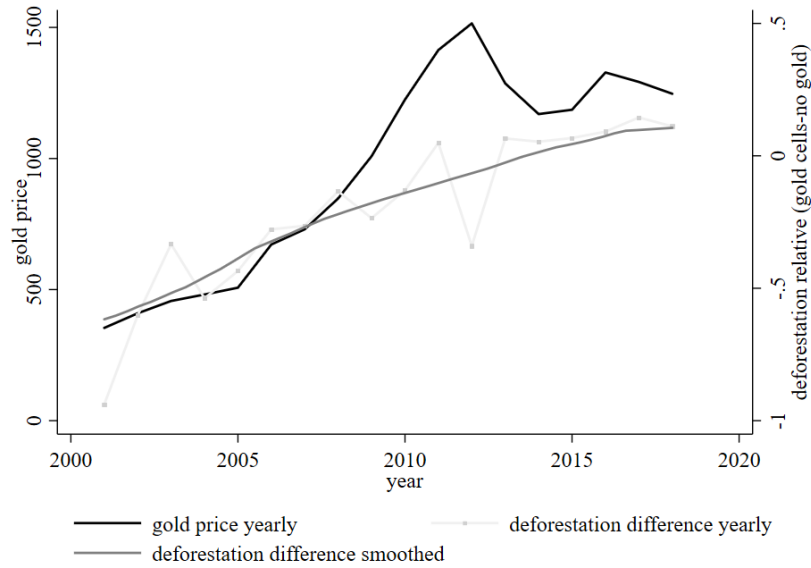
Figure 2 allows to visualize that cells suitable to artisanal gold mining had, on average, less deforestation taking place than other cells at the beginning of the 2000. However, over time, deforestation increased faster in ASM cells than in other cells. This increase coincides with the increase of the gold price over the period 2000-2018.

Vegetation health. Our second outcome of interest is vegetation health, which we measure using the Normalized Difference Vegetation Index (NDVI). The NDVI is a standard and widely used measure of vegetation health based on the difference between near infrared and visible lights (e.g. Alix-Garcia, Sims, and Yañez-Pagans, 2015; Asher and Novosad, 2020). We compute the annual average NDVI for each cell between 2000 to 2018.¹² As the sample consists of heterogeneous agro-climatic zones, many of them with reduced vegetation cover during the dry season, we compute the average of NDVI for the

¹¹Version 1.6 of Hansen et al. (2013) data available at https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.7.html. Hansen et al. (2013) provide estimates of annual tree cover loss for every pixel with more than 1% of forest cover (vegetation taller than 5m height) in 2000 that suffered an estimated loss of more than 50% of the forest cover over the period 2001-2018. Berman et al. (2021) data available at <http://doi.org/10.5281/zenodo.4916785>.

¹²The maximum year coverage available from the NDVI. Available at a resolution of 0.05 degrees in MODIS from MODIS/Terra Vegetation Indices Monthly L3 Global 0.05 Deg CMG.

Figure 2: Artisanal mining value and deforestation over time



Notes: The sample consists of all 0.5×0.5 degree cells in the African tropics, the time frame is annual observations, from 2001 to 2018. We measure deforestation as the share of the forest in a pixel which disappears each year. The “deforestation difference yearly” tells the average of the yearly deforestation in gold suitable cells - deforestation in non gold suitable cells. The “difference smoothed” shows a kernel-weighted local polynomial smoothing of the “deforestation difference yearly”.

three first months of each cells’ rainy season.¹³ To do so, we rely on the rainy season starting month for the cell as recorded in the PRIO-Grid data. Finally, we re-scale the NDVI such that the final variable ranges from -100 (unhealthy) to 100 (healthy).

Figure A-3 allows to visualize that the NDVI of cells suitable to artisanal gold mining is on average higher than the NDVI of cells which are not suitable for ASM. The figure also shows that this difference attenuates with time: as the gold price increases, the NDVI of cells suitable for ASM becomes smaller relative to that of other cells.

Results. Table 1 reports the baseline results for the most parsimonious specification and for a specification with full controls. Column 1 shows that ASM significantly increases deforestation. However, we may be worried that these estimates suffer from an omitted variable bias. In particular, climatic conditions and economic incentives such as high agricultural prices or the opening of industrial mines are important drivers of deforestation, and they might correlate with the gold price. In column 2 we see that the effect of ASM on deforestation is remarkably robust to controlling for climatic and economic conditions. We document a similar pattern for vegetation health. Columns 3 and 4 report a negative effect of ASM on vegetation health. This relation is independent from the effect of important alternative predictors. We also confirm that each variable is an important driver of vegetation health, highly significant, and with the expected sign.

¹³The rainy season information comes from the PRIO-GRID dataset. Any cell-level variability at the beginning of the rainy season is absorbed in our model by the cell fixed effects.

Taking stock, these first results confirm a significantly negative environmental impact of ASM. However, people still engage in the activity. To assess what may be the individual actors’ motivation leading to these environmental impacts, we turn to indicators of local wealth in the next section.

Table 1: The negative environmental impacts of artisanal mining

Dependent variable	(1) deforestation	(2) deforestation	(3) vegetation health	(4) vegetation health
gold suitable \times price index	0.50 ^a (0.18)	0.48 ^a (0.18)	-0.21 ^b (0.09)	-0.20 ^b (0.09)
SPEI		-0.049 ^d (0.03)		0.39 ^a (0.01)
crop suitable \times crop price index		0.021 ^c (0.01)		0.052 ^b (0.02)
industrial mine \times mineral price index		0.23 (0.28)		-0.067 (0.12)
Observations	87061	87061	200380	200380

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in columns (1)-(2) is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The dependent variable in columns (3) - (4) is the average NDVI during the first three months of PRIO cell’s rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. All specifications include country \times year level fixed effects as well as cell fixed effects. ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$. Robust standard errors in parentheses clustered at the cell level. See Appendix A-6.1 for further information on the variables.

4.2 Wealth impacts

Wealth measure. To estimate the impact of ASM on local wealth, we resort to the two most comprehensive proxies of household economic well-being available for the continent: nighttime lights, and an index of household wealth. The two measures are complementary. Nighttime lights inform us about yearly change in local economic activity (Bruederle and Hodler, 2018), reflecting net changes from the households, state and companies level.¹⁴ The data is for the entire continent between 1992 and 2012. We also resort to micro-data measures of households’ asset wealth. Although the asset wealth is less reactive than income to local economic shocks (Ngom et al., 2020), it has the advantage of focusing on households. The household wealth measure is present in 31 of the 54 African countries, where the Demographic and Health Surveys (DHS) have been collecting standardized survey data between 2003 and 2018. We restrict the analysis to all the DHS survey

¹⁴Data from Tollefsen, Strand, and Buhaug (2012), available at <https://grid.prio.org/>

rounds that have household location data (GPS coordinates).

Figure A-4 allows to visualize that cells suitable to artisanal gold mining had, on average, a lower level of nighttime light emissions throughout the time period (were poorer). Over time, as the gold price increased, the difference in nighttime lights between ASM cells and other cells shrinks down (gold suitable zones catch up with other zones).

Table 2: The positive economic impacts of artisanal mining

	(1)	(2)	(3)	(4)
Dependent variable	nighttime lights		wealth factor	
gold suitable \times price index	1.87 ^a	2.07 ^a	0.85 ^b	0.77 ^c
	(0.56)	(0.55)	(0.43)	(0.43)
SPEI		0.041		0.21 ^b
		(0.04)		(0.10)
crop suitable \times crop price index		0.11 ^c		0.031
		(0.06)		(0.26)
industrial mine \times mineral price index		-2.90 ^b		0.68 ^d
		(1.21)		(0.42)
Observations	221603	221603	452022	452022

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in columns (1)-(2) is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The dependent variable in columns (3)-(4) is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018 (see Appendix A-6.1 for the full list of countries and surveys included in the analysis). Specifications in columns (3)-(4) include household controls presented in Section 3. All specifications include country \times year level fixed effects as well as cell fixed effects. ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$. Robust standard errors in parentheses clustered at the cell level.

Results. Table 2 reports the significantly positive effect of ASM on local wealth. An increase in the international gold price increases nighttime light emissions in cells suitable for gold mining (columns 1 and 2). In column 2, good climatic conditions and a high price of the local crop appear to also have a positive relation to nighttime lights – although the effect is precise only for crops. In contrast, an increase in the price of the main mineral mined locally in industrial mines reduces local nighttime lights. We discuss in more detail the role of industrial mines in Section 4.4. In column 3 and 4 we confirm that the effect of ASM does reach households as a higher gold price translates in higher household wealth.

The DHS data includes information on the respondent, and her spouse, economic activity, allowing us to investigate the role of ASM behind the results we have seen so far. Table A-4 in the appendix, shows that ASM is positively correlated with the probability of working in the extractive sector, pointing out to a direct link between cell’s gold suitability and households’ income activities. Because the record of extractive activities varies through countries and years, and artisanal mining is prone to seasonal migration (Bazillier and Girard, 2020), we interpret these important results with caution.

4.3 Magnitude of the effects

In this section, we assess the economic relevance of artisanal gold mining by looking at the absolute magnitude of the impacts of ASM, and comparing it to the magnitude of other important determinants of local conditions identified in the literature, namely measures of climatic conditions or a crop price shock as both measures have direct and indirect links to local development as reviewed in [Dell, Jones, and Olken \(2014\)](#); [Blair, Christensen, and Rudkin \(2021\)](#). To render the importance of price shocks on crops, we consider, for each cell, the price series of the crop for which that cell is the most suitable (combining the approaches of [Nunn and Qian, 2011](#); [McGuirk and Burke, 2020](#)). To render the importance of climatic conditions, we follow two alternative approaches reviewed in [Dell, Jones, and Olken \(2014\)](#). First, we resort to the widely used continuous measure of the SPEI ([Harari and Ferrara, 2018](#)). Second, we note that climatic conditions are unlikely to have a linear effect (as measured through the SPEI), and inhabitants are likely to adjust their behavior to the average SPEI and the variance of the SPEI of the place where they live. To assess the magnitude of the effect of bad climatic conditions, we thus consider a dummy variable taking value one in case of a drought. Aligned with the literature focusing on climatic shocks ([Azzarri and Signorelli, 2020](#)), we define a cell to have a drought if the SPEI of that cell is two standard deviation below its historical mean in that cell. 10% of the cells in our sample experience a drought.

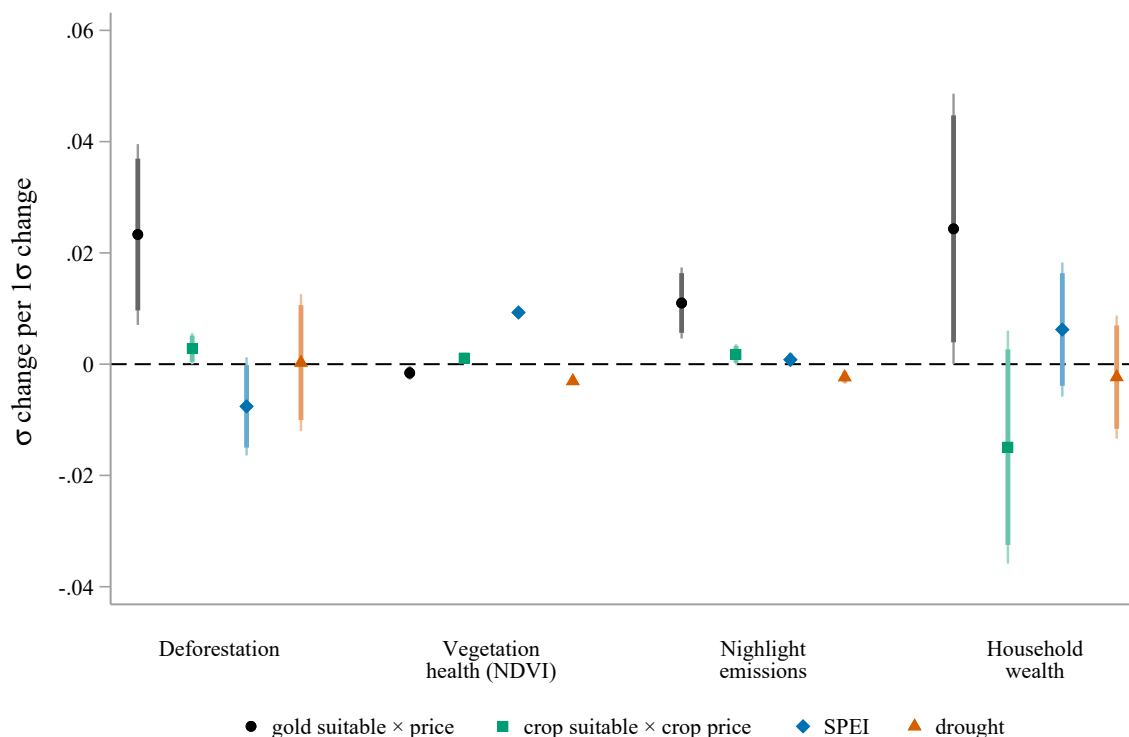
Figure 3 shows the estimated effect of a one standard deviation change of the ASM variable in terms of standard deviation change of the explained variables from Tables 1 and 2. For comparison of the magnitudes, Figure 3 also shows the estimated effect of agricultural shocks and climatic conditions.

Figure 3 documents the importance of the role played by ASM in deforestation and local wealth. ASM is a major driver of deforestation, with a standard deviation change in ASM leading to 0.2 standard deviation change in deforestation. This coefficient is larger than the effect on deforestation of a standard deviation change in the other three variables we consider. Overall, gold price variations are estimated to have contributed to 20% of the total predicted deforestation in the African tropics over the period 2001-2018.¹⁵ Interestingly the estimates we document for Africa aligns with the only quantification we know of, coming from a part of the Amazon. [Caballero Espejo et al. \(2018\)](#) estimate that, in the mining area of Madre de Dios in of the Peruvian Amazon, ASM accounted for 30 percent of the deforestation happening between 2001 and 2009. In contrast, for vegetation health, ASM and crop prices appear to have effects of comparable magnitudes. The positive effect of crop prices on both deforestation and vegetation health is consistent with farmers investing in crop health when the crop prices are high, potentially deforesting

¹⁵Comparing predicted deforestation in our baseline results of column 1 in Table 1 to predicted deforestation for a gold price set at its lowest level in the period 2001-2018.

to increase field sizes. Climatic conditions have the largest effect. Moving to economic outcomes, the effect of ASM on nighttime light emissions and household wealth is large, and larger than the effect of agricultural prices or adverse climatic conditions.

Figure 3: The effect of a standard deviation increase in artisanal gold mining and other key variables.



Notes: The figure depicts the estimated coefficients of how a standard deviation change in the explanatory variables translates in standard deviation changes of the explained variable. The bar around each coefficient’s symbol represents the 95 and 90% confidence intervals. The explained variables appear in the x-axis. The explanatory variables are represented by symbols of different colours. Each coefficient is estimated separately, in a specification akin to equation (1) for cell-level outcomes (deforestation, vegetation health and nighttime lights) and akin to equation (2) for household wealth, except that we sometimes replace the measure of artisanal mining by other key determinants of local development and environmental outcomes (namely, a crop price shock, the SPEI, and droughts). The sample consists of 0.5×0.5 degree cells. The “deforestation” variable is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The “vegetation health” variable is the average NDVI during the first three months of PRIO cell’s rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. The “nightlight emissions” variable is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The “household wealth” variable is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018.

4.4 Sensitivity analysis

We firstly want to make sure that the patterns we document are specific to artisanal extraction rather than to gold extraction in general, be it artisanal or industrial gold

extraction. To do so, Tables A-5 and A-6 show that results are robust to excluding cells which host industrial gold mines. We follow three different exclusion strategies to account for the presence and importance of industrial gold mining in a cell. We first exclude cells in which the main industrial mine that year is a gold mine, we then exclude all cells in which gold was the min industrial mineral over the period. Last, we exclude all cells that have any active industrial gold mine in a given year. The effect of ASM on both environmental and wealth outcomes is stable in all samples.

We also show that results are robust for alternative operationalization of the ASM proxy. Our baseline measure of ASM takes the share of each cell which overlaps with a gold as we want to convey a maximum precision of the information. Alternatively, in Table A-7 Panel A, we find similar results for a binary definition of cells that have any overlap with a gold prone geological layer as gold suitable. We also investigate the sensitivity of our results to the way we define the time treatment. Our baseline approach relies on the gold price in levels (like McGuirk and Burke, 2020). Table A-7 Panel B confirms that results are robust to considering prices in logs to account for the possibility of decreasing marginal returns (as in Berman et al., 2017). Alternatively, we may also be concerned that the overall upward trend of the gold price over the period leads to spurious results. We believe that this concern is limited as our results rest on the heterogeneous effect of price variations in cells that are gold suitable. Moreover, crop prices also trended upward over the period, but, aligned with economic intuition, ASM and crop prices both increase deforestation, while ASM and crop prices have opposite effects on vegetation health. We also can consider prices as a binary variables, taking value one when the gold price is high (in the upper third of the distribution), as this is the moment when ASM spillovers should be at their maximum. Results appear in Table A-7 Panel C.

Third, we document the stability of our estimates for different sets of controls, in particular controls related to weather conditions. There is a wide range of channels through which weather conditions may affect economic outcomes – ranging from agricultural output to health or conflicts. However, the literature has not yet reached a consensus as to what is the best way to account for weather shocks (Dell, Jones, and Olken, 2014). To control for these channels, we report the main estimates under different definitions of weather shocks. In addition, we vary the inclusion of the controls related to crop suitability and presence of industrial mines. Figures A-5 and A-7 show that the magnitude and precision of the estimated effects of ASM on deforestation, and on night light emissions, are remarkably stable to any of the specifications. The magnitude of the effect of gold suitability on vegetation health shows more variability, moving from -0.25 to -0.1 in Figure A-6, and the later effects are marginally insignificant. However, all the extreme values correspond to specifications in which we loose a large number of observations, namely, specifications where we consider the crops growing season (instead

of using the rainy season as in our baseline specification). Considering crops growing season reduces the sample by about a third. For wealth, we observe remarkably stable coefficients in Figure A-8. However, a few coefficients becoming marginally insignificant when we control for industrial gold mines, underlying the importance of the discussion above and results in Tables A-5 and A-6. For all four outcomes, we can see that our two baseline specifications give estimates that are either in the middle range, or in the conservative range, of the possible specifications.

Lastly, we may be concerned that our results from a potential spatial correlation in errors. The presence of artisanal mines, deforestation or wealth are local features. However, they may be clustered in space, and the cluster might span on a larger area than the cell (cells being of 55km×55km at the Equator). In Table A-8, we estimate standard errors with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation (Conley, 1999; Hsiang, Meng, and Cane, 2011; Collela et al., 2018).¹⁶ As we do not know the actual timing of the gold exploitation, we allow serial correlation to vanish only at an infinite time horizon. As ASM remains a low-scale activity, we consider a radius of up to 100km for the spatial kernel. Results in Table A-8 suggest that errors remain within a narrow value range as we increase the radius from 50 to 100km. Errors are smallest for the 50km buffer and largest for the 75km buffer. The magnitude of our baseline errors (clustered at the cell level) lies within the range of the estimated errors of Table A-8.

5 Mining when agriculture suffers from droughts

Qualitative accounts outline increases in artisanal mining activities when agricultural income falls short. Global warming is expected to increase adverse weather events, in particular droughts (Trenberth et al., 2014). On this final section, we investigate how droughts interact with gold presence.

Droughts are a localized negative shock for the livelihoods of agricultural households. The most immediate impact of weather shocks on rural livelihoods is on crop production. Droughts reduce agriculture yields, and can jeopardize household food security, and household income from crop sales (Dell, Jones, and Olken, 2014). The severity of the impact of drought varies depending on the extent to which the family relies on agriculture for food and income. Households who are able to diversify their income sources will be less vulnerable to the direct impact of adverse weather shocks (Barrett, Reardon, and Webb, 2001).

Given the low barriers to entry in areas where there are accessible mineral deposits smallholder farmers may turn to ASM for supplementary income (Hilson, 2016). We test

¹⁶The Table shows results for cell levels outcomes only, we lack computational power to estimate these errors for the household level wealth.

the role of ASM as a rural livelihood diversification strategy. We extend equations 1 and 2, and include an interaction term between drought and ASM cell's suitability.

Table 3 confirms the heterogeneous effects of droughts in areas suitable for gold mining. Two main findings emerge.

First, results are consistent with households resorting to artisanal mining as an alternative source of livelihoods during droughts. Column 1 shows that a drought, by itself, does not significantly affect deforestation, but that droughts in gold prone cells significantly increase deforestation. Put differently, a SPEI that is less than two standard deviation below its historical means during one rainy season is not enough to put a tree down. However, if that tree lies above a gold-suitable zone, that tree does have significantly more chances to be taken down during a drought, consistent with an extension of mining zones during these times. Column 3 of Panel A shows that vegetation health decrease with droughts, but also that it decreases even more in gold suitable cells (consistent with results on deforestation). In Panel B, effects are reversed: nighttime lights and household wealth decrease with drought, but the effects are over-compensated in gold suitable cells. The net effect of droughts on night lights in a cell that is fully gold suitable is positive and significant. We observe a similar pattern, albeit imprecise, on household wealth. Overall results confirm that turning to ASM during droughts may be a successful economic strategy, but coming at an environmental cost.

Second, the effect of the “push” drought factor, pushing people towards artisanal mining when they cannot make a living otherwise, appears to be orthogonal to the effect of the “pull” price factor. All the even columns in Panel A and B show that accounting for the heterogeneous effect of droughts in gold suitable zones does not affect our baseline results. The magnitude of the coefficient for ASGM value is remarkably similar in Table 3 and in Tables 1 and 2.

Table 3: Heterogenous effects of droughts in artisanal mining cells

	(1)	(2)	(3)	(4)
Panel A, dependent variable		deforestation	vegetation health	
drought	-0.14 (0.11)	-0.15 (0.11)	-0.20 ^a (0.02)	-0.20 ^a (0.02)
gold suitable × drought	0.60 ^c (0.32)	0.63 ^c (0.32)	-0.54 ^a (0.09)	-0.54 ^a (0.09)
gold suitable × price index		0.51 ^a (0.18)		-0.20 ^b (0.09)
P-val (drought+gold suitable × drought=0)	0.09		0	
Observations	87061	87061	200380	200380
Panel B, dependent variable		nighttime lights	wealth factor	
drought	-0.33 ^a (0.08)	-0.33 ^a (0.08)	-0.39 ^d (0.26)	-0.38 ^d (0.25)
gold suitable × drought	0.52 ^a (0.15)	0.50 ^a (0.15)	0.83 (0.60)	0.83 (0.59)
gold suitable × price index		1.86 ^a (0.56)		0.84 ^c (0.43)
P-val (drought+gold suitable × drought=0)	0.09		0.38	
Observations	221603	221603	452022	452022

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in Panel A columns (1)-(2) is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The dependent variable in Panel A columns (3) - (4) is the average NDVI during the first three months of PRIO cell's rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. The dependent variable in Panel B columns (1)-(2) is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The dependent variable in Panel B columns (3)-(4) is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018 (see Appendix A-6.1 for the full list of surveys included in the analysis). Specifications in Panel B columns (3)-(4) include household controls presented in Section 3. All specifications include country × year level fixed effects as well as cell fixed effects. ^c p<0.1, ^b p<0.05, ^a p<0.01. Robust standard errors in parentheses clustered at the cell level.

6 Conclusion

While artisanal mining provides us with 20% of the yearly gold production, we still know little about how this activity shapes our world and the societies where extraction takes place. This paper provides the first quantitative evidence of the environmental effects of ASM throughout the African continent, of its concomitant economic effects, and discusses the possibility that households turn to ASM as an adaptation strategy to droughts. To do so, we exploit a combination of satellite imagery, household surveys, and geological data, in an Africa-wide panel of fine-grained cells.

Our results show that artisanal gold mining is an environmental threat at the same time as a source of income diversification. Artisanal mining significantly increases deforestation, degrades vegetation health, and increases nighttime light emissions and household wealth. The effects appear to be economically and politically relevant, with magnitudes comparable to those of a price shock in agriculture (a key determinant of development [Nunn and Qian, 2011](#)). Results also confirm that artisanal mining may act as an important livelihood diversification strategy in periods of droughts.

These results suggest that mining, by increasing deforestation, may also increase future droughts ([Bagley et al., 2014](#)), leading to more mining, deforestation, and droughts. This pattern of results calls for further research, in particular on what are households alternative livelihood strategies or how artisanal mining environmental damages may be mitigated.

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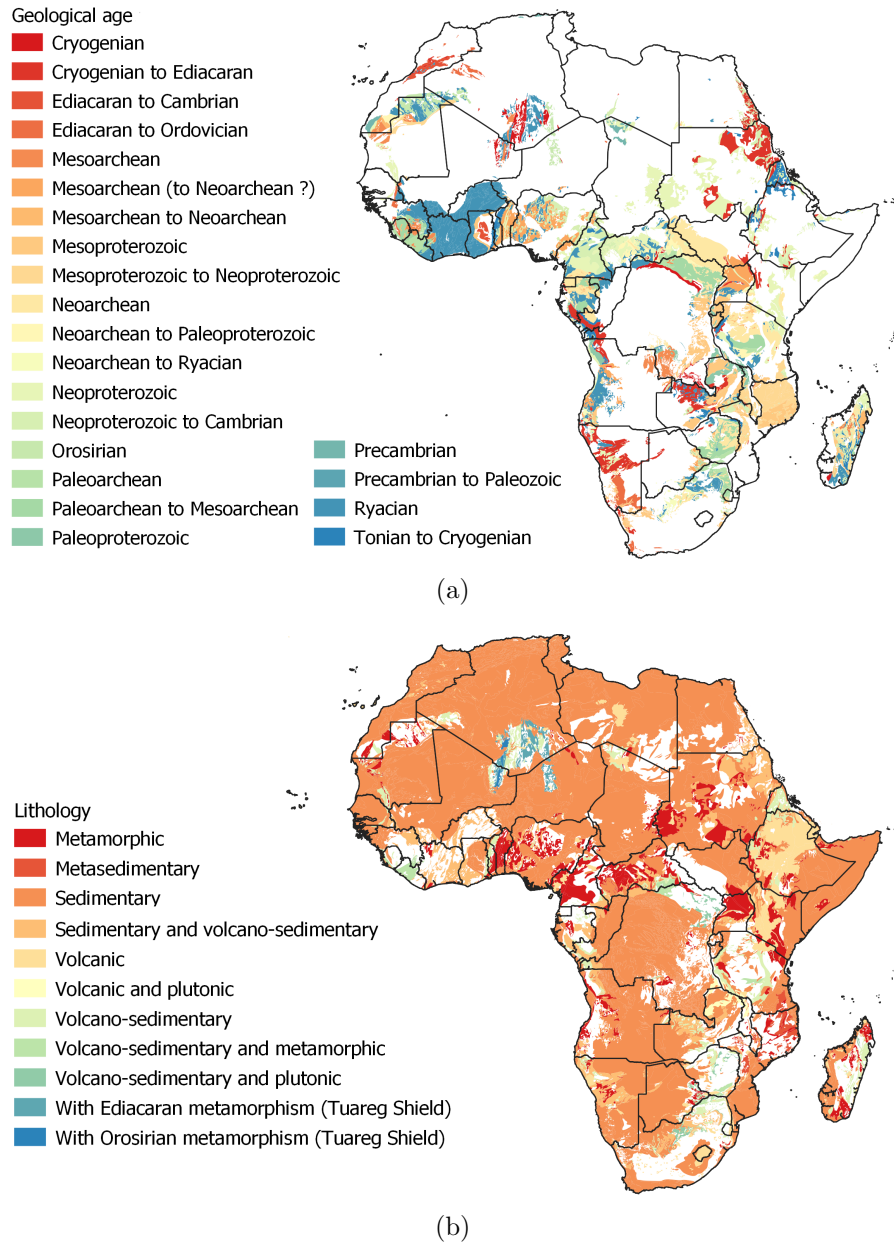
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Appendix

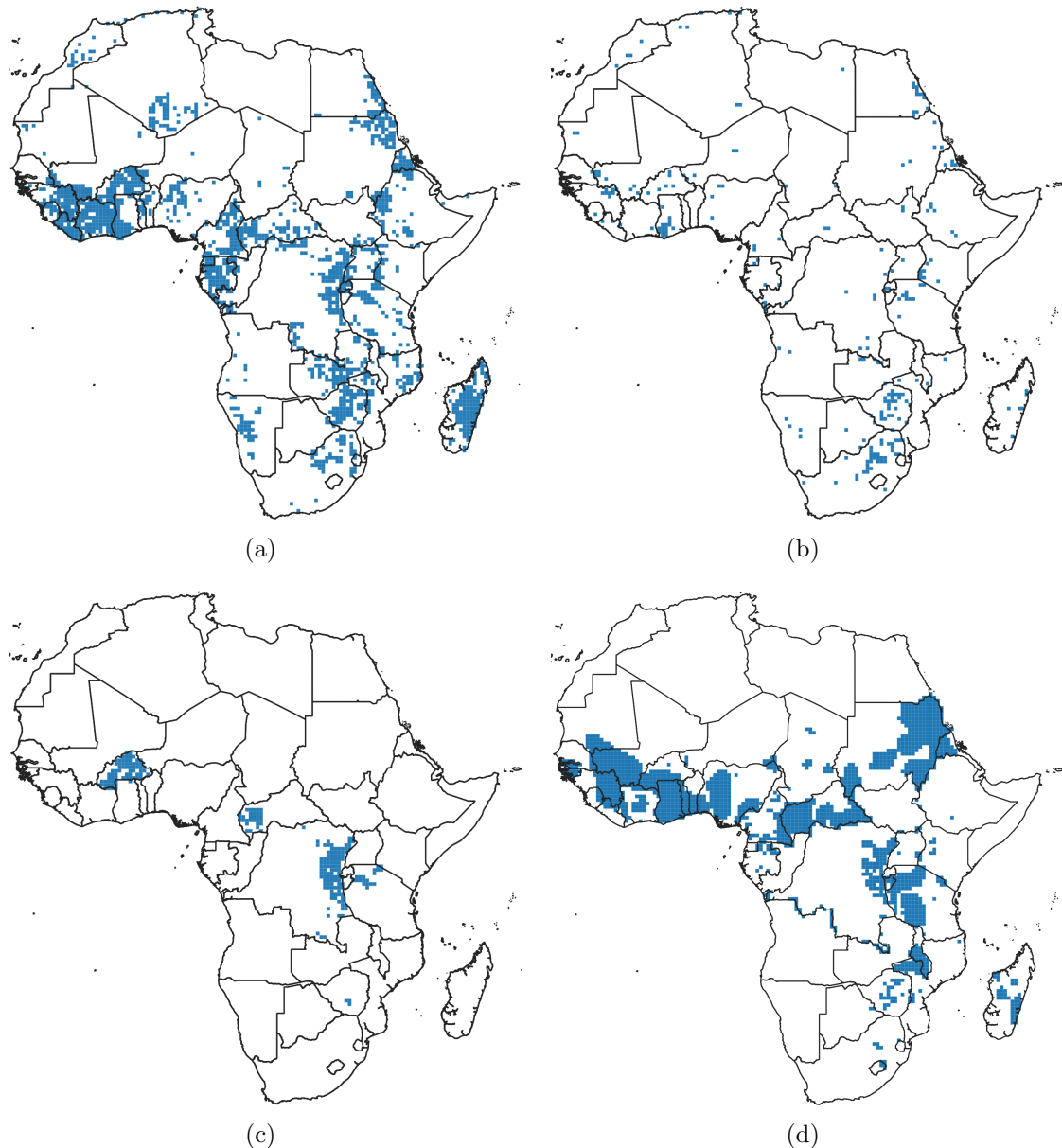
Appendix figures

Figure A-1: Geological suitability for artisanal gold mining



Notes: Panel (a) isolate the gold suitable strata, Panel (b) isolate the gold suitable lithologies, from the map of Thieblemont *et al.* (Thieblemont and BRGM, 2016)

Figure A-2: Known incidence of artisanal gold mining or gold hints.

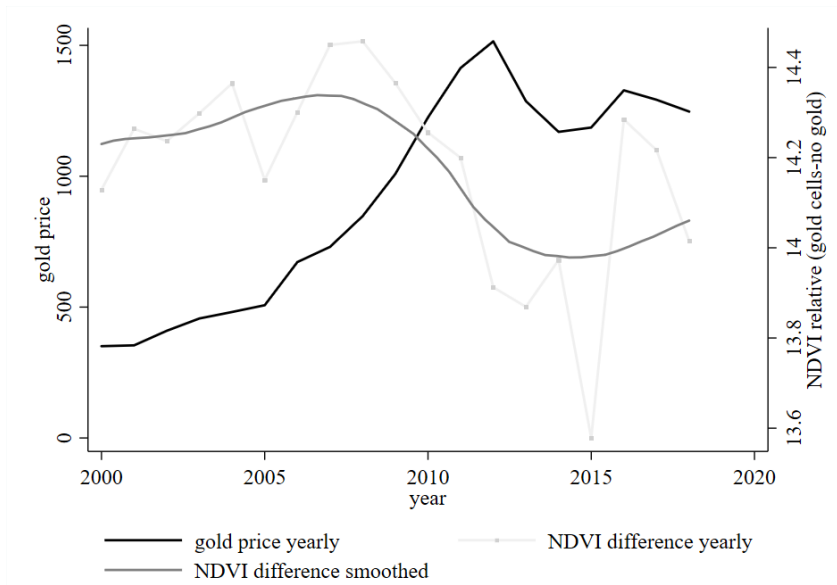


Notes: Panel (a): BRGM gold and ASM records. Shows the 1,577 cells with at least one of the 9,617 manual records made by the BRGM exploration geologists when they witness gold incidence during their field work.^a Many record descriptions refer to artisanal mining activities, with descriptions such as: “Gold panning pit and large worked quartz vein” or “Major artisanal mining site”(translation is ours). Panel (b) : PRIO - GOLDATA records (Balestri, 2015). Shows gold records from the GOLDATA source included in the PRIO (Balestri, 2015). Panel (c) : ASM in administrative and survey records. Shows administrative records of ASM obtained from the Ministry of Mines in Burkina Faso in 2015 (Bazillier and Girard, 2020), and Survey records of ASM made by the IPIS in sub-regions of the Central African Republic in 2019, the Democratic Republic of Congo in 2019, Tanzania in 2019 and Zimbabwe in 2018 and 2019.^b For all IPIS data recording artisanal mines of various type, we restrict attention to artisanal gold mines and omit other minerals. Panel (d) : ASM mercury (Steenhuisen and Wilson, 2019). Shows cells with mercury emissions due to ASM estimated to be superior or equal to 3kg per area of 0.05×0.05 degrees within that cell (Steenhuisen and Wilson, 2019).

^a<https://www.brgm.fr/en>

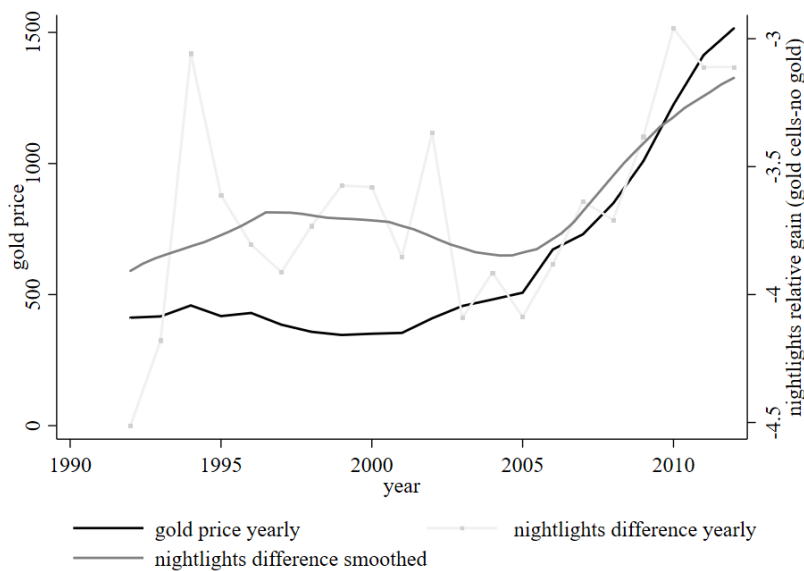
^b<https://ipisresearch.be/home/maps-data/>

Figure A-3: Artisanal mining value and vegetation health reduction over time



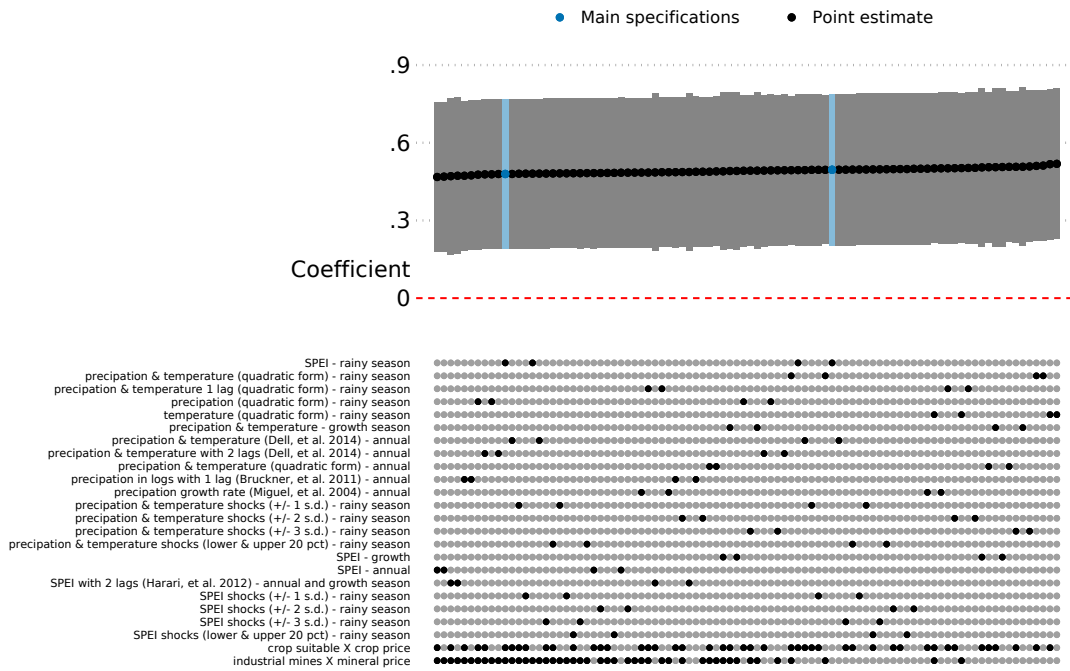
Notes: The “NDVI difference yearly” tells the average of the NDVI in gold suitable cells - NDVI in non gold suitable cells. The “difference smoothed” shows a kernel-weighted local polynomial smoothing of the “NDVI difference yearly”. The sample consists of all 0.5×0.5 degree cells in Africa, the time frame is annual observations, from 2000 to 2018.

Figure A-4: Artisanal mining value and nighttime lights over time



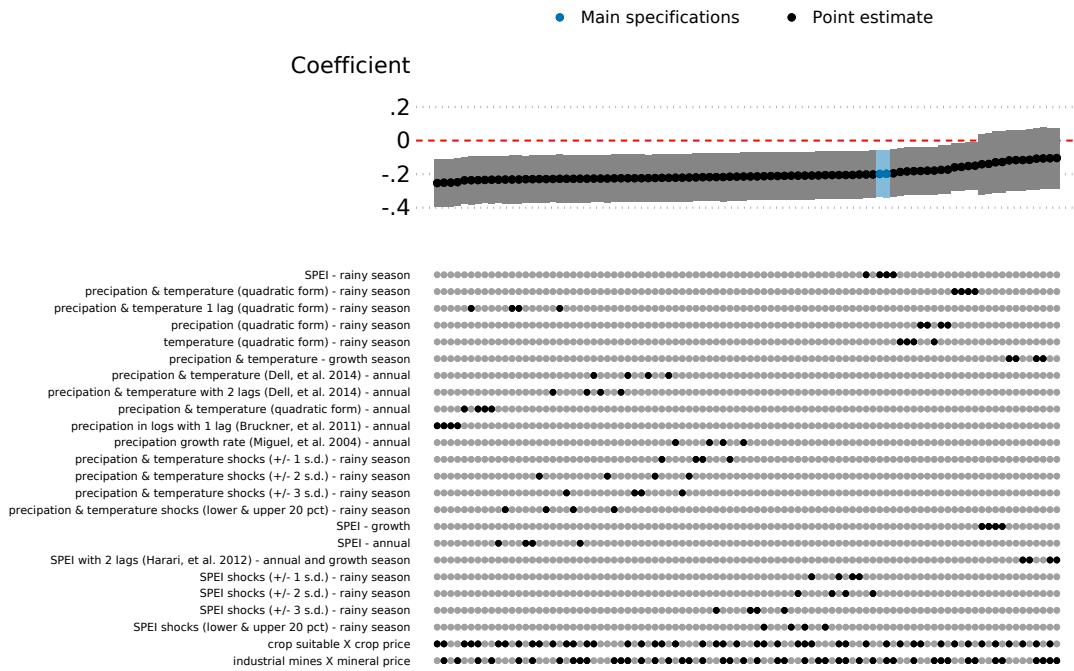
Notes: The “nightlights difference yearly” tells the average of the nighttime lights in gold suitable cells - emissions in non gold suitable cells. The “difference smoothed” shows a kernel-weighted local polynomial smoothing of the “nightlights difference yearly”. The sample consists of all 0.5×0.5 degree cells in Africa, the time frame is annual observations, from 1992 to 2013.

Figure A-5: Specification curve - deforestation



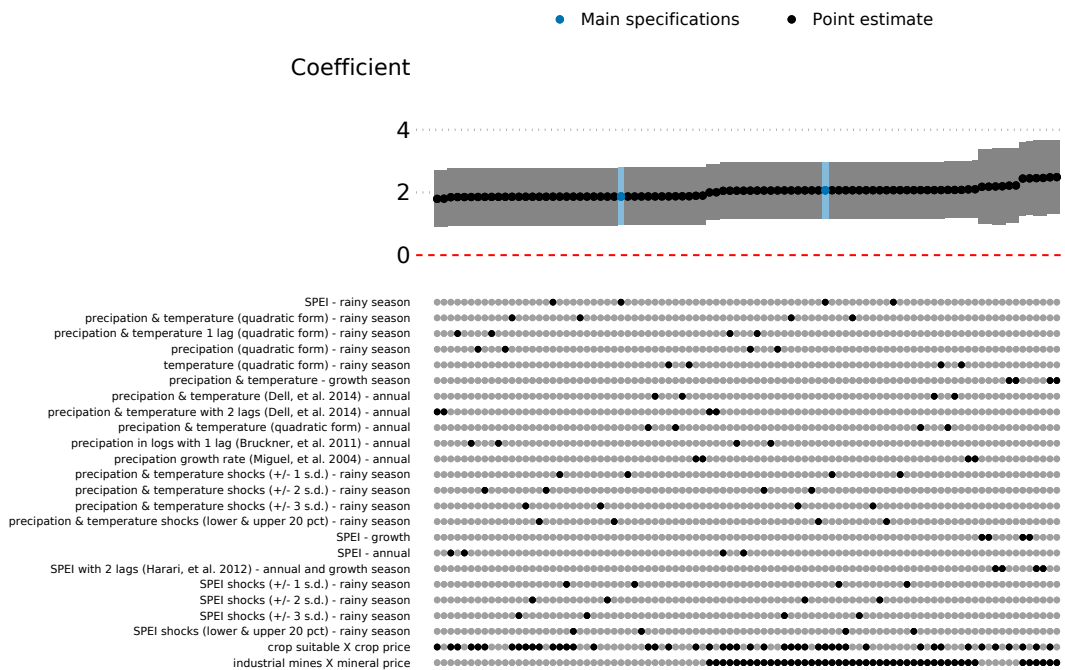
Notes: Estimates based on OLS regressions, using Equation 1. The dependent variable is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The blue markers correspond to our baseline estimates, the black markers correspond to all other estimates. Confidence intervals in grey indicate statistical significance at the 90 percent level. Standard errors are clustered at the cell level. The bottom panel of the Figure denotes the specification corresponding to the marker above it. We vary specifications with respect to the definition of the weather covariates included, and the inclusion of crop suitability and industrial mines presence. All specifications include country \times year level fixed effects as well as cell fixed effects.

Figure A-6: Specification curve - vegetation health



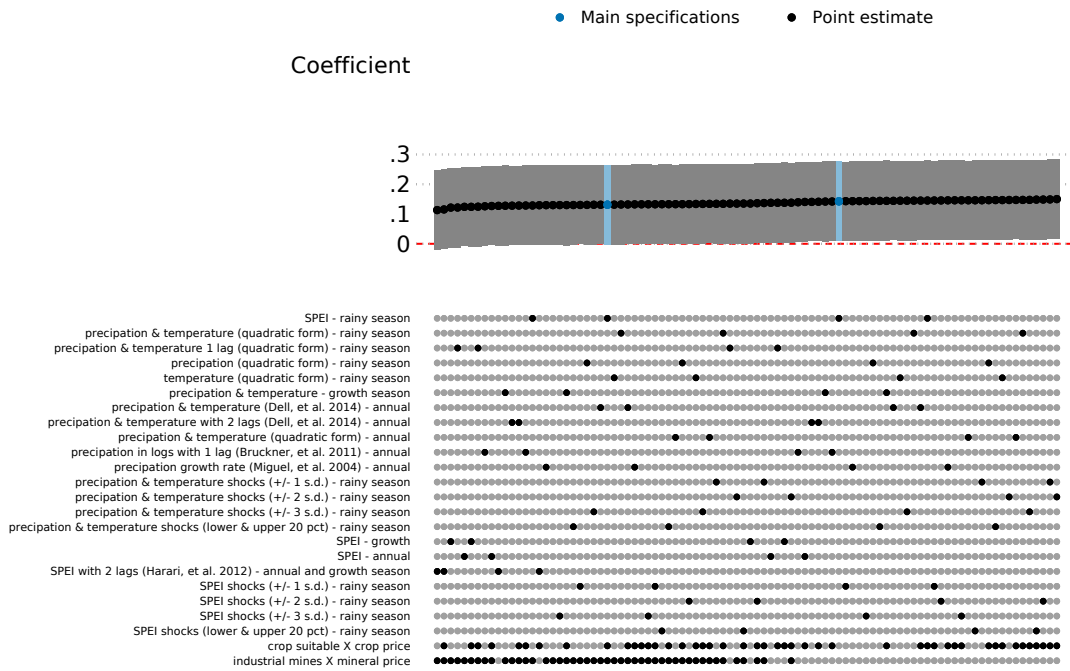
Notes: Estimates based on OLS regressions, using Equation 1. The dependent variable is the average NDVI during the first three months of PRIO cell’s rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. The blue markers correspond to our baseline estimates, the black markers correspond to all other estimates. Confidence intervals in grey indicate statistical significance at the 90 percent level. Standard errors are clustered at the cell level. The bottom panel of the Figure denotes the specification corresponding to the marker above it. We vary specifications with respect to the definition of the weather covariates included, and the inclusion of crop suitability and industrial mines presence. All specifications include country \times year level fixed effects as well as cell fixed effects.

Figure A-7: Specification curve - nighttime lights



Notes: Estimates based on OLS regressions, using Equation 1. The dependent variable is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The blue markers correspond to our baseline estimates, the black markers correspond to all other estimates. Confidence intervals in grey indicate statistical significance at the 90 percent level. Standard errors are clustered at the cell level. The bottom panel of the Figure denotes the specification corresponding to the marker above it. We vary specifications with respect to the definition of the weather covariates included, and the inclusion of crop suitability and industrial mines presence. All specifications include country \times year level fixed effects as well as cell fixed effects.

Figure A-8: Specification curve - wealth factor



Notes: Estimates based on OLS regressions, using Equation 2. The dependent variable is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018. The blue markers correspond to our baseline estimates, the black markers correspond to all other estimates. Confidence intervals in grey indicate statistical significance at the 90 percent level. Standard errors are clustered at the cell level. The bottom panel of the Figure denotes the specification corresponding to the marker above it. We vary specifications with respect to the definition of the weather covariates included, and the inclusion of crop suitability and industrial mines presence. All specifications include household controls presented in Section 3, and country \times year level fixed effects as well as cell fixed effects.

Appendix tables

Table A-1: Individuals related to artisanal mining, adapted from [Hilson \(2016\)](#)

extractive target	country	workers		dependent	
		number	share	number	share
gold alone	Burkina Faso	200,000		1,000,000	
	Chad	100,000		600,000	
	Eritrea	400,000		2,400,000	
	Ethiopia	500,000		3,000,000	
	Mali	400,000		2,400,000	
	Niger	450,000		2,700,000	
	Nigeria	500,000		2,500,000	
	South Africa	20,000		na	
	South Sudan	200,000		1,200,000	
	Tanzania	1,500,000		9,000,000	
	Uganda	150,000		900,000	
	<i>Total gold alone</i>	<i>4,420,000</i>	<i>54%</i>	<i>25,700,000</i>	<i>56%</i>
gold mainly	Central African Republic	400,000		2,400,000	
	Cote d'Ivoire	100,000		600,000	
	Ghana	1,100,000		4,400,000	
	Guinea	300,000		1,500,000	
	Liberia	100,000		600,000	
	Sierra Leone	300,000		1,800,000	
	Zimbabwe	500,000		3,000,000	
		<i>Total gold mainly</i>	<i>2,800,000</i>	<i>34%</i>	<i>14,300,000</i>
gold secondary	DRC	200,000		1,200,000	
	Madagascar	500,000		2,500,000	
	Malawi	40,000		na	
	Mozambique	100,000		1,200,000	
		<i>Total gold secondary</i>	<i>840,000</i>	<i>10%</i>	<i>4,900,000</i>
no gold	<i>Angola</i>	<i>150,000</i>	<i>2%</i>	<i>900,000</i>	<i>2%</i>
all		8,210,000	100%	45,800,000	100%

Notes: data from [Hilson \(2016\)](#)'s survey of all publicly available data on artisanal mining populations and their extractive target, here restricted to countries of Sub-Saharan Africa. The focus of extraction next to gold can be on either coltan, diamonds, colored gemstones or sand.

Table A-2: ASM geological suitability correlation with alternative ASM records

	ASM suitability			ASM record				
	share	any part	majority	BRGM	PRIO	admin. or survey	mercury	all but BRGM
ASM suitability any part	0.695	1						
ASM suitability majority	0.903	0.518	1					
BRGM record	0.353	0.392	0.284	1				
PRIO record	0.105	0.118	0.086	0.223	1			
Admin. or survey record	0.088	0.150	0.054	0.271	0.065	1		
Mercury record	0.256	0.272	0.204	0.320	0.117	0.239	1	
All record but BRGM	0.269	0.296	0.210	0.361	0.332	0.334	0.941	1
All record	0.373	0.419	0.059	0.733	0.306	0.265	0.749	0.797

Notes: Pearson’s pairwise correlations. The (omitted) p-values for all pairwise correlations are inferior to 0.001. Variables defined at the level of the PRIO-Grid cells and described in the note to Figure A-2. The variable “All record but BRGM” takes value 1 in a cell if any of the PRIO, admin or survey, or mercury record takes value 1 to check correlations between the different records that are independent from records made by the French Geological Survey to account for the concern that the later record may have influenced our selection of geological layers. The variable “All record” adds the information collected by the BRGM geologists. Sample: 10,678 PRIO-Grid cells which overlap with the African continent as represented in Figure A-2.

Table A-3: Descriptive statistics

variable	mean	sd	min	median	max
gold suitable \times gold price	0.1	0.2	0	0	1.18
NDVI	40.33	27.43	-10.1	38.11	87.16
deforestation	0.01	0.04	0	0	1
work extractive sector	2.29	14.96	0	0	100
wealth factor	0	10	-40.69	-3.10	114.9
nighttime lights	40	34.69	0	33.88	956.63
spei	-0.23	0.65	-4.31	-0.19	2.64
drought	0.11	0.31	0	0	1
crop suitable \times crop price	0.32	0.53	0	0	22.97
industrial mine \times mineral price	0.01	0.07	0	0	2.69

Notes: Variables defined at the level of the PRIO-Grid cells. Sample: 10,678 PRIO-Grid cells which overlap with the African continent as represented in Figure A-2.

Table A-4: The positive impacts of artisanal mining on extractive activity

	(1)	(2)
Dependent variable		extractive sector
gold suitable \times price index	2.71 ^a (0.93)	2.58 ^a (0.91)
SPEI average rainy season		0.29 (0.18)
crop suitable \times crop price index		-0.42 (0.77)
industrial mine \times mineral price index		1.46 (1.35)
Observations	340389	340389

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable is an indicator variable taking value equal to one if the respondent or her spouse was working in the extractive sector at the time of the interview (see Appendix A-6.1 for the full list of surveys included in the analysis). All specifications include household controls presented in Section 3, and country \times year level fixed effects as well as cell fixed effects. ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$. Robust standard errors in parentheses clustered at the cell level.

Table A-5: The environmental impacts of artisanal mining independently of industrial gold mining

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	—deforestation—			—NDVI—		
Sample exclusion: cells where industrial gold is	main _{<i>t</i>}	main _{90–19}	any	main _{<i>t</i>}	main _{90–19}	any
gold suitable × price index	0.48 ^a (0.18)	0.51 ^a (0.18)	0.48 ^a (0.18)	-0.19 ^b (0.09)	-0.18 ^b (0.09)	-0.19 ^b (0.09)
SPEI	-0.047 ^d (0.03)	-0.047 ^d (0.03)	-0.047 ^d (0.03)	0.39 ^a (0.01)	0.39 ^a (0.01)	0.39 ^a (0.01)
crop suitable × crop price index	0.021 ^c (0.01)	0.020 ^c (0.01)	0.021 ^c (0.01)	0.053 ^b (0.02)	0.054 ^b (0.02)	0.054 ^b (0.02)
industrial mine × mineral price index	0.24 (0.31)	0.56 ^a (0.20)	0.26 (0.32)	0.052 (0.13)	0.17 (0.15)	0.011 (0.14)
Observations	86452	85729	86377	199367	198366	199080

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in columns (1)-(3) is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The dependent variable in columns (4) - (6) is the average NDVI during the first three months of PRIO cell's rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. All specifications include country × year level fixed effects as well as cell fixed effects. ^c p<0.1, ^b p<0.05, ^a p<0.01. Robust standard errors in parentheses clustered at the cell level. See Appendix A-6.1 for further information on the variables. The variable main_{*t*} takes value 1 in the cell *c* and year *t* if the main mineral (that is, the mineral with the highest production value) exploited by the industrial mine(s) present in that cell and year is gold. The variable main_{90–19} takes value 1 in the cell *c* if the main mineral (that is, the mineral with the highest production value) exploited by the industrial mine(s) present in that cell is gold, considering all production that may have taken place between years 1990 and 2019. The variable any takes value 1 in the year and cell which host an active industrial mine.

Table A-6: The wealth impacts of artisanal mining independently of industrial gold mining

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	—nightlights—			—wealth factor—		
Sample exclusion: cells where industrial gold is	main _t	main ₉₀₋₁₉	any	main _t	main ₉₀₋₁₉	any
gold suitable × price index	2.37 ^a (0.51)	2.44 ^a (0.52)	2.39 ^a (0.51)	0.88 ^c (0.51)	0.94 ^c (0.51)	0.66 ^d (0.43)
SPEI	0.038 (0.04)	0.040 (0.04)	0.040 (0.04)	0.017 (0.10)	0.0087 (0.10)	0.19 ^c (0.10)
crop suitable × crop price index	0.13 ^b (0.06)	0.12 ^b (0.06)	0.13 ^b (0.06)	0.35 (0.26)	0.34 (0.27)	0.040 (0.26)
industrial mine × mineral price index	-1.56 (1.17)	-1.30 (1.31)	-2.37 ^b (1.19)	0.23 (0.85)	0.48 (1.11)	0.40 (0.51)
Observations	220722	219377	220489	736230	726857	444165

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in columns (1)-(3) is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The dependent variable in columns (4)-(6) is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018 (see Appendix A-6.1 for the full list of countries and surveys included in the analysis). Specifications in columns (4)-(6) include household controls presented in Section 3. All specifications include country × year level fixed effects as well as cell fixed effects. ^c p<0.1, ^b p<0.05, ^a p<0.01. Robust standard errors in parentheses clustered at the cell level. The variable main_t takes value 1 in the cell *c* and year *t* if the main mineral (that is, the mineral with the highest production value) exploited by the industrial mine(s) present in that cell and year is gold. The variable main₉₀₋₁₉ takes value 1 in the cell *c* if the main mineral (that is, the mineral with the highest production value) exploited by the industrial mine(s) present in that cell is gold, considering all production that may have taken place between years 1990 and 2019. The variable any takes value 1 in the year and cell which host an active industrial mine.

Table A-7: The impacts of artisanal mining independently of the ASM proxy formulation

Dependent variable	(1) deforestation	(2) NDVI	(3) nightlights	(4) wealth
Panel A: any part of the cell is gold suitable				
gold any \times price index	0.43 ^a (0.12)	-0.27 ^a (0.05)	1.31 ^a (0.39)	0.54 ^c (0.31)
Observations	87061	200380	221603	452022
Panel B: gold price in log				
gold suitable \times ln(price)	0.28 ^b (0.12)	-0.082 ^d (0.05)	1.04 ^a (0.31)	0.59 ^b (0.28)
Observations	87061	200380	221603	452005
Panel C: dummy for a high gold price				
gold_prone_shareXtprice_3	0.27 ^a (0.08)	-0.13 ^b (0.06)	1.09 ^a (0.30)	3.99 ^a (0.26)
Observations	87061	200380	221603	452005

Notes: Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in column (1) is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The dependent variable in column (2) is the average NDVI during the first three months of PRIO cell's rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. The dependent variable in column (3) is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. The dependent variable in column (4) is the wealth factor provided by the DHS program, for respondents from 31 countries surveyed between 2003 and 2018 (see Appendix A-6.1 for the full list of countries and surveys included in the analysis). Specifications in column (4) include household controls presented in Section 3. All specifications include country \times year level fixed effects as well as cell fixed effects. In Panel C, we define the dummy for a high gold price as taking value one for a price of gold that is in the upper third of the distribution; the variable change in each column as we consider the distribution of the sample of years for which we observe the dependent variable. ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$. Robust standard errors in parentheses clustered at the cell level.

Table A-8: Baseline results when we allow for spatial and serial correlation in errors

Dependent variable	(1) deforestation	(2) vegetation health	(3) nightlights
gold suitable \times price index	0.48	-0.20	2.07
Cluster robust errors (baseline)	(0.18)	(0.09)	(0.55)
Spatial 50km, time infinite	(0.17)	(0.09)	(0.55)
Spatial 75km, time infinite	(0.21)	(0.12)	(0.64)
Spatial 100km, time infinite	(0.19)	(0.10)	(0.59)
Observations	87061	200380	221603

Notes: Estimates based on OLS regressions. Variables are in levels. The dependent variable in column (1) is the share of the forest in a pixel which disappears each year, measured yearly for all PRIO cells in the African tropics, from 2001 to 2018. The dependent variable in column (2) is the average NDVI during the first three months of PRIO cell's rainy season; measured yearly for all PRIO cells in African continent, from 2000 to 2018. The dependent variable in column (3) is the average calibrated nighttime lights, available yearly for all PRIO cells in Africa, from 1992 to 2012. All specifications include country \times year level fixed effects as well as cell fixed effects. ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$. Estimated errors are in parenthesis. Baseline standard errors are robust and clustered at the cell level. We estimate the [Conley \(1999\)](#); [Hsiang, Meng, and Cane \(2011\)](#) errors, allowing for cross-sectional spatial correlation and location-specific serial correlation, using the Stata routine developed by [Collela et al. \(2018\)](#). We consider alternative radius for spatial correlation, results for each radius appear in a different line. We lack computational power to estimate these errors for the household level wealth.

A-6.1 Data

Weather: drought, temperature and precipitation We compute the drought, temperature, precipitation and drought information from the data provided by the Climatic Research Unit of the University of East Anglia (CRU) [Harris et al. \(2020\)](#). Our drought measure is built directly from the cell level Standardized Precipitation and Evapotranspiration Index, or SPEI provided by the CRU. We first take the average SPEI for the three first months of the cell’s rainy season as recorded in the PRIO dataset. The SPEI is designed to take into account both precipitation and potential evapotranspiration in determining whether a given cell is under climatic stress. The SPEI increases with the quality of the climatic conditions. Put differently, droughts increase as the SPEI decreases. We also consider a binary measure of droughts. Aligned with the literature focusing on climatic shocks ([Azzarri and Signorelli, 2020](#)), we define a cell to have a drought if the SPEI of that cell is two standard deviation below its historical mean in that cell. 10% of the cells in our sample experience a drought.

Agricultural resources Mirroring the construction of the artisanal mining data, we combine information on a cell crop suitability with the crop price. Based on the FAO’s Global Agro-Ecological Zones (GAEZ), which indicates a cell level suitability for different crops, we identify the crop(s) for which the cell is most suitable. We consider a cell as suitable for the cultivation of at least one crop if the GAEZ classifies it as “very suitable”, “suitable” or “moderately suitable.” It implies that we consider as improper for agriculture any cell where none of the crop can reach 40% or more of its potential yield under rain-fed conditions and medium-input intensity. [Nunn and Qian \(2011\)](#); [Fourati et al. \(2021\)](#) For the time variation, we associate to each crop the international price series of that crop, taking an index base 1 in 2013. The price series data comes from the UNCTAD, available at the WITS portal of the World Bank. We use a consistent version of the price variation for crops and for ASM within each specification (considering the price index lagged or its contemporaneous value).

Industrial mining For each cell, we record the “main mineral” produced industrially as computed and made public by earlier work [Berman et al. \(2017\)](#); [Fourati et al. \(2021\)](#). A cell’s main mineral is the mineral with the highest industrial production over the period of analysis. We omit diamonds from the analysis given the absence of a unique market price for diamonds, and as the market quasi-monopoly of De Beers only slowly erodes [Bergensstock, Maskulka et al. \(2001\)](#). We omit phosphate and tantalum for which we do not have price series. The international price of each mineral is associated to each cell where this mineral is the main one. We retrieve prices from the S&P price series. To ensure comparability, we take each mineral price series as an index base 1 in 2013. We

use a consistent version of the price variation for industrial minerals and for ASM within each specification (considering the price index either lagged, or current).

Wealth index The wealth index is provided directly in the DHS data. It is the result of a Principal Component Analysis, performed by the DHS team over key indicators of the household wealth, namely, household ownership of selected assets; the type of water and sanitation facilities of the house; house access to electricity; and the house quality. For each survey, the weights of these individual wealth indicators are derived by principal component analysis. As [Bruederle and Hodler \(2018\)](#), we consider the raw DHS data. The wealth factor is available for 31 countries surveyed repeatedly by the DHS between 2003 and 2018.¹⁷ The first DHS surveys recording the wealth factor and with available GPS coordinates for the households took place in 2003. The last DHS surveys included in our sample were collected in 2018. The wealth index ranges between -1 (poorest) and 11 (richest).

Work in the extractive sector We code manually the dummy variable telling whether the respondent or her partner works in the extractive sector based on the sector of activity data from the DHS. The data collection on sector activity varies from survey to survey, the codes on which we base the variable are available from the authors. The variable takes value one if either the respondent or her partner works in the extractive sector, and zero otherwise.¹⁸

¹⁷The data come from the following DHS country wave and survey years: AO5 2006, AO5 2007, AO5 2011, AO7 2015, AO7 2016, BF4 2003, BF6 2010, BF6 2014, BF7 2017, BF7 2018, BJ6 2011, BJ6 2012, BJ7 2017, BJ7 2018, BU6 2012, BU6 2013, BU61 2010, BU61 2011, BU7 2016, BU7 2017, CD5 2007, CD6 2013, CD6 2014, CI6 2011, CI6 2012, CM4 2004, CM6 2011, ET6 2003, ET7 2008, GA6 2012, GH4 2003, GH5 2008, GH6 2014, GH7 2016, GN4 2005, GN6 2012, GN7 2018, KE4 2003, KE5 2008, KE5 2009, KE6 2014, LB5 2006, LB5 2007, LB5 2008, LB5 2009, LB6 2011, LB6 2013, LB7 2016, LS4 2004, LS4 2005, LS5 2009, LS5 2010, LS6 2014, MD5 2008, MD5 2009, MD6 2011, MD6 2013, MD7 2016, ML5 2006, ML6 2012, ML6 2013, ML6 2015, ML7 2018, MW4 2004, MW4 2005, MW5 2010, MW6 2012, MW6 2014, MW7 2015, MW7 2016, MW7 2017, MZ5 2009, MZ6 2011, MZ6 2015, NG4 2003, NG5 2008, NG6 2010, NG6 2013, NG6 2015, NG7 2018, NM5 2006, NM5 2007, NM6 2013, RW4 2005, RW5 2007, RW5 2008, RW6 2010, RW6 2011, RW6 2014, RW6 2015, SL5 2008, SL6 2013, SL7 2016, SN4 2005, SN5 2008, SN5 2009, SN6 2012, SN6 2013, SN6 2014, SN6 2015, SN6 2016, SZ5 2006, SZ5 2007, TD6 2014, TD6 2015, TG6 2013, TG6 2014, TG7 2017, TZ5 2003, TZ5 2004, TZ5 2007, TZ5 2008, TZ5 2009, TZ5 2010, TZ6 2011, TZ6 2012, TZ7 2015, TZ7 2016, TZ7 2017, UG5 2006, UG5 2009, UG5 2010, UG6 2011, UG6 2014, UG6 2015, UG7 2016, UG7 2018, ZA7 2016, ZM5 2007, ZM6 2013, ZM6 2014, ZM7 2018, ZW5 2005, ZW5 2006, ZW6 2010, ZW6 2011, ZW7 2015.

¹⁸The data come from the following DHS country wave and survey years: AO7 2015, AO7 2016, BF3 1998, BF3 1999, BF4 2003, BJ3 1996, BJ6 2011, BJ6 2012, BJ7 2017, BJ7 2018, BU61 2010, BU61 2011, BU7 2016, BU7 2017, CI6 2011, CI6 2012, ET4 1992, ET4 1997, ET6 2003, ET7 2008, GA6 2012, GH3 1998, GH3 1999, GH4 2003, GH5 2008, GH6 2014, GN4 2005, GN6 2012, GN7 2018, KE4 2003, KE5 2008, KE5 2009, LB5 2006, LB5 2007, LB6 2013, LS4 2004, LS4 2005, LS5 2009, LS5 2010, LS6 2014, MD5 2008, MD5 2009, ML5 2006, MW4 2000, MW4 2004, MW4 2005, MW7 2015, MW7 2016, NG4 2003, NG5 2008, NG6 2013, NM4 2000, NM5 2006, NM5 2007, NM6 2013, RW4 2005, RW6 2010, RW6 2011, RW6 2014, RW6 2015, SL5 2008, SL6 2013, SZ5 2006, SZ5 2007, TD6 2014, TD6 2015, TZ5 2003, TZ5 2004, TZ5 2009, TZ5 2010, TZ7 2015, TZ7 2016, UG7 2016, ZM5 2007, ZM6 2013, ZM6 2014, ZM7 2018, ZM7 2019, ZW5 2005, ZW5 2006.

DHS households coordinates The DHS provides household coordinates which are key to our spatial approach as we want to know which household resides in a cell suitable for ASM. These coordinates bear some random noise as to ensure that individuals cannot be identified, the DHS displaces these coordinates randomly by 5 kilometers, and up to 10kilometres in 1% of the cases. As the displacement is random, it may attenuate our estimates but should not bias them.

A-6.2 Creating the map of geological suitability for ASM

We build the map of gold suitable areas by extracting the gold suitable geological bedrocks from the most recent and precise available map of the African geology, compiled by Thieblemont *al* [Thieblemont and BRGM \(2016\)](#). As summarized in the main text and detailed below, gold suitable bedrocks in Africa can be characterized by crossing their age and their lithology. Figure 1(a) is a visual summary of the state of knowledge in geology with respect to gold in Africa.

Virtually all gold suitable bedrocks lie in ancient geological strates which we isolate. In [Thieblemont and BRGM \(2016\)](#) these are the strates denoted as: Ediacaran to Cambrian ; Ediacaran to Ordovician ; Mesoarchean ; Mesoarchean (to Neoproterozoic ?) ; Mesoarchean to Neoproterozoic ; Mesoproterozoic ; Mesoproterozoic to Neoproterozoic ; Neoproterozoic ; Neoproterozoic to Paleoproterozoic ; Neoproterozoic to Ryacian ; Neoproterozoic ; Neoproterozoic to Cambrian ; Paleoproterozoic ; Paleoproterozoic to Mesoarchean ; Paleoproterozoic ; Cryogenian ; Cryogenian to Ediacaran ; Ediacaran ; Precambrian ; Ryacian ; Orosirian ; and Precambrian to Paleozoic. These strates appear in Figure ED-1(a).

Within these specific ancient strates, only some lithologies are suitable for ASM. We extract from [Thieblemont and BRGM \(2016\)](#) the lithologies prone and denoted as: the Metamorphic ; Metasedimentary ; Sedimentary ; Sedimentary and volcano-sedimentary ; Volcanic ; Volcanic and plutonic ; Volcano-sedimentary ; Volcano-sedimentary and metamorphic ; Volcano-sedimentary and plutonic ; With Orosirian metamorphism (Tuareg Shield) ; With Ediacaran metamorphism (Tuareg Shield). These lithologies appear in Figure ED-1(b).

To be more precise, the African continent occupies an emerged surface of more than 30 million km² and presents one of the richest and most varied geological contexts of the earth's surface since its formation 4.55 billion years ago. Most of Africa's geological basement is made up of Precambrian age formations that underwent various major phases of deformation until the end of the Neoproterozoic and the beginning of the Paleozoic, 540 Ma ago. Since this period, the African continent is stabilized and has not experienced any major orogeny. The only changes came from Phanerozoic extensions phases linked to the

Atlantic, Indian and East African Rift oceanic openings as well as a moderate influence of the Hercynian and Alpine orogeny in northern Africa. The overall ancient tectonic stabilization of the continent made it possible to conserve the Precambrian formations (Archean, Paleoproterozoic and Neoproterozoic) which constitute the bedrock on which Phanerozoic intracratonic sedimentary basins have been deposited. We here present the major formations of the continent starting from the oldest up until today.

The Archean cratons (4000 to 2500 Ma) [Kirk et al. \(2002\)](#); [Gabert \(1990\)](#) are known to be made up of the oldest rocks on the African continent. It consists mainly of series of gneisso-migmatitic TTG rocks type (Tonalite-Trondhjemite-Granodiorite), greenstone belts (basic, ultra-basic and metamorphosed sedimentary rocks) as well as later granites and granitoids from an important crustal fusion. These cratonic domains often defined by the age of the formations but also by their structural limits and their tectono-metamorphic evolutions outcrop in several places of the African continent: the West African Craton, the Congo Craton (center), the Tanzanian Craton in the east, the Kalahari Craton in the south and the supposed Sahara metacraton in the east of the Sahara. In post-Archean tectonics, these cratonic domains had an important influence by playing the role of thickened and particularly stable nuclei. These nuclei are essentially formed between 3.2 and 2.5 Ga. This period is characterized by the transition from Archean TTG intrusions to potassic granites and I-type granites. This change marked the geodynamic transition from a pre-plate tectonic, often referred to as stagnant lit, to mobile plate tectonics [Laurent et al. \(2014\)](#).

The Paleoproterozoic (2500 to 1600 Ma) [Goldfarb et al. \(2017\)](#); [Masurel et al. \(2019\)](#) is mainly represented by orogenic belts surrounding Archean cratons. The most representative orogeny of this period is the Birimian orogen (2270 to 1960 Ma) which re-mobilizes thick sedimentary series such as flyschs, turbidites and volcano-sedimentary series and volcanic series. All of these series have been strongly metamorphosed in the green schist to amphibolite facies, deformed and thrust onto the cratons before being remobilized by large crustal scale shear zones and intruded by late magmatic complexes (referred to as the Eburnean orogeny) [Grenholm, Jessell, and Thébaud \(2019\)](#). Locally, front-chain flexural sedimentary basins were poorly affected by Eburnean tectonics such as the Franceville basin in Gabon and conversely, the Birimian of West Africa shows an intense Eburnean deformation and metamorphism. On a regional to global scale, plate tectonics may thus have operated in a manner comparable to today. However, apparent absence of blueschists, boninitites and complete ophiolitic sections, indicate the effect of secular changes on a local scale.

The history of the Mesoproterozoic (1600 to 1000 Ma) is especially marked by the major magmatic event of the Kibarien (around 1375 Ma) with the intrusion of large volumes of magma. This episode is mostly recognized in the south of the equator, the

east of the Congo Craton, the south of the Tanzanian craton and around the Kalahari craton [Kpeou et al. \(2020\)](#).

The major event of the Neoproterozoic period (1000 to 560 Ma) is the Pan-African Orogeny (800 - 535 Ma) resulting from the breakup of the Rodinia super-continent before knowing an accretion phase leading to the formation of Western Gondwana in the west and the Eastern Gondwana to the east. The two blocks then collided in order to form the mega continent Gondwana. The mobile orogenic belts attributed to the Pan-African re-mobilize ancient cratonic borders along large shear zones in which numerous intrusions of magmatic suites are taking place. From the end of the Pan-African, the African basement is stabilized.

The Phanerozoic (540 Ma – present-day) covers a vast period from 542 Ma to the present day during which the African continent has been tectonically stable without orogenic influence at the continental scale. During the Paleozoic, gravity collapse accompanied by intense erosion of the various Pan-African orogens allowed the formation and filling of large intracontinental sedimentary basins mainly composed of sandstone. Locally, and especially in northern Africa, marine transgressions have led to the intercalation of maritime deposits. Finally, a Late Ordovician to Silurian glacial period allowed the deposit of tillites in a large number of these basins. Currently, these sedimentary basins cover more than 50% of the surface of the continent and its surrounding margins and the main ones are located in West Africa (Taoundeni basin), in the Congo basin, in the Kalahari or even in the rifts of East Africa. It was during the second half of the Phanerozoic, from the Triassic, that Gondwana cracks and Africa is isolated from other continents through passive margins linked to oceanic openings on both sides from the continent. Associated with this fragmentation of the continents, an intense magmatic and volcanic activity along the volcanic line of Cameroon, along the East African rift, or more locally in the Tibesti and the Hoggar is recorded.