GEOEssential ERA-PLANET

Essential Variables workflows for resource efficiency and environmental management

Deliverable 5.1
Report on EVs for extractives and artificial light monitoring

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Executive Summary

In this deliverable the concept of Essential Extractive Variable (EEV) and Essential Artificial Light Variable (EALV) are explored in order (1) to propose variables able to quantify the impacts mineral exploitation has on the environment, and (2) to discuss essential variables related specifically to artificial light at night, with a focus on defining potential variables and discussion of the difficulties associated with their measurement. For extractives, the variables are proposed in the perspective of creating monitoring tools for the implementation of the Sustainable Development Goals (SDGs). Various workflows involving geospatial data are proposed, and one of the EEVs is implemented as an operational GIS workflow aiming to contribute to SDG 15 'Life on Land'. This workflow allows estimating the surface of forest that is covered by mining concessions in the Democratic Republic of the Congo (DRC). The workflow is operationalized using a UNIX-GDAL script for automation of data processing, and published on a Virtual Laboratory Platform (VLab), a Cloud service based access platform that facilitates accessing input and output data and re-using the algorithm.

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Introduction

Mineral exploitation has a high price in terms of environmental impacts and potential threats for the health and prosperity of local populations. In this deliverable the concept of Extractive Essential Variables (EEVs) is explored with the aim to propose variables able to quantify the impacts that mineral exploitation has on the environment. These variables are developed with a view to contribute to the Sustainable Development Goals (SDGs). The proposed framework of EEVs is based on the use of Earth Observation (EO) products. Fourteen candidate EEVs are proposed and classified into three categories, depending on the extraction method, the installation of the mining site and the ore processing technique. Several workflows involving geospatial data are proposed, and one of the variables is operationalized into a GIS workflow, which aims at assessing the surface of forest overlapped by mining concessions in the Democratic Republic of Congo (DRC). The workflow is implemented using a Virtual Laboratory Platform (VLab), which facilitates accessing input and output data and re-using the algorithm. This work is mainly based on literature review and on personal reflection, therefore it still needs to be completed and improved along with experts of the sector and other stakeholders involved in the definition of essential variables in other topics (e.g., Climate and Biodiversity).

Light is one of the most important information sources available to organisms, and therefore strongly impacts behavior and physiology. For example, nearly all animals can be classified into the times in which they are active: diurnal (active during day), nocturnal (active at night) or crepuscular (active during twilight). For most organisms, light is the most important zeitgeber for the chronobiological processes that drive diurnal cycles and seasonal behavior (e.g. Gessler et al. 2017, Johansson & Köster 2019). In fact, there are even circalunar processes that are driven by exposure to moonlight (e.g. Kaniewska et al. 2015, Last et al. 2016). Changes to Earth's natural cycles of light and darkness by the addition of artificial light can therefore have dramatic consequences (Navara & Nelson 2007, Lunn et al. 2017), and light is therefore an essential variable of the Earth system. This text discusses essential variables related specifically to artificial light at night, with a focus on defining potential variables and discussion of the difficulties associated with their measurement. Variables related to natural light during daytime (e.g. solar insolation) drive weather and climate, and are therefore already established as essential climate variables. Moonlight is more variable, but because it comes from a single celestial source, moonlight can be treated in the same way as sunlight. Artificial light, on the other hand, is produced by uncountably many sources worldwide, for different reasons, at different times and intensities, and using different lighting technologies. We therefore start with an overview of how the extraordinary variability of artificial light complicates defining and measuring essential variables for artificial light. We then discuss possible essential variables for artificial light, divided into physical, social, and biological variables.

Essential Extractives Variables (EEVs)

Background

The extraction of minerals from natural deposits has been a constant in the history of human kind and one of the pillars supporting the economic and technological development we are benefitting today. But mineral extraction comes with a cost, which is mostly neglected due to the major benefits generated by this industry. In the form of raw material or processed ores, minerals are in every aspect of the daily life and the continuous demand fuels the quest for new lands to exploit, often generating land use conflicts with the existing soil occupation. Extraction and processing of minerals are associated with sustainability issues related to the use of natural resources in a way that will ensure their integrity to the benefit of future generations (IIED, 2002). Due to the destructive nature of mining activities, aquatic and land ecosystems are directly impacted; hence the need to include sustainable practices in the extractive field represents a prerequisite for the viability of this industry (Drielsma et al., 2016). These and other concerns have prompted the development of strategies to efficiently address the sustainability issues linked to mineral extraction and target the objectives of the Sustainable Development Goals (SDGs) and other policy frameworks. In this regard, one of the approaches considered is the concept of Essential Variables, largely used for climate monitoring and biodiversity. This section of the deliverable reports on developing indicators or Extractive Essential Variables (EEVs), which will assess the influence of mineral extraction on the area adjacent to the mine, the surrounding landscape and the ecosystems. The combination of Earth Observation (EO) products alongside additional ancillary data types, may allow the development of adequate instruments to quantify the impacts of extractive activities. GIS tools and spatial datasets are used as instruments for the implementation of extractive indicators and translated in the form of operation workflows. The outputs deriving from these workflows allow generating cartographic products, timely dashboards and supporting material for decision makers and stakeholders to ease the understanding of environment-related problematic linked to mineral extraction.

Life cycle of an extractive project

Previous to the exploitation of mineral deposits is the exploratory phase, which aims to detect the most profitable area for the development of the mining site. For the most part, these deposits are located in remote areas necessitating the construction of infrastructures and other facilities (roads, railways, access routes). Successively three phases can be identified in the process of mineral exploitation: extraction, mineral processing and waste handling. The first step is the extraction of the ore from the rock. In the case of open pit mines, the deposit is found near the surface and easily accessible by mechanical removal of rocks or through drilling and blasting to break the rocks. The size of the pit is linked to the availability of the mineral in the deposit and its accessibility. In general, when the amount of overburden extracted is superior to the amount of ore processed, the mine is no longer rentable. The ore extracted is successively processed through the use of chemical compounds.

Mining is a permanent commitment to the land and the production of waste is amongst the damaging outcomes of mineral extraction. The type and amount of waste generated are dependent from the geological characteristics of the ore deposit, the type of mine (underground or open pit) and the type of mineral being extracted (Durucan et al., 2006). The principal types of waste produced are:

- Tailings: what remains after the process of extraction of the mineral from the ore/rocks. Those are mostly grounded rock mixed with different type of chemicals according to the process of extraction used.
- Overburden: the soil and rock that need to be removed to access the mineral. It differs from tailing for being the layer of rocks covering the ore which is not processed but simply removed to access the mineral;
- Waste rock: a rock that does not contain any mineral of interest.

According to the type and use of the mineral resources extracted, the mineral industry can be divided into four subcategories: (1) energy mineral, (2) metallic minerals; (3) construction minerals; and (4) industrial minerals. The main techniques of extraction for metallic minerals such as iron, copper and zinc are both open pits and underground mines; while construction minerals, like calcium carbonate, are extracted mainly through quarrying. Depending on the technique used, mineral extraction can have different outcomes in terms of its footprint on the surrounding landscape (Awuah-Offei and Adekpedjou, 2011).

Environmental impacts of mineral extraction

Mining activities are responsible for a series of environmental impacts, which can vary according to the size of the mine and the nature of the deposit, its location, and the techniques and processes used to access the minerals (Ferreira and Garcia Praça Leite, 2015). These impacts ultimately influence the area surrounding the extraction site by changing, in an irreversible way, the original state of these ecosystems.

The ecological footprint of mines goes well beyond their perimeter and according to the distance from the mining site it is possible to determine a primary and secondary area of impact. The primary area represents the area directly impacted by the presence of the mine, processing facilities, roads, and energy transmission network. The secondary area concerns the zone near the mining site. It can be impacted at the level of its ecosystem and landscape integrity. The magnitude of the impacts on these areas decreases with increasing distance from the mining site (Frelich, 2014).

Below are a few examples of negative impacts due mineral extraction:

- **Decrease of the value and utility of land for agricultural and forestry purposes**. Vegetation will be gradually and incrementally removed to accommodate mines (Macdonald et al., 2015). Consequences of vegetation removal include increased soil erosion and differences between pre- and post-mining vegetative communities;

- **Disturbance to the flora and fauna of the area with consequent deterioration of the ecosystem integrity.** Direct impact of surface mining would occur on wildlife. They include: injuries or mortality caused by mine-related traffic; direct loss of less mobile wildlife species; restrictions on wildlife movement created by fences, roads, spoil piles and pits; displacement from existing habitat in areas of active mining including abandonment of nesting and breeding habitats for birds; increased noise, dust and human presence (Frelich, 2014). Loss of habitat can additionally lead to changes in species composition, as forested areas are converted to grassland after reclamation (Van Wilgenburg et al., 2013);

- **Increased rate of erosion, sedimentation and landslide, representing a threat for the water resources and the integrity of the landscape**. In open pit mines priority is given to the control of water entering the pit. A system of canalization is put in place to drain the pit from atmospheric precipitations. Additional measures are considered if the pit overlaps an aquifer to prevent flooding from groundwater. Pumping for removal of excess ground water in the mining pit can have consequences on the water table. This reduces the amount of water available to the base flow of surface watercourses that can ultimately affect water supplies for agricultural and human consumption (Karmakar and Das, 2012);
- **Risk of release of pollutants in the groundwater or superficial water.** Mineral processing is related to the risk of acid drainage. Acid generation takes place in the PH range when iron sulphide minerals are exposed to and react with oxygen and water. Exposing these materials and breaking them up can facilitate this process. Mining exposes sulphide rich materials in the walls of open pits, mine tunnels, waste rock. If leaking in water body or transported by run off, it poses a threat to aquatic life and makes water unfit for human consumption (Vela-Almeida and Wyseure, 2016);
- **Degradation of the quality of life of local communities to the benefit of short-term welfare**. Activities such as blasting, excavation, loading and hauling of overburden and coal, and wind erosion of disturbed land, produce fugitive dust. Nitrogen oxides are the principal fugitive gaseous emissions produced during surface coal mining operations (Hendryx, 2009).
- **Alteration of the watershed and hydrology of the basin.** Local destruction of stream segments through burial beneath valley fills or converted to waste treatment systems in the form of ponds have an impact on the integrity and functioning of the basin. Furthermore, the removal of vegetation and the compaction of soil alters the pattern of the water flowing through the watershed, changing the composition of water and altering the chemistry of the downstream receiver streams (Akiwumi and Butler, 2008).

Proposed EEV framework

The concept of EV: a tool to characterize and predict the Earth's systems development

The first definition of an essential variable was provided by the Global Climate Observing System (GCOS) in the 1990s in the context of climate monitoring. It defines Essential Climate Variables as: *"physical, chemical or biological variables or a group of linked variables that critically contribute to the characterization of Earth's climate*". The concept of essential variable derived from the need to have accurate and continuous information on the atmosphere, land, and oceans to monitor the Earth's climate, and ultimately understand past, current and future climate variability (Bojinski et al., 2014; Brummitt et al., 2017). Later on, the concept of EVs, was expanded to other domains, such as ocean and biodiversity, to assume a broader definition more inclusive of other Earth's systems: *"minimal set of variables that determine the system's state and developments, are crucial for predicting system developments, and allow us to define metrics that measure the trajectory of the system."* (Blonda et al., 2016).

In a context of changing environment, the use of essential variables is necessary to target the components of environmental systems on which variability can be observed and studied (Turak et al., 2016). The importance of understanding the dynamics of ecosystems allow to efficiently manage them and assess where the changes are occurring, at what rate and how

they will evolve in the future. The criteria followed for the development of essential variables are:

- **Relevance**. The variable is able to characterize the system and be of use in assessing its changes;
- **Feasibility.** Observing and deriving the variable is feasible on a global scale in terms of technical requirements. It is possible to collect the information linked to the variable by using proven and reliable scientific methods;
- **Cost effectiveness**. Generate and archive data on the variable is affordable (Bojinski et al., 2014).

Towards the implementation of EVs in the extractives field: a current state of knowledge

Despite the potential of extractive activities to alter the surrounding environment in terms of natural ecosystems and socio-economic realities, a list of formal Extractive Essential Variables (EEVs) is not yet being determined. Out of the three sustainability pillars --social, environment, economic-- the environmental one is the most advanced in term of research. Numerous are the studies conducted to assess the impact of mineral extraction on the environment, they mostly target the fauna and flora and the disruption of land and aquatic ecosystems. Nonetheless there is a lack of cohesion between the scientific research and its use for the implementation of political frameworks for sustainability.

The literature review conducted as part of this work shows a shift in thinking of the mineral industry, willing to abide by the definition and requirements of sustainable development as stated by the Brundtland commission. In the paper published by Azapagic (2004), the author introduces the idea of corporate sustainability, a concept encouraging mineral industry to tailor extractive practices oriented towards a more sustainable production. Presented in different guises, the concept of EEV emerges from this paper: the author's approach is to distinguish the different phases of the extractive supply chain and identify sustainability issues related to each of these processes. A set of variables is identified to contribute to the characterization of the system in terms of key economic, environmental and social sustainability issues.

Another relevant paper for the development of indicators for mineral extraction is presented by Marnika and Xenidis (2015). The study provides a list of indicators based on raw data to calculate qualitative and quantitative characteristics of the impact of mining activities in protected areas. The author provides a framework analyzing the different roles mineral extraction has on the social, economic and environmental fields and propose some indicators to assess their influence in each of these three fields.

Different methodologies are used to estimate the impact of mineral extraction on natural systems. One of the approaches used, sees the integration of GIS and geoprocessing on aerial images to detect the changes on the landscape. Considering the vast extent of mining sites and the extent of the impacted zones, the use of satellite images can facilitate the assessment of the changes on the soil occupation. Relevant in this field is the study carried out by Santo et al. (2002) in Brazil where a detailed workflow is implemented to assess the changes on the landscape subsequent the installation of sand mining facilities. This workflow uses satellite images previous and following the installation of the mine thus considering the temporal dimension of the changes. The indicators selected to measure the

environmental changes of the area are: (1) total mining area; (2) former agricultural land converted into open pits, open water ponds and mining ancillary installations; (3) deforested areas; (4) channel river morphology modifications; (5) vegetation growth in reclaimed areas; and (6) mining encroachments on legally protected riverside zones. A similar and more recent study using satellite images as a tool, gives information on the changes on the hydrology of the area impacted by mining activities. The study conducted by Padmanaban et al. (2017), explores the use of remote sensing and vegetation indexes (NDVI) to assess the changes on the vegetation and the landscape over a claimed area. Remote sensing and GIS have proven themselves as advantageous over field monitoring to assess long to short term landscape dynamics. The study aims to (1) examine the short-term land use and land cover dynamics in a claimed area; (2) quantify the emergence and growth of wetlands in the area interested by the mine and identify potential subsidence spots; and (3) examine the vegetation dynamics following ground water table fluctuation and ecological stress. Both studies include image processing, image classification and indices calculations to assess the impact of mineral extraction on the landscape components.

Based on what precedes, the current deliverable reports on the work that was conducted to develop an EEV framework. This framework aims to lay foundation for bridging the gap between (1) the previous researches conducted to assess the degree of environmental impacts of extractive industries and (2) the targets imposed by the SDGs. Environmental indicators for the extractive industry will represent the final output of a process unifying field-based observations and the political will for a sustainable and conscious use of natural resources for the social, economic and environmental welfare.

Proposed EEVs framework

The different components of the Earth's systems – lithosphere, hydrosphere, biosphere and atmosphere, are interdependent and mutually affecting each other so that a change in one sphere results in changes in one or more of the other spheres. This interconnection is perceived in the overlapping of essential variables created for other domains. In the case of mineral extraction, the use of existing Essential Biodiversity Variables (EBVs) (CBD, 2013) was considered in order to assess the impact of mining on the biodiversity and ecosystem structure. In the same way, the proposed EEVs proposed for assessing the impact of extractive activities on the atmosphere, are shared with the essential climate variables (ECVs). The interconnection between EVs should reduce the amount of new and redundant indicators and highlight the multidisciplinary nature that SDGs should have in targeting multiples aspects of the same system. Figure 1 is a graphical representation of the logic used to develop different workflows and to derive EEVs.

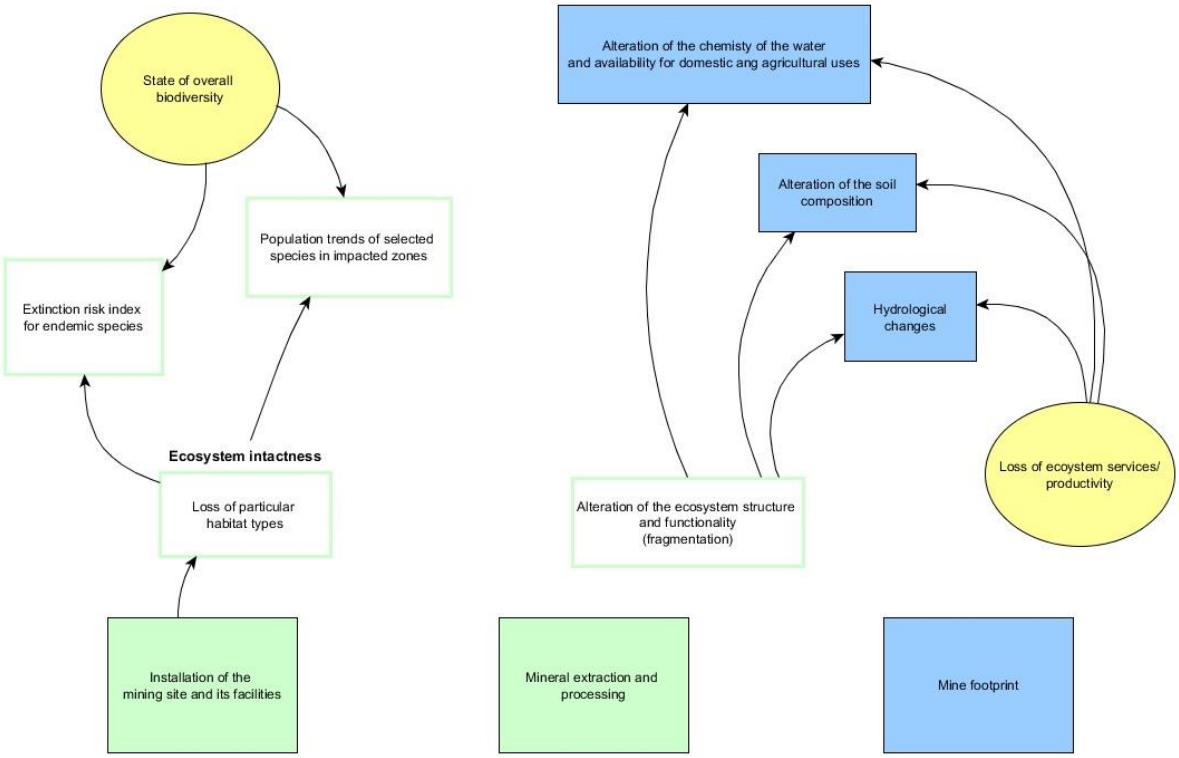


Figure 1. Flowchart for the development of the EEVs framework

In Figure 1 the blue boxes represent the anthropogenetic processes that are responsible for ecosystem degradation. Mineral exploitation has a negative impact on habitat, which will in turn affect species distribution. Similarly, mineral exploitation has a negative impact on ecosystems functions and structure, which leads to a loss of ecosystem services and productivity. The green boxes represent the footprint that mineral exploitation has on the ecosystems hydrology, soil quality and chemistry.

Considering all of the above, the Extractive Essential variables proposed in this work were distributed into 3 classes or categories: installation and exploration phase, mineral extraction, ore processing. The reasoning behind the selective process was driven by three questions: “Why is it changing?”, “How is it changing?”, “What are the consequences?”. Through these questions it was possible to break up the phases involved in the extraction process and understand at what level they interact with the surrounding natural environment. As a consequence, it was possible to select aspects of an ecosystem susceptible to changes and determine possible indicators to assess these impacts.

The first class of Essential Variables considers some of the impacts deriving from the explorative phase and the settlement of the mining site. Both these processes are responsible for changes in the ecosystem structure directly affecting natural habitats. This category will contain indicators relative to habitat fragmentation, changes in abundance of avian, terrestrial and endemic species.
The second class of EEVs revolves around the mineral extraction process. The extraction method varying according to the nature of the mineral deposit and the mineral to be extracted can lead to different impacts on the ecosystems (Frelich 2014; Ferreira and Garcia Praça Leite 2015). By identifying Essential Variables within this category, it will be possible

to develop indicators to monitor changes in the hydrology of the area and the chemical composition of the atmosphere.
A third class of EEVs will target the ore processing methods and some of the environmental issues such as water and soil pollution.

The proposed EEV framework is from Ambrosone et al. (accepted by Geo-spatial Information Science). It is summarized in Table 1 and further described in detail.

Table 1. Proposed EEVs framework

Group of EEVs	EEV category (function of the ecosystem which is affected)		EEV
1. Variables related to the installation of the mining site			
	Land	1.1 Ecosystem structure	1.1 Degree of fragmentation
		1.2 Sensitive species	1.2 Extinction risk index
		1.3 Avian species	1.3 Population abundance
		1.4 Terrestrial species	1.4 Population abundance
		1.5 Forest	1.5 Surface of forest lost
		1.6 Land use and agriculture	1.6 Surface of crop lost
		1.7 Species habitat category	1.7 Habitat loss
2. Variables related to the extraction method			
	Water resources/Hydrology	2.1 Mining related water use	2.1 Data on water extraction per year
		2.2 Groundwater	2.2 Groundwater volume changes
		2.3 Lakes and superficial water	2.3 Changes in water surface, lake extent
	Atmosphere	2.4 Atmospheric composition	2.4 Content of greenhouses gas and/or pollutants
3. Variables related to the ore processing technique			
	Land	3.1 Soil chemical pollution	3.1 Changes in soil chemical composition
	Water resources	3.2 Groundwater	3.2 Groundwater chemical pollution

(*) Function of the ecosystem that is affected

First group. Variables related to the exploration and installation of the mining site.

This group of variables targets some aspects of the exploration phase and the installation of the mining site susceptible of altering the ecosystem structure. It targets land use conflicts deriving from the installation of the mining facilities such as the loss of forested areas, species habitats and agricultural dedicated areas.

1.1 – ecosystem structure category. Determines the degree of fragmentation of ecosystem following the installation of a mining site. A large proportion of the world's mineral and energy resources are found in forested regions, which are consequently subject to severe disturbance by surface mining. This can lead to alterations in the ecosystem structure, function and services (McGarigal, Cushman and Regan 2005; Layman et al. 2007).

1.2 – sensitive species category. Expresses the percentage (%) of the surface of habitat lost over the total area inhabited by a particular species as a consequence of the occupation by mining facilities. As the availability of accessible mineral deposits decreases, the exploration of remote areas holding minerals of interest increases. This can represent a threat for the conservation of isolated species. In particular extractive practices requiring blasting can irreversibly damage unique ecosystems and biodiversity. Metallophyte plants represent an example of threatened species because they thrive on mineral deposits (Ginocchio and Baker 2004; Saad et al. 2011). The indicator is calculated from the mining activity area and the area covered by the habitat of a species.

$$\frac{\text{mining activity area}}{\text{total surface of the habitat}} \times 100$$

1.3 – avian species category. The loss or alteration of avian population habitats can lead to a decrease in the population abundance. Disturbances on habitat results in nesting sites loss, increased noise, habitat fragmentation (Kociolek et al. 2010; Van Wilgenburg et al. 2013). The indicator is a measure of the changes in the abundance of a given avian species as a consequence of the start of mining activities.

1.4 – terrestrial species category. Expresses the changes in the abundance of terrestrial species over the time following the start of extractive activities on the area. Mining has a direct impact on local habitat degradation through the removal of vegetation and soil. This can impact the mobility of terrestrial species, facilitate the introduction of alien species and other negative stress that affect the growth of populations. This can be reflected in a decrease in the population abundance (Kociolek et al. 2010; Bernhardt and Palmer 2011; Frelich 2014; Castro Pena et al. 2017).

1.5 – forest category. Expresses the percentage (%) of forest lost following the installation of the mining site. Vegetation will be gradually and incrementally removed to accommodate mining. Impacts associated with vegetation removal could include an increase in soil erosion and differences between pre-mining and post-mining vegetative communities.

$$\text{surface of forest lost (\%)} = \frac{\text{mining activity area}}{\text{total surface of the forested area}} \times 100$$

1.6 – land use agriculture category. Extractive activities are often in conflict with existing land use, creating conflicts of interest between different soil occupations. Despite the temporal economic benefits associated with the mine, the economic loss for the local communities can be large depending on agriculture for their livelihoods. For the regions where, agricultural production represents the main economic activity, an increase in land degradation can affect the communities' ability to sustain themselves. The indicator is calculated from the mined surface and the area covered by crops and represents the percentage (%) of crop surface lost following the installation of the mine (Waldner et al. 2017).

$$\text{surface of crop lost (\%)} = \frac{\text{mining activity area}}{\text{surface of the crop}} \times 100$$

1.7 – species habitat category. Direct impact of surface mining would occur on wildlife. They include: injuries or mortality caused by mine-related traffic; direct loss of less mobile wildlife species; restrictions on wildlife movement created by fences, roads, spoil piles and pits; displacement from existing habitat in areas of active mining including abandonment of nesting and breeding habitats for birds; increased noise, dust and human presence (Frelich 2014). This indicator expresses the percentage (%) of the habitat lost following the installation of the extractive site.

$$\text{habitat loss (\%)} = \frac{\text{mining activity area}}{\text{total surface of a species habitat}} \times 100$$

Second group. Variables related to the extraction method.

The variables proposed in this group consider some of the impacts deriving from different extraction methods. In particular they address the effects on the hydrology of the landscape where the mine is located in terms of changes in the volume of groundwater and superficial water, rivers diversion.

2.1 – mining related water use category. Quantify the annual consumption of water related to mining activities. Water extraction and water diversion for the operations carried out by the mine can influence the amount of water available for other uses. The amount of water used by the mine and the impacts they will have on the overall hydrology, depends on the type of the mine and the extraction method. Data on water extraction and water use will provide information on the availability of fresh water in the basin.

2.2 – groundwater category. Mining related activities are responsible for influencing the groundwater volume (Zhao, Ren and Ningbo 2017). In the case of open pit mines, measures are taken to prevent water from accumulating in the pit. In the case of a pit overlapping an aquifer, the water is pumped out to prevent flooding from groundwater. This practice is responsible for fluctuations of the water table and this can reduce the amount of water available to the baseflow of surface water courses.

2.3 – lakes and superficial water category. Mineral activities are responsible for alterations of the hydrology of the region and consequently the surface water will be affected.

2.4 – atmospheric composition category. Expresses the dispersion of dust, pollutants and greenhouse gases in the air within the mining facilities. Activities such as blasting, excavation, loading and hauling of overburden and coal, and wind erosion of disturbed land,

all produce fugitive dust (Hendryx 2009). Nitrogen oxides are the principal fugitive gaseous emissions produced during surface coal mining operations (Oluwoye et al. 2017).

Third group. Variables related to the ore processing.

The variables proposed for this group relate to some aspects of the ore processing phase that vary according to the nature of the mineral deposit being exploited. Some of the issues taken in consideration are the contamination of water resources and soil by metals' leachability, dust and pollutant dispersion from blasting.

3.1 – soil chemical pollution category. Is associated with the potential dispersion of pollutants and chemical substances in the soil as a consequence of leachability of waste rock disposal sites (Asami 1988). In calculating this indicator some parameters as waste rock leachability, coefficient of permeability of the soil should be taken into consideration.

3.2 – underground water pollution category. Ground water pollution can occur directly or indirectly as a consequence of surface mining. Direct pollution can occur from diversion of contaminated drainage from the mine or acid mine drainage. This pollution will pose danger for the entire basin

3.3 – superficial water pollution category. Mineral processing is related to the risk of acid drainage. Acid generation takes place in the pH range when iron sulphide minerals are exposed to and react with oxygen and water. If leaking occurs in a water body or is transported by run off it can pose a threat to aquatic life and make water unfit for human consumption (Naicker, Cukrowska and McCarthy 2003; Eisler and Wiemeyer 2004).

Links with SDGs

The EEVs proposed above can be linked to different SDGs, targets and indicators. This linkage is summarized in Figure 2.

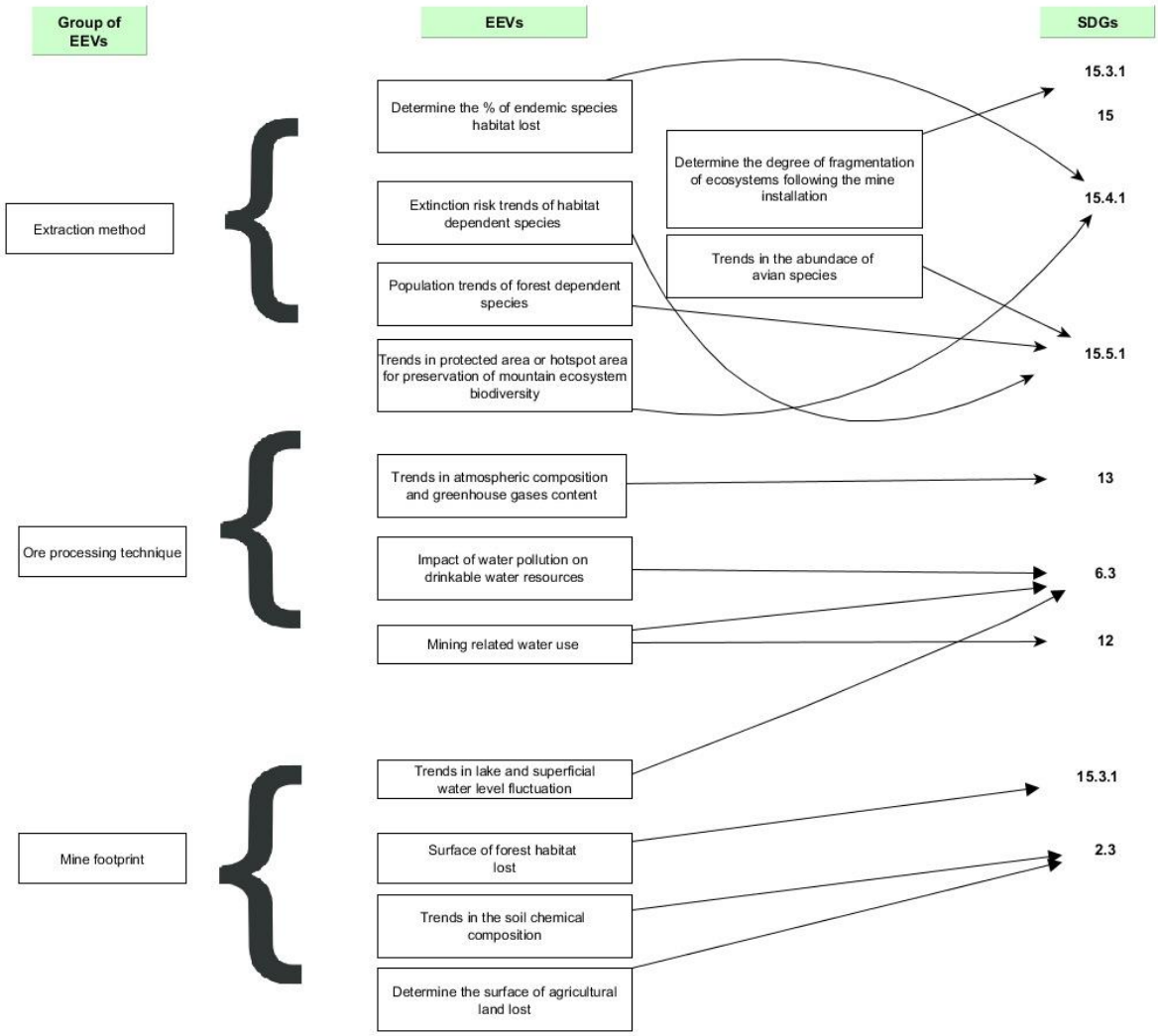


Figure 2. Link between the proposed EEVs framework and SDGs

Workflow implementation

The SDG15, "life on land", aims to preserve and restore key terrestrial habitats for biodiversity as well implements sustainable land management in order to combat desertification, restore degraded forests and halt the destruction and unsustainable exploitation of existing forests.

As mentioned previously, mineral extraction has an important impact on terrestrial ecosystems. In view of attaining the targets fixed by the SDGs for terrestrial biodiversity and ecosystem conservation, a workflow assessing the impact of mines on forest was developed (Figure 3, box 1a). This workflow allows quantifying the surface of forest lost as a consequence of the mine installation by comparison of two sets of data prior and subsequent the mineral exploitation. The indicator was developed starting from the assumption that mining sites and forests cannot coexist for the same site and that the presence of the mine corresponds to the loss of an area of the forest. The region chosen for this work is the Democratic Republic of Congo (DRC). This indicator does not exist yet but similarities can be found with the indicator 15.3.1 "*proportion of land that is degraded over*

total land area" proposed for the SDG15 and available on the UN SDG metadata repository (https://unstats.un.org/sdgs/metadata/files/Metadata-15-03-01.pdf).

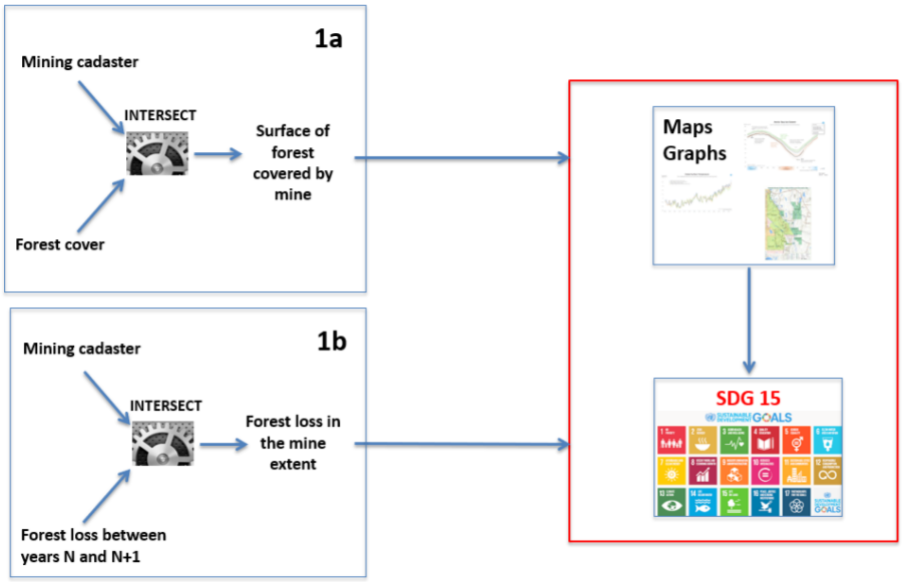


Figure 3. Implemented workflow to assess the surface of forest covered by mining concessions in DRC (1a), and possible extension of this workflow to monitor forest loss over time (1b)

The indicator is calculated from geospatial data of the forest cover and the surface occupied by mining concessions. The output of the workflow is derived from a spatial overlap between digital polygons of the DRC mining cadaster (CAMI 2018) and TIFF files representing the forest cover. The value of the indicator, given in km^2, is computed as the surface of forest occupied by mining concessions. Both tree cover and mining concessions are for the year 2015.

The data for the forest cover are obtained from the website Global Forest Change from University of Maryland, Department of Geographical Sciences (https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html). The tree cover is defined as canopy closure for all vegetation taller than 5m. The values of forest cover for each pixel of the image are encoded as a percentage per output grid cell which values range between 0 and 100. The size of the pixel is 25*25 m. The data for mining concessions are provided by the mining cadaster from Democratic Republic of Congo, provided by Ministry of Mines in DRC. Each concession is represented as a polygon (Figure 4).

The workflow, initially tested on ArcMap 10.3.1, consists of a series of geoprocessing tools linked together to carry out a complete data treatment from raw data to the outputs.

The workflow involves several steps, including: (1) download forest cover on the country extent; (2) mosaic forest cover tiles; (3) dissolve all mining concessions into one polygon in order to avoid topological error and to compute actual surfaces; (4) clip forest data by the dissolved mining concession; (5) compute the surface of forest currently recognized that is covered by mining concessions. A script was conceived to automatize the process of data treatment. The language chosen to develop the script to automatize the data treatment is Unix. The GDAL library (Geospatial Data Abstraction Library) for reading and writing raster and vector geospatial data was chosen to develop the script. A bash approach was privileged over a python script to avoid the installation of complex libraries for data treatment. The outputs are computed and printed in a text file.

The script is presented in detail in Annex 1. It is composed of:

- **A central part**. The extent and resolution of the TIFF image are obtained with the command *gdalinfo*. Successively a raster is created from the vector containing the information for the mining concessions with the command *gdal_rasterize*. The value attributed to this raster is 0 for absence of polygons and 1 for presence of polygon. At the end of this steps a raster with the same extent and resolution of the TIFF image of the forest is obtained. The command *gdal_calc.py* allows combining the new concessions raster with the raster of forest cover by multiplying the number of pixels of the two rasters. In an analogous approach to the *Extract by Mask* used in ArcGIS™, a new raster is created containing the area of the forest overlapping the concessions.
- The extent of the surface occupied by the mines is calculated in the newly created raster. This value is obtained by calculating the mean value of pixels present in the raster, multiply it for the total of pixels of the raster, multiply for the size of each pixel (25m*25m) and divided by 10^{-6} to obtain the surface of the forest in km^2;
- **A 'for' loop**. The TIFF files necessary to cover the total extent of DRC are inserted into a 'for' loop to automatically execute the central part of the script for each image in the input variable.
- **The outputs**. A variable containing the results of every 'for loop' is created. The final indicator is obtained by summing up the outputs of every single loop. The result obtained for the datasets provided in 2015 is: 143'617 km^2 (Figure 4).

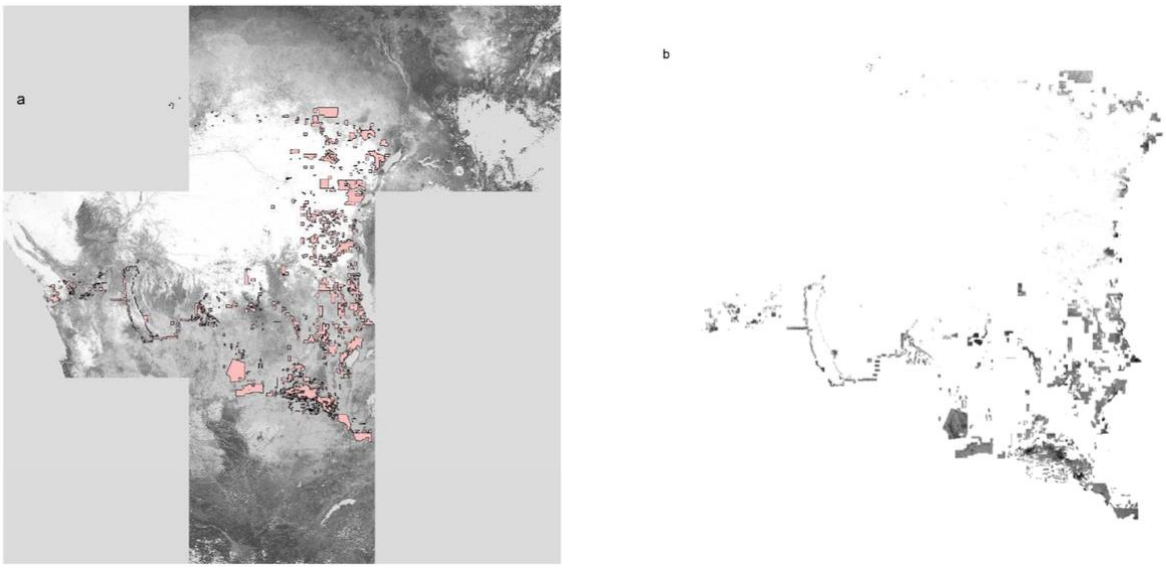


Figure 4**.** (a) Forest cover and mining concessions (in pink) in DRC (2015). (b) Result of the overlap analysis between the two layers

Moved by the need of sharing all these resources in an accessible way and re-using the algorithm with other parameters, the script was published into the Virtual Laboratory Platform (VLab) developed by the Consiglio Nazionale delle Ricerca (CNR). Initially developed in the frame of H2020 ECOPOTENTIAL[1] the VLab has been improved during H2020 GEOEssential. It is interoperable with the Global Earth Observation System of

[1] http://www.ecopotential-project.eu

Systems (GEOSS) and it includes a graphical interface. The process of uploading the script on the VLab platform required its publication on the cloud where the input data and the code were stored. The intermediate platforms used for this purpose were GitHub[2] and Docker Hub[3]. The use of Docker for the purpose of this work is to create the image supporting the model based on the implemented script. With the term 'image' it is intended a virtual environment containing an operative system (Ubuntu in our case), data files and the libraries needed to run the code. The Docker container and its files were uploaded on GitHub, which now contains all the elements necessary to run the model.

Mineral extraction and its surrounding: workflow propositions to determine the interaction of mineral extraction on ecosystems

In this section we propose 6 additional workflows (see Annex 2), based on geospatial data and quantitative information that could help to operationalize the EEVs presented above. These workflows are still at the state of preliminary research, and they would deserve further work and implementation. However they provide primary elements of thought in the context of operationalizing an EEV framework.

When considering the sustainability of mineral activities, two aspects should be taken into account: (1) the life cycle of natural products including the extraction and processing of the natural resource; (2) the life cycle of the mine and the production facilities. The 6 additional workflows that are proposed integrate these two aspects. Some of the data source that are considered for the design of these workflows are: (1) direct *in situ* biological and ecological monitoring and data collection to assess the abundance of species, their distribution and their behavior in their natural habitat; (2) remote sensing for the collection of data relative to the ecosystem attributes; (3) maps of land use and land occupation to determine the different uses of the study area.

The 6 proposed workflows are listed below. They are described in more detail in Annex 2:

- Mineral extraction and biodiversity: surface of a species habitat lost due to the presence of the mine
- Mineral extraction and agricultural activities of the surrounding area;
- Mineral extraction and areas of interest for the protection of mountain ecosystems;
- Mineral extraction and the hydrography of the landscape;
- Mineral extraction and habitat fragmentation;
- Mineral extraction and endemic species: the case of metallophyte plants;

Essential Artificial Light Variables (EALV)

[2] GitHub is an open source project that allows managing and storing revisions of projects. Each project requires the creation of a repository where all the input data and the code are stored. The repository can be access through a URL. A desktop version of GitHub was downloaded. Changes made in the code locally are directly transferred on the corresponding repository on GitHub.

[3] Docker Hub is a cloud-based registry service that allows creating code repository, building, testing, sharing and managing images.

The challenges of defining essential variables for artificial light

A main reason that defining light variables is challenging is due to the directional nature of light. In contrast, consider scalar variables such as air or water temperature or oxygen levels. These variables may change over time, but for any given location in space they are defined by a single value. Essential variables that are vector quantities add an additional complication, because in addition to a value, a direction must also be specified. For example essential climate variables related to wind must specify both wind speed and direction. In the case of light, however, there is not a single direction in which the light is traveling, but instead a different value of radiance (brightness) in every possible viewing direction (i.e. over 4π solid angle). This radiance can easily change by an order of magnitude when viewing a white vs dark colored object, and many orders of magnitude in the case of viewing directly towards a light source. The amount of artificial light present can also change by several orders of magnitude over a distance of only a few centimeters, from a position in a beam of light into a nearby shadow.

Essential variables for light are also challenging to define due to the fact that light consists of a spectrum. It is possible to define variables based on human vision (e.g. using $V\lambda$), but this will not be appropriate if the variable is meant to characterize the impact of light on other animals or plants. Even for human beings, the daytime spectral response that defines $V\lambda$ does not match the response of the visual system at the lower (mesopic or scotopic) light levels common at night, nor does it match the response of the human chronobiological system. Some lamps also emit ultraviolet (UV) light, such as mercury vapor lamps or UV-driven white LED. Ultraviolet light is not visible to humans, but can have major environmental impact due to its effect on animals, especially insects.

An idealized understanding of artificial light would consist of a complete characterization of the light field at all points in the Earth system. This would mean that for any given position, we would know the spectrally resolved radiance in all directions and at all wavelengths (or rather at least wavelengths ranging from the UV to the near infrared). Such a complete characterization is of course not possible to achieve experimentally. Therefore, when defining EVs in the following sections, the focus is on variables that are both feasible to experimentally measure and relevant for understanding changes to the Earth system. Both ground and space-based measurements are considered, but the main focus is on measures that can be remotely sensed.

Physical essential variables for artificial light

Several essential variables describe the physical state of areas of Earth, for example impervious surface or mined area. In line with these EVs, an obvious EV for artificial light would be lit area. This makes intuitive sense when one examines a satellite image of Earth at night: one may immediately ask what fraction of Earth's area is lit versus unlit? Unfortunately, the answer to this question will depend on the resolution of the instrument used to make the imagery. As resolution is reduced, lights appear to take up greater area (Figure 5). While cities appear completely lit on satellite imagery, the roofs of buildings are generally unlit. Using high resolution aerial data, Hale et al. (2013) reported that only 8% of the total land area of Birmingham (UK) was lit brighter than 10 lux, and even in densely built areas only about 30% of areas were this bright.

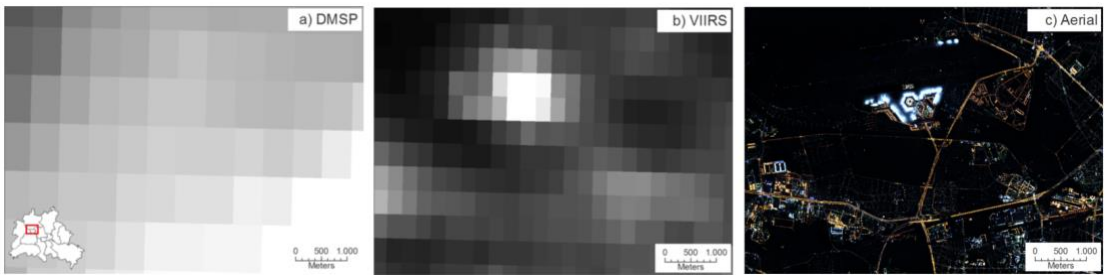
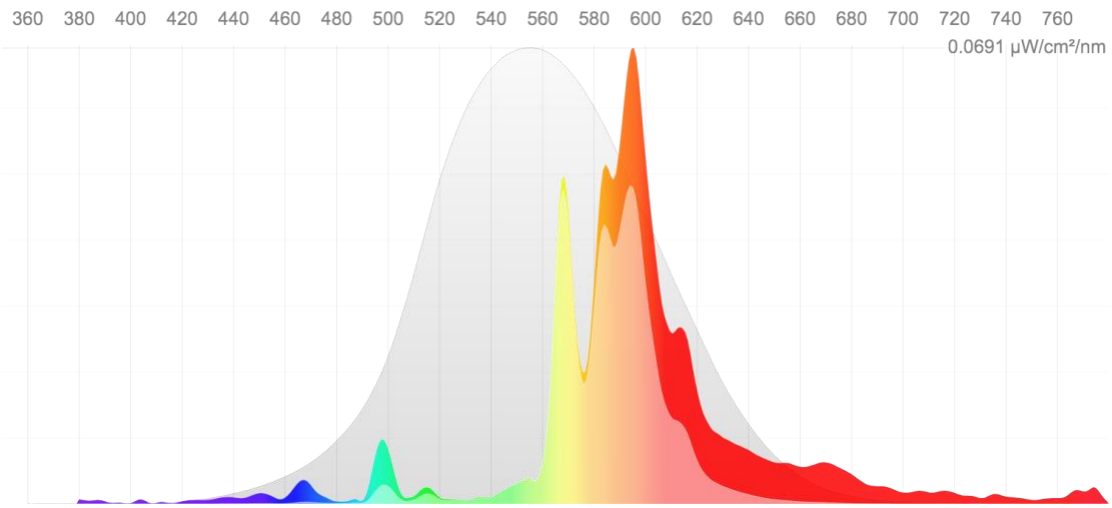


Figure 5: Images of Berlin's Tegel airport from sensors with three different resolutions. (a) Defense Meteorological Satellite Program-Operational Linescan System (DMSP); (b) VIIRS DNB; (c) aerial photography. The inset at the bottom left shows the area of Berlin displayed in each of the three panels. The resolution of DMSP was too coarse to identify light sources smaller than the city scale. Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by the U.S. Air Force Weather Agency. Figure and caption reproduced from Kyba et al. (2015).

Despite this problem, it is clear that estimated lit area is a useful variable. For example, Kyba et al. (2017) compared satellite imagery taken in 2016 to that taken in 2012 with the Visible Infrared Imaging Radiometer Suite Day/Night Band (DNB). They showed that the lit area of Earth increased on average by 2.2% per year during this period, with much faster growth in many developing countries (e.g. 19% per year in Ghana). Unfortunately, it is not possible to directly compare data taken with satellite instruments with different resolutions. Perhaps one solution to this problem could be to project such data into standard resolutions at which it is to be measured (e.g. 1m2, 100 m2, 1 ha, and 1 km2). Even if this was done, one must still decide on what brightness level should count as "lit".

The question of what brightness counts as lit is further complicated due to the wide variety in spectrum of lighting sources, combined with the spectral resolutions of different radiometers. In contrast to daytime, where the entire scene is lit by a blackbody source (the sun) with a stable and known spectral distribution, artificial urban lighting is characterized by lights of different colors, as can be seen in the right hand panel of Figure 5. Different artificial light sources have vastly different spectra (Figure 6). Because of this, space-based broadband radiometers measure different radiances when viewing the same city lights (Sánchez de Miguel et al. 2019). In addition to complicating the problem of setting a threshold to define an area as "lit", this means that broadband radiance from different satellite instruments cannot be directly compared.



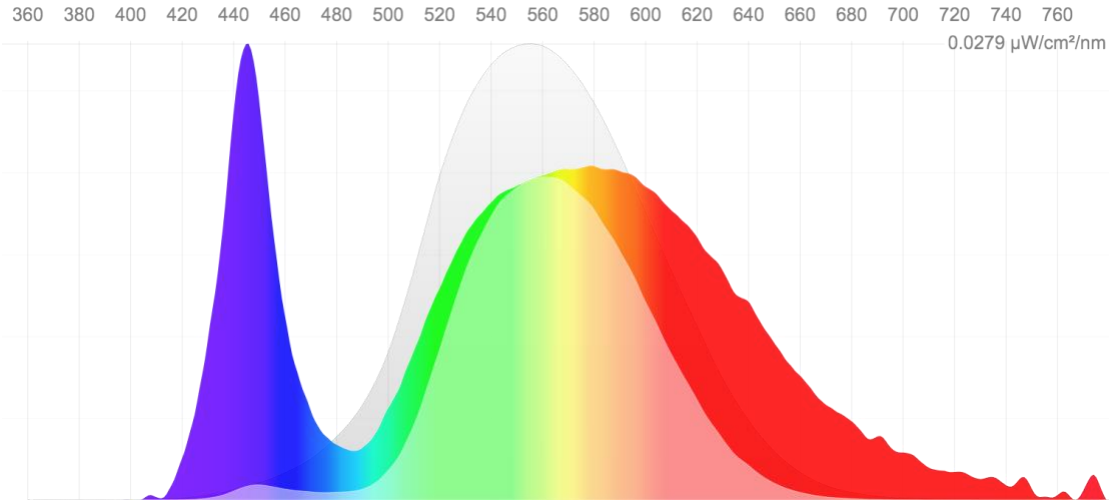


Figure 6: Spectra of two commonly used light sources compared in both cases to the human photopic action spectra (grey). A high pressure sodium lamp is shown above, and a 4300K "white" LED (below). Images generated using the spectral tool at https://fluxometer.com/, licensed for reuse under CC BY 4.0 by the fluxometer project.

Let us now suppose that a specific spatial resolution and band (or set of bands) was selected in order to define an essential variable for upward artificial light emissions. Two additional questions then arise: what time (or times) should the measurements be made, and at which angle? The acquisition time is an issue because urban light emissions are known to decrease as the course of the night goes on (Dobler et al. 2015, Kyba et al. 2015, Meier et al. 2018). Furthermore, at high latitudes, early or late acquisition times will restrict the times of year during which data can be taken (due to the long summer twilight). Imaging angle can be important, particularly in urban contexts, as tall buildings can screen light emissions, making them not visible in certain directions (Coesfeld et al. 2018).

While all of the issues discussed above will certainly complicate efforts to define essential variables for upward emissions of artificial light, one should not give up hope. Keep in mind that the alteration of the night environment compared to the natural starlit state is extreme: an illuminated street is typically over 100 times brighter than full moon illumination, and 10,000 times brighter than illumination from starlight alone (Hänel et al. 2018). Any compromise decision on essential variable definitions will not be perfect, but nevertheless be a useful variable.

The essential variables described thus far were defined in ways amenable to measurement via remote sensing from space. However, animals, plants, and humans rarely experience light emitted upwards. Rather, we generally experience light emitted or scattered sideways. Essential variables related to upward light therefore don't tell the whole story with regard to consumption of light, or negative environmental impacts of light (light pollution). It is possible to quantify light exposure for given locations using photographic or spectrographic techniques, but the number of locations that can be sampled is much lower, as it requires an observer to travel to the site with measurement equipment.

It is possible to obtain multispectral radiance data for half of the unit sphere (i.e. half of all possible viewing directions) using either a camera with a fisheye lens, or by making a mosaic of a large number of images with a wide-angle lens. This technique has been used extensively for measurement of skyglow, the artificial brightening of the night sky (e.g. Duriscoe et al. 2007, Kolláth 2010, Jechow et al. 2018). The technique can be extended by taking additional

photographs to include upward directed light, therefore measuring light exposure from all viewing directions. Either or both of these measures could be considered as a possible essential variable for artificial light.

In both cases, questions of spectral response are again problematic. One solution could be to specify the spectral bands over which the measurement is to be made. Measurements could then be taken using either specified filters (for a camera on a robotic mount) or by making an educated guess about the spectrum of the sources, and correcting the measurement via synthetic photometry (see Sánchez de Miguel et al. 2019).

Environmental factors, particularly clouds, snow cover, and foliage presence or absence, can have extraordinarily large impacts on the light exposure at both ground level and for observations from space (Levin 2017). Clouds have especially dramatic effects, as they darken the environment when artificial light is not present (Jechow et al. 2019), but brighten it dramatically near light sources (Kyba et al. 2015). It is therefore necessary to specify how often or under what meteorological conditions essential variables for artificial light are to be recorded.

All-sky or all-directional imaging does not lend itself easily to permanent monitoring, and thus has seen limited use thus far. A more common method of measurement has been to observe only the sky radiance at zenith, using a fixed device (e.g. Kyba et al. 2015). Designating zenith brightness as an essential variable for light would therefore be sensible, but two issues remain. First, as in the other cases, spectral response matters. This is particularly the case at the moment because of the worldwide transition to white LED light sources (Sánchez de Miguel et al. 2017). Second, zenith brightness is less effective as a proxy for the environmental impact of light than all-sky brightness (Duriscoe 2016), so this essential variable would be a complement rather than replacement for all-sky or all-directional imaging. Hänel et al. (2018) recently reviewed techniques for the measurement of sky brightness, and provide further detail on the points discussed above.

Social essential variables for artificial light

Artificial light presents a bit of a paradox from a social perspective, because it is simultaneously a necessity of urban life and also a pollutant. Artificial light allows economic and other activity to take place during the night, and therefore provides a benefit. Global inequalities are therefore highlighted in nighttime imagery, as millions of people worldwide do not yet have access to light at night (Pritchard 2017). One may therefore naively suggest that “lighting availability” could be considered an essential social variable for light. This parameter would be closely related to the “lit area” discussed above, but presumably only evaluated in inhabited areas. However, basing such a variable on remotely sensed data may not actually be a good idea for a number of reasons.

The only currently available global satellite dataset of night lights is acquired in the early morning, with a typical overpass time near 1:30 am (Elvidge et al. 2017). Since most people are asleep at this time, it is unclear that the presence of light is actually providing much public benefit. While light is popularly believed to reduce crime, evidence for this assumption is lacking (e.g. Steinbach et al. 2015). Since many communities turn off streetlamps late at night, current night light remote sensing instruments may overestimate lighting poverty. Furthermore, the mere presence of upward light emissions says nothing about the quality of the lighting at street level.

While much of the world experiences lighting poverty, a large fraction of the world's urban population experiences significant amounts of light pollution, particularly in wealthy countries. In 2016, it was estimated that 60% of Europeans and 80% of North Americans could not see the Milky Way from their home, due to artificial sky brightness (Falchi et al. 2016). To a large extent, this sky brightness may be blamed on poorly designed lamps, and non-essential lighting for purposes such as advertising. However, it is likely the case that even street lighting is brighter than is necessary. Fotios and Gibbons (2018) recently examined lighting policies and norms, and found that "recommendations for the amount of light do not appear to be well-founded in robust empirical evidence".

A useful essential variable for light may therefore be per capita light emissions. Such a variable would indicate both for areas that are likely suffering from lighting poverty as well as areas that are likely overlit. As in the previous section, the question of at which resolution this variable should be specified must be decided. Mixed pixels that contain both residential areas and commercial centers may present a challenge in the interpretation of this variable.

Biological essential variables for artificial light

Several factors make developing sensible essential biological variables for light challenging. For example, artificial light at night can have dramatic effects on animal and plant life, and changes to behavior or food webs can ripple out to affect other animals or plants that were not exposed to the light (e.g. Knop et al. 2017). Organisms differ in which spectra most strongly affect them (although shorter wavelengths are generally the most problematic, see Longcore et al. 2018), so the biological impact of a lamp may depend strongly on which species is under consideration. Individuals exposure to light may furthermore be poorly related to remotely sensed data, particularly at low spatial resolution, as animals may avoid the brightest areas (e.g. Hale et al. 2015, Raap et al. 2018). Finally, the biological impact of artificial light also depends on the context. An additional lamp installed in an urban context will have much less biological impact than the same lamp installed in the middle of a forest or wetland. Despite the challenges, developing sensible metrics for the biological impact of artificial light should be pursued, as light is an important factor in global change (Davies & Smyth 2018).

There is one biologically based variable that also has social significance: the number of stars that are visible to the unaided human eye. While observations of sky brightness with radiometers are generally easier to work with than visual observations, they are not well suited for predicting how the sky will appear to a human observer (Kyba 2018). The number of visible stars may be estimated via several citizen science techniques, so this variable can be relatively easily measured in any areas that humans regularly inhabit at night.

Conclusion and future outlook

In this deliverable the concept of essential variable was applied to the context of mineral exploitation and artificial light monitoring.
For extractives a set of candidate EEVs were proposed and classified into different categories depending on the installation of the site mine, the extraction method and the ore processing technique. One of the EEVs was implemented as a workflow. This workflow,

based on quantitative information and geospatial data, was developed and operationalized with the aim to assess the surface of forest covered by industrial mining concessions at national level in DRC. The workflow was first tested in ArcGIS™ and in a second step it was published into a Virtual Laboratory Platform (VLab) in order to facilitate access to input and output data and to re-use the algorithm with other data and other parameters. Mining concessions data were obtained from the DRC Ministry of Mines while forest cover were retrieved from EO data. This workflow targets SDG15 'Life on land' and presents similarities with indicator 15.3.1 "proportion of land that is degraded over total area". It is also related to Aichi Biodiversity Target 5.

We showed in this work that the definition and operationalization of EEVs could be useful in the context of mineral exploitation, as it would help to translate sustainability issues into a relevant and realistic measurement of environmental performances. In total 7 workflows were proposed to this direction. However, we noticed that in practice standardization of data is needed to ensure its quality and comparison with analogous set of data representative of other regions, with a view of creating a common monitoring framework across countries that exploit mineral resources. Addressing this issue requires considering the differences in terms of technology and infrastructure advancement of the regions of the world and therefore promoting doable data treatment and collection methods.

Another issue encountered in the development of the workflow was the lack of up-to-date data on mineral concessions and their locations. Despite most nations provide a cadaster of the mines present on their territory, the data are not always available for download. Mineral industry is trying to be more transparent in its activities and performances but the lack of data on mineral activities, still represents a major problem obstructing the deployment of efficient monitoring tools and indicators.

Equally difficult was to find recent data on forest cover and data for species distribution and their habitat. Concerning the avian species, data on their habitat, distribution and abundance are available on the Boreal Avian Modeling Project[4] but not as an open source. The IUCN website provides a platform where is possible to obtain shapefiles on the distribution of a determined species but no additional information on the abundance is available. This data source was of use in trying to implement the workflow assessing the metallophytes species distribution but the lack of information on the abundance, rendered complicated the identification of species hotspots to quantify to what extent a mine overlapping a portion of the habitat could be dangerous for the survival of the species.

Finally, the work on EEVs is mainly based on literature review and on personal reflection, therefore it still needs to be completed and improved along with experts of the sector and other stakeholders involved in the definition of essential variables in other topics (e.g., Climate and Biodiversity).

For artificial light monitoring, two main reasons why defining light variables is challenging were discussed: the directional nature of light, and the fact that light consists of a spectrum. It was shown that an idealized understanding of artificial light would consist of a complete characterization of the light field at all points in the Earth system, which is not possible to achieve experimentally. Nevertheless, possible artificial light essential variables were proposed, divided into physical, social and biological variables. Their implementation was discussed as well as possible limitations and issues.

[4] http://www.borealbirds.ca/index.php/avian_data

Finally, note that both the EEVs and EALVs could become part of a broader category of EVs linked to socio-economical essential variables which are most needed in the global effort to define for instance indicators for the SDGs.

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ANNEX 1: Script developed to monitor the surface of forest covered by mines in DRC

```
#!/bin/bash
tar -zxvf concessions.tar.gz
VECT="concessions_agregees_2015_one.shp"
vec_RAST=("Hansen_GFC2015_treecover2000_00N_010E.tif"
"Hansen_GFC2015_treecover2000_00N_020E.tif"
"Hansen_GFC2015_treecover2000_10N_020E.tif"
"Hansen_GFC2015_treecover2000_10N_030E.tif"
"Hansen_GFC2015_treecover2000_10S_020E.tif")
vec_OUT=("concessions1.tif" "concessions2.tif" "concessions3.tif" "concessions4.tif"
"concessions5.tif")
# Create a counter to dynamically create vect_OUT
cnt=0
# Create an empty rast_sum variable
sum_sum=0
# Create an empty detailed_sum_rast.txt file
echo "" > detailed_rast_sum.txt

for i in "${vec_RAST[@]}"
do
   # increment the counter
   ((cnt+=1))
   RAST=$i
   echo "* processing: $RAST"
# Get extent
   meta=`gdalinfo $RAST | grep 'Lower Left' | sed 's/Lower Left  (//g' |  sed 's/) (/,/g'`
   w=`echo ${meta}| awk -F ',' '{print $1}'`
   s=`echo ${meta}| awk -F ',' '{print $2}'`
   meta=`gdalinfo $RAST | grep 'Upper Right' | sed 's/Upper Right (//g' | sed 's/) (/,/g'`
```

```
  e=`echo ${meta}| awk -F ',' '{print $1}'`
  n=`echo ${meta}| awk -F ',' '{print $2}'`

# Get resolution (necessary to use the -tap option to guarantee proper overlay with RAST)
  meta=`gdalinfo $RAST | grep 'Pixel Size' | sed 's/Pixel Size = //g' | sed 's/(//g' | sed 's/)//g'
| sed 's/ - /, /g'`
  rez=`echo ${meta}| awk -F ',' '{print $1}'`

# RASTerize VECT as 1 overlaying perfectly RAST using information just collected
  rm -f concessions$cnt.tif # Remove the file if it already exists
  gdal_rasterize -te $w $s $e $n -tr $rez $rez -tap -burn 1 -init 0 -co COMPRESS=LZW $VECT
concessions$cnt.tif

 # Combine both rasters
  rm -f masked_$RAST # Remove the file if it already exists
  gdal_calc.py -A $RAST -B concessions$cnt.tif --co COMPRESS=LZW --
outfile=masked_$RAST --calc="A*B"

 # Calculate pixels sum, multiply by surface (km2) and take percentage into account
  stat=`gdalinfo -stats masked_$RAST | grep 'Size is ' | sed 's/Size is //g' | sed 's/) (/,/g'`
  xpx=`echo ${stat}| awk -F ',' '{print $1}'`
  ypx=`echo ${stat}| awk -F ',' '{print $2}'`
  cellmean=`gdalinfo -stats masked_$RAST | grep 'STATISTICS_MEAN=' | sed
's/STATISTICS_MEAN=//g' | sed 's/) (/,/g'`
  rast_sum=`echo $cellmean*$xpx*$ypx*625/100/1000000 | bc`
# Write the sum of each loop in a detailed file
  echo $rast_sum >> detailed_rast_sum.txt
# Sum up the result of each loop
  sum_sum=`echo $sum_sum+$rast_sum | bc`
done
# write the total sum in a file
echo $sum_sum > rast_sum.txt
```

ANNEX 2: Workflow propositions to determine the interaction of mineral extraction on ecosystems

Mineral extraction and biodiversity: surface of a species habitat lost due to the presence of a mine

The present workflow is proposed to build an indicator addressing the SDGs goal 15 "Life on land" in the attempt to preserve the forest ecosystems and the role they play as habitat for terrestrial species. This indicator can also apply to Aichi Biodiversity Target 5 aiming to reduce the loss of natural habitats. The workflow proposed quantifies the habitat of avian species lost after the installation of a mining site. The consequences of habitat loss are species specific: some avian species avoid edge habitat created from segmentation for reasons such as microclimatology or increased predation and other species, preferring early successional habitats, will thrive as a consequence.

The indicator derived from the workflow will be the result of a spatial overlap between polygons representing the habitat of an avian species and a raster or other data type identifying the surface occupied by the mine and its facilities.

Inputs

- Mining surface extent
- Birds' habitat surface: One possible data source is the data from the Boreal Avian Modeling Project (http://www.borealbirds.ca/index.php/avian_data), available on request with additional information on the abundance. Another source of layer is represented by the IUCN website that provide shapefiles on the distribution area of a species (http://www.iucnredlist.org)

Algorithm

- Download input layers
- Intersect of the input data (e.g., ArcGIS™ analysis tools → overlay → intersect)
- Perform zonal statistic between the two areas to obtain the area of the habitat intersecting the mine facilities (e.g., ArcGIS™ spatial analyst tools → zonal → zonal statistics)

Output

- A number representing the surface of habitat lost
- A map of the mine zone overlapping the natural habitat.

Mineral extraction and agricultural activities of the surrounding area

The present workflow aims to create an indicator suitable for the SDG 2 "*End hunger, achieve food security and improved nutrition and promote sustainable agriculture*" and in particular it could address the target 2.3 which aim to *"double the productivity and incomes of small scale food producers […] through secure and equal access to land […]"*.

Mining is responsible for subtracting land devoted to farming activities and to turn soil unproductive and not usable on the long term. In some regions mining activities are responsible for the loss of livelihood for local communities, their displacement and affect their independency in terms of food production. The indicator will provide information on the surface of crop lost over the total extent of the cultivated area. The value obtained will be given as a percentage and derived by the ratio of the extent of the mining surface over

the total extent of the farmed land. By providing information on the type of crop present in the area of interest, is possible to determine the percentage of the loss per crop type.
The most standard method used for land use - land cover change detection is the post classification comparison method, which entails the comparison of independently produced classified images

change percentage (%) = (present LULC area – previous LULC area) * 100 / previous LULC area

This method could be implemented in the proposed workflow.
Inputs

- Agricultural surface. It can either be a single crop variety or multiple crops, which will give as output the percentage of lost surface per crop type. An example of data type is available for South Africa showing the surface occupied by agricultural area. https://figshare.com/articles/Updated_cropland_map_of_South_Africa_for_the_2013-2015_period_/5322970 ;
- Mining concessions or mining surface extent

Algorithm

- Download input layers
- Intersect of the input data (e.g., ArcGIS™ Analysis tools → overlay → intersect)
- Perform zonal statistic between the two areas to obtain the area of the habitat intersecting the mine facilities (e.g., ArcGIS™ Spatial Analyst tools → zonal → zonal statistics)

Outputs

- The surface of cropland lost expressed as a percentage

Mineral extraction and areas of interest for the protection of mountain ecosystems

This workflow is conceived to assess the impact of mineral extraction on hotspots areas for the preservation of mountain ecosystems biodiversity and integrity. The present workflow is targeting the SDG15 aiming to "ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development". The indicator proposed is in line with the SDG 15.4.1 "*Coverage by protected areas of important sites for mountain biodiversity*" which estimates the mean percentage of mountain ecosystems dedicated to protected areas (https://unstats.un.org/sdgs/metadata/files/Metadata-15-04-01.pdf).
Mountain top ecosystems where Mountain Top Removal is practiced are the most exposed to a decline in biodiversity. Mountain Top Removal Mining is a form of surface mining at the summit of a mountain. The mineral deposit is accessed through consecutive blasts to expose underlying deposits. This practice is usually employed for coal mining.
Inputs

- Mining concessions/ancillary data on the surface occupied by the mine;

- Satellite image prior and subsequent mineral exploitation to assess the changes in the habitat. An affected area can be identified and an appropriate satellite image can be downloaded from the Earth Explorer website (https://earthexplorer.usgs.gov/) ;
- Ancillary data on the ecosystem to identify the presence of important sites for biodiversity conservation. Georeferenced data containing information on key biodiversity areas can be found on the World Database on Key Biodiversity Areas and could be considered as a data source for this workflow (http://www.keybiodiversityareas.org/site/requestgis)

Algorithm

- Spatial overlap between digital polygons indicating the extent of mountain top habitat and the extent of the surface affected by the extractive activities

Outputs

- Surface of mountain ecosystem disappeared or compromised by mining activities
- Measure of the habitat lost in km^2; or measure of the degree of fragmentation of the habitat following the blasting and the extraction.

Mineral extraction and the hydrography of the landscape

The present workflow aims to determine the extent of the impacts of mineral extraction on the hydrology of the impacted area. The workflow objective is to create an indicator suitable for the SDG 6*"Ensure availability and sustainable management of water and sanitation for all"* and in particular for the target 6.4 which aims to "ensure water-use efficiency […] and ensure sustainable withdrawals and supply of freshwater […] to reduce the number of people suffering from water scarcity".

Through the comparison of satellite images of a given area, acquired at different years, it is possible to reveal the scale of the impact of mineral extraction on the hydrology of the area and to identify alterations such as buried streams, the creation of ponds and other mining related surface of water.

The approach chosen for this indicator is based on satellite images processing, to obtain a thematic map categorizing the different objects in the image and distinguish superficial water. The comparison between images taken in different years will allow making an estimation of decrease or alterations of superficial water patterns since the installation of the mine.

Inputs

- Landsat images or other satellite images of the area of interest. After examination of the interested area, satellite images can be downloaded from the Earth Explorer website (https://earthexplorer.usgs.gov/);
- Ancillary data on the hydrology and topography of the region (hydrological and biophysical data). These data can be obtained from literature research, archival mining company records for Environmental Impact Assessment (EIA);
- Data on the nature of the mining site and it extent to validate the image classification.

Algorithm

- Land use change estimation can be made from multi date satellite images collected in different years, preferably choosing those years where intense mining activities

are recorded. The creation of a composite image based on infrared bands can help to classify the biophysical parameters and mine features.

- The ancillary data on the extent of the mine help in the classification process to accurate select the training fields for the use of the Maximum Likelihood Classification.
- The classification will then help in the estimation of the surface dedicated to each category and make comparison between the images of previous years. The difference between the classes is made based on different spectral reflectance of the objects on the ground. For example, the distinction between natural and man-made water bodies can be based on different concentration of suspended particles or hydro-chemical properties.

Outputs

- The surface occupied by each category in the classified image for each of the considered years

Mineral extraction and habitat fragmentation

The present workflow is conceived as an indicator toward SDG 15 "life on land" and in particular the target 15.3.1. "*Proportion of land that is degraded over total land area*" and Aichi Biodiversity Target 5. The parameter considered is habitat fragmentation, intended as a landscape level process in which a specific habitat is progressively divided into smaller fragments as a result of both natural and human activities.

The use of the FRAGSTATS software[5] can be considered to provide the degree of fragmentation of the habitat. FRAGSTATS is a spatial pattern analysis program for quantifying the structure of landscapes. The landscape is used defined and can represent any spatial phenomenon.

The degree of fragmentation and so the impact of the mine on the integrity of the habitat can be assessed by defining a scale going from "low fragmented" to "highly fragmented". Another metric that can be considered to assess the degree of fragmentation posterior the installation of the mine is connectivity. This can be achieved by determining the extent to which movements between patches are facilitated or discouraged in relation to the matrix and the distance occurring between patches.

Mineral extraction and endemic species: the case of metallophyte plants

The workflow is intended to measure the impact of mineral extraction on the endemic species inhabiting the area of concern, in particular metallophyte plants which survival is strictly dependent from mineral deposits. The indicator derived from the workflow addresses the Aichi Biodiversity Target 12, on the prevention of extinctions and improvement and sustainability of species most in decline" and the SDG 15.5.1 "*Red list index*" to reduce the degradation of natural habitats and protect and prevent the extinction of threatened species.

[5] https://www.umass.edu/landeco/research/fragstats/fragstats.html

Classified as metallophyte are those plant species that can tolerate high levels of heavy metals. Such plants range between “obligate metallophytes” which can only survive in the presence of the metals they are dependent on, and “facultative metallophytes” which survivor is not strictly dependent from the presence of the metal.

This indicator is calculated from the intersection of spatial data on the distribution of a metallophyte plants and data on the surface occupied by the mine. The result obtained from the intersection of the two layers will provide a measure of the habitat loss and can be used for conservatory purposes to assess the changes in the species abundance when mining activities are present.

Inputs

- Surface of the area occupied by the mine as surface allocated to mining concessions or the surface of individual mines.
- Surface designated to be the habitat of a given species. IUCN Red list spatial data http://www.iucnredlist.org

Algorithm

- Intersect of the input data (e.g., ArcGIS™ Analysis tools → overlay → intersect)
- Perform zonal statistic between the two areas to obtain the area of the habitat intersecting the mine facilities (e.g., ArcGIS™ Spatial Analyst tools → zonal → zonal statistics)

Outputs

Area of the species habitat occupied by the mine and surface of the habitat lost because of the presence of the mine in km^2.