Master's Thesis Sustainable Development

Monitoring land cover change in an Environmental Impact Assessment follow-up processes:

A low-cost replicable method using remote sensing imagery and citizen science.

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Abstract

Environmental impact assessment (EIA) has become an essential requirement for project development and has grown even more with increased environmental awareness worldwide. The purpose of EIA is to ensure the potential environmental impacts are addressed and mitigation efforts are in place at the pre-decision stage of a project; it also aims to provide information on the consequences of the development to ensure the implementation criteria are met at the post-decision stage. EIA follow-up is the last phase of the process in an EIA to achieve the post-decision stage goal that was set during the EIA process. However, the follow-up process is rarely done in practice since it requires substantial resources in terms of money, time and expert for different stakeholders.

With the development of Earth Observation (EO) and Geographic Information System (GIS) technologies, there is an opportunity to enhance data collection and processing in a more accessible and low-cost way to meet the needs of the EIA follow-up phase. With the development of the internet and mobile devices, Citizen Science (CS) is a valuable tool to collect ground truth data, commonly used to validate satellite imagery processing methods.

Land use and land cover (LULC) change is a significant environmental variable addressed in EIA and monitored by EO. This research developed and tested a feasible workflow to monitor and evaluate an environmental impact on LULC from two proposed EIA follow-up using freely accessible EO and GIS software, Google Earth Engine. Then a CS app was developed using ArcGIS Field Maps to collect ground truth data in a test area. The results showed it is a replicable workflow in terms of the availability of the open dataset and algorithms, the accuracy of the monitoring outcomes, availability of CS application, and quality of ground truth data collected by CS. It provides an achievable entry point regarding low-cost and low technical skills needed for related parties and raises public engagement to establish a better EIA follow-up monitoring network. Further efforts should focus on building a framework for implementing this monitoring process properly to different types of EIA cases in terms of land use categories.

KEY WORDS: Environmental Impact Assessment, Environmental Impact Assessment follow-up, Earth Observation, Remote Sensing, Google Earth Engine, Geographic Information System, Citizen Science, Land use land cover classification

Table of Contents

1. Introduction

Human-induced changes to the environment often provoke unintended consequences. For example, a new dam may bring opportunity for hydroelectric power reducing dependence on fossil fuels which cause substantial greenhouse gas emissions, but a dam will also significantly alter other aspects of environmental livelihood and change the river hydrology. For this reason, environmental impact assessment (EIA) has become an essential requirement for project development over the last three decades and has grown even more with increased environmental awareness worldwide (Glasson et al., 2013). The purpose of EIA is to ensure the potential environmental impacts are addressed and mitigation efforts are in place at the pre-decision stage of a project; it also aims to provide information on the consequences of the development to ensure the implementation criteria are met at the post-decision stage (Arts et al., 2001). EIA, therefore, is important for decision-makers to assess if the benefits of a project outweigh any negative environmental effects.

The environmental variables that are included in an EIA are dictated by the type of project and the specific location. Terrestrial ecosystem function is one common environmental category mentioned in EIA, and habitat, surface water and deforestation are all important aspects in this category. Land use and land cover (LULC) change is the fundamental indicator when assessing the potential impact on terrestrial ecosystem function. Land cover change refers to the materials covering the land surface. Changes to any land use that are caused by human activities is defined as land-use change (McConnell, 2002). Such LULC change will affect the land function, which includes the provision of material goods and the value of cultural heritage. Monitoring land functioning can be achieved by establishing a land-use system, which inspects the relation between land cover, land use, and land function (Verburg et al., 2009). Monitoring is, meanwhile, the starting point of the EIA follow-up.

There are eight main steps of EIA for the pre-decision stage. The first step of EIA is screening and the second is scoping. These steps establish whether the proposed project should be subject to EIA and identify the potential impact and issue, then establish terms of reference for EIA. The third step is the examination of alternatives, which aims to establish the preferable alternatives to achieve the same proposed objective. Step four to six are impact analysis, mitigation and impact management, and evaluation of significance. These steps aim to identify and predict the impacts with different levels and then propose a management framework to mitigate and monitor those impacts. Steps seven and eight are the preparation of an environmental impact statement (EIS) and a review of the EIS, which aim to elaborate the results from previous steps to the interested public and sufficient information for decision making. In short, EIS is the report of EIA process conclusion except for the follow-up phase. After the decision making, the follow-up step aims to ensure the terms and condition of approval are met.

EIA follow-up is the last phase of the process in an EIA with the aim of achieving the post-decision stage goal that was set during the EIA process (Arts et al., 2001). However, this follow up phase process is rarely done in practice, even though it should (Marshall et al., 2005). To achieve that, better practical methods and techniques are needed since the conventional method requires substantial resources in terms of money, time and expert for different stakeholders (Arts & Morrison-Saunders, 2012). Often, local citizens are affected greatly and directly by the consequence of projects requiring EIA. Based on the EIA framework currently in practice, they do not have sufficient involvement in the EIA process yet (Marshall et al., 2005). Local citizens, which include the public, NGOs, and any interested parties, are likely to have the motivation to engage the EIA. Especially at the follow-up phase, they could provide follow-up information of the actual environmental changes.

Earth Observation (EO) uses devices to capture the phenomenon on earth surface, for instance, satellite imagery and aerial imagery. Geographic Information System (GIS) is a framework for gathering, managing, and processing data. EO and GIS have been widely used to detect the environmental impacts induced by human beings, such as deforestation and over grazing (Mitchell et al., 2017). It can also be utilized to observe the natural hazards in time, such as flooding and forest fires (Yuan et al., 2015). EO and GIS's characteristics, including large spatial coverage, quick data collecting, informative data content, and various data processing methods, have been helping human beings understand the earth system and govern human activities. With the development of easier to use and lower cost EO technology and GIS, there is an opportunity to enhance the data collection and data processing to meet the needs of EIA follow-up steps (Pasetto et al., 2018). The increased frequent acquisition and high spatial resolution of satellite imagery provide a better resource for monitoring the temporal change of environmental variables. An increased data availability and processing power may increase the feasibility of related parties to use them in an effort to implement EIA follow-up processes--for instance, NGOs, fieldworkers, policymakers, and even the interested public could use them to monitor changes to the environment over time after a project is completed or while it is being done.

Though there are plenty of methods to improve the data quality, the measurement uncertainty is still a limiting factor for application at local scales (Pasetto et al., 2018). Satellite imagery's inherent drawbacks, the uncertainty of data processing due to the heterogeneous ground-truthing data within a pixel, and the retrieval models are usually simplified and empirical (Li et al., 2020). For instance, several land uses might exist in one 30 meters times 30 meters pixel, and satellite imagery must classify the pixel into one type of land use. Theoretically, the ground truth data is used to validate the model, which refers to the data processing method (Baker et al., 2018). Citizen Science (CS) has become relevant to EO through providing quality data from geographically dispersed heterogenous populations. It has been shown that CS can be valuable to obtain ground truthing data to augment, complement and verify the information from satellite imagery (Fritz et al., 2017). Even if data is not directly contributing to the model validation, it is valuable to combine the ground truth data with the satellite imagery in a monitoring system (Njue et al., 2019).

Thus, the aim of this research is to develop and test a feasible workflow in an effort to monitor and evaluate an environmental impact from a proposed EIA follow-up. The workflow uses freely accessible EO and GIS software and combines it with CS to develop a replicable and low-cost method for broader use in EIA follow-up implementation. This is expected to offer an achievable entry point for related parties and raise public engagement to establish a better EIA follow-up monitoring network. Furthermore, participants will be able to raise environmental awareness about a specific project or human induced land use change through participation in the follow up phase (Phillips et al., 2018).

2. Conceptual framework

2.1 EIA follow-up

The purpose of EIA is to ensure that environmental considerations are identified and addressed. Typically, the aim is to mitigate or compensate the negative environmental impacts at the pre-decision stage of a construction project or other human induced change to the environment. It also aims to provide information on the consequences of the project development by monitoring compliance with implementation requirements at the post-decision stage (Arts et al., 2001). UNECE gives the definition of EIA, "a national procedure for evaluating the likely impact of a proposed activity on the environment" (United Nations, 1991). With the legislation introduced by the United States, the European Commission and the United Nations, EIA planning practices have been drastically expanding as it has become a requirement for most projects (Glasson et al., 2013).

The definition of EIA follow-up is given as "the monitoring and evaluation of the impacts of a project or plan for management of, and communication about, the environmental performance of that project or plan." (Arts & Morrison-Saunders, 2012). According to the definition, EIA follow-up consists of four key activities: monitoring, evaluation, management and communication (Arts et al., 2001). It is a crucial EIA process as it provides the actual environmental impact instead of the predicted effects. Additionally, it creates opportunities for stakeholders to mitigate these impacts. However, this post-decision process is not commonly implemented in practice and not easy to fit how it should work in an EIA report (Marshall et al., 2005). There are several challenges for EIA follow-up that might explain its low implementation rates. For instance, lack of guidance increases the uncertainty of the process for the proponent to follow; and lack of legislation makes it unclear when responsibility needs to be allocated; deficiencies in environmental impact statements mean there are no environmental impact benchmarks to be reviewed. Among these challenges, the need for practical methods and techniques is addressed (Arts & Morrison-Saunders, 2012). A lot of challenges regarding one of the main functions of EIA follow-up, namely providing information about the project's consequences, arise because activities require much time, money, and labor. Providing information with conventional methods and techniques require money for data collecting, expertise in data processing, and is time consuming overall. Therefore, this research will focus on the first part of the EIA follow-up, monitoring, and evaluation, to improve the method of data collection and providing information for further environmental management.

2.2 Earth observation for monitoring the environmental

Earth observation (EO) refers to the use of remote sensing technologies, typically from satellite data or data collected from sensors mounted to planes or drones, to obtain information about planet Earth, including its physical, chemical, and biological systems. With the development of space-based technologies, satellite imagery has become widely used for monitoring and assessing environmental phenomena. Higher temporal and spatial resolution satellite imagery enables more detailed observation; multi-spectral satellite imagery provides various methods to identify different environmental variables; Higher time-frequency satellite imagery offers a more reliable monitoring system in terms of temporal change. A geographical information system (GIS) is a framework for gathering, managing, and processing data. A GIS can be used to perform analyses and share and communicate information by visualizing data and creating maps. It is widely used to identify problems, monitor changes, perform forecast etc. Thus, EO and GIS in environmental development can be used together to create a path to better environmental management, mitigate risks and advocate environmental sustainability.

Commonly, the environmental monitoring by EO and GIS can be categorized into the following categories: climate change, conservation, change detection, natural hazards, and natural resources. For example, assessing glacier retreatment and snowmelt runoff and its hydrology effect on climate change (Seidel & Martinec, 2004); assessing and analyzing the water temperature, salinity, phytoplankton, shoreline changes, bathymetry, soil moisture for better coastal management (Green et al., 1996); detecting the conservation status of forest for habitat mapping (Corbane et al., 2015); mapping Environmental sensitivity index (ESI) for oil spills for natural hazards management (JENSEN et al., 1990). The development of EO and GIS provide an opportunity to strengthen the EIA follow-up monitoring and evaluating process in practice.

EO is particularly well suited to monitor and measure land-use change. Therefore, EIA related to land-use change could benefit most from EO and GIS monitoring. Though every EIA contained land-use change impact, some types of EIA had a negligible environmental impact due to a land-use change too small to measure. For example, a hydropower dam project without forming a reservoir only resulted in few onsite power plant facilities. In addition, the satellite imagery is pixel-based, raster data. Some EIAs had dispersed and linear facilities in terms of spatial distribution, which was not ideal for analyzing with raster data. For instance, for the electricity distribution project mainly focused on connecting the communities with cable and electricity lines, the unit used in the EIA was kilometer which is a linear dimension. In this case, it is difficult for satellite imagery to detect the spatial changing from the project. Regarding the direct land use change, a mining related EIA project has the most identifiable land use change due to the land clearing for open pits, waste rock dumps, tailing dams, and milling infrastructures (Werner et al., 2019). Hence, mining related EIAs' land use change is ideal for inspection by EO and GIS.

Combined with the development of internet technologies, internet mapping technologies have been developed rapidly. The terminology "GeoWeb" emerged to describe the use of all these applications. For instance, OpenStreetMap, Google Earth. Furthermore, the technologies started allowing users to share data and processing (Peng & Tsou, 2003). This is an important step for geospatial science since data collection by internet users is possible. It is an evolution for GeoWeb from one-direction to an interactive collaboration technology ("Citizens as Voluntary Sensors: Spatial Data Infrastructure in the World of Web 2.0," 2007). However, there remained a lot of difficulties in terms of technical skills needed from an end use perspective in this era. For instance, the speed of the internet or purchasing expensive background maps and licenses. Web Mapping 2.0 is a new era due to the development of global positioning system (GPS), XML, and application programming interface (API) (Muki Haklay et al., 2008). The GPS combined with the development of mobile devices enable the user to upload the coordinates which is crucial collecting geospatial data. XML improved the user experience in terms of making the web mapping more similar to desktop applications. APIs are easier for users to access and make use of data compared to previous programing frameworks in terms of basic programming and server management knowledge. The outcome of Web Mapping 2.0 aligns with the core idea of the Neogeography, which refers to the technologies and tools that are not within the conventional GIS scope (Turner, 2006). It inlcudes the public activities related to using APIs, sharing GPX, KML, and geotags. In other words, a user using Google map and sharing hiking trails data or holiday's recommended place can be defined as neogeography. With this trend, it has a profound impact on not only data collection but also resource managing by the public.

Google Earth Engine (GEE) "combines a multi-petabyte catalogue of satellite imagery and geospatial datasets with planetary-scale analysis capabilities and makes it available for scientists, researchers, and developers to detect changes, map trends, and quantify differences on the Earth's surface." (*Google Earth Engine*, 2020). It is a cloud-based platform providing higher accessibility to satellite imagery and geospatial datasets with the higher computational capability of data analysis through its free Integrated Development Environment (IDE). Though the data processing for project-oriented environmental impact might still be challenging to the public, it has a chance to accelerate the ability of environmental discovery for a much wider audience by offering a relatively low-cost analysis in terms of time, money and experts compared to conventional technologies (Gorelick et al., 2017). Users can produce geospatial images by applying pre-developed algorithms without requiring much information technology management skill.

Among the various satellite imagery datasets in GEE, Landsat is a joint program of the U.S. National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS). It has been providing earth observation data since 1972. With its global coverage, continuous data, and multi-spectral properties, it is the most widely used dataset. The latest satellite, Landsat 8, was launched in 2013 with 30 meters resolution and two weeks' time frequency. Sentinel is another series of satellites launched by the Copernicus Program which is supported by the European Commission and Europe Space Agency since 2014. There are presently 6 Sentinel missions, and each Sentinel mission has different objective from land service, weather to air quality. Sentinel 2 is a multi-spectral and 15 meters resolution satellite launched in 2015 with land service functionality including vegetation, soil and water cover etc. Therefore, Landsat 8 and Sentinel 2 are the ideal satellite datasets could be valuable for EIA follow up and this research due to their affordance of multi-spectral, resolution, time frequency and global coverage. A significant challenge with EO research is ground truthing data, to verify the accuracy of what appears in the satellite imagery or how it is classified. This step is difficult because it requires expensive travel and manpower.

2.3 Citizen science for providing ground-truth data

Citizen Science refers to data collection by individuals. One common data type is spatial data including either a photo, a recording, or a string of characters with coordinates. CS is a useful tool to collect the data at a local scale in any geographic locations around the world (Ricker, 2020). This data collection tool provides an alternative for lower cost, up-to-date data, and lower equipment requirements compared to conventional geographic data collection. The terminology 'Citizen Science' was first used in 1995 by social scientist Irwin referring the experts first from outside the scientific field (Irwin, 1995). After over a decade, it started to be re-defined as a method that provides scientific data from the general public (Bonney et al., 2009). In practice, CS has become recognized as a method that utilizes contributions of volunteers for any type of project and approach (Science Communication Unit, University of the West of England, Bristol, 2013). In the environmental science field, collecting data by incorporating volunteers has a long tradition. In 2013, the European Commission and the European Environmental Agency acknowledged the contributions citizen science could make in environmental monitoring and policymaking. In the same year, the European Citizen Science Association was established to get citizens involved and strengthen the environment's sustainable development (Storksdieck et al., 2016). However, CS represents multidimensional approaches, in terms of level of geography, policy application areas, and level of engagement of the CS. The trade-off of employing the CS outcomes between local citizens, awareness of science, a contribution to scientific research need to be made aware to the policymaker (Mordechai Haklay, 2013).

Nowadays, CS can be categorized into different levels based on the depth of expertise needed and the level of engagement as a volunteer. The basic level is so-called 'crowd sourcing', which only asks the participant to collect data with a given device. At the highest level, the citizen is the driving force of the whole research instead of the scientist (Sui et al., 2013). With the drastic progresses regarding the internet, mobile phone technologies, and increased accessibilities, opportunities for and contributions of CS have been demonstrated in many real-life cases (Science Communication Unit, University of the West of England, Bristol, 2013), for instance, the Zooniverse team provides a platform connecting local people and scientists to collect the local data which would not be possible in conventional data collection method (*Zooniverse*, 2021). With this trend, CS is a very valuable information source for EO by providing in situ data for calibration and validation of RS imagery (Fritz et al., 2017). It is also identified as a valuable new source of information for land cover and land use classification (Laso Bayas et al., 2016). However, EO and CS are not yet well integrated in the application and monitoring system due to lack of the motivation of citizens and strategies for sustainability of participation. In addition, CS is also an effective approach to educating participants and raising their awareness (Dean et al., 2018). With these advantages of utilizing citizen science in EO and environmental science, this research aims to include citizen science in the EIA follow-up process.

Research Questions:

What is the feasibility of the development of a low-cost replicable method for monitoring land cover change in EIA follow-up processes using remote sensing imagery and citizen science?

In this research, feasibility refers to the availability of the open dataset and algorithms, the accuracy of the monitoring outcomes, availability of CS application, and quality of ground truth data collected by CS. These variables are further reviewed in the discussion based on the results.

Sub-questions:

1. What is an example of a feasible method and workflow for identifying and measuring the actual land cover change in EIA follow-up using EO and GIS technologies?
2. How could CS help with the collection of ground-truth data of land cover for EIA follow-up?

3. Methodology

The following steps were conducted sequentially to answer the research question and the sub-questions. The first step to answer these research questions was identifying two representative EIAs with identifiable land cover changes. The next step was using freely accessible EO software to test the chosen EIAs. In this step, an open-source land use classification algorithm was modified according to the need of this research. The modified algorithm will be referred to as "LULCC algorithm" in the rest of this paper. The third step was combining the EO outcomes with CS to test ground truthing. These three main steps were taken in an effort to reach the aim of this research: use freely accessible EO and GIS software and combine it with CS to develop a replicable and low-cost method for broader use in EIA follow-up implementation (Figure 1). Each method was selected to answer each research question and a full methodology framework represents the whole process can be found in the Appendix 1.

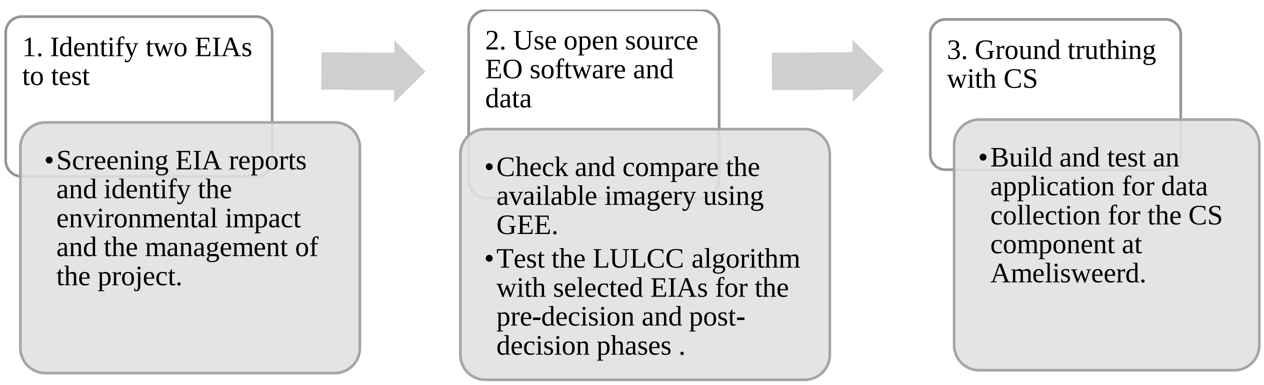

Figure 1 Overarching methods or components of this research that were conducted in an effort to answer the research questions.

3.1 Screening EIA reports and identify the environmental impact and the management of the project.

3.1.1 Look for EIA reports that have common environmental variables.

Since this research aimed to identify how EO and GIS can be used to monitor EIA follow-up, it was first necessary to identify an EIA that could benefit from this sort of monitoring. As already mentioned, EO and GIS are particularly well suited to identify and measure the spatial extent of land cover changes over time. For this reason, I conducted a targeted search for a specific EIA to use to develop this workflow.

To identify these EIAs I took the following steps: First, I screened two EIA reports from The World Bank (*The World Bank)* and European Bank (*European Bank)* websites. These two websites were chosen as EIA reports are more readily available in English. Second, as mentioned in the conceptual framework chapter, mining related EIAs have significant environmental impacts due to the land clearing. Therefore, the keywords that were used for searching were "Environmental Impact assessment", "Natural resources", and "Mining". Third, the filter used for searching was the date range from 2013 to 2018 due to the satellite data available for both pre-decision and post-decision stages. The construction phase of a development project typically takes more than one year after the project is approved. Thus, it was possible the environmental impact was not observable yet if the chosen EIA project was approved within two years. After the filters were applied, two important criteria that were considered were that it was an approved EIA and there was an available management document on the website for this EIA project. Since the websites also showed the cancelled EIAs, it was important to ensure the project was approved before identifying the environmental impacts written in the EIA report. The management document provided the monitoring indicator of the land use change, which was helpful to check the predicted impact with the actual impact. In the end, the two EIAs that were selected to test were the Lapseki Project and Gatsuurt Mine Project.

3.1.2 Three locations for case studies description

To build and test the proof of concepts for this research, three different case study locations were selected. Two locations were selected to test the land use classification algorithm to monitor an actual EIA. Unfortunately, due to time, cost and COVID 19 restrictions, it was impossible to do any ground truthing of data in these two locations. For this reason, a third local location was chosen to conduct CS app for ground truthing.

Case 1: The Lapseki Gold and Silver Mine and Project

The Lapseki Gold and Silver Mine and Project is an open mining project planned by the company called TÜMAD Madencilik San. ve Tic. A.Ş. (TÜMAD) at Lapseki District in Çanakkale province in Turkey (EBRD, 2017). In the project, four open pits, called Karakovan, Karatepe, K-Zone, and SBX, were mined to obtain gold and silver minerals by using explosive mining methods. According to the EIS, an enrichment process was to take place to obtain the final product. The plan was to start construction in December 2016 and complete in October 2017. According to the reserve volume, the operation stage of the mining activity was expected for ten years. Thus, the Mine Closure and Reclamation Plan were expected to start in 2027. As shown in Figure 2, the project map has addressed significant land cover changes due to the land clearing for following land use related to mining activities including infrastructure construction, pits, tailings dump area, etc. It was also addressed that 7.15 Mt, 60 Mt, and 8.2 Mt of ore, waste rock and filtered tailings will be produced during the operation phase, respectively. There are four villages close to the project area, and one of them is only 0.6 km away. This illustrates the importance of this project's actual environmental impacts and the potential of getting residents involved with the monitoring system.

The permits for deforestation for non-agricultural use were received in 2015, and it covered 123 hectares, which was approximately 31% of the EIA designated area. The rest of the permits are to be received step by step while operating. As shown in Table 1, 395 hectares of state-owned agricultural (9.5 ha) and forestry (385 ha) areas were planned to be acquired for the project, including 282.7 hectares where the mining operation area was designated. Thus, 282.7 hectares of agricultural and forestry land were expected to change into land-use as shown in Figure 2 according to area size shown in Table 1. Meanwhile, the deforested area was expected to be rehabilitated and restored step by step before the permits expire when the onsite mining activity is completed according to the management framework.

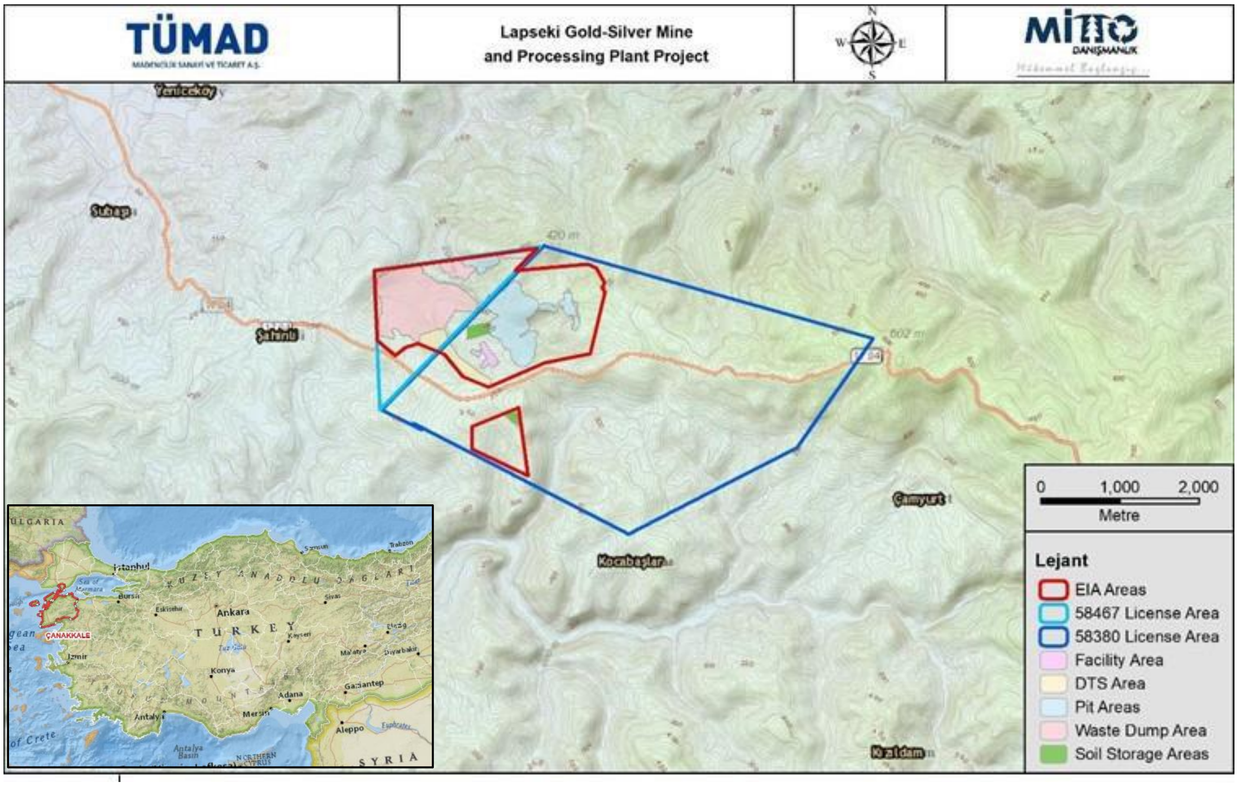

Figure 2. The Lapseki Gold and Silver Mine and Project unit locations and land use map (European Bank for Reconstruction and Development [EBRD], 2017). Important land uses, pits, facilities, and waste dump area can be observed in the map.

Case 2: Gatsuurt Mine Project

Gatsuurt Mine project is an open mining project producing gold by mining oxide, sulphide, and transition ore in Mongolia. This project is established to support the 'Gold' program, which was expected to increase State Monetary reserves and reduce the Mongolian government's unemployment (EBRD, 2014). The project site is in the Gatsuurt river valley in central-northern Mongolia. A conventional mining method was used in this project with an excavator and dump trucks to dig a large pit to extract the raw materials. The operation phase of the project started in 2016. According to the reserve volume, the operation stage of the mining activity was expected for nine years. The land cover before the project was all forested, with 50% of the designated EIA area to be disturbed by historical alluvial mining activities. Alluvial mining is a conventional way of mining stream bed deposits for minerals by simply using shovels and sieves to dig and sift through materials such as mud, sand or gravel. Regarding the Gatsuurt project, 25 direct environmental impacts were addressed in the EIA report including for example: noise from machinery movement, air pollution from toxic gas emissions, habitat loss and deforestation from land acquisition, etc (EBRD, 2014). Significant land cover change and deterioration due to the mining activity and several onsite infrastructures were also addressed in the EIA. For instance, two open pits, waste rock dumps, an ore stockpile, access and haul roads, etc. As shown in Table 1, the project was expected to result in 47.7 hectares of land destruction and create 80-200 meters deep open pits. The waste rock dump, stormwater diversion, and sedimentation pond were also considered highly disturbed areas with 77.3 hectares. Other land uses were considered as moderate disturbed, with 36.4 hectares. Thus, the total destroyed area of the project was 161.4 hectares.

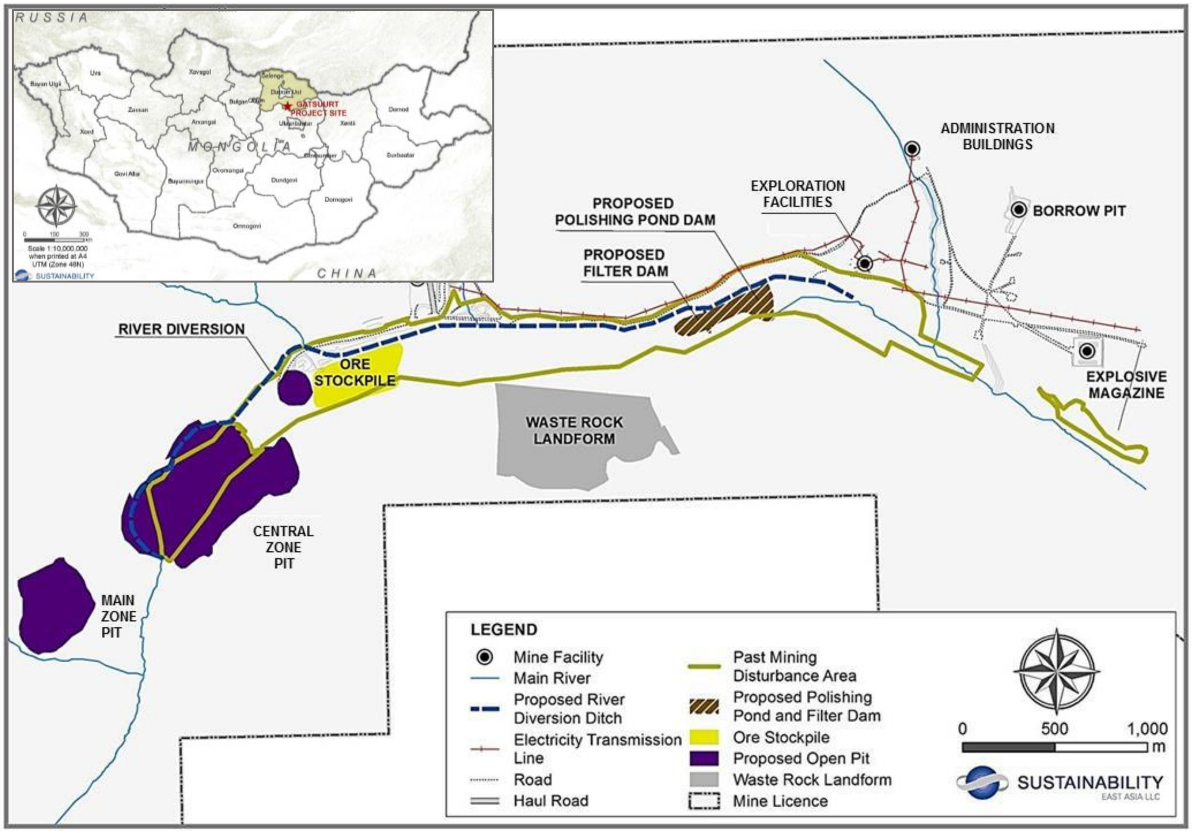

Figure 3. Gatsuurt Mine project unit locations and land use map (EBRD, 2016, p:10). Important land use, river, pits, waste rock landform, stockpile and facilities, can be observed in this map.

Case 3: Amelisweerd

Amelisweerd, a diverse land cover area located in east Utrecht in the Netherlands, was chosen to conduct the proof of concept that CS can provide useful ground truth data. This smaller and local area was selected as a 'learning ground' for the other two EIA sites since it was not feasible to access the EIA research areas.

Amelisweerd terrain consists of three estates: Oud Amelisweerd, Nieuw Amelisweerd and Rhijnauwen estates. In 1964 the municipality of Utrecht bought the estates and formed one large recreational area. Nowadays, around 150 people live in the terrain. Two farmers within the estates use approximately 100 hectares of agricultural land for mainly dairy farming purposes. There are two historic market gardens that work organically at Nieuw and Oud Amelisweerd. From the Figure 4, the main land use of Amelisweerd are forest and agricultural land. The river Kromme Rijn flows through the region from the north-west to the south-east. A cultural-historical fort is located at the north-east of the region. There are also some recreational facilities such as a restaurant, museum, café, bakery, and tennis club within the area. Amelisweerd has a unique river deciduous forest ecosystem with beech, oak trees, hundreds of species of mushrooms, and hundreds of species of animals, such as deer, blue herons, buzzards, kingfishers and bats. Over the centuries, nature and culture have merged at Amelisweerd, and it has become an important recreational area for the citizens of Utrecht.

The construction of the A27 highway was opened to car traffic in 1986. Protests arose when the tree house village was evicted in 1982. Unfortunately, a widening plan of the A27 highway was approved by the minister in 2020 despite resistance from related parties including residents, traffic experts, and EIA commissions.

Figure 4. An introduction map of Amelisweerd for recreational purpose. In this map, diverse land use of this region can be seen including agricultural land, forest, river, highway, and artificial buildings (www.amelisweerd.com, 2021).

3.1.3 Identify the predicted/ planned environmental variable to monitor in each EIA report

The two EIA projects mentioned above were selected, and the area of land cover change and land-use change that are addressed in the reports will be measured. EO and GIS can be used to measure and quantify these changes to verify that the initiators of a project remain in compliance with the EIA. Therefore, the land cover area for the post-decision stage was subtracted from the pre-decision stage. Then the result was compared with the planned land use in terms of area size. Also, the spatial distribution was reviewed by comparing classified land use maps with land use maps from EIA.

Table 1 Variables to measure over time in the two case studies. Project schedule, before project land cover, and predicted land use are identified from two EIA reports. Times of area Imagery are decided based on project schedule and satellite imagery dataset availability. Actual change will be measure by area change and land use distribution change.

Project	Project schedule	Area Imagery	Before project land cover	Predicted land use	Actual Change
The Lapseki Gold and Silver Mine and Project	Construction start date	T1 (Before Project)	395 ha (EIA area from state-own agricultural and forestry land);	Pit area (97.5 ha). Facilities area (29.6 ha). Wasted dump area (104.7 ha). Soil storage area (11.9 ha). Dry stack tailings storage area (39.2 ha).	Area change: Area T1-Area T2 Spatial distribution: Land use distribution
	December 2016	2015			
	Operation period	T2 (After project)			
	October 2017 - 2027	2020			
Gatsuurt Mine Project	Construction start date	T1 (Before Project)	161.4 ha (50% forest; 50% bare soil)	Pit area (47.4 ha). Facilities area (36.4 ha). Wasted rock dump, storm water diversion and sedimentation pond (77.3 ha)	Area change: Area T1-Area T2 Spatial distribution: Land use distribution
	2016	2015			
	Operation period	T2 (After project)			
	2016 - 2025	2020			

3.2 Use open source EO software and data

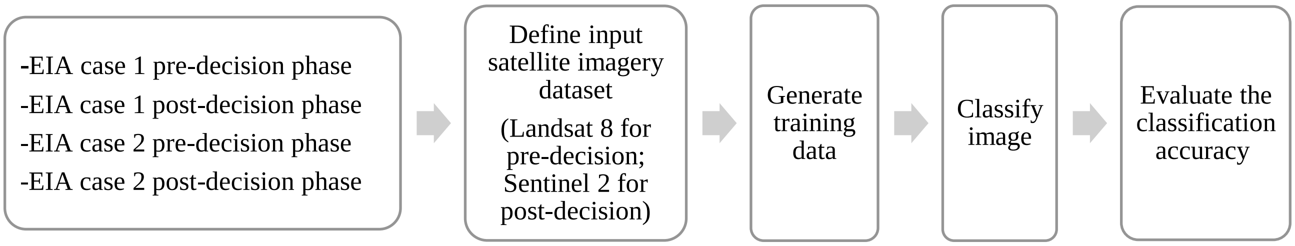

Figure 5. Schematic of the process that was taken in the GEE to generate the land use classification map for each EIA case at pre- and post-decision phase.

3.2.1 Identify the available dataset for the research area and algorithms in the GEE.

GEE was chosen as the tool for this research due to the advantages mentioned in the conceptual framework. It is freely available and can be run using an internet browser alone. Anyone is able to use the software and access the data through the IDE for free. In addition, this research aims to broaden the availability of useful tools for implementing EIA follow-up, and GEE is the optimal tool to prove the concept that EO provides useful information for EIA procedures. Sentinel-2 and Landsat-8 were used in this research due to their accessibility, and the specifications of the datasets are shown in Table 2. First, these two datasets have the adequate spatial and temporal resolution with global spatial coverage, meaning they could be useful to monitor any EIA in the world. Second, they are ongoing, regular data collection with a high temporal frequency, which is essential for use in practice. Furthermore, both datasets provide a multi-spectral image, which includes visible and near-infrared (VNIR) bands and short-wave infrared (SWIR) bands, offering additional spectral information and more flexibility for diverse land cover classifications. For example, for an EIA covering a project that will have a significant impact on deforestation or agricultural land clearing, Normalized Difference Vegetation Index (NDVI) can be easily calculated with these datasets, which is a widely used dimensionless index to assess land degradation (Yengoh et al., 2015).

Table 2. Dataset properties of Sentinel 2 and Landsat 8. This table shows the specifications of the datasets including the bands, wavelength range, spatial and temporal resolutions, and spatial and temporal coverage. These are the reasons why these two datasets are chosen for this research.

Satellite data	Bands		Wavelength range (nm)	Nominal resolution	Temporal granularity	Temporal coverage	Spatial coverage
Sentinel 2A MSI (Multi-Spectral Instrument, Level-2A)	B2	Blue	492.1-496.6	10 meters	5 Days	2017.03.28 - 2021.07.30	Global
	B3	Green	559-560	10 meters			
	B4	Red	664.5-665	10 meters			
	B8	NIR	833-835.1	10 meters			
	B11	SWIR1	1610.4-1613.7	20 meters			
	B12	SWIR2	2185.7-2202.4	20 meters			
			Wavelength range (μm)				
Landsat 8 OLI/TIRS (Level 2, Collection 2, Tier 1)	B2	Blue	0.45-0.51	30 meters	16 Days	2013.04.11 - 2021.07.30	Global
	B3	Green	0.53-0.59				
	B4	Red	0.64-0.67				
	B5	NIR	0.85-0.88				
	B6	SWIR1	1.57-1.65				
	B7	SWIR2	2.11-2.29				
	B10	TIR	10.60-11.19				

3.2.2 Description of the modification of an existing and openly available algorithms for detecting the environmental changes

The algorithm I was searching to modify had to meet the following criteria: accessible in GEE, include drawing the training pixels process before classifying the data, visualize and charting the result, and easy to adjust to another region. The script in GEE is written in JavaScript.

The algorithm developed by Philip Kraaijenbrink, a postdoctoral researcher at Utrecht University, was used to test the land cover classification in GEE (Kraaijenbrink, 2020) for the two test cases described above. This algorithm was designed initially to generate a Landsat 8 composite image, perform a land cover classification of the image, and compare class distribution over elevation in the Netherlands. Thus, I adjusted the research area according to the selected EIA and eliminated parts of the script related to elevation since this is outside the scope of my research related to these mining case studies. The modified algorithm will be referred as "LULCC algorithm" in the rest of this paper. Sentinel 2 was also tested in this LULCC algorithm which only used Landsat 8 as the input dataset in the initial algorithm. Sentinel 2 was used because of the higher resolution of the dataset compared to Landsat 8. However, Sentinel 2 can only be used for the post-decision stage in these two EIAs since the pre-decision stage is prior to the dataset start date.

3.2.3 Test LULCC algorithm with selected EIAs for the pre-decision and post-decision phases.

Two input satellite imagery datasets for pre-and post-decision phases of each EIA case were applied four times.

The input data was defined in this step and included Landsat 8 and Sentinel 2 were tested separately with one years' time range in this research based on the following criterion as shown in Table 2. For the Sentinel 2A MSI, 10 meters spatial resolution was used when classifying the various land cover of the study area. The 5-day temporal resolution provided sufficient cloud-free images when filtering out cloud and cirrus. For both EIA cases, images from April 30th, 2020 to April 30th, 2021 were selected for the post-decision stage based on the latest updated time when this research was being conducted. Then a mean reducer was used to generate a single composite image to reduce the noise within the pixel. Sentinel 2 was not suitable for the pre-decision phase in this research since both EIA cases' construction phases started in 2016. Thus, Landsat 8 was the ideal alternative. For the Landsat 8 OLI/TIRS, 30 meters spatial resolution was used, and 16 days temporal resolution also provides sufficient cloud-free images from January 1st, 2015 to December 31st, 2015 for the pre-decision phase for two EIA cases. A median reducer was used to generate a single composite image to reduce the noise within the pixel. The scripts of the dataset description on the GEE dataset catalogue were employed to generate cloud masked and visualize the true color image. Spectral bands shown in the Table 2 were selected to draw training areas and LULCC algorithms.

Vector outlines of the research area were introduced in this step by drawing a rectangle as a "feature collection" in GEE. It was an easy alternative in this case since the precise EIA area were not available online.

3.2.4 Generate training data.

The training data were defined by drawing polygons on the true color satellite image to sample pixels of a land cover class. According to the selected EIAs, the following fine classes were first classified: pit, facility, soil storage, waste dump, forest, and road. After, coarse classes were employed for generic use: forest, grassland, agriculture area, built-up, bare soil, and water. In this case, bare soil included open pit, waste dump and dry stack tailings. Based on the experience, multiple polygons for one class provided more accuracy instead of only draw one polygon for each class.

3.2.5 Classify image.

After the spectral bands were selected for LULCC algorithm, training pixels were sampled from the image. A simple minimum distance classifier based on a simple Euclidean distance to the closest training class mean in n-dimensional spectral feature space was used and applied to the research area.

3.2.6 Evaluate the classification accuracy.

After the classification, an accuracy assessment was conducted by using the confusion matrix function in EE. The resubstitution error matrix and the training accuracy provided a rough evaluation of the accuracy of the classification. Meanwhile, visual judgement on the classified land cover map was also necessary based on the true color satellite image. It can be quickly done by changing the land cover classification map's transparency and comparing it with the layer of true color satellite imagery. When the overall accuracy was lower than 0.85, the classification was considered as poor performed. In that case, more polygons were added in step 3.2.4. Then the image was classified again until the overall accuracy was higher than 0.85.

3.3 Build and test an application for data collection for the citizen science component at Amelisweerd.

A smaller local area was selected to answer this sub-question as a' learning ground' for the other two EIA sites since it was not feasible to access the EIA research areas. Amelisweerd, a diverse land cover area located in east Utrecht in the Netherlands, was chosen to conduct the proof of concept that CS can provide useful ground truth data.

3.3.1 Generate a classified map of Amelisweerd by using the same method in step 3.

The method described in step 3 was employed to generate a classified land cover map of Amelisweerd to conduct further analysis. Sentinel 2 satellite imagery dataset in 2020 and the coarse-scale land use categories were used. The only difference was the vector outlines were drawn as a rectangle that includes the whole Amelisweerd area.

3.3.2 Prepare the ArcGIS Field Maps.

The ArcGIS Field Maps, a mobile data collection app that allows everyone with a mobile device to collect accurate data, was chosen to build the CS portion of this research. This application was chosen because it is included in a well-integrated online ArcGIS platform, ESRI. It is relatively user friendly in terms of importing image, configuring the field research application, and collecting data with mobile device application. First, a paper prototype of the CS app was created. During a pilot test, the paper prototype was tested to make sure questions were worded appropriately and interpreted as intended. These questions were then incorporated into the data collection app.

Multiple software from Esri were used to prepare the application. The classified Amelisweerd land cover map generated using the same methodology as described above for the two different EIA case studies, using GEE and Sentinel 2. It was exported as a "tif" file and was migrated from GEE to ArcGIS to prepare a base map for ground-truthing. In ArcGIS Pro, a topographic base map was selected as a base layer since it is an easy map for public reading. The "tif" file was imported using the "add data" function, and the "classify" and "equal interval" were selected for primary symbology to visualize the classification map. After, the map was shared as a tile layer for further use in ArcGIS Field Maps.

As shown in Table 3, these questions were designed to answer sub-question 3. Question one is what the actual land use at the data point is among six land use categories. Question two is if it is the same land use as shown in the classified land use map. Question three is can you describe the current function of the land use, which was an optional question. Question four is whether it is permanent or temporary land use, which was also an optional question. Three more questions related to providing user feedback were added. These questions were only answered once for each user among all the data points in an effort to provide some qualitative information. The first feedback question was asked to know the relation between the research area and user to know the cultural value of the place. The second feedback question was asked to retain more in-depth local land use information that was not noticed when classifying the satellite imagery. The third feedback question was asked to improve the user’s experience of the app. Based on the type of each question, integer type was selected if it was a multiple-choice question, for instance questions one, two and four. String type was selected when it is a descriptive question, such as question three and the feedback questions. Coordinates of each data point were automatically recorded while using the ArcGIS Field Maps.

Table 3. Feature layer set up for ground-truthing using ArcGIS Field Maps.

Question	Display Name	Type		List of Values
1	Land Use Type	Integer	Required	Grassland Forest Water Built-up Bare Soil Crop
2	Correspondence	Integer	Required	Same Different
3	Functionality	String	Optional	
4	Permanent or Temporary	Integer	Optional	Permanent Temporary
5	Open ended question	String	Submit once	
6	Feedback 2	String	Submit once	
7	Feedback 3	String	Submit once	
8	Photos	Attachment	Required	

Next, configuring the order of the questions and adding a description for each question were done in ArcGIS Field Maps. The completed version of this map can be found and accessed via the mobile device with this link: https://arcg.is/1CHiCK. Figure 6 includes screenshots of the user interface of the completed research application on ArcGIS Field Maps.

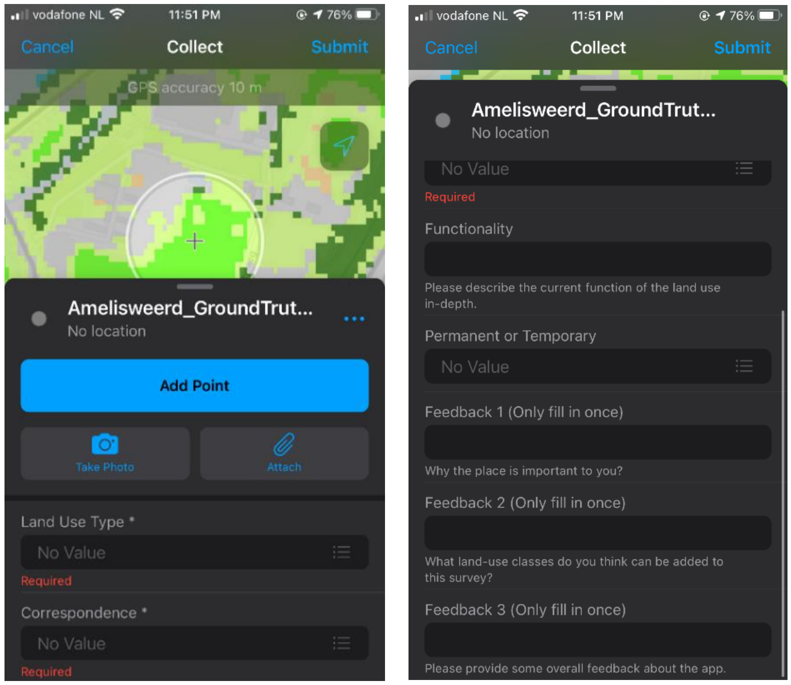

Figure 6. Screenshot of user interface of the ArcGIS Field Maps for ground truthing at Amelisweerd. All questions and the description for each question are shown.

3.3.3 Field research with the ArcGIS Field Maps app

After the ArcGIS Field Maps were prepared and ready, a short manual document and an introduction video about collecting the ground truth data for this research were made and can be found in Appendix 2 and be accessed via this link: https://youtu.be/q0YVj0gtgiI. Ground truthing was conducted for two weeks in mid-June. A convenient sampling strategy was employed due to time limitations for data collection and location of the field site. This proved to be a representative sample since the target users are various groups, including the public. All the users for ground-truthing in this research were students and staff from Utrecht University, as shown in Figure 7. As this field research was a proof of concept, 50 data points were expected to be sufficient when planning the ground-truthing.

Figure 7. Ground truthing using ArcGIS Field Maps in Amelisweerd.

4. Result

Here I present the results that were collected from the research methods described in the previous section. The results section is organized by research question.

4.1 An appropriate method and workflow for identifying actual land cover change in EIA follow-up using EO and GIS technologies

To identify and measure an appropriate method and workflow for EIA follow-up monitoring process utilizing EO and GIS technologies, the following section illustrates the land use classification maps for each selected EIA case for pre-and post-decision phases. The land use classification maps were generated by LULCC algorithm in the GEE. The accuracy of each land use classification map was assessed by a resubstitution error matrix.

4.1.1 EIA case 1: Lapseki Gold and Silver Mine and Project

The land use classification map of the Lapseki Gold and Silver Mine and Project in 2020 was generated from Sentinel 2 satellite imagery from the 30^{th} of April, 2020 to the 30^{th} of April, 2021. The land-use categories were designated and adjusted according to the mining project. The result shown in Figure 8 depicts that the mining activities were distributed discretely, which does not correspond with the predicted land use distribution. In the map, roads do not always have a linear characteristic, some of them are patchy. The open pit area is mixed with the waste dump and soil storage land use. As shown in Figure 9, pit, soil storage, and waste dump are all approximately 0.35 km2. The major land cover class is forest, which has almost 4 km2, and the second-largest land cover class is the road with 1.6 km2. The facilities class is small, which has only 0.04 km2.

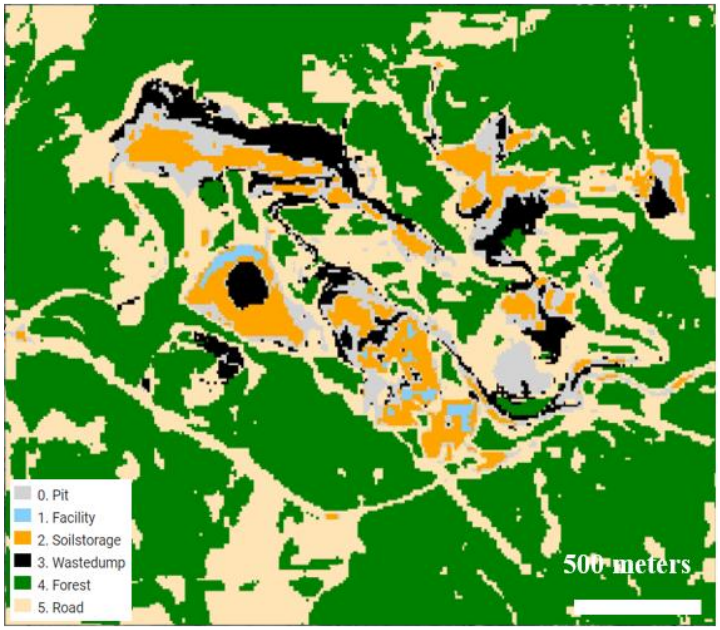

Figure 8. Land use classification map of Lapseki Gold and Silver Mine and Project in 2020 using Sentinel 2 satellite imagery. The land use categories are adjusted to mining activities.

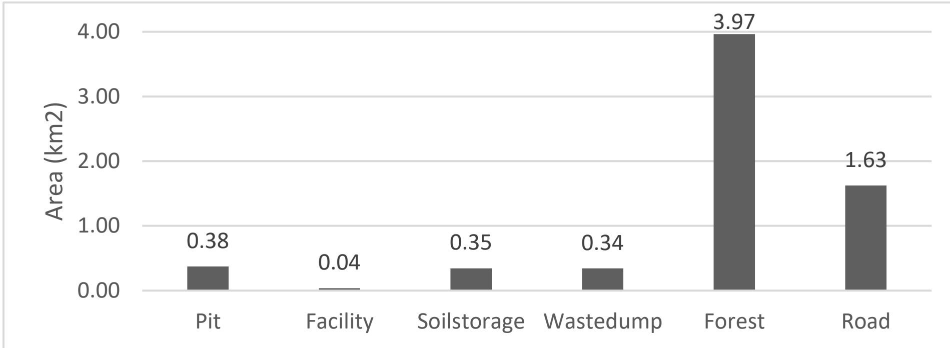

Figure 9. Land use size of each mining land use class of Lapseki Gold and Silver Mine and Project in 2020.

The resubstitution error matrix and the training accuracy for the accuracy assessment are shown in Table 4. The producer's accuracy is calculated by dividing the number of correctly classified pixels in each category, which is on the major diagonal, by the number of training pixels used for the categories. The result indicates the performance of the classification of the given land-use type. The producer's accuracy of soil storage, waste dump, and the road is very low with 19%, 64%, and 35%, respectively. It shows that open-pit is misclassified into soil storage and road. The land use difference between pit, soil storage, waste dump, and the road cannot be well classified. The user's accuracy is calculated by dividing the number of correctly classified pixels by the total number of pixels that were classified in the category. This number only indicates what the probability of the pixel being correctly classified is in reality. Thus, it shows open pit has the lowest probability to be correctly classified in this area. Forest and road are more likely to be correctly classified in the map according to the high user's accuracy. Upon further inspection by applying visual judgement on the road with the true color satellite imagery due to the low producer's accuracy of road class, it seems the pixels that were classified as roads on the map commonly include multiple other land uses. The overall training accuracy is 0.7, which also provides an overview that the classification strategy employed in this area can be significantly improved.

Table 4. The resubstitution error matrix of the land use classification of Lapseki Gold and Silver Mine and project in 2020 using mining land use categories.

	Training Data							
Classification data	Pit	Facilities	Soil Storage	Waste Dump	Forest	Road	Row total	**User's Accuracy**
Pit	161	0	76	26	1	41	305	53%
Facilities	0	20	6	0	0	0	26	77%
Soil Storage	1	0	24	0	0	0	25	96%
Waste Dump	0	0	22	46	0	0	68	68%
Forest	0	0	0	0	156	0	156	100%
Road	0	0	0	0	0	22	22	100%
Column total	162	20	128	72	157	63	602	
Producer's Accuracy	99%	100%	19%	64%	99%	35%		
Overall accuracy	71%							

Due to the result from the previous section, mining land use categories were adapted to coarse-scale land use categories. Pit, soil storage, and waste dump were grouped up as bare soil in the new categories. Forest was further categorized into grassland, forest, and cropland. An updated land use classification map of Lapseki Gold and Silver Mine and Project in 2020 using the Sentinel 2 satellite imagery is shown in Figure 10. Overall, the land use distribution is more concentrated, and the mining area can be detected more precisely with the shape of open pits. Road class is not included as a single category, but it can be observed as the linear characteristic bare soil land-use class. The road is not classified as built-up land use since the road is mainly unpaved with bare soil instead of concrete. Built-up area is well detected when comparing this map with the EIA land use map. Some bare soil area seems to be included in the built-up area. From Figure 11, the major land cover from the result is still green area, which implies forest, cropland, and grassland with 3.49, 1.7, and 0.4 km2, respectively. Bare soil is also evident, an area size of 1.25 km2. Built-up area is relatively small with 0.22 km2, and water is negligible with only 0.01 km2.

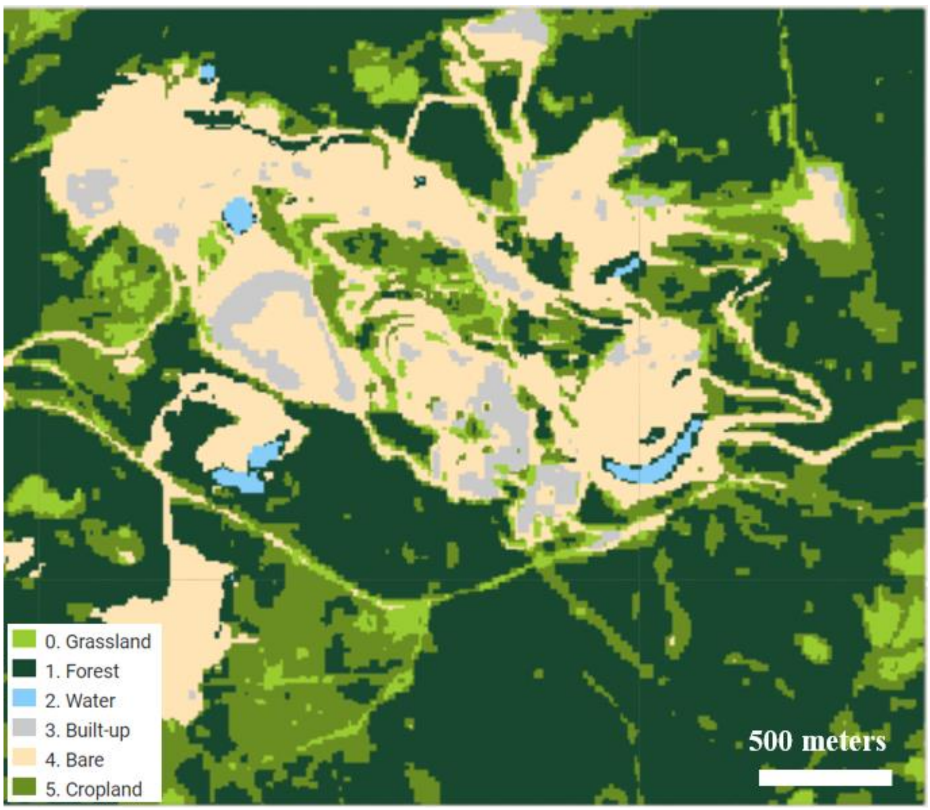

Figure 10. Land use classification map of Lapseki Gold and Silver Mine and Project in 2020 using Sentinel 2 satellite imagery.

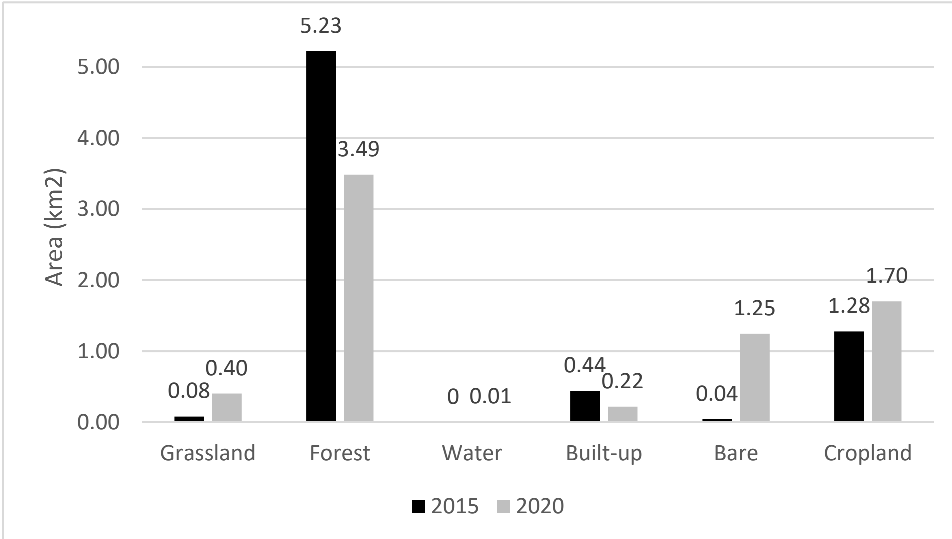

Figure 11. Land use size of each land use class of Lapseki Gold and Silver Mine and Project in 2015 and 2020.

The resubstitution error matrix and the training accuracy are shown in Table 5. Forest, water, and bare soil have high producer's accuracy with over 95%, which imply these land-use types perform well in this classification. Grassland, built-up, and cropland have relatively low producer's accuracy with 75%, 68%, and 61%, respectively. 25% of grassland is misclassified to either cropland or bare soil, and 39% of cropland is misclassified to either grassland or bare soil. 32% of built-up is misclassified to bare soil. For the user's accuracy, forest and water perform the best with 100% probability according to the number. Bare soil and cropland also have a high probability with 86% and 92%. Grassland and Built-up have low user's accuracy compared to others with 59% and 70%. When conducting visual judgement, it is aligned with the result shown in the classification map and error matrix. Forest, water, and bare soil are well classified, and part of the built-up area is bare soil in reality. The only difference is the cropland and grassland are misclassified frequently. The overall accuracy is 86%, which implies this classification method is suitable for these categories and this research area.

Table 5. The resubstitution error matrix of the Land use classification of Lapseki Gold and Silver Mine and project in 2020.

	Training Data							
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Cropland	Row total	**User's Accuracy**
Grassland	168	0	0	0	4	115	287	59%
Forest	0	507	0	0	0	0	507	100%
Water	0	0	29	0	0	0	29	100%
Built-up	0	0	0	47	20	0	67	70%
Bare soil	39	7	0	22	470	10	548	86%
Cropland	17	0	0	0	0	193	210	92%
Column total	224	514	29	69	494	318	1648	
Producer's Accuracy	75%	99%	100%	68%	95%	61%		
Overall accuracy	86%							

The result of using the same land use categories to classify the Lapseki Gold and Silver Mine and Project land use in 2015 for the pre-decision stage is shown in Figure 12. This result is based on Landsat 8 satellite imagery from January 1st, 2015 to December 31st, 2015, which provides the pre-decision stage imagery but has relatively lower spatial resolution than Sentinel 2. From the map, forest and cropland are the dominant land use at the pre-decision phase. The other major land-use shown on the map is built-up. Little bare soil and no water are shown on the map. Figure 13 also shows the forest and cropland have the largest land use size with 5.23 km2 and 1.28 km2, respectively. Built-up is 0.4 km2, and bare soil and water are approximately 0 km2.

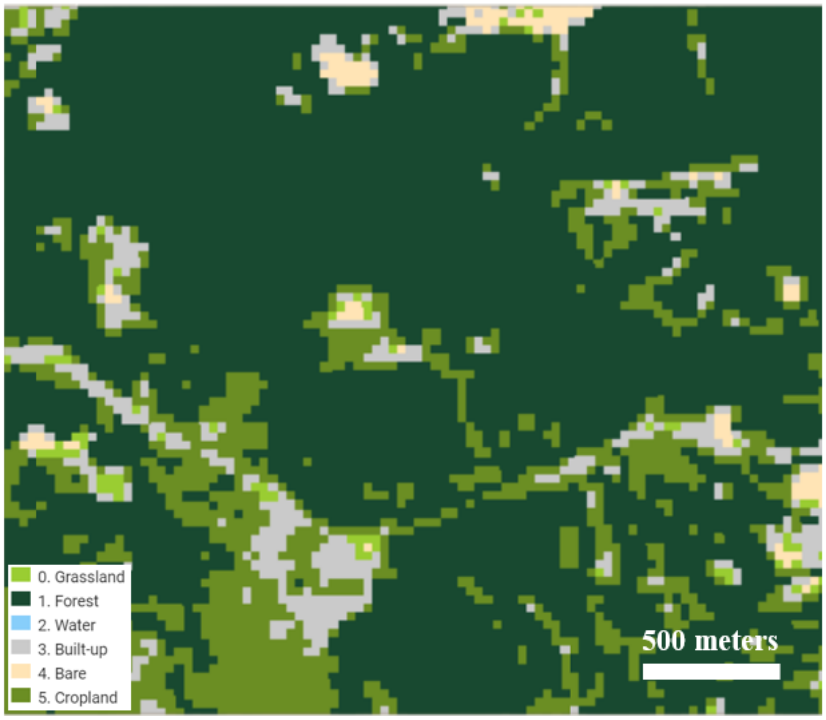

Figure 12. Land use classification map of Lapseki Gold and Silver Mine and Project in 2015 using Landsat 8 satellite imagery.

The resubstitution error matrix and the training accuracy are shown in Table 6. Forest and cropland have high producer's accuracy with over 95%, which imply these land-use types perform well in this classification. Grassland, built-up, and bare soil have relatively low producer's accuracy with 62%, 71%, and 62%, respectively. No water is detected at the pre-decision phase in the area. Although the producer's accuracy of grassland, built-up and bare soil is low, the error matrix also indicates that the sample number of these land cover types in the area is low. For the user's accuracy, forest and cropland have the highest probability of being correctly classified on the map. Grassland, built-up, and bare soil have a lower probability of being correctly classified on the map. When conducting visual judgement, it is generally aligned with the result shown in the classification map and error matrix. Forest is well classified, and no water in the area. But as the common error happened in the post-decision phase's land use classification map, grassland and cropland are commonly misclassified. The same issue can be observed between bare soil and built-up. The overall accuracy is 89%, which implies this classification method is suitable for these categories and this research area. However, it is worth noting that the high accuracy might be because of the homogeneous land at the pre-decision phase. This will be further discussed in the discussion section.

Table 6. The resubstitution error matrix of the Land use classification of Lapseki Gold and Silver Mine and project in 2015.

	Training Data							
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Cropland	Row total	**User's Accuracy**
Grassland	8	0	0	1	5	0	14	57%
Forest	0	57	0	0	0	0	57	100%
Water	0	0	0	0	0	0	0	n. a
Built-up	2	0	0	5	0	1	8	63%
Bare soil	3	0	0	1	8	0	12	67%
Cropland	0	0	0	0	0	26	26	100%
Column total	13	57	0	7	13	27	117	
Producer's Accuracy	62%	100%	n. a	71%	62%	96%		
Overall accuracy	89%							

The area size difference for each land-use type is shown in Figure 11 to identify the actual changes of the EIA case. Deforestation is evident with 1.74 km2 lost between the pre-and post-decision phase. Bare soil has increased 1.2 km2, and so do the grassland and cropland with 0.32 km2 and 0.43 km2, respectively. Surprisingly, the built-up area has decreased by 0.22 km2. The sum of the actual changes is equal to zero, which means the deforestation area has changed into either grassland, cropland, or bare soil area. Compared to the predicted changes, it is predicted bare soil area will increase by 2.5 km2, and the built-up area will increase by 0.29 km2 based on the EIA. The other land use classes are not addressed in the EIA.

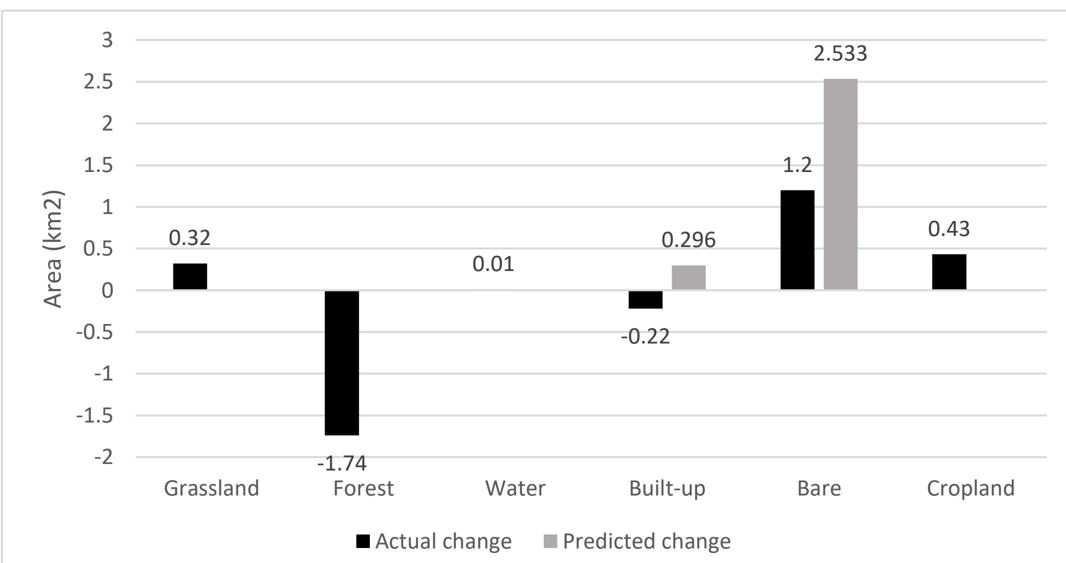

Figure 13. Comparison of actual land use change and predicted land use change of Lapseki Gold and Silver Mine and Project. Actual change is between 2015 and 2020. Predicted change is between 2015 and 2027 addressed in the EIA report.

4.1.2 EIA case 2: Gatsuurt Mine project

The land use classification map of the Gatsuurt Mine project in 2020 was classified using Sentinel 2 satellite imagery from the 30th of April, 2020 to the 30th of April, 2021. The land-use categories follow the coarse categories used in EIA case 1 except the cropland, which does not exist in this area. The result is shown in Figure 14. Overall, the forest is the major land cover in the area, and the bare soil along the river valley is well detected. The grassland along the side of the valley is rational, and a small waterbody is observed in the river valley. However, a discrete built-up area within the forest and grassland area is not logical and aligns with the common land use distribution. From Figure 16, the forest has the largest land-use area of 18.87 km2, and grassland has the second-largest land-use area of 7.17 km2. Water can be observed on the map, which has the smallest land-use area of 0.05 km2. Bare soil and built-up land use areas are 2.38 km2 and 1.31 km2, respectively.

The resubstitution error matrix and the training accuracy are shown in Table 7. The overall accuracy is 89%. The producer's accuracy of grassland and forest are very high with 92% and 100%, which means these two land-use types are well classified in this area. Bare soil has only 58% of producer's accuracy, and most of the errors are related to misclassified grassland. Water and built-up have low producer's accuracy of 34% and 30%. Two thirds of water training data is misclassified as bare soil, and built-up area is misclassified as bare soil and grassland. The forest has the highest probability of 100% correctly classified on the map for the user's accuracy. Built-up has the second-highest number of 86%, and the rest of the land-use types are all lower than 80%. When visually inspecting the true color satellite imagery, some similarities can be observed aligned with the error matrix. For instance, the forest area is classified accurate, and grassland too. As for the bare soil area, it is often seen that it is misclassified as a built-up area or a grassland area.

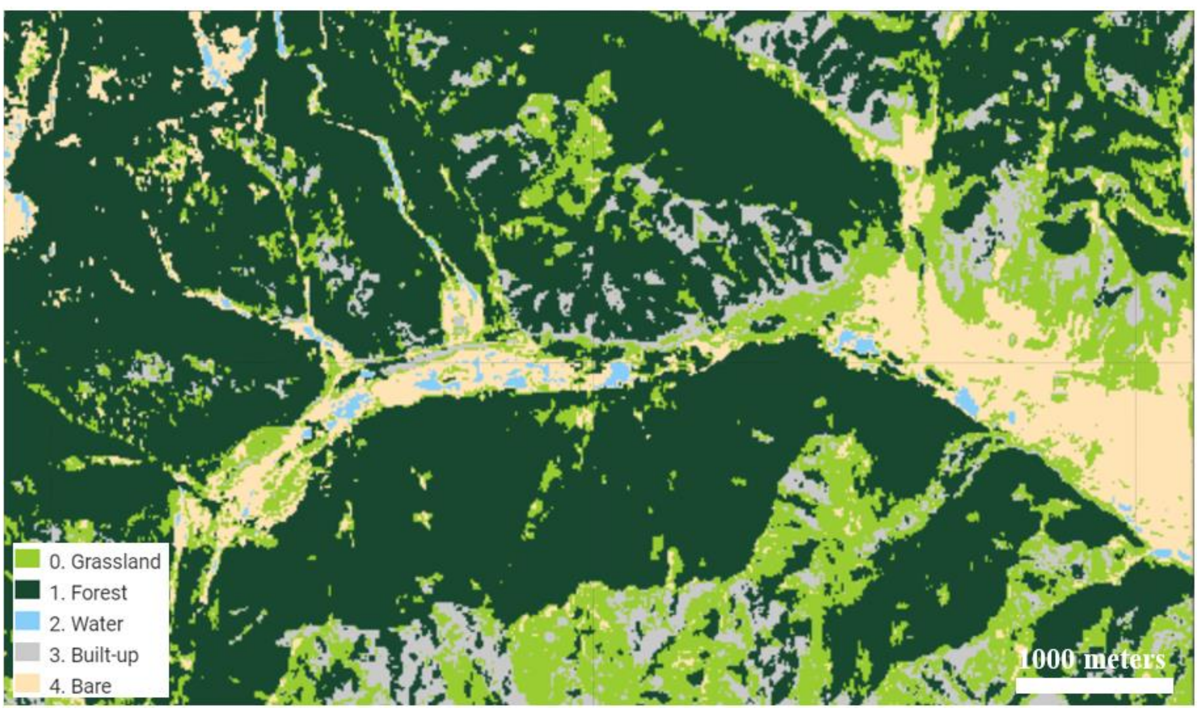

Figure 14. Land use classification map of Gatsuurt Mine project in 2020 using Sentinel 2 satellite imagery.

Table 7. The resubstitution error matrix of the Land use classification of the Gatsuurt Mine project in 2020

	Training Data						
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Row total	**User's Accuracy**
Grassland	971	1	0	54	257	1283	76%
Forest	0	3333	0	0	0	3333	100%
Water	0	1	51	0	14	66	77%
Built-up	6	0	0	49	2	57	86%
Bare soil	74	0	100	62	377	613	62%
Column total	1051	3335	151	165	650	5352	
Producer's Accuracy	92%	100%	34%	30%	58%		
Overall accuracy	89%						

The result using the same land use categories to classify the land use of the Gatsuurt Mine Project in 2015 for the pre-decision stage is shown in Figure 15. This result is based on Landsat 8 satellite imagery from January 1st, 2015 to December 31st, 2015, which provides the pre-decision stage imagery. The major land uses are forest and grassland of 18.11 km2 and 9.4 km2, respectively. Bare soil is also distributed along the river valley with 1.69 km2 in total. The built-up area is located in between bare soil and grassland with only 0.54 km2.

Figure 15. Land use classification map of Gatsuurt Mine project in 2015 using Landsat 8 satellite imagery.

The resubstitution error matrix and the training accuracy are shown in Table 8. The overall training accuracy is 89%. Producer's accuracy of grassland and forest is higher than 95%, implying these two land-use types are well classified in this area. The producer's accuracy of bare soil is 68%, which has some misclassified error with grassland. The built-up area has a very low producer's accuracy of only 3%, which a lot of training pixels are misclassified as grassland. As for the user's accuracy, forest and bare soil have the highest probability with 100% and 92% probabilities of being correctly classified on this map. Grassland and built-up have low user's accuracy with 64% and 14%. Water is not applicable since it does not exist in the pre-decision phase in the area. When applying visual judgement, it is corresponding with the result from the classification map and error matrix. Forest and bare soil area are well identified, and some bare soil area is misclassified to grassland and built-up area. Built-up is barely seen, and the water area is not visible in the pre-decision phase.

Table 8. The resubstitution error matrix of the Land use classification of the Gatsuurt Mine project in 2015.

	Training Data						
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Row total	**User's Accuracy**
Grassland	90	0	0	26	24	140	64%
Forest	0	370	0	0	0	370	100%
Water	0	0	0	0	0	0	n. a
Built-up	4	0	0	1	2	7	14%
Bare soil	0	0	0	5	54	59	92%
Column total	94	370	0	32	80	576	
Producer's Accuracy	96%	100%	n. a	3%	68%		
Overall accuracy	89%						

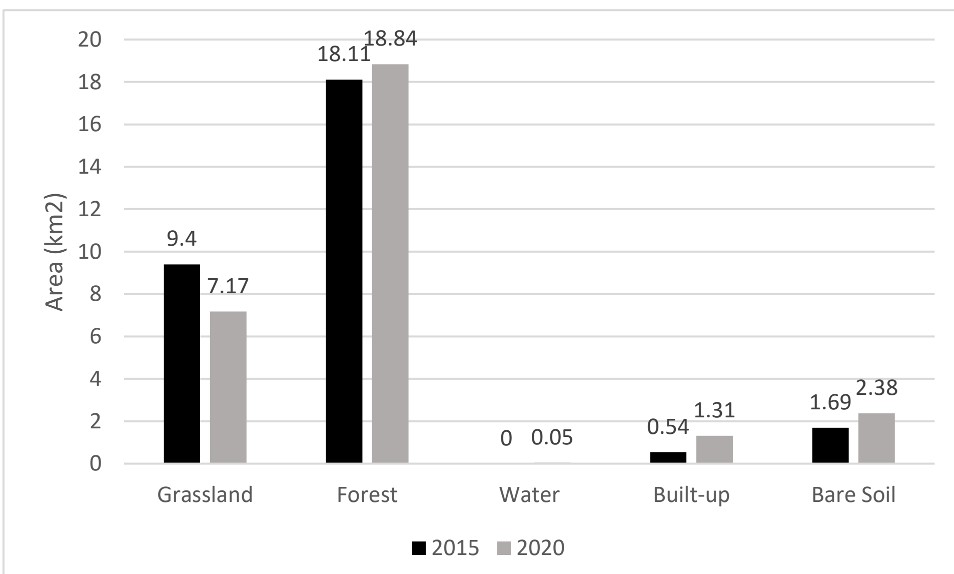

Figure 16. Land use size of each mining land use class of Gatsuurt Mine Project in 2015 and 2020.

To identify the actual changes between pre-and post-decision phases, the area size of each land-use type in 2020 is subtracted by the area size in 2015, and it is compared to the predicted changes from the EIA. The result is shown in Figure 17. The main actual land-use change is grassland, which has decreased by 2.23 km^2. Forest, built-up, and bare soil area have increased by 0.73 km2, 0.78 km2, and 0.69 km2, respectively. The built-up area already has a larger actual change than the predicted change, which is 0.36 km2. Though bare soil has a smaller actual change than the predicted change, the actual change of bare soil might have a slightly higher number than it is now based on the findings from the error matrix and visual judgement.

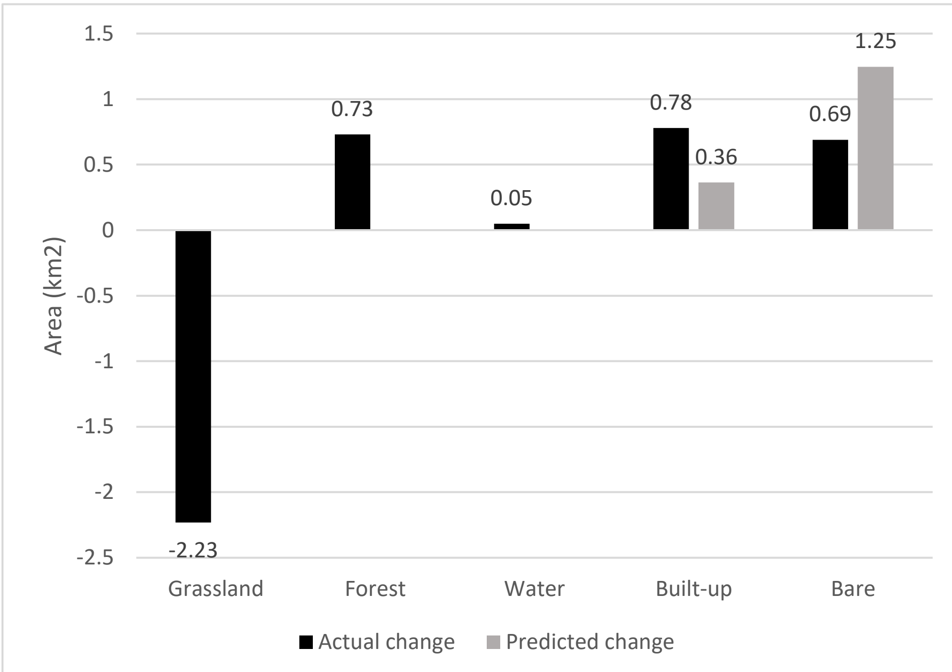

Figure 17. Comparison of actual land use changes and predicted land use changes of Gatsuurt Mine project. Actual change is between 2015 and 2020. Predicted change is between 2015 and 2025 addressed in the EIA report.

4.2 A CS app for collecting ground-truth data of land cover for EIA follow-up by CS

To identify how a CS application can help for collecting ground truth data for EIA follow-up monitoring processes, the following section illustrates the land use classification maps of Amelisweerd, and the ground truth data collected at Amelisweerd first. The land use classification map was generated by LULCC algorithm in the GEE. The accuracy of land use classification map was assessed by a resubstitution error matrix, and the accuracy of the ground truth data was assessed by error matrix. Then further information that can be collected by CS app is shown in the second part in this section.

4.2.1 Ground truth data from citizen scientists

The land use classification map of Amelisweerd in 2020 was classified using Sentinel 2 satellite imagery. The land-use categories follow the same coarse categories used in EIA cases. In total, 138 ground truth data points were collected from volunteers during a two week period of field research. The results are shown in Figure 18 and Figure 19. From the land use classification map, the grassland is the major land cover in the area, and the forest and cropland are also the majority on the map. The built-up area shows the highway and the residential area at the top left on the map. Some waterbodies can be found around Fort Rhijnauwen at the top right on the map. Bare soil is barely seen from the land use classification map. From Figure 18 and Figure 19, ground truth data points are not well distributed. More data points were collected along the walking paths in the Amelisweerd. Fewer ground truth data points were collected away from the walking paths. Figure

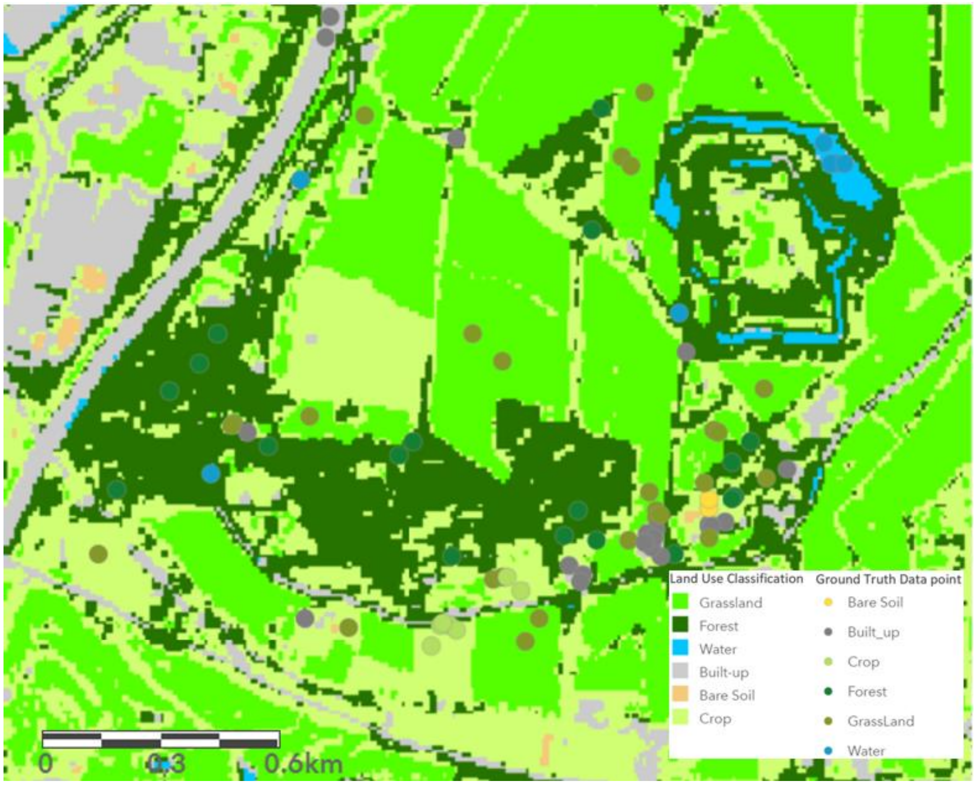

Figure 18. Ground truth data points represented as circles or dots and the color match the legend classes, which are correspondence with the land use in the classification map generated by Sentinel 2 satellite imagery.

18 depicts the ground truth data points, which are in correspondence with the land use classification map. From a rough visual interpretation, grassland and forest have many correctly classified points. Bare soil and water only have few correctly classified points. Figure 19 depicts the ground truth data points, which are different from the land use classification map. Most of the misclassified points are water areas, which are located along the Kromme Rijn, from visual judgment. Also, some misclassified points are built-up areas, which are located in the forest area. Grassland, cropland, and bare soil sometimes were misclassified as each other.

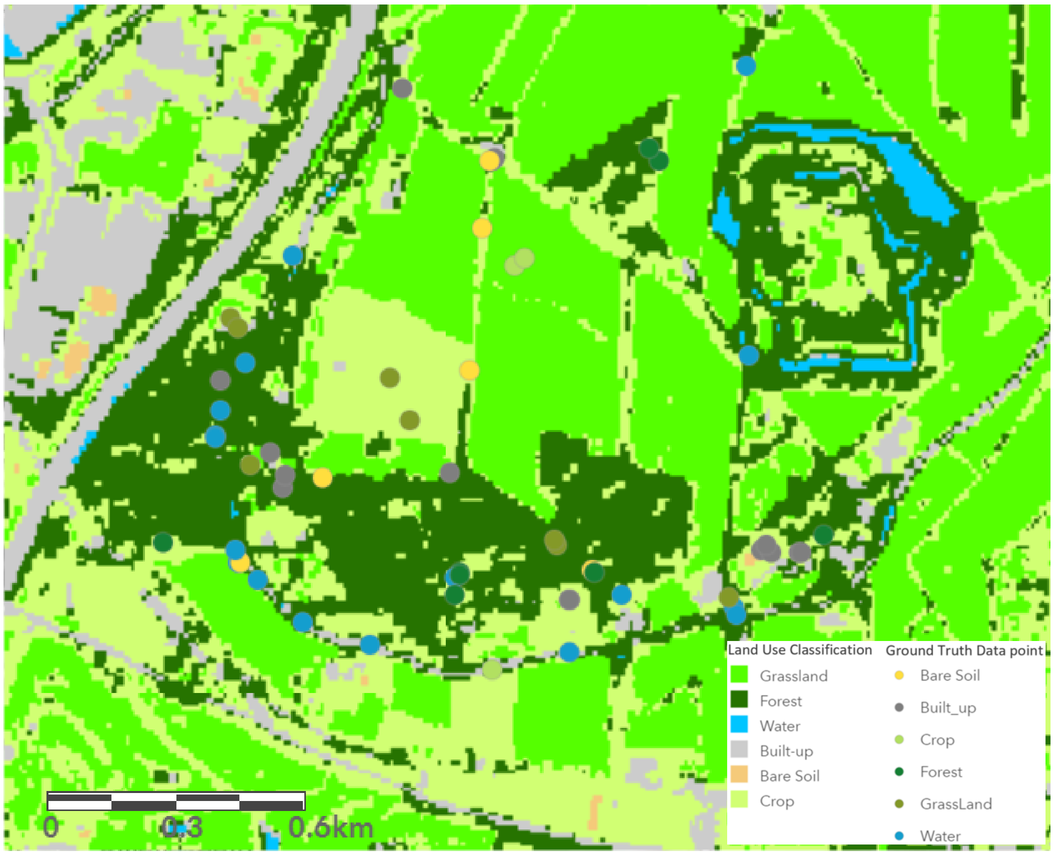

Figure 19. Ground truth data points, which are different from the land use in the classification map generated by Sentinel 2 satellite imagery.

The resubstitution error matrix and the training accuracy of Amelisweerd are shown in Table 9. The overall training accuracy is 90%. Producer's accuracy of all land use types is over 99% except cropland, which is only 31%. It implies these land-use types are well classified in this area, and cropland has some misclassified errors with grassland and bare soil. As for the user's accuracy, only bare soil has a probability lower than 85%. The rest of the land use types have a high probability of being correctly classified in this map. When applying visual judgement, it is corresponding with the result from the classification map and error matrix. Forest and grassland areas are well identified, but the cropland is difficult to distinguish from the satellite imagery. The main misclassified area is the water body, the Kromme Rijn, which is classified as built-up area.

The error matrix and the overall accuracy of ground truth data are shown in Table 10. The overall accuracy is a low number of only 59%. For the producer's accuracy, all the land use types have low numbers, which implied the ground truth data provided very different types of land use compared to the land use classification map. Over 70% of the water and bare soil from ground truth data were not detected, and 43% of the built-up was not detected by the land use classification method. Approximately 30% of grassland, forest, and cropland were misclassified based on ground truth data. However, the error matrix for ground truth data was interpreted in an opposite way to identify the value of ground-truthing, which implied the ground truth data is valuable for calibrating the classification method.

Table 9. The resubstitution error matrix of the land use classification of Amelisweerd in 2020.

	Ground Truth Data							
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Cropland	Row total	**User's Accuracy**
Grassland	26	0	0	1	3	2	32	81%
Forest	2	19	6	6	0	1	34	56%
Water	0	0	7	0	0	0	7	100%
Built-up	1	0	7	20	0	0	28	71%
Bare soil	0	0	0	3	2	0	5	40%
Cropland	5	8	4	5	3	7	32	22%
Column total	34	27	24	35	8	10	138	
Producer's Accuracy	76%	70%	29%	57%	25%	70%		
Overall accuracy	59%							

Table 10. The ground truth data error matrix of the land use classification of Amelisweerd in 2020.

	Training Data							
Classification data	Grassland	Forest	Water	Built-up	Bare soil	Cropland	Row total	**User's Accuracy**
Grassland	12377	20	0	0	0	1551	13948	89%
Forest	0	4804	0	0	0	0	4804	100%
Water	0	0	10809	0	0	0	10809	100%
Built-up	0	34	0	2516	0	20	2570	98%
Bare soil	0	1	0	14	13172	3013	16200	81%
Cropland	133	0	0	0	16	2012	2161	93%
Column total	12510	4859	10809	2530	13188	6596	50492	
Producer's Accuracy	99%	99%	100%	99%	100%	31%		
Overall accuracy	90%							

4.2.2 Citizen Science app

Using a customized ArcGIS Field Maps app, the volunteers provided further information while ground-truthing, as shown in Table 11. More in-depth land functions were described and observed according to the information. Grassland was used as a recreation area, pastureland; water was categorized to river, canal or pond; built-up was described in the road, buildings, farm; bare soil was described in tennis court, walking path, and dirt road; cropland was described in multiple agricultural activities. A significant challenge was that some functionalities are overlapped from different land-use types. For instance, walking path was addressed in the forest, built-up, and bare soil; tennis court was mentioned in both built-up and bare soil. Besides the ground truth data collected by ArcGIS Field Maps, qualitative information regarding perceptions of the place and of the app were collected. See Table 12 for responses.

As for the other optional question of permanent or temporary, only a few ground truth data points were marked as temporary land use. Three temporary land use data points for grassland were a cattle field and grass fields; two temporary land-use points for built-up were a dairy shelter and a bakery; one temporary land use data point for cropland was a greenhouse. However, these temporary land use functionalities were also found in the permanent land use data point's description. Hence, the photos submitted by users provided important information showing the real picture of the land use when confusion was observed at some data points. An example shown in Figure 20a is a bakery, which was described as temporary built-up land use. Figure 20b also shows a misinterpreted answer of describing a dairy farm as temporary land use. The photos also proved the misclassified land-use types, as shown in Figure 21. For instance, the Kromme Rijn was not detected on the classification map, but it was observed in several ground truth data points. Then the photo provided the visualization of what exactly the river looks like.

Table 11. ArcGIS Field Maps collected the Functionality information of the ground truth data location in Amelisweerd.

Land Use Type	Functionality	Permanent or Temporary (Number of data point)		
		Permanent	Temporary	No data
Grassland	Recreation area, pastureland, garden, farm, cattle field, no function	16	3	15
Forest	Forest 100%, walking path in the forest	12	0	15
Water	River, canal, pond	8	0	16
Built-up	Concrete road, tennis court, dairy farm, gravel road, hostel, restaurant, residency, bakery, highway, farm	26	2	7
Bare Soil	Tennis court, walking path, dirt road,	6	0	2
Cropland	Cornfield, greenhouse, cherry farm, local mixed farm	5	1	4

Figure 20. The land use photos submitted by users which can clarify the confusion from the ground truth data points. (a) A bakery was misinterpreted as a temporary land use. (b) A dairy farm was misinterpreted as a temporary land use.

Figure 21. These photos are examples of photos submitted from the citizen scientists and can help to visualize the actual land use. (a) A photo of the Kromme Rijn. (b) A misclassified dirt walking path.

Table 12 shows the qualitative information regarding perceptions of the place and of the app. The responses for first qualitative feedback question imply the opinion of missing categories in this app from user’s experiences for a specific area. Residential area needs to be extracted from built-up, and grazing land needs to be extracted from grassland in the Amelisweerd. The second feedback question provides the relationship between users and Amelisweerd. All responses address this area as important to them in terms of green spaces for walking and relaxation. Third feedback question provides the opinions of user’s experiences on the application. In general, the responses show it is a user-friendly app. One thing is addressed that the land use classification map sometimes disappeared while zooming-in or zooming-out.

Table 12. All responses from open ended feedback questions posed to Citizen Scientists. These are direct quotes.

What land-use classes do you think can be added in this survey?
- Residency - We noticed some agricultural areas that could be hard to classify, or perhaps even the dirt walking/biking paths - Gardens and grazing land (for cattle) - Different types of built-up, e.g., residential, commercial, recreational - Pasture, open public spaces, farms.
Why is the place important to you?
- It is the green area around the neighborhood. - Good place for a walk - I love taking long walks in Amelisweerd, and as a water nerd, I love the different waterways running through the forest. - Because I come there to relax and it's a beautiful area to walk around in - Great walking place - Living in a densely populated city like Utrecht, Amelisweerd is a great place to escape the city and be immersed in a calm, green and quiet space. - Getting out of the city and find a quiet place.
Overall, please provide some feedback about the app.
- I found it to be fairly user friendly! - It is interesting to see how different the satellite images (so the colors) are from what there is in real life sometimes - I think it is quite clear and user friendly - The app is user friendly! but sometimes, you can get lost if you zoom in too much - The app is very user-friendly and easy to use after a short introduction. However, zooming out or in is difficult as it loses the map.

5.Discussion

This research aimed to develop a feasible workflow to test in an effort to monitor and evaluate an environmental impact from a proposed EIA follow-up. The workflow uses freely accessible EO and GIS software and combines it with Citizen Science (CS) to develop a replicable and low-cost method for broader use in EIA follow-up implementation. As mentioned in the conceptual framework section, feasibility refers to the availability of the open dataset, land use classification algorithms, and CS application, the accuracy of the monitoring outcomes, and quality of ground truth data collected by CS.

5.1. Availability of the open dataset, LULCC algorithms, and CS application

5.1.1 Availability of the open dataset and LULCC algorithm

For the scope of this research, the availability of an open dataset on the GEE is sufficient in terms of spatial coverage and temporal granularity. The global coverage for both datasets allows any EIA project area to be implemented with this monitoring process. The temporal granularity for 5 and 16 days is enough to generate composite satellite imagery for further classification for the pre- and post-decision phases. As for the spatial resolution of 10 -30 meters, it is not ideal for this monitoring process yet since EIA is mostly for specific regions(Glasson et al., 2013). While there are more satellite imagery datasets expected to become open datasets in the future, it is foreseen that higher spatial resolution satellite imagery datasets will be available with the development of EO technologies (Pasetto et al., 2018). Further research will then be needed to identify the more appropriate and updated dataset to improve the monitoring process on a local scale.

As for the LULCC algorithm, this research modified the land use classification algorithm written by Philip Kraaijenbrink. This algorithm was developed in JavaScript for practicing the GEE, and it is available on GitHub and can be accessed by the public. With the development of XML and APIs, it allows users to access and utilize the database with very user friendly interface and little programing skills (Muki Haklay et al., 2008). While modifying the algorithm, the GEE provides a developers discussion group where most of the difficulties can be discussed and solved with other GEE users around the world. This platform lowers the challenge of JavaScript programing skills, and it allows broader users to process satellite imagery via the GEE. To use the LULCC algorithm in GEE, the user needs basic knowledge of reading JavaScript in collaborate with the notes and explanation in the scripts to adjust the algorithm according to the needs. Basic remote sensing knowledge, such as the theory behind spectral signature, will be helpful for users if further analysis is needed. For instance, using different satellite imagery datasets, or selecting different bands.

5.1.2 Availability of the CS app

ESRI develops ArcGIS Field Maps, which was used for ground-truthing in this research. ArcGIS requires an expensive software license that is not likely feasible for most public interest groups, but it was chosen for two reasons. First, considering the goal of this part is to prove the CS data can provide useful data for land cover classification. Second, the potential participants and those who may replicate this study in terms of ground-truthing in this research scale are Utrecht University students and researchers, which means they all have the ArcGIS license. Compared to

ArcGIS, QGIS is a widely used free GIS software, which does not have the interactive and mobile functions to meet the research needed in terms of collecting data, location, photo etc. There are open source alternatives to field maps, they are just not as easy to set up and implement as Esri Field Maps. As for the commonly used CS website, such as Zooniverse, it allows citizens to upload multiple formats of data. However, it doesn't have a mobile version to provide a simple and consistent way for a citizen to upload the ground truth data with precise coordinates from the field directly. ArcGIS provides a comprehensive and integrated online GIS environment to import the land use classification map, configure the field research app, upload the ground truth data, and export the result. Hence, further research is needed to develop a workflow focus on how to use the existing open-source GIS software and CS website to conduct ground-truthing.

5.2. Accuracy of the monitoring processes

5.2.1 Pre-processing the satellite imagery

For the pre-processing of the satellite imagery, the characteristic of multi-spectral composites that are used in this research is a crucial element affecting the result. First, cloud-free composites were generated by the filter. Second, the mean or median spectral reflectance value of one year period was also generated by the reducer. Based on these pre-processing steps and it is pixel-based composites, the following deviations need to be considered when implementing the method and interpreting the results. First, the pixel size of 10 to 30 meters is too large to distinguish the agricultural pattern of cropland from grassland. A visual judgment can easily observe if the spatial resolution is sufficient. Also, such a pixel size in a small-scale region often contains heterogeneous properties within a single pixel, where mixed pixel properties might lead to some important land use invisible on the map. For instance, a stream with 10 meters width might not be identified instead of a riverside grassland because the water body can be split up into two or more pixels which have more grassland in each pixel. Second, the reducer provides a single composite that intends to give a better overview of the area. However, it can miss out or even misguide some important information in terms of temporal wise. For instance, the phenology of cropland and grassland might therefore become bare soil in the composite. Or deciduous forests might be ignored, especially in high latitude regions since the longer wintertime. Those deviations will exaggerate the result's error when classifying the image by training areas based on the same composite. Thus, ground truthing is needed locally and is expected to increase the accuracy of the land use classification method apart from conducting visual judgement on true color satellite imagery.

Overall, remote sensing technology has developed various methods to detect different materials on the earth surface. More accurate methods have been developed with the development of multi-spectral, higher spatial and temporal resolution sensors. Most of the methods make use of choosing different spectral bands and identify the unique absorption wavelength of each band to identify the material. Some other methods use a specific formula to calculate a value from selected bands to detect specific material. Therefore, selecting spectral bands based on a specific purpose is a crucial step for processing satellite imagery. Reflecting on this research, six bands ranging from red, green, blue, near-infrared, and two short-wave infrared are selected to identify the spectral signature for land use classification. First, fine-scale mining land use categories were employed, but the accuracy was low since different types of land use related to mining activity are rock and soil, which have a similar spectral signature with the selected bands. Then coarse-scale land use categories were employed, which result in higher accuracy. Therefore, selecting proper spectral bands and even utilizing a specific formula to perform better land use classification can vary from different types of EIA projects. For instance, statistical linear regression analysis indicate that NDVI coupled with Normalized Difference Moisture Index (NDMI) is an effective indicator if deforestation is the main predicted impact of the region (Karan et al., 2016). For the mining activities, hyperspectral Longwave Infrared (LWIR) remote sensing data can provide a well-performed classification (Notesco et al., 2015). Though these other methods might need the dataset that is either not on GEE or has a less temporal resolution, this research provides an insight that a replicable satellite imagery processing via the GEE is achievable. Once the type of dataset is available on GEE, more project-oriented image processing methods can be implemented in the monitoring process.

5.2.2 Classifier used in LULCC algorithm

For the classifier employed in LULCC algorithm, this research selected the minimum distance classifier as the supervised classification method in LULCC algorithm. Though the classification method results in sufficient overall accuracy, many different commonly used classifiers are available for land use classification. For instance, parallelepiped, Mahalanobis distance, binary encoding, maximum likelihood, and Random Forest, each of these different classifiers have various suitable characteristics depending on the point cloud shape in the spectral feature space (Lillesand et al., op. 2015). For instance, if there is not a correlation in brightness between the different ranges of the spectrum, it is better to choose the minimum distance classification than other classifiers, theoretically. It was not tested comprehensively since comparing different classifiers is not the intention of this research. I tried to classify the Sentinel 2 image of EIA cases and Amelisweerd by Random Forest classifier, which has been recognized as one of the best performance classifiers (*Random Forest Algorithm for Land Cover Classification*, 2016). The accuracies of the classified result of two EIA regions were extremely high, approximately 0.99, as with the result of Amelisweerd. However, the high accuracy does not necessarily mean the classifier worked perfectly when applying visual judgment. For instance, a large area of forest is misclassified as grassland. Therefore, it is suggested to test different classifiers and conduct a visual judgement to get a better classification result (Lillesand et al., op. 2015). For further research, I would suggest to first try different classifiers, such as those mentioned above. Then choose two classifier results with the highest accuracy to conduct visual inspection based on the main land-use change addressed in the EIA project.

5.2.3 Calculating the actual land use size for each category

From section 4.2, the actual land cover changes for two EIA cases were identified and interpreted. However, some inaccuracy of using training pixels to classify the land use should be considered in this research based on the outcomes from the error matrixes and visual judgement. First, grassland and cropland are often misclassified into other classes. Also, these two land-use types and built-up sometimes are actually bare soil when checking the true color satellite image. Therefore, the bare soil area is potentially larger than the result. As shown in Figure 22, the built-up, cropland and grassland might partially be bare soil on-site, and it means the post-decision phase might have a more significant increased bare soil than what is shown on the map. Even though the overall accuracy shows that the classification method performs well, this type of confusion will deviate from the result of calculating each land use type's area size. EIA projects are mostly on a regional scale, which implies the pixel size range from 10 to 30 meters is still relatively big pixel size when classifying a small area. High accuracy comes from the major land-use type, such as forest, the lowest accuracy comes from the minor land use type, such as built-up. Sometimes, it is difficult to find a homogeneous training area for the minor land-use type in such a small area. A small number of the training pixels easily result in lower accuracy once it has a few misclassified pixels. Especially for the pre-decision phase in this research, the pixel size of the available dataset is 30 meters instead of 10 meters for the post-decision phase. Since the available satellite imagery has a lower spatial resolution, it becomes an important factor of deviation when the actual change is calculated by subtracting the pre-decision phase area size from the post-decision phase area size. Hence, the satellite imagery classification method can only give a rough overview of what is really happening in the EIA project area but answering what is the actual size of each land-use type precisely.

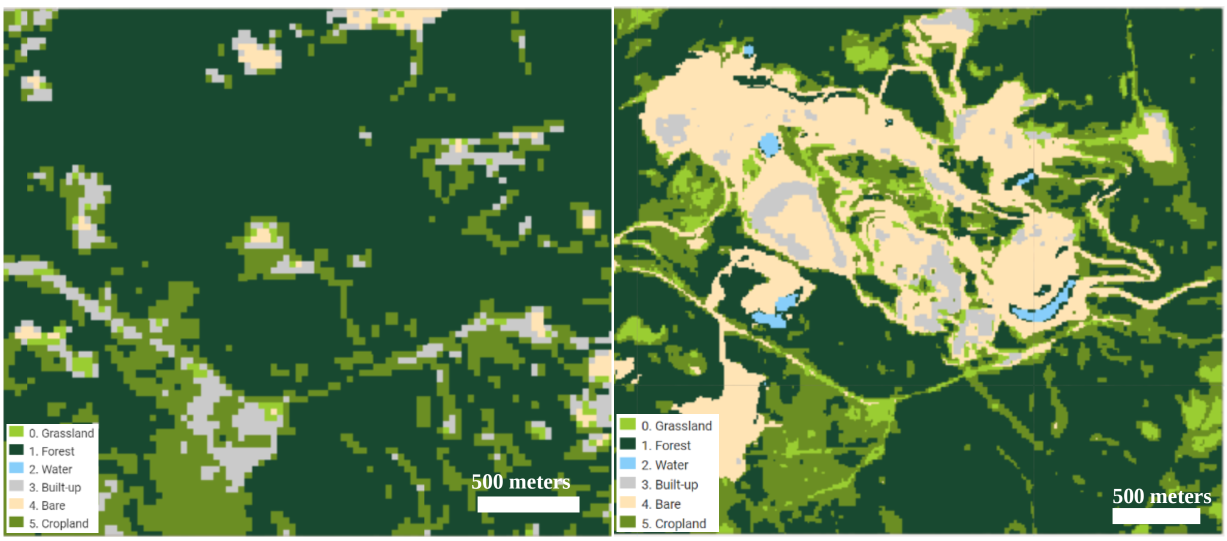

Figure 22. Land use classification map for EIA case 2. The left one is for pre-decision phase in 2015, and the right one is for post-decision phase in 2020. These two maps were shown in result section 4.2.

5.2.4 Comparing the actual changes to the predicted changes

Figure 23 below was shown in the result section. The predicted changes are always larger than the actual changes since two selected EIAs are ongoing projects, which will only be finished in 2027 and 2025. Deforestation for 1.74 km^2 in EIA case 1 and grassland lost for 2.23 km^2 in EIA case 2 both indicate the land clearing for open pits and other mining activities. Though these number didn’t equal to the increased number for bare soil and built-up area, it still gives an overview of the drastic land clearing happened during the development. Also, the built-up area has already passed the predicted land-use size in the EIA case 2. It is useful information for interested parties to check what is happening on site. Additionally, it is valuable for the EIA follow-up monitoring process in detecting the land use distribution. For instance, an evident bare soil area appears on the south side of the road as shown in Figure 22, which is not mentioned in the first EIA project.

Though the actual change of bare soil is smaller than the predicted change, such an extra area that is not planned in the EIA should be addressed and checked what is happening on the ground. However, the main purpose of EIA follow-up is to check if the actual impact meets the predicted impact (Arts et al., 2001). As two ongoing EIA cases in this research, the predicted impact cannot be well-identified during the operating phase. Therefore, it is important for further research to focus on identifying the predicted land-use change of EIA for the post-decision phase to check compliance with implementation requirements by year instead of an overall impact.

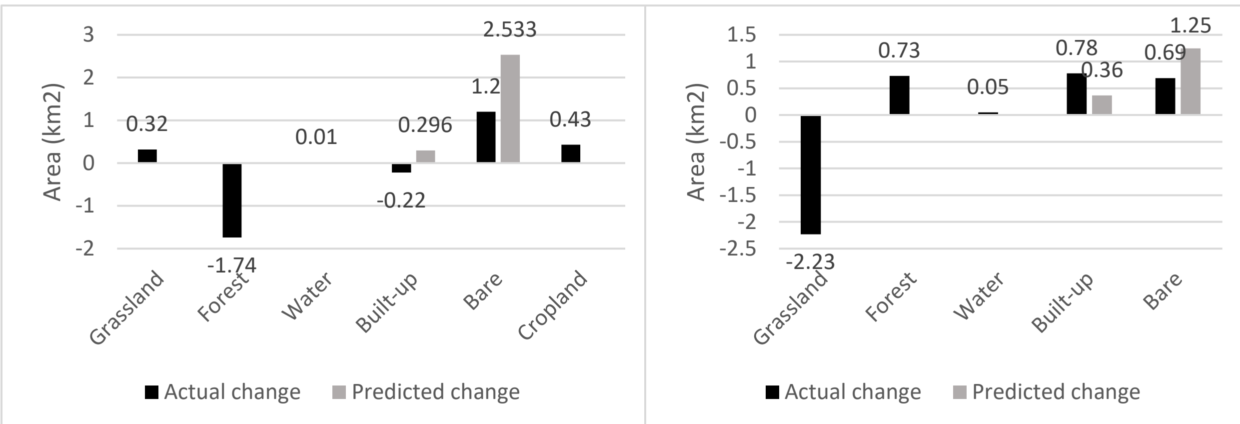

Figure 23. The actual land use change and the predicted land use change for two EIA cases. The left one is EIA case 1, and the right one is the EIA case 2. The predicted land use change is based on EIA report, and the actual land use change is subtracting the land use area in 2015 from the land use area in 2020.

5.3. Quality of ground truth data collected by CS

First, the accuracy of each EIA case and Amelisweerd are shown and compared in Table 13. It provides insight into the contribution of the collected ground truth data with the low accuracies in most of the land use categories. For instance, the producer's accuracies of water and bare soil for ground truth data are lower than 30%, but these two land use types were shown to have 100% producer's accuracy for the LULCC algorithm. All land use categories have significantly lower user's accuracy for ground truth data than the LULCC algorithm, the same as the overall accuracy. This indicates that the ground truth data can be used for validating the LULCC algorithm and improve the accuracy of the classification results (Fritz et al., 2017). One exception in this research case is that the producer's accuracy of cropland is higher for ground truth data. This might be because the LULCC algorithm often misclassified cropland into grassland and bare soil. Then the ground truth data has the higher producer's accuracy due to the ground truth data points, which are cropland, were collected by random data collection strategy. Therefore, there is a need for further research to conduct the validation step to optimize the LULCC algorithm and the monitoring process, as mentioned in the previous discussion section 5.2.1.

Table13. The accuracy for each EIA project and Amelisweerd for pre-and post-decision phases.

			Grassland		Forest		Water		Built-up		Bare Soil		Cropland		Overall
Case	**Year**	**Data**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**Accuracy**
Tumad	2015	Landsat 8	62%	57%	100%	100%	n. a	n. a	71%	63%	62%	67%	96%	100%	89%
	2020	Sentinel 2	75%	59%	99%	100%	100%	100%	68%	70%	95%	86%	61%	92%	86%
Gatsuurt	2015	Landsat 8	96%	64%	100%	100%	n. a	n. a	3%	14%	68%	92%	n. a	n. a	89%
	2020	Sentinel 2	92%	76%	100%	100%	34%	77%	30%	86%	58%	62%	n. a	n. a	89%
Amelisweerd	2020	Sentinel 2	99%	89%	99%	100%	100%	100%	99%	98%	100%	81%	31%	93%	90%
	2020	Ground Truth	76%	81%	70%	56%	29%	100%	57%	71%	25%	40%	70%	22%	59%

*PA=Producer's Accuracy; UA=User's Accuracy

Second, there were some errors found in misclassifying the land use due to misunderstanding the definitions of the types of land use when inspecting the ground truth data. With ArcGIS online, it is easy to filter the error of choosing the wrong land use type, and it is easy to fix errors made by users by interpreting the photo. For instance, mixing up the permanent/temporary, or bare soil/built-up. Editing the errors is needed, and it can be simply done. In addition, defining the land use type clearly and avoiding misunderstanding between different land-use types (Laso Bayas et al., 2016). In this research, bare soil or built up and permanent or temporary need a more precise definition. For instance, offseason for the cropland might be seen as grassland, which then confuses citizens whether it is a temporary grassland or permanent cropland. Minimizing errors due to misunderstanding the definition of questions and options requires further research. For those planning to use this method in the future, I would recommend remedying this difficulty for citizens who volunteer to contribute data collection efforts.

Third, some land use classes were forced to be classified into certain land-use classes, which might lead to important information being lost. For instance, the pasture at the Amelisweerd is dominant land use, but it was forced to be classified as grassland. In this case, the functionality of the land use was missing though it is correctly classified. Thus, the land use categories might be developed based on the project type to give better options for the public to provide more informative data (Busch et al., 2016). If this concept can be implemented when designing the CS app, the ground truth data collected by the app can provide more informative data to improve the monitoring process.

Lastly, the qualitative feedback collected by the CS app provides insight into the relation between CS and the research area. This is valuable since it implies that the ground-truthing gets local citizens involved, the intended interest parties. Getting interested parties involved in the monitoring system can raise environmental awareness (Dean et al., 2018). It is expected the ground-truthing by CS can provide ground truth data for calibration and raise the environmental awareness of interest parties, which is crucial for the EIA follow-up in practice.

6. Conclusion

The aim of this research is to develop and test a feasible workflow in an effort to monitor and evaluate an environmental impact from a proposed EIA follow-up. The workflow uses freely accessible EO and GIS software and combines it with CS to develop a replicable and low-cost method for broader use in EIA follow-up implementation.

It was found that the availability of the open satellite imagery dataset is sufficient for monitoring EIA due to its global coverage and frequent temporal granularity. In addition, two datasets that were used in this research are both ongoing missions, which implies they will be able to be used for other EIA projects in the future. With the development trend of EO technologies, more satellite imagery datasets with higher spatial resolution can be expected to open to provide a continuous monitoring process. The LULCC algorithm modifies the existing open algorithm, and the need for programming skills can be lowered with the aid of the GEE developers' discussion group. ArcGIS Field Maps is a well-integrated GIS tool for conducting CS and ground-truthing, but it is not free software. Further research is needed to develop a workflow focus on how to use the existing open-source GIS software and CS website to conduct ground-truthing.

The LULCC algorithm generates a high accuracy classified land use classification map for each EIA case for both pre-and post-decision phases. Due to the inherent remote sensing characteristics of composites satellite imagery and classification method, the high overall accuracy does not necessarily equal ideal land use classification. The GEE and LULCC algorithm provide an overview of the land use situation in the area, and visual judgement is still needed to increase the accurate interpretation of the classification map. In addition, the predicted changes are always smaller than the actual changes since both EIAs are ongoing projects. Therefore, it is important in practice for further research to focus on identifying the predicted land-use change of EIA for the post-decision phase to check compliance with implementation requirements by year instead of an overall impact.

Using the CS app is a useful tool to collect ground truth data, and further research can include this ground truth data in validation to increase the accuracy of the LULCC algorithm. However, a clearer definition of the land use categories is needed to minimize the misunderstanding for the citizen to collect the data. The land-use categories should also be adjusted based on the project type to collect the important land-use class in the project area. The CS app also provides qualitative data to increase the involvement of related parties. Thus, utilizing the CS app to collect more relevant information from locals is possible and effective for EIA follow-up. In conclusion, though this was a proof of concept research, it can be concluded that integrating EO and CS to develop a low-cost method for monitoring land-use change in EIA follow-up process is feasible in terms of the availability of the open dataset, algorithm, and CS app; accuracy of the monitoring outcomes; and quality of the ground truth data collection by CS app. For those who would like to use these methods in the future, I would recommend further efforts should focus on building a framework for implementing this monitoring process properly to different types of EIA cases in terms of land use categories.

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Appendix 1: Methodology framework

By answering the sub-questions, the research question was answered at the end of the research. Some important intermediates are shown in the diagram.

What type of project is easiest to monitor the EIA follow up procedure using EO and CS?

Step 1: Screening EIA reports and identify the environmental impact and the management of the project.

↓

Intermediates: A table with selected EIA reports and predicted land use changes.

⬇

SQ 1: What is an appropriate method and workflow for identifying both predicted and actual land cover change in EIA follow-up using EO and GIS technologies?

Step 2: Check and compare the available imagery using GEE.

↓

Step 3: Test the LULCC algorithm with selected EIAs for the pre-decision and post-decision phases.

↓

Intermediates: Land use classification map

Case	Satellite imagery time	Dataset
Case 1 (Fine-scale categories)	T2 (4.30.2020 – 4.30.2021)	Sentinel 2
Case 1 (Coarse-scale categories)	T2 (4.30.2020 – 4.30.2021)	Sentinel 2
	T1 (1.1.2015 – 12.31.2015)	Landsat 8
Case 2 (Coarse-scale categories)	T2 (4.30.2020 – 4.30.2021)	Sentinel 2
	T1 (1.1.2015 – 12.31.2015)	Landsat 8

⬇

SQ 2: How could CS help with the collection of ground-truth data of land cover for EIA follow-up?

Step 4: Ground truthing with the ArcGIS Field Maps app with a smaller area.

↓

Intermediates:
Land use classification map of Amelisweerd

Case	Area Imagery Time	Dataset
Amelisweerd	2020	Sentinel 2

ArcGIS Field Maps app and 138 field research data points

⬇

What are the benefits and drawbacks of combining GEE and CS for monitoring land cover in EIA follow-up?

Step 5: Identify and compare the benefits and drawbacks of using GEE and CS for land classification.

⬇

A low-cost replicable method for monitoring land cover change in EIA follow-up processes using remote sensing imagery and citizen science

Appendix 2: LULCC algorithm used in the Google Earth Engine

This is the LULCC algorithm used for EIA case 1 in 2020 for the post-decision phase. The original algorithm in the Google Earth Engine can be found via this link: https://code.earthengine.google.com/?scriptPath=users%2Fmaster_thesis%2Ftest%3AEIA_Tumad%2FTumad_2020

1. Set the map center

- Different map center of the research area can be set in order to provide a faster and easier interpretation of the result.

```
/*This script is based on PK's script.
2020 Sentinel-2 with PK's land use classification.*/

//1. Set the map center according to the research area
Map.setCenter(26.78761942022299,40.29953888104223,14);
```

2. Define input data

- First, ideal cloud mask filter is varying from different datasets. Utilizing the scripts of the dataset description on the EE dataset catalog to mask cloud and also visualize the image.
- Second, add the "filterBounds" according to the research area when using Sentinel-2.
- Third, the "filterDate" can be easily changed regarding the research needed. However, it is important to check whether there are sufficient images for certain period of time before further coding and processing.
- Fourth, 'nir','swir1','swir2','tir' in Sentinel-2 is different band compared to Landsat-8. Therefore, corresponding band's number need to be adjusted in the scripts.
- Fifth, different reducers are used for Landsat-8 and Sentinel-2 in the EE Data catalog. Try both "median" and "mean" to get a better imagery.
- Sixth, different vector outlines need to be used when applying this algorithm to different research area. Drawing a rectangle as a "featureCollection" at very beginning to replace "nl" is a easy alternative in this case.

```
//2. Define input data

//Lin added_import the same geometry for same EIA project
//Import the Sentinel-2 imagery by using the code from EE data catalog
function maskS2clouds(image) {
  var qa = image.select('QA60');

  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = 1 << 10;
  var cirrusBitMask = 1 << 11;

  // Both flags should be set to zero, indicating clear conditions.
  var mask = qa.bitwiseAnd(cloudBitMask).eq(0)
      .and(qa.bitwiseAnd(cirrusBitMask).eq(0));

  return image.updateMask(mask).divide(10000);
}
```

```
var dataset = ee.ImageCollection('COPERNICUS/S2_SR')
                  .filterDate('2020-04-30', '2021-04-30') //According to the
EIA time
                  .filterBounds(Tumad)//Lin added_According to the research
area
                  // Pre-filter to get less cloudy granules.
                  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE',20))
                  .map(maskS2clouds);

//Lin added_Select the corresponding band from Sentinel-2
dataset = dataset
  .select(['B2','B3','B4','B8','B11','B12'])
  .map(function(x){return x.rename(['blue','green','red',
'nir','swir1','swir2'])})

var satimg = dataset.mean()

// clip the result to the outline of Tumad
var satimg = satimg.clip(Tumad)
```

3. Visualize satellite imagery

```
//3. Visualize satellite imagery

//Lin added_ visualize the rgb map for research area
var visualization = {
  min: 0.0,
  max: 0.3, //change the value accroding to the higher latitude
  bands: ['red', 'green', 'blue'],
};
Map.addLayer(satimg, visualization, 'RGB'); //or median?
```

4. Obtain training data

- It is important to draw the polygon in the order of land use class that was written in the script. Otherwise, it is essential to adjust the order in step 1.5.

```
//4. Obtain training data

//Draw the training area
// combine the sample regions you've create into a single collection
var sampleregs  =
ee.FeatureCollection([grass,forest,water,built_up,bare,crop])
```

1.5 Classify image

- First, different satellite dataset contains different pixel resolution. In Sentinel-2, SWIR1 and 2 have 20 meters pixel size, which are larger than green, red and NIR. Though changing the scale to 20 meters in this part in the script is rational, the best resolution still can be selected to give a better classification result. Same concept applies in the next step.

```
//1.5 Classify image

// selection of bands to use for classification algorithm
var bands   = ['green','red','nir','swir1','swir2']

// sample pixels from the image using the regions
var training = satimg.sampleRegions({
  collection: sampleregs,
  properties: ['class'],
  scale: 10 //Lin_adjust the resolution
})

// define classifier and train with the samples
var mdmodel  = ee.Classifier.minimumDistance('euclidean')
//var mdmodel  = ee.Classifier.smileRandomForest(10)
var trained  = mdmodel.train(training, 'class', bands)

// apply classifier to the image
var classimg = satimg.classify(trained)

// lists with class names, values and colors (for colors use hex RGB or html5
color names)
var classlab = ['Grassland','Forest','Water','Built-up','Bare','Cropland']
var classval = [0,1,2,3,4,5]
var classcol = ['YellowGreen', '184930', 'LightSkyBlue', '#cacaca',
'Moccasin', 'OliveDrab']
Map.addLayer(classimg, {min:0, max:5, palette: classcol},
'Classification',true)
var lg = require('users/philipkraaijenbrink/tools:legends')
lg.classLegend(classval, classlab, classcol)
```

6. Accuracy assessment

```
//6. Accuracy assessment

// Meng Chiao Lin added_ Get a confusion matrix representing resubstitution
accuracy.
var trainAccuracy = trained.confusionMatrix();
print('Resubstitution error matrix: ', trainAccuracy);
print('Training overall accuracy: ', trainAccuracy.accuracy());

//Define the validation pixels by creating validation pixels set

// combine the validation pixels you've create into a single collection
var validationpixels  =
ee.FeatureCollection([grass_v,forest_v,water_v,built_up_v,bare_v,crop_v])

//Sample the input with a different random seed to get validation data.
var validation = satimg.sampleRegions({
  collection: validationpixels,
  properties: ['class'],
  scale: 10 //Lin_adjust the resolution
})

// define classifier and train with the samples
//var mdmodel  = ee.Classifier.minimumDistance('euclidean')
var validated  = mdmodel.train(validation, 'class', bands)
```

```
// apply classifier to the image
var classimg_validated = satimg.classify(validated)

// Get a confusion matrix representing expected accuracy.
var testAccuracy = validated.confusionMatrix();
print('Validation error matrix: ', testAccuracy);
print('Validation overall accuracy: ', testAccuracy.accuracy());
```

7. Visualize using charts

- Make sure the chart has corresponding land use classes and color in the label. The scale is also chosen according to the smallest pixel size. However, it still work if the value is set smaller than that. This would be a useful information when a land use class has too small area to show in the chart. For instance, water body will show up in the chart when the scale changes to 5*5 meters in this case.

```
//7. Visualize using charts

// chart that shows class area distribution

var chart = ui.Chart.image.byClass({
  image: ee.Image.pixelArea().multiply(1e-6)        // pixel area in km2
             .addBands(classimg.rename('classification')),
  classBand: 'classification',
  region: Tumad,
  reducer: ee.Reducer.sum(),
  scale: 10*10, //Lin_adjust the resolution(ok to be smaller than pixel size)
  classLabels: classlab,
})
chart.setOptions({title:'Area per class', hAxis: {title: ''}, vAxis: {title:
'Area (km2)'},
                  colors: classcol})
     .setChartType('ColumnChart')
print(chart)
```

8. Export the classified map

- This is step is to export a classified map for further GIS analysis.
- Region need to be set according to the research area which is define at the very beginning.

```
//8. Export the Geotif file
Export.image.toDrive({
  image:classimg,
  description:"Tumad_2020",
  region:Tumad,
  scale:10,
})

//End
```

Appendix 3: ArcGIS Field Maps manual

Environmental Impact Assessment Citizen Science tool

Field data collection_Meng Chiao Lin

Goal of the project

Environmental Impact Assessment (EIA) is a tool to evaluate the impacts a proposed project may have on the environment. For example, if a prospecting company wants to build a mine in a nature preserve or if a developer wants to build a highway through a park, what are the environmental implications? To find out, EIA involves multiple phases and includes multiple actors. The weakest phase of EIA is the follow-up phase. During this phase, it is important to monitor what changes occurred as a result of a project. Do the results match what was promised in the Environmental Impact Statement (EIS) as part of the original EIA?

In an effort to answer this question for an EIA, I have developed a series of tools to assist the EIA follow-up phase. I need your help in testing these tools. **I need your help collecting data In Amelisweerd!**

The first tool I developed is an automated land use classification tool. I need your help verifying if it worked, is the land use classification accurate?

Here you are invited to be a citizen scientist and provide a classification and a photo of an area of the park to see if my automated land use classification is correct.

This leads me to my second tool is the mobile citizen science data collection application. In this app, you look around, are you in a cow field? Forest? Built-up urban area? In this app, you can automatically put your location on the map and select classify the land use at a specific point. This data will be used to compare to the automated map to see if the classification was correct. Also, I am interested in your opinion of the app and the place itself. Another important aspect of EIA is public participation in the project, how valuable is a certain area to you?

With your help, the aim of the master thesis research is to test to monitor and evaluate an environmental impact from a proposed EIA follow-up, using ArcGIS Field Maps to collect ground truth data.

Your input will help evaluate if this combination of methods using Earth Observation (EO) and Citizen Science (CS) is a feasible, replicable method for broader use in Environmental Impact Assessment (EIA) follow-up implementation. This is expected to offer an achievable entry point for related parties and raise public engagement to establish a better EIA follow-up monitoring network. Furthermore, participants will be able to raise environmental awareness from their participation.

Your input is valuable. If you would like a copy of the results of this project, please email me
m.lin2@students.uu.nl

Research area and land cover map

This field research will be conducted at Amelisweerd in east Utrecht city in the Netherlands as proof of concept research. Land cover classification map was produced by utilizing the same satellite imagery processing method in the Google Earth Engine as the other EIA projects in this master thesis research. The satellite imagery data of this map is from Sentinel-2 in 2020 with a pixel resolution of 10 meters.

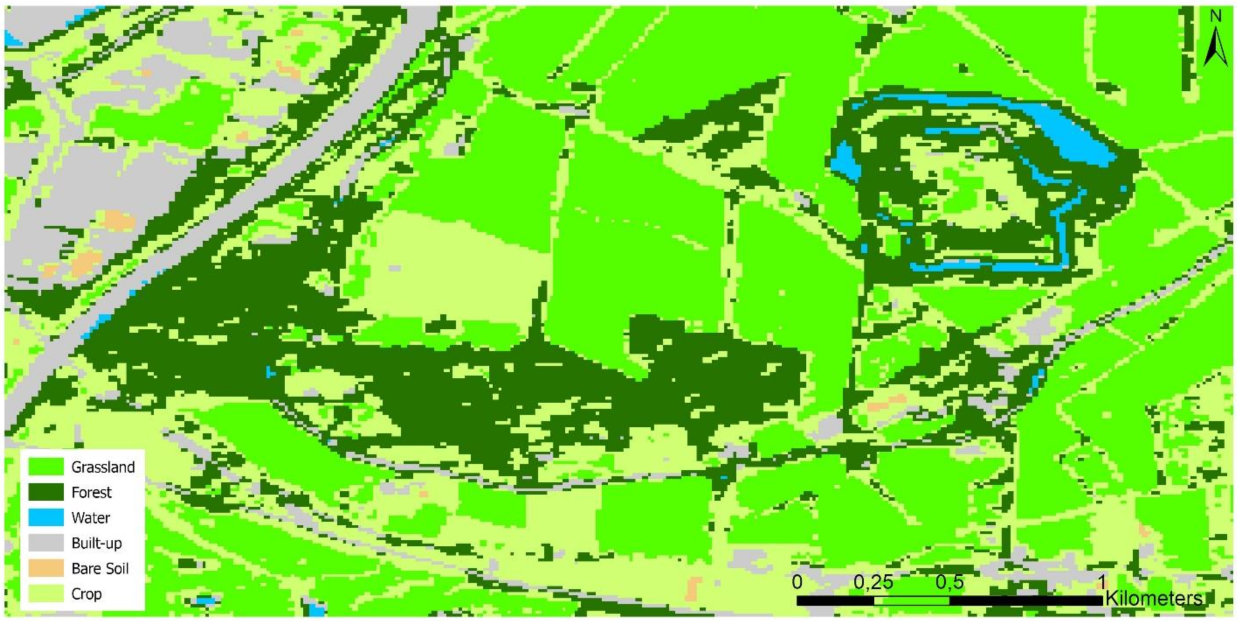

Figure 21 Land cover classification map of Amelisweerd.

Before you leave, Install the app following these directions.
Configure ArcGIS Field Maps

Step 1: Install ArcGIS Field Maps Mobile app

Search ArcGIS Field Maps in your mobile phone's app store. The mobile device needs to meet the requirement as shown below.

Android:
Android 8.0 (Oreo) or later; Processor: ARMv7 or later; OpenGL ES 2.0 support
iOS:
iOS 13.5 or later; iPhone, iPad, iPod touch

Step 2: Sign In

As an employee or student at Utrecht University, the following steps can be used to log in to the app. First, choose “Sign in with ArcGIS Online”, and then insert “Uni-utrecht” in “Your ArcGIS organization’s URL”. Second, insert your personal Solis-id.

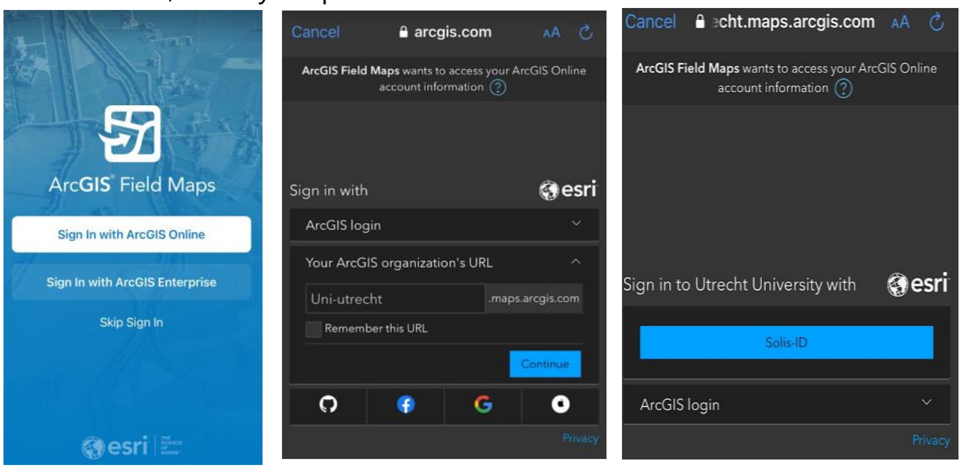

Figure 22 The screen shot of logging in to esri field maps.

Step 3: Asses to the mobile device

After signing in to the app, make sure the Field Maps can access the "Location” and “Camera” of the mobile device.

Step 4: Search the map

In the search bar, search “Amelisweerd_GroundTruthData_Test2”. You can view the summary and description of the map by clicking “View Details” in “more options”. After you click on the map, the land cover classification map of Amelisweerd will appear in the app. Note that this map only shows when the map is in proper scale for data collection, so you might need to zoom in or zoom out if the land classification map disappeared on the map. The label can be found when you click the “more options” button at the top right corner of the app.

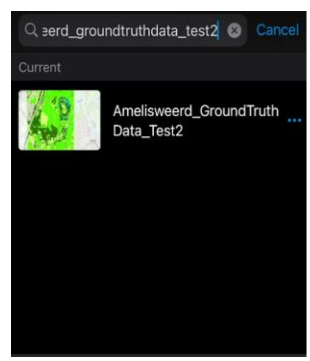

Figure 23 Thumbnail of Amelisweerd map in the app.

When you are in the Amelisweerd – add points to the map.

Instruction of data collection

Step 1: Land use type (Required)

According to the land cover categories, grassland, forest, water, built-up, bare soil, and crop are classified and mapped from the satellite imagery. The first question in this field research is to verify what the actual land use from within the scene is. Thus, select what type of land use based on your current location by clicking the add button at the bottom-left corner of the app.

Step 2: Take Photo (Required)
After selecting a land use class of your current location, use the "Take Photo" function to provide a clear image of the land use of your current location.

Step 3: Correspondence (Required)
Based on your finding, please verify if the current land use correspondent with the land cover class shown on the map.

Step 4: Functionality of the Land cover (Optional)
If you know the function of the land cover of your current location, please describe in-depth what kind of activity is taking place on this land use. For instance, what kind of agriculture activity on the cropland cover classification; is it a water body of the river, lake, artificial reservoir, or canal?

Step 5: Permanent or Temporary (Optional)
If you can distinguish the land use at your current location is permanent or temporary based on your experience, please provide the information—for instance, a temporary construction cabin.

Step 6: Submit data (Required)
After filling in the information, click "submit" at the top right corner of the app to submit the data.

Step 7: Feedback (Only fill in once per user, optional)
After collecting multiple data points, please fill in the three feedback questions in one of your collected data points. First, why the place is important to you? As a participant in this field research, what is the connection between you and this place? Second, what land-use classes do you think can be added to this survey? During collecting data, do you think there is an essential land-use class missing in the categories? Third, please provide some overall feedback about the app in terms of usability, concept, or research theory.

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Step 8: Edit data
If you want to edit the data that you have submitted, you can click on the dot, which you want to edit, on the map.