D5.1: Environmental metrics methodology for ML-system

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Abstract:	The current report provides a set of recommendations for solid and measurable indicators with a focus on addressing environment and climate priorities within the framework of Common Agricultural Policy (CAP) implementation. In this context, DIONE generalizes and integrates the concept of Essential Variables (EVs) and Goal Based approach (GBA) across the main environmental objectives of the modernized new CAP (2021-2027). The work is driven by the need to support substantial monitoring and reporting by combining data primarily from satellites and novel aerial and in-situ solutions in the fields of land, soil, crop, water, air quality and climate change, and putting forward robust methodologies and well-defined workflows for linking the monitoring of EVs to key agricultural indicators. This is done by weighing in the readiness and maturity of existing agri-environmental indicators and monitoring methodologies, laying out EO-driven approaches for up-to-date and valid monitoring and paving the ground for a machine learning inferencing system. The report considered the implementation of CAP and other related environmental policies (e.g. SDGs), the outcomes and future perspectives of key research papers and relevant projects. Within the framework of "D5.1 Environmental metrics methodology for ML-system" DIONE brought together an interdisciplinary team of highly-performing scientists (agronomists, meteorologists, software engineers, EO experts), to jointly study the challenges to provide a comprehensive approach for environmental assessment of CAP.

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List of Abbreviations and Acronyms	
ARD	Analysis Ready Data
CAMS	Copernicus Atmosphere Monitoring Service
CAP	Common Agricultural Policy
CGLS	Copernicus Global Land Service
CLC	Corine Land Cover
CMEF	Common Monitoring and Evaluation Framework
DG AGRI	Directorate-General for Agriculture and Rural Development
DIAS	Data and Information Access Services
EC	European Commission
ECVs	Essential Climate Variables
EFFIS	European Forest Fire Information System
EGVs	Essential Geodiversity Variables
EO	Earth Observation
ESA	European Space Agency
ESDAC	European Soil Data Centre
EU	European Union
EVs	Essential Variables
FAO	Food and Agriculture Organization
GCOS	Global Observing System for Climate
GEO	Group on Earth Observation
GEOSS	Global Earth Observation System of Systems
HNV	High Nature Value
LMCS	Land Monitoring Core Service
LUCAS	Land Use and Cover Area frame Survey
LSWI	Land Surface Water Index
NDVI	Normalized Difference Vegetation Index
ISRIC	International Soil Reference and Information Centre
RUSLE	Revised Universal Soil Loss Equation
SDGs	Sustainable Development Goals
UAA	Utilized Agricultural Area

1 Introduction

The goal of this deliverable is to identify and define a set of environmental indicators or metrics which can be deduced using Earth Observation (EO) means to address the priorities laid out by the Common Agricultural Policy (CAP) of the European Union (EU). The use of EO enables the large-scale processing and analysis of the large agricultural areas that may be found across the EU. In essence, the idea is to identify layers of high-level information (the metrics) which would quantify the effect of the multi-faceted functionalities of the agricultural fields. This information may be readily available as e.g. part of the Copernicus progamme or ingested into the Global Earth Observation System of Systems (GEOSS) platform as part of other research efforts, or may be derived from the combination of satellite imagery and in-situ data using proven methodologies. In any case, in the next steps of the project these layers of information will be appropriately combined and visualized in the Environmental Performance Tool to assist in the environmental monitoring and associated checks of the CAP.

1.1 Context and Background

The main findings from the European Commission's (EC) public consultation[1], held in 2017, concluded that the majority of the environmental challenges, that where designated for achievement by the previous CAP, have not been sufficiently met. Hence, agriculture in EU-27 remains among the major drivers of negative impacts on the environment. Among the points with greater concern, the agricultural sector causes more than 10% of the total greenhouse gas emissions in the European territory, almost 44% of total water withdrawals (with higher rates in water-scarce Mediterranean countries; FAO, 2016) and is a driver for soil erosion (European Environment Agency (EEA), 2020[2]). Consequently, the loss of EU biodiversity has accelerated, indicating that EU is not on track to halt the biodiversity loss and the ecosystem services degradation by 2020 (EEA, 2020).

This startling information alone was enough for the EC to re-align the CAP's objectives to efficiently reflect the environmental challenges that the Union faces, without overlooking necessary support for farming community, as well as strengthening rural development. This will entail a profound transformation. At the same time, the paying agencies and respective national or regional governments will need to showcase and bring proof of a tangible positive environmental impact of the payments, as was strongly noted by the independent review of a recent report from the European Court of Auditors (ECA, 2019[3]). In the latter, the CAP was criticized in that current measures are yet to prove a real increase in environmental improvements. This is also highlighted by recent studies (Solazzo et al., 2016). The same has also been advocated by EC officials (statement of Bérénice Dupeux - Policy Officer for Agriculture at the European Environmental Bureau: "*with so much European taxpayers' money being spent on farm payments, we need real accountability to ensure the cash is supporting farmers to produce safe and healthy food in a way that works in harmony with the environment and not against it*"). In that regard, as a first step towards updating the CAP after 2020, the Commission dedicated three of the nine general objectives, in the regulation (EC, 2018[4]), towards reinforcing the CAP's environmental and climate performance, as those highlighted by including a set

[1] https://ec.europa.eu/info/consultations/modernising-and-simplifying-common-agricultural-policyhttps://ec.europa.eu/info/consultations/modernising-and-simplifying-common-agricultural-policy

[2] https://www.eea.europa.eu/publications/soer-2020

[3] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018AA0007&rid=1

[4] https://eur-lex.europa.eu/resource.html?uri=cellar:aa85fa9a-65a0-11e8-ab9c-01aa75ed71a1.0003.02/DOC_1&format=PDF

of priorities to i) **protect biodiversity**, ii) **foster sustainable use of natural resources** and iii) **contribute to climate change mitigation and adaptation**.

In that direction, the ongoing osmosis amongst policy-makers (EU policy Directorates-General and beyond) confirmed the growing interest, trust and utilization of EO related data and information as a key for evaluating compliance with policies in force. EO means have demonstrated their capacities to monitor the planet's ecosystems on regular intervals, as shown by e.g. the Copernicus programme. A common need identified across recent efforts, is to translate the policy requirements into EO system requirements and promote adoption of EO technologies for the attainment of the environmental policy making (Anderson et al., 2017). Twenty years ago, environmental policy-making often relied on anecdotal evidence and expert opinion. Nowadays, the world has entered a new era of data-driven environmental policy-making, since national entities are increasingly being asked to explain their performance on natural resource management challenges with reference to quantitative metrics and bring proof of a tangible positive environmental impact of the payments. Two decades of progress on data-driven policy-making has shifted the global agenda toward a much greater emphasis on scientific analysis and robust metrics. This trend has been culminated with the adoption of the Sustainable Development Goals (SDGs), underpinned by a set of quantitative targets.

To do so, national entities need to enhance environmental sector diagnostics, development indicators, programme monitoring and service delivery. This requires access to unbiased quantified information at a large scale. In this context, EO is an irreplaceable tool that provides wide coverage, high quality and unbiased data on the physical, chemical and biological processes of our planet. Consequently, EO technologies are contributing and have the potential to contribute more in the need to provide information services (Kavvada et al., 2020). A more EO data-driven and empirical approach to environmental protection promises to make it easier to spot problems, track trends, highlight policy successes and failures and optimize the gains from investments in environmental protection. It is noteworthy that, the domain of EO-driven environmental monitoring in terms of data and services is currently undergoing a significant shift. Undoubtedly, EO is closely intertwined with the fourth industrial revolution, since it is being driven by emerging technologies such as deep learning and cloud computing, (Yao et al, 2020). Furthermore, the forthcoming increase in space-based missions covering different spectral domains and higher resolution data (in terms of both spatial and spectral resolution) provided by commercial providers offering new data, results in a massive increase of EO big data. All of this and much more enter the environmental decision-making in a new era; redefining the very meaning of what the future holds for EO-driven environmental monitoring.

In that context, and since the launch of the previous CAP, a wide range of activities promoting EO as a key enabler for services in support of compliance monitoring have been carried out. These range from EU projects (e.g. RE-CAP), to ESA-funded projects (e.g. Sen4CAP) and large-scale demonstrators under the NIVA. Whilst these activities have made great strides towards developing technological solutions (e.g. validated algorithms, products, workflows and best practices) to gradually substitute 'on-the-spot-checks' with a system of automated checks based on EO, the use of EO to extract tangible environmental impact performance metrics by paying agencies in Europe is still not adequately taken up or is completely lacking. This is partly because information integration at a scale sufficient to support the environmental assessment of CAP performance, has until now been difficult and expensive to setup and run. Adoption has been further hindered by long established practices, multifaceted regulatory requirements and lack of trust. Also, until now developments have been driven by the scientific interests of different stakeholders' groups, in absence of a trans-disciplinary research. This creates overlapping technology solutions, with a limited potential to contribute to the implementation of an environmental performance tool able to deploy at national level.

1.2 Common Agricultural Policy – Beneficiary and Driver of Earth Observation Solutions

EU counties have allocated the "lion's share" of their income support (30%) to direct green payments[5] offering to paying agencies the jurisdiction, capacity and resources to allocate payments and monitor the compliance process. In this context, the Commission's Directorate-General for Agriculture and Rural Development (DG AGRI) is considered as a main user of remotely sensed imagery data and the utilization of EO data products seems mature, for more than a decade. Till now, within the context of "Checks with Remote Sensing", very high resolution data (<5m) has succeeded broad scale adoption across the paying agencies of EU, to carry out checks for area-based CAP payments.

The aforementioned could serve as a basis for additional EO-driven services further facilitating the digitalization of the CAP. EO data will be massively promoted, in the post 2020 CAP's timeframe, moving towards continuous monitoring and reporting, rather than spot checks of agricultural land in Europe, enhancing the Integrated Administration and Control System (IACS) and making it more cost efficient. As an additional step forward, Copernicus data and relevant services information (e.g. Copernicus Land Monitoring Service) will also be utilized to improve the environmental performance of farms, through systems such as the proposed Farm Sustainability Tool and Platform, which can supplementary support both environmental compliance measures and relevant commitments. It has been argued that the actual environmental objectives are defined in a generic manner, and are measured with quantitative technical parameters at national level (Eksvärd and Marquardt, 2018). This creates a precedent and testament to the applicability of EO data in contributing to environmental objectives compatible with the mandatory standards (e.g. standards on good agricultural and environmental condition of land, GAECs[6]). Therefore, to support more result-driven, feasible and adequate reporting processes, there is a need to evolve from merely monitoring EO-based indicators to quantitative and multidimensional environmental assessment and monitoring frameworks. In this context, monitoring and assessment systems related to CAP's environmental performance should move forward in order to evaluate long-term effects and sustainability outcomes (Fischer and Wagner, 2016). This will also contribute to the alleviation of the various reactions related to the often-unambitious nature of CAP targets (Eksvärd and Marquardt, 2018). Such a transition requires to be supported by practices based on scientific evidence built on quantitative, spatio-temporally distributed monitoring assessments (Verschuuren, 2018). For instance, with the new CAP, environmental indicators monitoring progress towards targets can be developed using Copernicus data. Smart use of combined technologies, with high revisit Sentinels satellite data (1, 2, 3, 5P), the LPIS, e-government tools and novel in-situ sensors (incl. handheld) will allow a move towards a year-round monitoring of the environmental footprint of the agricultural activities.

1.3 Purpose of the report

The overarching objective of the current report is to present a **comprehensive approach** based on the provision of a set of **recommendations for solid and measurable indicators** with a focus on addressing environment and climate priorities within the framework of CAP implementation. This is done by weighing in the readiness and maturity of existing agri-environmental indicators and essential climate variables, laying out EO-driven methodologies for up-to-date and valid monitoring and paving the

[5] https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/income-support/greening_en#:~:text=Through%20greening%2C%20the%20European%20Union,income%20support%20to%20%22greening%22.

[6] https://marswiki.jrc.ec.europa.eu/wikicap/index.php/Good_Agricultural_and_Environmental_Conditions_%28GAEC%29

ground for the development of a machine learning inferencing system that will be deployed on larger scales.

In section 2 we define the main CAP objectives related to the environmental and climate issues and we introduce the goal-based approach to guide the determination of Essential Variables (EVs) and relevant indicators. In section 3, we discuss different aspects of the EO ecosystem in which DIONE operates in order to support the implementation of the EO driven monitoring. Then, we introduce the EV concept and reviews relevant work of this concept to different domains to select the most appropriate. Finally, we provide a synthetic description, for each indicator that is complemented by definitions, measurement methods, a summary of the current state of play and context needed to interpret it correctly. In section 4, we summarize the findings and we provide initial ideas to efficiently combine this wealth of information to support EO driven environmental assessment of the new CAP. In the last section (5), we provide a short summary of the current work.

2 Methodology

The future CAP will play a fundamental role in developing a fully sustainable agricultural sector that supports environmental care and climate change as indicated by the recently adopted objectives. For an EO-driven environmental assessment of CAP performance, it is necessary to translate the EO data into actionable knowledge, which will monitor CAP's agri-environmental indicators. Obviously, there is no single indicator which could unambiguously report on CAP's environmental performance. Monitoring efforts are nevertheless feasible when considering a set of variables in combination, given that they are measurable, compatible and faithful in capturing trends that are comparable within the European territory.

2.1 The environmental objectives of the future CAP

Agricultural productivity, climate change and natural resources form a mutually interdependent nexus, in which changes in one area have direct consequences for others. For instance, the Climate-Smart Agriculture concept of the United Nations Food and Agriculture Organization (FAO) places emphasis on the fact that higher sustainability is required; particularly while increasing productivity and improving the soil nutrient content and eliminating the negative consequences on water quality (Lipper et al., 2014). Thus, a deeper understanding and continuous monitoring of this nexus is needed to provide the informed and transparent framework required to meet increasing resource demands and pressures, without compromising sustainability.

Considering the envisaged multi-functionality of the EU-27 agricultural sector and its direct relationship with the environment, CAP plays a central role in reducing the negative impact of our agricultural practices wherever possible in the complete spectrum of the agri-food sector. In addition, other core EU Directives (Water Framework Directive, Nitrate Directive and Groundwater Directive), Climate Change Protocols (Kyoto, etc.) and the Soil Thematic Strategy set the framework upon which optimization of agricultural production should balance out negative environmental pressures. It should be mentioned that the EU has often been acted as a primer in the implementation of environmental measures, starting from the Environmental Policy Integration in 1993 up to the recent common monitoring and evaluation framework[7] (CMEF) in order to assess the performance of the CAP and improve its efficiency (including the environmental direction). During this period, the CAP has widened its aims from modernization of the agricultural sector to the development of a fully sustainable agricultural sector that supports environmental care and climate change mitigation actions among others. This is also being highlighted by recent studies that suggest a re-alignment of the objectives of various sectorial policies to enhance natural resources management (Salmoral et al., 2017). This will support the EU-27 aspiration to deliver a higher level of environmental and climate action by the promotion of practices and standards for mitigating and adapting to climate change; addressing water challenges; soil protection and quality; land management; and protection and quality of biodiversity.

The 2017 public consultation stressed the need for a stronger CAP action in addressing climate change, unsustainable management of natural resources (e.g., water, soil, and air), and loss of biodiversity and landscapes (EC, 2017[8]). The European Commission included these priorities in the regulation for the CAP 2021–2027 by dedicating three of the nine general objectives to these issues (EC, 2018[9]), in the

[7] https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/cmef_en

[8] https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/key_policies/documents/summary-public-consul-modernising-simplifying-cap_2017_en.pdf

[9] https://eur-lex.europa.eu/resource.html?uri=cellar:aa85fa9a-65a0-11e8-ab9c-01aa75ed71a1.0003.02/DOC_1&format=PDF

attempt to address to the environmental challenges set by SDGs, the Paris agreements on climate change, and Aichi convention of biodiversity (EC, 2018[10]). In that regard, the scientific research on CAP should thus adopt a multi-criteria and systemic approach in order to detect conflicts and synergies between different environmental dimensions (e.g., climate change, biodiversity conservation and water and soil management).

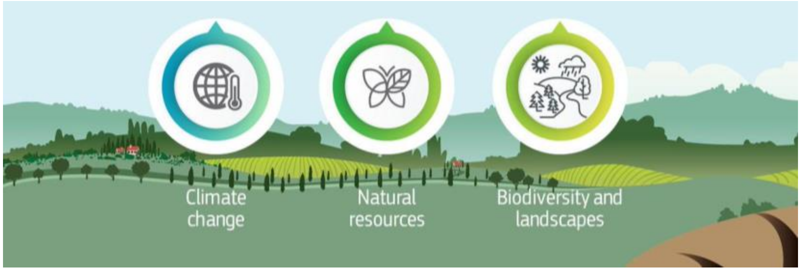


Figure 1: Selected CAP specific objectives related to environment and climate

2.2 The goal-based approach to CAP environmental objectives

We introduce here a complementary approach to the assessment of CAP environmental performance denoted as Goal Based Approach (GBA) as introduced by Plag and Jules-Plag (2020). It starts with the agreed-upon environmental priorities and determines those variables that are essential for the development of knowledge and the monitoring of progress towards these environmental goals by considering the current feasibility of observing these variables with EO and geospatial information data. Recent efforts have been made to apply the concept of EVs to the challenge of environmental monitoring and reporting. A relevant example is illustrated by Reyers et al. (2017), where they applied a set of EVs within the framework of the implementation and monitoring of SDGs. Here, we extend the EV concept to environmental CAP objectives (Figure 1).

In the light of the above, DIONE is following an approach by introducing the concept of EVs, as an intermediate value between environmental CAP Goals and their appropriate observations (data sources). Indeed, DIONE proposed the implementation of the **Observations > EVs > Indicators > Policy Goals** workflows (Figure 2). Once established, this procedure will be ready to be replicated for relevant entities or stakeholders by lifting the barriers from data to knowledge contributing to a speeded-up implementation of the environmental assessment of CAP.

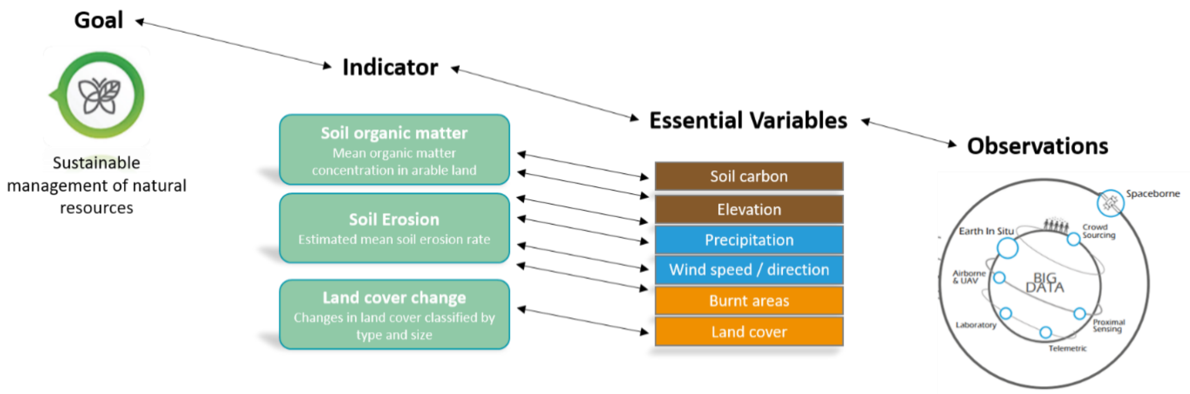


Figure 2: Goal based approach - Links between CAP environmental goals including the corresponding indicators and EVs that can be derived from EO

[10] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018AR1019&from=EN

3 Setting the scene

3.1 The role of international initiatives and DIONE in environmental monitoring and reporting

The EC gathers environmental statistics as bases for an informed and data-driven CAP (Agri-environmental indicators). Although, the development and maintenance of these datasets are a collaborative effort among several European Directorates and organizations with a strong mandate in the environmental sector (e.g. EEA), they fail to capture spatial variations due to the coarse resolution of the underlying data, as well as an actual representation of the current state since they are based on historical data archives. Several other data sets of interest are available from international organizations (e.g. International Soil Reference and Information Centre, ISRIC). For instance, the world soil database is available at a 1 km resolution, which has integrated existing regional and national soil data sets (including Soil Organic Carbon, SOC), many of which are available from the ISRIC. However, this spatial product has been criticized for its coarse resolution and the fact that it does not represent the current soil condition but rather combines existing soil data sets from different time periods and of differing quality (Grunwald et al., 2011).

In the absence of, or as a complement to European data, DIONE strongly advocates that continental and regional data sets must be contextualized with information at the national and sub-national level. The most common approach involves the use of site-based data to assess the accuracy of the sub-indicators derived from EO and geo-spatial information. Another approach uses site-based data to calibrate and validate EO indices and measures where the remote sensing variable is used to predict the same biophysical variable on the ground. A mix-methods approach, which makes use of multiple sources of information and combines quantitative and qualitative data, can also be used.

Quality, accessible, timely and reliable data will be needed to help with the measurement of progress towards many of the CAP indicators. It should be mentioned that data and information from existing reporting mechanisms (JRC, EEA) should be used where possible. Monitoring approaches should build on existing platforms and processes, and minimize the reporting burden on national administrations by exploiting the contribution to be made by a wide range of data, including Earth observation and geospatial information. However, the ability to collect, storage and process multimodal EO data is directly connected to the level of observational and data exploitation capacities. International initiatives (e.g. Copernicus, GEOSS) not only provide the framework within which national EO capacities can be developed, but also the necessary impetus to do so (e.g. data sharing advocacy).

3.1.1. Copernicus

Copernicus was designed by the EU and the European Space Agency (ESA) to help the EC member states to develop environmental policies and monitor the results. In this context, ESA is developing the Sentinel missions for the operational needs of the Copernicus programme, which they address issues related to the availability of coarse and medium resolution imagery. It is well stated that the Sentinels and Copernicus have the potential to become the world's most comprehensive Earth-monitoring system (Butler, 2014).

The flagship Sentinel-2 multispectral satellite program has already revolutionized land-cover and land use change monitoring and analysis (Copernicus Global Land Cover Layers - Buchhorn et al., 2020), since its specifications is superior to those of Landsat-8, with a spatial resolution down to 10 meters and shorter revisit times of just 3-5 days over European territory. In a complementary context, the launch of Sentinel-1, synthetic aperture radar, mission and its synergistic use with Sentinel-2 could really change the update every few days in crop changes even in areas with high cloud cover (Van Tricht et al., 2018). In addition, Sentinel-3 already provides 300m data at two days revisiting intervals, enabling the development of archives for anomaly and change detection (e.g. land), at larger scales. Earlier Sentinel missions mainly focused on land, while the Sentinel-5 Precursor will further support the Copernicus Atmosphere Monitoring Service (CAMS) to quantify among other greenhouse gases (Abida et al., 2017). The Sentinel's operational value can be further maximized if data from various existing or upcoming missions will be combined to create virtual, as well as practical, constellations. In that regard, several research groups have been working together to make Sentinel-2 and Landsat 8 data compatible and to develop joint archives, promoting a concept of a virtual satellite constellation (Claverie et al., 2018). Last but not least, unlike most previous EO missions, the Sentinels will be replaced regularly as they age, enabling the generation of long-term cross-calibrated datasets of a variety of imagery data. This will facilitate to more efficiently connect data series such as measurements of greenhouse gases and opens up research into new areas. This is driven by the Copernicus' fundamental principle to also be responsive to current and emerging EU policy priorities (e.g. The European Green Deal, 2019[11]) and periodically undertake gap analyses to ensure that the observations, products and services remain fit for-purpose.

Copernicus needs to manage these geospatial data and to provide user driven products, services and predictions for policies where a Commission mandate is essential. In this context, Copernicus data is already used to develop spatially explicit indicators in near real time for practical applications including Land Monitoring and Climate Change, among others. In the light of the above, the Copernicus services along with the wide Sentinel data coverage means the outcomes of the activities can be monitored on the overall national level, providing a framework for the analyses of impact of agricultural policies and activities on the environment.

Last but not least, Copernicus ensures the availability not only of high-quality data but also enabling easy combination of different datasets. The new cloud-based platforms, providing centralized access to Copernicus data and information and to processing tools, known as the Data and Information Access Services (DIAS) should be the vehicle for this transformation.

3.1.2. GEOSS

Since 2008, the Group on Earth Observation (GEO) has worked closely with national entities to harness the benefits of EO in global sustainable development. This is now increasingly available because of the operation of Global Earth Observation System of Systems (GEOSS) that enables the interaction and provision of access to diverse information for a broad range of users in both public and private sectors. It must be noted that GEOSS is a portal and acts as a gateway to diverse datasets at different levels of processing (i.e. raw information or high-level data); this means that the data are neither hosted at nor served by GEOSS. It thus facilitates data and information accessibility of heterogeneous collections of Earth observations.

Therefore, a set of diverse services of GEO relevance, having been already funded for development under different funding mechanisms e.g. via H2020, Copernicus Services, and national programmes, may contribute to the goal of the environmental assessment of CAP performance.

[11] https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF

3.1.3. In situ component

Space borne data products could be significantly improved if these were not limited to individual sensors but could combine complementary information not only across space agencies but also by in situ sensor types. DIONE studies the limitations whereby standalone remote sensing is not sufficient to reach the desired accuracy, reliability, precision, and especially completeness of the data requested. On that basis, the most fit-for-purpose and cost-effective in situ methodologies as derived by pilot activities will be selected to be integrated in the workflows. We must underscore the fact that the remote sensing data not only need to be validated by the in-situ component, but also crucially the in-situ data are important in order to derive tailored products to a specific area and user need from the satellite data. In situ data is thus used to calibrate, verify and supplement the information provided by satellites, which is essential in order to deliver reliable and consistent data over time.

In situ data may be derived from the GEOSS portal, the [Copernicus In situ Component](), and from the DIONE pilot demonstrations in the National Paying Agency of Lithuania and Cyprus, respectively.

Figure 3 illustrates the complete EO-ecosystem in which DIONE operates.

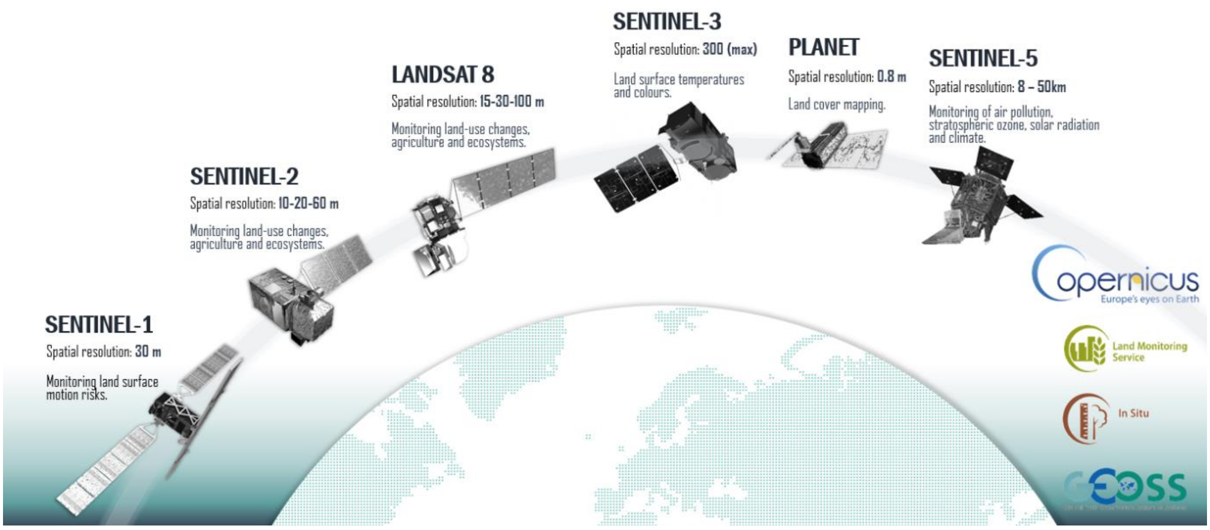


Figure 3: The EO ecosystem in which DIONE operates

3.2 Essential variables and associated metrics

It is acknowledged that the environmental dimension of sustainability is decently characterized by the EV approach (Lehmann et al., 2020). EVs are a minimal set of variables that are required to develop, validate, and monitor transformation policies and interventions that aim at achieving agreed-upon goals, like the environmental objectives of the CAP. Subsequently, the concept of EVs has been used in a number of EO communities to identify and prioritize variables and observations that are key to the missions of these groups. Relevant examples are considered the Global Climate Observing System (GCOS) under the United Nations Framework Convention on Climate Change (UNFCCC), which developed a set of Essential Climate Variables (ECVs) (Bojinski et al., 2014). Likewise, in geodiversity community a discussion is in progress with the goal to identify a set of variables (EGVs) (Zarnetske et al., 2019), in order to take into consideration the abiotic surface and sub-surface geology, geomorphology and pedology of an area (e.g. Digital Elevation Model).

In addition, DIONE seeks to exploit lessons learned and best practices from past and ongoing projects and initiatives. In this context, a significant contribution in the evaluation of existing EVs and integration of them across the societal benefit areas of GEO has been made by the EU projects ConnectinGEO and GEOEssential (Lehmann et al., 2020). Hence, DIONE EVs list was not developed in a vacuum. DIONE identified a set of ECVs and EGVs, as defined by GCOS and geodiversity community (see Current Single EV lists from GEOEssential[12]), and Agri-Environmental Indicators (AEI), as imposed by EU CAP, and their relevant observations (e.g. vegetation indices), towards developing concrete workflows that translate the observations into composite indicators, that encode environment's status metrics.

It should be noted that the EVs and agri-indicators proposed for observing CAP indicators include among others atmospheric, hydrospheric, biospheric and non-living nature variables, which can be measured with remote sensing (Table 1). RS Satellite data from Sentinel constellations, taking also into account generated agricultural indices (e.g. NDVI, NDWI, EVI, CVI) will be used, and in situ solutions (e.g. high spatial aerial data and spectral image spectroscopy), to overcome the limitations whereby standalone space-borne data is not sufficient to reach the desired spatial representativeness and reliability (e.g. soil nitrogen).

Table 1: EVs list that can support the monitoring of CAP environmental objectives

Thematic	Essential Variables (EVs)	Short definition (unit)
ECVs	Surface atmosphere	Precipitation
		Surface wind speed direction
	Atmospheric composition	Carbon Dioxide, Methane & Other Greenhouse Gases
	Biosphere	Land cover
		Land surface temperature
		Soil carbon
		Fire – Burnt areas
	Hydrosphere	Lakes – Water quality
EGVs	Non-living nature	Elevation

3.3 Indicators for integrating environmental concerns into the CAP

It is acknowledged that the future CAP requires both diversified environmental targets and actions defined according to regional or context-based characteristics, in order to achieve environmental benefits throughout Europe. Aiming to construct a thorough picture related to CAP environmental challenges, the present deliverable is based on the last public consultation (EC, 2017a), on recent reviews (Recanati et al., 2019) on which a well-structured analysis was performed. Thus, a list of research terms (i.e. search keywords) including "Common Agricultural Policy", "climate change", "environment", "natural resources" and "biodiversity" has been selected to carry out the literature review. The terms restricted to those corresponds with CAP's general environmental objectives, while the research performed to the period 2017-2020 to be compatible with the period after the public consultation. Some earlier articles cited in the selected list that were deemed particularly relevant were also reviewed (Recanati et al., 2019). As for scientific databases, Scopus, ScienceDirect, PubMed,

[12] http://www.geoessential.eu/wp-content/uploads/2019/10/GEOEssential_Deliverable-2-2_v3.1_FINAL.pdf

Google Scholar and Wiley were used. To complete the picture with relevant grey literature, qualifying documents published by EU and other environmental agencies and international organizations (e.g. EU COM (2006) 508) were considered. Besides the broad principles are set out, and the need to fulfill CAP objectives other existing agreed objectives and targets for environment and SDGs should be taken into account.

The reviewed literature analyzed a set of indicators that contribute to the assessment of CAP performance by serving to: i) provide information on the farmed environment; ii) track the impact of agriculture on the environment; iii) assess the impact of agri-environmental policies on environmental management of farms; iv) inform agri-environmental decisions; and v) illustrate agri-environmental relationships to the broader public. Thus, after a first screening phase focused on titles, abstracts and key words, we excluded a number of documents which did not make any recommendations to monitor the integration of environmental concerns into the CAP. It is noteworthy that a few of the selected indicators are also used as CAP context indicators or sustainable development indicators.

The themes resulting from the literature review are consistent with the environmental priorities underlined in the last CAP consultation and support the transition towards a more sustainable EU food system. Thus, in a first step we have included a set of indicators that are directly related with the environment priorities as they can be grouped into three major challenges a) **soil and land**; b) **water** and c) **air quality and climate change**. It should be highlighted that indicators related to biodiversity have not been considered, since these indicators are the elements that can be related to multiple in situ observations that are not taken into account in DIONE project or are the ones with an undefined methodology. For instance, the "Genetic biodiversity" and "Population trends on farmland birds" do not currently have any indicator that can be reliably estimated from EO data. However, even in those cases, EO data can provide supporting information related to other indicators (High Natural Value (HNV) farmlands). Thus, we have expressed some relations between existing indicators since some of them can be estimated from others. In this context, we identified a suite of indicators that can be used to measure progress against the environmental assessment of CAP performance (Table 2).

Table 2: Selected indicators for monitoring and reporting CAP environmental performance

Environmental priorities	Agri-environmental indicators	Short definition (unit)
Land and soil	Land cover change	Changes in land cover classified by type and size (%)
	Soil erosion	Estimated mean soil erosion rate in (t ha^{-1} yr^{-1})
	Soil organic matter	Mean organic matter concentration in arable land (g/kg)
	Organic farming	Area under organic farming as a ratio of the total utilized agricultural area (UAA)
Water	Water quality	Chl- α, TSM, Temperature (°C)
	Land irrigation	Irrigated land (ha)
Air quality and climate change	Greenhouse gases emissions	methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2)
Protected/ vulnerable	HNV farmland	Agricultural areas (ha) under HNV areas
	Natura 2000 areas	Agricultural areas (ha) under Natura 2000 areas

3.4 DIONE workflows from data sources to environment indicators with essential variables

The translation of policy requirements, targets and indicators into EO requirements is a complex process of continuous dialogue between different communities with different jargon. A prime examples of such "translation" is given for EU policies, where scientists of the JRC of a specific thematic evaluated a set of data, which can be EO-related, in order to support the DG GROW in translating the policy requirements into EO system requirements. The enhanced version of the Revised Universal Soil Loss Equation (RUSLE) model (Panagos et al., 2015) has succeeded to be accepted by the EU on the soil erosion indicator and creates a precedent of an Earth-observation driven indicator dataset that make use of the most recent and available pan-European datasets. Other examples, such as the Copernicus Land Productivity Dynamics are expected to follow.

In this section we determine and document definitions, methodologies and data options for EVs and key parameters (e.g. vegetation indices) to derive quantitative and spatially explicit indicators, using traceable and scientifically sound methods. In this context, DIONE aspires to drive the development of reference datasets of EVs and key parameters that are critical for monitoring CAP indicators, including data of different spatial and spectral resolutions. The relationships among variables and parameters with each indicator have been set out clearly and where uncertainties remain (by including EO) these explicitly have been made transparent.

DIONE have already seen the refining and promotion of a range of user-driven services built on e.g. Copernicus Sentinel data, Inspire Geospatial data, ESA TEP outputs, relevant H2020 projects outputs and European research infrastructures data. In that context, the largest growth is in the development of detailed workflows, from input parameters and algorithms applied via machine learning tools (*Task 5.3 Development of the DIONE Environmental Performance Tool*) to outputs that comprise tailored composite indicators and are also consistent with specific CAP indicators (Table 2). Last but not least, in dataset usage is envisaged to be in the field of pilot in-situ datasets – ensured through the very extensive involvement of paying agencies relevant data and pilot collected information, which will be necessary to support the geographical exploitation range of pilot services. In addition, we highlighted some deficiencies in the current data sets related to certain indicators, in terms of harmonization data quality, geographical coverage and temporal resolution. Potential methodological improvements or further validation (e.g. soil erosion; soil quality) are also presented and furthermore we highlighted if some indicators still require further conceptual improvement (GHG emissions).

European landscapes are dominated by agriculture, which accounts for almost half of the total EU land surface (Halada et al., 2011). In this context a first indicator is the Utilized Agricultural Area (UUA) that can be considered as the total area taken up by arable land, permanent grassland, permanent crops and kitchen gardens. Moreover, EU prioritizes the protection of high nature value (HNV) farmlands, during its next CAP reform post-2020, as well as Natura 2000 areas. This information can be considered as primary indicators to support a more effective use of the Common Agricultural Policy (e.g. what percentage of HNV farmlands within the EU has undergone changes in land-cover?). In ANNEX A, a complete list of the selected indicators is presented.

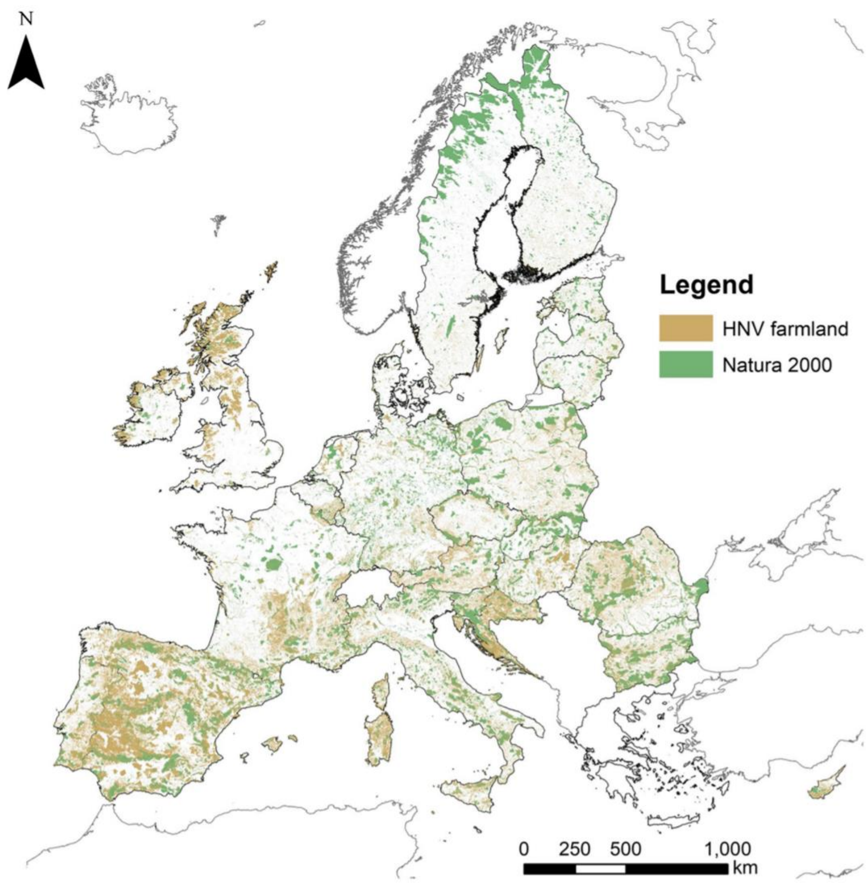


Figure 4: The distribution of HNV farmlands—inside and outside the Natura 2000 network—within the 27 EU member states (source: Anderson and Mammides, 2020)

3.4.1 Land cover change

This indicator provides a **qualitative and quantitative assessment of the change of land cover**. In particular, land cover change is defined as the loss of natural areas, particularly loss of forests and agricultural areas to urban or exurban development. It has numerous ecological, physical and socioeconomic consequences. On the positive side, agricultural expansion may increase food production for a growing population and help meet the growing global demands for food, although it is unsure how productive the last exploited lands will be as they are typically the least favorable. However, on the negative side, there are numerous adverse consequences with both known and unknown links as well as feedback mechanisms.

Converting the natural vegetation to agricultural land may result in changes to the radiation balance of the given unit of area. In principle, the albedo increases as land is without vegetation at least part of the year causing more solar energy to reflect back from the surface and onto the space. Other environmental impacts include the decrease in soil water–holding capacity. As natural vegetation is replaced by agriculture, soil porosity may be reduced by soil compaction, decreasing infiltration capacity and increasing the risks of soil erosion. Furthermore, in mountainous areas, the conversion of the forests to agricultural lands decreases as does the occult precipitation as croplands capture less atmospheric moisture than multilayered indigenous forest or forest of any kind. This is additionally exacerbated by the fact that cloud formation over the land unit also decreases as the evapotranspiration rate is less from fields than from forests causing evidently reduced precipitation. Moreover, detrimental changes in land cover and land use are the leading contributors to terrestrial biodiversity loss. From the above, it is easy to understand why measuring land cover change helps monitor pressures on ecosystems and biodiversity. The alterations it effects in the surface of the earth hold major implications for sustainable development and livelihood systems and also contributes to changes in the biogeochemical cycles of the earth and affect the concentration of the atmospheric greenhouse gases.

The Corine Land Cover (CLC) provides consistent information (44 classes) on land cover and land cover changes across Europe. In addition to land cover maps, CLC also provides a set of datasets referring to land cover / land use changes between two consecutive land cover maps (e.g. between 2012 and 2018). It should be mentioned that, the CLC products are based on the photointerpretation of satellite images by the national teams of the participating countries; i.e. the EEA member or cooperating countries. Subsequently, the resulting national land cover inventories are further integrated into a seamless land cover map of Europe. More recently, collection-2 of the Copernicus Global Land Cover layers was released (Buchhorn et al., 2020). In this product a land cover map at 100 m resolution, while a set of cover fraction layers is also provided depicting the perceptual cover of the main land cover types in a pixel (Figure 5).

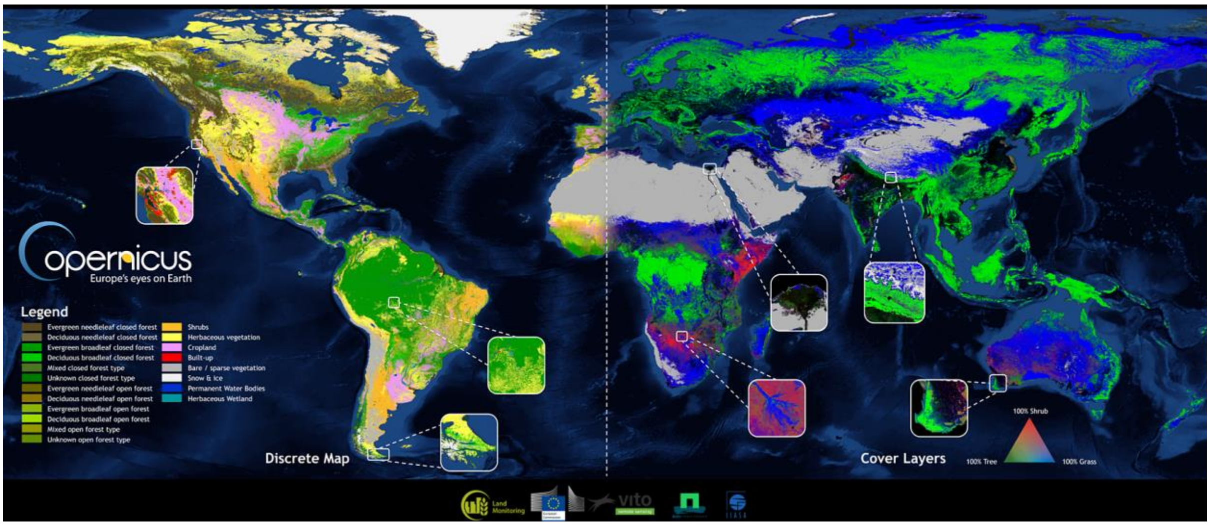


Figure 5: The image illustrates the Copernicus Global Land Cover Layers and more specific a global discrete classification for the year 2015 (left side) and an example of combining three out of nine cover fraction layers into a False Color Composite (right side), (source: Buchhorn et al., 2020).

The Land Cover was all processed on PROBA-V MEP cluster, using novel processing techniques (e.g. non-linear machine learning algorithms), in the Sentinel-2 tiling grid and UTM projection. The aforementioned products can be further assisted by the outputs of data fusion and super resolutions techniques that will take place in DIONE, in order to derive more accurate land use and cover classification. A detailed outline of the dependent variables of the proposed indicator is presented in Table 3.

Table 3: Dependent variables of land cover change indicator

CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Land cover
Data sources	Sentinel-2, IACS and CLC
Inputs	Normalized Difference Vegetation Index (NDVI)

3.4.2 Organic farming

This indicator provides an **assessment of the area under organic agriculture**. It should be noted that, the area under organic farming may be classified as i) fully converted to organic farming; ii) under conversion to organic farming; and iii) total fully converted and under conversion to organic farming. Due to the specific agronomic interventions (e.g. exclusively organic fertilization and the exclusion of pesticide) organic farming fields tends to differ from conventional ones by several aspects, among which lower plant nitrogen and chlorophyll concentration, higher intra field heterogeneity of the canopy (crop's height, disease extent) and a higher SOC content (Denis and Tychon, 2015).

The proposed methodology to derive this indicator is based on a machine learning approach, which will leverage EO-based spectral indices and metrics to assess the spatial variability (e.g. heterogeneity, biophysical indices derivation etc.) and thus utilize them as input in the model to discriminate organic fields from conventional ones. For this indicator, the use of high spatial resolution satellite images and soil quality estimations in the field is particularly important, since mixed pixels and coarse satellite pixel size greatly affect the value of indicator changes. In this context, UAV flights (*Task 3.3 Drone flights and tenure of data in specified regions*) and the outputs from handheld sensors (*Task 4.4 Processing with historical and open EO data*) will be also utilized, to assess the limitations, where standalone satellite remote sensing is not sufficient to reach the desired representativeness and reliability. The training-testing dataset (i.e. the provision of labeled ground truth data) is created according to the annual farmers' declarations in both pilot areas, where the parcels cultivated with organic methods are denoted. A detailed outline of the dependent variables of the proposed indicator is presented in Table 4.

Table 4: Dependent variables of organic farming indicator

CAP Related objective(s)	Sustainable management of natural resources
EVs	Land cover, Soil carbon
Data sources	Sentinel-2, drone imagery, soil spectral measurements
Inputs	NDVI, soil predictions

3.4.3 Soil erosion

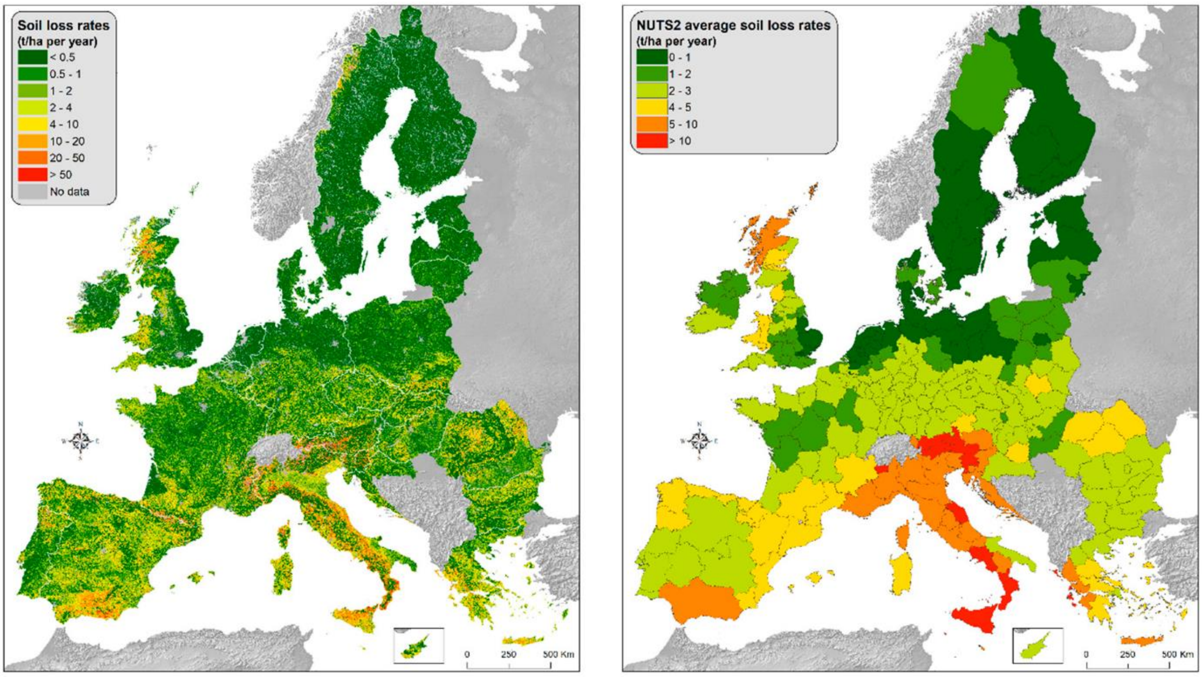
Soil erosion by water is one of the most widespread forms of soil degradation in Europe. Other forms of erosion such as wind erosion, gully, and erosion by harvesting crops have less significant effects in EU. It is well stated that, erosion can affect all types of lands, not only cultivated parcels (Alewell et al., 2019). The process of erosion is described in three steps, containing soil detachment, movement and deposition. Through this process, the most important part of soil in terms of soil health, topsoil, is relocated, affecting organic and mineral nutrient pools, fertility and soil life in general. In this context, the proposed **soil erosion indicator** refers to the agricultural areas affected by a certain rate of soil erosion by water.

The indicator is predicted based on the empirical model RUSLE that calculates soil loss due to sheet and rill erosion, and is expressed as the product from five distinct factors that describe the main erosivity indicators (Panagos et al., 2015). The five following major factors such as rainfall pattern, soil type, topography, crop system, and management practices are to be used in RUSLE for computing the expected average annual erosion:

- R-factor: Rainfall-runoff erosivity factor, which accounts for the effect of raindrop impact and also shows the amount and rate of runoff associated with the precipitation events.

- K-factor: Soil erodibility factor is an empirical measure of soil erodibility, the susceptibility of a soil to erode, as affected by intrinsic soil properties (Fu et al. 2006), such as organic matter content, soil texture, soil structure and permeability. It is noteworthy that DIONE relies on promoting existing soil databases and Sentinel-2 data to generate spatial explicit indicators over agricultural regions with an enhanced spatial representatives and reliability. These products can be leveraged to further enhance the estimation of K-factor.
- LS-factor: Slope length factor is a topographical factor, which directly depend from Digital Elevation Model variables and especially the length and gradient of the slope. It has been demonstrated that increases in slope length and slope steepness can produce higher overland flow velocities and correspondingly higher erosion.
- C-factor: Vegetation cover and management factor describes the relation between soil erosion and vegetation, associated cropping methodologies and the level of plant production.
- P-factor: Support practice factor, quantifying the applied practices to reduce erosion extend. Terracing, mulch application, vegetated waterways or contouring and strip cropping are the most common and effective erosion control practices.

This approach has already been implemented at European scale (Figure 6) by Panagos et al. (2020), as well as in East Africa region (Fenta et al., 2020).



(a) (b)

Figure 6: a) The updated soil loss rates by water erosion in 2016; and b) the indicator "estimated mean soil erosion rate in NUTS 2 level (Source: Panagos et al., 2020)

The most up-to-date European datasets mainly used to model the input layers, such as the CLC, the European Soil Data Centre (ESDAC) Land Use and Cover Area frame Survey (LUCAS) for soil measurements and relevant DEM products. The proposed soil erosion approach can incorporate the latest burned areas recorded by European Forest Fire Information System (EFFIS) to update the land cover/use factor C, as well as detailed databases on crop types and soil characteristics collected at the field parcel scale in pilot areas. A detailed outline of the dependent variables of the proposed indicator is presented in Table 5.

Table 5: Dependent variables of soil erosion indicator

CAP Related objective(s)	Sustainable management of natural resources biodiversity and landscapes and climate action
EVs	Land cover, Burnt areas, Surface wind speed direction, Precipitation, Elevation
Data sources	Sentinel-2, CLC, ESDAC
Inputs	NDVI, EFFIS products, DEM, LUCAS, DIONE soil spatial explicit indicators

3.4.4 Soil organic matter

Soil organic matter is essential for preserving a healthy soil, maintaining soil fertility, managing water storage, control the soil structure and supply and store carbon for climate change mitigation. Current analytical techniques determine Soil Organic Carbon (SOC) concentration as the main component of soil organic matter. In particular, carbon sequestration is regarded as a positive procedure that improves soil's productivity and soil quality, while protecting the environment of the excess release of Green House Gases (GHGs). In the opposite, the excessive management of soils, the exposure of organic matter and the subsequent release of GHGs is regarded as a negative procedure that decreases soil's quality and has negative effect on climate change. For these, the soil organic matter is the primary and fundamental indicator of soil's quality (see CAP context indicators, C.41) in regard to land productivity and climate change, while it is an indicator that gets affected by mismanagement, thus reflecting the management practices in arable land.

The ESDAC provides a soil database and associated property layers. The available dataset consists of a number of data layers (raster GRID maps) including among other the current SOC at continental scale (Yigini and Panagos, 2016). Similarly, Soilgrids also provides SOC profile data and its associated layer. It should be mentioned that these SOC maps consist of rather coarse grid cells and based mainly on legacy data (e.g. the LUCAS 2009 topsoil database) that is generally not up-to-date.

Recently, the availability of Copernicus data (Sentinel-1 and Sentinel-2), has dramatically changed the paradigm. Spectral data can be transformed to soil properties, as is SOC, by using machine and deep learning models (Tziolas et al., 2020a). In this context, EO driven topsoil monitoring becomes feasible in a coherent manner from regional to global scales. In this context Safanelli et al. (2020) provided a synthetic soil image of European cropland areas that can be the basis for the generation of SOC maps (Figure 7). It should be mentioned that, the accuracy of the SOC maps depends on the calibration dataset.

Like in every EO-based approach, the in situ component here is crucial for providing data from the field in order to calibrate and validate the proposed methodology. In DIONE this important task will be undertaken in *Task 4.4 – Processing with historical and open EO data* where the in-situ field spectral measurements using handheld VNIR spectrometers will be transformed to soil properties to provide ground truth data. Moreover, the analysis strategy (*Task 4.4 - Processing with historical and open EO data*) of the DIONE team focuses on computing SOC maps from a reflectance composite that is built by merging large time series with in situ spectral measurements and large spectroscopic libraries (Tziolas et al., 2020b).

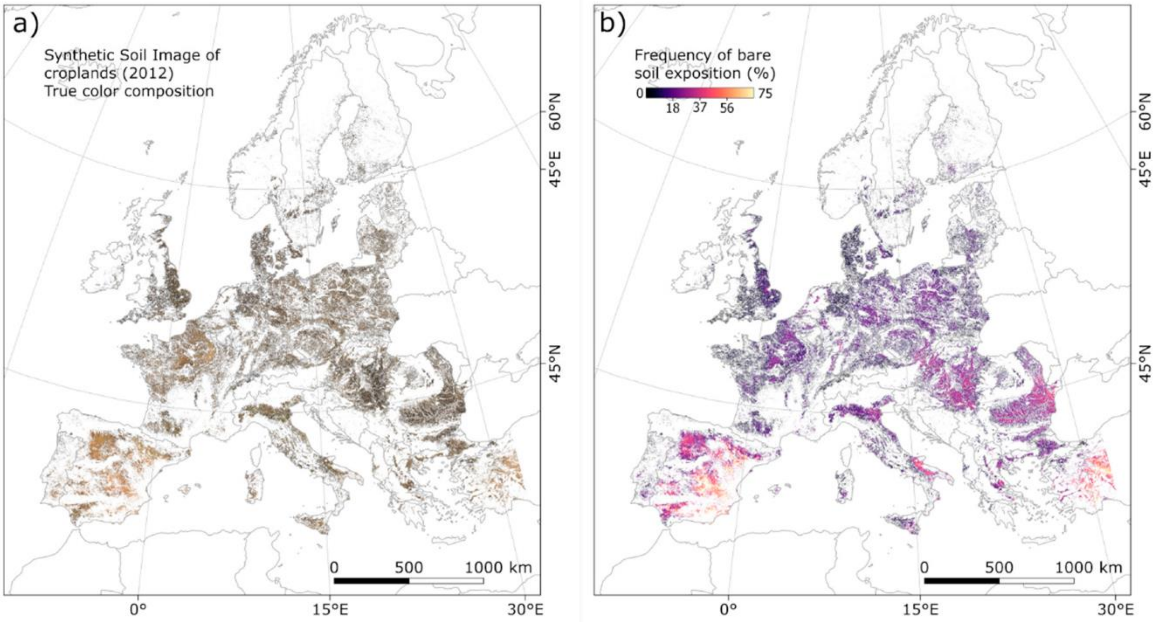


Figure 7: a) Full synthetic soil image of croplands as a product of time series analysis of space borne data; b) the equivalent bare soil frequency product (source: Safanelli et al., 2020)

A detailed outline of the dependent variables of the proposed indicator is presented in Table 6.

Table 6: Dependent variables of soil organic matter indicator

CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Soil organic carbon, Elevation
Data sources	Copernicus (Sentinel-1 and Sentinel-2), LUCAS, ESDAC, spectral handheld sensors
Inputs	Spectral measurements (space borne and in situ), DEM

3.4.5 Water quality

Conventional agricultural practices may also have negative consequences on water quality. EO-derived water quality information is essential to assess the ecological state of inland waters and to identify changes or trends in water quality over time that correspond to intensification of the farming practices. The proposed water quality indicator provides an assessment regarding a set of lake water quality characteristics within agricultural river basins. In particular, the indicator is a combination of three important water quality sub-indicators that can be readily monitored from space: Chlorophyll concentrations, Total Suspended Matter (TSM), and water temperature (Sagan et al., 2020).

The EC through the Copernicus Global Land Service (CGLS) program has been offering a tool that monitors the water surface (lakes >50ha) and provides reliable Lake Water Products that are directly available for normal users. The CGLS is a component of the Land Monitoring Core Service (LMCS) and the current observation application uses Copernicus satellite data. Production and delivery of the trophic state index (derived from Chl-α observations) and turbidity are over 10-day intervals on a set grid (starting from the 1st, 11th and 21st day of each month) and are mapped on a common global grid (Figure 8).

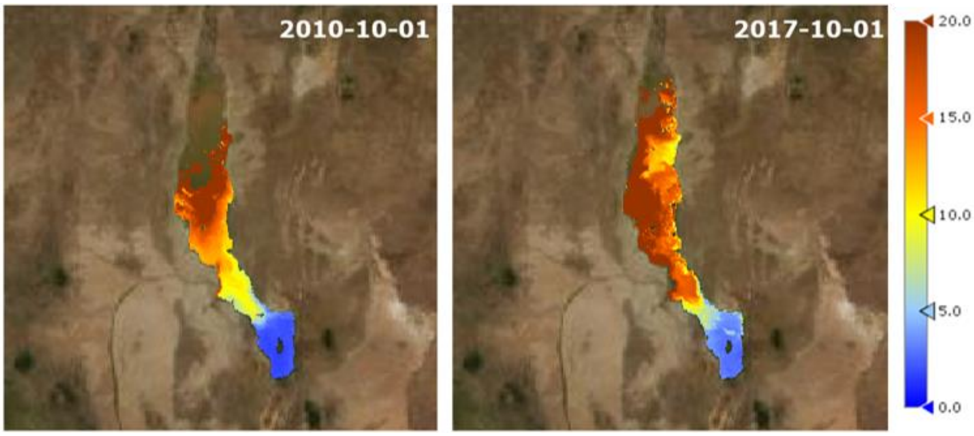


Figure 8: Lake water quality products based on observations from MERIS (source: Copernicus Global Land Service)

These products are complemented since January 2019 by water quality products in 100m resolution in demonstration mode. Those products are available for selected tiles over Europe and can be utilized as supplementary information into a holistic approach to enable us study and address the "agricultural-water" interdependency in depth. Moreover, the CGLS gives the capability to compute the water level as time series over lakes and over rivers at the intersections of the river network with satellite ground tracks. This product can also be used whenever possible. A detailed outline of the dependent variables of the proposed indicator is presented in Table 7.

Table 7: Dependent variables of water quality indicator

CAP Related objective(s)	Sustainable management of natural resources
EVs	Water quality
Data sources	CGLS
Inputs	TSM, temperature, Chl - α

3.4.6 Land irrigation

Agriculture currently accounts for 70% of global freshwater withdrawals. Within the framework of sustainability, the increase in agricultural production may need to come from greater water productivity as well as expansion of irrigated areas. In this context, the impact of farming systems needs to be addressed in terms of their efficiency. The proposed indicator provides a qualitative assessment of the total irrigated land (ha) as percentage of the overall UAA.

The concept of mapping irrigated areas has also been mentioned in the CAP context indicators (C.20 Irrigation Land), where Irrigated area is defined as the area of crops which has actually been irrigated at least once during the 12 months prior to the reference day of the survey. Crops under glass and kitchen gardens, which are almost always irrigated, should not be included.

However, this CAP indicator is still a subject of development. DIONE will achieve notable progress by identifying the EVs related to mapping irrigated lands and perform a spectral index time series analysis to monitor them in a comprehensive way (Xiang et al., 2019). In this context, an EO-based land surface water index (LSWI) derived by Sentinel-2 data will be calculated to reveal different values among the irrigated fields and the non-irrigated cultivated land and natural vegetated areas. The examined periods will be restricted during the arid seasons, where irrigation activities are accomplished in pilot areas. To identify irrigated regions a comparison will be performed between the satellite-based moisture index of cropland with that of the adjacent (buffer zone of 10km) natural vegetation (i.e., forests, mean LSWI).

In a similar way we can evaluate a second approach to monitor irrigated lands, based on the calculation of the $LSWI_{Diff} = LSWI_{C}$ – mean ($LSWI_{F}$) for all the prefectures of the regions of interest. By evaluating the produced differences (by descending) the greater values are more possible to be labelled as irrigated. Then, prefecture-level statistical data can be utilized to determine the number (N) of pixels with the largest $LSWI_{Diff}$ as irrigation at a given prefecture. The $LSWI_{Diff}$ value of the Nth is the threshold ($LSWI_{Diff0}$) for differentiating the irrigation and non-irrigation. Afterwards, the mean annual precipitation measures within the examined prefectures with the $LSWI_{Diff0}$, will be examined hypothesizing that if the relation is verified the irrigated cropland pixels can be identified, where the $LSWI_{Diff}$ is greater that the $LSWI_{Diff0}$.

As the discrimination of the irrigated areas from the non-irrigated is performed the calculation of the percentage of the irrigated croplands in relation with the total agricultural area can also be achieved. For validation purposes we will use the IACS system where farmers denote every year the permanent irrigated areas. In case that this information is not available the LULC 2018 class denoting the permanent irrigated areas will be utilized. A detailed outline of the dependent variables of the proposed indicator is presented in Table 8.

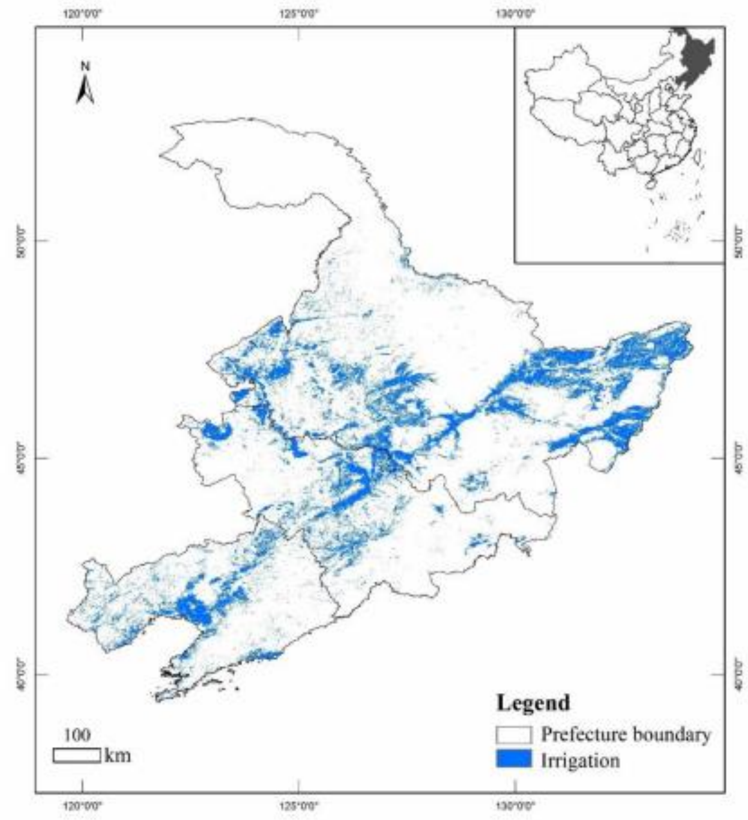


Figure 9: Spatial distribution of estimated irrigated land based on EO-based indicators (source: Xiang et al., 2019)

Table 8: Dependent variables of land irrigation indicator

CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Land Cover (irrigated areas)
Data sources	Sentinel-2, CLC
Inputs	LSWI, NDVI

3.4.7 Greenhouse Gases emissions

Together with forestry and other land use processes, agriculture emits about a quarter of all global GHGs. The **Greenhouse Gases** indicator is a further development of the agri-environmental indicator 19, 'Greenhouse Gas Emissions from Agriculture', which, however, only covers CH_4 and Nitrous Oxide (N_2O) from agricultural activities. This indicator is composed of two sub-indicators, one assessing the GHGs and one the ammonia emissions.

Considering the GHG emissions from agriculture, we take into account the annual emissions of methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) from agricultural land. The annual CH_4 emissions can be estimated through the exploitation of the newly Sentinel-5P Tropomi CH_4 data, which provide methane estimations products (Omrani et al., 2020). The annual N_2O emissions could be provided through the utilization of the daily Aura MLS N_2O, (Figure 10).

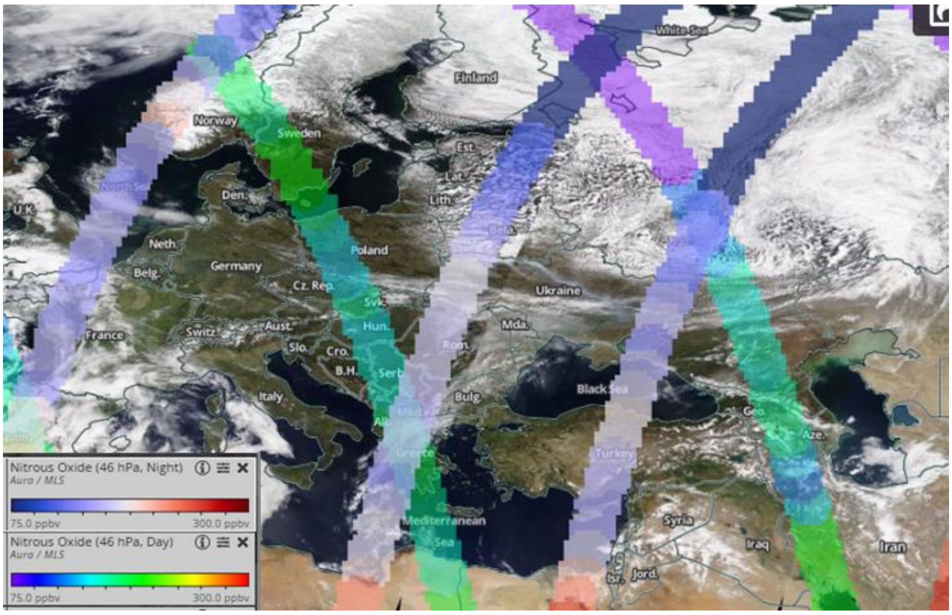


Figure 10: N_2O day and night observations at 17/04/2020 from Aura instrument

The annual status of carbon dioxide can be estimated through the exploitation of the daily Net Ecosystem CO_2 exchange measures, acquired from Soil Moisture Active Passive (SMAP) spacecraft at 9km spatial resolution. In a recent work Oertel et al. (2016) indicate an efficient way to report the primary CO_2 fluxes. In their work, the examination of the daily behavior exchange measures (negative or positive values) between the ecosystem and the atmosphere reveal the status of the CO_2 emissions in the atmosphere. The association of the aforementioned measures with the agriculture fields can present the contribution of the agricultural activities to the daily CO_2 status. The contribution of GHGs in arable lands and permanent crops will be estimated based only on the quantity of the values that corresponds to land cover patterns, which can be defined based on the CLC and the updated highly detailed crop type map that will be produced in DIONE. A detailed outline of the dependent variables of the proposed indicator is presented in Table 9.

Table 9: Dependent variables of Greenhouse Gases indicator

CAP Related objective(s)	Climate action
EVs	GHGs, land cover (croplands, grasslands)
Data sources	Sentinel-5, SMAP, CLC
Inputs	Level-2 products, Sentinel-5p and SMAP

4 Where do we go from here?

The development of an EO-based environmental assessment framework is an essential prerequisite to provide feedback to professionals of paying agencies and the EC about the environmental performance of CAP and respective green payments.

The DIONE Environmental Performance Tool will make use of the nine selected indicators (Table 2) and heterogeneous data from multiple monitoring sources (i.e. low-cost spectral sensors, drone imagery data, user-generated geo-tagged images, and Commercial EO data). Then, the system employing ML and scientific sound methods will allow insightful decision making on a regional and/or national level. The tool will complementarily act with a beneficiaries' compliance tool in an overall Green Accountability toolbox within DIONE system. Hence appropriate approaches to combine the existing information are prioritized and represented below.

4.1 The main findings of the DIONE environmental metrics indicators

Overall, the nine selected indicators reflect the complexity of CAP and the variety of potential environmental effects on an EU level and summarizes the necessary EO-derived data to derive actionable information. The selected indicators can also be used to show progress towards fulfilling the EU standards on good agricultural and environmental condition of land (GAEC). These interdependencies could be easily represented in a multidimensional matrix of relations, as indicated in Table 10.

Table 10: Interdependencies among GAECs and selected indicators

Agri-environmental indicators	GAEC 1*	GAEC 2	GAEC 3	GAEC 4	GAEC 5	GAEC 6	GAEC 7	GAEC 8	GAEC 9	GAEC 10
Land cover change	X							X	X	
Soil erosion	X		X			X	X			
Soil organic matter	X		X				X			
Organic farming		X	X							
Water quality				X						
Land irrigation					X					
Greenhouse Gases emissions		X								
High nature value farmland				X					X	
Natura 2000 areas										X

** **GAEC 1** – Permanent pastures; **GAEC 2** – Preservation of carbon rich soils; **GAEC 3** – Maintenance of soil organic matter; **GAEC 4** – Establishment of buffer strips along watercourses; **GAEC 5** – Compulsory use of the new Farm Sustainability Tool for Nutrients; **GAEC 6** – Minimum land management under tillage to reduce risk of soil degradation including on slopes; **GAEC 7** – No bare soil in most sensitive period; **GAEC 8** – crop rotation; **GAEC 9** – Maintenance of non-productive features; and **GAEC 10** - Ban on converting or ploughing permanent grassland in Natura 2000 sites.*

Considering the EO domain, medium spatial-resolution sensors (5–100m) contribute highly to six indicators and to two additional ones (GHGs, Natura 2000) with medium importance, mostly associated to land and soil indicators. Low resolution sensors (>100m) are relevant for two indicators (GHGs, water quality). Radar systems are considered relevant for one indicator (land cover) and complementary to another two (soil carbon and irrigated land). In terms of ancillary data, all indicators require other datasets for an accurate retrieval. The most common are elevation data (derived from EU Copernicus product), spatial databases (soil, climate, Natura areas and HNV farmlands) and field data (e.g. fixed sensors).

A preliminary analysis was performed to assess how, when and where we can (and cannot) meet efficient monitoring of the selected indicators by available EO technologies and DIONE proposed solutions (Table 11). The requirements are broken down by spatial and spectral range (How?), frequency (When?), geographic extent (Where?) as well as the indicator product for which the data would be used (What?)

Table 11: Requirements for EO-based (both in situ and space borne) data, developed by the DIONE team.

	How?		When?	Where?		What?							
Requirements	Spatial resolution (m)	Spectral range	Effective observation frequency	Regional	Field	Land cover change	Soil erosion	Soil organic matter	Org. farm	Water quality	Land irrigation	GHGs emissions	HNV / Natura 2000
Coarse resolution sampling (>100m)													
1	300	VNIR	Continuous	X						X			
2	5000	passive	Continuous	X								X	
3	1000	Active passive	Continuous	X								X	
Moderate resolution sampling (10 to 100m)													
4	10-30	VNIR-SWIR	Approx. weekly; 5 min per season	X	X	X	X	X			X		
5	30	SAR	Continuous	X								X	
Very fine resolution sampling (0.1m-10m)													
6	<10m	VNIR	1 to 2 per phenolocical stage		X	X		X	X		X		
7	<1m	VNIR-SWIR	1 to 2 per agronomic applications		X		X	X	X				
Auxiliary Data													
8	10-30m	-	static	X	X	X	X	X					X

4.2 Developing an EO-driven performance-based monitoring framework

Having defined a key set of environmental indicators that are essential towards the realization of the CAP objectives shown in Figure 1, the question then is how this information may be best presented to and utilized by the end-users. The end-users comprise a wide variety of stakeholders, including scientists, decision makers, planners, emergency managers (see *D2.1 - DIONE stakeholder list, personas and co-designed scenarios*); they thus have different needs and requirements. Two different methodologies will be realized to visualize the results: a simple visualization of the different layers of information, and a fusion of information using a custom decision system.

To this end, and as far as the first methodology is concerned, DIONE introduces a "layered approach" which aspires to offer a paradigm shift from single access points for users seeking specific data, imagery and machine learning techniques, to geographically tagged, diverse yet complementary and interdisciplinary information Figure 11. This information will be presented as a series of overlaid layers, such that the end-users gain access to thematically combined information that can be used for holistic and cross-cutting research, solutions and decisions. Each end-user will thus be able to visualize the different layers of information as needed for each use case. Apart from the thematic layers (water, land and soil and GHGs), the different spatial (local to national regional) and temporal (current state to historical data archives) scales will be also incorporated, to allow down-scaling and up-scaling according to the users' competence and need. The layered approach will function in a dynamic way, and the incorporation of new component (layers) to the Environmental Assessment approach and other cross-cutting information streams will be facilitated in a user-friendly manner. Where user needs and use cases are clearly defined (e.g. paying agencies), specific dashboards or information systems tailored to those needs will be proposed as user-friendly access of the information to the environmental assessment services (*D5.4 - DIONE Visualization Component*). Considering that with the last reforms, the Member States have more flexibility with the last reforms of CAP in designing strategic plans and specific agro-environmental schemes (Pe'er et al., 2019) at the end of the line, the national paying agencies would be in a position to augment its contributions at the DIONE Environmental Performance tool.

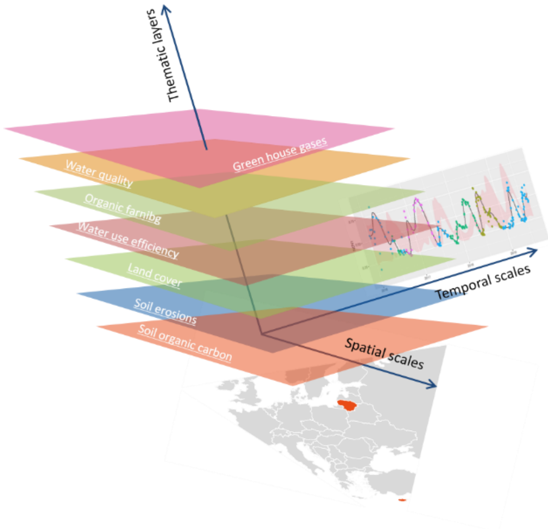


Figure 11: The concept of "Layered" approach, along with the various thematic EO-layers

However, the development of the second methodology (i.e. the fusion of these individual layers) is also important. Because the individual layers can be considered as non-additive components of environmental status that are sensitive to different changes, this presents distinct challenges when "combining" them to assess the environmental performance. For instance, a few of the sub-indicators tend to vary at different rates. Land cover may transition over years in response to changes in moisture availability, or over hours from land use activities. In contrast, substantial changes in SOC typically occur much more slowly, and may take years to respond to changes in land cover or productivity conditions (Brandão et al., 2011). Differences in the rates of change, and differences in the sensitivity of methods to determine current state and/or changes in each of the metrics, make it likely that in any given location, some indicators will indicate change or de-gradation, while others will not. There are a number of possible approaches for combining metrics and indicators to assess environmental status and potential degradation level (Borja et al., 2014) . Each method has its advantages and disadvantages and may be suited to smaller or larger datasets, combining particular types of metrics such as those that are sensitive to the same pressure (averaging approaches) or be better suited for use with preference metrics to determine an overall degradation level (probabilistic approaches). The proposed approaches will be studied in depth during the *Task 5.3 Development of the DIONE Environmental Performance Tool* to sharpen the focus of developing an **environmental performance scorecard** providing the opportunity to make environmental decision-making more data-driven and thus more thoughtful and durable (Figure 12).

Figure 12: The environmental performance scorecard in support of a more data driven decision making

5 Conclusions

The present deliverable has laid out some key EO–based environmental indices in support of the environmental objectives set out by the CAP of the EU. These indicators proposed herein may then be appropriately deployed and used to assist end-users to identify, quantify, and monitor the levels of some of the monitored parameters and consequently extract tangible environmental impact indicators for an entire region. The target is to provide indicators for three major objectives of the CAP, namely climate change, natural resources, and biodiversity and landscapes.

More concretely, the proposed course of action consists of a goal-based strategy to build up from primary and intermediate sources of information (i.e. from raw and processed data) to develop higher-level products that quantify specific environmental impact indicators. These data stem from open EO, like in-situ measurements or remote sensing imagery from satellites. Setting EO as a priority with the purpose to take up observation-based evidence has proven to be essential for its increased uptake, its transnational boundaries, and its high spatio-temporal coverage. Particularly noteworthy are the recent Copernicus satellite missions: bringing these latest products and data into the policy field to define tailor made products requires a proactive building-up of collaboration between the EO scientists on the one hand and the policymakers and end-users on the other. These new working methods are envisaged to generate efficient feedback loops that include, first and foremost, the final users of the information product.

The present work proposes some concrete ideas on how this performance-based monitoring framework could be made to work from an environmental perspective, considering the setting of objectives, targets, indicators and the data required to monitor progress. It examines a range of specific environmental objectives, organized by environmental priority. These outline some preliminary thinking on what the relevant objectives, targets and indicators might be, starting from the baseline of EU legislation.

The proposed agri-environmental indicators are: 1) land cover change, 2) soil erosion, 3) soil organic carbon, 4) areas of organic farming, 5) water quality, 6) land irrigation, 7) GHGs emissions, 8) high nature value farmlands, and 9) Natura 2000 areas. These layers of information may be derived either as ready products through the Copernicus Land Monitoring Service or through the GEOSS portal, or be calculated through primary or intermediate data therein using proven methodologies as detailed in the respective sections of the present deliverable. It is noteworthy that DIONE's proposed methodology aspires to support the monitoring and reporting of the indicators aforementioned via well-defined workflows and analysis ready data. Future work should elaborate on how to best visualize as well as combine this information for the end-users.

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ANNEX A

Below a complete list of the selected indicators is presented.

Land cover change	Land
CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Land cover
Data sources	Sentinel-2, IACS and CLC
Inputs	Normalized Difference Vegetation Index (NDVI)
Organic farming	Land
CAP Related objective(s)	Sustainable management of natural resources
EVs	Land cover, Soil carbon
Data sources	Sentinel-2, drone imagery, soil spectral measurements
Inputs	NDVI, soil predictions
Soil erosion	Land
CAP Related objective(s)	Sustainable management of natural resources biodiversity and landscapes and climate action
EVs	Land cover, Burnt areas, Surface wind speed direction, Precipitation, Elevation
Data sources	Sentinel-2, CLC, ESDAC
Inputs	NDVI, EFFIS products, DEM, LUCAS, DIONE soil spatial explicit indicators
Soil organic matter	Land
CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Soil organic carbon, Elevation
Data sources	Copernicus (Sentinel-1 and Sentinel-2), LUCAS, ESDAC, spectral handheld sensors
Inputs	Spectral measurements (space borne and in situ), DEM
Water quality	Water
CAP Related objective(s)	Sustainable management of natural resources
EVs	Water quality
Data sources	CGLS
Inputs	TSM, temperature, Chl - α
Land irrigation	Water
CAP Related objective(s)	Sustainable management of natural resources and climate action
EVs	Land Cover (irrigated areas)
Data sources	Sentinel-2, CLC
Inputs	LSWI, NDVI
Greenhouse Gases	Air Quality and Climate change
CAP Related objective(s)	Climate action
EVs	GHGs, land cover (croplands, grasslands)
Data sources	Sentinel-5, SMAP, CLC
Inputs	Level-2 products, Sentinel-5p and SMAP
HNV areas and Natura 2000 Areas	Protected/ vulnerable
CAP Related objective(s)	Sustainable management of natural resources biodiversity
EVs	Land cover
Data sources	CLC
Inputs	HNV areas, Natura 2000 areas