Regen Network

Ecological State Protocols

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1. Data Sources

1.1. Remote sensing

There are three main types of sensors used in the protocols of Regen Network:

- Optical and Near Infrared
- Microwave (Radars)
- Laser scanners (LiDARs)

1.2. Sensors

1.2.1. Optical and Near Infrared (NIR) sensors

Optical and NIR sensors are widely used in the assessment and analysis of a wide range of characteristics of different ecosystems. This is due to a high variety of reflective properties of plants under different growth stages and environmental conditions in the spectral regions across different species. Optical (or visual) reflectance (400–750 nm) of plants is determined mainly by pigments—predominantly chlorophyll and carotenoids and to a lesser degree by minor pigments (i.e. xanthophylls). NIR reflectance (750–1000 nm) is determined by cellulose from plant cell walls. Going further to short-wave infrared (SWIR) spectrum (1000–2500 nm), it becomes possible to detect water effects by water-absorption bands at 1400 and 1900 nm. Optical and near infrared (NIR) sensors can capture light in just a few or in many spectral bands. Dependant on the quantity of spectral bands, the sensors are classified into multispectral (usually 2–5 wide bands) and hyperspectral (usually 100 or more narrow bands). Specially-designed multispectral cameras are widely used. In contrast to regular RGB cameras where the signal is split inside the sensor by filtering, professional multispectral cameras usually have separate lenses and sensors for each spectral channel. In hyperspectral sensors, the division of the signal into many narrow bands is achieved by light diffraction by prisms or grates. Light intensity is also divided between the channels which causes a need for longer exposure or a bigger sensor matrix. Due to such complexity, hyperspectral sensors are used more rarely, although they are superior in many ways. RGB, multispectral and hyperspectral imagery all enable the acquisition of ecological information by applying algorithms to the different spectral bands of the imagery.

1.2.2. Radar

Microwave sensors are also known as radar. They measure the strength of the back-scattered signal from a surface. Synthetic-aperture radars (SARs) use the motion of an antenna to create high-resolution 2-D and 3-D maps. SARs have lower signal-to-noise ratio compared to optical sensors but can be operated under almost all weather and light conditions. SARs are used in cases when optical data is not available, for example at night or above clouds.

1.2.3. LiDAR

LiDAR stands for Light Imaging, Detection, and Ranging. It emits and detects reflected laser beam (usually within 600–1000 nm) to reconstruct an object's shape by the creation of point clouds. LiDAR sensors are not limited by the same signal saturation for the estimation of Above Ground Biomass (AGB) as optical and radar sensors. This is because LiDAR retrieves canopy height from the distance measurements between the sensor and the target in contrast to optical and radar, which correlate AGB with spectral reflectance or radar backscatter signals. A high LiDAR point density allows for more ground returns to be obtained through gaps in the canopy. In particular, airborne and ground-based imaging LiDARs provide direct and very accurate measurements of canopy height. LiDAR is used primarily on UAVs. There is no LiDAR satellite in orbit at the present time, but some are in the development stage.

1.3. Platforms

1.3.1. UAV (Drones)

Using drones for remote sensing has become extremely popular because of progress in robotics. Relatively affordable amateur drones such as the DJI Mavic Pro or 3DR Solo can be effective remote sensing instruments providing hundred hectare-maps within hours. In addition to the RGB camera that the drone is usually equipped with, manufacturers provide NIR-modified cameras and multispectral cameras designed specially for drones. One of the simplest yet most effective cameras is MapIR in which the blue channel is replaced with NIR by means of filters. Different versions have either a Red-NIR or a Red-Green-NIR channel combination to allow allow the mapping of various vegetation indices utilizing these bands. Tetracam is one of the most experienced manufacturers of airborne multispectral cameras. They started by producing cameras for piloted planes and heavy drones. Recent models such as Tetracam ADC-Micro can be mounted on a small UAV. Tetracam served as the prototype for several novel developments such as Micasense and Sentera. These cameras also have multi-lens construction and capture signals in separate channels. For instance, Micasense Parrot Sequoia has Green, Red, Red-Edge and NIR bands. In addition, it is equipped with a regular RGB sensor. Despite hyperspectral cameras being much more complicated and expensive, there are some devices developed specially for UAV—for instance, Gamaya with about 50 narrow spectral bands in visual and NIR regions. Another approach for obtaining hyperspectral data onboard a UAV is by using a single-beam spectrophotometer instead of a camera. For example, Ocean Optics STS developers kit has been used for this purpose. UAVs can be equipped with LiDAR—for example RIEGL VUX-1UAV or YellowScan Mapper. No commercial implementation of Synthetic Aperture Radar (SAR) onboard of a light drone has been reported. There are some prototypes that hopefully will be mass-produced in future.

1.4. Satellites

1.4.1. Landsat

Landsat imagery goes back to 1972, circles the Earth every 99 minutes and scans the whole surface of the Earth every 16 days. Satellite images are freely available and come in 30 m spatial resolution and 11 spectral bands.

1.4.2. MODIS

MODIS stands for Moderate Resolution Imaging Spectroradiometer and is a sensor often used for ecosystem monitoring. The sensor is carried onboard the TERRA satellite launched in 1999. MODIS has 36 spectral bands in visual and infrared regions with spatial resolution between 250–1000 m. 250 m resolution refers to the Red and NIR bands which are the most useful for plant study. There are also 5 other bands in the Blue, Green and SWIR regions with 500 m resolution. With the 99-minute orbit of TERRA, MODIS maps the whole Earth every 1–2 days. MODIS data is freely available.

1.4.3. Sentinel-2

In 2015, Sentinel-2a satellite was launched and was followed by the Sentinel-2b in 2017. This constellation of satellites has been developed by the European Space Agency for land monitoring with a strong focus on vegetation. Both satellites are equipped with a Multi-Spectral Instrument (MSI) with 13 spectral channels in the visible, NIR and SWIR regions. Spatial resolution in Blue, Green and NIR bands is equal to 10 m. There are 3 Red Edge bands, 1 narrow NIR band and 2 SWIR bands with 20 m resolution. The other 3 bands refer to atmospheric study and have a 60 m resolution. By combining both satellites, an update of freely available data occurs every 5 days.

1.4.4. Sentinel-1

In 2014 and 2016, Sentinel-1a and Sentinel 1b were launched. The satellites carry a single C band SAR capable to deliver information about land cover with 5 m spatial resolution every 16 days.

1.4.5. Commercial satellites

Besides listed above, there are a number of commercial satellites with their image data available for purchase. Spatial resolution of commercial satellites is much higher (1–2 meters). For example, Pleiades HR 1A and Pleiades HR 1B constellation developed by AIRBUS Defence & Space provides data in Blue-Green-Red-NIR bands with 2 m resolution and 26-day update. World-View-3, owned by DigitalGlobe, updates every day and has a super-spectral, high resolution camera with 29 spectral bands. Ikonos, QuickBird, GeoEye1 and Worldview 1-2 and 4 are other commercial satellites operated by Digital Globe. Planet Labs has over 192 satellites in orbit and refreshes its dataset daily. They operate the

PlanetScope, RapidEye and SkySat constellations and have a maximum resolution of 1 meter and 4 or 5 spectral bands.

1.4.6. Synthetic Aperture Radar (SAR)

Satellites with Synthetic Aperture Radar (SAR) orbit the Earth in a sun-synchronous LEO polar orbit and data acquisitions can be made at any time of day or night and independent of cloud coverage, collecting both amplitude and phase data. The SAR satellites have repeating paths which, using two phase datasets for the same location at different times, allows for interferometric SAR (InSAR) showing relative ground displacements between the two datasets along the direction of the radar beam. The SAR satellites operate at designated frequencies with L-band, C-band, and X-band being the predominate wavelengths. Below is a chart of past, present, and projected SAR satellite missions.

Various agencies support the different SAR missions:

- European Space Agency (ESA): ERS-1, ERS-2, Envisat, Sentinel-1
- Japan Aerospace Exploration Agency (JAXA): JERS-1, ALOS-1, ALOS-2
- Canadian Space Agency (CSA): Radarsat-1, Radarsat-2, Radarsat constellation
- Deutsches Zentrum für Luft- und Raumfahrt e.V. (DLR): TerraSAR-X, TanDEM-X
- Indian Space Research Organization (ISRO): RISAT-1, NISAR (w/ NASA)
- Comisión Nacional de Actividades Espaciales: SAOCOM
- Italian Space Agency (ASI): COSMO-Skymed
- Instituto Nacional de Técnica Aeroespacial (INTA): PAZ
- Korea Aerospace Research Institute (KARI): KOMPSat-5
- National Aeronautics and Space Administration (NASA): NISAR (w/ ISRO)

Source

1.5. GIS datasets

Open GIS datasets enable an integration of global, regional and local data. The inclusion of these information sets enables correlation of ecosystem data, enhanced classification and identification of specific areas of interest. The datasets that will be integrated fall into the following categories:

- Hydrological data
- Conservation data
- Point-clouds and Digital Elevation Models (DEM)
- Climate data
- Air quality data
- Exceptional biodiversity hotspots
- Regional and national soil databases
- Threatened species
- Historical changes in global land cover
- Socioeconomic data
- Coastal datasets
- Benthic cover

- Different ecological classifications
- Watershed boundaries
- Forest cover and evapotranspiration datasets
- Agriculture

1.6. IoT ecological monitoring sensors

The sensors used in the different algorithms and protocols enable the acquisition of real time ecological information in a variety of different categories. IoT environmental monitoring is especially relevant and important in the domains of air pollution, agriculture, soil, water quality and weather. Below is a list of relevant sensors for Regen Network protocols and algorithm development. Sensors allow cross correlation of different data sources and a realtime data feed based on actual time-stamped ecosystem data.

List of the relevant sensors for Regen Network protocol and algorithm development:

- Air pollution and emissions (including forest fires)
    - Oxygen
    - NO2
    - SO2
    - Hydrocarbons
    - CO
    - CO2
    - PM1, PM2.5, PM10
    - Ozone
    - Hydrogen Sulfide
    - Ammonia
    - Acetylene
- Agriculture
    - Nitrogen
    - Soil methane emission
    - Soil spectrometer
    - Soil probe
    - Rainfall
    - Rainfall drop size and distribution
    - Canopy temperature
    - Leaf wetness
    - Soil heat flux
    - Stomatal conductance
- Soil
    - Soil water
    - Soil carbon
    - Soil nitrate
    - Soil potassium
    - Soil phosphorus
    - Soil aeration
    - Soil respiration
    - Soil nitrogen
    - Soil texture
    - Soil organic matter
    - Photosynthetic photon flux density
    - Gas flux
    - Carbon exchange
    - Color
    - pH
- Water Quality
    - Bromide Ion (Br-)
    - Calcium Ion (Ca2+)
    - Chloride Ion (Cl-)
    - Cupric Ion (Cu2+)
    - Fluoride Ion (F-)
    - Iodide Ion (I-)
    - Chlorophyll a
    - Blue-Green Algae
    - Rhodamine WT
    - Colorimeter pH

- Full wavelength spectrum spectrophotometer
- UV-VIS spectrophotometer
- Weather stations
  - Wind speed and direction
  - Rainfall distribution
  - Temperature
  - Humidity

1.7. User input

In addition to data collected from the technological sources above, there is also a strong role for data generated through human observations. Organizations such as Savory Institute are leading the way with dynamic and peer reviewed methodologies for land stewards to measure ecological outcomes and use that information to adapt management practices to increase both profit and ecosystem health (Savory EOV program and land to market). User Input aso refers to data collected for the Data Quality Protocol such as ratings of other data or algorithms, data collected through third party apps, and Eco-Apps built on top ofRegen Ledger. These data sources are especially importable for the Ecological Supply Protocols (ESPs) so as to link customers back to the source of the products they enjoy.

2. Pending Protocols

2.1. Endangered species habitat protocol

As of 2017, the IUCN reported over 25,000 threatened species; those include species listed as Critically Endangered (CR), Endangered (EN) or Vulnerable (VU) (IUCN, 2017). The endangered species habitat protocol would use satellite data, GIS datasets and smart IOT monitoring to track and map habitat for endangered species, identify and predict their movements and help direct conservation efforts towards certain areas. The protocol could allow manufacturers to make claims about not containing materials derived from either endangered species or having directly impacted the habitat of endangered species. It can also inform botanists, wildlife managers and governments on how to optimize the boundaries of reserves and fund conservation efforts based on updated species, topography, soil, precipitation, landcover and climatic data. Thus, the endangered species habitat protocol could optimize to achieve the highest rate of preservation while balancing social and economic needs with habitat and species conservation.

2.2. Pollinator density protocol

Globally, 35% of food crop production depends on pollinators. Agricultural intensification jeopardizes wild bee communities and their stabilizing effect on pollination services at the landscape scale (Klein, 2007). For bees to persist on a landscape, they need two things: suitable places to nest and sufficient food (predicated by floral quality indicators) near their nesting sites (InVEST, 2018). By pairing landuse to nesting suitability and floral resources across seasons, this protocol would be able to verify likeliness of pollinator density and match sensor measurements with satellite predicted pollinator visitation rates.

2.3. Water quality protocol

Water pollution has many different causes; these include but are not limited to sewage, nutrients, plastics, chemical, radioactive compounds, oil and wastewater. By developing this water quality protocol, the quality of both surface and groundwater could be tied to verifiable sensor input and satellite data. Water quality monitoring systems could measure dissolved oxygen, temperature, turbidity, Chlorophyll a (chl-a)and many more factors correlated to global water pollution. Because of the high temporal coverage, Landsat imagery has been widely used for chl-a assessment. For rivers and other cases that need more spectral and spatial resolution, the multispectral ALOS/AVNIR-2, IKONOS and hyperspectral CASI and AISA imagery has successfully been used to determine turbidity and Total Suspended Solids (TSS).

2.4. Habitat quality protocol

Habitat is of a high quality when it is relatively intact and has the structure and function within the range of historic variability. Habitat quality depends on a habitat's proximity to human land uses and the intensity of these land uses. Generally, habitat quality is degraded as the intensity of nearby land-use increases (Nelleman 2001, McKinney 2002, Forman et al. 2003). The habitat quality protocol would measure the distance to the anthropogenic impact, identify the location (upstream or downstream) and the magnitude of the landscape threat. In order to assess externalities from the surroundings, the choice of appropriate spatial units is a key decision that will influence most aspects of the habitat quality protocol. The watershed is a relevant eco-geographic spatial unit to analyze because it possesses biogenic and hydroclimatic integrity as well as having a socioeconomic and cultural identity. By using smart IOT monitoring combined with high resolution satellite imagery and GIS datasets, the habitat quality protocol could help protect the world's most sensitive habitats and allow decision makers to incorporate this protocol into their legal frameworks.

2.5. Erosion and sediment delivery protocol

We have lost a third of our arable soils to erosion; human activity and related land use change continues to be the primary cause of accelerated soil erosion, which has substantial implications for nutrient and carbon cycling, land productivity and in turn, worldwide socio-economic conditions (Borrelli, 2017, FAO 2015). The erosion and sediment delivery protocol would rely on the latest erosion and sediment delivery models, GIS datasets and real-time erosion sediment delivery monitoring using satellite and UAV. It has never been more important to re-engineer our agricultural system and this protocol will incentivize and reward ecological regeneration that combats erosion and rebuilds our soils.

2.6. Urban tree protocol

In our modern cities, trees provide cleaner air, lower stress, cooler temperatures, reduced flood risk and increased biodiversity. While the importance of trees is clear, they still get cut down in order to make space for city expansion. The urban tree protocol could calculate the canopy projected areas of trees based on high resolution satellite data and identify the cooling effect of trees using UAV thermal imagery. The protocol could help tree advocacy groups to better protect our urban forests and help governments prioritize and incentivize certain areas for planting.

2.7. Aquifer carbon sinks protocol

Massive aquifers beneath the world's deserts might store more carbon than all living plants (Li et al. 2015). When fossil fuels are burned, 30% of the CO2 is trapped in the atmosphere, causing warming, 40% ends up in the oceans, and the rest winds up elsewhere, mostly in plants which absorb it through photosynthesis. Not all CO2 taken up by plants is used and converted into sugars and oxygen. Scientists have been trying to figure out where all the "leftover carbon" ends up in the planet's system. One of these many places might be beneath the world's deserts. Chinese researchers sampled water from an underground aquifer in the Tarim Basin and found it stores vast quantities of carbon dioxide as a result of human activities, particularly farming. If the same holds true for all the desert aquifers around the world, the trapped carbon would amount to about a quarter more than the amount stored in living plants on land. Previously, the carbon trapped in aquifers was thought to be negligible. Clearly, this isn't the case and these should not be disturbed so that the carbon doesn't wash up into the atmosphere. Moreover, if the process identified in the new study happens in the same way at other regions around the world's deserts where agriculture and over-irrigation are present, the process could account for the storage of about 1 trillion tons of carbon.

In sandy soil, when plants soak up CO2, some of it leaches into the ground. Microbes that breakup plant nutrients also contribute. Because conditions are arid, desert farmers have to irrigate more;the extra water dissolves the CO2 and deposits it in the aquifer below. The carbon is then stored in these geological structures covered by thick layers of sand, where it may never return to the atmosphere. Collectively, the world's underground desert aquifers cover an area the size of North America and may account for at least a portion of the "missing carbon sink". Knowing the precise location of these underground carbon sinks will thus prove extremely important to improve carbon-stock models. If the extent of the carbon trapping is really this large, then farmers could work together with authorities to manage the carbon that goes underground.

The aquifer C-sinks protocol would calculate the area of arid and semiarid aquifers that could be potentially farmed based on integrated remote sensing and GIS. The Gravity Recovery and Climate Experiment (GRACE) mission should provide accurate data of aquifer size and distribution when data are missing. The protocol would help governments to prioritize and incentivize certain areas for farming.

2.8. Air quality protocol

Air pollution is currently one of the most important environmental issues in many regions around the world. Apart from its direct impacts on human health and climate change, air pollutants can also adversely affect ecosystems which can indirectly impact human health and welfare through food and water contamination. Satellite remote sensing is a good complement for ground-based data and air quality models. While ground-based air quality sites provide the most accurate measurements of air quality at a specific location, satellite imagery provides data with global, consistent coverage. Since variations in air quality are complex in time and space, the air quality protocol would take into account many different data sources and identify pollution hotspots, highlight relationships between the spatial and temporal distribution of pollution and allow ecological claims to be made about an increase in air quality and a decrease in pollution.

3. Carbon Sequestration indicators

3.1. Soil carbon

The different techniques used for determining SOC based on remote sensing employ the shape of the reflectance spectrum, for example by using band depth analysis and principal component analysis. Alternatively, multivariate regression modelling such as Partial Least-Square Regression (PLSR) and multiple linear regression can be used. By means of these methods, different topsoil parameters are determined from the spectral signature contained in a single imaging spectrometer image, where the various variables are represented by different combinations of absorption features across the spectra.

Spaceborne imaging spectrometer data have not often been used for predicting soil organic carbon, but advanced spectral unmixing methods applied to Hyperion data have obtained similar SOC fractions as those in field observations (Mulder et al. 2011). When mapping soil organic carbon on a large scale without extensive calibration with soil samples, a solution could be to use indices based on spectral reflectance. The amount of SOC is then detected with reflectance spectroscopy based on the constituents of SOC: cellulose, starch and lignin. Good relations have been found for indices based on the visible part of the spectrum (R2=0.80) and for the absorption features related to cellulose (around 2100 nm) (R2=0.81) (Bartholomeus et al 2008). Alternative approaches to determining exact soil carbon include Regression kriging of predictor variables (Tasseled cap brightness, greenness and wetness indices, NDVI, Vegetation Temp. Cond. Index [VTCI], DEM, slopes, Compound Topography Index [CTI] and Leaf Area Indices for grasslands; Mondal et al 2017), and the construccion of soil indices based on brightness, darkness, and greenness (Bingwen et al 2017).

3.2. Biological indicators

The relation between nutrient requirements of plants and nutrient availability in soils can be used to derive soil attributes. Accordingly, the concept of plant functional types (PFT) can be used to derive the specific type or group of species that grow on typical soils. Functional types can be distinguished largely on the basis of optical properties detectable by remote sensing. To fully utilize the potential of remote sensing, data must be combined with ecological models linking structural, physiological and phenological traits based on resource constraints. Hence, PFT regulate or are regulated by ecosystem processes and have discrete different functions within the ecosystems. Different PFT have a particular distribution in relation to geography or environment, e.g. species of ultramafic soils or acidophilus bog species. Therefore, PFT could be explained by the DEM derived terrain variables which describe the landscape structure (Ustin & Gamon 2010).

In addition to PFT, Ellenberg indicator values can be used as a numerical system to classify species' habitat niches and their peak occurrence along gradients. By finding correlations of Ellenberg indicator values with morphological or ecophysiological properties, it is possible to identify determinants of species distributions with respect to environmental factors. Schmidtlein (2005) showed that imaging spectroscopy can be used as a tool for mapping Ellenberg indicator values for soil water content, soil pH and soil fertility. The Ellenberg indicator values scale the flora of a region along gradients reflecting light, temperature, moisture, soil pH, fertility and salinity. In this way, the flora can be used to monitor environmental change and thereby changes in the soil (Wulf et al 2014).

3.3. Above Ground Biomass (AGB)

Accurate measurement and mapping of biomass is a critical component of the proposed carbon sequestration protocol. The Intergovernmental Panel on Climate Change (IPCC) has listed five terrestrial ecosystem carbon pools involving biomass: above-ground biomass, below-ground biomass, litter, woody debris and soil organic matter. Of these five, above-ground biomass (AGB) is the most visible, dominant and dynamic pool of the terrestrial ecosystem, constituting around 30% of the total terrestrial ecosystem carbon pool. While detailed estimates of biomass are necessary for accurate carbon accounting (biomass as dry weight is 50% carbon), there are few reliable estimation methods. Biomass derived from field data measurements is the most accurate, but it is not a practical approach for broad-scale assessments. Using remote sensing has a key advantage; it can provide data over large areas at a fraction of the cost associated with extensive sampling and enables access to inaccessible places.

Data from remote sensing satellites are available at various scales, from local to global, and from a number of different platforms. Optical remote sensing probably provides the best alternative to biomass estimation through field sampling due to its global coverage, repetitiveness and cost-effectiveness. Optical Remote Sensing data is available from a number of platforms, such as IKONOS, Quickbird, Worldview, SPOT, Sentinel, Landsat and MODIS. New space-borne sensors to be launched in the coming years will allow accurate measurements of AGB in high biomass forests (>200 t ha^{-1}) for the first time across large areas (Rodríguez-Veiga et al, 2017). Recent developments in high resolution space-borne and airborne satellite data have provided an opportunity to better estimate and map AGB across different spatial and temporal scales.
The use of drones and UAVs has opened up avenues for super-fine resolution biomass estimation for targeted applications. Recent sensors, such as the Worldview series, now

provide meter level spatial resolution while Sentinel and Landsat 8 provide free data for the whole world, opening up accessibility and more applications of Remote Sensing data, including for biomass estimation. Radar Remote Sensing has gained prominence for above-ground biomass estimation in recent years due to its cloud penetration ability as well as detailed vegetation structural information. Light Detection and Ranging (LiDAR) has the ability to sample the vertical distribution of canopy and ground surfaces, providing detailed structural information about vegetation. This leads to more accurate estimations of basal area, crown size, tree height and stem volume. A number of studies have established strong correlations between LiDAR parameters and above-ground biomass (Asner et al. 2018; Kumar & Mutanga 2017).

3.4. Surface water quality

By monitoring water quality parameters (i.e. suspended sediments [turbidity], chlorophyll, and temperature), it is possible to assess wetland degradation or changes in their carbon sequestration capacity (Foster et al 2012). Optical and thermal sensors can provide both spatial and temporal information needed to monitor changes in water quality parameters. Integration of remotely-sensed data, GPS, and GIS technologies provide a valuable tool for monitoring and assessing waterways and wetlands (Ritchie et al 2003). Remotely-sensed data can be used to create a permanent geographically located database to provide a baseline for future comparisons. The spectral characteristics of water and pollutants—which are functions of the hydrological, biological and chemical characteristics of water—are essential factors in the monitoring and assessment of water quality. The different methodologies to interpret images and to evaluate the turbidity are non-linear multiple regression, principal components analysis (PCA) and neural networks. Colored Dissolved Organic Matters (CDOM) in water can be determined using hyperspectral imagery like EO-1/Hyperion, EO-1/ALI, and ALOS/AVNIR-2. In addition, high-resolution spectroradiometer can be used for in situ hyperspectral measurements for validation purposes (Gholizadeh et al. 2016).

3.5. Water and nutrient runoff

Agriculture intensification and expansion causes soil deterioration, which implies a lower capacity of soil carbon and nutrient retention, and thus higher export loadings of nutrients from non-point sources to downstream surface water bodies during and after storm events. Nutrients are then transported by surface and sub-surface runoff, contributing to non-point source pollutions of surface waters. Water runoff volumes can be estimated by the Curve Number Method. The Soil Conservation Service Curve Number (SCS-CN or NRCS-CN) method is a simple, widely used and efficient procedure for determining the expected amount of runoff from rainfall in a particular area. Coupled with thematic maps like LULC

maps, soil types and climate maps, and hydrological tools in GIS, the NRCS-CN method can be used to calculate the runoff transport and accumulation through the watershed.
CN is an empirical parameter used for predicting direct runoff or infiltration from rainfall excess. Regardless of some weaknesses, the CN method presents some advantages such as quantification of the effect of land use changes on runoff formation (Rietz and Hawkins 2000). The widespread popularity of the NRCS-CN method attributes to the wide availability of the required data and its simplicity. As result, the NRCS-CN method which originally intended for the study of agricultural land, became a fundamental part of hydrological practice and was adopted for application in different climate and conditions. Moreover the CN method has been integrated into different hydrological models, including CREAMS, FEST, EPIC, AGNPS, HEC-HMS and SWAT. Some of these models have been used used to calculate runoff in GIS, like the AnnAGNPS or the SWAT (ArcSWAT).

Empirical or locally measured event mean concentrations (EMCs) for different water quality parameters as BOD, COD, ammonia, nitrate, TKN, hardness, TDS, TSS, chlorides, sulfates, phosphate, fluorides and TC are often available for many agricultural areas, and can be used to calculate the amounts of nutrients in the runoff after a storm event in GIS. Also, models like AnnAGNPS ans SWAT have shown good results when estimating nutrients in runoff.

3.6. Land conversion

Land-cover change and management can alter the amount of organic carbon stored in the soil and this in turn affects both soil fertility and atmospheric carbon dioxide concentrations. There is empirical information that could be used along with LULC maps to globally map and monitor changes in carbon stocks due to land conversion.

Land Use Change	Mean Sequestration Rate		Level of Certainty	
	Metric tons CO_2 equivalents acre^{-1} yr^{-1} ± S.D.	Relative Rate	about the mean rate	that carbon sequestration > 0
Annual row crop to short-rotation woody crops	7.0 ± 2.6	High	High	Very High
Annual row crop to forest	5.5 ± 1.8	High	High	Very High
Prairie pothole restoration	4.5 ± 6.9	High	Low	Very High
Annual row crop to perennial grassland	1.6 ± 1.6	Medium	Low	High
Turfgrass to urban woodland	0.9 ± N.A.	Medium	Low	Very High
Enhanced forest stocking	0.8 ± 1.0	Medium	Low	High
Peatland restoration	0.74 ± 0.4	Low	Medium	Very High
Inclusion of cover crops in row crop rotation	0.6 ± 0.3	Low	Medium	High
Annual row crop to pasture / hayland	0.4 ± 0.1	Low	High	High
Conventional to conservation tillage	0.3 ± 0.5	Very Low	Low	Very Low
Low diversity to high diversity grassland	0.1 ± 1.39	Very Low	Low	Very Low

Empirical information from http://files.dnr.state.mn.us/aboutdnr/reports/legislative/terrestrial_carbon.pdf. Minnesota, US.

3.7. Biodiversity

Recognizing the imperative need for biodiversity protection, the Convention on Biological Diversity (CBD) has recently established new targets towards 2020, the so-called Aichi targets, and updated proposed sets of indicators to quantitatively monitor the progress towards these targets. There are generally three ways to measure ecosystem variables: 1) functional processes measured as fluxes, using in situ sensors, 2) precise monitoring of composition, abundance, extent and change, is commonly done by in situ monitoring through habitat surveillance combined with vegetation plots, 3) structural change monitoring using in situ combination with remote sensing from space, aircraft, or drone (Jongman et al 2017).

Some of the important biodiversity indicators that are required for building prediction models could be measured in enough detail by using high-resolution remote sensing data collected with UAVs (Saarinen et al 2018). Remote sensing has been increasingly contributing to timely, accurate, and cost-effective assessment of biodiversity-related characteristics and functions during the last years. Novel approaches integrating multi-sensor acquisitions can help to improve understanding of the various environmental, physical, climatic, and human factors influencing biodiversity, by monitoring spatial and temporal variations in species composition.

Several biodiversity-related international projects have recently been implemented, such as the 7th European Framework Programme (FP7) , MS.Monina (Multi-scale Service for Monitoring Natura 2000 Habitats of European Community Interest), and BIO_SOS (Biodiversity multi-Source monitoring System: from Space to Species); the latter two focusing on biodiversity monitoring from space (Petrou et al 2015).

3.8. Sediment delivery and soil loss due to erosion

The loss of soil leads to a decline in organic matter and nutrient content, the breakdown of soil structure and a reduction of the available soil water stored, which can lead to an enhanced risk of flooding and landslides in adjacent areas. Nutrient and carbon cycling can be significantly altered by mobilization and deposition of soil, considering eroded soil may lose 75 - 80% of its carbon content, with consequent release of carbon to the atmosphere (Agri-Environmental Indicator, 2018). The total land area subjected to human-induced soil degradation is estimated at about 2 billion hectares. From this, the land area affected by soil degradation due to erosion is estimated at 1100 Mha by water erosion and 550 Mha by wind erosion. Using conventional methods to assess soil erosion risk is expensive and time consuming.

The soil loss model, Revised Universal Soil Loss Equation (RUSLE) can be integrated with GIS in order to estimate soil loss (El Jazouli et al 2017; Andersson & Linus 2010). The RUSLE model can predict erosion potential on a cell-by-cell basis, which is effective when attempting to identify the spatial pattern of the soil loss present within a large region. GIS can then be used to isolate and query these locations to identify the role of individual variables contributing to the observed erosion potential value. The soil erosion assessment depends upon the regional characteristics of the area, namely climate, soil condition, land use/land cover, topography, and lithology. A DEM (Digital Elevation Model) is one of the essential inputs required for soil erosion modelling. Other inputs include thematic factor maps that can be generated in GIS from climate and geological data, and landsat images.

3.9. Net Primary Productivity (NPP)

Net primary productivity (NPP) is an indicator of land productivity. NPP represents how much carbon dioxide vegetation takes in during photosynthesis minus how much carbon dioxide the plants release during respiration (metabolizing sugars and starches for energy). Land productivity can be assessed through estimates of NPP (tDM/ha/yr), where a change in the absolute numerical value may be positive or negative. NPP can be quantified using indices derived from Earth observation data such as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI). Dry Matter Productivity (DMP) represents the overall growth rate or dry biomass increase of the vegetation, expressed in kilograms of dry matter per hectare per day (kgDM/ha/day). DMP is directly related to NPP, but its units are customized for agro-statistical purposes. According to Atjay et al. (1979), the efficiency of the conversion between carbon and dry matter is on the average 0.45 gC/gDM. DMP images available at Copernicus Hub, derive from SPOT-VGT (until December 2013) and PROBA-V (from January 2014) imagery combined with (modelled) meteorological data from ECMWF, are made available at 1km resolution and are updated every 10 days. Also new products are being prepared at 300m and 100m resolution. Similar products could be built for moderate to high resolution images by following methods from the Copernicus Global Land Operations "Vegetation and Energy"

3.10. Covariables

Covariables	**Scale/type**	**Source of information**	**Indicators affected**
Climate: humidity, rainfall	Landscape/remote sensing and pluviometric maps	Multitemporal series data of rainfall events, or accumulated rainfall thematic maps from meteorological databases. Intensity of rainfall events.	Changes in area of surface waters. Changes in runoff volumes between years. Changes in hydric erosion gullies (increase in number or sizes)
Soil moisture	Landscape/remote sensing	Topographic Wetness Index (TWI), Temperature-Vegetation Dryness Index (TVDI), Vegetation Temperature Condition Index (VTCI)	AGB, NPP, soil erosion, runoff

3.11. Climate: rainfall

When analyzing changes in ecosystems or species that are directly affected by the availability of water, it might be necessary to perform very long-term monitoring in order to detect changes due to other causes, like land management or other anthropic impacts. Otherwise, the weather variable should be somehow considered or subtracted from the data in order to “denoise” the data and find patterns. For example, changes in the area of surface water bodies could vary between years according to both, anthropic and climatic causes. A wetland that shows erratic changes in size through a 10 year-period could be indeed shrinking or increasing its area due to drainage, irrigation or channelization practices in the area, but some rainy years could mask the real trend, so that it could be detected after more than 15 years, maybe too late for mitigation.

3.12. Soil moisture

Soil moisture influences many potential indicators for carbon monitoring, like soil erosion, AGB, NPP and water and nutrient runoff. So measuring and monitoring soil moisture variations in time could help to denoise the measures from these indicators and identify changes due to human actions in moderate time periods.

Soil moisture changes can be monitored by remote sensing and GIS:

- Soil Water Index (SWI) with a resolution of 1 km, tracks only changes in soil water content over time, does not quantify
- Recently launched microwave SMOS (Soil Moisture and Ocean Salinity)
- Future satellite SMAP (Soil Moisture Active Passive), temporal resolution of 3-5 days and 1 km resolution
- Surface energy balance models with ASTER and MODIS images as surface variables
    - Soil Energy BALance (SEBAL),
    - Two-Source Energy Balance (TSEB)
    - Surface Energy Balance System (SEBS)

4. Main Indicators for Carbon Sequestration

Indicator	Predictors	Data type	Data sources
Above Ground Biomass (AGB)	Combination of different sources of spectral data, radar (SAR), Land Use/Land Cover (LULC) maps, terrain sampling, Regression models, classifications. Algorithms (e.g. BIOMASAR).	Radar, LiDAR and optical remote sensing imagery. Sometimes terrestrial samplings are needed.	RapidEye, UAV datasets, Worldview, SPOT, Sentinel, Landsat and MODIS, SAR platforms.
Land Conversion	Changes in LULC maps, vegetation indices, Forest Canopy Density model (FCD)	Spaceborne sensors, hyperspectral imagery on airborne sensors	Landsat TM, ALOS/AVNIR-2, IKONOS . EO-1/Hyperion, EO-1/ALI, and ALOS/AVNIR-2
Net Primary Production (NPP)	NPP (tDM/ha/yr) can be quantified using indices derived from earth observation data such as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI).	UAV or airborne remote sensing spectral composites (i.e. vegetation indices)	Sentinel, Landsat, Modis
Biodiversity	CBD Indicators Habitat rarity (InVEST) Habitat Quality (InVEST)	LiDAR, UAV and optical remote sensing imagery, and derived thematic maps.	Sentinel, Landsat, Modis, Copernicus, Big Data

	Habitat Connectivity (FRAGSTATS) Habitat fragmentation (FRAGSTATS) Indicator Species.	Mapable data showing changes in the distribution and/or richness patterns of certain indicator species under monitoring programs can be downloaded from Big Data.	
PFT/Ellenberg	Landsat seasonal composites and vegetation indices, or from multisource evidential reasoning (ER) algorithm.	UAV or airborne remote sensing spectral composites (e.g. vegetation indices), local calibration	DEMs, LULC, soil maps from various platforms.
Soil Erosion	Compound Topographic Index (CTI) or TWI, RUSLE or RUSLE2/GIS methodology.	Radar, LiDAR and Optical remote sensing. Thematic Maps for RUSLE factors.	DEMs, LULC, soil maps from various platforms
Water and nutrient runoff	Curve Number from the Soil Conservation Service of the US (SCS-CN) Nutrient runoff estimates from models, e.g. Swat, AnnAGNPs.	Radar and Optical remote sensing, local calibration from terrain surveys, Empirical data and equations. Hydrological tools in GIS.	Thematic maps: DEMs, LULC maps, climate maps, soil type maps. Empirical equations and values (e.g. SCS-CN equations, EMCs values)
Soil Organic Carbon	Multivariate regression modelling such as Partial Least-Square Regression (PLSR) and multiple linear regression based on soil colour attributes (visible bands). Indices based on spectral reflectance Regression kriging of predictor variables:	Hyperspectral imagery from Orbital, UAV or airborne remote sensing	Updated satellite hyperspectral imagery databases, drone imagery.

	Tasseled cap brightness, greenness and wetness indices, NDVI, Vegetation Temp. Cond. Index (VTCI), DEM, slopes, Compound Topography Index (CTI)- Leaf Area Indices for grasslands		
Surface water quality	Turbidity, TSS, Chl-a, CDOM	Spaceborne sensors, hyperspectral imagery on airborne sensors	Landsat TM,ALOS/ AVNIR-2, IKONOS . EO-1/Hyperion, EO-1/ ALI, and ALOS/ AVNIR-2

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