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A geospatial framework for the assessment and monitoring of environmental impacts of agriculture

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ABSTRACT

The agriculture sector plays a critical role in global food security and economy, but it is also among the greatest contributors to environmental degradation and global warming through practices such as clearing of forests and wetlands, water management, and use of fertilizers and pesticides. This study proposes a geospatial framework for the systematic assessment and monitoring of environmental impacts of agriculture practices using agri-environmental impact indicators and the environmental impact assessment (EIA) method. Geospatial approaches are identified and synthesized for four key phases of the EIA method: (1) screening; (2) scoping; (3) impact prediction & assessment; and (4) impact management, monitoring & follow up. The study shows the potential of remote sensing and geospatial methods such as mapping, geostatistical interpolation, spectral indices, image classification, multi-criteria decision analysis, and GIS watershed analysis for the different EIA phases. The proposed framework can assess impacts at flexible spatial (within-farm up to the national level) and temporal scales (daily to annual). The framework was exemplified for Canada, where its use could integrate existing programs from Agriculture and Agri-Food Canada, such as environmental farm plans and agri-environmental indicators. The framework can be used by farmers, farmer organizations, environmental agencies, and consultancies, as well as provincial, territorial and federal agencies.

1. Introduction

While the agriculture sector is essential for global food security, it is also one of the greatest contributors to environmental degradation and climate change. Agriculture production relies intensively on natural resources (e.g., soil, water) and unsustainable agriculture practices can contribute to significant resource depletion (Friel et al., 2009). Clearing of forests for crop production can lead to an increase in soil erosion (García-Ruiz, 2010). Inappropriate drainage systems may cause water logging, leading to bacterial, viral, and parasitic diseases in humans and animals. Globally, agriculture accounts for about 10–12% of anthropogenic greenhouse gas (GHG) emissions (including nitrous oxide, methane, and carbon dioxide) with most of them being generated during farming (Friel et al., 2009). Waste generated from farms such as animal manure, crop residues, chemicals like fertilizers and pesticides can enter the surrounding water bodies and alter water composition and the water ecosystem. Due to practices like land conversion and use of pesticides and fertilizers, at least 43% of the world's amphibian species have declined (Piha, 2006). Agriculture impacts on the environment are extensive and can be local (e.g., increased phosphorous in the soil within the farm area), regional (e.g., eutrophication of waterbodies surrounding the farm), and global (e.g., increased greenhouse gas emissions contributing to climate change).

The environmental impacts of farms and farm regions can be assessed using methods such as environmental risk mapping (ERM), life cycle analysis (LCA), environmental impact assessment (EIA), multi-agent system (MAS), linear programming (LP), and agri-environmental indicators (AEI). A comparison of these methods for farm regions showed that the EIA and AEI methods covered the widest variety of environmental objectives related to inputs (e.g., fertilizers, pesticides), emissions (e.g., greenhouse gases), and system state (e.g., biodiversity, air, soil, and water quality) (Payraudeau and van der Werf, 2005). These two methods can also be used to evaluate impacts at both local and global levels. The AEI approach uses indicators to characterize environmental impacts, while EIA provides a complete framework for the assessment, mitigation, and monitoring of environmental impacts (Noble, 2020). On a broader scale, a study on methods for land use impact assessment by Perminova et al. (2016) reviewed 177 articles and

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Table 1
Overview of the consulted literature with a focus on reports and peer-reviewed review articles of each topic.

Step	Review focus	References
1. Determine the key indicators to support the EIA phases	Agriculture practices and impact pathways, VCs and VC indicators	**All practices** (agri-environmental indicators): Clearwater et al. (2016); Reytar et al. (2014) **Tillage**: McLaughlin and Mineau (1995); McRae et al. (2000) **Fertilizers:**Statistics Canada (2014); Trautmann et al. (1985) **Pesticides:**Aktar et al. (2009); McLaughlin and Mineau (1995); Piha (2006) **Water management** (drainage, irrigation): Mati (2014) **Land use change:**Galbraith et al. (2005); García-Ruiz (2010); McLaughlin and Mineau (1995)
	Remote sensing and GIS applied to monitoring of the VC indicators (VC monitoring is part of all EIA phases)	**Biodiversity indicators:**Bongaarts (2019); Cavender-Bares et al. (2020); Walters and Scholes (2017); Wang and Gamon (2019) review paper **Water-quality indicators:**Gholizadeh et al. (2016) review paper; Mobley et al. (2004); Simon-Mayer (2020) **Air-quality indicators:**Gupta et al. (2006); Hoff and Christopher (2009) review paper; Song et al. (2021) **Soil-quality indicators:**Ben-Dor (2002); Ge et al. (2011) review paper; Kerr et al. (2012); Mulla (2013); Ahmadi et al. (2021) review paper; Gholizadeh et al. (2018) Review paper **Crop-health, public-health, and climate-change indicators:**Atzberger (2013); Homolová et al. (2013) Review paper; Kross et al. (2020); Shanahan et al. (2001); Weiss et al. (2020) Review paper; Verrelst et al. (2015)
2.1. Determine screening criteria	EIA (and similar) regulations for agriculture	**EC, food and agriculture organization (FAO), Wales, Canada:**EC (2011); FAO (2011); EIA Wales (2017), Agricultural programs and services - agriculture.canada.ca
2.2. Determine suitable remote sensing and GIS data and methods for use in EIA	Remote sensing and GIS applied to the four EIA phases	**Screening and scoping:**Haklay et al. (1998); Jayasinghe and Machida (2008); Kaur et al. (2018); Satapathy et al. (2008); Sholarin and Awange (2015); Statuto et al. (2016); Sharma et al. (2018) review paper; González et al. (2011), Merem et al. (2012) **Impact assessment, prediction and management:**Amdihun (2006); Geneletti (2008); Kaur et al. (2018); Patil et al. (2002); Narumalani et al. (1997); Sharma et al. (2018) review paper; Butt et al. (2015); Kamińska et al. (2004); Paiboonvorachat and Oyana (2011); Tola et al. (2019); Ward et al. (2000)

presented LCA, material flow analysis (MFA) / input-output analysis (IOA), EIA, and ecological footprint (EF) as the most commonly used methods. The study identified EIA as the only direct method to support land use planning decisions, but suggested complementing methods for a full impact assessment (e.g., ecological, economic, and social impact assessment).

EIAs are usually applied to proposed new development projects such as mines, highways, pipelines, or industrial facilities. The nature of agriculture projects, which includes existing farms with many annual activities, may have complicated the use of EIA for this sector. The literature we consulted for this study revealed several countries that established EIA regulations for their agriculture sector, such as the European Community (EC: EC, 2011) and Wales (EIA Wales, 2017*)*. In the EC, environmental assessment regulations came into force in September 2011. They apply to projects that include a restructuring of rural land holdings, commencing intensive agriculture on uncultivated or semi-natural areas, or establishing land drainage works for agriculture. Any project that exceeds a set threshold, is within or near a natural heritage area/protected area, or is predicted to have a significant effect on the environment must undergo an initial screening. If the effects of the project are deemed significant, then the proponent is required to submit an application for consent along with an Environmental Impact Statement (EIS) (EC, 2011). In Wales, EIA Regulations for Agriculture were formulated in 2007 (updated in 2017). The primary objective of the 2017 EIA for Agriculture Regulations is to protect sites with significant ecological and/or historic value from agricultural development work and to preserve Wales' biodiversity and historic landscape for future generations.

The EIA method involves a variety of procedures and approaches from literature analysis and public consultation to land use maps and habitat simulation models (Noble, 2020). The importance of geospatial technologies and geographic information systems (GIS) for EIA has been highlighted since the early 1990s (Antunes et al., 2001; João and Fonseca, 1996; Satapathy et al., 2008). Yet, recent studies have shown that GIS integration in environmental impact assessment is still underdeveloped. Documented studies (mostly case-studies) focus on only one or two of the EIA phases, such as impact assessment (Geneletti, 2008; Patil et al., 2002) and scoping (Haklay et al., 1998). More recent examples (summarized by Sholarin and Awange, 2015) focus on data collection using GPS and the use of GIS multi-criteria analysis in screening, scoping, and impact assessment. A review study on methods for land use impact assessment (Perminova et al., 2016) showed that only about 10% of the reviewed articles used GIS and remote sensing.

Our review highlighted the suitability of the EIA method in combination with geospatial technologies for the assessment of agriculture impacts. Yet, the combined approach has seldom been used for agriculture impact assessments. To support the systematic environmental impact assessment and management of agriculture practices, our study proposes the use of geospatial technologies in combination with the EIA method and impact indicators to assess and monitor agriculture activities and their environmental impacts. The geospatial EIA framework includes four key EIA phases: (1) screening; (2) scoping; (3) impact prediction & assessment; and (4) Impact management, monitoring & follow up (Noble, 2020). The specific objectives of this study are:

1) To determine the key indicators for assessing components of the biophysical environment that are susceptible to impacts from agriculture practices (i.e., valued components, VCs), and to identify the most suitable remote sensing and GIS tools to estimate these indicators.
2) To identify screening criteria for agriculture projects, and to identify and synthesize the most suitable remote sensing and GIS tools for each EIA phase for agriculture projects.
3) To develop a geospatial EIA framework and to exemplify its use through selected examples in Canada.

Impact assessment is a critical step towards the development and implementation of sustainable agriculture practices, and towards the restoration of our natural resources. The proposed framework provides a systematic approach to assess agriculture impacts at flexible spatial and temporal scales and can be used by farmers, farmer advisor groups, as well as local, provincial, and federal agencies.

2. Methods

For this study, we synthesized the findings from EIA regulation documents, governmental reports, and peer–reviewed review papers to integrate EIA, environmental impact indicators, and geospatial data and methods into a framework for the assessment of agriculture projects. Table 1 gives an overview of the consulted literature on:

- Agriculture practices, their impact pathways, the components of the biophysical and human environment that are susceptible to impacts from the practices (i.e., valued components, VCs), and key impact indicators to assess and monitor the VCs.
- Screening criteria for agriculture projects.
- Suitable remote sensing and GIS data and methods for use in the EIA framework (including the assessment of VCs).

The selective review of peer-reviewed review papers was an efficient approach to synthesize the key findings of the many different topics involved in this study.

2.1. Agriculture practices, impact pathways, and key impact indicators

The modification of natural ecosystems to support agriculture production involves many practices that can impact the environment, including but not limited to: tillage, use of fertilizers, pesticides and herbicides, water managements practices (irrigation, drainage), and land use conversion (forest, wetland conversion to agriculture). Valued components (VCs) are components of the biophysical and human environment that are susceptible to impacts from a project activity, and are considered important or highly valued and therefore require evaluation (Noble, 2020). The VCs of the biophysical environment typically include species of concern (i.e., endangered species, threatened species), biodiversity, water and soil quality, topography, and air quality and climate. For the human environment, the VCs typically include attributes of community health, employment, and aboriginal lands.

The VCs can be characterized, assessed, and monitored using VC indicators. Indicator selection depends on the type of study to be conducted, the nature and the scale of assessment, and the available resources (Noble, 2020). In 1993, Agriculture and Agri-Food Canada (AAFC) launched a five-year-long agri-environmental indicator project to develop a set of indicators for studying the changes in the environment due to agriculture practices (McRae, 1994). The indicators would provide sufficient information to stakeholders and decision makers to enable them to make environmentally sound decisions and assess the effectiveness of best management practices and agricultural policies (Appendix: Tables A1 and A2; Clearwater et al., 2016; Reytar et al., 2014). Agri-environmental indicators (AEIs) are defined as a "*measure of a key environmental condition, risk, or change resulting from agriculture, or of management practices used by producers*" (Reytar et al., 2014; Niemeijer and Groot, 2006, p. 91). AAFC's AEI maps are available to the public, but the most recent dataset is from 2016. Very similar indicators are also presented by the EC (Agri-environmental indicators (AEIs) - Agriculture - Eurostat (europa.eu)) and the Organization for Economic Co-operation and Development (Environmental Indicators for Agriculture – Methods and Results (oecd.org)).

Spatial data related to VCs can be collected on the farm (e.g., by using a drone or GPS) or can be obtained from other reliable sources that manage spatially referenced data (e.g., GeoGratis in Canada, OpenTopography, U.S Geological Survey). Satellite and proximal sensing provide satellite or drone images, which combined with other spatial datasets (e.g., elevation, temperature, precipitation) enable continuous assessment and monitoring of the VCs over time and space, locally to globally.

Most satellite image-based approaches use spectral indices, which are combinations of spectral reflectances from two or more wavelength bands that indicate relative abundances of features of interest. Spectral vegetation indices are the most popular ones, but there are other indices for soil, water, built-up areas, and other features of interest (see the index database *https://www.indexdatabase.de/)*. Relationships between satellite-derived data and ground measurements are commonly established through correlations, regressions, classification algorithms, and machine learning methods (e.g., Verrelst et al., 2015).

The present study summarizes the VCs affected by agriculture activities in seven broad groups based on the literature and AAFC AEIs: (1) biodiversity and wildlife habitat quality, (2) soil quality, (3) air quality, (4) water quality, (5) crop health, (6) public health, and (7) climate change. Below follows an overview of geospatial approaches to assess the VCs, with an emphasis on the first five (the synthesis is illustrated in Fig. 1.

2.1.1. Biodiversity and wildlife habitat quality indicators

Biodiversity loss is one of the most alarming global environmental challenges (Bongaarts, 2019; IPBES, 2019). All main agriculture practices have direct or indirect impacts on wildlife habitats and biodiversity. Remote sensing can be used to monitor biodiversity continuously over space and time using methods such as wildlife habitat mapping, species mapping, functional diversity and spectral diversity mapping (Wang and Gamon, 2019). Spectral vegetation indices are at the core of many of these methods including the normalized difference vegetation index (NDVI), simple ratio (SR), enhanced vegetation index (EVI), atmospherically resistant vegetation index (ARVI), chlorophyll vegetation index (CVI), green NDVI (GNDVI), soil adjusted vegetation index (SAVI), normalized difference water index (NDWI), green chromatic coordinate (GCC), excess green index (ExG), modified triangular vegetation index (MTVI), and NDVI red edge (see index database *https://www.indexdatabase.de/* for references). A summary of the geospatial data and methods is presented in the Appendix, Fig. A1.

2.1.2. Water-quality indicators

Water-quality indicators are traditionally determined by laboratory analysis of water samples. Remote sensing studies have frequently used the visible and near infrared bands (mostly from blue to near infrared region) to obtain information about physical and biogeochemical constituents such as transparency, chlorophyll-a (Chl-a), secchi disk depth, temperature, colored dissolved organic matters, total organic carbon, dissolved organic carbon, total suspended matters, turbidity, sea surface salinity, total phosphorus, ortho-phosphate, chemical oxygen demand, biochemical oxygen demand, electrical conductivity, and ammonia nitrogen (reviewed by Gholizadeh et al., 2016). The main indicators related to agriculture practices that can be inferred reliably through remote sensing are temperature and Chl-a, which can indicate the level of eutrophication in a waterbody (Gholizadeh et al., 2016). A summary of the use of satellite images for retrieval of Chl-a (as an indicator of eutrophication among others) and temperature is shown in the Appendix, Fig. A2. Other water quality indicators, such as pesticide and herbicide residuals, total nitrogen, and ammonia nitrogen are more challenging to estimate through imagery due to their weak optical characteristics, low signal-to-noise-ratio, and the need for hyperspectral data (Gholizadeh et al., 2016). These indicators can be mapped through a combination of water samples, laboratory analysis, and geostatistical interpolation.

2.1.3. Air-quality indicators

Similar to temperature and precipitation, air-quality properties are commonly monitored by ground stations. Remote sensing of air pollution can be done using the measurements of pollution in the troposphere (MOPITT) sensor, which provides carbon monoxide concentrations profiles at a $\sim$ 22 km spatial resolution along with other atmospheric measurements such as surface temperature and atmospheric moisture.

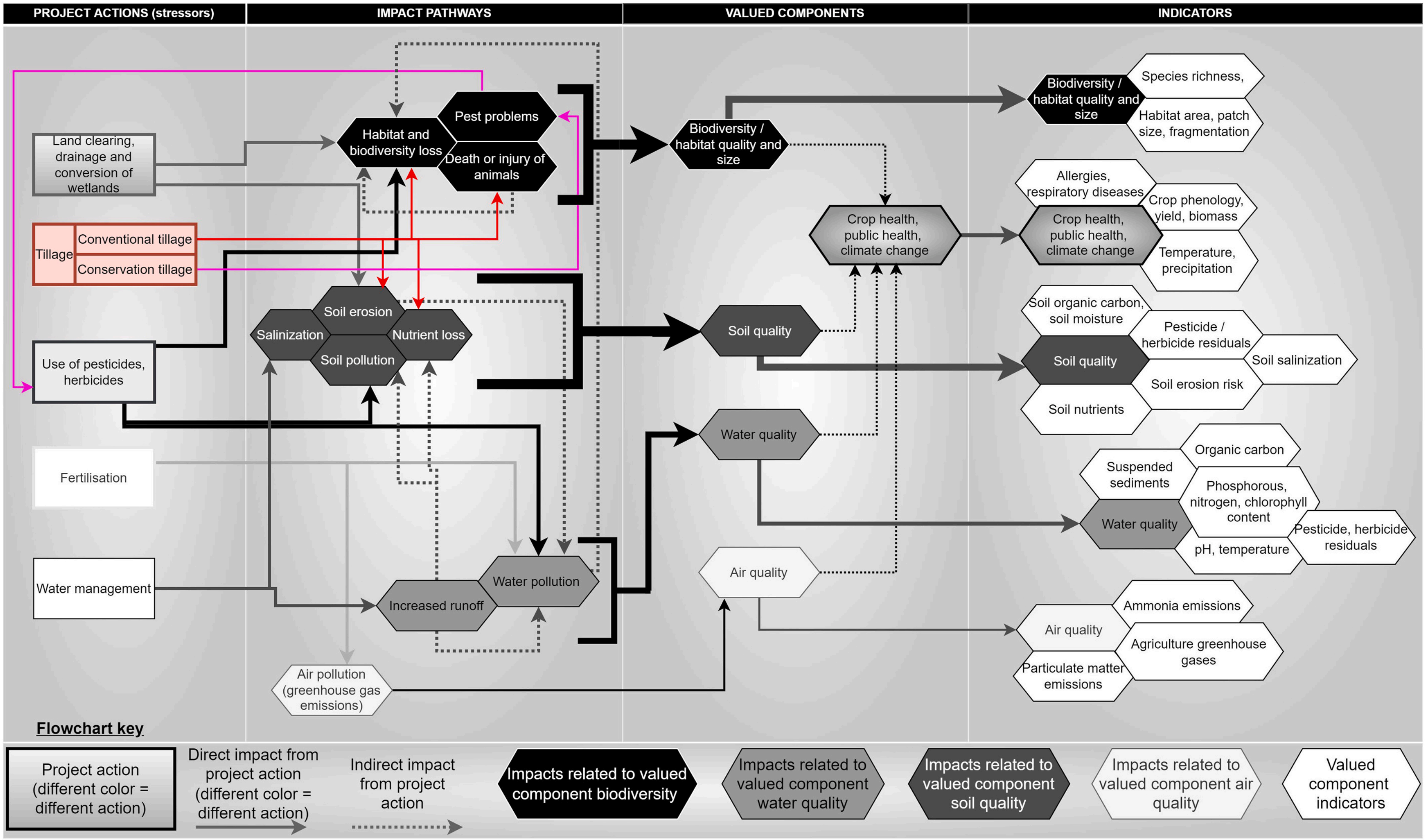

Fig. 1. A simplified summary of agriculture practices (stressors) with their impact (effect) pathways, valued components, and indicators. In the "project actions" column, the number of arrows leaving the action box indicates the number of environmental impact pathways from that action. Solid arrow lines indicate direct impacts; dashed arrow lines indicate indirect impacts. Tillage, for example, has direct effects on soil and biodiversity, and indirect effects on water quality. In the "Impact Pathways" column, the number of arrows entering the impact boxes indicates the number of practices that cause an impact. For example, wildlife habitat and biodiversity loss is the most affected valued component (VC) with potential impacts from all the practices presented in this summary, either directly or indirectly. The "Valued components" column summarizes the impacts for each of the broad VC groups. The thickness of the arrows indicates the combined effect of project actions and effect pathways on the VCs. The four VCs combined can impact crop health, public health, and the climate. The "Indicators" column gives an overview of suggested indicators for each of the VC groups.

The moderate resolution imaging spectro-radiometer (MODIS) provides measurements of ozone and aerosols at a spatial resolution between 250 m and 1000 m globally. MODIS aerosol optical thickness (AOT) and Aerosol optical depth (AOD) have shown strong relationships with PM2.5. Yet, the AOT is affected by the aerosol concentrations, ambient relative humidity, fractional cloud cover, and height of the mixing layer (Gupta et al., 2006; Hoff and Christopher, 2009). The relationship between satellite data and ground measurements was established through linear regressions and machine learning (random forest) (Gupta et al., 2006; Hoff and Christopher, 2009; Song et al., 2021). The MODIS sensor is most commonly used for air pollution studies, but there are many other potential sensors (reviewed by Hoff and Christopher, 2009). However, the spatial resolution of most these datasets would limit their practical use for mapping detailed variations over smaller areas. For greenhouse gas (GHG) monitoring (specifically methane), there is currently a high spatial resolution (25 m) satellite sensor from GHGSat (*https://www.ghgsat.com/*). Examples of air pollution related maps are shown in the Appendix (Maps A1 and A2).

Environment and Climate Change Canada (ECCC) maintains the Canadian Air and Precipitation Network (CAPMoN), which measures atmospheric pollutants in the air and in precipitation. The National Air Pollution Surveillance (NAPS*)* provides additional data on air quality across Canada. Air pollutants that are monitored include: carbon monoxide, nitrogen dioxide, nitric oxide, nitrogen oxides, ozone, Sulphur dioxide, particulate matter $\leq$ 2.5 (PM2.5) and 10 μm (PM10). These programs provide temporally continuous high-quality point data. Farms or farm regions that are not near the stations will not be able to benefit from the programs, but could use local ground sensors in combination with data from the air pollution stations and geostatistical interpolation methods to create continuous spatial datasets.

2.1.4. Soil-quality indicators

Soil-quality indicators are traditionally determined by laboratory analysis of soil samples and include physical (e.g., soil structure and macropores, bulk density, infiltration), chemical (e.g., phosphorus, reactive carbon, soil electrical conductivity, soil nitrate, soil pH) and biological indicators (e.g., organic matter, earth worms) (Soil Quality Indicator Sheets, n.d). Soil properties are often difficult to assess using remote sensing due to the complexity of soil components and overlapping spectral signatures (Ben-Dor, 2002; Ge et al., 2011) and the presence of vegetation (Gholizadeh et al., 2018). The mid-infrared and thermal-infrared regions show fundamental soil absorption features, but the combination of fundamental features affects the spectral signatures in the visible and near infrared regions, making these regions useful for estimating soil components. For salinity, however, due to its complex nature, it was suggested to use the entire spectral region to evaluate salinity levels in different environments and unknown soil systems (Ben-Dor, 2002). Suggested spectral indices of soil salinity include the normalized difference salinity index (NDSI, which is based on bands in the shortwave infra-red region) and the simple ratio salinity index (SI, which is based on bands in the shortwave infrared range; see references in the index database *https://www.indexdatabase.de/*). The use of the entire reflectance spectra was also suggested for the estimation of soil contaminants such as potential toxic elements and petroleum hydrocarbons (Gholizadeh et al., 2018).

To relate spectral reflectance data (determined in the laboratory using a benchtop spectrometer or determined by hyperspectral field or satellite sensors) and chemical/physical soil properties (determined in laboratory), studies have suggested the use of multiple regression analysis, principal component regression, and partial least square regression (Ge et al., 2011; Ahmadi et al., 2021).

One soil indicator related to agriculture practices that can be inferred reliably through remote sensing is soil moisture. Microwave data, specifically the L-band, have shown potential for soil moisture retrieval. Soil moisture products are produced globally based on the soil moisture and ocean salinity (SMOS) sensor and the soil moisture active and passive (SMAP) sensor (Kerr et al., 2012). Other soil properties such as soil organic carbon, total nitrogen, soil organic matter, total carbon, inorganic and texture have also been estimated using visible and near infrared reflectance in combination with soil samples and machine learning and statistical methods (Ahmadi et al., 2021).

In mixed soil-vegetation landscapes, a combination of soil samples and geostatistical interpolation methods can be used to create soil property maps.

2.1.5. Crop-health, public-health, and climate-change indicators

Indicators of crop health, public health, and climate change can be considered end-point impact indicators as they represent the combined effects of all the VCs. Crop health can be reliably estimated through remote sensing using specifically the visible, near-infrared, red-edge, mid-infrared, and/or thermal bands. Numerous spectral vegetation indices have been developed to study vegetation health (see references in the index database *https://www.indexdatabase.de/*). A summary of the data and methods for remote sensing of vegetation is presented in the Appendix, Fig. A3 (e.g., Homolová et al., 2013; Weiss et al., 2020).

Public-health data can be collected from government health agencies and can be summarized for geographic units (census tracts, cities, districts, agriculture ecumenes, etc.). Thematic maps or heat maps can be used to show spatial occurrences and relations (e.g., see data from the world Health Oranization: GIS, geospatial solutions for health, Geographic Information System, Storymap, GIS Center (who.int). In Canada, the main federal resources provide data at provincial, health-region, and census-metropolitan scales (e.g., Public Health Infobase | Public Health Agency of Canada, Access Data and Reports | CIHI, and Health Research Data: Resources – CIHR (cihr-irsc.gc.ca), but provincial sources may provide data at local scales.

Temperature data can be obtained directly from satellite images (MODIS and Landsat). Temperature and precipitation data are available from national weather stations and can be used in combination with geostatistical interpolation models to create continuous temperature and precipitation spatial datasets.

2.2. Suitable remote sensing and GIS tools for the impact assessment of agriculture

The most suitable remote sensing and GIS tools are synthesized for the four key EIA phases: screening; scoping; impact prediction & assessment; and impact management, monitoring & follow up.

2.2.1. Screening criteria for agriculture projects

The first phase of the EIA method is the screening phase, which determines whether a project needs an environmental assessment or not. It usually results in a decision about the requirement of a full EIA, a limited EIA (preliminary assessment or further analysis), or no EIA (Noble, 2020). We used the EIA regulations from the EC, Food and Agriculture Organization (FAO), and Wales to propose agriculture projects that would require an assessment.

We define agriculture projects as farming operations that change the way land is farmed so that it is used more intensively, or that change the species composition (and biodiversity) of the surface vegetation over the longer term (FAO, 2011; EC, 2011; and EIA Wales, 2017). FAO's EIA guidelines (FAO, 2011) classify agriculture projects into three categories with regard to their environmental and social impacts: A) Projects with significant, or irreversible adverse impacts (requiring mandatory EIA); B) Projects with less significant adverse impacts which may be easily mitigated or prevented (requiring EIA to identify and manage the negative impacts); and C) Projects with minimal or no adverse impacts (no EIA required). The main difference between categories A and B is the magnitude of the operations. Category A projects include large-scale land use change (conversion of forests and wetlands), large-scale shifts to intensive production technologies, and drainage and irrigation projects. Category B includes small- and medium-scale land use change and

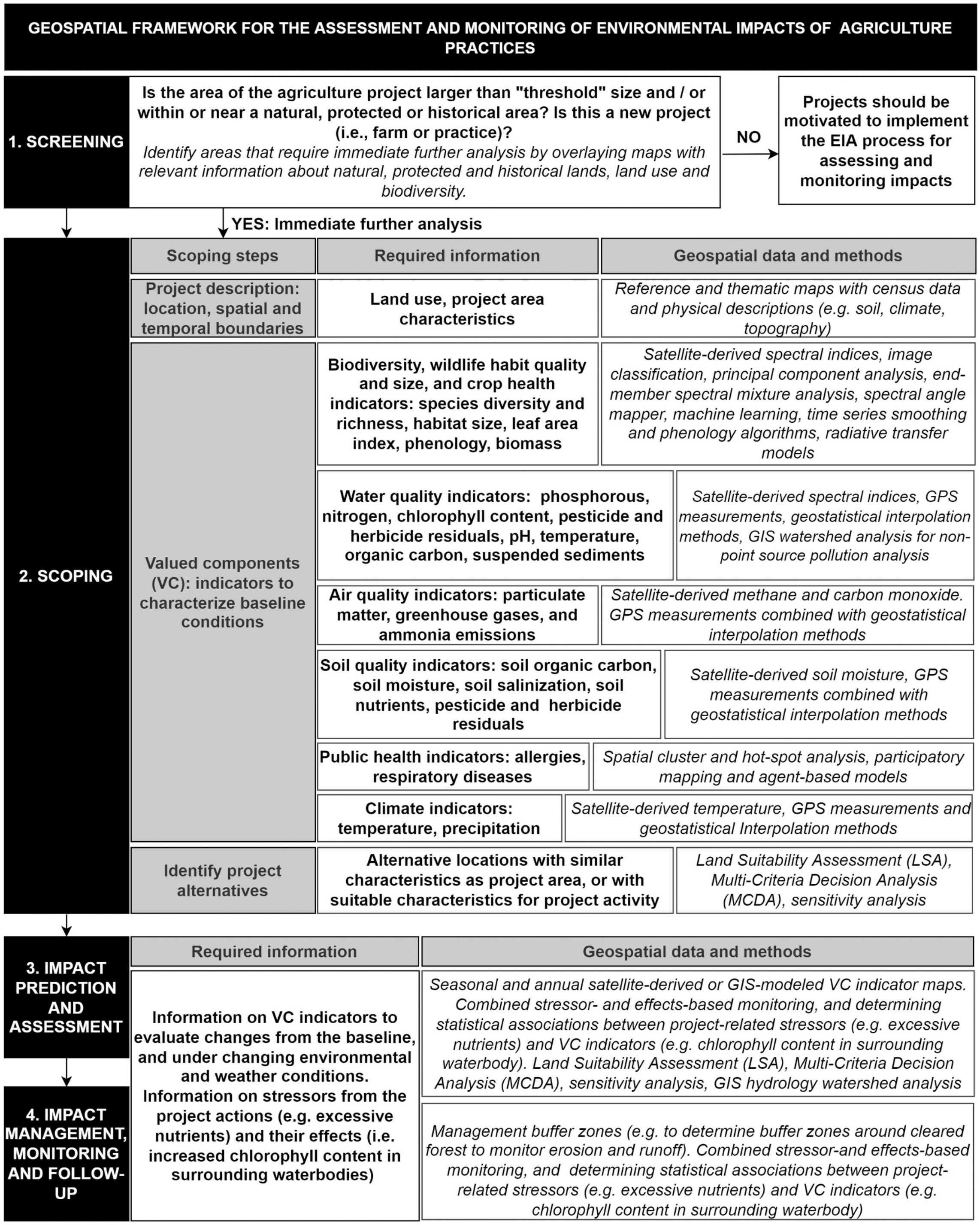

Fig. 2. Proposed geospatial EIA framework for the assessment of agriculture projects (for more details, see Appendix, Table A3).

practice shifts. Category C projects include agriculture research and training projects.

FAO does not specify area thresholds to differentiate large-scale operations from medium- and small-scale operations (they use budget thresholds); yet, the EC EIA regulations (and the one from Wales) give an indication of thresholds for projects that require a full EIA vs. projects that require a limited EIA or further analysis to identify negative impacts. Restructuring of rural land holdings (field boundary removal, re-contouring, land restructuring) above 2 ha, new agriculture projects (that will commence to use uncultivated or semi-natural land for agriculture development) above 5 ha, and land drainage works above 15 ha need further analysis to identify the magnitude of the impacts and to determine the need for a full EIA. New agriculture projects and land-drainage works above 50 ha or re-contouring above 5 ha need a full EIA. Projects that are smaller than the thresholds indicated above would not need an EIA. Yet, when a project is located within a natural reserve, a protected area, or a historical area, a limited EIA is required independently of the size of the project. Projects located on grassland (or other vegetation) that has been established for more than 5 years (e.g., permanent pasture) or land that is semi natural (includes less than 25% of improved agricultural species like perennial ryegrass or white clover) also require a limited EIA.

Table 2
Summary of most recent key AAFC initiatives to support sustainable agriculture in Canada.

Program or policy name	Purpose	Active period
Environmental Farm Plan (EFP)	A voluntary risk assessment program through which farmers and land managers can identify the environmental risks associated with their farm operations and develop plans to mitigate them. Program was developed in Ontario in 1993, and is federally supported and promoted since 2005 (AAFC, 2009).	2005 – ongoing
Growing Forward 1 (GF1) Growing Forward 2 (GF2)	Programs to support a profitable and innovative agriculture, agri-food and agri-based products industry with three strategic outcomes: 1) a competitive and innovative sector; 2) a sector that contributes to society's priorities (includes the promotion of environmentally responsible agriculture); 3) a sector that is proactive in managing risks (AAFC, n.d.; AAFC, 2017; Miller, 2012).	2008–2013 2013–2018
Canadian Agriculture Partnership (CAP)	Programs to support: 1) growing trade and expanding markets; 2) innovative and sustainable growth; 3) diversity and a dynamic, evolving sector (McCormick, n.d.; CAP, n.d.).	2018–2023
AAFC Departmental Sustainable Development Strategy (DSDS)	The DSDS presents AAFC's commitments to support the sustainable development goals of the Federal Sustainable Development Act (FSDA, S.C.2008, c. 33) though three goals: (1) effective action on climate change (includes the living laboratories stream, on-farm climate action stream and the agriculture greenhouse gases programs); (2) greening government; (3) sustainable food (includes research on environmental impacts of agriculture and use of agri-environmental indicators) (DSDS, n. d.).	2020–2023
Next Policy Framework (NFP)	The government is currently preparing for the NFP for agriculture, which will replace the CAP.	2023–2028

For specific sub programs, see https://agriculture.canada.ca/en/agricultural-programs-and-services#dataset-filter, filter by "Sustainable farming" and "Innovation, research and development".

The main data used in screening are land use plans and field surveys (Noble, 2015). GIS and remote sensing can be used to create land use maps to determine land use class areas, proportions, and changes over time and space. Wales, for example, requires an EIA if the vegetation of the area to be converted to cropland has been established for more than 5 years. Google Earth Pro's historical timeline can be used to provide a snapshot of land-cover and land use changes for this purpose. Land-cover maps can be created based on free (e.g., MODIS, Landsat, Sentinel) and commercial satellite images (e.g., Planet, Ikonos) using image classification methods (e.g., maximum likelihood, clustering, object based, machine learning). Existing regional to global land-cover maps (e.g., MODIS land cover maps, EC landcover maps) can also be used, but would need ground validation of the classes.

In conclusion, key screening criteria include: the size of the project, and the location of the project in relation to natural reserves, protected areas, or historical areas. Examples of agriculture projects include: land preparation (e.g., plowing, tilling, or harrowing), land drainage or irrigation, or the use of herbicides, pesticides, or fertilizers.

2.2.2. Scoping

Scoping is a critical early phase of an EIA process. Its purpose is to identify the major issues and impacts related to the proposed project. The scoping phase directly focuses on the EIA process and places limits on the information to be collected and analyzed (Noble, 2020, Canadian Environmental Assessment Agency[1]). A scoping process gives information about: (1) the proposed activity, (2) the environmental baseline, and (3) the project alternatives.

2.2.2.1. Proposed activity. This step provides information about the location and spatial and temporal boundaries of the project, and provides a physical description of site. The physical description typically includes information about soils, topography, drainage, vegetation, wildlife, temperature, precipitation, land use, biodiversity, utilities, roads, features of historic importance, existence of nearby properties that could be adversely affected. GIS can provide a visual representation of the project location (Satapathy et al., 2008). Reference and thematic maps provide an overview of the location and attributes of the study area where different features can be properly labeled and color-coded. This is likely the most common use of GIS in EIA projects (González et al., 2011). For example, in a study on the contribution of farming activities to climate change in Mississippi, researchers used existing resource and land-cover maps to determine spatial (state level of Mississippi) and temporal (1992–2002) boundaries (Merem et al., 2012). The spatial boundaries should also include adjacent areas based on the sensitivity of the receiving environment. For example, if there is a waterbody near the project location, it is important to include it in the spatial boundaries to evaluate eutrophication risks. In the absence of existing spatial data for the project, satellite images from free and commercial sensors can be used to show the biophysical characteristics of the location and the spatial and temporal boundaries of the study area.

2.2.2.2. Baseline assessment. The baseline assessment involves the selection of VCs to be included in the assessment, and the assessment of the condition and changes in the VCs. There are many potential VCs and related indicators (Fig. 1). The baseline assessment determines on which key VCs the EIA should focus. For example, if an agriculture project is to implement an irrigation system, a key VC may be soil quality, and a key VC indicator may be soil salinization. Monitoring and interpretation of baseline data can help in observing the current environmental condition of an area against which future impacts can be determined. Baseline data can also be used to study the changes that may have occurred due to activities in the past years. For example, in 2016, a study revealed how agricultural land use changes in the last century have impacted the rural environment in southern Italy, in the Basilicata region (Statuto et al., 2016). The study was carried out over a period of 179 years (for 1829, 1876, 1955 and 2008). Historical hand-drawn maps were scanned, imported into a GIS system and georeferenced. Researchers were able to evaluate the agricultural impacts on the forest ecosystem from 1829 to 2008. Baseline conditions of the VCs can be determined through GPS point sampling alone or in combination with geostatistical interpolation methods to create continuous spatial datasets. Satellite images can be used to create continuous VC datasets (as described in section 2.1.).

2.2.2.3. Project alternatives. This step entails identifying project alternatives and determining their feasibility (Satapathy et al., 2008). Alternatives can be determined for demand (e.g., improving food distribution vs. increasing production), input or supply, for activities, locations, or processes.[2] Location alternatives can be determined using a

[1] http://publications.gc.ca/collections/collection_2010/ec/En106-88-2010-eng.pdf
[2] https://unep.ch/etb/publications/EIAman/SecETopic5.pdf

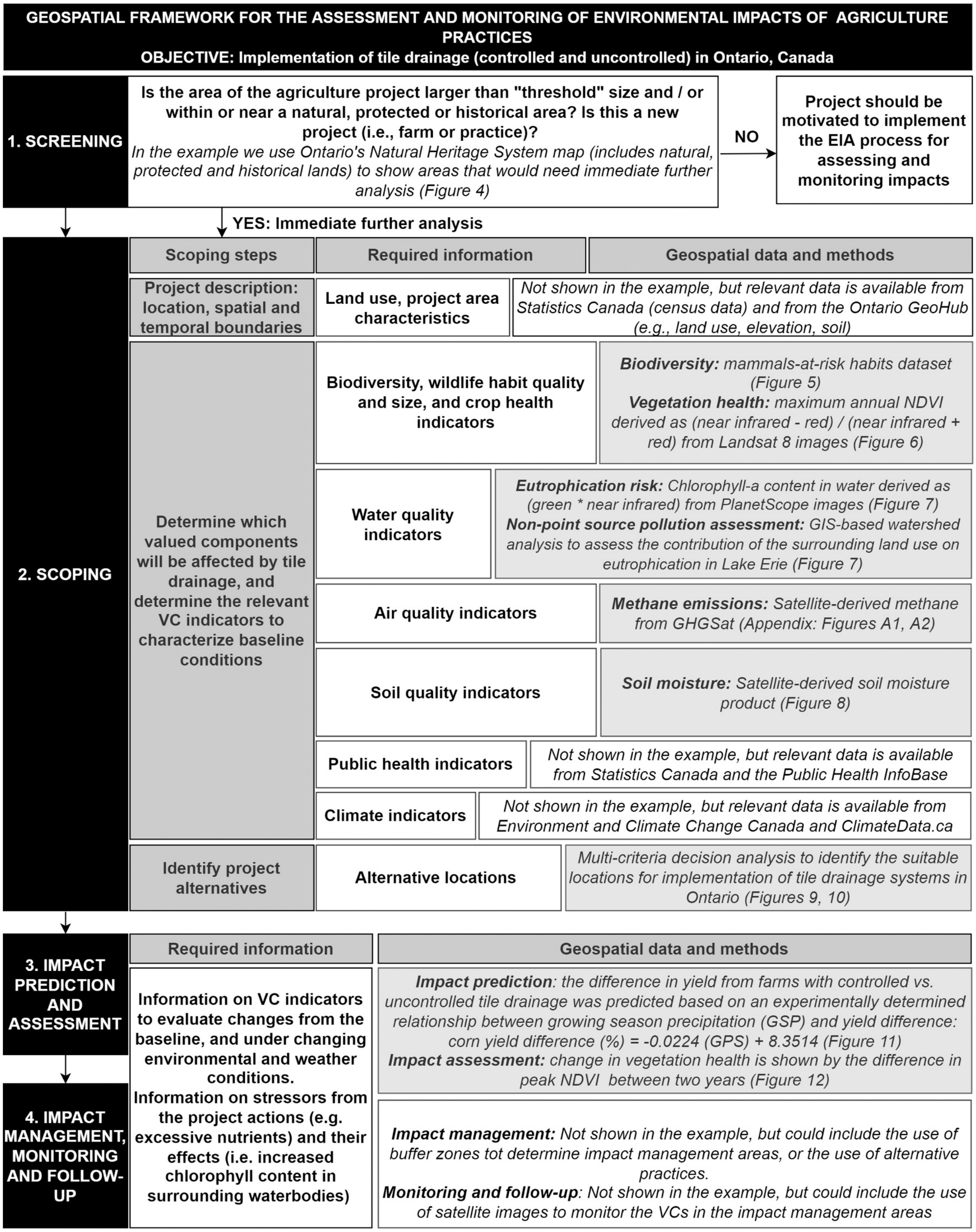

Fig. 3. Flowchart illustrating the application of the framework. Examples related to this application are shown in Figs. 4 to 12.

Land Suitability Assessment (LSA) or a Multi-Criteria Decision Analysis (MCDA). These methods include selecting different criteria, assigning weights to them, and combining them to identify the best location for the project (Abdelkawy et al., 2010). For example, LSA has been used to determine areas suitable for tomato and cabbage cultivation in several districts in Sri Lanka (Jayasinghe and Machida, 2008). The criteria included soil type, topography, rainfall, temperature, and land use. Using LSA, the authors were able to obtain and classify areas that were highly suitable, moderately suitable, marginally suitable, or not suitable for the cultivation of tomatoes and cabbage.

2.2.3. *Impact prediction and assessment*

Impact assessment entails predicting and assessing the potential environmental impacts resulting from the proposed project (Noble, 2020). GIS can be used to overlay spatial datasets such as VC indicators, water bodies, urban areas, and pollutant distributions. LSA, MCDA, and sensitivity analysis can be used to characterize, predict, and assess the impacts associated to agriculture activities. A review of the use of big GIS analytics in agriculture by Sharma et al. (2018) identified an increasing use of MCDA-based prescriptive analytics in all domains of agriculture. While the most common application was for land use suitability analysis, MCDA methods have a great potential for impact

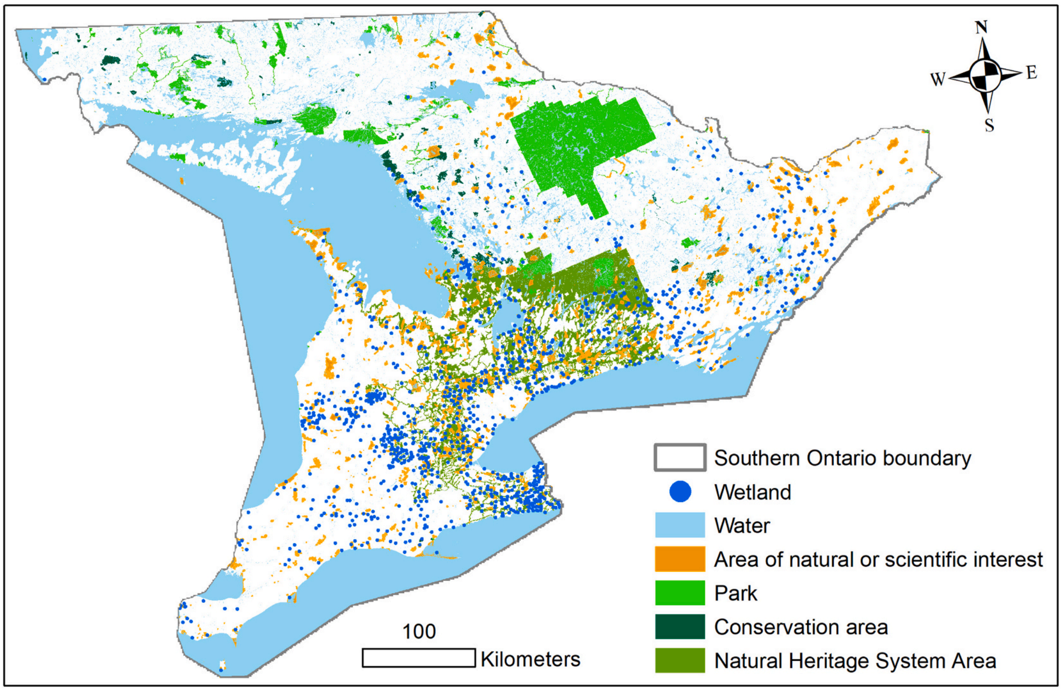

Fig. 4. Natural, protected, and heritage areas in Southern Ontario.
Data source: *https://geohub.lio.gov.on.ca/*

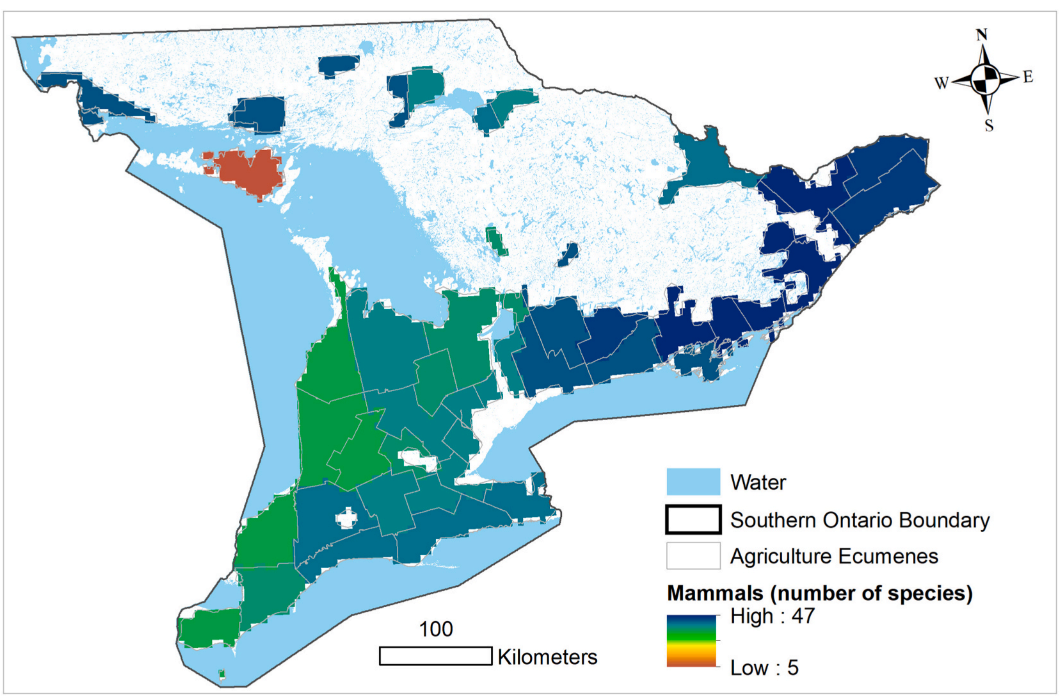

Fig. 5. Illustration of the distribution of international union for conservation of nature (IUCN) mammal species at risk in Ontario.
The map shows the distribution of species in Census subdivisions within Agriculture ecumenes. The highest distribution areas correspond with agriculture lands in Southern Ontario.
Data sources: *https://www150.statcan.gc.ca/n1/pub/92-639-x/92-639-x2011001-eng.htm*; International Union for Conservation of Nature (IUCN): *https://www.iucnredlist.org/;https://www.iucnredlist.org/resources/spatial-data-download*

assessment analysis (Sharma et al., 2018).

In Thailand, for example, researchers used a combination of classification algorithms and the MCDA method to evaluate the impacts of land use change on soil erosion in the Nan watershed, between 1995 and 2005 (Paiboonvorachat and Oyana, 2011). They used Landsat 5 data and the supervised maximum likelihood classification (MLC) algorithm to classify the images, followed by an MCDA analysis with the following factors: slope (derived from DEM data), land use (from the classified satellite images), rainfall (interpolated with the Thiessen polygon method from rainfall weather stations), and soil parent material (data

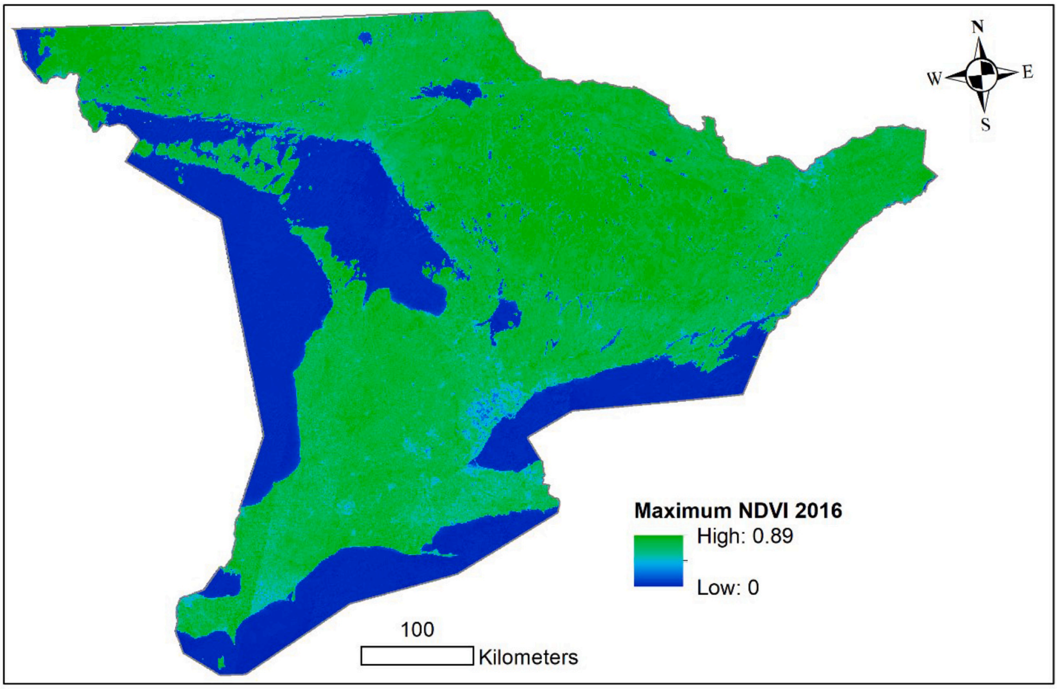

Fig. 6. Peak annual NDVI for 2016.
Annual peak NDVI values were calculated from Landsat 8 images in the Google Earth Engine (GEE) platform.
Data source: Landsat 8, https://code.earthengine.google.com/

from FAO). The MCDA used the weighted linear combination approach to combine the layers. The study showed an increase in croplands, paddy fields, and open-canopy forests at the loss of closed-canopy forests. Soil-erosion risk was highest in the areas where forests changed to agricultural lands. Another study on land use change impacts used data from Landsat 5 and SPOT 5 and the MLC algorithm to create land use maps. The objective of the research was to predict the impacts of land use changes between 1992 and 2012 in the Simly watershed in Pakistan (Butt et al., 2015). The study identified a large increase in agriculture land use (163.7%) posing serious threats to watershed resources. The long-term impact of tillage practices on soil organic carbon was assessed using multivariate regression models that were developed from the NDVI, the bare soil index (BSI), and field collected soil organic carbon (Tola et al., 2019). The study was conducted in Saudi Arabia between 1990 and 2016. The results demonstrated a decrease in soil organic carbon between 1990 and 2000 when conventional tillage was the predominant practice; and an increase in SOC at the end of the study period, when conservation tillage was the predominant practice in the fields. Similarly to the tillage assessment, researchers in Western Ethiopia used satellite-derived vegetation indices to assess the impact of the Finchaa irrigation project on vegetation. They predicted a decline in natural vegetation due to the increase in agricultural activities (Amdihun, 2006).

While land use change, tillage, and irrigation practices have direct impacts on the environment, pesticide pollution has direct impacts on both the environment and public health. A study by Kamińska et al. (2004) showed the importance of geospatial technologies for the management of public health related to pesticide pollution. Ward et al. (2000) used historical agriculture crop data and pesticide and herbicide application rate estimates to characterize the spatial relationship between pesticides and herbicides, and the locations of non-Hodgkin lymphoma patients in Nebraska, USA. Their results demonstrated the potential of GIS for the identification of residential zones at risk of exposure to agricultural pesticides.

2.2.4. *Impact management, monitoring and follow up*

Impact management involves developing management strategies and mitigating the impacts resulting from the proposed project (Noble, 2020). Buffer zones can be used to determine impact-management areas after the activity is implemented. For example, Narumalani et al. (1997) determined buffer zones around the Iowa River basin to prevent non-point-source pollution from agricultural activities. The researchers used satellite images to identify and characterize the land cover and used spatial techniques to develop buffer zones around the various land-cover types.

Monitoring and follow-up include monitoring of the effects of the mitigation measures proposed and implemented (Noble, 2020). Satellite data and remote sensing can be used for the monitoring of environmental conditions after the implementation of mitigation measures as they provide good visual differences between before and after conditions. The relevant VCs can be monitored across the farm or farm regions, including potential buffer areas defined by the impact management step.

3. Proposed geospatial framework for the assessment of agriculture projects

Based on the review of geospatial methods used in EIA, and for monitoring of agri-environmental indicators, we propose the following geospatial framework for agriculture projects (Fig. 2). More details and suggested spatial datasets are shown in Table A3 in the Appendix.

4. Example application of the framework in Ontario, Canada

To demonstrate the application of the framework, we present selected examples of data and maps for the assessment of an agriculture project in Southern Ontario, Canada. The agriculture and agri-food sector (i.e., primary agriculture, food and beverage processors, food retailers, food service providers) is a major contributor to the economy in Canada, generating around 7.4% of Canada's gross domestic product (GDP) (AAFC, 2020). The primary agriculture industry (within the

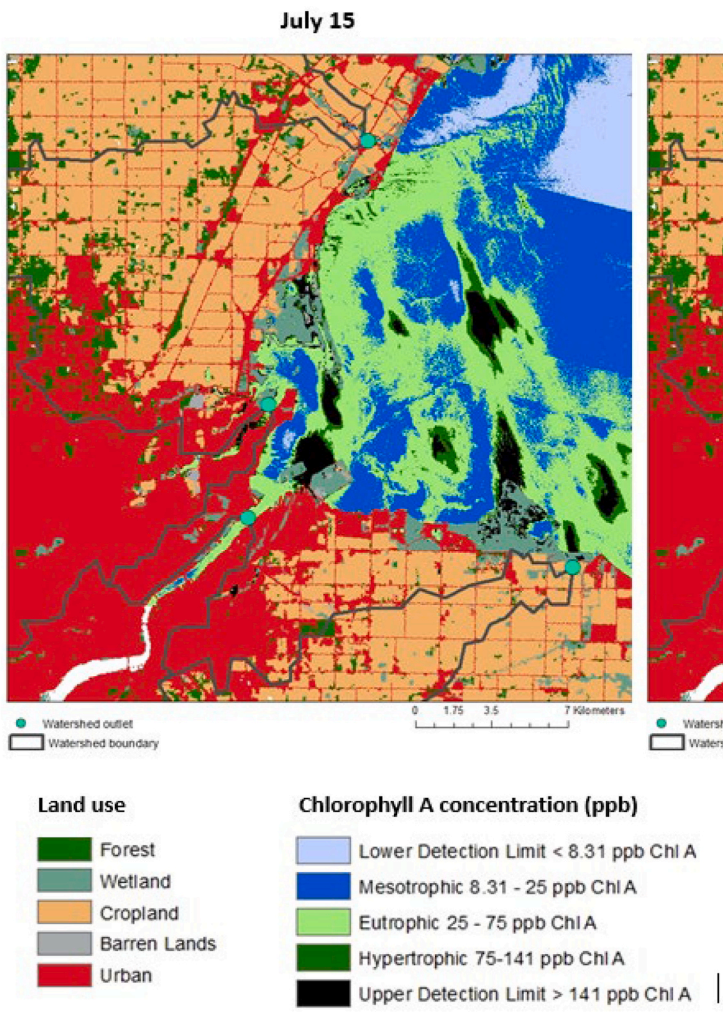

Fig. 7. Illustration of satellite-derived Chl-a in lake Erie (July 15 and 26, 2019).
The Chl-a values were classified based on the level of eutrophication. Chl-a concentrations were estimated through the relationship established between ground measured Chl-a and a satellite-derived spectral index (product of Green and NIR band reflectances derived from Planetscope satellite, https://www.planet.com/products/monitoring/). Source: Simon-Mayer (2020).

boundaries of a farm, nursery, or greenhouse) accounted for around 2.1% of the GDP (AAFC, 2020). Ontario accounted for the largest share (33.3%) of the combined GDP of primary agriculture and food and beverage processing ($47.2 billion) and was also the major employer in the two industries (32.6%).

In spite of the country's relatively large land area, farms cover only around 69 million hectares or 6.9% of Canada's land area. Factors such as adverse climate conditions, low soil fertility, and topography make a large proportion (about 93%) of the country's land area unsuitable for agricultural purposes (AAFC, 2006, 2016). The continuity of the Canadian agricultural system depends on the protection and environmentally responsible modification of the remaining natural ecosystems and the continuous sustainable use of existing arable lands.

In Canada, EIA is regulated by the Impact Assessment Act (IAA, 2019), but agriculture projects are not subjected to environmental assessment under this act. Environmentally responsible agriculture is promoted by AAFC in collaboration with provincial and territorial governments, through different federal initiatives summarized in Table 2.

The agriculture project assessed in this example is subsurface tile drainage. Subsurface tile drainage is a water management practice that forms an integral and important part of crop production in Canada. Tile-drainage systems are commonly categorized into controlled tile drainage (CTD) and uncontrolled tile drainage (UCTD). Fig. 3 gives a schematic overview of the four phases of this assessment at a regional scale. Examples illustrating the framework are centered on Southern Ontario, and were either created for this paper (based on available geospatial data) or were examples or results from our previous work.

4.1. Screening

Spatial datasets of the study area, protected lands, natural reserves, historical areas, wetlands or water bodies can be obtained through municipal, provincial, and federal platforms (e.g., Open Data Canada, *https://open.canada.ca/en/open-data,https://geohub.lio.gov.on.ca/)*. Fig. 4 shows the locations of protected, natural, and heritage areas in Southern Ontario. Based on the location and the size of a drainage project, this map could be used to determine the need for an assessment. Note that the threshold size mentioned in the application flowchart should be determined. As a reference, the EC EIA uses a threshold of 15 ha for further analysis and 50 ha for a full assessment (for drainage). Smaller areas do not need an assessment unless located in a natural, protected, or heritage area.

4.2. Scoping

4.2.1. Determine relevant VC indicators

The first step in this phase is to determine the VCs that can be

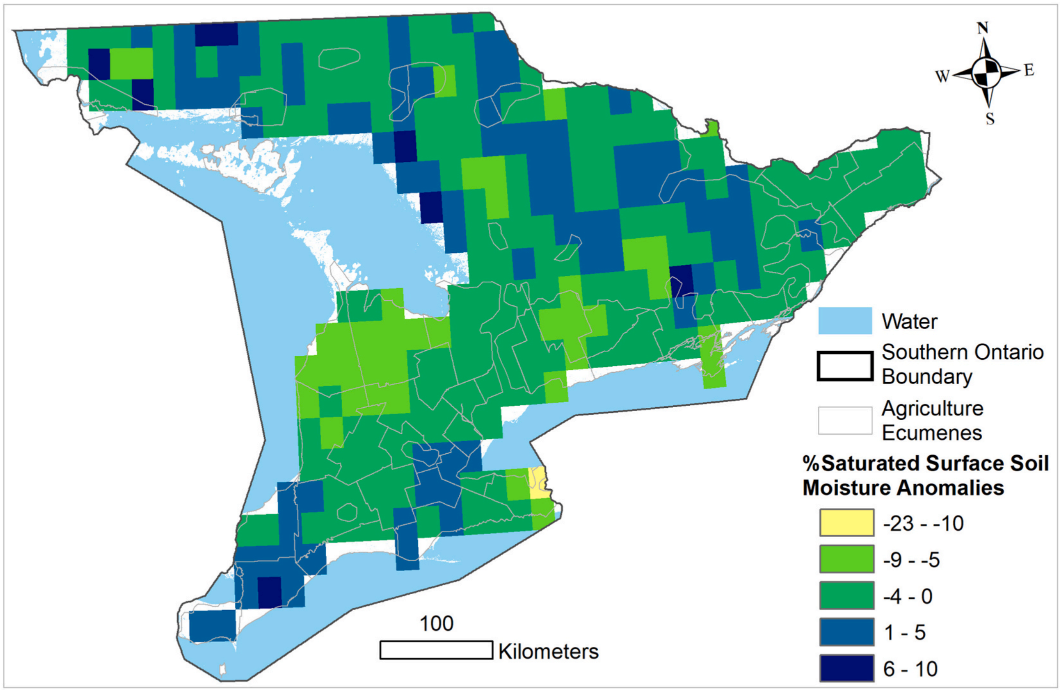

Fig. 8. Illustration of the percentage of saturated surface soil moisture anomalies in the month of June 2021.
Positive (negative) values indicate areas with higher (lower) soil moisture compared to the long-term monthly average.
Data source: *Percent Saturated Surface Soil Moisture - Open Government Portal (canada.ca)*.

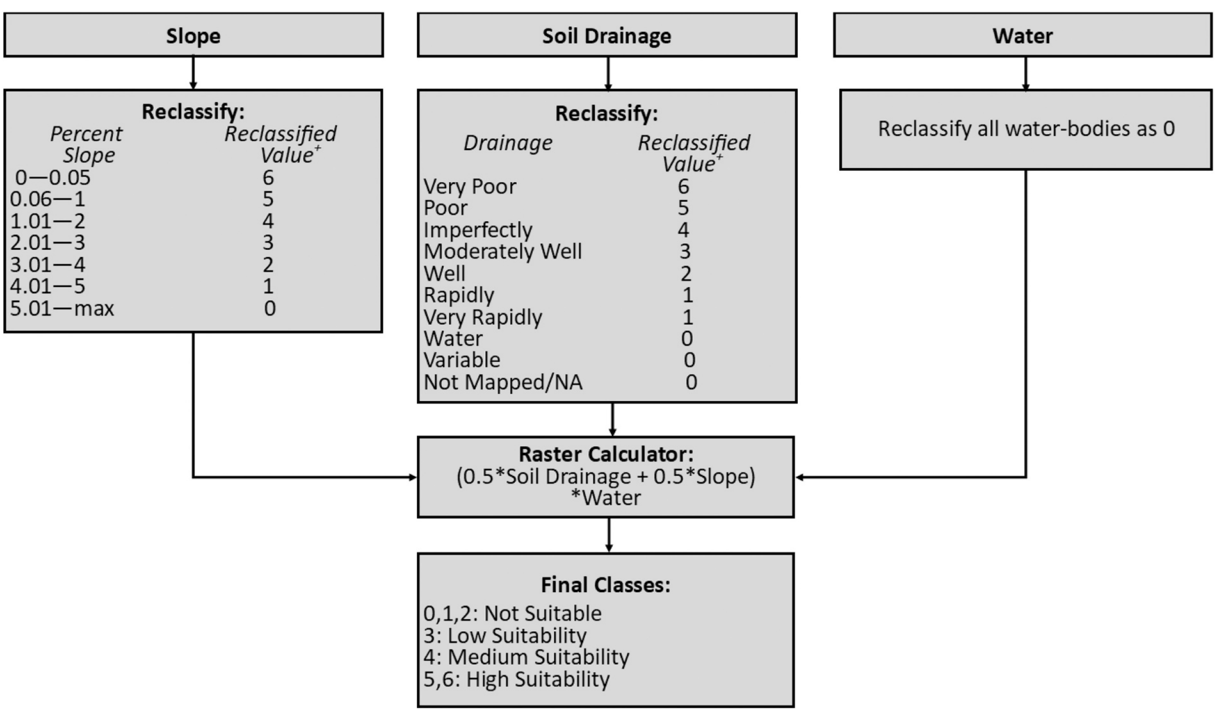

Fig. 9. Illustration of the MCDA method used to determine potential sites for the implementation of tile drainage systems. "0" represents least suitable, "6" represents most suitable for tile drainage. Details about the method are given in Kaur et al. (2018).

impacted by the proposed activity (i.e. tile drainage). We used Fig. 1 to determine the VCs and the relevant VC indicators: biodiversity (example VC indicator is species-at-risk richness), crop and vegetation health (example VC indicator is the NDVI), water quality (example VC indicator is Chl-a content), soil quality (example VC indicator is soil moisture), and public health (no example shown). Figs. 5 to 7 show examples of the selected VC indicators.

4.2.1.1. Biodiversity and wildlife-habitat-quality indicator. Fig. 5 illustrates mammals-at-risk habitats in Ontario and can be used as a baseline to assess the impacts of agriculture activities on biodiversity.

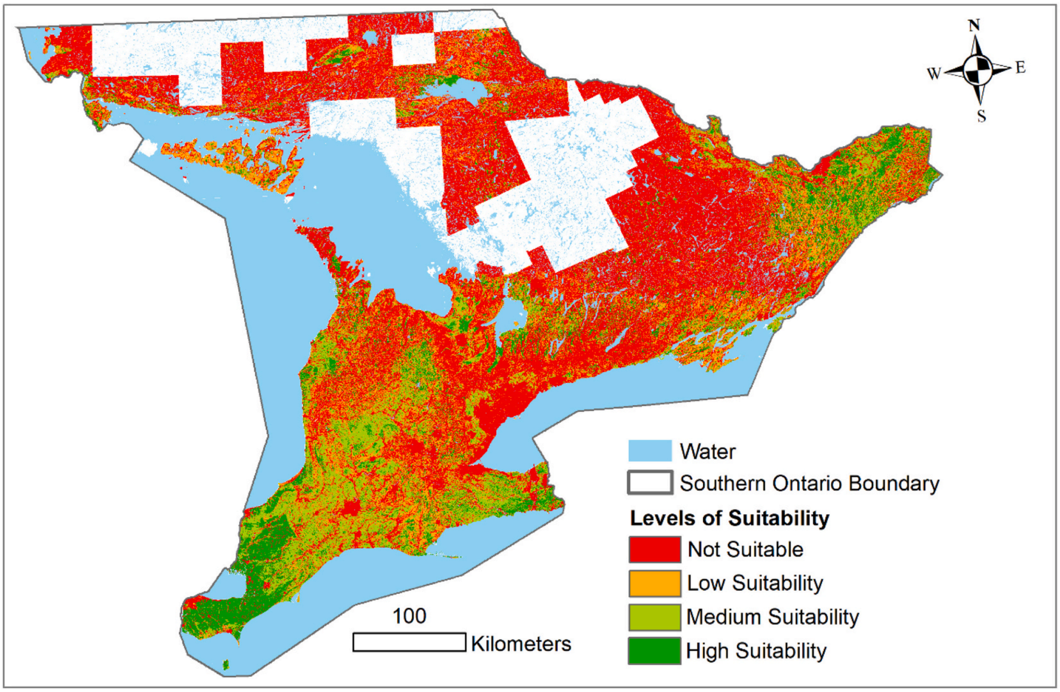

Fig. 10. Map of potential areas with varying levels of suitability for the installation of tile drainage systems in Ontario.
Source: Kaur et al. (2018)

4.2.1.2. Crop-health indicator. Seasonal peak NDVI can be used as an indirect indicator of water and soil quality (measured through plant development) and a direct indicator of vegetation health (Fig. 6).

4.2.1.3. Water-quality indicator. The example in Fig. 7 shows satellite –derived Chl-a content in Lake Erie. A watershed analysis was also used to determine non-point-source areas of contribution, and the dominant land use types within those areas. The two images illustrate the levels and growth of eutrophication in July 2019 (Simon-Mayer, 2020).

4.2.1.4. Soil-quality indicator. The example in Fig. 8 shows satellite-derived percent saturated surface-soil moisture across Southern Ontario.

4.2.2. Identification of project alternatives

GIS-based MCDA can be used for the identification of alternative locations. Kaur et al. (2018) used this method to identify alternative locations for the implementation of tile drainage in Ontario (Fig. 9).

Soil drainage and slope were selected as two main factors considered for tile implementation. One of the most important variables influencing plant growth is the soil's drainage capacity, which can be determined by its texture. Soil data were reclassified to rank the soils with very poor drainage as “Most Suitable” and the soils that drain rapidly as “Least Suitable”. Slope was the second factor. Artificial drainage systems are considered more suitable for flat surfaces as they do not drain easily as compared to steep slopes (Cooke et al., 2008). Various studies have suggested installation of tile drainage in fields with slopes ranging from 0 to 4% and sometimes from 0 to 6% (AAFM, 2017; Franzmeier et al., 2001). Therefore, fields with slope below 5% were considered as “Most Suitable”, whereas fields with slopes above 5% were ranked as “Least Suitable”. Water was considered as a constraint and all water bodies were classified as zero. The two factors (soil and slope, with equal weight of 50%) and the constraint (water) were combined to obtain final sites ranging from “Not Suitable” to “Highly Suitable” (Fig. 10).

4.3. Impact prediction and assessment

Project impacts can be predicted by regression models as is shown in Fig. 11. Kaur et al. (2018) predicted crop yield percentage differences for an average (2006, 308 mm), wet (2008, 386 mm) and dry (2007, 255 mm) year to illustrate the extent of the response of two crops to two tile-drainage systems (CTD and UCTD) under varying precipitation conditions. Geostatistical interpolation served to create continuous precipitation datasets for Ontario based on point data from weather stations. Linear regressions between growing season rainfall and yield difference (yield from CTD fields minus yield from UCTD fields) were established and used in a sensitivity analysis to evaluate the impact of normal, wetter, or drier years on the yield, which represented the VC of this study. Corn development responded well to the CTD system, especially in dry years. Soybean did not show a strong response to the system (results not shown here).

Impacts caused by the project can be assessed based on changes in the VC indicators (Fig. 12).

5. Limitations and recommendations

5.1. Challenges and limitations

From basic mapping to more advanced spatial models, it is important to acknowledge the following challenges and limitations of their use for EIA:

1. Not all critical VC indicators can be obtained from GIS and remote sensing data. Some of the critical soil and water properties, for example, are challenging to estimate from satellite images. As an alternative, spatial interpolation methods can be used in combination with ground-collected data or other sources, like statistical summaries. It is thus important to determine the right VC indicators (for the project purpose and scale) and to determine suitable data collection methods (GIS or other) early in the process.
2. In spatial analyses, the scale of the study is often determined by the available datasets. Data at coarser resolution are usually more readily available than data at higher resolution. Therefore, for assessments at the farm level, the collection of appropriate data should be carefully planned.

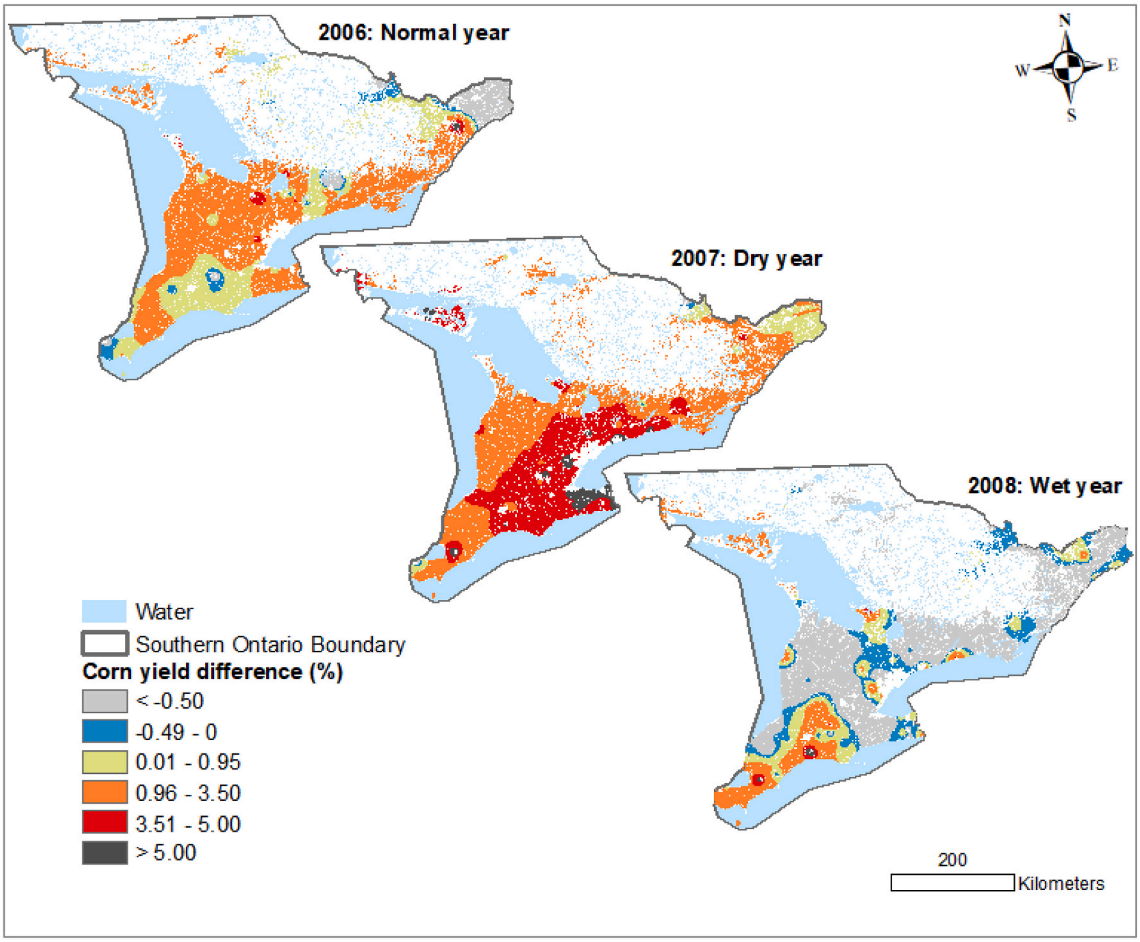

Fig. 11. Maps depicting spatial clusters of predicted yield difference percentage for corn in 2006 (normal year), 2007 (dry year) and 2008 (wet year) in Southern Ontario.
Source: Kaur et al. (2018)
Negative yield difference % values indicate lower yields for corn fields under CTD management, positive values indicate higher yields for corn fields under CTD management. The study was conducted for rainfall ranging between 150 mm and 400 mm. Beyond this rainfall range, interpretation of the results should be done with caution.

3. The temporal coverage of the data is also determined by the available datasets. Datasets should be carefully screened for their acquisition or creation dates, as outdated information can lead to incorrect results.
4. With regard to air pollution, satellites provide a snapshot in time and do not provide information on the movement of pollution. Daily data are available but at coarse resolution.

5.2. General recommendations

The following recommendations should also be considered to improve the accuracy of the spatial analysis:

1. Spatial data management and metadata documentation should be planned and maintained from the start of the project.
2. An appropriate projected coordinate system should be chosen for the project and all datasets should be projected or georeferenced to this coordinate system.
3. The use of remote sensing models (e.g., spectral indices, spatial interpolation) requires proper calibration and validation. Common difference statistics can be used for validation purposes including the root mean squared error (RMSE) and the mean absolute error (MAE). The collection of validation data should be carefully planned.
4. Agriculture practices can be a source of point-source pollution (e.g., loss of biodiversity in the farm area due to the direct application of herbicides) and non-point-source pollution (e.g., runoff can flush pesticides and fertilizers from farm fields). VC indicators related to point-source pollution can be estimated directly through satellite derived spectral indices, like the loss of natural vegetation or biodiversity within the farm area or region, but it is more challenging to attribute changes in VC indicators related to non-point-source pollution, like changes in chlorophyll content in waterbodies surrounding the farms. However, GIS-based hydrology analyses can be used to determine risk areas of high flow accumulation within the basin or watershed of the farm. MCDA can also be used for this type of analysis as was shown by Yaghi & Salim (2017a), who used GIS and remote sensing to produce a surface water pollution risk map for the Al-Abrash coastal basin in Syria based on a suite of datasets: slope gradient, slope length, soil type, soil depth, land use, fertilizers, pesticides, rainfall, and distance from drainage.
5. Finally, the present study focused mainly on the impacts of agriculture activities on the biophysical environment, but participatory mapping and agent-based models are suitable GIS approaches that can be used for assessing the impacts on the human environment.

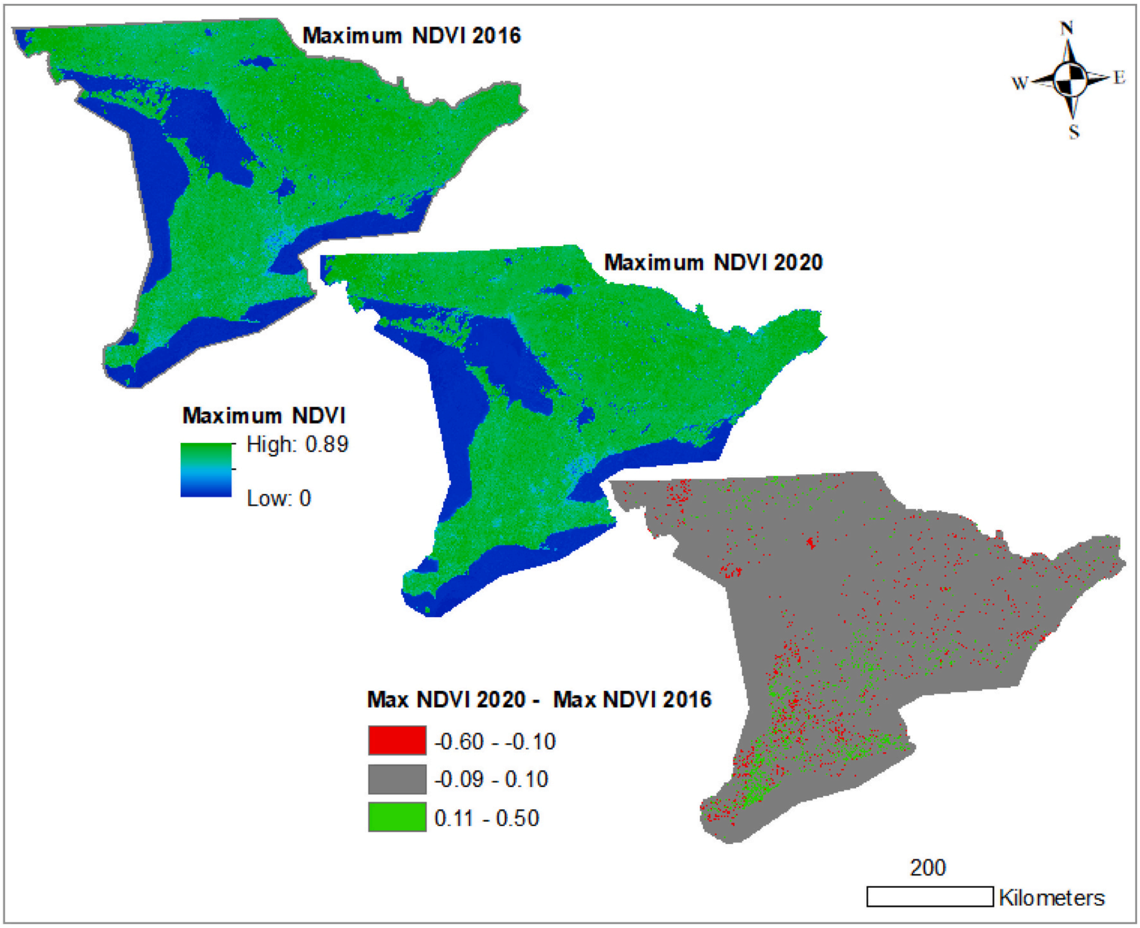

Fig. 12. Peak NDVI maps for 2016 and 2020, and the change between the two years.
We can create a change map by subtracting the 2016 data from the 2020 data. In the difference map, negative values (red) indicate a loss in vegetation health or amount in 2020 compared to 2016; positive values (green) indicate an increase in vegetation health or in vegetation amount in 2020. The grey color indicates no change between 2016 and 2020.
Data source: Landsat 8, https://code.earthengine.google.com/

5.3. Recommendations related to the framework application example

While agriculture activities are not subjected to an EIA under the impact assessment act in Canada, sustainable agriculture practices and strategies have been promoted and implemented by AAFC in collaboration with provincial and territorial governments and organizations. The key programs that are related to our proposed EIA framework are summarized in Fig. 13.

The living laboratories, on-farm climate action, and agriculture greenhouse program will support the development of sustainable practices or beneficial management practices (BMPs) and will support farmers with the development and implementation of their EFPs (in collaboration with available financing programs).

The AEIs of AAFC will provide information to farmers related to the sustainable status of the larger region (soil landscape polygon scale) that includes their farm and the changes over time. The latest publicly available AEI dataset is from 2016, but AAFC is predicting the production of this indicator at higher spatial and temporal resolutions.

The proposed geospatial EIA framework integrates information from the EFPs and AEIs with the advantage that it can perform the impact assessment process at flexible spatial (pixel-based) and temporal scales (daily to annual), depending on the resolution of the input data.

6. Conclusions

Increasing demands for global food supply and the problems associated with food wastage and proper food distribution have led to agricultural intensification on existing farms and formation of new farms with technological advancements. Any new conventional agriculture project would require clearing and preparing of land including practices such as tilling, plowing, and harrowing. New or existing agriculture project would require the use of fertilizers and or herbicides, the establishment of an appropriate drainage system if needed and construction of farm infrastructures. These activities have resulted in ongoing depletion of natural resources.

The proposed EIA framework with its four phases can be used to assess any newly proposed agriculture project, the screening criteria described in section 2.1 can be used to guide the selection of projects that need more active monitoring. For existing farms, the framework can also be conducted to assess the impacts associated with annual practices, or for new agricultural practices before they are implemented (for example the installation of irrigation or drainage systems).

This study presents a synthesis of suitable geospatial data and methods for the systematic assessment and monitoring of environmental impacts of agriculture practices based on the EIA method. The review shows that remote sensing and GIS methods - especially interpolation, spectral indices, image classification, multi-criteria analysis, GIS

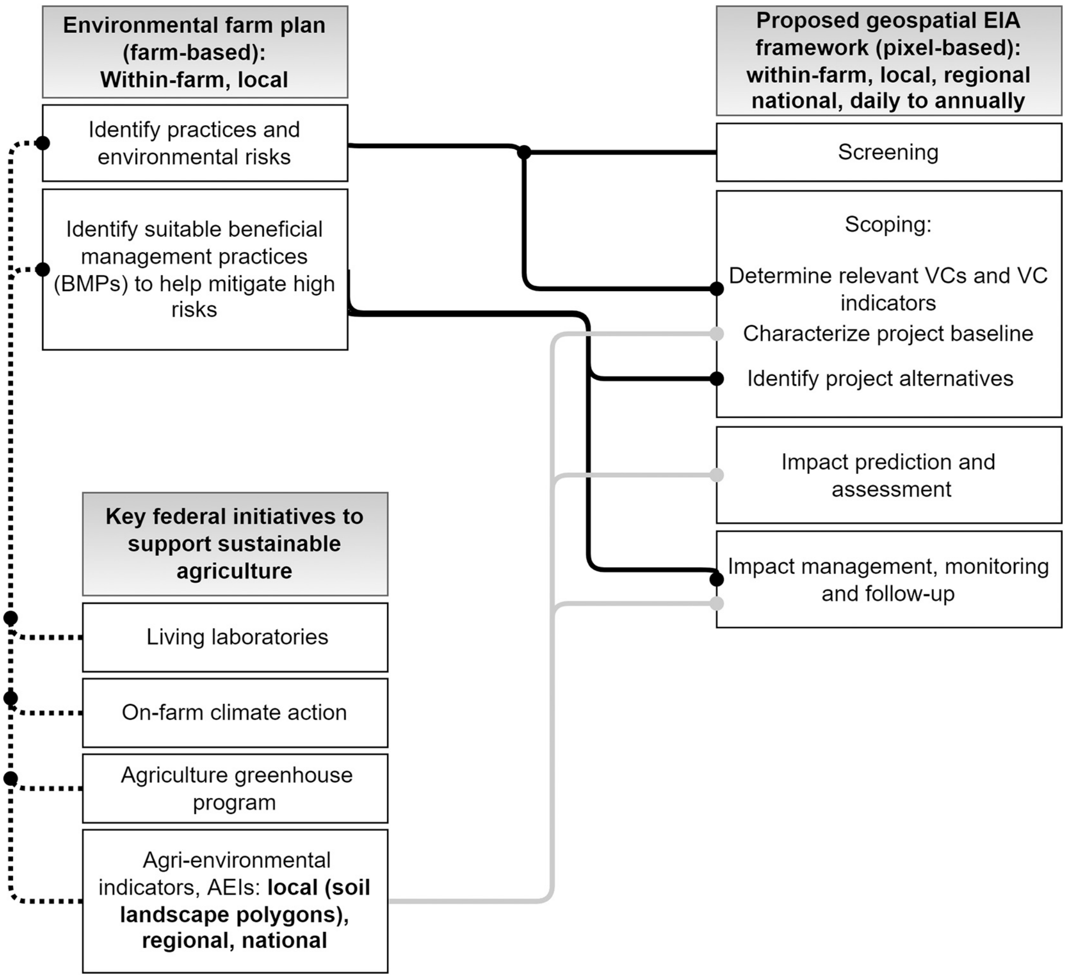

Fig. 13. Schematic overview of the proposed geospatial EIA framework and its relation with the key programs from AAFC: the environmental farm plan, living laboratories, on-farm climate action, agriculture greenhouse program and agri-environmental indicators. Different arrow colors and lines are used to differentiate the relationships between the three blocks.

watershed analysis, and sensitivity analysis - can play an important role in scoping (baseline characterization) and impact assessment. Mapping tools can be used in all phases of the EIA process and web mapping can be used to share the data and results with different stakeholders. The results from this study can support farmers, farmer organizations, environmental agencies, and government agencies in the monitoring of agriculture impacts at flexible spatial (pixel-based) and temporal scales (daily to annual), depending on the resolution of the input data.

For Canada, this framework could be used to integrate existing programs from AAFC, such as environmental farm plans and agri-environmental indicators.

Future research should focus on: (1) the evaluation of spectral indices for identification of the most suitable ones for each VC indicator; (2) the development of VC indicator thresholds to classify the impacts on the valued components; (3) the evaluation and development of stressor – effect models to predict impacts spatially.

Declaration of Competing Interest

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Appendix

Table A1. Agri-environmental performance indicators.

Category	Group	Indicators
Driving Force	Economic and social	Market Demand Population Globalization Status of Beneficial Management Practices Buyer demands for sustainable attributes Government Policies in Canada and International initiatives Farm financial resources Technological change
	Environmental	Climate change Agricultural Land Use
State	Farmland Management	Farm Environmental Management Soil Cover Wildlife Habitat Capacity on farmland
	Soil Quality	Soil Erosion Risk Soil Organic Carbon Soil Salinization
	Water Quality	Residual Soil Nitrogen Risk of Water Contamination by Nitrogen Risk of Water Contamination by Phosphorus Risk of Water Contamination by Coliforms Risk of Water Contamination by Pesticides
	Air Quality and GHG Emissions	Agricultural Greenhouse Gases Ammonia Emissions Particulate Matter Emissions
Response		Greenhouse Gas Emission Intensities of Agricultural Products Integrated Economic and Environmental Modelling – Linking Science to Policy

Source: McRae (1994)

Table A2. Summary of the agri-environmental performance in Canada between 1981 and 2011 (based on the AEI indicators).

Category	Group	Indicators	Findings
Driving Force	Economic and social	Market Demand Population Globalization Status of Beneficial Management Practices Buyer demands for sustainable attributes Government Policies in Canada and International initiatives Farm financial resources	There has been a considerable increase in global demand for food due to increase in population, higher life expectancies, higher income and food wastage leading to agricultural intensification using advanced technology. Impacts of this intensification can be managed by implementing beneficial Management Practices. Government policies such as Pest Control Products Act, Montreal protocol help in managing agriculture impacts.
		Technological change	In addition, awareness among consumers and buyers has also brought attention towards consuming more environmentally sound products.
	Environmental	Climate change	Fluctuations in temperature can greatly alter the crop production. Increase in temperature and growing season has allowed the expansion of agriculture in northerly regions of Ontario and Quebec.
		Agricultural Land Use	There has been a decrease in summer fallow due to increase in reduced till and no-till. Farmland has been consolidated into fewer farms with increased production intensity on the consolidated farms.
State	Farmland Management	Farm Environmental Management	Positive adoption of nutrient management practices such as nutrient testing, application, and incorporation of fertilizer in the form of soil and liquid manure.
		Soil Cover	It has increased from poor in 1981 to moderate in 2011.
		Wildlife Habitat Capacity on farmland	Wildlife habitat capacity has decreased since 1986, mainly due to intensification of farming.
	Soil Quality	Soil Erosion Risk	The risk of soil erosion has declined due to adoption of reduced tillage, no-till.
		Soil Organic Carbon	The content of soil organic carbon has increased from 1981 to 2011.
		Soil Salinization	There has been a decline in the risk of soil salinity due to tillage practices.
	Water Quality	Residual Soil Nitrogen	Due to the increase in fertilizer use across the country, the residual soil nitrogen has increased since 1981.
		Risk of Water Contamination by Nitrogen	The risk of water contamination by nitrogen was low.
		Risk of Water Contamination by Phosphorus	The risk of water contamination by phosphorus has drastically increased since 1981 mainly due to the increase in use of mineral fertilizers.
		Risk of Water Contamination by Coliforms	The risk of water contamination by coliforms is low but still has deteriorated slighting since 1981 due to concentrated livestock production.
		Risk of Water Contamination by Pesticides	There has been an increase in the risk of water contamination by pesticides since 1981.

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Category	Group	Indicators	Findings
Response	Air Quality and Greenhouse Gas Emissions	Agricultural Greenhouse Gases	Due to improvement in production efficiency and enhanced carbon storage capacity of soils, the greenhouse gas emissions from agricultural activities have remained relatively constant since 1981.
		Ammonia Emissions	There has been an increase in ammonia emissions since 1981.
		Particulate Matter Emissions	There has been a drastic reduction in particulate emissions since 1981 due to adoption of reduced and no till. Initiate research into on farm practices to reduce emissions.
		Greenhouse Gas Emission Intensities of Agricultural Products	Use tools such as Unified Livestock Industry and Crop Emissions Estimation System (ULICEES) calculator and the Canadian Food Carbon Footprint calculator (Cafoo) to get information about emissions.
		Integrated Economic and Environmental Modelling – Linking Science to Policy	Canadian Regional Agriculture Model (CRAM)-AEI model: Can estimate change in resource use based on changes in market conditions. It has been used to estimates changes in emissions due to change in land use. Implementation of programs such as Growing Forward 2.

Source: Clearwater et al. (2016).

Table A3. Geospatial EIA framework for the assessment and monitoring of environmental impacts of agriculture projects.

EIA Key Phases	Steps	Required data	Commonly used data and methods	Geospatial methods	Suggested spatial datasets
1. Screening		Land use, land cover (class, area, proportion, changes). Natural reserves, protected areas, historical areas, aboriginal lands	Land use plans, field surveys	Satellite image classification, Google Earth Pro historical timeline, field survey, GPS data collection, Land use maps	**Satellite images***, **land cover** (e.g. https://esa-worldcover.org/en, ESA CCI Land cover website (esa-landcover-cci.org), National Land Cover Database | U.S. Geological Survey (usgs.gov)), **spatial datasets****,
2. Scoping	Project description: location, Spatial and temporal boundaries	Census data, historic records, land use	Land use plans, field surveys	Digital reference and thematic maps with census data and physical descriptions (e.g., soil, climate, topography, etc.)	**protected areas** (e.g. https://www.lioapplications.lrc.gov.on.ca/Natural_Heritage/index.html?viewer=Natural_Heritage.Natural_Heritage&locale=en-CA), **topography** (e.g Home | OpenTopography, GeoGratis / GéoGratis)
	Identify valued components (VC) and VC indicators to characterize baseline conditions	Wildlife habitat area and size, species diversity and richness, plant functional traits (e.g. leaf area index, phenology, biomass)	Species population models, habitat simulation modelling, ecological risk assessment, biological assessments, crop models, vegetation production models	Satellite-derived spectral indices, image classification, principal component analysis, end member spectral mixture analysis, spectral angle mapper, machine learning, time-series smoothing and phenology algorithms, radiative transfer models	**Species data** (https://www.iucnredlist.org/resources/spatial-data-download)), **plant trait data** (https://www/try-db.org/TryWeb/Home.php), **biodiversity data** (Mapping the World's Biodiversity (biodiversitymapping.org), UN Biodiversity Lab, GBIF) **Satellite images***
		Water quality: phosphorous, nitrogen, chlorophyll *a*, pesticide and herbicide residuals, pH, temperature, organic carbon, suspended sediments	Waste load allocations, statistical and hydrological models, water usage and allocation studies	Satellite-derived spectral indices, GPS measurement, geostatistical Interpolation methods, GIS watershed analysis for non-point source pollution analysis	GEMStat - The global water quality database, HABs Monitoring: NOAA Great Lakes Environmental Research Laboratory - Ann Arbor, MI, USA, Freshwater quality monitoring: online data - Canada.ca
		Air quality: greenhouse gases, particulate matter, and ammonia emission	Dispersion modelling (eg. Gaussian Dispersion model), box models, air quality indices, monitoring from analogues	GPS measurements, geostatistical interpolation methods, satellite derived products methane and carbon monoxide	Air pollution (who.int), GHGSat - https://www.ghgsat.com/, https://data.ec.gc.ca/data/air/monitor/networks-and-studies/canadian-air-and-precipitation-monitoring-network-capmon/; https://www.canada.ca/en/environment-climate-change/services/air-pollution/monitoring-networks-data/national-atmospheric-chemistry-database/data.html;https://www.ghgsat.com/, https://data-donnees.ec.gc.ca/data/air/monitor/national-air-pollution-surveillance-naps-program/?lang=en)
		Soil quality: soil organic carbon, salinity, soil moisture, soil nutrients,	Pollution source surveys, mixing models, flow and transport models, soils and	Satellite-derived spectral indices, GPS measurement,	Soil Geographic Databases | ISRIC, Global Soil Organic Carbon on Cropland | CIAT (cgiar.org),

(*continued on next page*)

(*continued*)

EIA Key Phases	Steps	Required data	Commonly used data and methods	Geospatial methods	Suggested spatial datasets
		pesticide and herbicide residuals	groundwater vulnerability indices	geostatistical Interpolation methods	NASA-USDA Global Soil Moisture Data | Earth, Soil moisture gridded data from 1978 to present (copernicus.eu), (Percent Saturated Surface Soil Moisture - Open Government Portal (canada.ca)
		Public health: socio-demographic and health records, allergies and respiratory diseases	Social: demographic models, participatory mapping, health-based risk assessment, intention surveys Economic: economic multipliers (eg. Keynesian multipliers), total economic productivity models, input-output analysis, Monte Carlo analysis Cultural: traditional knowledge, participatory mapping, community dialogues, analogue techniques	Spatial cluster and hot-spot analysis, participatory mapping, agent-based models	World Health Organization: GIS, geospatial solutions for health, Geographic Information System, Storymap, GIS Center (who.int), Public Health Infobase | Public Health Agency of Canada, Access Data and Reports | CIHI, and Health Research Data: Resources – CIHR (cihr-irsc.gc.ca). Census Canada data.
		Climate: temperature, precipitation	Weather station climate measurements	GPS measurements, geostatistical interpolation methods, satellite derived temperature	http://climate.weather.gc.ca, Climate Data Canada, Maps & Data | NOAAClimate.gov, GPM - Global Precipitation Measurement | NASA (continuation of TRMM program), High-resolution gridded datasets (uea.ac.uk)
	Identify project alternatives	Alternative locations with similar characteristics as project area, or with suitable characteristics for project activity	Contingent ranking and valuation, cost-benefit analysis, decision trees, life-cycle assessment, linear programming, expert systems, moment estimation methods, paired comparisons, weighted scoring, social choice theory, queuing models	Land Suitability Assessment (LSA), Multi-Criteria Decision Analysis (MCDA), sensitivity analysis.	
3. Impact prediction & assessment		Information on VC indicator to evaluate changes from the baseline and under changing environmental or climate conditions. Information on stressors from the project actions (e.g., excessive nutrients) and their effects (i.e. increased chlorophyll content in surrounding waterbodies)	Technical approaches: fixed-point scoring, rating approach, paired comparisons, etc. Collaborative approaches: open houses, community forums, interactive web based forums, key informant interviews, community and regional profiling, rapid rural appraisal, etc. Reasoned argumentation: decision support aids, matrices, network diagrams, etc. Composite approaches: public consultation methods, land use plans, local social methods, literature analysis, case study reviews, etc.	Seasonal and annual satellite derived or GIS-modelled VC indicators maps. Combined stressor-and effects-based monitoring (e.g., statistical associations between project-related stressors and VC indicators). Land Suitability Assessment (LSA), Multi-criteria decision analysis (MCDA), sensitivity analysis, GIS hydrology watershed analysis.	
4. Impact management, monitoring and follow-up			Land use maps, VC indicator maps, impact prediction maps, environmental management systems as per ISO standards, environmental protection plans, impact benefit agreements	Management buffer zones (e.g., to determine buffer zones around cleared forest to mitigate and manage erosion and runoff). Combined stressor-and effects-based monitoring (eg. statistical associations between VC indicators and stressors)	

* Satellite images: https://glovis.usgs.gov/ GloVis - Home (usgs.gov), https://earthexplorer.usgs.gov/ EarthExplorer (usgs.gov), https://code.earthengine.google.com/, https://neo.gsfc.nasa.gov/ NASA Earth Observations (NEO), https://terra.ipums.org/ Integrated Population and Environmental Data | IPUMS Terra, https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/home FAO https://scihub.copernicus.eu/dhus/#/home Map Catalog.

** Spatial datasets: https://hub.arcgis.com/search ArcGIS Hub, Natural Earth (naturalearthdata.com), https://sedac.ciesin.columbia.edu/ Socioeconomic Data and Applications Center | SEDAC (columbia.edu), https://www.unep.org/publications-data Publications & Data (unep.org), Global Map data archives (globalmaps.github.io), https://openlandmap.org, https://open.canada.ca/en/open-data, Canadian Open Data and Free Geospatial Data (canadiangis.com), https://www150.statcan.gc.ca/n1/pub/92-639-x/92-639-x2011001-eng.htm; Land Cover Products (nrcan.gc.ca), https://gdg.sc.egov.usda.gov/ USDA:NRCS:Geospatial Data Gateway:Home.

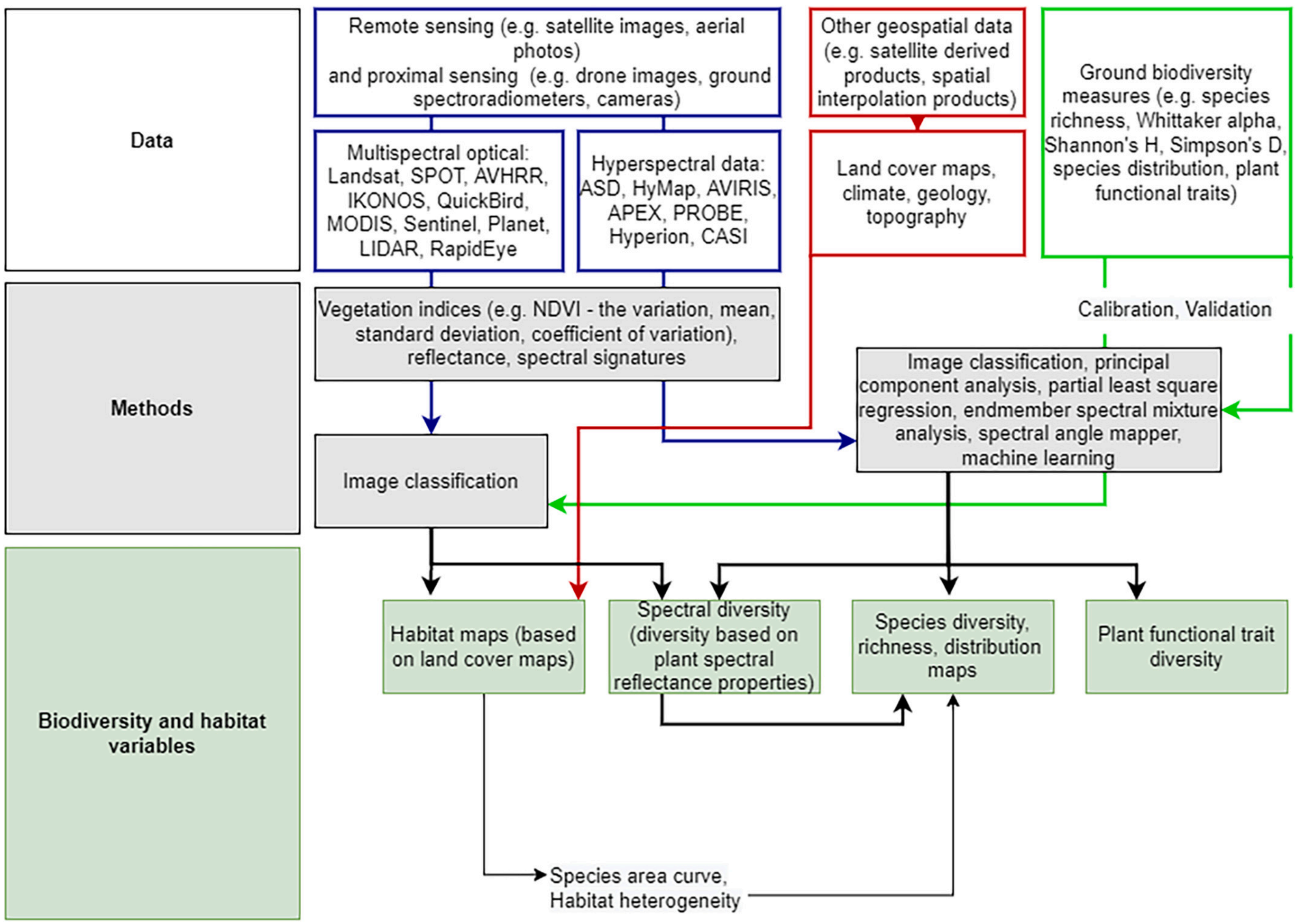


Fig. A1. Schematic overview of the use of remote sensing and GIS for biodiversity and wildlife habitat assessment and monitoring.
Sources: Cavender-Bares et al. (2020); Walters and Scholes (2017); Wang and Gamon (2019).
Plant functional traits include structural (e.g., leaf area index, plant height), biochemical (e.g., nitrogen content, chlorophyll content, water content), and phenology features (e.g., leaf unfolding, onset of flowering) that can impact plant fitness indirectly via its effects on growth (biomass), reproduction, and survival (Violle et al., 2007).

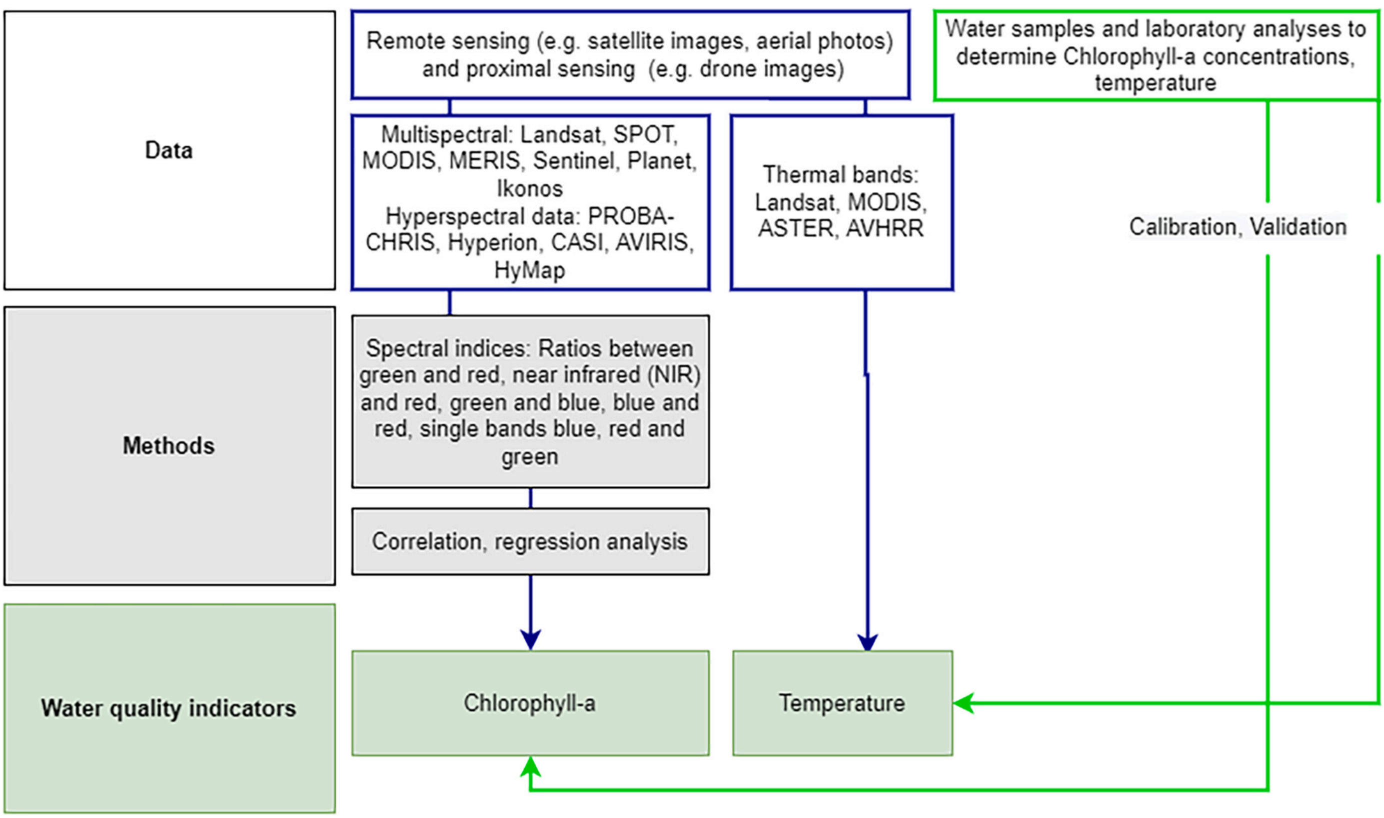


Fig. A2. Schematic overview of the use of remote sensing for the assessment and monitoring of chlorophyll-a and temperature in waterbodies.
Source: Gholizadeh et al., 2016

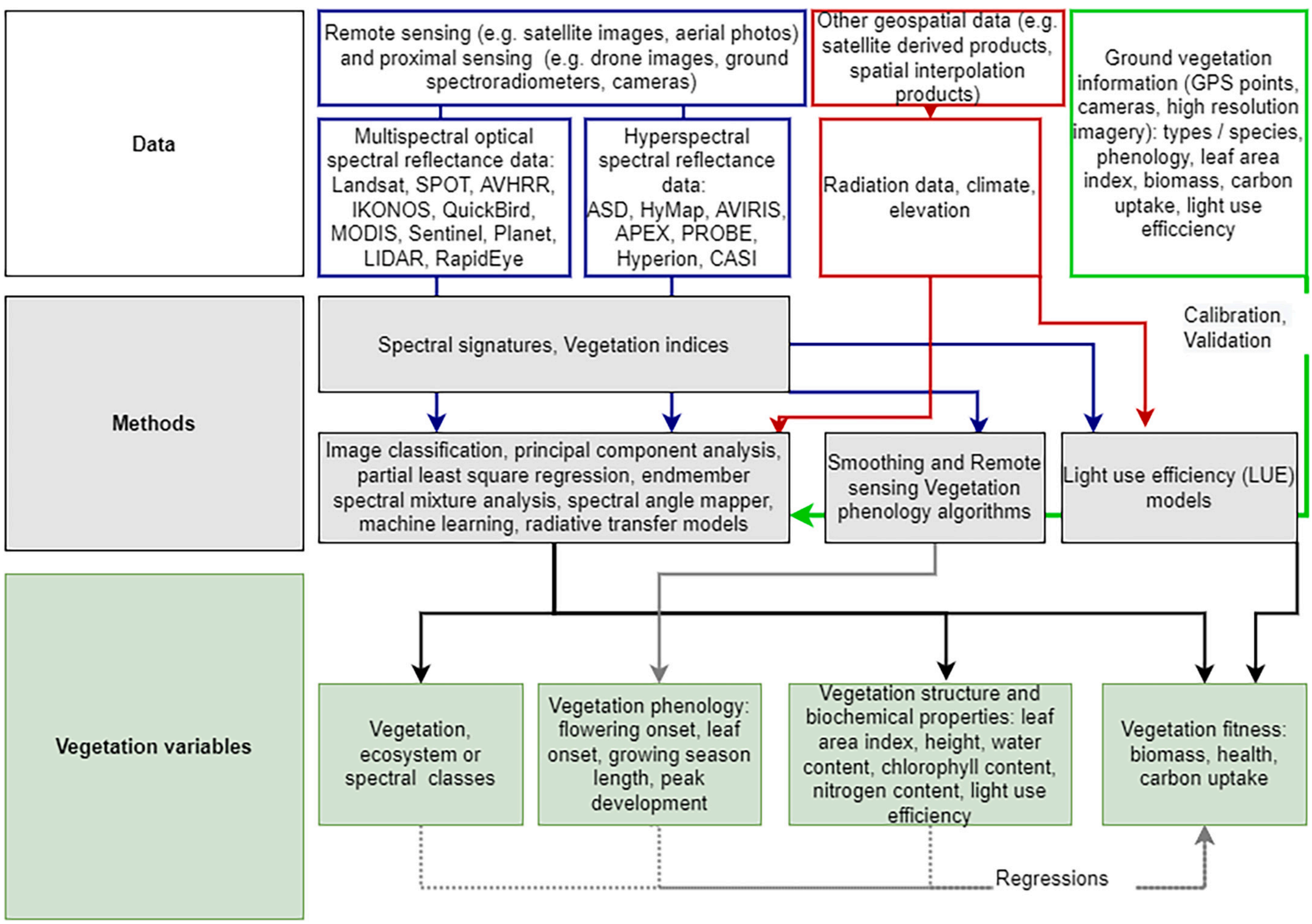
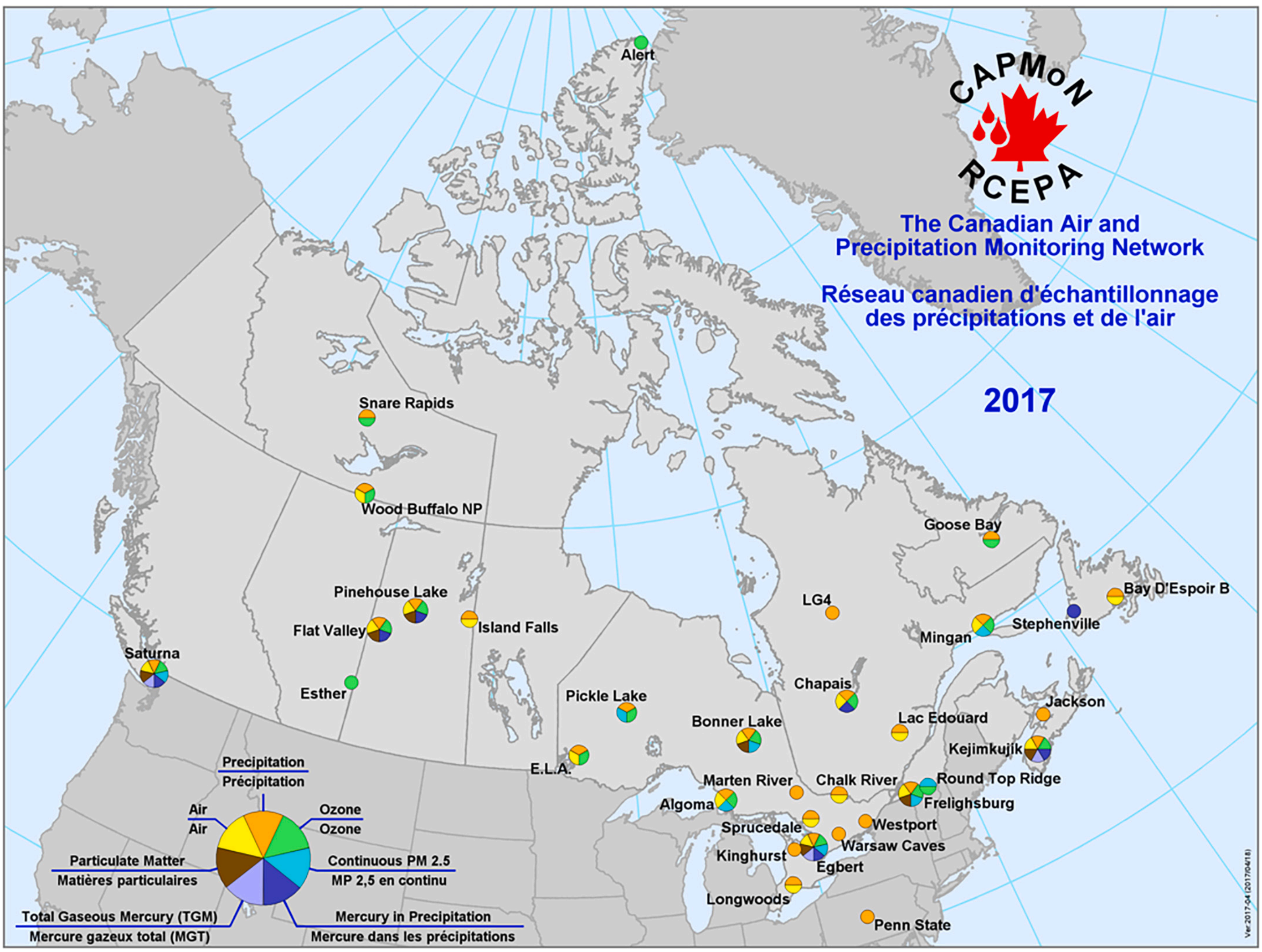
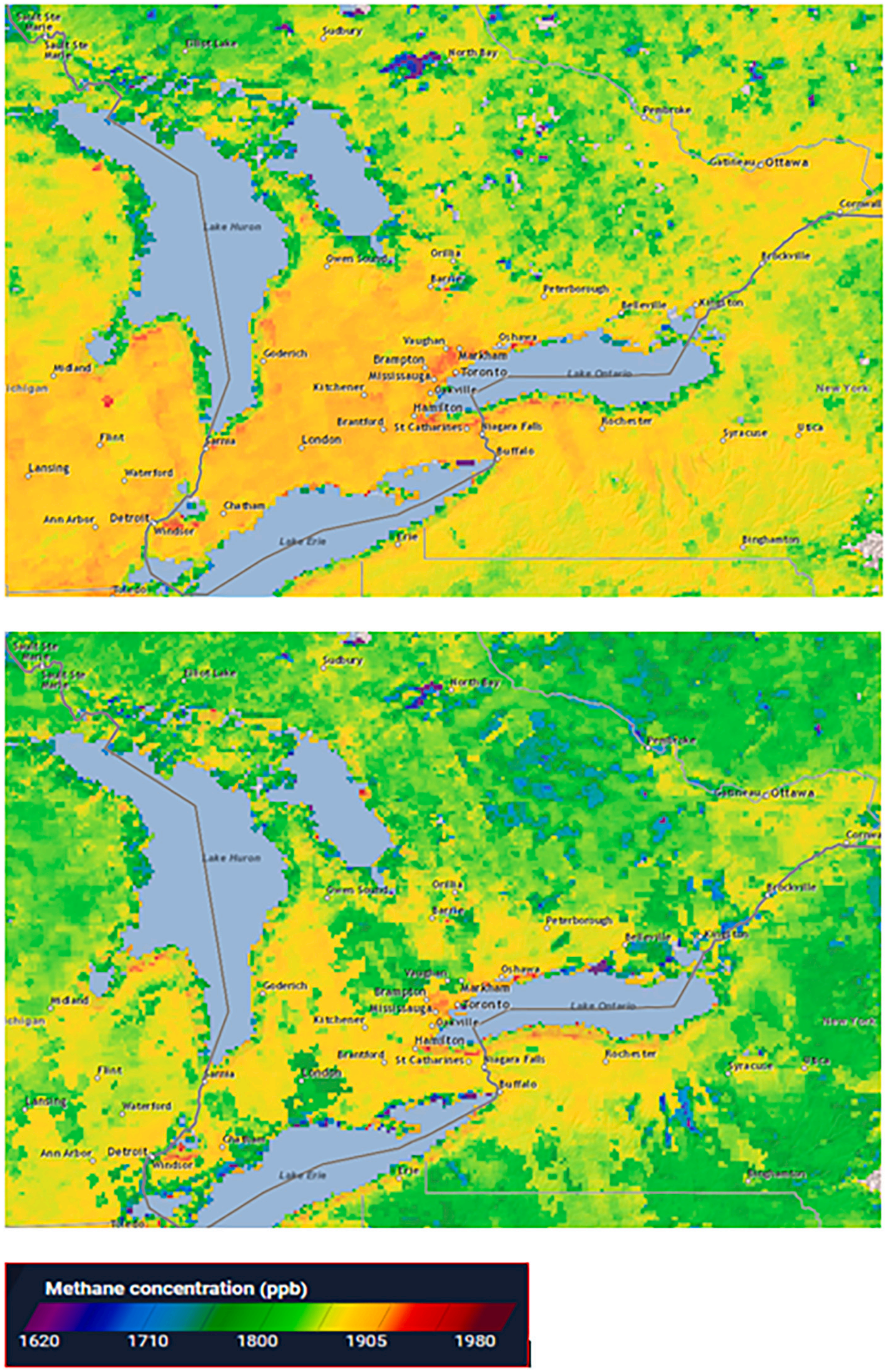


Fig. A3. Schematic overview of the use of remote sensing and GIS for vegetation assessment and monitoring.
Sources: Homolová et al. (2013); Weiss et al. (2020).



Map A1. Overview of CapMon ground stations across Canada, providing information on the regional variability.
Ground monitoring stations from the Canadian Air and Precipitation Network.
Source: CAPMoN, https://data.ec.gc.ca/data/air/monitor/networks-and-studies/canadian-air-and-precipitation-monitoring-network-capmon/;https://www.canada.ca/en/environment-climate-change/services/air-pollution/monitoring-networks-data/national-atmospheric-chemistry-database/data.html



Map A2. Illustration of satellite-derived methane concentrations over Southern Ontario.
The upper panel shows concentrations on October 3rd 2020, the lower panel shows concentrations on May 8th 2021. Source: https://pulse.ghgsat.com/?lat=43.52&lng=-77.89&zm=7

References

AAFC, 2006. Snapshot of Canadian Agriculture. Retrieved on May 29, 2022 from. https://www150.statcan.gc.ca/n1/ca-ra2006/articles/snapshot-portrait-eng.htm.

AAFC, 2009. Environmental Farm Planning in Canada: A 2006 Overview. Farm Environmental Management in Canada, Technical Series Report. Agriculture and Agri-Food Canada, Ottawa, Ontario. Retrieved on May 29, 2022 from. https://publications.gc.ca/collections/collection_2011/agr/A125-15-2011-eng.pdf.

AAFC, 2016. An Overview of the Canadian Agriculture and Agri-Food System 2016. Retrieved on May 29, 2022 from. https://publications.gc.ca/collections/collection_2016/aac-aafc/A38-1-1-2016-eng.pdf. https://publications.gc.ca/site/eng/9.505772/publication.html.

AAFC, 2017. Growing Forward 2 - Agriculture and Agri-Food Canada (AAFC). Agr.gc.ca. Retrieved on May 29, 2022 from. http://www.agr.gc.ca/eng/about-us/key-departmental-initiatives/growing-forward-2/?id=1294780620963.

AAFC, 2020. Overview of Canada's agriculture and agri-food sector. Retrieved on May 29, 2022 from. https://agriculture.canada.ca/en/canadas-agriculture-sectors/overview-canadas-agriculture-and-agri-food-sector.

AAFC. (n.d.). Growing Forward: A Federal-Provincial-Territorial Framework Agreement on Agriculture, Agri-Food and Agri-based Products Policy. Retrieved on May 25, 2022 from http://www5.agr.gc.ca/resources/prod/doc/apf/pdf/GFFA_e.pdf.

AAFM, 2017. Vermont Subsurface Agricultural Tile Drainage Report. Retrieved on May 29, 2022 from. http://www.vtfb.org/cms-assets/documents/265282-467115.vermont-subsurface-agricultural-tile-d.
Abdelkawy, O.R., Ismail, H.A., Rod, J.K., Suliman, A.S., 2010. A developed GIS-based land evaluation model for agricultural land suitability assessments in arid and semi-arid regions. Res. J. Agric. Biol. Sci. 6 (5), 589–599.
Ahmadi, A., Emami, M., Daccache, A., He, L., 2021. Soil properties prediction for precision agriculture using visible and near-infrared spectroscopy: A systematic review and Meta-analysis. Agronomy 11 (3), 433. https://doi.org/10.3390/agronomy11030433.
Aktar, W., Sengupta, D., Chowdhury, A., 2009. Impact of pesticides use in agriculture: their benefits and hazards. Interdiscip. Toxicol. 2 (1), 1–12. https://doi.org/10.2478/v10102-009-0001-7.
Amdihun, A., 2006. GIS and Remote Sensing Integrated Environmental Impact Assessment of Irriga-tion Project in Finchaa Valley Area. Addis Ababa University. Retrieved on May 29, 2022 from. https://publications.iwmi.org/pdf/H044105.pdf.
Antunes, P., Santos, R., Jordão, L., 2001. The application of geographical information systems to determine environmental impact significance. Environ. Impact Assess. Rev. 21 (6), 511–535. https://doi.org/10.1016/S0195-9255(01)00090-7.
Atzberger, C., 2013. Advances in remote sensing of agriculture: context description, existing opera-tional monitoring systems and major information needs. Remote Sens. 5 (2), 949–981. https://doi.org/10.3390/rs5020949.
Ben-Dor, E., 2002. Quantitative Remote Sensing of Soil Properties. In Advances in Agronomy, vol. 75. Academic Press, pp. 173–243. https://doi.org/10.1016/S0065-2113(02)75005-0.
Bongaarts, J., 2019. Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services. Popul. Dev. Rev. 45 (3), 680–681. https://doi.org/10.1111/padr.12283.
Butt, A., Shabbir, R., Ahmad, S.S., Aziz, N., 2015. Land use change mapping and analysis using remote sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. Egypt. J. Remote Sens. Space Sci. 18 (2), 251–259. https://doi.org/10.1016/j.ejrs.2015.07.003.
CAP (n.d.) Canadian Agriculture Partnership Factsheet. Retrieved on May 25, 2022 from https://agriculture.canada.ca/sites/default/files/legacy/resources/prod/doc/cap/cap_factsheet_feb18-eng.pdf.
Cavender-Bares, J., Gamon, J.A., Townsend, P.A., 2020. Remote Sensing of Plant Biodiversity. Springer Nature. https://doi.org/10.1007/978-3-030-33157-3.
Clearwater, R., Martin, T., Hoppe, T., 2016. Environmental Sustainability of Canadian Agricul-ture: Agri-Environmental Indicators Report Series, Report #4. Agriculture and Agri-Food Canada. Retrieved on May 29, 2022 from Environmental Sustainability of Canadian Agriculture: Agri-Environmental Indicator Report Series – Report #4 - agriculture.canada.ca.
Cooke, R., Sands, G., Brown, L., 2008. Drainage Water Management: A Practice for Reducing Nitrate Loads from Subsurface Drainage Systems. St Joseph. Retrieved on May 29, 2022 from. https://www.epa.gov/sites/default/files/2015-07/documents/2006_8_24_msbasin_symposia_ia_session2.pdf.
DSDS (n.d.). Agriculture and Agri-Food Canada's 2020–21 Departmental Sustainable Development Strategy Report, Retrieved on May 25, 2022 from https://agriculture.canada.ca/sites/default/files/documents/2021-10/2020-21_report_on_the_departmental_sustainable_development_strategy-eng-oct12.pdf.
EC, 2011. European Communities (Environmental Impact Assessment) (Agriculture). www.irishstatutebook.ie/eli/2011/si/456/made/en/pdf retrieved on May 29, 2022.
EIA Wales, 2017. The Environmental Impact Assessment (Agriculture) (Wales) Regulations 2017 General Guidance. Retrieved on May 29, 2022 from EIA Agriculture a4 document (gov.wales),. https://gov.wales/assessing-environmental-impact-agriculture.
FAO (Ed.), 2011. Environmental Impact Assessment: Guidelines for FAO Field Projects. Food and Agriculture Organization of the United Nations. Retrieved on May 29, 2022 from. http://www.fao.org/3/i2802e/i2802e.pdf.
Franzmeier, D., Hosteter, W., Roeske, R., 2001. Drainage and Wet Soil Management - Drainage Recommendations for Indiana Soils (Retrieved on May 29, 2022 from). https://engineering.purdue.edu/SafeWater/Drainage/AY300.pdf.
Friel, S., Dangour, A., Garnett, T., Lock, K., Chalabi, Z., Roberts, I., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: food and agriculture. Lancet 374 (9706), 2016–2025. https://doi.org/10.1016/S0140-6736(09)61753-0.
Galbraith, H., Amerasinghe, P., Huber-Lee, A., 2005. The Effects of Agricultural Irrigation on Wetland Ecosystems in Developing Countries: A Literature Review. CA Discussion Paper 1. Comprehensive Assessment Secretariat, Colombo, Sri Lanka. Retrieved on may 29, 2022 from. https://www.iwmi.cgiar.org/assessment/files_new/publications/Discussion%20Paper/CADiscussionPaper1.pdf.
García-Ruiz, J., 2010. The effects of land use on soil erosion in Spain: A review. CATENA 81 (1), 1–11. https://doi.org/10.1016/j.catena.2010.01.001.
Ge, Y., Thomasson, J.A., Sui, R., 2011. Remote sensing of soil properties in precision agriculture: A review. Front. Earth Sci. 5 (3), 229–238. https://doi.org/10.1007/s11707-011-0175-0.
Geneletti, D., 2008. Impact assessment of proposed ski areas: A GIS approach integrating biological, physical and landscape indicators. Environ. Impact Assess. Rev. 28 (2), 116–130. https://doi.org/10.1016/j.eiar.2007.05.011.
Gholizadeh, A., Saberioon, M., Ben-Dor, E., Borůvka, L., 2018. Monitoring of selected soil contaminants using proximal and remote sensing techniques: background, state-of-the-art and future perspectives. Crit. Rev. Environ. Sci. Technol. 48 (3), 243–278. https://doi.org/10.1080/10643389.2018.1447717.
Gholizadeh, M.H., Melesse, A.M., Reddi, L., 2016. A comprehensive review on water quality parameters estimation using remote sensing techniques. Sensors 16 (8), 1298. https://doi.org/10.3390/s16081298.
González, A., Gilmer, A., Foley, R., Sweeney, J., Fry, J., 2011. Applying geographic information systems to support strategic environmental assessment: opportunities and limitations in the context of Irish land-use plans. Environ. Impact Assess. Rev. 31 (3), 368–381. https://doi.org/10.1016/j.eiar.2010.12.001.
Gupta, P., Christopher, S.A., Wang, J., Gehrig, R., Lee, Y., Kumar, N., 2006. Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmos. Environ. 40 (30), 5880–5892. https://doi.org/10.1016/j.atmosenv.2006.03.016.
Haklay, M., Feitelson, E., Doytsher, Y., 1998. The potential of a gis-based scoping system: an israeli proposal and case study. Environ. Impact Assess. Rev. 18 (5), 439–459. https://doi.org/10.1016/S0195-9255(98)00017-1.
Hoff, R.M., Christopher, S.A., 2009. Remote sensing of particulate pollution from space: have we reached the promised land? J. Air Waste Manage. Assoc. 59 (6), 645–675. https://doi.org/10.3155/1047-3289.59.6.645.
Homolová, L., Malenovský, Z., Clevers, J.G.P.W., García-Santos, G., Schaepman, M.E., 2013. Review of optical-based remote sensing for plant trait mapping. Ecol. Complex. 15, 1–16. https://doi.org/10.1016/j.ecocom.2013.06.003.
IAA, 2019. Impact Assessment Act. S.C. 2019, c.28, s.1. Retrieved on May 29, 2022 from. https://laws.justice.gc.ca/eng/acts/I-2.75/index.html.
IPBES, 2019. Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Zenodo. https://doi.org/10.5281/zenodo.3831674
Jayasinghe, P., Machida, T., 2008. Web-based GIS online consulting system with crop-land Suita-bility identification. Agricul. Inform. Res. 17 (1), 13–19. https://doi.org/10.3173/air.17.13.
João, E., Fonseca, A., 1996. The role of GIS in improving environmental assessment effectiveness: theory vs. practice. Impact Assess. 14, 371–387. https://doi.org/10.1080/07349165.1996.9725913.
Kamińska, I. A., Ołdak, A., & Turski, W. A. (2004). Geographical information system (GIS) as a tool for monitoring and analysing pesticide pollution and its impact on public health. Ann. Agric. Environ. Med., 11(2), 181–184. http://www.aaem.pl/Geographical-Information-System-GIS-as-a-tool-for-monitoring-and-analysing-pesticide,72879,0,2.html.
Kaur, G., Kross, A., Callegari, D., Sunohara, M., Van Vliet, L., Rudy, H., Lapen, D., McNairn, H., 2018, June 24. Spatial Decision Support System: Controlled Tile Drainage – Calculate your Benefits. 14th International Conference on Precision Agriculture, Montreal, Quebec, Canada. Retrieved on May 29, 2022 from. https://www.ispag.org/proceedings/?action=download&item=5224.
Kerr, Y.H., Waldteufel, P., Richaume, P., Wigneron, J.P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A., Cabot, F., Gruhier, C., Juglea, S.E., Leroux, D., Mialon, A., Delwart, S., 2012. The SMOS soil moisture retrieval algorithm. IEEE Trans. Geosci. Remote Sens. 50 (5), 1384–1403. https://doi.org/10.1109/TGRS.2012.2184548.
Kross, A., Znoj, E., Callegari, D., Kaur, G., Sunohara, M., Lapen, D.R., McNairn, H., 2020. Using artificial neural networks and remotely sensed data to evaluate the relative importance of variables for prediction of within-field corn and soybean yields. Remote Sens. 12 (14), 2230. https://doi.org/10.3390/rs12142230.
Mati, B., 2014. What You Need to Know About Waterlogging in Agricultural Lands. Jomo Kenyatta University of Agriculture and Technology.. http://www.jkuat.ac.ke/departments/warrec/?p=1323
McCormick, W. (n.d.). The Next Agricultural Policy Framework (Growing Forward 3). Alberta Agriculture and Forestry, Red Deer Alberta. Retrieved on May 25, 2022 from http://www1.agric.gov.ab.ca/$Department/deptdocs.nsf/all/epw16243/$FILE/WendyM.pdf.
McLaughlin, A., Mineau, P., 1995. The impact of agricultural practices on biodiversity. Agric. Ecosyst. Environ. 55 (3), 201–212. https://doi.org/10.1016/0167-8809(95)00609-v.
McRae, T., 1994. Developing Agri-Environmental Indicators for Canada. General Proposal. Retrieved on May 29, 2022 from. https://atrium.lib.uoguelph.ca/xmlui/bitstream/handle/10214/13958/AEI_develop_agri_env_indic_canada94.pdf?sequence=1&isAllowed=y.
McRae, T., Smith, C., & Gregorich, L. (2000). Environmental Sustainability of Canadian Agriculture: Report of the Agri-Environmental Indicator Project. A Summary. Agriculture and Agri-Food Canada, Ottawa, Ontario. Retrieved on may 29, 2022 from https://publications.gc.ca/Collection/A22-201-2000-1E.pdf.
Merem, E., Richardson, C., Romano, C., Joan, W., Twumasi, Yaw, 2012. Using GIS to assess the contribution of farming activities towards climate change in the state of Mississippi. Br. J. Environ. Clim. Change 2 (2), 113–136. https://doi.org/10.9734/BJECC/2012/1371.
Miller, L., 2012. Growing forward 2. Report of the Standing Committee on Agriculture and Agri-Food. Retrieved on May 29, 2020 from. https://www.ourcommons.ca/Content/Committee/411/AGRI/Reports/RP5561522/agrirp03/agrirp03-e.pdf.
Mobley, C., Stramski, D., Bissett, P., Boss, E., 2004. Optical Modeling of ocean waters: is the case 1 - case 2 classification still useful? Oceanography 17 (2), 60–67. https://doi.org/10.5670/oceanog.2004.48.
Mulla, D., 2013. Twenty-five years of remote sensing in precision agriculture: key advances and re-maining knowledge gaps. Biosyst. Eng. 114 (4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009.
Narumalani, S., Zhou, Y., Jensen, J., 1997. Application of remote sensing and geographic information systems to the delineation and analysis of riparian buffer zones. Aquat. Bot. 58 (3–4), 393–409.
Niemeijer, D., Groot, R., 2006. Framing environmental indicators: moving from causal chains to causal networks. Environ. Dev. Sustain. 10 (1), 89–106. https://doi.org/10.1007/s10668-006-9040-9.
Noble, B.F., 2015. Introduction to Environmental Impact Assessment: A Guide to Principles and Practice, 3rd ed. Oxford University Press.

Noble, B.F., 2020. Introduction to Environmental Assessment: A Guide to Principle and Practice, 4th ed. Oxford University Press.

Paiboonvorachat, C., Oyana, T.J., 2011. Land-cover changes and potential impacts on soil erosion in the Nan watershed, Thailand. Int. J. Remote Sens. 32 (21), 6587–6609. https://doi.org/10.1080/01431161.2010.512935.

Patil, A.A., Annachhatre, A.P., Tripathi, N.K., 2002. Comparison of conventional and geo-spatial EIA: A shrimp farming case study. Environ. Impact Assess. Rev. 22 (4), 361–375. https://doi.org/10.1016/S0195-9255(02)00013-6.

Payraudeau, S., van der Werf, H.M.G., 2005. Environmental impact assessment for a farming region: a review of methods. Agric. Ecosyst. Environ. 107 (1), 1–19. https://doi.org/10.1016/j.agee.2004.12.012.

Perminova, T., Sirina, N., Laratte, B., Baranovskaya, N., Rikhvanov, L., 2016. Methods for land use impact assessment: A review. Environ. Impact Assess. Rev. 60, 64–74. https://doi.org/10.1016/j.eiar.2016.02.002.

Piha, H., 2006. Impacts of Agriculture on Amphibians at Multiple Scales (Doctoral dissertation). University of Helsinki, Helsinki. http://urn.fi/URN:ISBN:952-10-3472-6.

Reytar, K., Hanson, C., Henninger, N., 2014. Indicators of Sustainable Agriculture: A Scoping Analysis. Working Paper, Instalment 6 of Creating a Sustainable Food Future. World Resources Institute, Washington DC. Retrieved on May 29, 2022 from. https://files.wri.org/d8/s3fs-public/wrr_installment_6_sustainable_agruiculture_indicators.pdf. http://www.worldresourcesreport.org.

Satapathy, D., Katpatal, Y., Wate, S., 2008. Application of geospatial technologies for environmental impact assessment: an Indian scenario. Int. J. Remote Sens. 29 (2), 355–386. https://doi.org/10.1080/01431160701269002.

Shanahan, J., Schepers, J., Francis, D., Varvel, G., Wilhelm, W., Tringe, J., 2001. Use of remote-sensing imagery to estimate corn grain yield. Agron. J. 93 (3), 583. https://doi.org/10.2134/agronj2001.933583x.

Sharma, R., Kamble, S.S., Gunasekaran, A., 2018. Big GIS analytics framework for agriculture supply chains: A literature review identifying the current trends and future perspectives. Comput. Electron. Agric. 155, 103–120. https://doi.org/10.1016/j.compag.2018.10.001.

Sholarin, E.A., Awange, J.L., 2015. Geospatial in support of EIA, SEA, and SA. In: Sholarin, E.A., Awange, J.L. (Eds.), Environmental Project Management: Principles, Methodology, and Processes. Springer International Publishing, pp. 263–293. https://doi.org/10.1007/978-3-319-27651-9_14.

Simon-Mayer, J., 2020. Mapping and Monitoring Surface Water Chlorophyll α Using Satellite Imagery: Investigation of Industrial Impacts on Western Lake Erie's Water Quality. Planning and Environment, Concordia University, Department of Geography.

Soil Quality Indicator Sheets (n.d.). Retrieved on May 29, 2022 from URL https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/health/assessment/?cid=stelprdb1237387.

Song, Z., Bai, Y., Wang, D., Li, T., He, X., 2021. Satellite retrieval of air pollution changes in central and eastern China during COVID-19 lockdown based on a machine learning model. Remote Sens. 13 (13), 2525. https://doi.org/10.3390/rs13132525.

Statistics Canada, 2014. Human Activity and the Environment: Section 5: Environmental management. Statcan.gc.ca. Retrieved on May 29, 2022 from. http://www.statcan.gc.ca/pub/16-201-x/2014000/part-partie5-eng.htm.

Statuto, D., Cillis, G., Picuno, P., 2016. Analysis of the effects of agricultural land use change on ru-ral environment and landscape through historical cartography and GIS tools. J. Agricul-Tural Eng. 47 (1), 28. https://doi.org/10.4081/jae.2016.468.

Tola, E., Al-Gaadi, K.A., Madugundu, R., 2019. Employment of GIS techniques to assess the long-term impact of tillage on the soil organic carbon of agricultural fields under hyper-arid conditions. PLoS One 14 (2), e0212521. https://doi.org/10.1371/journal.pone.0212521.

Trautmann, N., Porter, K., & Wagenet, R. (1985). Modern Agriculture: Its Effect on the Environment. Groundwater Effects of Agriculture. (Fact Sheet retrieved on may 29, 2022 from) https://ecommons.cornell.edu/bitstream/handle/1813/3909/Groundwater%20-%20Effects%20of%20Agriculture%20(Fact%20Sheet).pdf?sequence=2.

Verrelst, J., Camps-Valls, G., Muñoz-Marí, J., Rivera, J.P., Veroustraete, F., Clevers, J.G.P.W., Moreno, J., 2015. Optical remote sensing and the retrieval of terrestrial vegetation bio-geophysical properties – A review. ISPRS J. Photogramm. Remote Sens. 108, 273–290. https://doi.org/10.1016/j.isprsjprs.2015.05.005.

Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., Garnier, E., 2007. Let the concept of trait be functional! Oikos 116 (5), 882–892. https://doi.org/10.1111/j.0030-1299.2007.15559.x.

Walters, M., Scholes, R.J. (Eds.), 2017. The GEO Handbook on Biodiversity Observation Networks. Springer International Publishing. https://doi.org/10.1007/978-3-319-27288-7.

Wang, R., Gamon, J.A., 2019. Remote sensing of terrestrial plant biodiversity. Remote Sens. Environ. 231, 111218 https://doi.org/10.1016/j.rse.2019.111218.

Ward, M.H., Nuckols, J.R., Weigel, S.J., Maxwell, S.K., Cantor, K.P., Miller, R.S., 2000. Identifying populations potentially exposed to agricultural pesticides using remote sensing and a geographic information system. Environ. Health Perspect. 108 (1), 5–12. https://doi.org/10.1289/ehp.001085.

Weiss, M., Jacob, F., Duveiller, G., 2020. Remote sensing for agricultural applications: A meta-review. Remote Sens. Environ. 236, 111402 https://doi.org/10.1016/j.rse.2019.111402.

Yaghi, Y., Salim, H., 2017. Integration of RS/GIS for surface water pollution risk MODELING. Case study: al-ABRASH SYRIAN coastal basin. Int. Arch. Photogramm. Remote. Sens. Spat. Inf. Sci. XLII-2/W7, 949–954. https://doi.org/10.5194/isprs-archives-XLII-2-W7-949-2017.