Environmental Indicator Principium with Case References to Agricultural Soil, Water, and Air Quality and Model-Derived Indicators


Abstract

Environmental indicators are powerful tools for tracking environmental changes, measuring environmental performance, and informing policymakers. Many diverse environmental indicators, including agricultural environmental indicators, are currently in use or being developed. This special collection of technical papers expands on the peer-reviewed literature on environmental indicators and their application to important current issues in the following areas: (i) model-derived indicators to indicate phosphorus losses from arable land to surface runoff and subsurface drainage; (ii) glutathione–ascorbate cycle-related antioxidants as early-warning bioindicators of polybrominated diphenyl ether toxicity in mangroves; and (iii) assessing the effectiveness of using organic matrix biobeds to limit herbicide dissipation from agricultural fields, thereby controlling on-farm point-source pollution. This introductory review also provides an overview of environmental indicators, mainly for agriculture, with examples related to the quality of the agricultural soil–water–air continuum and the application of model-derived indicators. Current knowledge gaps and future lines of investigation are also discussed. It appears that environmental indicators, particularly those for agriculture, work efficiently at the field, catchment, and local scales and serve as valuable metrics of system functioning and response; however, these indicators need to be refined or further developed to comprehensively meet community expectations in terms of providing a consistent picture of relevant issues and/or allowing comparisons to be made nationally or internationally.

Core Ideas

• Highly diverse environmental indicators are in use or in development.
• Agricultural environmental indicators function efficiently at various scales.
• Environmental indicators need to be improved to provide consistent performance and allow comparability.

A S A RESULT of growing concerns for environmental issues and developmental sustainability, the long-standing, widespread, and multidisciplinary use of “indicators” has recently been applied in the field of environmental assessment (Bockstaller et al., 2008). With the plethora of global environmental initiatives developed in the last 20 years, several closely interrelated terms, all expressing similar concepts, have emerged: environmental indicators, environmental quality indicators, environmental performance indicators, ecosystems health indicators, environmental risk indicators, and natural resource indicators, among others (McRae et al., 1995). The USEPA (1972) defined an environmental indicator as a measure of change in the state of the environment, or in human activities that affect the state of the environment, preferably in relation to a standard value, objective, or goal. Clearly, an environmental indicator is not a single environmental datum but instead addresses attributes of environmental change, while having significance extending beyond that directly associated with the value of a specific environmental parameter.

In the 21st century, the sustained global efforts of researchers and policymakers toward developing environmental indicators have resulted in a wealth of knowledge regarding indicator development delineation. This extends from conceptual frameworks to case- and country-specific guidelines, such as the Pressure–State–Response framework, National Resource Accounting framework, Ecological Sustainability framework, and Sustainable Development framework (T unstall et al., 1992; Newton and Erickson, 1998). Currently, the Pressure–State–Response framework, developed by the Organization for Economic Cooperation and Development, constitutes the most popular framework for environmental indicator development. The Pressure–State–Response framework is based on the notion that human activities exert pressure on the environment, resulting in pollution or resource depletion (change in state or condition of environment) as well as societal responses to environmental change (Organization for Economic Cooperation

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Abbreviations: PBDE, polybrominated diphenyl ether.

The European Environmental Agency (2003) categorized the wide number and diversity of environmental indicators that are presently in development and use into four typologies: descriptive, performance, efficiency, and policy effectiveness. Usually presented as a line diagram, descriptive indicators highlight temporal changes in a variable, for example, pollutants in water over time. In contrast, performance indicators represent the discrepancy between the current environmental situation and a desired target value, such as greenhouse gas emission rates relative to national or international targets. Efficiency indicators provide an insight into the efficiency of processes and products in terms of resources, emissions and waste per unit output, such as emissions generated per unit of gross domestic product. Policy effectiveness indicators portray the practical change in environmental variables in response to policy efforts, for example, attempts toward national emission reduction resulting in the adoption of a clear energy policy.

In comparison to the European Environmental Agency, the Organization for Economic Cooperation and Development classified environmental indicators into four categories based on their nature and purpose: core, key, sector, and decoupling environmental indicators (Organization for Economic Cooperation and Development, 2003, 2008). Core environmental indicators are designed to track environmental dynamics (and the factors involved) and analyze environmental policy. Key environmental indicators are a subset of the core environmental indicators, selected for communication purposes to inform the public and to provide key signals to policymakers (Table 1). Sector environmental indicators are devised to help integrate environmental concerns into sector-specific (e.g., agriculture, transport, energy, tourism, and household consumption) policies. Decoupling environmental indicators measure the decoupling of environmental pressure from economic growth and are targeted to monitoring progress toward sustainable development.

Environmental indicators can be further divided between retrospective and prospective indicators, depending on whether they measure historical change up to the present or report the predicted direction and magnitude of change based on future scenarios’ assumptions (McRae et al., 1995; Warren, 1997).

Environmental indicators can be a simple measurement, calculated or directly measured, or an aggregation of indicative variables or simple indicators, such as (i) the composite indicator of Bockstaller et al. (1997) or (ii) the index of environmental integrity, an aggregative indicator of a set of subindicators, developed to evaluate overall environmental conditions throughout a region (Paul, 2003). While there are many debates over how to evaluate quality criteria of environmental indicators, such quality is clearly important in an application-specific indicator selection. Generally, a “good” environmental indicator should possess desirable characteristics of scientific rigor and reliability, sensitivity, measurability and collectability (in terms of costs to acquire data), understandability, and policy relevance (Alfen and Sabo, 1993; Organization for Economic Cooperation and Development, 2003; Yli-Viikari et al., 2007). The Organization for Economic Cooperation and Development ranks policy relevance, scientific soundness, and measurability over other criteria. Canada’s experience shows that policy orientation, scientific creditability, and regional sensitivity are the three agricultural environmental indicator quality criteria that stand out above all others (McRae et al., 1995).

### Agri-Environmental Indicators

The agricultural sector’s economic viability is intimately tied to the environment because soil and water resources are vital to agricultural productivity and both affect and are affected by

<table>
<thead>
<tr>
<th>No.</th>
<th>Issue</th>
<th>Available indicators‡</th>
<th>Medium-term indicators§</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Climate change</td>
<td>CO₂ emission intensities&lt;br&gt; Index of greenhouse gas emissions</td>
<td>Index of greenhouse gas emissions</td>
</tr>
<tr>
<td>2</td>
<td>Ozone layer</td>
<td>Indices of apparent consumption of ozone depleting substances</td>
<td>Same, plus aggregation into one index of apparent consumption of ozone depleting substances</td>
</tr>
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<td>3</td>
<td>Air quality</td>
<td>SO₂ and NOₓ emission intensities</td>
<td>Population exposure to air pollution</td>
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<td>4</td>
<td>Waste generation</td>
<td>Municipal waste generation intensities</td>
<td>Total waste generation intensities, indicators derived from material flow accounting</td>
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<td>5</td>
<td>Fresh water</td>
<td>Wastewater treatment connection rates</td>
<td>Pollution loads to water bodies</td>
</tr>
<tr>
<td>6</td>
<td>Natural resource and assets</td>
<td>Intensity of use of water resources</td>
<td>Same plus subnational breakdown</td>
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<td>7</td>
<td>Forest resource</td>
<td>Intensity of use of forest resources</td>
<td>Same</td>
</tr>
<tr>
<td>8</td>
<td>Fish resource</td>
<td>Intensity of use of fish resources</td>
<td>Same plus closer link to available resources</td>
</tr>
<tr>
<td>9</td>
<td>Energy resource</td>
<td>Intensity of energy use</td>
<td>Energy efficiency index</td>
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<tr>
<td>10</td>
<td>Biodiversity</td>
<td>Threatened species</td>
<td>Species and habitat or ecosystem diversity area of key ecosystems</td>
</tr>
</tbody>
</table>

‡ Indicators for which data are available for a majority of OECD countries.
§ Indicators that require further specification and development (availability of basic datasets, underlying concepts, and definitions).
the environment. Agricultural production often occurs at the expense of the environment (e.g., soil degradation, water quality decline, loss of wildlife habitats, reduced biodiversity, and increased emissions of greenhouse gas, volatile organic compounds, ammonia, and odors), thereby undermining its environmental sustainability. In fulfilling its mission of environmental sustainability, today’s agriculture must balance a wide array of food and fiber demands against several environmental challenges. Accordingly, agricultural environmental indicators are increasingly key to gauging the environmental consequences of agricultural practices and policies and monitoring progress toward sustainable development (Riley, 2001). Although the term agri-environmental indicator is already in use, its exact definition varies widely according to the background and disciplines of those using this term. Those seeking to assess agroecosystem health or biodiversity might define agricultural environmental indicators as biophysical measurements (e.g., a soil’s physicochemical properties, the abundance of species of a given taxon; Carignan and Villard, 2002), whereas agronomists would focus on indicators of agronomic or economic outputs (e.g., cropping intensity, yield or economic benefits; Meyer-Aurich, 2005).

As managed ecosystems, agroecosystems vary widely in production practices largely due to variability in the production environment itself—soil type, water availability, land topography, and weather. Accordingly, many agricultural environmental indicators and the related methods have been developed to assess the environmental impacts of agriculture and sustainability of agroecosystems since the 1990s. These indicators address many different agroecosystem sustainability issues, including nutrient loss from arable land to surface water (ten Berge et al., 2002; Sharpley et al., 2003; Buczko and Kuchenbuch, 2010; Drewry et al., 2011), pesticide and drug ecotoxicology (Adams and Greeley, 2000; Maud et al., 2001; Falconer, 2002; Kookana et al., 2005; Topp et al., 2010), agricultural greenhouse gas emissions (Mosier, 1994; Johnson et al., 2007; Oertel et al., 2016), and others (e.g., soil erosion) (Huffman et al., 2000; Hajkowicz et al., 2009; Massé et al., 2013).

The spatial scale of agricultural environmental indicators, which ranges from plot or field scale to major ecological zone or political jurisdiction, further extends their diversity. Given data availability constraints and the overall ill-advisedness of data extrapolation from one spatial scale to another (e.g., for agroecosystem species diversity), indicators at one scale are not necessarily applicable at other scales (McRae et al., 1995; Payraudeau and van der Werf, 2005). For example, a soil–root interface bioindicator, while appropriate at the plot scale, is not appropriate at the regional or national scale (Smith et al., 2000; Dantsis et al., 2010). To account for spatial scale, assessment methods based on multiple agricultural environmental indicators have been developed at the international and national (Smith and McRae, 2000; Delbaere and Serradilla, 2004; Yli-Viikari et al., 2007), regional (Payraudeau and van der Werf, 2005; Dantsis et al., 2010), farm (Eckert et al., 2000; Rigby et al., 2001; van der Werf and Petit, 2002; Meyer-Aurich, 2005), and field or cropping system scales (Bockstaller et al., 2008).

As the generic term agri-environmental indicator applies to a wide range of environmental indicators applied at a variety of thematic and spatial scales, some clarification of what constitutes a specific agri-environmental indicator is necessary. Meyer et al. (1992) drew on 21 indicators, of which they deemed crop productivity, soil productivity, quantity and quality of water, abundance and diversity of beneficial insects, genetic diversity, and agricultural chemical use the most important to generate an agri-environmental indicator representative of the ecological status of agroecosystems.

It must be recognized that agricultural activities have both harmful and beneficial impacts on environmental quality and that these impacts are frequently complex, site specific, and nonlinear. In light of this, the Organization for Economic Cooperation and Development (1999) modified its Pressure–State–Response framework into the Driving Force–State–Response and developed sectorial environmental indicators for agriculture, which address eight distinct themes: soil, water, air, diversity, wildlife habitat, landscape, farm management, and farm inputs. On a similar basis, Agriculture and Agri-Food Canada identified 14 main agricultural environmental indicators pertinent to Canadian conditions, grouping them into six related themes: (i) environmental farm management (soil cover by crop and residue); (ii) soil quality (risks of water, wind, and tillage erosion, soil organic carbon (C), risks of soil compaction, and salinization); (iii) water quality (risks of water contamination by nutrients and pesticides); (iv) agroecosystem greenhouse gas emission (agricultural greenhouse gas budget); (v) agroecosystem diversity (availability of wildlife habitat on farmland), and (vi) production intensity (energy use, residual N) (Huffman et al., 2000; Smith and McRae, 2000). Smith et al. (2000) reviewed a variety of environmental indicators related to agroecosystems and classified them into four groups: (i) biological indicators (e.g., soil organic C pool, soil microbial, pesticide residence in insects, crop diversity, and fecal pathogens), (ii) physical indicators (e.g., risks pertaining to soil degradation), (iii) chemical indicators (e.g., nutrient bioavailability and toxicity), and (iv) landscape indicators (e.g., crop coverage and status, and GIS-based indicators). Payraudeau and van der Werf (2005) and Bockstaller et al. (2008) distinguished three groups of agricultural environmental indicators based on a cause-effect chain of impacts:

1. Simple indicators based on a single type of variable obtained through a survey or database, but not directly measured, e.g., nutrient balance. Such indicators provide an indirect assessment of agriculture’s environmental impacts and show a poor predictive capacity (Riley, 2001).
2. Integrated indicators based on calculation and integration of multitype factors (e.g., soil conditions and farming practices), such as those are imbedded in the Phosphorus (P) Index (Sharpley et al., 2003). The indicators of this group are often used to assess emissions of a contaminant or the contamination of an environmental component (e.g., water, soil, and air), with or without using a modeling approach.
3. Measured indicators based on one or several measurements, (e.g., microorganisms in water as indicators of water quality and human health risks; Topp, 2015). Biodiversity indices fall into this category (Carignan and Villard, 2002). Emissions can also be assessed through measurement-based agri-environmental indicators (e.g., water extractable P serving as an agri-environmental indicator for P runoff risk; Kleinman et al., 2002).
Although somewhat complex in their classification, agri-environmental indicators are mainly developed to assess issues related to greenhouse gas emissions, soil quality, water quality, and biodiversity in agroecosystems and align with the Organization for Economic Cooperation and Development key indicators listed in Table 1.

Given the broad diversity of environmental indicators and agri-environmental indicators, nothing is gained in scrutinizing a specific indicator, and a critical thematic review of indicators is beyond the scope of this introductory review. Instead, we highlight here some examples of emerging environmental indicators and methodologies currently being developed mainly related to agriculture.

Case Reference 1: Soil Organic Carbon as an Environmental Indicator

Soil organic matter content, prevalently expressed as the soil organic C pool, plays predominantly beneficial roles in determining a soil’s biological, physical, and chemical qualities (Smith et al., 2000; Lal, 2009). A nutrient source for plants and an energy source for soil organisms, soil organic matter improves soil structure, strengthens soil aggregates, increases water retention, chelates metals, buffers soil pH, modifies soil temperature, interacts with xenobiotic substances, and retains cations and anions in soil, thereby improving crop yield, enhancing eco-efficiency, and promoting food security (Smith et al., 2000; Lal, 2004a, 2004b, 2009, 2010a).

In addition to its agronomic functions, soil organic C closely interacts with the atmosphere, hydrosphere, and biosphere (Lal, 2015a, 2015b). Globally, soil contains approximately 2500 Pg of organic C (1 Pg C =1015 g or gigatonne of C) and is the largest terrestrial organic C pool (Lal, 2004a, 2004b; Stockmann et al., 2013). In addition, Cryosols and soils under permafrost contain an additional ~1700 Pg of organic C. Small changes in soil organic C stock could cause significant impacts on atmospheric CO2. For example, a 10% decline in the soil organic C pool is equivalent to 30 yr of anthropogenic CO2 emissions (Kirschbaum, 2000). Depletion of the soil organic C pool between 1750 and 2015 has contributed 130 Pg of C to the atmosphere (Lal, 2018), although not all of it was retained in the atmosphere.

Moreover, soil organic C–mediated soil properties and processes affect the hydrological cycle through the well-known positive link between soil organic matter and available water capacity (Hudson, 1994; Smith et al., 2000) and effects of soil organic matter on water quality through its impacts on soil erodibility, sediment transport, and nonpoint-source pollution (Mbagwu and Auerwald, 1999; Borda et al., 2010). In addition, the quantity, quality, and dynamics of soil organic C are strongly tied to species diversity and the activity of soil and water biota (Six et al., 2004; Topp, 2015). In this context, soil organic C is not only a soil quality indicator but also descriptive of CO2 emissions (Smith et al., 2000; Lal, 2015a). Soil C sequestration refers to the plant removal of atmospheric CO2 and storage of fixed C as soil organic matter by plants grown within the same land unit (Lal, 2004a, 2008). The potential soil C sink capacity of managed ecosystems approximately equals the cumulative historic C loss from 1750 to 2000 (Lal, 2004a). Currently, the attainable soil C sink capacity is only 50 to 66% of the potential capacity (Lal, 2004a; Stockmann et al., 2013). Soil C sequestration and its potential as a sink for atmospheric CO2 for mitigating climate change have been broadly discussed in the scientific literature (Kirschbaum, 2000; Smith et al., 2000; Lal, 2004b, 2008; Johnson et al., 2007; Stockmann et al., 2013; Oertel et al., 2016). Strategies to increase the soil C stock vary regionally, depending on both environmental and socioeconomic conditions (Paustian et al., 1997). Broadly speaking, it consists of restorative land use and adoption of recommended management practices (Smith et al., 2000; Lal, 2003, 2004a, 2004b, 2010b; Johnson et al., 2007), such as restoration of degraded soil and ecosystems, woodland regeneration, desertification prevention, no-till farming, use of cover crops, manure and sludge application, integrated nutrient management (e.g., balanced fertilization and combined application of inorganic fertilizer with organic amendment), efficient irrigation, water conservation and harvesting, and growing energy crops on spare lands.

Case Reference 2: Phosphorus Index as an Aggregative Environmental Indicator

Like nitrogen (N), phosphorus (P) is an essential crop nutrient. Animal production can accelerate eutrophication of fresh water by directly (e.g., improper manure storage) or indirectly (e.g., nutrient losses from manure-amended fields) contributing P to waterways, which is one of the leading causes of water impairment in many regions of the world, including Asia (Dai et al., 2011; Li et al., 2015; Novotny et al., 2010; Sun et al., 2012), Europe (Hilton et al., 2006; Withers and Jarvie 2008), and the United States (Dale et al., 2010; Dubrovsky et al., 2010). In response, the USDA and USEPA proposed a new nutrient management policy for animal feeding operations and requested that the USDA–NRCS in each state address agricultural P management in Code 590 (Nutrient Management) by 2008 to receive cost share using one of three approaches:

1. agronomic soil test P recommendations, developed to predict crop performance rather than water quality protection;
2. environmental soil P thresholds, which do not fully reflect potential P loss as they ignore factors other than soil P contributing to P losses to the environment (Sharpley et al., 2003); or
3. P Index ranking of fields by their vulnerability to potential P loss.

Given the limitations of options 1 and 2, 48 states selected a P indexing approach to target P management (Sharpley et al., 2012).

Initially developed by Lemunyon and Gilbert (1993) to identify the vulnerability of field sites to P loss, the P Index for a given site summed source and transport factors weighted according to the magnitude of risk that each factor level represents into a simple risk index. Since its inception, the P indexing framework has undergone revision and reformulation based on field research to increase its adaptability and reliability (Nelson and Shober, 2012; Sharpley et al., 2003, 2012), so that (i) P Index scores are now mainly calculated using a multiplicative or component approach, rather than additively; (ii) transport factors have been revised to include subsurface losses (i.e., tile drainage
and leaching) and distance from site to stream; (iii) the use of continuous, open-ended variable scaling for erosion, soil test P, and P application rate, has replaced the use of fixed weighting and risk values; and (iv) initial “screening tools,” based on soil test P, are used to decide whether a “full” P Index calculation is required.

Currently, the P Index is broadly adopted in 48 US states (Sharpley, 1995; Sims, 1996; Jokela, 2000; Sonnmez et al., 2009), Canada (Bolinder et al., 1998; van Bochoven et al., 2006), and Europe (Heathwaite et al., 2003; Bechmann et al., 2005; Heckrath et al., 2008), with source and transport factors tailored to reflect the unique site characteristics, such as adding the regional extent of irrigation and subsurface tile drainage to transport factors. Justification for the P Index was summarized by Sharpley et al. (2003).

In addition to serving to identify management options for high P soils (Sharpley et al., 2003, 2012), the P Index has been tested at several different scales, including plots (Eghball and Gilley, 2001; Sharpley et al., 2001), fields (DeLaune et al., 2004; Djodjic and Bergstrom, 2005; Veith et al., 2005; Bolster, 2011; Good et al., 2012), catchment (Sharpley, 1995; Schendel et al., 2004; Harmel et al., 2005; Andersen and Kronvang, 2006), and even larger scales (Birr and Mulla, 2001). In general, strong (mostly $R^2 > 0.80$) correlations have been found between measured (or simulated) P in waters and P Index ratings (Fig. 1). A critical review of the overall performance of P Index in North America and Europe endorsed the P Index as an agri-environmental indicator to assess the potential risk of P loss (Osmond et al., 2012, 2017), although there is not a standardized P Index and further field evaluations worldwide are warranted (Buczko and Kuchenbuch, 2007; Sharpley et al., 2017).

Case Reference 3: Model-Derived Agricultural Environmental Indicators

Ideally, agricultural environmental indicators should have a predictive capability, linking changes in production activities and practices to environmental consequences. Because of the time, expense, and inconvenience involved in direct field measurements or the monitoring of indicators, a modeling approach is often a more efficient and feasible means of evaluating management alternatives (Giupponi, 1995; Sharpley, 2006). Today, computer-based models are extensively applied to make such forecasts and to aid in management decision making. Process-based models, particularly those simulating the environmental fate of nutrients and pesticides, are capable of explicitly presenting complex mechanisms and interactive processes in agroecosystems, which are otherwise difficult to measure in situ due to the spatial and temporal heterogeneity between management actions taken and environmental responses at different scales. Models, therefore, allow far wider ranging impact assessments than conventional field studies (Bouraoui and Grizzetti, 2014). One of the fundamental roles of such models is to predict possible large-scale (e.g., regional, national, or continental) environmental effects of agricultural activities and policy under projected future scenarios. For example, Valin et al. (2013) projected that closing yield gaps by 25% for livestock and 50% for crops by 2050 would reduce agriculture and land use change emissions by 12% per calorie produced and by 8% overall using the global partial equilibrium model GLOBIOM to simulate greenhouse gas mitigation associated with various pathways (Fig. 2).

Since the 1970s, many models targeted to specific environmental indicators have been developed and gradually improved. These vary widely in their levels of complexity (rule-based, empirical-conceptual, causal, or process-based), spatial description (lumped or distributed), spatial scale (field to global), representation of the system (screening or detailed system assessment), and resource (data and time) requirements (Giupponi, 1995; Kronvang et al., 2009; Radcliffe et al., 2015). The models Chemicals, Runoff and Erosion from Agricultural Management Systems (CREAMS) (Knisel, 1980), Environmental Policy Integrated Climate (EPIC) (Williams et al., 1990), Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), Agricultural Non-Point Source Pollution (AGNPS) (Young et al., 1989), Simulateur multifidisciplinaire pour les Cultures Standard (STICS) (Brison et al., 2003), Agricultural Drainage and Pesticide Transport (ADAPT) (Chung et al., 1992), Agricultural Policy Environmental Extender (APEX) (Williams and Izaurralde, 2010), DRAINMOD (Youssouf et al., 2005), Hydrological Simulation Program–FORTRAN (HSPF) (Bicknell et al., 2005), HYDRUS (Šimůnek et al., 2008), ICECREAM (Tattari et al., 2001), Phosphorus LEAching from Soils to the Environment (PLEASE) (Schoumans et al., 2013), Nutrient Losses at Catchment Scale (NL-CAT) (Groenendijk et al., 2008), and Transport–Retention–Kalfordelning (TRK) (Brandt and Eijhed, 2002) are among the ones most commonly used capable of simulating diffuse pollution of nutrients and
pesticides. DeNitrification–DeComposition (DNDC) (Li et al., 1992), CH4MOD (Huang et al., 1998), FarmGHG (Olesen et al., 2006), and the Integrated Farm System Model (IFSM) (Rotz et al., 2015) are examples of well-known models for estimating greenhouse gas emissions from land and livestock farms. Some models are derived from others; for example, DAYCENT (Daily Century Model) (Parton et al., 1994) is included in IFSM. The EPIC model is a precursor of the APEX, just as CREAM is to DRAINMOD (Radcliffe et al., 2015). Evaluations and comparison of those agronomic and environmental models, with respect to their capacity to estimate environmental indicators in particular, have been intensively discussed in the literature (e.g., Rossing et al., 2007; Schils et al., 2007; Kronvang et al., 2009; Vadas et al., 2013; Bouraoui and Grizzetti, 2014; Radcliffe et al., 2015).

In light of persistent data gaps and the spatial and temporal heterogeneity of landscapes, scaling up of modeling approaches to the regional, national, or global scales, as well as over time, still poses considerable challenges. Satellite- and other aerial-based remote sensing can overcome such gaps by providing wall-to-wall coverage of important landscape complexity parameters (e.g., diversity, factuality, and function) over decadal time scales. However, significant barriers to the access and use of satellite data remain (Papadimitriou, 2002; de Sherbinin et al., 2014). In the last two decades, integrations of simulation models and satellite data have frequently been used to estimate regional crop yields and to supply data for large-scale yield gap analyses (Lobell, 2013), although the approach rejects the variability of management practices among farms.

Today, the use of satellite data in combination with simulation models has emerged as an environmental indicator development tool, especially at high levels of both spatial and temporal scales. For example, DeFries et al. (1999) used a global terrestrial C cycle model (the Carnegie–Ames–Stanford Approach) and a satellite-derived map of existing vegetation to estimate the effects of land cover change induced by human activities on global terrestrial carbon losses and primary productivity from 1980 to 1999. Similarly, Yang et al. (2000) used SPOT satellite imagery and the Enhanced Stream Water Quality Model QUAL2E to estimate water quality bioindicators of algal growth rate and respiration rate for a large reservoir in Taiwan. Likewise, de Sherbinin et al. (2014) combined the GEOS–Chem chemical transport model and satellite data from NASA’s Moderate Resolution Imaging Spectroradiometer and Terra satellite’s Multi-angle Imaging Spectroradiometer instruments to develop an annual global air quality indicator (particulate matter with a diameter >2.5 μm; PM$_{2.5}$).

Environmental Indicators: Knowledge Gaps and Future Research Directions

Increasing concerns about environmental issues, ecosystem sustainability, and the occurrence of detrimental environmental incidents call for the development of scientifically sound, sensitive, and policy-oriented indicators to assess the state of the environment, estimate environmental trends, and inform policy decision making. Criteria for determining “good” indicators depend on the users of the indicator. The Organization for Economic Cooperation and Development (2003) highlights the importance of policy relevance in environmental indicator development. Accordingly, it is impossible to identify indicators that are “good” for all purposes. The data quality and measurability or collectability of indicators is often cited as key to environmental
indicator quality (Organization for Economic Cooperation and Development, 2003, 2008; Yli-Viikari et al., 2007; Bockstaller et al., 2008). However, one is often forced to compromise between, for example, scientific soundness and feasibility constraints (e.g., the ease of a technique vs. the costs to acquire data), especially at a large scale, such as at the national level (Yli-Viikari et al., 2007). The final effect of such compromises on the relevance of an environmental indicator relative to its purposed objectives is often unknown.

From environmental indicator design to validation, there remain important knowledge gaps regarding indicator development. Selected environmental indicators should ideally address critical environmental issues and be available to provide information regarding thresholds or reference points of indicators over long time series and wide geographic areas (Alfen and Sæbø, 1993; van der Werf and Petit, 2002). Unfortunately, many indicators lack either standard thresholds or reference points, or these are still in development either conceptually or in terms of data availability. This is particularly true for P Indices, although they have been widely adopted in most of the United States as a planning tool to assess the risk of P runoff during development of farm nutrient management plans (i.e., 590 Conservation Practice Standard; USDA–NRCS, 2011). Several regional project teams recently completed reliability assessments of various state P Indices to estimate P runoff. These teams had to rely on calibrated field-based nonpoint-source models to generate water quality data in the absence of adequate field data to evaluate the indices (Sharpley et al., 2017).

The development of environmental indicators clearly relies closely on environmental monitoring and assessment. Given the existence of knowledge gaps regarding environmental indicators’ indicative themes, well-designed methods for data collection and interpretation of their significance are essential. For example, our understanding of the process of C stabilization in soil, the linkage between how C is sequestered in soil and its consequences for soil functions and greenhouse gas emission, is still limited and contributes to a growing list of “known unknowns” (Stockmann et al., 2013).

One of significant challenges in the application of environmental indicators is the scaling up of indicator outputs to larger scales (e.g., national or global) based on small-scale measurement of indicators. Uplinking to a larger scale is generally achieved by calculating an area- and quantity-weighted average of lower-scale measurements, with or without the intervention of simulation models (Bockstaller et al., 2008; Van Cappellen and Maavara, 2016). This upscaling approach omits several factors that may be of key importance in particular situations, such as spatial and temporal heterogeneity of landscapes. Satellite remote sensing has the potential to overcome those heterogeneities, especially when combined with simulation models, but it poses new challenges, such as difficulties in accessing and using the data, gaps between what satellites measure and what decision makers’ find of interest, limited collaboration between the environmental monitoring and Earth Observation satellite communities, and different sources of errors in data acquisition (Papadimitriou, 2002; Lobell, 2013; de Sherbinin et al., 2014). On the other hand, while producing internationally comparable data on environmental performance is politically important, their worth will always be scientifically ambiguous, since national or global datasets are generally aggregated and likely include different sources of uncertainty (Yli-Viikari et al., 2007). This is particularly the case when ecological changes are described, as the structure and function of ecosystems are always local and system specific. Accordingly, the functional properties—strengths and weaknesses—of aggregated datasets are still inadequately known.

Evaluation of environmental indicator quality is clearly indispensable for scientific diagnosis, as any indicators should embrace its uncertainty and limitations in use. This is especially true for bioindicators, as a species existing in one region may simply be absent in another (Smith et al., 2000; Dantsis et al., 2010).

An example of an aggregative environmental indicator, the P Index, when adapted to local conditions, requires a calibration of weights to improve agreement between potential and actual loss (Sharpley et al., 2003; Heckrath et al., 2008). If measured data are available, validation of indicator outputs is straightforward: indicator outputs are compared with the ones measured using statistical methods to evaluate accuracy (i.e., probability test, or expert judgment and consensus). However, due to its subjectivity, the expert judgment approach should be considered as the minimum criterion for indicator validation (Bockstaller and Girardin, 2003; Bockstaller et al., 2008).

One of the challenges in evaluating environmental indicators is the uncertainty underlying the indicators, including their sensitivity to change. Besides comparative studies of different indicator-based methods’ influence on impact assessments, few environmental indicator developers have proposed detailed procedures to address these issues (Hertwich et al., 1997; van der Werf and Petit, 2002; Payraudeau and van der Werf, 2005). Van der Werf and Petit (2002) evaluated indicators by using an additional set of indicators to qualify the degree to which the objectives of the environmental indicators were attained. Bockstaller and Girardin (2003) and Bockstaller et al. (2008) proposed a three-step methodological framework for sensitivity analysis and validation of environmental indicators:

1. Design validation— to evaluate the scientific reasonability of the indicator at an early stage.
2. Output validation— to assess the soundness of the indicator output.
3. End use validation— to assess indicator usefulness and its relevance to policy-making.

Fuzzy logic and Monte-Carlo approaches have also been used to evaluate simplified environmental indicators (Mertens and Huwe, 2002; Oenema et al., 2003). Despite efforts devoted toward the uncertainty evaluation of environmental indicators, it still receives little attention, both from reluctance to implement and lack of methodology and because of unavailability of sufficient measured data (Rigby et al., 2001). Recommendations on uncertainty assessment of environmental indicators, especially the analysis of sensitivity, together with thresholds and reference points, should be provided to users to help them recognize the nature of these indicators and appropriately interpret them. This decisive step in evaluating model quality requires that a standard environmental indicator evaluation procedure be developed.

Human disturbance to ecosystems further expands the “known unknowns” of environmental indicator development. Niemi et al. (2007) demonstrated that increased human disturbance, measured on a human disturbance gradient and occurring
primarily in the form of agricultural activities and population density, was the main contributor to the impaired environment of the North American Great Lakes coastal region. Similarly, the damming of rivers represents one of the major anthropogenic disturbances to the natural cycles of water and nutrients on the continents (Maavara et al., 2017). Dams profoundly affect riverine nutrient fluxes, water quality, and river–floodplain ecosystems. In particular damming decouples riverine nutrient fluxes, which results in marked differences in nutrient stoichiometry in dam reservoirs compared with receiving water bodies, such as lakes and coastal marine areas (Van Cappellen and Maavara, 2016). While landscape development-related environmental disturbance may seem inexorable and inevitable, the most appropriate questions are:

1. How much farther will the environmental degradation proceed?
2. At what pace, and
3. How should the environmental assessment be adjusted in response to a major anthropogenic disturbance?

A wide spectrum of models is in use for estimating environmental indicators, especially process-based ones. All model-predicted environmental indicators have a certain level of uncertainty, arising from our insufficient understanding and imperfect representation of the underlying processes involved, intentional simplifications of processes for practical considerations, the limited data available to drive the models, and the inherent randomness of natural systems (Giupponi, 1995; Radcliffe et al., 2015; Zhang et al., 2017). This uncertainty is intimately linked to the validity of model assumptions, quality of data input and data used for model evaluation, and how well the model parameters are estimated. Sources of uncertainty are often interrelated, and in many cases the magnitude of uncertainty is unknown. The persistent challenge in model development and improvement is to balance the complexity of the model between maximization of accuracy and practical considerations (e.g., ease of use, short run time). A recent study on uncertainty of national CH\textsubscript{4} emissions using a modeling approach revealed the dilemma between model performance and data availability: a model with better performance reduces uncertainty, but data scarcity can increase uncertainty (Zhang et al., 2017). Accordingly, it is important to select models with the required predictive accuracy, input data availability, while considering the spatiotemporal scales of the simulation (Sharpley, 2006).

With environmental indicator modeling, the question also arises as to whether models that are useful in informing scientists about environmental changes can also be useful for policymakers. A model that can allow a researcher to understand a complex system may be irrelevant to a policymaker due to its complexity, lack of comprehensiveness, or the transaction costs involved in accepting environmental indicators modeling (Rossing et al., 2007).

Since this introduction covers a wide diversity of environmental indicators currently in use, future goals and approaches in indicator development, drawn from the literature (Alfen and Sebo, 1993; McRae et al., 1995; Smith et al., 2000; van der Werf and Petit, 2002; Riley, 2001; Organization for Economic Cooperation and Development, 2003, 2008; European Environmental Agency, 2003; Ramos et al., 2004; Bockstaller et al., 2008; de Sherbinin et al., 2014; Radcliffe et al., 2015), are summarized here:

- Improve the quality and comparability of existing indicators over time. This requires the development of harmonized methods for data collection, monitoring, interpreting, and reporting.
- Continue the development of new indicators addressing new environmental and policy concerns, and ensure that environmental indicators are scientifically credible, sensitive to change, and easy to understand and interpret.
- Ensure environmental indicators’ policy relevance; that is, target environmental indicator development to specific objectives or goals of the authority using them.
- Continue field studies to explore linkages between ecological processes and temporal/spatial status of the environment in ecosystems.
- Develop standardized procedures or guidelines for the evaluation of environmental indicators, including the standards, thresholds, reference points, and other complementary information for the validation of indicators.
- Improve linkages of environmental indicators with indicators tracking economic and social changes, in terms of both causes and effects.
- Recognize existed lacunae in data and develop or improve the methodologies of data upscaling, uncertainty assessment or contradictory analyses of indicators.
- Improve or adapt (rather than develop new) environmental models for environmental indicators modeling; encourage incorporation of earth observation data into modeling; reduce barriers in accessing and using remote sensing data by, for example, strengthening cooperation between modelers and earth observation communities.
- Provide cross-cutting technical and funding resources for cooperative research.

**Contents of This Special Section**

Nutrient loading from arable land to water with respect to water quality is one of the key applications of agricultural environmental indicators. Modeling P losses lags behind that of N losses, largely because of the more complex physical, (geo)chemical, and biological processes involved in P transformations in soils and transportation from soil to water that constitute the basic structure of relevant process-based models. Qi et al. (2018) report using the ICECREAM model, an empirical and process-mixed Finnish model mainly based on the CREAMS (Knisel, 1980) and the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) models (Leonard et al., 1987), to simultaneously simulate surface and subsurface P losses from a clay loam soil in southwestern Ontario, Canada. The model proved satisfactory for predicting dissolved reactive P losses through both pathways of surface and subsurface (tile drainage), as well as plant P uptake, but not overall subsurface P losses, due to the model’s poor simulation of particulate P. Both observed and simulated P losses indicated that the predominant P losses occurred outside the growing season, particularly during the spring snow melt. Accordingly, special care should be taken to simulate particulate P loss under high tile drainage flows typical
of this season. Simulation under alternative practices suggested a 10% reduction of total P losses by shifting tillage from autumn to spring and a 25.4% decline if fertilizer was injected instead of surface broadcast. The authors conclude that the ICECREAM model is effective for P management of subsurface drained fields but warrants further validation on manured soils and under other climatic conditions.

Bioindicators, more particularly biomarkers, naturally incorporate a broader concept of contamination or toxicity integrity than do chemical and toxicological indicators, because biological integrity is affected and determined by multiple physical, chemical, and biological factors (Smith et al., 2000). Wang and Tam (2018) introduce the antioxidants related to the glutathione–ascorbate cycle as early-warning biomarkers of toxicity of BDE-47 (2,2',4,4'-tetrabromodiphenyl ether), one of the most prevalent and toxic polybrominated diphenyl ethers (PBDEs) congeners. In an 8-wk hydroponic culture study, the authors found that the content and activity of five enzymatic and nonenzymatic antioxidants (ascorbate peroxidase [APx], dehydroascorbate [DHA], glutathione reductase [GR], glutathione peroxidase [GPx], and oxidized glutathione [GSSG]) in the roots and leaves of mangrove (Kandelia obovata) seedlings exposed to the BDE-47 treatments of 5 and 10 mg L⁻¹ changed significantly in Week 1, whereas such changes were much more limited when exposure occurred between Weeks 4 and 8. These results suggest that antioxidants related to glutathione–ascorbate play indicative roles with respect to PBDE toxicity in mangrove plants. Wang and Tam (2018) also speculate that the mangroves’ defense system may be inadequate to counterbalance the oxidative stress caused by high levels of BDE-47, and/or that the system may have broken down after long-term PBDE exposure.

Whereas improper application of agricultural pesticides can result in nonpoint-source contamination of surface or groundwater, centralized on-farm sites used to fill spray tanks with pesticides and clean pesticide application equipment may constitute point sources of pesticide contamination, contributing up to 90% of the surface water pesticide loads (Reichenberger et al., 2007). One approach to minimizing such point-source pollution is to install biobeds to dissipate pesticides. Chu and Eivazi (2018) constructed biobeds and tested the effects of four types of biomixes (a mixture of straw, topsoil, peat, or compost in different proportions, or soil alone [control]), on dissipation of four commonly used herbicides (acetochlor, atrazine, pendimethalin, and trifluralin) under standardized incubation conditions. Atrazine and pendimethalin dissipated faster in the biomixes than in soil, showing greatly reduced half-lives (DT₅₀). The dissipation rates and DT₅₀ of acetochlor were comparable to those in soil, and trifluralin took longer to dissipate in the biomixes than in soil. The study reveals that biobeds, especially those biomixes with peat, were effective in degrading selected herbicides and controlling on-farm point-source pesticide pollution.

Conclusions

Environmental indicators have been developed steadily and become more sophisticated over recent years, particularly in the case of agricultural environmental indicators designed to assess the environmental consequences of agricultural activities and progress toward a sustainable management of ecosystems. The Pressure–State–Response framework developed by the Organization for Economic Cooperation and Development is the cornerstone of environmental indicator development and is the precursor of many derived frameworks, such as the Driving Forces–Pressures–States–Impact–Responses by the European Environmental Agency and the Stewardship–State–Productivity by Agriculture and Agri-Food Canada. Due to the broad coverage of environmental disciplines, a diverse number of environmental indicators are in use and the typology or classification appears to be somewhat disjointed. The key environmental indicators, however, are mainly those used in assessing environmental issues in relation to the degradation of natural resources (e.g., soil, water, and air quality), the sustainability of ecosystems (e.g., biodiversity) and climate change (e.g., greenhouse gas emissions).

The ideal environmental indicators possess desirable characteristics of policy relevance, scientific soundness and reliability, sensitivity, measurability or collectability, and understandability, although in practice not all of these may be met at the same time. The policy oriented, scientific soundness, and measurability criteria often outrank other criteria when selecting environmental indicators (Organization for Economic Cooperation and Development, 2003). Because of the large diversity of environmental assets, the validation of indicators, in the sense of model validation, is not straightforward. The existence of knowledge and methodological gaps further complicates the evaluation of uncertainties associated with environmental indicators. Moreover, the difficulty in upscaling indicator outputs due to the hierarchy of spatial scales existing in ecosystems and the need for harmonization of data collection, monitoring, and reporting methods for national and international comparisons represent challenges for the development and improvement of today’s environmental indicators.

As the three examples presented here illustrate, environmental indicators may be close associates rather than direct measures of the amounts, concentrations, or abundance of that in which we are interested, for example, soil C stock as an indirect indication of CO₂ emissions. An environmental indicator may not be a simple and single measure; for example, the P Index represents the ensemble of a number of risk indicators as an aggregated indicator of water quality. Environmental models, alone or drawing on remote sensing data, are increasingly used in environmental indicator modeling. However, without comparisons to ground-based measurement, there may still be challenges for policymakers to rely on model- or satellite-based environmental indicators during their decision-making process. As such, a collaborative effort for ground observation and model calibration should ultimately improve the applicability of model-derived indicators in environmental management.

While the existing environmental indicators are powerful tools of environmental assessment and management, they do not constitute omnipotent measures of the state of the environment. They need to be complemented with background information, economic and social indicators, scientific analysis, and legitimate interpretation. The future works outlined herein are only, we believe, a part of what is needed to mobilize environmental indicators’ prospective capacities of tracking environmental progress, measuring environmental performance, and providing help in policy making.


