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REVIEW

Scientific considerations and challenges for addressing cumulative effects in forest landscapes in Canada

L.A. Venier, R. Walton, and J.P. Brandt

Abstract: Traditionally, forest management has focused on forestry-related practices whereas other industries have been managed separately. Forest management requires the integration of all natural resource development activities, along with other anthropogenic and natural forest disturbances (e.g., climate change, pollution, wildfire, pest disturbance) to understand how human activities can change forested ecosystems. The term cumulative effects has been used to describe these attempts to integrate all disturbances to develop an understanding of past, current, and future impacts on environmental, social, and economic components of the system. In this review, we focus on the science required to understand the past, current, and future impacts of the cumulative effects of anthropogenic and natural disturbances on forested ecosystems or their components. We have primarily focused on the terrestrial system with an emphasis on northern forests in Canada. Our paper is not intended to be a comprehensive review of all cumulative effects science but a synthesis of the challenges and approaches currently being used. Central repositories were identified as an approach to deal with issues of availability of remotely sensed data on anthropogenic and natural disturbances. Data integration projects, open data, and well-designed large-scale data collection efforts are needed to provide sufficient data on environmental responses to cumulative effects. As well, large-scale integrated, modularized ecosystem models are needed to bring stressor and environmental response data together to explore responses to, and interactions between, multiple stressors to project these effects into the future and to identify future data collection needs.

Key words: Cumulative effects, natural disturbance, anthropogenic disturbance, integrated natural resource management, forest management, environmental stressor.

Résumé : Traditionnellement, la gestion des forêts s'est concentrée sur les pratiques liées à la foresterie, alors que les autres industries ont été gérées séparément. La gestion des forêts nécessite l'intégration de toutes les activités de développement des ressources naturelles, parallèlement aux autres perturbations anthropiques et naturelles des forêts (par exemple, le changement climatique, la pollution, les incendies de forêt, les perturbations dues aux phytoravageurs) pour comprendre comment les activités humaines peuvent modifier les écosystèmes forestiers. Le terme « effets cumulatifs » a été utilisé pour décrire ces tentatives d'intégration de toutes les perturbations afin de développer une compréhension des impacts passés, présents et futurs sur les composantes environnementales, sociales et économiques du système. Dans cette synthèse, les auteurs se concentrent sur la science requise pour comprendre les effets passés, actuels et futurs des effets cumulatifs des perturbations anthropiques et naturelles sur les écosystèmes forestiers ou leurs composantes. Ils se sont principalement concentrés sur le système terrestre, en mettant l'accent sur les forêts du nord du Canada. Leur document ne se veut pas un examen exhaustif de toute la science des effets cumulatifs, mais une synthèse des défis et des approches actuellement utilisées. Les dépôts centraux ont été identifiés comme approche pour traiter les questions de disponibilité des données de télédétection sur les perturbations anthropiques et naturelles. Des projets d'intégration des données, des données ouvertes et des efforts bien conçus de collecte de données à grande échelle sont nécessaires pour fournir suffisamment de données sur les réponses environnementales aux effets cumulatifs. De même, des modèles d'écosystèmes intégrés et modulaires à grande échelle sont nécessaires pour rassembler les données sur les facteurs de stress et les réponses environnementales afin d'explorer les réponses à de multiples facteurs de stress et les interactions entre eux, de projeter ces effets dans le futur et d'identifier les besoins futurs en matière de collecte de données. [Traduit par la Rédaction]

Mots-clés : effets cumulatifs, perturbation naturelle, perturbation anthropique, gestion intégrée des ressources naturelles, gestion forestière, facteur de stress environnemental.

1. Introduction

1.1. Context

Forests cover more than 347 million ha of the Canadian landscape (Natural Resources Canada 2017), providing many benefits, but balancing economic, cultural, and ecological values is challenging (Brandt et al. 2013). Traditionally, forest management has focused on harvesting and forestry-related practices whereas other industries have been managed separately. A recent report by the Council of Canadian Academies (2019) on integrated

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natural resource management argues strongly for the integration of all natural resource development at appropriate scales in the management of forests and other lands. This form of integrated management necessarily requires the development and use of cumulative effects science, which is most generally defined as the analysis of how multiple stressors interact to alter ecosystems. In this paper, we are interested in the challenges and current approaches of cumulative effects science as it is used to address natural resources management in Canadian forests, but this science is also relevant globally to issues of all land-use planning and management.

Although the forest industry extracts economic value from wood biomass directly, other industries affect forest ecosystems incidentally as well. Expansion of agricultural land can lead to direct loss of forest area but it can also affect forests through changes in invertebrate and vertebrate communities, exposure to drift from herbicide and insecticide applications, or nutrient exports for example (Benton et al. 2002; Foley et al. 2005; Sánchez-Bayo and Wyckhuys 2019). The mining industry directly removes forest area and can impact ground and surface water quality and aquatic ecosystems. Across Canada, there are more than 10 000 sites where mining or metal and mineral exploration has affected the landscape (Tremblay and Hogan 2006). The oil and gas industry also affects forests, especially in the western provinces and territories. In 2011, the boreal zone, for example, contained approximately 220 000 active and abandoned well sites, 441 000 km of pipeline, and 1.7 million km of seismic lines (Brandt et al. 2013). Impacts from these and other industries are cumulative with the development of supporting infrastructure such as access roads, railways, power lines, and dams, all of which remove additional forest area and lead to increased fragmentation of remaining forests. As well, nonconsumptive activities such as livestock grazing, recreation, and tourism can have impacts on forest ecosystems (Fleischner 1994; Marion et al. 2016). Impacts are not restricted to localized disturbances. Forests are also affected by long range transport of air pollutants such as sulphur dioxide and nitrogen oxides, which are precursors to acid rain (Singh and Agrawal 2007), and by global influences such as climate change (Price et al. 2013).

1.2. Rationale

Efforts to protect and manage forests sustainably can be impeded by multiple impacts from discrete industries falling under separate jurisdictions and regulatory frameworks. It is important to find ways to address these overlapping effects to minimize unintended impacts and to enable more efficient, transparent, and consistent decision-making (Council of Canadian Academies 2019). Understanding cumulative effects was highlighted as a priority and a knowledge gap in a series of review papers on the impacts of natural resource management and climate change on the boreal recently published in *Environmental Reviews* (Brandt et al. 2013; Kreutzweiser et al. 2013; Price et al. 2013; Venier et al. 2014; Webster et al. 2015). Government agencies and nongovernmental organizations (NGOs) agree that understanding cumulative effects is critical to ensuring the health, productivity, and sustainability of terrestrial and aquatic ecosystems and is a priority for research (e.g., BC Government 2016; CEAA 2018). The issue of cumulative impacts of multiple anthropogenic stressors is also recognized as a dominant factor in conservation of wildlife (Johnson et al. 2005; Johnson et al. 2015). Although there is consensus that assessing cumulative effects is important for land-use planning, there is recognition that we have been unsuccessful at generating adequate knowledge around cumulative effects to date (Brandt et al. 2013; Duinker and Greig 2006; Harriman and Noble 2008; Kreutzweiser et al. 2013; Venier et al. 2014).

1.3. Objectives

Our objective in this paper is to review the scientific aspects of cumulative effects research and to identify and explore existing scientific approaches that measure and forecast cumulative effects of anthropogenic and natural disturbances. Our review is directed towards scientists, policy makers, and decision-makers who must incorporate cumulative effects thinking into strategic land use planning. Many process- and policy-related issues limit the incorporation of cumulative effects into impact assessment and land-use planning, but they are outside the scope of the current synthesis. We focus on forested ecosystems where forestry and other natural resource development is the dominant anthropogenic disturbance and at multiple spatial scales with an emphasis on studies that explore the consequences of cumulative effects on elements of biodiversity or landscape characteristics. We focus on this area because of our specific expertise in natural resource management and related issues in this area and the need to limit the scope of this very broad topic. We only consider the environmental science of cumulative effects, leaving regulatory, economic, social, and cultural considerations aside. We acknowledge that there are many factors beyond science that have limited the evaluation of cumulative effects, and that in the past cumulative effects have been sometimes minimized or excluded in regulatory assessments (Duinker and Greig 2006; Gunn and Noble 2011; Gibson 2012, 2017).

1.4. Organization of the paper

The study of cumulative effects is a broad topic and we have partitioned our review into 12 sections (Fig. 1) to provide structure. We acknowledge that some of these divisions are arbitrary and that topics overlap. Fig. 1 provides an overview of how our review is organized to assist the reader.

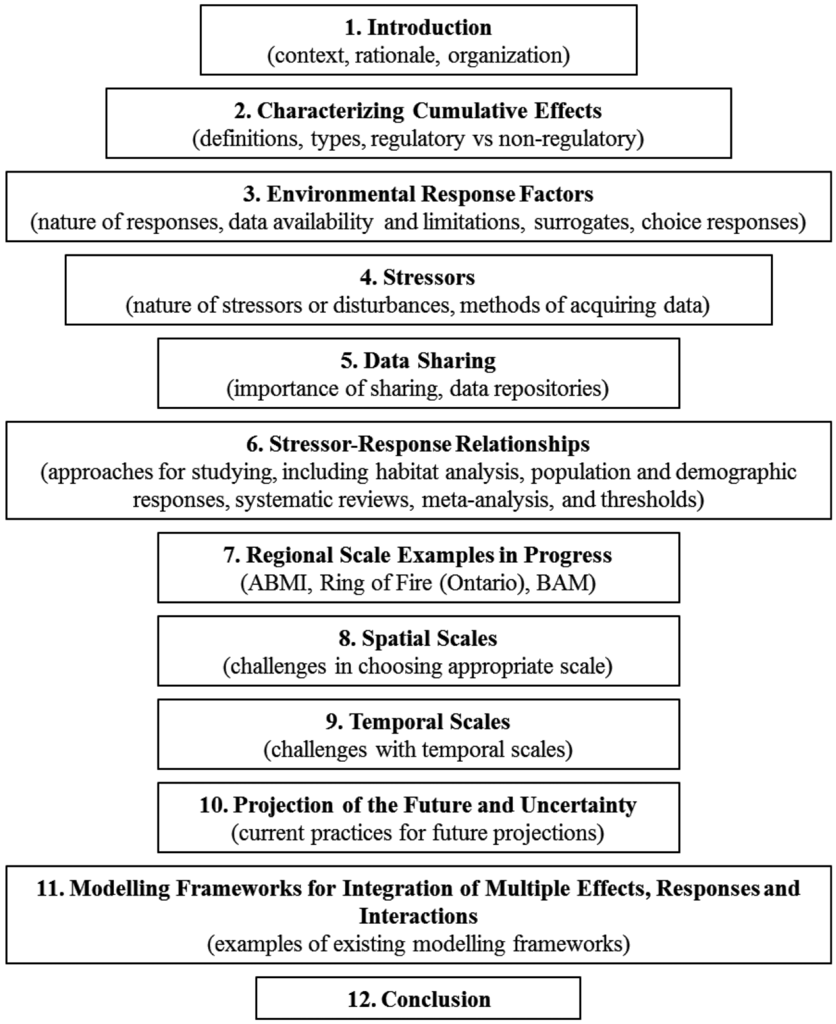
2. Characterizing cumulative effects

2.1. Definitions

As noted by many (Noble 2010; Bragagnolo and Geneletti 2012; Duinker et al. 2013), there is no internationally accepted definition of cumulative effects. Cumulative effects are sometimes characterized as "death by a thousand cuts", the idea that apparently negligible environmental effects by an activity in isolation of other landscape disturbances can contribute to major impacts when its effects are combined with other activities across space or time or both (MacDonald 2000). Cumulative effects often result from interactions among different natural resource sectors. In the South Peace region of British Columbia, for example, forestry, agriculture, natural gas, wind energy, and coal mining all operate on the same land base (Johnson 2015), and their impacts combine to generate larger effects. Cumulative effects can also occur within a single industry. In forestry, a single small clearcut in a large watershed is unlikely to have a significant impact on habitat or water quality at the landscape level, but an extensive array of clearcuts can have a substantial impact, which can increase with time as new clearcuts interact with previously harvested blocks and future harvest entries (Wintle et al. 2005; Kreutzweiser et al. 2008). Climate change is a human impact that can have both direct and indirect effects on ecosystems and that can combine with effects of natural resource development to further influence these ecosystems (Cadieux et al. 2020). Regardless of the anthropogenic disturbances in play, the common thread is that multiple disturbances or stressors interact across space and time to result in a greater impact on the state of the ecosystem, whether that is broadly defined, such as ecosystem integrity, or narrowly defined, such as the abundance of a single species.

Some definitions of cumulative effects focus solely on anthropogenic activities, whereas others explicitly include the interaction of human activities with natural processes such as fire and pests that are both common in much of Canada's forests. Sidle and Hornbeck (1991) proposed that the concept of cumulative effects should include "environmental changes caused by the interaction of natural ecosystem processes with the effects of

Fig. 1. Organization of paper.



land-use activities distributed through time or space, or both". In British Columbia, the provincial government defines cumulative effects as "changes to environmental, social and economic values caused by the combined effect of past, present and potential future human activities and natural processes" (BC Government 2016). As Boyle et al. (1997) argued, cumulative effects of forestry practices, in particular, have to be considered "in the context of natural ecosystem dynamics and disturbance patterns". Whether natural disturbances are considered as additional to anthropogenic disturbances or used to help to define the baseline range of natural variability against which anthropogenic disturbances are measured, depends largely on the response of interest that is being affected. For some species and ecosystems, it would be misleading to ignore the influence of extensive disturbance events such as wildfires and pests on habitat values. In their study of cumulative effects on boreal caribou (*Rangifer tarandus caribou*), for example, Sorensen et al. (2008) found both wildfires and proximity to anthropogenic activities interacted to reduce caribou habitat and population growth rates. Studies evaluating cumulative effects on timber supply should also consider fire and insect outbreaks that reduce available timber volumes (Boucher et al. 2018). In addition, studies that forecast cumulative effects into the future often incorporate climate change as a stressor (Boucher et al. 2018) because climate change alters natural disturbance regimes such as fire (Bergeron et al. 2006) and insect outbreaks (Price et al. 2013). Thus, altered natural disturbances are no longer entirely natural but are now interacting with anthropogenic processes to generate change in ecosystems. If the objective is to understand how human activity influences an ecosystem-level concept like forest integrity, then natural disturbance should be considered as part of the natural system that supports ecological integrity in contrast to anthropogenic disturbance, which may undermine ecological integrity. In this review, we take the broad interpretation of cumulative effects science to mean the study of environmental responses to multiple human disturbances (plus natural disturbances, depending on the appropriate reference condition).

2.2. Types of cumulative effects

Within cumulative effects research, as with most ecological research, we think in terms of agents of change, also known as stressors, which accumulate and interact to generate an environmental response. Interactions among ecosystem stressors have been classified as additive, synergistic or antagonistic (Côté et al. 2016). Additive effects behave linearly, with the total effect on the environmental response equal to the combined effects from individual stressors. For example, in a large-scale study of wolverines (*Gulo gulo*) in the central Canadian Rockies, a cumulative effects model that combined the influences of habitat, anthropogenic disturbances, climate change (indicated by a persistent spring snow pack), and competition best explained wolverine distribution (Heim et al. 2017) suggesting additive effects. Synergistic effects behave nonlinearly, with a combined effect that exceeds the sum of effects from individual activities, and they are caused by amplifying feedbacks (Brook et al. 2008). Synergistic interactions between climate change and logging and trapping were demonstrated for lynx and marten (*Martes americana*) using spatially explicit population models (Carroll 2007). Antagonistic effects result from different stressors that work in opposition to reduce the expected total effect. For example, factorial experiments showed that invasive grasses reduced the susceptibility of native plant communities in regenerating longleaf pine (*Pinus palustris*) forests to the effects of drought (Fahey et al. 2018). Synergistic effects are the most concerning from a cumulative effects perspective because their impacts will be larger than expected and difficult to anticipate. The effects of mutiple stressors can be magnified by synergistic interactions resulting in unpredictable "ecological surprises". However, recent work suggests that synergistic effects are not the most prevalent type of interaction and that identifying the nature of the interaction is important for mitigation (Côté et al. 2016).

2.3. Cumulative effects in regulatory versus nonregulatory context

Cumulative effects studies are often associated with regulatory practice (Sinclair et al. 2017), usually at the level of major infrastructure and resource development projects. Formal cumulative effects assessments (CEA), conducted by the former Canadian Environmental Assessment Agency (now known as Impact Assessment Agency of Canada) or provincial equivalents, are often at a project-level and generally follow a stressor-based approach. This process begins with identifying potential environmental stressors caused by the project, identifying environmental response factors that may be impacted by these stressors, and then assessing the interactions (Dubé 2003). Project-based CEA has its limitations, however, and scientific criticisms include: (*i*) difficulties determining appropriate spatial and temporal scales for the environmental responses (Dubé 2003; Duinker and Greig 2006; Noble 2010); (*ii*) assumption that all stressors and their effects are known for a project, including other existing projects in the area and future projects (Dubé 2003; Harriman and Noble 2008; Duinker et al. 2013; Squires and Dubé 2013); (*iii*) lack of or poor understanding of environmental baseline conditions prior to development (Dubé 2003; Jones 2016); and (*iv*) lack of effective follow-up monitoring to document and understand changes (Dubé 2003; Seitz et al. 2011).

Effective management of cumulative effects is also limited by what triggers a full environmental impact assessment review. Forestry, land conversion, and urban growth typically do not require formal impact assessments, yet they may have a large impact on the environment that requires considerations by land managers and policy makers. In addition, time constraints can limit the amount of science conducted to understand a project's cumulative effects in a formal assessment context. Additional science could involve the testing of hypotheses about the underlying cause and effect relationships and interactions of stressors and environmental responses using empirical and simulation data. An examination of spatial and temporal scales beyond the immediate needs of decision-makers could also be useful. Finally, a broader scientific approach may require a longer time commitment for data collection than is typically allowed for in a regulatory assessment. We think that this broader approach is a necessary activity to facilitate progress in our understanding of cumulative effects and that limiting cumulative effects science to the regulatory context will greatly limit potential ecological insights that could inform integrated resource management and land-use planning in the longer term. Investment in this science needs to extend beyond the confines of the regulatory process.

To avoid some of these limitations, there is general agreement that cumulative effects science be conducted at larger, more ecologically meaningful scales, such as a watershed, across an ecotype, or a region (Kennett 1999; Dubé 2003; Duinker and Greig 2006; Harriman and Noble 2008), and with science-based objectives that test hypotheses about causal relationships between stressors and environmental responses. Typically, large-scale cumulative effects science use an effects-based approach (Dubé 2003), where the focus is on assessing the condition of an environmental response factor (e.g., water quality) first and then identifying the stressor(s) impacting that factor. However, in our opinion, it is not necessary to a priori identify a single approach. In some cases, identified responses may help understand the potential stressors and, at the same time, identified stressors may help choose appropriate environmental responses. Identifying specific cumulative effects hypotheses can be approached with a consideration of both relevant stressors and relevant environmental responses at the same time.

For project-level CEAs, there is no shortage of step-by-step procedures or frameworks (Canter and Ross 2010; Duinker et al. 2013; Jones 2016), but there is no single broadly accepted standard approach (Seitz et al. 2011; Squires and Dubé 2013). It is arguably necessary to define a consistent formal approach to CEA in a legislative context, but it is not necessary and potentially detrimental in a scientific context where exploratory approaches could lead to scientific breakthroughs (e.g., Lindenmayer and Likens 2010).

Although much of the science on cumulative effects has been conducted within the context of formal CEAs, our interest here is in the science rather than the formal assessment. Scientific approaches should be driven by the scientific objectives, which are often more about the underlying cause and effect relationships between multiple stressors, their interactions, and the associated ecological responses. Additionally, not all studies that could be classified as "cumulative effects" science use that terminology. For example, landscape modelling studies, which project cumulative interactions of anthropogenic and natural disturbances on environmental responses decades or longer into the future, often do not mention cumulative effects specifically (Bergeron et al. 2017; Boulanger et al. 2019). Rockström et al. (2009) expanded cumulative effects principles to a global scale without specifically using the term. Any ecological study that examines the interactions of multiple stressors and their impact on environmental factors should be considered as cumulative effects science. In disciplines like conservation biology, understanding cumulative effects is critical for protection of most threatened or endangered species. In other words, although environmental assessments often include cumulative effects science, the science of cumulative effects is not limited to environmental assessments.

3. Environmental response factors

3.1. Responses and indicators

The environmental impact literature uses the term Valued Ecosystem Component (VEC), to describe the ecosystem component of interest that is responding to stressors in an environmental assessment (Beanlands and Duinker 1984) but we will use the more generic term of environmental response factor to distinguish cumulative effects science from the more formal process of CEA. Environmental response factors are ecosystem components that could potentially be affected by cumulative effects. These factors can be defined relatively broadly (e.g., ecosystem integrity, sustainability, biodiversity, soil quality, water quality) or more narrowly (e.g., individual species at risk). Metrics or indicators capture the state of the response factor and are even more narrowly defined so as to be measurable. It is common to have multiple indicators to reflect a single environmental factor. For example, if caribou are the environmental response factor of interest, then herd size and rates of reproduction could be indicators (Sorensen et al. 2008). The distinction between environmental response factors and indicators can be ambiguous and partly reflects how broadly or narrowly environmental response factors are defined. The important point is that there must be a measurable response variable that may be of direct interest or because it reflects some broader ecosystem component.

Cumulative effects studies can be driven by a desire to understand the broad impacts of multiple stressors on an ecosystem or, conversely, to understand how an individual ecosystem component is affected by multiple stressors. If the study is driven by an individual ecosystem component, then the study objective defines the environmental response factor. For example, there is a great deal of concern presently about the viability of caribou herds in boreal Canada. There are many studies attempting to understand and ameliorate the cumulative stressors on this animal with the objective of maintaining viable populations (see the National Boreal Caribou Knowledge Consortium at https://www.cclmportal.ca/portal/boreal-caribou/about). Thus, the choice of environmental response factor of concern in this situation is predetermined, although the selection of indicators is not. A more general environmental response factor such as forest integrity, sustainability, or water quality is often the desired outcome in a natural resource development context. In this case, a subset of factors and (or) indicators should be selected that are sensitive to the predetermined stressors. If the study is intended to understand the impact of specific stressors, then response factors could be selected based on expected responses to the stressors, anticipated future risk, or the presence of high-value ecosystem components that drive decision-making (Canter and Ross 2010). Environmental response factors that are effective in supporting land-use planning and conservation need to be relevant to diverse stakeholders to be considered meaningful and worth studying and to be factored into decision-making (Canter and Ross 2010; Duinker et al. 2013). Ungulates, for example, are often chosen as environmental response factors, as much for their socioeconomic and cultural value as for their ecological role. Forest sustainability is another important environmental response factor and its protection helps to maintain social license for resource development and to secure Canada's environmental reputation.

Measurable and validated indicators that are sensitive, possess sufficient precision to detect effects, and allow for the prediction of trends are most desirable (Jones 2016). Data availability and sampling practicality are necessary factors in selecting indicators (Jones 2016). For wildlife species, indicators at the population and community level are the most important because cumulative effects are more severe and irreversible as the biological, spatio-temporal, and management scales increase (Johnson and St-Laurent 2011). Environmental responses and their indicators also need to be meaningful and appropriate at the spatial and temporal scales relevant to the study and project objectives, recognizing that some indicators are only relevant or feasible at certain scales (Olagunju and Gunn 2015; Jones 2016; Sutherland et al. 2016). For example, forest connectivity or population viability is most relevant at landscape and larger scales (Sutherland et al. 2016), whereas water quality and habitat availability can address multiple scales, and soil quality is difficult to expand beyond small scales because of its inherent heterogeneity.

The type and severity of impacts resulting from cumulative effects vary depending upon the environmental response under consideration. In Alberta, for example, agricultural areas in winter induced negative responses by gray wolves (*Canis lupus*) and lynx (*Lynx canadensis*) but positive responses by white-tailed deer (*Odocoileus virginianus*) and coyotes (*Canis latrans*) (Toews et al. 2018). It could be argued that ecosystem components that we value should be those that are more "natural", as is the case in forest ecosystem management in Canada (Gauthier et al. 2009), where natural is defined as resulting from natural processes free from anthropogenic disturbance. However, sometimes our objectives are at odds such as in the case of caribou where fire, a natural disturbance that helps to maintain forest integrity more generally, reduces the amount of caribou habitat, a valued species at risk.

3.2. Data availability and limitations

Choosing indicators that can adequately reflect the environmental response factor of interest is a difficult task, especially for broader and less easily defined response factors such as forest integrity or sustainability (Venier and Pearce 2004; Pearce and Venier 2006; Rempel et al. 2016*b*). As well, because indicators must be measurable, selection is often limited to metrics where data are already available or where data are logistically and financially feasible to collect. This is most limiting when the scale of the study is large such that data collection is often limited to remote sensing approaches or existing large-scale databases. Data availability for environmental response factors is often the greatest limitation in cumulative effects science.

Remote sensing data are one exception to this general limitation of response data. The last two decades have seen an explosion in availability of continuous spatial and temporal landscape data at increasingly finer resolution. Satellite imagery, air photos, LiDAR, and maps of topography, vegetation cover, watersheds, soils, roads, land use, climate, and natural and anthropogenic disturbances are available for many landscapes. Significant data processing and manipulation are often required, however, to make these data useful to address common cumulative effects questions. Spatial information can be processed to form even more detailed coverages such as terrain and predictive ecosystem maps or interpretations of vegetation composition and structure (e.g., Bater et al. 2009). Many of these data layers are available for multiple time periods. The relative availability of spatial landscape data has resulted in the prevalence of GIS-derived vegetation cover metrics and classifications as indicators of environmental response factors (Gustafson et al. 2007). Landscape metrics such as connectivity, fragmentation, forest age-class distribution, and tree species composition are all commonly used indicators of forest integrity or sustainability (Montreal Process Working Group 1999; Gustafson et al. 2007; Yamasaki et al. 2008; SFI 2015; Sutherland et al. 2016; FSC Canada 2020).

More limiting are ground-based point measurements of important environmental responses such as species distribution, abundance, and demographics as well as measurements of soil and water quality, all of which can be surrogates for a broader concept like forest integrity. Technical innovations are addressing this limitation, and data collection using remote environmental sensors is becoming more commonplace. Autonomous recording units for measuring vocalizing species such as birds, bats and amphibians, and camera traps for mammals are effective at collecting large amounts of environmental response data (Steenweg et al. 2017; Venier et al. 2012). New technologies, platforms and metadata standards are being developed to aggregate, analyse, and share large amounts of remotely sensed wildlife data (Forrester et al. 2016; Ahumada et al. 2020; see also WildTrax at https://www.wildtrax.ca/home.html). These advancements will improve the availability, usability, and accessibility of large-scale distribution data for many species and, thus, enhance cumulative effects science.

When empirical data are missing, expert knowledge is often substituted at all stages of a study, from conceptual modelling and hypothesis generation to study design and interpretation (Martin et al. 2012). Expert knowledge is also routinely used to provide missing parameters for habitat and population models as well as succession and other process models used in simulation. Despite its potential, expert knowledge can be biased if rigorous methods are not used to select experts, quantify uncertainty and assess accuracy, and its outcomes can be greeted with skepticism (Martin et al. 2012; Bridger et al. 2016). Robust procedures, however, exist for capturing expert knowledge (e.g., Martin et al. 2012). In their study of the cumulative effects of forestry on furbearers, for example, Bridger et al. (2016) selected 10 biologists and 10 trappers through a rigorous screening process to build habitat models for lynx, fisher (*Pekania pennanti*), and marten. Selected experts used the analytical hierarchy process to develop models based on pairwise comparisons of selected habitat attributes. Experts showed high levels of consistency in scoring habitat features and the final habitat maps were strongly validated on the traplines. Lack of data are a reality for most cumulative effects studies but tapping expert knowledge can produce data quickly for even large spatial areas. Expert knowledge provides a practical way to generate predictions and to explore relationships until sufficient empirical data become available. Expert-derived models can also be used to assess the sensitivity of outcomes to various assumptions, thereby helping to focus future data collection (Wintle et al. 2005).

One of the main goals of cumulative effects science is to separate cumulative anthropogenic effects from natural variability; this requires repeated, long-term measurements (Gunn and Noble 2009; Magurran et al. 2010; Schultz 2010; Johnson and St-Laurent 2011). Data collection, however, must be cost-effective to be sustainable (Lindenmayer and Likens 2010; Tulloch et al. 2011), and designing scientifically rigorous but cost-effective data collection programs at large scales is challenging. Clear research questions and objectives can help reduce costs by keeping data collection focused. Carvalho et al. (2016), for example, tested a systematic approach to site selection to optimize multi-species monitoring by comparing it to nonoptimized approaches. They found that the optimized approach outperformed the nonoptimized approach, resulting in higher species diversity estimates, better representation of environmental space, and better coverage of rare species with less survey effort.

3.3. Surrogates

For logistical reasons, cumulative effects studies often use surrogates to represent larger concepts such as biodiversity or ecosystem integrity. One approach to choosing surrogates is to select a suite of complementary options that represent the range of scales and key gradients present in the system (Coppolillo et al. 2004) or that respond to the key stressors in the system. To monitor the effects of the Alberta oil sands development on terrestrial biodiversity, for example, Environment Canada (2011*a*) recommended choosing a group of species with a range of sensitivities to development, arguing that a variety of wildlife taxa was necessary because impacts could vary with the ecology of each surrogate. They suggested that species could be selected based on expert knowledge and literature review as well as from analyses of existing data (Environment Canada 2011*a*). Alternatively, surrogates can be chosen that have strong functional roles in an ecosystem such as keystone species (Soulé et al. 2005). Increasing the number of surrogates monitored improves the capacity to represent the whole system, but logistical and experimental costs may also increase. When choosing a suite of complementary surrogates to represent change in forested ecosystems, Rempel et al. (2016*b*) divided the ecosystem into three environmental gradients (age, connectivity, and hardwood/conifer ratio) and then chose key species to represent the corners of this three-dimensional space, reducing the total number of species required to reflect the entire system. Multi-species monitoring techniques, such as audio recorders (Venier et al. 2012) and camera traps (Steenweg et al. 2017; Buxton et al. 2018) can help reduce cost. As a rule, the more taxonomically diverse the selection of species to be monitored, the more costs will increase.

3.4. Choosing environmental responses

In Table 1, we present examples of how and why environmental response factors or their indicators were chosen for 14 studies of cumulative effects on wildlife or biodiversity, emphasizing studies conducted at large spatial scales. We chose these examples because cumulative effects science is most likely to inform decision-making at large scales and biodiversity is a key environmental response driving many decisions. Response choice was often straightforward, dictated by the objectives of the study. Many studies were specifically interested in conservation or sustainability of specific species such as fur-bearing animals (Bridger et al. 2016). Although our choice of studies was not random, larger mammals were often selected by the studies in Table 1, either because of their conservation status (Johnson et al. 2015), their ecosystem role (Johnson et al. 2005; Houle et al. 2010), their usefulness in modelling cumulative effects at larger spatial scales (Heim et al. 2017; Toews et al. 2018), or the availability of existing data.

Several approaches were used for choosing indicators for more complex environmental response factors like biodiversity or sustainability. Gustafson et al. (2007) selected environmental response factors from the Montreal Process Working Group (1999) criteria and indicators (a voluntary agreement created to formulate global recommendations for sustainable management of forests) to test the effects of different forest harvesting scenarios on forest sustainability. Species responses were also selected on the basis of their conservation status ranking from several organizations and their importance to First Nations (Nitschke 2008). Alternatively, regional policy and management objectives have been used as a basis for choosing environmental response factors and their indicators (Spies et al. 2007; Valdal and Lewis 2015; Sutherland et al. 2016). Data availability was a stated factor in some choices (e.g., Valdal and Lewis 2015; Sutherland et al. 2016; Shackelford et al. 2018), and coarse-filter spatial indicators such as percent cover of a forest type were used by more than one study (Gustafson et al. 2007; Yamasaki et al. 2008; Sutherland et al. 2016). Study objectives should drive the environmental response factor selection with the caveat that the necessary data be available or feasible to collect within budgetary constraints of the project.

4. Stressors

As mentioned in relation to environmental responses, we have seen a significant increase in the availability of continuous spatial and temporal landscape data from satellite imagery, air photos, LiDAR, and maps of topography that can be used to map natural and anthropogenic disturbances, although significant data processing is often required to make the data useful. The spatial extent of anthropogenic disturbances on a landscape is sometimes referred to as the "human footprint" (Burton et al. 2014). Footprints can include features like urban and residential areas, transportation corridors, forestry harvest blocks, mines, seismic lines, pipelines, agricultural areas, and campgrounds (e.g., see Table 1 in Toews et al. 2017). Footprints represent direct effects, like habitat loss and degradation, as well as indirect effects, such as habitat fragmentation, all of which impede species movements or lead to changes in ecological communities (Burton et al. 2014). Footprints are most useful for cumulative effects analysis when they are temporal in nature, that is, when there is a time stamp associated with each disturbance as this allows for an examination of change through time. The Alberta Biodiversity Monitoring Program footprint trend data are available from 1999 to 2016 (https://abmi.ca/home/reports/2018/human-footprint). Temporal data sets describing landcover changes are also being developed using Landsat (Hermosilla et al. 2015; White et al. 2017), including characterization of disturbances.

Footprints can also act as a proxy for other types of human disturbances that do not directly alter habitat such as hunting pressure or noise pollution. Footprint effects are unique to each environmental response and may differ by location (Burton et al. 2014). Human footprint analysis is often considered to be the first

Table 1. Examples of large-scale cumulative effects studies demonstrating a variety of environmental response factors and rationale for selection.

Study	Title	Area (ha)	Study environmental response factors or indicators	Approach and rationale for choice
Bridger et al. 2016	Assessing cumulative impacts of forest development on the distribution of furbearers using expert-based habitat modeling	Central British Columbia (6027 km^2)	Lynx, fisher, marten	Based on survey of experts on fur-bearing species likely to be most sensitive to resource development
Burton et al. 2014	A framework for adaptive monitoring of the cumulative effects of human footprint on biodiversity	Alberta (661 848 km^2)	More than 2000 species and 200 habitat elements	A broad spectrum of species and habitat elements cover a range of ecological roles, social values, and potential sensitivities to anthropogenic disturbances
Gustafson et al. 2007	Simulating the cumulative effects of multiple forest management strategies on landscape measures of forest sustainability	Michigan (681 km^2)	Three Montreal Process Working Group indicators under Criterion 1, namely (10.1.a) proportion of area by forest type, (10.1.b) proportion of area by age class and (10.1.e) fragmentation of forest types; and one indicator under Criterion 2, namely (2.c) the area of plantations of native and exotic species.	These indicators reflect accepted standards for sustainable forest management.
Heim et al. 2017	Cumulative effects of climate and landscape change drive spatial distribution of Rocky Mountain wolverine (*Gulo gulo* L.)	Central Canadian Rockies (15 000 km^2)	Wolverine	Wolverines were used as a model to test multiple stressors on a species' distribution because they have a large range that spans multiple stressors, habitat types and climatic conditions.
Houle et al. 2010	Cumulative effects of forestry on habitat use by gray wolf (*Canis lupus*) in the boreal forest	Central Quebec (10 000 km^2)	Gray wolf	Wolves of key importance in predator-prey systems
Johnson et al. 2005	Cumulative effects of human developments on arctic wildlife	Northwest Territories/ Nunavut (190 000 km^2)	Barrenground caribou, grizzly bear, wolf, and wolverine.	These three carnivores are keystone predators in these ecosystems; caribou is the major large herbivore of cultural and subsistence value for First Peoples
Johnson et al. 2015	Witnessing extinction– Cumulative impacts across landscapes and the future loss of an evolutionarily significant unit of woodland caribou in Canada	Eastern British Columbia (41 000 km^2)	Woodland caribou (Central Mountain designatable unit)	Based on caribou's threatened conservation status
Nitschke 2008	The cumulative effects of resource development on biodiversity and ecological integrity in the Peace-Moberly region of Northeast British Columbia	Northeast British Columbia (4100 km^2)	41 wildlife species	Wildlife species were chosen because of concerned conservation status ranking and importance to First Peoples
Shackelford et al. 2018	Threats to biodiversity from cumulative human impacts in one of North America's last wildlife frontiers	British Columbia (945 000 km^2)	16 regional ecosystems and 7 large mammal species	Mammal species with available data that show negative impacts from natural resource use were chosen; all vegetation zones in the province were assessed

Table 1 (*concluded*).

Study	Title	Area (ha)	Study environmental response factors or indicators	Approach and rationale for choice
Sorensen et al. 2008	Determining sustainable levels of cumulative effects for boreal caribou	N. Alberta (4912 km^2 is kernel home ranges for 6 populations)	Boreal caribou populations and their rates of population change	Indicators were chosen based on concerns about caribou population decline
Spies et al. 2007	Cumulative ecological and socioeconomic effects of forest policies in coastal Oregon	Coastal Oregon (23 000 km^2)	Several focal species (marbled murrelet, spotted owl, bluebird) as well as vegetation types	Species reflect conservation concerns and general biodiversity, as well as preservation of diverse vegetation types. These are management goals.
Sutherland et al. 2016	Developing a systematic simulation-based approach for selecting indicators in strategic cumulative effects assessments with multiple environmental valued components	Southwest British Columbia (9,090 km^2)	VECs such as Old Forest Condition or individual species of concern like Spotted Owl, with related landscape indicators like % old forest and % area of nesting habitat for Spotted Owl	Indicators selected meet criteria for valued ecosystem components within British Columbia Cumulative Effects Framework (including being projectable both spatially and temporally using available data)
Toews et al. 2018	Mammal responses to the human footprint vary across species and stressors	North Central Alberta (400 000 km^2)	Gray wolf, lynx, coyote, white-tailed deer, and moose	Large mammals require large areas for dispersal and home ranges, are ecologically and socio-economically important, may act as umbrella species, and respond at the scale of cumulative effects management.
Valdal and Lewis 2015	Cumulative Effects Assessment for the Merritt Operational Trial, Draft v30.0	Southern British Columbia (13 000 km^2)	Fish stream habitat, moose populations, mule deer populations, visual quality objectives, grizzly bear populations and old growth management areas	Values that have legal or policy objectives in existing legislation, land use plans, or other forms of management direction. 2. Values identified in strategic agreements with First Nations or otherwise identified as supporting an Aboriginal or treaty right. 3. Values that can be mapped and have robust existing data.
Yamasaki et al. 2008	Making the case for cumulative impacts assessment: Modelling the potential impacts of climate change, harvesting, oil and gas, and fire	Central Alberta (4336 km^2)	11 coarse filter indicators of biodiversity and forest productivity (e.g., forest core area, edge contrast index)	Not specified but likely based on type of data output available from simulation models

step in doing large-scale cumulative effects assessment (Shackelford et al. 2018). Anthropogenic disturbances can be combined into a single composite footprint or treated separately, but combining disturbances eliminates the possibility of examining interactions between disturbances and it also fails to recognize the potential for different relationships between specific disturbances and the environmental response factor. For example, if a main driver of population change is predation facilitated by treeless travel corridors, then length of seismic lines and roads might have a disproportionate effect relative to their area of disturbance when compared with forest harvest blocks with a much larger areal footprint. It is important to understand the mechanisms of impact to translate the disturbance into effects on an environmental response factor.

The zone of influence concept extends the effects of stressors beyond their physical footprint based on an understanding of the mechanisms at play. The zone of influence is often used to represent the area adjacent to a disturbance where the behaviour of wildlife species is altered, but it can also represent the spread of a pollutant (i.e., nitrogen oxides, sour gas, chlorides) or contaminant (i.e., road dust) beyond its source. Zones of influence can be difficult to quantify, changing by disturbance type, geographic location and sensitivity of the environmental response factor (Johnson and St-Laurent 2011). Part of the difficulty in establishing zones of influence is that avoidance of disturbance features may vary seasonally (Houle et al. 2010) or even within a population (Wilson et al. 2016). For wildlife species, zones of influence can be estimated by comparing presence/absence or abundance data across a gradient of disturbances, tracking movements of individuals in relation to disturbance features, or through models simulating movement behaviour (e.g., Bennett et al. 2009; Semeniuk et al. 2014). Zones of influence should be considered crude proxies representing direct or indirect spatial effects of a disturbance on an environmental response factor. Particularly in areas with multiple disturbances and overlapping zones of influence, attributing direct effects to a single source is unrealistic. Despite these difficulties, zones of influence can provide useful spatial indicators of potential impacts from disturbances.

5. Data sharing

Improved sharing and co-ordination of aspatial and spatial data are a key gap in cumulative effects science. A national or central data portal would reduce redundancy in large-scale cumulative effects science by ensuring publicly available data are easy to access and acquire. In support of the Government of Canada's new *Impact Assessment Act*, Natural Resources Canada in partnership with other federal departments is establishing an Open Science and Data Platform. This platform is intended to provide integrated public access online to information that supports cumulative effects assessments, as well as project impact assessments and other associated regulatory processes. The new platform builds on the existing Federal Geospatial Platform (https://www.nrcan.gc.ca/science-and-data/earth-sciences/geomatics/canadas-spatial-data-infrastructure/geospatial-communities-and-canadian-geosecretariat/federal-geospatial-platform/11031) and the broader Government of Canada open government initiative (https://open.canada.ca/en/open-data). Data sharing on federal platforms will not necessarily include provincial and proponent data for which the federal government does not have jurisdiction, so these central repositories could be limited in their utility unless agreements can be reached to house data from other jurisdictions or at least provide links to these other repositories. The federal platforms are just one example of how data might be shared but there are increasing requirements, opportunities and initiatives to share data both nationally and internationally (Federer et al. 2018). These include publisher policies, which both encourage and require the open access of data (Nature Publishing Group 2017; Science 2017), and a broader sentiment in scientific communities (National Science Foundation 2010; Wilkinson et al. 2016) to make data open.

6. Stressor–response relationships

6.1. Approaches for exploring stressor–response relationships

6.1.1. Conceptual models

Conceptual models can be an important first step in designing research to understand stressor–environmental response factor relationships. Usually in the form of box-and-arrow diagrams or matrices, conceptual models are simplified versions of our understanding of reality that identify key stressors, ecological processes, and their predicted interactions with responses based on current knowledge (scientific and grey literature, expert knowledge, traditional ecological knowledge) (Lindenmayer and Likens 2010; CEAA 2018). They are useful qualitative tools for integrating current knowledge, identifying knowledge gaps, focusing questions for investigation, and providing useful guidance. Network and systems analyses are similar approaches to conceptual models, but have more formalized procedures and a more detailed focus on pathways and their interactions (Fath et al. 2007).

6.1.2. Experimental approaches

Designing rigorous, replicated factorial experiments to study multiple cause–effect relationships is logistically difficult, especially at large spatial scales and in an ecological context. Even at small scales, studies that examine multiple stressors are not very common and generally examine only two or three stressors at a time. As an example, one study in regenerating longleaf pine forests used a common garden field experiment to show an antagonistic interaction where biotic stress from an invasive grass significantly altered native plant communities, but the presence of this invader partially ameliorated the abiotic stress from drought (Fahey et al. 2018). This interaction was mediated through higher soil moisture when the grass was present because it uses water efficiently (Sage and Monson 1999). The study was able to demonstrate interactions because the small scale permitted controlled manipulation of the stressors. However, examining additional interactions such as the influence of the grass on fire severity (Brooks et al. 2004) was not possible in this context. Other studies have used small-scale manipulation experiments to examine interactions between stressors on environmental responses in forest contexts (Rifai et al. 2010; Smith et al. 2016). These examples demonstrate both the value of conducting small-scale experiments to identify the range of potential interactions and the overwhelming complexity inherent in ecological systems under multiple stressors. As well, small-scale manipulations can permit the examination of the full gradient of expected stress on the system. Unfortunately, scaling-up from manageable small-scale experiments may be misleading and inaccurate (Johnson and St-Laurent 2011; Jones 2016; Toews et al. 2017). In contrast, at large scales, the effects of natural variation may be larger than the experimental effects themselves (Johnson and St-Laurent 2011).

6.1.3. Observational approaches

Statistical models or observational studies are frequently used to examine interactions in the absence of experimental manipulations across a gradient of disturbances. For example, Merriam et al. (2015) used a generalized linear modeling framework to model chemical and biological impairment in 170 streams as a function of multiple stressors including surface mining. Such statistical approaches require large data sets, inclusion of a large number of potentially important variables and their interactions, and they can be limited by the available range of disturbance intensities along the gradient for stressors (Johnson and St-Laurent 2011; Jones 2016). Observational studies, for instance, cannot capture the expected range of climate change impacts. Despite these challenges, observational techniques are the most common approaches used for investigating stressor–response relationships, particularly for past and current conditions and especially in formal CEA assessments (Campbell et al. 2020). Many of the studies in Table 1 used this approach to examine evidence of multiple stressors on components of the ecosystem (e.g., Nitschke 2008; Yamasaki et al. 2008; Toews et al. 2018).

6.1.4. Habitat analyses

A common methodology for estimating cumulative effects on faunal responses is the use of habitat suitability approaches and maps. This habitat-based approach is often qualitative (Boyce et al. 2002), typically using literature reviews and expert knowledge to rank the quality of each habitat type for a species in a study area (Campbell et al. 2020). These efforts are commonly called habitat suitability index models or HSI models (Brooks 1997). Alternatively, habitat relationships can be established using statistical techniques based on observational data, which we discuss as species distribution models (Elith and Leathwick 2009). Whether based on expert opinion or quantitative analyses, habitat can be described as classes or as continuous variables. Habitat classes can be created based on unique requirements of the species or they may pre-exist in a detailed base map. For example, terrain ecosystem maps combine climatic, terrain, and ecosystem data into fine-scale habitat classes that can be used for multiple species (e.g., Resources Inventory Committee 1999). Additional details such as buffered distances, which separate forest interior from forest edge habitat, may be incorporated into these detailed classes. After the landscape is classified, habitat patches are created by combining map units with similar suitability rankings. It has been recently argued that the use of landcover classes in habitat assessments are problematic for several reasons: they are not effective at capturing change over time, habitat classification is not a consistent process over time and space, and it is difficult to incorporate classes into traditional ecological modelling approaches such as regression (Coops and Wulder 2019). Where possible, continuous habitat variables could ameliorate these issues, but they are more difficult to assess with expert opinion.

When presence/absence, abundance or other spatial data are available for species, statistical species distribution models (SDM) can be used to identify relationships between species, habitat, and disturbances (Elith and Leathwick 2009). These models are generally more quantitative and data-driven than habitat suitability indices based on expert opinion. Species distribution models can be generated using a number of different approaches, including resource selection functions, range maps, ecological niche models, regression models and bioclimatic models (Elith and Leathwick 2009). Species distribution models develop mathematical relationships between habitat or other environmental attributes and the probability of a species' occurrence. Distribution models commonly assume that habitat is the most important factor driving distribution of a species, often ignoring other potential influences like competition or whether a species is at equilibrium with its environment (Guisan and Zimmermann 2000). Most species distribution models are correlative and rely on statistical techniques to identify relationships, and an information-criterion approach is often used to identify best models (e.g., Ehlers et al. 2016). Statistical options for determining relationships are vast, including generalized linear mixed models, machine learning methods, compositional analyses, classification and regression trees, maximum entropy models, discriminant function analyses, and spatial capture–recapture analyses (Boyce et al. 2002; Manly et al. 2002; Elith and Leathwick 2009; Guisan et al. 2018; Royle et al. 2018; Araújo et al. 2019). The strengths and limitations of species distribution models are well documented and include reviews by Johnson (2007), Elith and Leathwick (2009), de Souza Muñoz et al. (2011), and Jarnevich et al. (2015). Species distribution models are commonly used tools for cumulative effects research to link habitat and disturbances to species (e.g., Johnson and Gillingham 2005; Houle et al. 2010; Johnson et al. 2015; Heim et al. 2017; Guisan et al. 2018).

Habitat suitability maps can be developed from either qualitative or quantitative approaches and can then be overlaid with maps showing disturbance footprints and associated zones of influence to identify activities and locations where cumulative effects may be an issue. However, these maps must be viewed as potential habitat, because they are derived from assumed or modelled species–habitat relationships rather than from direct observations of the organisms over the entire range. Field sampling should be used to validate the accuracy and precision of mapped habitat types. The reliability of the habitat suitability predictions should be verified through measures such as physiological condition, density, home range size, survival rate, or reproductive success (Dussault et al. 2006; Johnson 2007). Depending on the level of detail required for an assessment, this validation may not always be performed (Campbell et al. 2020). The habitat suitability approach allows spatial maps of habitat quality to be generated for large areas relatively easily, particularly if the underlying habitat relationships are already defined. This method, however, relies heavily on assumptions linking habitat types to species, which may be tenuous, especially if independent data are not used to validate the predictions. Mapping accuracy and resolution may also be too coarse to identify important habitat features for some species. For example, some cavity nesting species require large, dead or dying trees (Edworthy and Martin 2014), which are not easily captured in remotely sensed habitat data. Pre-existing habitat suitability models were used to assess potential cumulative effects from resource development on wildlife in a 6.4 million ha region in northern British Columbia with little history of industrial development (Suzuki and Parker 2016). Maps of high-quality habitat were overlaid for seven large mammal species with maps of high resource use potential. Layers for forestry, oil and gas, mining, wind power, and road development were mapped individually as well as being combined into a single cumulative footprint. For all seven mammal species, there was a large degree of overlap between high-quality habitat areas and resource development footprints, drawing attention to areas with potential conservation concerns prior to development. Additional studies have used habitat suitability models for estimating anthropogenic effects on wildlife (e.g., Nitschke 2008; Bridger et al. 2016). Habitat suitability approaches are particularly useful for projecting the effects of conditions on a landscape into the future when data are, by definition, unavailable. This approach has been used to simulate the cumulative effects of 100 years of harvesting in forest simulation models for example (Gustafson et al. 2007; Spies et al. 2007). Habitat suitability models are useful for highlighting areas of concern, generating hypotheses, and (or) identifying issues that are important for planning of future land use. They can help identify loss of important habitat for a species, but they cannot measure changes in population or viability.

6.1.5. Population and demographic responses

Cumulative effects on populations can also be studied more directly. Impacts on response factors at the population level manifest through changes in abundance, dispersal and distribution, or demographic characteristics such as survival or reproductive rates (Johnson and St-Laurent 2011). Assessing population viability rather than just habitat recognizes the complex interactions between species movement and demographics and the spatial configuration of habitat (Environment Canada 2011*b*; Ranius et al. 2014; Haché et al. 2016; Bonnot et al. 2017), and it can improve predictions of habitat suitability. Carvajal et al. (2018), for example, demonstrated a 54% improvement in predicting habitat suitability by incorporating spatially explicit population parameters. Unfortunately, population viability analyses (PVA) require multiple years of movement or survey data, which are unavailable for most species (Whitehead et al. 2017; Leasure et al. 2019). This level of effort is commonly reserved for threatened species or species with high cultural value such as large mammals like grizzly bear (*Ursus arctos*) (Wielgus et al. 1994) and woodland caribou (Wittmer et al. 2005). There are, however, some examples of more common species where this effort has been made, such as brown creeper (*Certhia americana*), ovenbird (*Seiurus aurocapilla*), Montserrat oriole (*Icterus oberi*), red-backed salamander (*Plethodon cinereus*), and a beetle (*Stephanopachys linearis*) (Wintle et al. 2005; Gordon et al. 2012; Oppel et al. 2014; Ranius et al. 2014; Haché et al. 2016), but sometimes with rough parameter estimates based on best guesses rather than rigorous empirical data (Wintle et al. 2005; Gordon et al. 2012). Spatial scales are often relatively small because of the intensity of computer resources needed per unit area increases with the decreasing scale of movement. We expect computing limitations to lessen as models become more efficient and computing resources become more sophisticated.

PVA is more appropriate when management objectives are linked to conservation of a particular species rather than a more general objective. The threatened boreal caribou has been extensively studied and data are available to examine population-level cumulative effects. Fryxell et al. (2020), for example, used PVA to assess viability of woodland caribou across 14 ranges in Ontario. They found that higher levels of forestry led to lower annual caribou population growth rates related to regional variation in wolf densities and likelihood of predation. Repeated censuses are commonly used to detect changes in the abundance of a population, and tools such as PVA or variants such as multi-population viability analysis (Leasure et al. 2019) can be used to estimate or predict population trends. Because of problems with detectability and other challenges related to measuring a population's abundance directly across large spatial areas and multiple time periods, focusing on vital demographic rates such as survival or recruitment is often considered a more achievable approach to estimating population change (Johnson and St-Laurent 2011; Hervieux et al. 2013). Hervieux et al. (2013), for example, used annual survival and recruitment rates combined with population modelling to estimate population declines in 10 out of 14 caribou populations. Similarly, Sorensen et al. (2008) used survival and recruitment measurements for six boreal caribou populations to show a relationship between the rate of population change and cumulative habitat loss from recent wildfires and industrial activities. The range of boreal caribou coincides with multiple stressors including natural resource development and climate change (Venier et al. 2014); therefore, caribou conservation is best viewed as a cumulative effects issue. PVA is a particularly relevant tool in this context (Environment Canada 2011*b*; DeCesare et al. 2014; Beguin et al. 2015; Fryxell et al. 2020).

6.1.6. Systematic reviews and meta-analysis

Many cumulative effects studies are designed to address specific and somewhat small-scale aspects of cumulative effects. Integrating data and results from these short-term studies, however, can be useful for large-scale analyses as well (Barker et al. 2015; Cooke et al. 2016; Mahon et al. 2016; Stralberg et al. 2019). Using systematic reviews to support evidence-based decision-making has been demonstrated to be effective in the health care field (Pullin and Knight 2001), and systematic reviews are being suggested as an efficient approach to use existing knowledge to support environmental management (Cooke et al. 2016). A systematic review relies on formal protocols aimed at achieving reproducibility and reducing bias (Gurevitch et al. 2018). Meta-analysis is a useful technique in this context for combining results from multiple studies to generate an overall understanding of a problem and its associated sources of variation (Stewart 2010; Gurevitch et al. 2018). Although results and conclusions from existing studies are readily available in the scientific literature, data from these research projects are usually more difficult to access and often have some form of restriction for sharing, making their use more complicated. The movement towards more open data in science may alleviate this problem in the future (Federer et al. 2018).

6.2. Thresholds

An important role of cumulative effects science is the identification of ecological thresholds, which are nonlinear, abrupt changes in an environmental response beyond a given level of disturbance (Martin et al. 2009; Johnson 2013; Jones 2016). At the ecosystem level, for example, a shift from sparsely treed savannah to dense woodland can be triggered by a change in fire and grazing regimes (Scheffer et al. 2001). Habitat fragmentation (Groffman et al. 2006), low genetic diversity (Spielman et al. 2004), and phenological mismatches for events such as flowering and pollinator emergence (Morton and Rafferty 2017) are examples of factors that can cause ecological thresholds to be exceeded. Transition from closed forest to lichen woodland has been demonstrated due to the combined negative effects of fire, insect defoliation, and harvest on regeneration (Payette et al. 2000; Girard et al. 2008, 2011). A major concern of cumulative effects is the possibility that many small, relatively minor effects in isolation could have surprising impacts when combined. Some consider the determination of ecological thresholds to be a key goal of CEA (Duinker et al. 2013). Sorensen et al. (2008) argued that knowledge of habitat thresholds is an essential tool for managing cumulative effects because it establishes acceptable levels of risk from resource development. Because crossing ecological thresholds can result in sudden, significant, and possibly irreversible changes, the identification of ecological thresholds is a highly desired objective of resource managers (Groffman et al. 2006).

Unfortunately, there are many reasons why the idea of ecological thresholds may not be particularly useful, especially for the management of large areas with multiple objectives. Although statistical methods exist for measuring ecological thresholds (e.g., Swift and Hannon 2010; Foley et al. 2015), there is no scientific consensus on methodology (Groffman et al. 2006; Johnson 2013), ecological thresholds can be difficult or impossible to determine (Duinker and Greig 2006; Cronmiller and Noble 2018), or they may not even exist when relationships are linear. Even selecting the appropriate response variable can be complicated (Swift and Hannon 2010; Johnson 2013). The threshold level of habitat disturbance for a wildlife population, for example, will likely differ depending on whether the response variable is the rate of population change, the birth rate, or estimates of survival (Johnson 2013).

For broad regional goals, such as protecting biodiversity or ecosystem integrity, ecological thresholds will differ by species, habitat type, and spatial scale (Swift and Hannon 2010), defying widespread application. There is potential for community-level thresholds, but it will still be difficult to use ecological thresholds in the context of complex management objectives. Thompson et al. (2003), for example, observed that marten and lynx have different thresholds of sensitivity to the proportion of area under forest management. Ecological thresholds can also give a false sense of certainty and predictability, making it tempting for decision-makers to allow anthropogenic disturbances to approach a critical level without sufficient consideration of uncertainty (Polasky et al. 2011; Johnson 2013). Harm can occur to an environmental response factor at levels below a disturbance threshold, however, and stochastic events such as wildfires can undermine any management plan based on precise ecological thresholds (Scheffer et al. 2001; Groffman et al. 2006).

Despite these issues, management decisions to minimize cumulative effects are necessary. In this context, decision and utility thresholds become important. Utility thresholds are values of a state variable where small changes yield substantial changes in the value of the management outcome, whereas decision thresholds are values of state variables that trigger specific management actions (Martin et al. 2009). Decision thresholds are generally derived from both ecological and utility thresholds. In their recovery strategy for threatened boreal caribou, Environment Canada (2012) prescribed that the combined effects of wildfire (on forests <40 years old) and human disturbances should not exceed 35% of the range of a caribou population on an areal basis. A recent amendment to the recovery strategy provides a maximum threshold of 60% disturbance for the northern Saskatchewan Boreal Shield caribou range (Environment and Climate Change Canada 2019*a*). These risk-based thresholds are based on adult caribou survival estimates combined with an empirically derived relationship between calf recruitment and habitat disturbance for a number of populations across Canada (Environment and Climate Change Canada 2019*b*). At 35% disturbance, it was estimated that caribou populations have a 60%–71% chance of maintaining stability or increasing through time. These decision thresholds are just one point on an empirically derived curve and do not necessarily represent an ecological threshold. Ultimately, the setting of a decision threshold is a social/policy activity that is informed by science (Johnson 2013). Similarly, in British Columbia, Valdal and Lewis (2015) used a risk-based approach to set qualitative thresholds for selected environmental factors in a large landscape. For moose (*Alces alces*) populations, they used an expert judgement-based model to classify planning cells within the landscape as having a low, moderate, or high level of risk of supporting a stable population. If moose populations in a planning cell crossed the threshold into high-risk status, mitigation would be required. In both examples, the need for more data was acknowledged and proponents took an adaptive management approach to addressing uncertainty around the threshold values.

The process of seeking ecological thresholds advances the understanding of stressor–response relationships, which is of critical importance to advancing cumulative effects science. Identifying an ecological threshold may also help anticipate potentially catastrophic ecological consequences. Because cumulative effects must be assessed and managed in the face of imperfect knowledge, management or decision thresholds like those used for the preceding boreal caribou and moose examples have value, particularly if they are approached from an adaptive management perspective, which acknowledges uncertainty and the importance of iteratively incorporating new information. However, it is important to be skeptical of simplistic thresholds that are unlikely to be applicable across large areas or for multiple ecological values. In addition, it may become necessary to make decisions in the absence of ecological thresholds, whether it is because thresholds are not identifiable or do not exist. In this case, the science can inform decision-making, but there are inevitable social drivers that will also be at play (Brandt 2019).

7. Regional scale examples in progress

Cumulative effects science is data intensive and often data limited. Data are required to establish baselines, to quantify response–stressor relationships, to validate models and to test predictions. As we discussed in Section 3.4., large-scale and long-term data are not readily available for many environmental response factors but there are a few notable exceptions. The Alberta Biodiversity Monitoring Institute (ABMI) program is perhaps the most extensive Canadian example of a large, regional monitoring program created to study current cumulative effects on biodiversity. The core of the ABMI is a surveillance-style program that proposed to systematically monitor more than 2000 species, 200 habitat elements and 40 human footprint variables at 1656 permanent sites evenly distributed across the province on a 20 km × 20 km grid (Burton et al. 2014). With repeated sampling, this system allows researchers to detect trends in occurrence or relative abundance for a wide variety of environmental response factors. Using surveillance data, researchers generate working hypotheses to create targeted, predictive models relating abundance of elements of biodiversity to human footprint and other factors. Extra, nonpermanent sampling sites are added where necessary to improve coverage and test hypotheses. Deviations between predictive models and future observations lead to new, refined hypotheses in an adaptive cycle of learning. This combination of surveillance and targeted approaches allows the ABMI to investigate cumulative effects at the regional scale.

Lindenmayer and Likens (2010) criticized the program for several reasons. They suggested that the program lacked identified questions that could focus the data collection. This criticism was echoed by several scientific reviewers of the ABMI program's 10-year review (https://abmi10years.ca/scientific-review/). The program is also criticized for its sample stratification based on space rather than other factors more likely to be influencing the key organisms or other attributes of interest. As well, this spatial stratification generates samples that are representative of their abundance on the landscape but, therefore, provides very little information on the rarer ecosystem types. There is also concern that the sampling design is passive, meaning it is not characterized by management interventions and therefore cannot provide much insight into mechanisms that explain any perceived trends. An advantage of this large-scale passive approach is that it samples a large region with no preconceived ideas about what might be causing trends and, therefore, has the potential to identify patterns that were not anticipated. There was also concern that the program was attempting to sample too many things that led to lower quality sampling and made the initiative vulnerable to potential future resource constraints. The monitoring has recently been pared down to fewer indicators to make sampling more feasible, especially in remote areas (ABMI 2016). Overall, the ABMI program is a significant and valuable effort, especially in the context of limited response data to address cumulative effects. Ongoing evaluation and refinement of the program has and will enhance outputs (ABMI 2016).

We noted that there are not many examples of peer-reviewed regional analyses conducted with the environmental response data from ABMI to date, although there are some results available online (https://www.abmi.ca/home.html). There are two notable examples, however. The first is work conducted to look at the cumulative effects of a variety of human disturbances on large mammals (Toews et al. 2017, 2018). The latter work found that the strongest responses were to agriculture, roads, and recent harvest blocks but that total human footprint was also predictive. They also found high variability in the direction and magnitude of the response depending on species. The second example is simulation work parameterized by data from ABMI and other sources that examine the combined effects of forest harvest and climate change on boreal landbird communities (Cadieux et al. 2020). Cadieux et al. (2020) demonstrated how anthropogenic disturbances accentuated predicted effects of climate change. Additionally, the ABMI 2018–2019 annual report suggests that the program is influencing land-use planning in the province (ABMI 2020). The program has provided scientific and logistical support for the development of the Biodiversity Management Frameworks (part of Alberta's Land-Use Framework) for several regions as well as providing technical calculations for others in the province, and it is working closely with the Alberta government to develop key biodiversity indicators that will be used to measure how species and habitats are changing. However, some argue that the ABMI lacks explicit links with management agencies that could encourage more integrated adaptive management (Burton et al. 2014). In addition, the resource requirements for an extensive program like ABMI are significant and likely out of reach for most other regions in Canada.

Another large-scale effort to assess cumulative effects is just beginning in Ontario's far north. The Ring of Fire is a crescent shaped area that covers about 5000 km^2 and is one of the largest potential mineral reserves in the province (Chetkiewicz and Lintner 2014). The Minster of Environment and Climate Change Canada recently announced the decision to conduct a Regional Impact Assessment on the region centred on the Ring of Fire (see https://iaac-aeic.gc.ca/050/evaluations/proj/80468). The need for a cumulative effects assessment in the area had been strongly argued in a report in 2014 (Chetkiewicz and Lintner 2014).

Prior to the announcement, the Ontario Ministry of Natural Resources and Forestry (OMNRF) and the Ontario Ministry of the Environment, Conservation and Parks had been actively conducting environmental science in the far north (https://www.ontario.ca/page/science-and-information-support-planning, https://geohub.lio.gov.on.ca/datasets/ec185084835e41049bfc598bcc8e6654). OMNRF had developed a monitoring framework and data collection protocol to support cumulative effects science and inform land use and natural resource development decision-making in the Ontario Ring of Fire area (Rempel et al. 2016*a*). In addition, OMNRF had conducted significant modelling research on caribou and aquatic systems using the ALCES cumulative effects modelling platform to conduct scenario analyses (R. Rempel, personal communication 2020). This research has been presented at several forums but has not yet been published. Other relevant ongoing science in the Far North includes studies on (*i*) the ecology and food quality of fish (Lescord et al. 2018), (*ii*) socioeconomic effects and community values (C. George, personal communication 2020), and (*iii*) hydrology and peatland research (McLaughlin and Webster 2014).

To date there has only been mineral exploration and no infrastructure development in the Ring of Fire area, providing an unusual opportunity for the establishment of environmental baselines prior to development. It is the stated intent of the Impact Assessment Agency of Canada (Impact Assessment Agency of Canada 2019) to work with the Ontario government to complete the assessment, and negotiations are ongoing. Ultimately, the cumulative effects assessment will need to be a collaboration of several federal government departments, provincial ministries, academics, and First Nations if a comprehensive analysis of cumulative effects is to be achieved.

Poor coordination among scientists, resource managers, and policy makers, especially across large areas and multiple jurisdictions, can lead to less effective monitoring programs that inadequately address management goals and objectives (Lindenmayer and Likens 2010; Schultz 2010; Jones 2016; Cronmiller and Noble 2018; Lima and Wrona 2019). In their assessment of cumulative effects for the Athabasca River basin, for instance, Lima and Wrona (2019) reviewed hundreds of studies and found that the lack of a coordinated approach to monitoring and the absence of data sharing among groups left significant knowledge gaps despite 49 years of piecemeal data collection. Coordination among scientists, policy makers, and resource managers is also essential for designing a monitoring program to support rigorous assessment and effective adaptive management. An effective model for coordination among scientists can be found in the Boreal Avian Modelling Project (BAM; Boreal Avian Modelling Project 2019). This project uses an effective centralized approach to integrating data from multiple programs and scientists to generate large-scale and long-term data for birds in the boreal and hemiboreal. The key to this program is that data integration is centralized and resourced so that the time requirements for individual scientists to share data are minimal. In addition to compiling data from individual research projects, BAM also integrates large-scale citizen science data collection efforts, including the Breeding Bird Survey data and individual provincial atlas data. One of the more valuable functions that BAM performs is the harmonization of data collected in different ways using a novel statistical approach (Sólymos et al. 2013). These methods deal with differences in avian detectability and variation in survey protocols to generate comparable data from different studies. The BAM project uniquely blends research data and citizen science into a single large-scale data set, which can then provide critical and uncommon data for cumulative effects science (see Cadieux et al. 2020, for example).

8. Spatial scales

Establishing the appropriate scale for cumulative effects studies is difficult because cumulative effects and associated environment response factors operate across multiple scales of time and space (Boyle et al. 1997), and because the apparent ecological significance of impacts can shift with both spatial and temporal scale (McGarigal et al. 2001). Nonetheless, the question of scale is central to any analysis of cumulative effects.

As with choice of environmental responses and their indicators, the appropriate spatial scale is dictated by the objectives of the research as well as the ecological processes of interest; within a management and assessment framework, spatial scale is also determined by the values that are to be conserved or protected. For example, loss of a species in a small portion of its range may not be significant to the global population for a widely distributed species, but it may be important to a First Nation community in that area. Thus, the scale of the research should reflect the scale of the concern. It is highly likely that concerns will be present at multiple scales, but that not every scale will have equal importance.

The smaller the area an environmental response factor occupies, the smaller the scale required to find an effect (Environment Canada 2011*a*). The significance of habitat indicators for marbled murrelet (*Brachyramphus marmoratus*) habitat, for instance, which occupies a small area within a larger regional study, was masked if the indicators were averaged across the broader region (Sutherland et al. 2016). In Brazil, including nonhabitat (nonforested areas adjacent to rivers or streams) in assessments for stream-dwelling amphibians underestimated the likelihood of a species being considered at risk of extinction (Almeida-Gomes et al. 2014). Indicators should be measured at spatial scales relevant to a study's objectives; otherwise, quantifying and interpreting cumulative effects will be difficult (Sutherland et al. 2016). This can be an issue within a study and when synthesizing results from unrelated studies where data were collected at different spatial scales. A review of 386 environmental studies conducted during 49 years within the Athabasca River Basin concluded that significant knowledge gaps still existed around the cumulative effects of multiple stressors for the entire basin because individual studies could not be combined (Lima and Wrona 2019). Much of the information was not measured at an appropriate spatial resolution or was irrelevant at the larger scale. Similarly, Toews et al. (2017) reported that not only the magnitude but also the direction of large mammal responses to human disturbances could be scale dependent. For example, they found that wolves avoided vegetated roads and trails at the 400 000 km^2 study extent, but noted a positive response in previous studies at smaller extents This suggests that small-scale studies cannot always be "scaled up" to be relevant at larger, regional scales.

Study objectives determined the spatial scales established for studies in Table 1. Objectives related to wildlife population levels used geographic ranges of the study animal (caribou and wolf) (Sorensen et al. 2008; Houle et al. 2010). Studies designed to assess landscape-scale response to cumulative disturbance used biophysical regions to define the study area (Spies et al. 2007; Toews et al. 2018). Forest management areas (e.g., Sustainable Forest Licenses or Timber Supply Areas) were chosen as the unit of study in cases designed to inform forest management practices, because these areas are at the scale of operational decision-making for forest management (Valdal and Lewis 2015; Sutherland et al. 2016). Other studies (Table 1) chose more subjective spatial boundaries based on the specific requirements of their study objectives. Gustafson et al. (2007), for example, selected a study area with a range of forest management strategies to examine the effects on sustainable forestry, and Heim et al. (2017) chose a landscape that contained important climatic and anthropogenic disturbance gradients. Data availability can be an important consideration. Johnson et al. (2015), for example, set spatial boundaries for their study to match the spatial extent of an associated project for which data already existed.

Some important factors or types of disturbances cannot be captured within a study boundary but can and should still be accounted for, at least to some degree. For example, many migratory bird species are influenced by habitat loss or other disturbances in their wintering grounds. This situation presents a dilemma. Habitat management where birds breed is critical but may not be sufficient to maintain the population. We may be able to measure how anthropogenic disturbance influences the species on the breeding grounds but still be unable to mitigate population decline through management of these disturbances. This does not mean that breeding habitat is not worth measuring or conserving but that the interpretation of the results must take into account the full context of the species biology and distribution and all the factors at play (i.e., the cumulative effects of what is happening where they breed, where they overwinter, and during migration). Another example is a regional or provincial government strategic-level assessment to evaluate the cumulative effects on biodiversity within its jurisdiction. In this case, the administrative boundary may be set as the spatial extent of the study because it is relevant to decision-making. Administrative boundaries rarely match ecological boundaries, however, and disturbances external to the area may also be relevant, especially for wide-ranging species.

9. Temporal scales

Measurement of cumulative effects generally requires comparison to some temporal baseline, often chosen as a point in the past. Current baseline conditions need the context of past actions and influences to illustrate how the environmental responses have changed through time (Seitz et al. 2011). Determining how far back to go in the past is not straightforward, particularly if the goal is to choose a reference time period with minimal human impacts. Historical baselines can often be arbitrary, especially with ecosystems that change dynamically through time, such as the fire-prone systems of the boreal zone (Jones 2016). Extending too far back in time also runs into the practical issue of limited data availability. However, major shifts in conditions from the past (e.g., beginning of industrial logging, conversion of forested land to agriculture) should be identified to understand how present-day conditions relate to natural variability (e.g., Cyr et al. 2009). In forestry, for example, it is difficult to assess if landscape structure resulting from roads and logging activities is within the natural range of variation or if it represents novel conditions to which endemic organisms are poorly adapted (McGarigal et al. 2001). Understanding the context of current conditions for an environmental response factor may also require consideration of natural ecosystem cycles, such as predator–prey relationships. For a species like lynx, numbers can vary 7.5-fold during snowshoe hare (*Lepus americanus*) cycles (O'Donoghue et al. 1997). Some forest bird populations are also known to vary significantly across large scales with changing spruce budworm (*Choristoneura fumiferana*) outbreaks (Drever et al. 2018; Venier and Holmes 2010). External factors may also be important, like unusually high or low population numbers in the baseline reference period (Magurran et al. 2010). In the United Kingdom, herring gulls (*Larus argentatus*) are on the UK red list as a species of highest conservation concern mainly due to population declines relative to a reference period when the widespread use of open garbage dumps and fish discards led to unusually high gull populations (Magurran et al. 2010). Another concern is the issue of shifting baselines (Pauly 1995). Each generation accepts as a baseline their perception of the condition of the ecosystem at the beginning of their memories, and they tend to use this subjective and limited baseline to evaluate changes to the environment during their lifetime (Pauly 1995). Objective measures of the natural range of variability are necessary to identify valid reference conditions (Gauthier et al. 1996). There are many examples in the literature of the application of the natural range of variability concept to forest management (Cissel et al. 1999; Landres et al. 1999; Moore et al. 1999).

Depending on their objectives, nonregulatory cumulative effects studies may include past conditions directly, indirectly, or ignore them completely. Often, temporal changes from past activities are compressed into a single, composite spatial footprint set in the present (Houle et al. 2010; Heim et al. 2017; Toews et al. 2018). These spatial proxies can incorporate temporal effects coarsely, for example, by separating recent harvest blocks (<5 years) from regenerating harvest blocks (5–15 years) (Houle et al. 2010). Baseline reference conditions can also be defined by using older maps and harvesting records to repopulate recent harvest blocks with forested stands, backdating their landscapes to a common, preharvest reference year (Bridger et al. 2016; Nitschke 2008). Some studies have also used simulation of ecosystem processes to recreate past landscapes (McGarigal et al. 2018). Practicality can influence selection of past reference conditions. More recent baselines (e.g., 10 years before present) are sometimes chosen because of data availability (Valdal and Lewis 2015). Other studies have compared historical data to present-day forest inventories. For example, Danneyrolles et al. (2019) compared 19th century tree lists from township surveys to present-day forest inventories in temperate eastern Canada to test the effects of anthropogenic disturbance, temperature, and moisture on tree species distribution. Other studies have also shown the primacy of past land-use change over climate change in influencing tree species migration using available historical data sets (Ameztegui et al. 2016; Miller and McGill 2018). Even studies focused on predicting future conditions can benefit from anecdotal descriptions of past conditions to establish context. Spies et al. (2007), for instance, described the major natural disturbance regimes and anthropogenic disturbances affecting the study area during the past several centuries before projecting different harvesting scenarios into the future. Another option is to establish baselines based on a space-for-time substitution approach across a range of disturbance gradients (for examples see Nielsen et al. 2007). This approach is generally less useful for studies at the largest spatial scales where no relevant undisturbed areas exist. The past can also sometimes be recreated from museum records (Moritz et al. 2008).

A significant temporal challenge is accounting for time lags, which occur when there is a gap in time between an activity and its consequences. For example, plant species diversity in patches of semi-natural grassland in Sweden took 50–100 years to respond to habitat changes (Lindborg and Eriksson 2004). Species with longer life spans and slower generation turnover rates are more likely to display time lags with environmental stressors (Kuussaari et al. 2009; Environment Canada 2011*a*). Similarly, it may take several generations for a population to recover from a disturbance (CEAA 2018). Some environmental effects also take time to build up, such as chronic exposure to a pollutant. This temporal uncertainty around the expression and persistence of impacts make it difficult to set ecologically realistic future endpoints for the effects on the environment of some stressors.

10. Projections of the future and uncertainty

Achieving ecological sustainability requires not only understanding past and present response–stressor relationships but also anticipating future stressors and changing conditions. Although future projections require a solid empirical understanding of cause–effect relationships and current conditions (Duinker and Greig 2007; Sutherland et al. 2016), ecological systems are inherently complex (MacDonald 2000; Noble 2010) and cumulative effects can create unexpected ecological surprises that are difficult to anticipate (Christensen et al. 2006). High levels of natural variability in a system (MacDonald 2000), sensitivity of cause–effect analyses to scale (Merriam et al. 2015), and the potential for synergistic and antagonistic interactions can frustrate current understanding and increase future uncertainty. Additional effects from less localized and more pervasive disturbances, such as climate change or air pollutants, make predicting future conditions even harder. Projecting resource development in a region for just a few years into the future can be challenging (Duinker and Greig 2007; Valdal and Lewis 2015), and uncertainty will increase with time. Despite chronic uncertainty (Gunn and Noble 2009) and imperfect knowledge, however, effective management relies upon consideration and prediction of future cumulative effects (Therivel and Ross 2007; Gunn and Noble 2009; Martin et al. 2012; Halpern and Fujita 2013).

Many approaches have been used to project future conditions. When uncertainty is high because of data limitations or when predicting conditions far into the future, often only coarse, qualitative assessments are possible. Predictions may be limited to estimating positive or negative impacts or characterizing the magnitude of cumulative effects into broad classes such as large or small impacts (Therivel and Ross 2007). Expert knowledge is critical and can be incorporated into future predictions informally through mechanisms like polls or surveys, or through more structured processes such as the Delphi method (Duinker and Greig 2007), and includes traditional ecological knowledge (Wiles et al. 1999). Trend analysis and extrapolation techniques are commonly used to make qualitative or quantitative predictions about future conditions based on previous causal relationships (Duinker and Greig 2007; Barnosky et al. 2012; Jones 2016). For systems with more extensive data, procedures such as decision theory use available information such as likelihood of alternative states, how actions lead to outcomes, and net benefits of outcomes to maximize expected benefits under uncertainty

(Polasky et al. 2011). The outcomes of decisions are analyzed to determine optimal decisions under the given constraints and assumptions. The advantage of decision theory is that it clearly identifies the objective of decision-making and uses available quantitative information to provide a transparent and repeatable approach (Polasky et al. 2011). However, for large-scale cumulative effects problems with global change drivers, the information required to feed the decision theory framework is often unavailable. Scenario analysis is an alternative approach that creates a range of multiple plausible futures rather than predicting a single "most probable" outcome (Duinker and Greig 2007; Strimbu and Innes 2011), and it requires less quantitative information. Scenario analysis can range from a set of qualitative "stories" about future conditions or different management options to highly quantitative analyses (Duinker and Greig 2007; Polasky et al. 2011). A recent series of papers in *Environmental Reviews* used scenario analysis techniques to explore the future of the boreal zone in Canada relative to identified drivers of change, including demand for ecosystem services and industrial innovation (Erdozain et al. 2018; Lamothe et al. 2018; Musetta-Lambert et al. 2019). Scenario analysis can be especially useful for exploring the potential effects of alternative management actions or different resource development strategies. Simulation models, both process-based and mechanistic, are commonly used tools for predicting future cumulative effects.

Data availability, study objectives and current knowledge of stressor–response relationships help determine which method of projecting future conditions is appropriate. The simplest approach conceptually is overlaying maps of predicted development on important areas of biodiversity defined by habitat suitability maps (e.g., Suzuki and Parker 2016; Whitehead et al. 2017). This approach allows managers the opportunity to avoid or to minimize future impacts on species before development occurs. Alternatively, a qualitative approach based on a combination of expert knowledge and trend extrapolation has been used to predict short-term levels of risk for several species from cumulative effects (Valdal and Lewis 2015). Risk assessments were partly based on consultations with regulatory agencies to identify 1–3-year development plans for mining, forestry, wind power, and pipeline expansion in the region. Valdal and Lewis (2015) estimated that for moose populations, 90% of the planning cell units in the study area could be affected by proposed resource use activity within a few years, although overall level of risk to moose populations was low. This approach created a single "best guess" of future conditions.

Other studies have projected the effects of alternative management approaches into the future by generating multiple scenarios, using either aspatial or spatially explicit models. An aspatial modelling approach was used to project the impacts of alternative forest management scenarios on 12 wildlife species in boreal forests (Thompson et al. 2003). The Ontario Strategic Forest Management Model was used to simulate the effects of harvesting and three different regeneration approaches on a 12 560 km^2 forested landscape. Simulations were run 200 years into the future. Thompson et al. (2003) estimated the relative density of each wildlife species on the landscape by combining expert-defined wildlife suitability indices with the proportion of the landscape in each forest, stand age, and regeneration type, and assessed and compared cumulative effects on each species from each management approach through time. Schneider et al. (2003) also used an aspatial modelling approach to investigate cumulative effects of forest harvesting, petroleum exploration and development, road construction, and wildfires on a 59 000 km^2 landscape in Alberta. They used the ALCES model to simulate two alternative management scenarios: a "business as usual" scenario using conventional management practices, and a "best practices" scenario emphasizing ecological and economic sustainability. Wildfires were included at a constant burn rate of 1% of the study area per year. Schneider et al. (2003) tracked cumulative effects of these alternative scenarios for 100 years into the future for a number of economic and ecological indicators, including habitat availability for caribou. Caribou habitat availability was calculated by removing habitat situated close to human disturbances based on avoidance distances provided by expert knowledge. Among other results, Schneider et al. (2003) found that cumulative effects of harvesting, roads, fires, and petroleum disturbances resulted in reduced habitat availability for caribou, dropping from 43% to 6% of the landscape within 30 years under conventional management, but that available habitat remained greater than 20% in the alternative "best practices" scenario for the entire 100-year period.

Spatially explicit landscape models have been used to predict future impacts of cumulative effects. Nelson et al. (2009) used a modelling tool (InVEST) to explore cumulative effects of alternative management scenarios on biodiversity across a 29 728 km^2 landscape. Three management scenarios were created that continued development under current trends, allowed for increased development, or emphasized conservation. Each scenario was considered plausible by stakeholders and all scenarios were projected 60 years. Model outputs compared trade-offs among biodiversity conservation, ecosystem services, and commodity production across the different management scenarios. Three of the studies shown in Table 1 used spatially explicit models to predict cumulative effects. Gustafson et al. (2007) used the HARVEST model to simulate the cumulative effects of different forest management practices on biodiversity in Michigan, combining expert-based species habitat models with an aspatial habitat tool (MI WILD) and landscape model output to predict habitat change for 153 wildlife species over 100 years (Gustafson et al. 2007). Yamasaki et al. (2008) used a combination of a stand model, a landscape model (Athabascan Plains Landscape Model) and a global climate model to explore potential cumulative effects from oil and gas activity, forest harvesting, climate change, and wildfires on a landscape in Alberta. They modelled nine scenarios 200 years into the future, ranging from scenarios without management to scenarios with all human and natural disturbances included. Sutherland et al. (2016) employed a set of individual models within the SELES landscape-modelling framework to project the combined effects of forest harvesting and run-of-river hydropower resource management activities for 100 years on an array of environmental responses. Many landscape-level models are available to explore future cumulative effects, especially in forested ecosystems (e.g., Seidl et al. 2012; Wang et al. 2013). Although many of these models require extensive data and are computationally intensive, they have the capacity to incorporate complex disturbance interactions through time to produce a set of plausible future conditions. The modelling process itself is also valuable as a tool for uncovering important knowledge gaps.

Other approaches are also possible. Heckbert et al. (2010) explored the interacting effects of forest harvesting, hunting, and road deactivation schedules on moose populations using a multi-agent-based simulation model. In this example of complex systems modelling, forestry roads were deactivated at 2, 5, or 10 years following harvesting and the number of local moose populations that were extirpated from the resultant hunting patterns was estimated. Simulations suggested that deactivating roads after 2 years had a concentrating effect on hunting pressure, leading to more localized extirpations of moose than scenarios that delayed deactivation. To predict the cumulative effects of petroleum drilling and forest harvesting on three moose and marten populations, Strimbu and Innes (2011) adapted a multiple scenario analysis approach originally developed for statistical thermodynamics. As part of this structured process, they created a total of 144 independent and equally likely futures consistent with current regulations. Models were spatially explicit and simulated cumulative effects from different harvesting and drilling scenarios for the next 100 years. They used habitat suitability index models to link habitat changes through time across the three study areas to project population sustainability of marten and moose. The multi-scenario approach is a way to explore patterns in potential futures rather than presenting one "improbable" future.

Although approaches taken to projecting future cumulative effects differ in the preceding studies, all share the challenge of creating useful and informative predictions in the face of uncertainty. To achieve the goal of sustainability, resource managers are required to address uncertainty transparently and attempt to reduce it as much as possible (Burton et al. 2014). Four important types of uncertainty have been identified in the literature (Nichols et al. 2007; Martin et al. 2009). Environmental uncertainty reflects natural temporal and spatial variation in composition, structure, and function in ecosystems. Structural or model uncertainty reflects the potential mismatch between how the system functions and how we think the system functions. Partial controllability reflects an imprecise translation of management actions into system outcomes. Lastly, partial observability reflects sampling or observational error (Nichols et al. 2007; Martin et al. 2009).

Producing multiple future scenarios instead of a single "best guess" of future conditions is one way to address uncertainty. The multi-scenario approach acknowledges that changing assumptions or management approaches can have a large effect on the impact of future cumulative effects, and it produces a range of possibilities to assist planning. This approach can be especially useful for identifying worst-case scenarios. Where data and appropriate models exist, landscape-level modelling can be a powerful tool, offering an almost infinite array of future scenarios to explore. Landscape models can benefit from incorporating stochasticity (MacDonald 2000) and natural disturbances (Yamasaki et al. 2008) to better understand the consequences of interactions between human and natural disturbances. As part of the modelling approach, sensitivity analysis is a critical technique for identifying key variables and processes driving uncertainty (MacDonald 2000). Sensitivity analysis examines how variations in model outputs are driven by variations in model inputs with the goal to assess the robustness of the results to assumptions or uncertain inputs (Pianosi et al. 2016). Adaptive management and adoption of an iterative learning process are also effective methods for dealing with uncertainty in cumulative effects predictions (MacDonald 2000; Polasky et al. 2011; Bragagnolo and Geneletti 2012; Burton et al. 2014). Effective monitoring is especially critical as a means of iteratively validating assumptions and predictions and refining adaptive management models (Lyons et al. 2008).

Some argue that it is not always necessary to have detailed, accurate predictions to manage for anticipated cumulative effects, and that detailed predictions should be expected for short-term assessments but predictions for longer time periods require only a "broad-brush picture" of effects due to high levels of future uncertainty (Therivel and Ross 2007). Similarly, Noble (2010) argued that at the regional scale it is more useful to understand broad trends and patterns of disturbances under alternative development scenarios than it is to provide detailed predictions of impacts. In a review of four strategic regional CEA case studies, Gunn and Noble (2009) found that in some cases regional-level cumulative effects were too difficult to measure or predict and some stakeholders were uncomfortable dealing with specific and potentially controversial quantitative output. Stakeholders and resource managers preferred establishing broad "goalposts" for managing future development in a region rather than producing detailed cumulative effects predictions (Gunn and Noble 2009). Scientists should communicate their results in a way that fully recognizes assumptions and uncertainty in their predictions and that provides proper context so that results are not misinterpreted.

11. Modelling frameworks for integration of multiple effects, responses, and interactions

An obvious role for models is the prediction of future cumulative effects, which require modelling to generate plausible futures under changing disturbances. Alternative land-use management scenarios can be modelled in conjunction with known response–stressor relationships to predict future conditions for habitat or populations as discussed earlier. There are existing landscape modelling frameworks that can reduce the work of predicting the future including, for example, ALCES (Schneider et al. 2003), SELES (Spatially Explicit Landscape Event Simulator) (Fall and Fall 2001), or SpaDES (https://spades.predictiveecology.org/index.html). ALCES is a well-developed landscape-scale simulation framework used to quantify the state of the landscape in one-year time steps. The user specifies the starting landscape condition, and provides scenarios for future industrial activities, natural disturbance, and regeneration trajectories for each disturbance type. It is flexible but provides only the framework for the simulation and with no embedded ecological information. ALCES online (Carlson et al. 2014) is a newer tool that is currently parameterized for Alberta with plans to create versions for additional jurisdictions. It is more user friendly and requires much less technical and ecological understanding to use but at a cost of less flexibility (Carlson et al. 2014). SELES is a landscape ecology-specific language developed to facilitate the construction of models of landscape dynamics that are more directly relatable to conceptual models. The SELES framework guides the development of spatial and temporal landscape models that are more tractable for landscape ecologists. SpaDES (https://spades.predictiveecology.org/) is a modularized event simulator written in R (see https://www.r-project.org/) that allows the user to take advantage of existing models (modules) that simulate relevant ecosystem processes such as fire, insect behaviour, climate change, and vegetation dynamics and allows them to interact to predict cumulative effects on important environmental responses. This modularized approach serves to reduce redundancy of creating every model from scratch and promotes synergies between cumulative effects studies and assessments across large areas. In addition, it allows for ensemble modelling to contrast and compare alternative modules to support an exploration of uncertainty. It also has the advantage of being fully open that, if well adopted, will allow it to grow quickly and generate efficiencies. Although the SpaDES framework is fully operational, the development of modules is still in the early stages and examples of its use to date are limited to a few practitioners (see https://spades.predictiveecology.org/). It does offer an approach that has potential for effective long-term development of sharable modules to address cumulative effects questions but requires a heavy investment in R programming, making it less appealing to nontechnical users.

There are other models available to address the prediction of future ecosystem condition as a function of current and future ecosystem processes and anthropogenic disturbances. In general, however, desirable characteristics of models to explore cumulative effects include transparent and open algorithms, an ability to explore uncertainty in assumptions and parameters, support by a network of users, user-friendly interfaces for decision-makers, and modularity to support discipline-specific development by experts and synergies through sharing.

12. Conclusions

Much of the cumulative effects literature relates directly to the formal legislated process of assessment in the context of natural resource development. Cumulative effects science, however, is much broader than that and has been conducted as ecological research for much longer than the term "cumulative effects" has been around. In fact, much of the science literature on cumulative effects never mentions the term, making a systematic review difficult. Cumulative effects science beyond the confines of the regulatory process can be more flexible and comprehensive. It is a necessary activity that requires investment to facilitate progress and generate insights that could inform integrated resource management and land-use planning in the longer term.

Our paper is not intended to be a comprehensive review of all cumulative effects science but a synthesis of the challenges and approaches currently used to address the science of cumulative effects. We defined cumulative effects science very generally to mean the study of environmental responses to multiple human disturbances (and natural disturbances depending on the appropriate reference condition). We focused most of our examples on boreal forests in Canada where there are multiple forms of natural resource development in the context of both climate change and significant natural disturbance. Cumulative effects science explores the relationship between stressors (anthropogenic and natural disturbances) and environmental responses. Data are much more readily available for the former than the latter. Also, for large-scale studies that are most likely to address integrated resource development and land-use planning, remotely sensed data are often all that are available. Environmental response data must, more often, be collected using on-the-ground approaches, which are more costly and time consuming to collect. In fact, the lack of environmental response data, both baseline and after disturbance, is one of the largest challenges to cumulative effects science.

The appropriate environmental response data for cumulative effects science clearly depends on objectives. If the goal is integrated resource management or land-use planning, then an ecosystem-based approach is recommended. An ecosystem approach requires consideration of broad objectives like maintaining forest integrity or sustainability. These concepts are difficult to define but are likely best captured by a suite of environmental responses and indicators that reflect the ecosystem composition, structure, and function. Data collection should also respond to the specific concerns that are anticipated in an ecosystem under stress. A conceptual model of the system is a good tool for supporting the selection of environmental data to be collected (Lindenmayer and Likens 2010).

Data management and integration will be key to supporting cumulative effects science. A centralized data repository would improve national capacity to conduct cumulative effects science and reduce redundancy in the effort to generate useful data products from remote sensing. Additionally, the current general trend towards more open data will improve our capacity to do cumulative effects science. Data integration efforts like those of the Boreal Avian Modelling Project are strong models for how do deliver harmonized, large-scale environmental response data from multiple sources and for multiple uses. Large-scale monitoring efforts are also extremely valuable for producing relevant environmental response data for cumulative effects science but approaches should follow recommendations for effective ecological monitoring (see Lindenmayer and Likens 2018 for example). Stable long-term funding is required for data collection and should be guided by best available multidisciplinary science.

Despite the importance of understanding how multiple stressors interact to impact environmental responses, there are few large-scale studies that have comprehensively demonstrated the cumulative effects of all relevant stressors and, in particular, any interactions between those stressors. Interactions are notoriously difficult to demonstrate in observational studies conducted at large scales. Small-scale, manipulative experimental studies have been more successful at demonstrating interactions but usually focus on only 2 or 3 stressors and are difficult to scale up. One possible solution to this issue is the development of comprehensive integrated models of ecosystems that can allow scientists to explore the impact of stressors and their interactions, generate hypotheses, and test with new data. These integrated models, if modularized and built on an open platform, could harness the synergies of scientists from many disciplines to create expert modules for all relevant processes for the ecosystem of concern. Outputs from these integrated models could then be used to guide data collection to advance our knowledge of cumulative effects and interactions.

An important but unanswered question in this review is: how much impact will enhanced and robust cumulative effects science have on decision making? In this review we focused on the science. As scientists we work to use strong, repeatable scientific methods to produce robust results that can then be used for decision-making. The decision-making process, however, is a political process and one that factors in social and economic considerations. Decisions are about trade-offs and the goal of decision-makers is maximize benefits and minimize costs. Understanding if and when our science informs decisions could help move our approaches to cumulative effects science in new directions and likely warrants its own analysis and review.

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