Environ Monit Assess (2014) 186:3605–3617
DOI 10.1007/s10661-014-3643-7

A framework for adaptive monitoring of the cumulative effects of human footprint on biodiversity

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Received: 7 August 2013 / Accepted: 20 January 2014 / Published online: 1 February 2014

Abstract Effective ecological monitoring is imperative in a human-dominated world, as our ability to manage functioning ecosystems will depend on understanding biodiversity responses to anthropogenic impacts. Yet, most monitoring efforts have either been narrowly focused on particular sites, species and stressors — thus inadequately considering the cumulative effects of multiple, interacting impacts at scales of management relevance — or too unfocused to provide specific guidance. We propose a cumulative effects monitoring framework that integrates multi-scaled surveillance of trends in biodiversity and land cover with targeted evaluation of hypothesized drivers of change. The framework is grounded in a flexible conceptual model and uses monitoring to generate and test empirical models that relate the status of diverse taxonomic groups to the nature and extent of human "footprint" and other landscape attributes. An adaptive cycle of standardized sampling, model development, and model evaluation provides a means to learn about the system and guide management. Additional benefits of the framework include standardized data on status and trend for a wide variety of biodiversity elements, spatially explicit models for regional planning and scenario evaluation, and identification of knowledge gaps for complementary research. We describe efforts to implement the framework in Alberta, Canada, through the Alberta Biodiversity Monitoring Institute, and identify key challenges to be addressed.

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Keywords Cumulative effects · Ecological monitoring · Human footprint · Biodiversity conservation · Adaptive monitoring · Impact assessment

Introduction

Effective ecological monitoring is imperative in an increasingly human-dominated world (Lindenmayer and Likens 2010; Steffen et al. 2011). The success of initiatives to sustain functioning ecosystems will depend on an understanding of biodiversity responses to rapidly changing anthropogenic impacts (Butchart et al. 2010;

Hooper et al. 2012). To date, ecological assessment and monitoring have been narrowly focused on particular sites, species and stressors, failing to adequately consider broader spatio-temporal contexts and the cumulative effects of multiple, interacting impacts (Boutin et al. 2009; Schultz 2010; Hill and Arnold 2012). Yet, it is an understanding of such large-scale, complex interactions among a myriad of anthropogenic and natural disturbances, and across many components of biodiversity, that is required for effective landscape management and conservation planning (Lindenmayer et al. 2008; Barnosky et al. 2012). Current approaches to landscape management typically rely on coarse-filter or piecemeal data sources, combined with subjective expert opinion, and generally fail to learn from management "experiments" (Walters and Holling 1990; Noon et al. 2003; Boutin et al. 2009). Pervasive uncertainty regarding ecological processes and their management hinders progress toward sustainability. Management agencies must transparently confront uncertainty in decision-making while seeking to reduce it through monitoring programs capable of linking patterns and processes at relevant scales (Lyons et al. 2008; Haughland et al. 2010).

While there is broad agreement that current approaches to monitoring and managing cumulative environmental effects are inadequate (Duinker and Greig 2006; Schultz 2010; Johnson 2011), there is less agreement on how to improve monitoring. A dichotomy between "targeted" and "surveillance" monitoring has emerged (Wintle et al. 2010), with proponents of the former favouring causal inference through focused questions and experimental design (e.g., Nichols and Williams 2006; Lindenmayer and Likens 2010), and advocates for the latter emphasizing broader standardized systems for tracking complex dynamics across multiple ecological and management foci (e.g., Manley et al. 2004; Boutin et al. 2009; Johnson 2012). However, both approaches have limitations with respect to effective assessment and monitoring of cumulative effects. For example, it is increasingly clear that complex coupled human–natural systems are not always amenable to traditional, reductionist experimental designs, particularly given the ephemeral and often unanticipated nature of socio-political and ecological conditions over the long term (Liu et al. 2007; Gitzen et al. 2012). It is impractical to efficiently implement targeted programs to separately assess the array of species, stressors or questions of relevance to regional biodiversity managers, let alone synthesize their various outcomes. Yet it is also argued that passive, "omnibus" surveillance devoid of tractable questions is less likely to advance ecological understanding or direct specific management actions (Nichols and Williams 2006; Lindenmayer and Likens 2010). Rather than perpetuate the dichotomy, we suggest that broad surveillance of biodiversity status needs to be integrated with focused hypothesis testing for more effective and adaptive monitoring of cumulative environmental effects.

In this essay, we present an overarching framework for monitoring the cumulative effects of anthropogenic activities on biodiversity across broad spatial and temporal scales, emphasizing why both targeted and surveillance monitoring are required. The key feature of our framework is the integration of multispecies status monitoring and hypothesis testing in an adaptive cycle guided by a conceptual model of the socio-ecological system. The broadly defined conceptual model highlights central relationships of interest between landscape management, anthropogenic disturbance, and biodiversity response, with disturbance measured primarily as human "footprint" (i.e., physical disturbances on the landscape attributable to human activities; cf. Sanderson et al. 2002; Haines et al. 2008) and response measured across a diverse suite of taxa and habitat features. Measurement is done at multiple scales, linking field-based site sampling with coarser characterization from remote sensing. Working hypotheses describing specific associations between anthropogenic disturbances and biotic elements are generated as empirical models parameterized with monitoring data. Subsequent cycles of monitoring are then used to test the working hypotheses, with deviations between model predictions and empirical observations providing the means by which to learn about the system and adapt hypotheses. This framework is well suited to support regional land use planning and management efforts, and is widely applicable to the monitoring and assessment of cumulative environmental effects in different ecosystems and regions. We provide a brief overview of efforts to implement the framework through the Alberta Biodiversity Monitoring Institute (ABMI) in Alberta, Canada.

Conceptual model of the socio-ecological system

Ecological monitoring programs are most effective when guided by a conceptual model of the system of interest (Lindenmayer and Likens 2010). Linking monitoring to a model makes assumptions explicit and can help move a program beyond simply documenting ecological changes toward providing stronger inference on underlying mechanisms. Our cumulative effects monitoring framework centers on a conceptual model of the broad relationships between human development activities and resulting changes in natural systems within a region (Fig. 1). Choice of location and size for the region of interest is dictated by management objectives (e.g., land use planning region). The overarching question of interest is "What are the cumulative effects of anthropogenic disturbances on biodiversity?" Thus, the two principal components of the model are: (a) biodiversity, represented by the diverse species and habitat elements monitored; and (b) anthropogenic disturbance, embodied by the range of human footprints. Key assumptions inherent in the conceptual model are that (1) land use (i.e., footprint) is the prevailing impact of the region's human population on biodiversity and the primary driver of changes in regional biodiversity; (2) monitored taxa and habitat elements sufficiently indicate patterns representative of unmonitored components of biodiversity; and (3) the nature and extent of footprint is under the control of "landscape management," which loosely refers to the collection of land use decisions made (deliberately or not) across the diverse set of stakeholders in the region.

The conceptual model implicitly assumes that the cumulative effects of human footprint on biodiversity stem from direct, indirect or interactive effects. Direct effects of footprint include habitat loss and degradation (i.e., physical alteration of vegetation and soil), while indirect effects may include edge effects, changes in biotic connectivity (e.g., movement or dispersal), altered species interactions (e.g., competition, predator–prey), impaired ecological function (e.g., changes to hydrology or productivity), or other human disturbances associated with footprint (e.g., hunting, noise, pollution; Forman and Alexander 1998; Laurance et al. 2002). Importantly, footprint

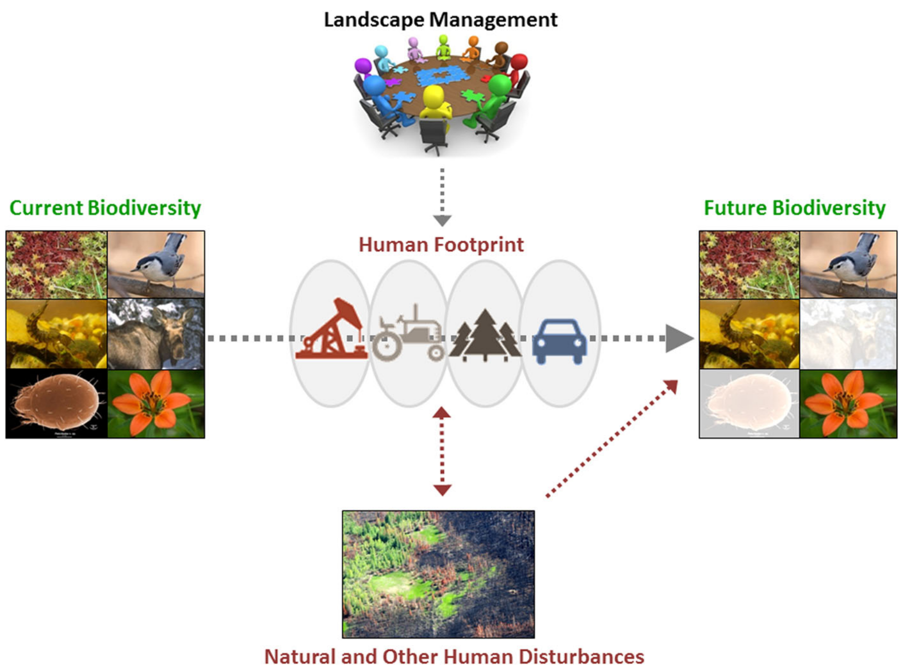

Fig. 1 Conceptual model of the general socio-ecological system underlying the cumulative effects monitoring framework. Primary focus is directed at human "footprint" as the major driver of biodiversity change over time (i.e., physical disturbances from anthropogenic activities such as energy development, cultivation, forest harvesting, and transportation infrastructure). Footprint is assumed to be controlled by "landscape management" — that is, the collection of land use decisions made by stakeholders in the region. Interacting factors of potential importance to biodiversity change are broadly recognized, such as natural disturbance regimes and anthropogenic impacts unrelated to footprint (e.g., climate change, disease), and can be more directly addressed within the adaptive framework as hypotheses are tested and refined. Image credits: Alberta Biodiversity Monitoring Institute, D. Haughland, C. Lemmon, D. Walters, J. McKinnon (Parks Canada), ClipartOf.com

effects may be interactive rather than additive, and may vary according to taxon, ecosystem, geographic location, etc. Anthropogenic and natural factors other than footprint can also influence biodiversity dynamics (Fig. 1; e.g., climate change, introduced species, altered disturbance regimes, long-range pollution, management intervention) and may operate interactively with footprint, potentially exacerbating or mitigating their effects. While the generation of specific predictions from more explicit empirical models is a key part of our framework (see next section), the overarching conceptual model provides an integrated context to guide multispecies cumulative effects monitoring.

Our central focus on the effects of human footprint represents an important management hypothesis, since the nature and extent of footprint created lies under more direct control of local and regional management than do other potential influences (e.g., climate change). However, the ultimate value of the conceptual model lies in structuring knowledge acquisition to facilitate learning based on systematic deviations from model predictions. It is thus designed to be adaptive over the long term, remaining flexible enough to accommodate new management practices and disturbance dynamics on the landscape, and amenable to being updated as new information is collected and new understanding of the system is synthesized.

Cumulative effects monitoring framework

The conceptual model guides implementation of our cumulative effects monitoring framework (Fig. 2). Principal, iterative components of the framework are: (a) field and remote sensing sampling of current biodiversity and land cover conditions across the landscape, including representative surveillance sites and complementary targeted sites along gradients of hypothesized drivers (e.g., human footprint); (b) construction of empirical models describing relationships between species (or other biodiversity elements) and drivers across sampled sites; (c) model-based projections of species responses to observed land cover changes; (d) repeated sampling of biodiversity elements in the new landscape to assess actual changes; (e) evaluation of observed biodiversity responses against those predicted by the models (i.e., testing of ecological hypotheses); and (f) model refinement and ancillary targeted research. This is a cyclical process in which new predictions are developed and tested with each monitoring cycle (Fig. 2), thereby documenting and improving understanding of changes across the system over time, and aiding evaluation of management effectiveness and design of more focused research questions.

Sampling biodiversity and land cover

The first step in the framework is to establish the current condition of biodiversity and land cover in the focal region by sampling across the range of species and other monitoring targets (Fig. 2a). For each taxonomic or functional group of interest, standardized protocols for estimating status (e.g., occurrence, abundance) are developed and implemented on a regular basis across a representative sampling grid (e.g., random, systematic), which is the basis for unbiased monitoring of long term regional trends. Sampling includes both field-based protocols for diverse species assemblages and localized habitat and disturbance features, and remote sensing protocols for broader characterization of land cover and use (e.g., Table 1; ABMI 2012a, b). The application of standardized protocols across the entire monitoring region overcomes the limitations associated with current piecemeal, project-by-project approaches to assessment and monitoring (e.g., heterogeneous detection probabilities due to variation in sampling methods and intensities; Sólymos et al. 2013). In addition to the representative regional sampling, complementary targeted sampling is used to ensure adequate short-term coverage of gradients in hypothesized drivers of biodiversity change, such as types and amounts of human footprint. These targeted sites are chosen in an adaptive manner to improve discriminatory power for the development of empirical models relating biodiversity and land cover (Fig. 2), and thus might be sampled only once (cf. Lookingbill et al. 2012, hybrid sampling approach).

Biodiversity–land cover model development

Empirical data from the monitoring program are used to parameterize statistical models generalizing relationships between the status of monitored biodiversity and the hypothesized drivers of biodiversity change (e.g., nature and extent of human footprint; Fig. 2b). We envision species-specific models for which results could be aggregated into higher levels of biodiversity (Nielsen et al. 2007; Schwenk and Donovan 2011), although integrated

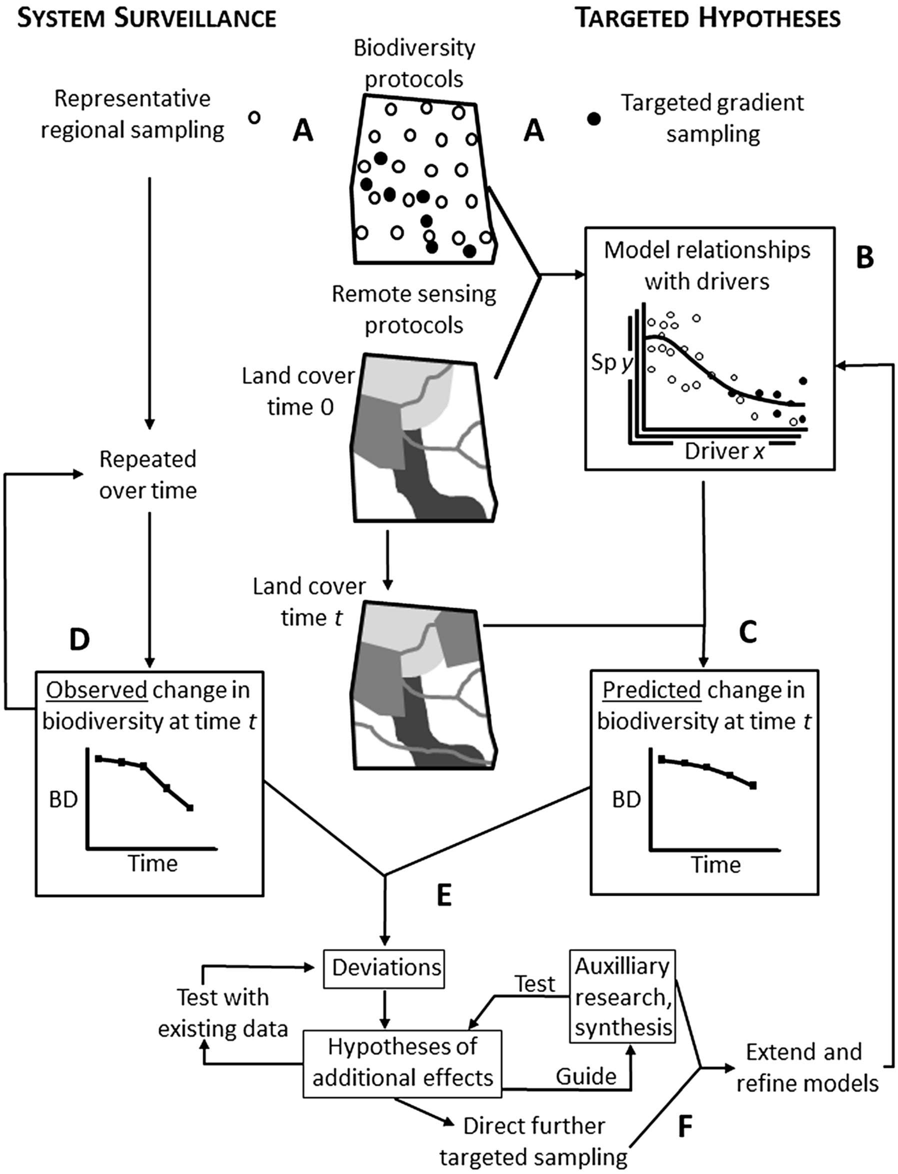

Fig. 2 Schematic of primary components of the cumulative effects monitoring framework. The approach involves a cycle of **a** sampling biodiversity and land cover elements across both representative and targeted sites, **b** building models relating species abundances to human footprint and other hypothesized drivers of change, **c** predicting models onto observed changes in the landscape, and **d**, **e** comparing predicted changes with those observed from repeated sampling (i.e., hypothesis testing). Deviations between observations and predictions provide a basis for refining hypotheses, designing complementary research, and ultimately improving understanding of the socio-ecological system (**f**)

multispecies models are also plausible (DeWan and Zipkin 2010; Vackar et al. 2012). Specific model structure can vary depending on assumptions about the distribution of response variables and their relationships to explanatory variables (e.g., generalized linear models and variants, Zuur et al. 2009; machine learning methods such as boosted regression trees, Elith et al. 2008). An information theoretic approach can be used to assess support across a set of plausible a priori models — representing different hypotheses about system response — and to estimate parameters with multimodel inference (Burnham and Anderson 2002). Our conceptual model focuses on human disturbance as a primary hypothesized driver of biodiversity changes (Fig. 1), so

Table 1 Taxonomic groups and land cover elements monitored by the terrestrial program of the Alberta Biodiversity Monitoring Institute, as an example of multi-target monitoring within the cumulative effects framework

Monitoring target	Method[a]	Scale[b]	Example variables[c]
Mammals	Snow track surveys	100 km^2 (10 km transect)	Species occupancy per transect (25 species)
Birds	Unlimited radius point counts	1 km^2 (9 stations)	Species occupancy per point count (>200 species)
Vascular plants	Timed plot searches	1 ha (4×250 m^2 quadrants)	Species occupancy per plot (>1100 species)
Bryophytes	Timed plot searches	1 ha (4×375 m^2 plots)	Species occupancy per plot (>300 species)
Lichens	Timed plot searches	1 ha (4×375 m^2 plots)	Species occupancy per plot (>200 species)
Soil mites	Soil cores	1 ha (4 cores)	Species occupancy per core (>200 species)
Habitat structure	Plot sampling Surface substrate transects Soil cores	1 ha (4× nested plots 25–625 m^2) 1 km^2 (9×7 ha plots)	Ecosite type, % vegetation cover, slope, tree DBH and age, woody debris, depth of organic soil
Land Cover	Air photo and satellite interpretation	21 km^2 (3×7 km plot around site) Province-wide (2 ha minimum mapping unit)	Proportion of area covered by vegetation type (e.g., grassland, shrubland, coniferous forest)
Human Footprint	Field plots Air photo and satellite interpretation	1 km^2 (9×7 ha plots) 21 km^2 (3×7 km plot around site) Province-wide	Proportion of area covered by, e.g., forestry cutblocks; residential development; industrial infrastructure; roads and other linear features; cultivation

[a] Further details on ABMI sampling protocols are available at www.abmi.ca/ (e.g., ABMI 2012a,b)
[b] Approximate scale over which sampling methods are applied. Sampling sites cover the entire province of Alberta (Fig. 3) and can be aggregated at multiple spatial scales (e.g., management planning regions)
[c] Examples of variables used in species–land cover models (Fig. 2b). The approximate number of species being sampled by ABMI protocols is given, although the program is not yet at full implementation, and not all species are currently modeled (further details at www.abmi.ca/)

explanatory variables describe the degree of human footprint at each sampled site (total and individual components), as well as other site covariates expected to influence the species being modeled, such as topo-edaphic features, vegetation type and structure, and climate (at ecologically relevant scales). Covariates related to sampling variability can be included to address species detectability (e.g., effort, weather, time; Sólymos et al. 2013). Measures of model accuracy evaluate the explanatory power of top models for a particular species or group, and estimates of parameter uncertainty provide direction for targeted research to strengthen model development.

Predicting species responses to observed land cover change

Parameters estimated from specific biodiversity–land cover models are used to generate predictions of species' status in the new landscape of a subsequent monitoring cycle (Fig. 2c). Fundamental to the framework are predictions across the sites being resampled, given the observed footprint (and other covariates) at those sites. A predicted response for each species or group is thus generated for the region of interest based on the previously modeled relationships and the current land cover conditions (resampled using consistent protocols). Recognizing uncertainty inherent in ecological models, the predictions represent hypotheses to structure learning, rather than concrete expectations of the new landscape. Nevertheless, given adequate models, projection of biodiversity responses to alternative future landscape scenarios can be a valuable tool for management planning (e.g., Nelson et al. 2009). Moreover, this monitoring framework could be extended to include development and testing of predictive models of land cover change in order to aid creation of realistic future scenarios.

Repeated sampling to estimate actual biodiversity trends

Resampling of biodiversity indicators and covariates across monitoring sites is performed using the same standardized, field-based protocols as for initial sampling, thus controlling for effects of methodology on observed changes. Resampling is focused on the representative regional sampling design to ensure unbiased trend measurement (Fig. 2d). Additional targeted sampling can also be implemented as needed to test or refine model-based hypotheses. Given the long-term nature of the monitoring framework, it may be necessary to adjust sampling protocols, for instance due to technological changes or improvements stemming from methodological research. If this occurs, calibration across methodological changes and inclusion of relevant sampling covariates in subsequent modeling are essential for maintaining the integrity of the long-term record and ensuring that observations and model predictions can be confidently applied across methods (Lindenmayer and Likens 2010; Johnson 2012).

Model evaluation and hypothesis testing

Predictions of biodiversity–land cover models developed from initial sampling are confronted with observations from resampling (Fig. 2e). A key point is that model predictions are tested at the regional scale at which they are used in landscape management, not just at the scale of individual sampling plots. For example, a model predicting species occupancy as a function of human footprint is tested not only at resampled sites with particular amounts and types of footprint (e.g., using measures of predictive accuracy such as AUC; Franklin 2009), but also by comparing actual regional changes in the species occupancy to model-predicted changes based on observed changes in regional footprint (i.e., aggregated across sites).

Monitoring results that show significant deviations from model predictions provide evidence that the working hypotheses of system dynamics are inadequate. For instance, the cumulative effects of human footprint might be inadequately represented by existing model structures, and unexpected interactions or nonlinearities may need to be considered (Barnosky et al. 2012). Alternatively, other factors besides footprint may be of greater importance, such as natural disturbance, climate change, or disease. Given our generally poor understanding of the complexities of cumulative effects on ecological systems, the potential for mismatch between observations and model predictions is high. Nevertheless, systematic patterns of deviations across space, ecosystems, disturbance levels, and species, can lead to further hypotheses about the nature of unmodeled effects, and thereby guide additional targeted monitoring or research. Climate change effects, for example, would be suggested by consistent shifts in species distributions along climate gradients, which a systematic grid of revisited sites is well-designed to detect. Differences between areas with a diversity of resource development activities and those dominated by one activity could imply unaccounted interactions among footprint types, which could then be subject to more targeted sampling. Targeted monitoring alone, which is generally done at more localized scales, is far less likely to detect such patterns. Comparisons of deviations among taxa can also suggest additional factors to consider; for instance, greater deviations for migratory species relative to resident species might focus attention on conditions in other seasonal ranges or along migratory pathways.

Ancillary research and model refinement

As indicated by the above examples, using a conceptual model and hypothesis-testing framework to guide the monitoring program will help identify complementary research questions (Fig. 2f). Comparing monitoring results to predictions makes identification and testing of factors that influence biodiversity trends faster and more efficient than monitoring not guided by an underlying model. Linking monitoring with ancillary research can also be used to address uncertainty in ecological relationships derived from the large-scale monitoring. For example, the effects of some footprint types, such as narrow linear features, may be difficult to extract from large, systematic plots, and may thus be best addressed by targeted research using finer-scale sampling (e.g., Bayne et al. 2005). Similarly, research focused on mechanisms of species responses to stressors can improve confidence in causality inferred from coarser patterns (e.g., Latham et al. 2011). Complementary research in remote sensing and GIS analysis can improve measurement of habitat and footprint features across a range of ecologically relevant scales, and methodological research can reduce uncertainty related to sampling biases (e.g., Castilla et al. 2011; Lele et al. 2012). When such research activities are directly linked to the monitoring program, they lead to more robust models and improved understanding of broader system dynamics.

Additional benefits of the monitoring framework

In addition to the core cumulative effects monitoring framework—designed to guide management over the long term (e.g., several decades) — our approach produces other useful short- and long-term products. Firstly, the initial cycle of sampling provides a systematic baseline of biodiversity and land use for immediate management application (e.g., identifying biodiversity "hotspots"). Subsequent cycles generate valuable documentation of regional change, irrespective of the accuracy of model predictions (Boutin et al. 2009). For instance, quantifying trend in the type and extent of footprints is essential for evaluating land use management (e.g., Haines et al. 2008).

Monitoring across a representative sampling grid provides a set of "reference" sites for targeted assessment of specific management treatments (e.g., how well do forestry practices mimic natural disturbance?) or unplanned disturbances (e.g., pipeline leaks, pest outbreaks). The availability of such reference data — and the underlying standardized sampling protocols — encourages other research and monitoring projects to use comparable methodologies, ultimately facilitating broader data synthesis (Haughland et al. 2010). Furthermore, our framework's modeling strategy facilitates status assessment over short time scales, as biodiversity-footprint models can be used to estimate the ecological "intactness" of species and habitats for any time period (Nielsen et al. 2007). These spatially explicit empirical models represent improvements over coarse-filter, locally restricted, or data-deficient habitat suitability indices often used for management purposes (Roloff and Kernohan 1999). They can also be used in planning exercises such as comparing likely outcomes of alternative landscape scenarios (Nelson et al. 2009). These kinds of additional benefits and shorter-term products help maintain support and funding for the core, long-term adaptive monitoring framework.

Implementing the framework: the Alberta Biodiversity Monitoring Institute

Our proposed cumulative effects monitoring framework has been developed through evolution of the ABMI (www.abmi.ca/), a regional initiative striving to implement the framework in western Canada. Reliable cumulative effects monitoring is in demand in Alberta (Environment Canada 2011; Johnson et al. 2011), where wilderness values are increasingly juxtaposed with the rapid pace of human-caused environmental change (Timoney and Lee 2001). Alberta has a human population of ~3.7 million (5.8 people/km^2) and one of the biggest economies in Canada, with a rapidly expanding petroleum industry and significant contributions from agriculture, forestry, and tourism (Government of Alberta 2012). Population and economic growth have led to substantial changes in Alberta's landscape over recent decades, and the pace of development is expected to increase, particularly in the oil and gas sector (Schneider and Dyer 2006; Giesy et al. 2010). Major components of Alberta's human footprint include agricultural crops and pastures, forestry cutblocks, roads and other linear features (e.g., pipelines, seismic lines), energy developments (e.g., wellpads, surface mines), and urban and residential areas, several of which often co-occur (ABMI 2012a). While industrial development has been implicated in the decline of some species (e.g., woodland caribou, Sorensen et al. 2008) and ecosystem services (e.g., carbon storage; Rooney et al. 2012), assessment and mitigation of anthropogenic impacts have been hindered by the lack of a regional approach to land-use planning and cumulative effects monitoring (Schneider and Dyer 2006; Boutin et al. 2009; but see Government of Alberta 2008 and Johnson et al. 2011 for emerging regional-scale initiatives).

The ABMI was established to meet a societal desire for independent and transparent monitoring of large-scale responses of biodiversity to Alberta's changing landscapes (Stadt et al. 2006; Boutin et al. 2009). Its core approach centres on regional surveillance of trends in species and land cover through repeated, standardized sampling of a range of taxa at 1656 permanent sites distributed evenly across the province (Table 1; Fig. 3). Sites are situated along a systematic 20 km grid, generating a representative sample of Alberta's biodiversity features that is not tied to stratification schemes subject to change over time (e.g., political units, vegetation communities, disturbance gradients). A series of

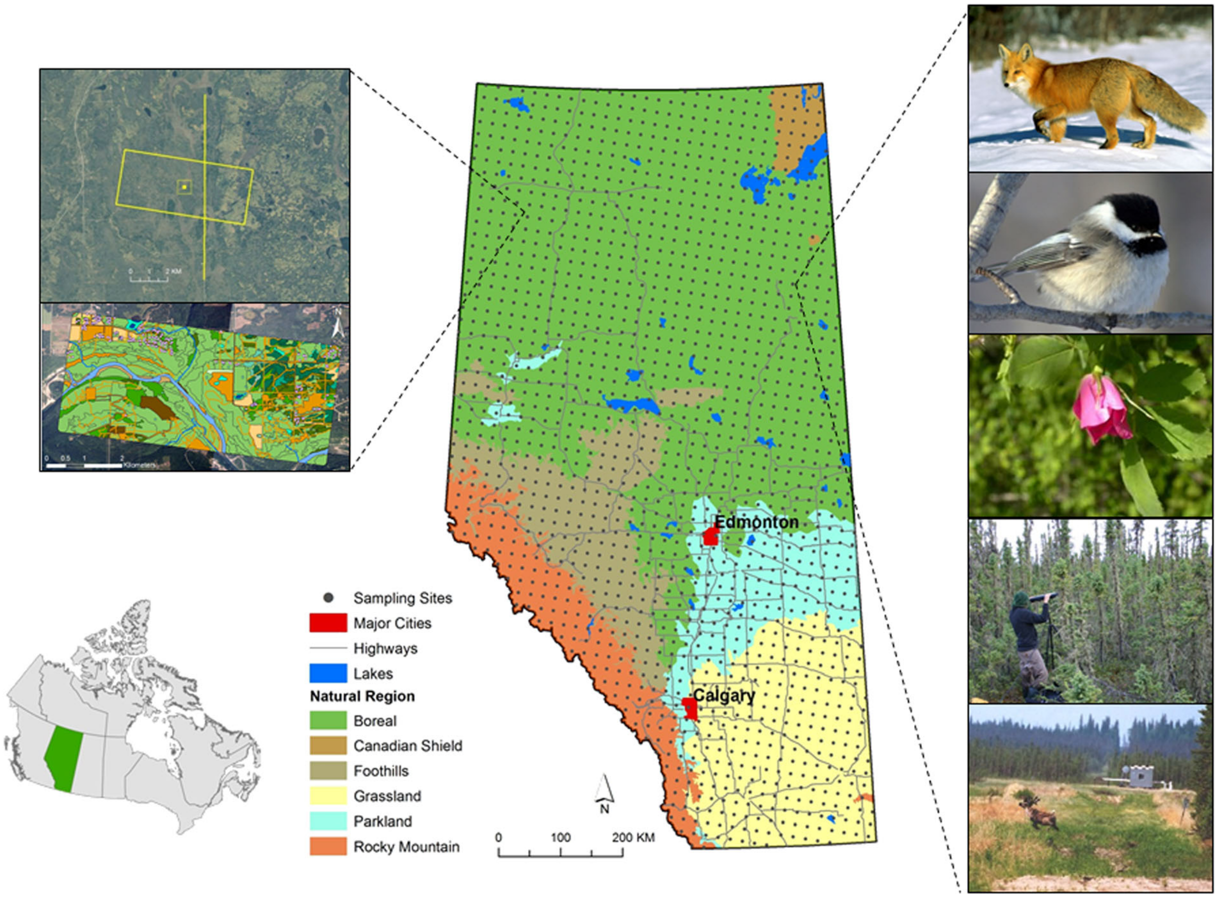

Fig. 3 Systematic grid of sites sampled by the Alberta Biodiversity Monitoring Institute across Alberta, Canada (targeted off-grid sites are not shown). *Photos on right* show examples of taxonomic groups and habitat features sampled at each site; *upper left images* convey different scales of site-level sampling (*yellow lines*; see Table 1 for description of sampling scales) and remote-sensing characterizations of land cover for an example site (i.e., composition and configuration of human footprint and major vegetation types). Image credits: Alberta Biodiversity Monitoring Institute, C. Burton, W. Lynch, C. Kolaczan

field-based sampling protocols (ABMI 2012b) are implemented at each site on a proposed 5-year monitoring cycle, generating a time series for trend analysis (with an estimated 90 % power to detect 3 % annual declines over 20 years in regional prevalence of common species, see Nielsen et al. 2009). Focal taxonomic groups are surveyed at relevant scales (Table 1) and were chosen to cover a range of ecological roles, social values, and potential sensitivities to anthropogenic disturbances (Stadt et al. 2006; Boutin et al. 2009). Species-level monitoring is complemented by monitoring other components of ecosystem structure and function, including site-level measures of habitat complexity and remotely sensed measures of landscape composition (Table 1). A key aspect of the ABMI is characterization of human footprint at site and regional scales through field sampling, remote sensing, and synthesis (and validation) of existing government and industry data sources (ABMI 2012a). Currently, the ABMI surveys more than 2,000 species, 200 habitat elements, and 40 human footprint variables (Table 1).

Trend monitoring in species and land cover across the ABMI's systematic grid is complemented by sampling additional sites targeted to increase coverage of important landscape gradients. These "off-grid" sites are sampled as needed in an adaptive manner reflecting working hypotheses about drivers of biodiversity change, with a goal of improving empirical models describing change. For example, targeted sampling has focused on improving resolution of gradients in human footprint by sampling heavily (locally) disturbed sites within the boreal forest region where the overall (regional) footprint is relatively low, and sampling less disturbed sites within the grassland and parkland regions where overall footprint is high (particularly agricultural footprint).

Using data collected thus far, the ABMI is developing statistical models relating the occurrence (or relative abundance) of individual species to human footprint and other land cover covariates (e.g., Nielsen et al. 2007; ABMI 2012c). These models represent working hypotheses of expected species responses to changing footprint across the provincial landscape, and provide the basis for comparisons with observed species trends (Fig. 2). Observed trends are only preliminary to date, given that the program has still to complete multiple monitoring cycles. The ABMI is thus not yet fully implementing the framework of testing model-based hypotheses with observed changes and learning from deviations (Fig. 2), although an empirically grounded "proof of concept" is being developed for forest songbirds in Alberta's boreal forest region (Huggard et al. in prep.). Technical details of model development and assessment are beyond the scope of this essay, but an example of an interesting preliminary result is that songbirds dependent on spruce budworm (e.g., bay-breasted warbler, Tennessee warbler) appear to be declining much more than predicted based on observed changes in human footprint, more so than other songbirds (Huggard et al. in prep.). Such deviations between observed and predicted trends provide the impetus to refine mechanistic hypotheses, direct complementary research or adapt monitoring (e.g., to incorporate measurements of budworm dynamics in models), and influence management planning.

Summary and future challenges

We have outlined an integrated approach to monitoring and assessing the cumulative effects of anthropogenic activities on biodiversity. This broadly applicable approach resolves the supposed conflict between general surveillance and focused hypothesis testing, and is being implemented in Alberta as part of the ABMI initiative. Its key feature is the explicit coupling of hypothesis testing and trend monitoring across a large spatio-temporal scale and wide breadth of biodiversity and anthropogenic foci. The monitoring framework is guided by a broad conceptual model, underpinned by rigorous empirical science, and motivated to spur complementary research and adaptive land use planning and management at regional scales.

The approach is timely, given anticipated effects of rapid industrial development and the associated need for reliable monitoring in Alberta and across the planet (Butchart et al. 2010; Lindenmayer and Likens 2010). The standardized and transparent framework generates data and models that can be scrutinized by external reviewers, used for complementary purposes, and applied toward regional management targets (such as those being developed as part of Alberta's emerging Land-use Framework; Government of Alberta 2008). This is in sharp contrast to current EIA-related assessment and monitoring processes, which generate data-rich but project-specific reports not easily scaled up for regional assessments and typically providing little ancillary benefit (Duinker and Greig 2006; Johnson 2011). Unlike monitoring restricted to specific management treatments, ABMI's regionally representative sampling design facilitates varied applications and detection of unanticipated future changes (Johnson 2012). At the same time, explicit integration of monitoring with predictive models focused on key anthropogenic drivers (i.e., footprint) guides management when adverse effects are detected (as opposed to unfocused surveillance). The broad-scale systematic design avoids dependency on strata that change with changing policy directives or evolving landscapes, and is grounded in the management-relevant hypothesis that the cumulative effects of human footprint drive biodiversity change. Complementary research will be important for addressing specific uncertainties and causal mechanisms, but will not substitute for broad-scale monitoring given that controlled experiments are not tenable for such large, complex systems.

Despite the promise of more effective cumulative effects assessment, many challenges remain. Successful implementation of this framework requires sustainable funding over the long term, and it is a key challenge to avoid "mission drift" tied to short-term funding opportunities (Lindenmayer and Likens 2010). Nevertheless, cost should not be seen as a reason to dismiss the framework, since cost-effectiveness will improve relative to the large expenditures currently made by governments and industries for smaller scale, uncoordinated monitoring projects (Boutin et al. 2009). Formalizing links between monitoring, research and management will ensure the integrated vision of the framework is realized. Explicit links between monitoring and management are essential for adaptive management (Nichols and Williams 2006; Lyons et al. 2008), but their formation is not trivial when monitoring is designed to be independent from management agencies for purposes of transparency and credibility. Acceptance of program outcomes in the scientific community will depend on continuous testing and improvement of methodologies (both sampling and analytical) to reduce uncertainty while maintaining long-term consistency. Statistical challenges associated with testing cause–effect hypotheses using "unplanned experiments" require particular attention (Smart et al. 2012). Another challenge relates to rare and endangered species, which are of interest to managers and the public, yet for which a systematic multispecies monitoring design needs to be complemented by targeted sampling to increase sample sizes (and thus model reliability; Franklin 2009). Ultimately, rare or intensively managed species may require separately tailored monitoring programs to provide timely information to managers. Effectively linking loosely related environmental monitoring programs may also be an important challenge; for instance, linking the ABMI program to existing air and water quality monitoring efforts, traditional ecological knowledge and citizen science programs, shorter term project-specific assessments, and cross-jurisdictional efforts appropriate for broader biogeographical units. We see such challenges as opportunities for growth of specific programs like the ABMI, and for broader partnerships across multi-scaled research and monitoring networks (Peters et al. 2008). We believe that the core framework presented here represents an important advancement in the scientific monitoring and assessment of the cumulative effects of anthropogenic development on biodiversity.

Acknowledgements We thank D. Stralberg, R. Serrouya, J. Nichols, three anonymous reviewers and members of the Boutin-Bayne laboratory at the University of Alberta for comments on previous drafts of this manuscript.

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