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An analytical framework to assist decision makers in the use of forest ecosystem model predictions

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Abstract

The predictions from most forest ecosystem models originate from deterministic simulations. However, few evaluation exercises for model outputs are performed by either model developers or users. This issue has important consequences for decision makers using these models to develop natural resource management policies, as they cannot evaluate the extent to which predictions stemming from the simulation of alternative management scenarios may result in significant environmental or economic differences. Various numerical methods, such as sensitivity/uncertainty analyses, or bootstrap methods, may be used to evaluate models and the errors associated with their outputs. However, the application of each of these methods carries unique challenges which decision makers do not necessarily understand; guidance is required when interpreting the output generated from each model. This paper proposes a decision flow chart in the form of an analytical framework to help decision makers apply, in an orderly fashion, different steps involved in examining the model outputs. The analytical framework is discussed with regard to the definition of problems and objectives and includes the following topics: model selection, identification of alternatives, modelling tasks and selecting alternatives for developing policy or implementing management scenarios. Its application is illustrated using an on-going exercise in developing silvicultural guidelines for a forest management enterprise in Ontario, Canada.

1. Introduction

The number of forest ecosystem models that deal with environmental issues has increased rapidly over the last several decades. Many of these models were developed by scientists in universities or research institutes as tools to better understand how ecosystems function. Emphasis was placed on theoretical development either by examining and testing different model structures or by undertaking experiments to obtain estimates of basic parameters. Model developers legitimately justified their efforts by arguing that models could help address complex environmental issues, such as particulate pollution, biodiversity loss, or climate change. As these issues often affect the long-term viability of habitats or survival of species, ecosystem models are increasingly viewed as efficient and valuable tools to assist in developing mitigation strategies and policy (McIntosh et al., 2007; Jakeman et al., 2008). However, as is the case with most sophisticated tools, misuse can lead to major risks if the limits of models and modelling exercises are not well recognized (Jakeman et al., 2008). Ultimately, there is a danger that incorrect conclusions may be drawn based on inappropriate or misinterpreted model output.

It is therefore imperative that model developers pay more attention to the use of their products by “model users,” a diverse group that includes stakeholders, environmental managers, decision makers, academics and the general public, who typically rely...
on models to predict the potential outcomes of different management scenarios or to develop resource management policy. Model users have access to a wide variety of models characterized by different theoretical foundations. However, documentation and model capabilities, especially with respect to the type and accuracy of ecosystem characteristics that are simulated, differ considerably. As a consequence, the selection of an appropriate model (or models) can be problematic.

It could be argued that these issues may be dealt with simply by ensuring that the capabilities and limitations of ecosystem models are clearly stated to include sufficient information on model uncertainty for model users. One of the stated purposes of models is to facilitate the transfer of knowledge on complex processes to model users (Brugnach et al., 2008); however, clearly written model documentation is often lacking, or where it does exist, it often overwhelms model users with language more suited to its developers rather than model users. Decision makers may therefore prefer, or be forced, to rely on familiar and relatively simple models for their prediction needs instead of using the most recent version of relatively complex models that would allow them to simulate alternative scenarios (see Landsberg, 2003; Kimmins et al., 2007; Kimmins, 2008). A good example is the use of traditional stand tables or growth curves by forest managers in several North American forest jurisdictions (states or provinces). In many cases, these models, based on stand tables or growth curves, are preferred either because they have a long history of acceptability or reliability or there are administrative barriers to change. It should be remembered that stand tables or growth curves are abstractions of the natural dynamics of a forest stand, and often encompass growth, mortality, and other changes in stand composition and structure. Furthermore, they are not designed to predict the future growth of a forest stand from its current state nor can the underlying equations be directly measured with relevant accuracy from the field. With future environmental conditions changing to an extent that is largely unknown, we cannot rely on past history to serve as a template for the future. Model users, in an attempt to transcend such subjective decision making, must therefore negotiate this maze of model selection and deal appropriately with two types of model output information. First are the model outputs (representing all the inputs and processes captured by the model) and second are the estimates of the uncertainties associated with that output. Ideally, such an approach avoids the dichotomous, simplistic, and ultimately unhelpful thinking identified by Myers et al. (2008). We believe that these observations clearly support the need for the development of protocols to help model users make sound choices.

Uncertainty estimates can take the form of percent errors, standard deviations, confidence intervals, or any other type of error coefficient for each prediction. Using recognized numerical methods, these estimates should contribute to establishing a comfort level with model predictions. For example, if model users knew that the estimated error of a model’s predictions were on average 10% instead of 25%, it would make a big difference in a user’s level of confidence in the model’s predictions. Despite the importance of uncertainty analyses, very few ecosystem models explicitly provide them, particularly the forest ecosystem models on carbon or nutrient cycles (Smith and Heath, 2001; Verbeeck et al., 2006). Bradshaw and Borders (2000) concluded that model developers emphasize uncertainty analysis out of concerns for their “professional credibility,” promoting indecision among decision makers. The counter-argument to this is that uncertainty estimates provide model users with the relevant information allowing them to realize that models consist of imperfect and incomplete representation of reality. Uncertainty analyses may also contribute to identifying knowledge gaps, obviously important to the processes of scientific and policy advancement.

Dealing with all these issues may appear cumbersome for non-modellers or model users, particularly if they do not have much knowledge on topics related to model development, evaluation or selection. For this reason, several analytical frameworks have been developed to provide guidance on model evaluation or selection for appropriate use in decision making for policy development. Recent examples can be found in Watson and Rahman (2004), Refsgaard et al. (2007), Xu et al. (2007), Maier et al. (2008) or Rizzoli et al. (2008). However, examination of the decision flow charts outlined by these frameworks have allowed us to identify new components that should be included or existing components that should be better described. For instance, Refsgaard et al. (2007) outlined the procedures involved in the development of a specific model, but only briefly described the interactions with model users. Some other frameworks focused on determining appropriate models for decision making, but without much emphasis on model development and user input (e.g., Watson and Rahman, 2004; Xu et al., 2007; Maier et al., 2008; Rizzoli et al., 2008), or emphasized user input without describing the modelling process or including uncertainty analysis (e.g., Giupponi, 2007). Thus, in order to provide better guidance to model users, there is a need for analytical frameworks that can illustrate concisely the linkages between the comparison, selection or simultaneous use of several models, uncertainty issues, decision making, and management actions.

In this paper, we discuss the importance of developing relevant and appropriate decision making process flow charts and software for facilitating the concurrent use of a wide variety of models by non-modellers. We believe these are helpful towards increasing the visibility and acceptance of various types of models, which would ultimately contribute to improving the confidence levels of model users. In this way, model selection would be geared to the particular problem and the quality of forest management would likely improve. In order to achieve this goal, we briefly review different model evaluation methods and discuss the importance and application of uncertainty estimates. We then present a decision flow chart for use by the modelling community in the form of an analytical framework that has the desirable features suggested above and apply it to an on-going exercise in developing silvicultural guidelines for a forest management enterprise in Ontario, Canada.

2. Methods for model evaluation

The transfer of knowledge from scientists to decision makers and other model users is still a difficult process, enough so that Beven (2006) wondered whether the results of hydrologic uncertainty analyses would undermine the confidence of stakeholders in the science being performed. Montanari (2007) attempted to address the concerns of Beven (2006) by communicating different types of model evaluation methods that may be appropriate under various situations, including approximate analytical methods (e.g., first-order variance and point estimation approaches), statistical analysis of model errors, sensitivity analysis, and non-probabilistic methods (e.g., fuzzy set theory and possibility theory). Matott et al. (2009) identified seven categories of methods for quantitative model evaluation:

1. data analysis, 2. identifiability analysis, 3. parameter estimation, 4. uncertainty analysis, 5. sensitivity analysis, 6. multimodel analysis, and 7. Bayesian inference. Data analysis refers to analytical, statistical and graphical procedures for evaluating and summarizing input, response, or model output data (Matott et al., 2009). Simple statistical (regression) models have proven to be useful tools for description of relationships and for prediction. A common reason for preferring regression models over dynamic models is that they include an estimate of the confidence limits for prediction (van Tongeren, 1995). Data analysis capabilities typically include data screening and parameterization of distributions for input and response data (Matott et al., 2009). The purpose of identifiability analysis in ecological modelling is the identification of the model structure and a corresponding parameter set that are most representative of the area under investigation, while considering aspects such as modelling objectives and available data (Wagener et al., 2003). Thus, identifiability analysis can be split into two stages: a model structure selection stage and a parameter estimation stage which do not have to be treated as completely separate (Sorooshian and Gupta, 1985). In many cases, identifiability analysis utilizes sequential parameter estimation or performance-based sensitivity analysis to
identify divergence of the model from expected behavior (Wagener et al., 2003; Matott et al., 2009). Uncertainty analysis strategies, including approximation and sampling methods, promulgate sources of uncertainty through the model to generate statistical moments or probability distributions for model output responses (Matott et al., 2009). Approximation methods characterize model output uncertainty by propa-
gating one or more moments (e.g., mean, variance, or skewness) of the various input data distributions through the modelling system. Useful approximation techniques for uncertainty analysis include derived distribution techniques, integral transformation techniques, first-order variance estimation methods (Melching et al., 1992), probabilistic point estimation methods (Harr, 1989), and resampling techniques such as the jack knife and bootstrap methods (Efron, 1979; Efron and Tibshirani, 1993). Simplicitic approximation techniques are rather restrictive in practical applications since most of the models or design procedures used for ecological research are nonlinear and highly complex. As a practical alter-
native, researchers frequently use sampling methods which characterize model output distributions by propagating an intensive random sampling of each input distribution. Common sampling methods for uncertainty analysis include Monte Carlo (random) sampling (MCS), stratified sampling, importance sampling, or a combination (Helson et al., 2006; Matott et al., 2009). Traditional MCS involves uniform random sampling of parameters and subsequently the determination of model output uncertainty (Beven and Binley, 1992). MCS generates a large number of simulations in order to make a probability distribution and typically requires a large number of model runs as the statistical validity of the results increases with the sampling intensity (Smith and Heath, 2001). Stratified sampling methods such as the Latin Hypercube Sampling approach esti-
mate the output of a system by dividing the range of each input variable or parameter into N ranges with an equal probability (1/N) of occurrence (Helson and Davis, 2003). The order of ranges is randomized and the model is executed N times with the random combination of each basic variable or parameter values from each range. According to Smith and Heath (2001), this approach more efficiently estimates the statistical output of an than MCS and also reduces the computation time required. Importance sampling is another variance-reducing modification to the Monte Carlo method (Helton et al., 2006). In this method, the samples are concentrated in the region of interest and weighted in such a way as to make the total number of samples from a given distribution, a new sampling design is designed to take random from a given distribution, a new sampling design is designed to take additional (and biased) samples from a region of importance. In order to unbiased the results (i.e., counteract the bias introduced by using the sampling distribution in place of the true distribution), a weighting function is applied to each observation. Importance sampling is particularly valuable because the largest gains are possible in some of the most difficult simulation applications, e.g., those involving the simula-
tion of rare events which may be extremely important in ecological risk analysis.

Sensitivity analysis (SA) can be used as an aid in identifying important uncer-
tainties for the purpose of prioritizing additional data collection or research (Frey and Patil, 2002). In addition, SA can play an important role in model verification and validation throughout the course of model development and refinement (Campolongo et al., 2007). SA techniques are typically grouped into screening, local, and global approaches (Frey and Patil, 2002). Screening methods such as the Morris screening approach (Morris, 2006) are typically used to make a preliminary identi-
fication of the most sensitive model inputs. However, such methods are often relatively simple and may not be robust to key model characteristics such as nonlinearity, thresholds, and interactions. Local (i.e., differential) SA focuses on relatively small perturbations near a fixed point in the model domain. For small perturbations in the inputs, a linear approximation may be reasonable even if the model response over a larger variation of the inputs appears to be nonlinear. Global perturbations in the inputs, a linear approximation may be reasonable even if the model response over a larger variation of the inputs appears to be nonlinear. Global SA methods such as the Fourier Amplitude Sensitivity Test (FAST, Saltelli et al., 2004) and Sobol (Sobol, 2001) approaches typically have the following properties: (a) the sensitivity estimates of individual inputs take into account the effect of the range and the shape of the probability distribution for each parameter, and (b) the sensitivity estimates of individual parameters are obtained while all parameters vary simultaneously and parameter interactions are implicitly accounted for (Saltelli et al., 2004; Muleta and Nicklow, 2005). Few studies explicitly discuss the effect of parameter interactions on parameter identifiability, and Bastidas et al. (1995) point out that such interactions may be weak in dealing with the issue of parameter over-
dependency. Thus, the focus of many ecosystem model sensitivity analyses partly reflects the fact that model input data and parameter uncertainty are usually considered the most important sources of uncertainty in the ecosystem models. More advanced numerical simulation approaches such as Bayesian methods have been introduced to overcome some of the limitations attributed to MCS. These methods commonly apply random sampling procedures to explore the feasible parameter space in search of acceptable parameter sets (Gupta et al., 2006). The techniques are based on the theory of statistical inference; when enough data are available, allowing for multiple acceptable models or parameter sets based on some likelihood measure, and is the basis for the well-known Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven and Binley, 1992). Bayesian probability can also provide clear statements about the plausibility of alternative ecological hypotheses for processes that may be structuring ecological communities, such as the responses of populations to exploitation (McAllister and Kirchner, 2002).

Applications of Bayesian statistical methods (e.g., hierarchical modelling, decision trees, influence diagrams, and belief networks) have rapidly expanded in the environmental management and ecological management arena (Yaris and Kuikka, 1999; Wade, 2000) including forestry and forest ecology (Crome et al., 1996; MacFarlane et al., 2000). In particular, Bayesian data analysis permits the relative credibility of each alternative model to be evaluated against the data, taking into account uncertainty over the range of values for the parameters in each model. However, Bayesian inference has been criticized for its subjectivity and apparent lack of explanatory power (Dennis, 1996), and in some cases it may indeed be difficult to use true Bayesian methodologies.

Model analysis (or inference) has been suggested as a robust method that circumvents the problem of overly optimistic predictive or inferential uncertainty through improved representation of model structure uncertainty (Link and Barker, 2006; Valle et al., 2009). Multimodel analysis can be an important component of model evaluation (Burnham and Anderson, 2002), and has been proven useful when multiple credible models can be developed by using alternative modelling processes and codes, or by defining alternative boundary conditions (Valle et al., 2009). Quantitative multimodel analysis methods assign performance scores to each candidate model (e.g., Kleijnen and Sargent, 2000; Burnham and Anderson, 2002; Ye et al., 2008; Valle et al., 2009) in order to rank the “best” models or assign impor-
tance weights (e.g., for use in an ensemble forecasting). The weighting of individual models (according to their past performance) has been shown to result in a higher predictive ability than individual models and simple multimodel averages (Kleijnen and Sargent, 2000). Multimodel inference provides a framework for the purpose of extrapolation (e.g., to predict the future) and, assuming there is a set of plausible models that have similar fits to the data, multimodel projections are useful to avoid underestimating the uncertainty on model predictions.

All of these practical methods for model evaluation are directly or indirectly linked to uncertainty. Thus, sources of uncertainty need to be properly quantified so that efforts are directed at reducing those sources that have the greatest impact on output uncertainty. Furthermore, efforts should be directed at those sources where there is a reasonable expectation of reducing the uncertainty in such a way as to ensure decision makers are placed in comprehensive and defendable forestry decision making situations. Failure to do so invites potential unreliability of the results with subsequent loss of public trust and confidence. Implicit in the above statement is a need to consider environmental, social, and economic systems in an integrated fashion, particularly for dealing with community- or regional-based forestry prob-
lems or issues addressing forest ecosystem variability.

3. The importance of addressing uncertainty in forest ecosystem models: some case studies

As previously mentioned, there are limited cases where it can be demonstrated that forest ecosystem models have explicitly addressed the issue of uncertainty during the model development phase. We believe that the examination of uncertainty is essential not only during model formulation and model development, but also during the implementa-
tion phase of the predictions by model users who develop poli-
cies. To illustrate this, we present the following case studies. Covington (1981) developed a model to describe the change in the forest floor organic matter content in the years following secondary succession and, subsequently, Yanai et al. (2003) repor-
ted that this model was widely utilized to predict the effects of clearcutting on soil carbon change in several forest ecosystems following harvesting and to make assumptions on the effects of forest disturbance on large scale global carbon change trends. However, Yanai et al. (2003) also pointed out several studies that contradicted the pattern described by the Covington model. A previous review by Johnson (1992) concluded that the assumption that forest disturbance leads to decreases in soil C was not sup-
ported by the literature. He determined that fire effects on soil C were dependent on fire severity and intensity, while C losses were negligible with harvesting and reforestation. In an additional review of literature reporting on various forest ecosystems and a meta-analysis, Johnson and Curtis (2001) reinforced their original conclusions in support of Covington’s theory, i.e. that forest disturbance does not alter soil C content permanently. While forest soil C content normally decreases after fire or harvest disturbance, their results further confirmed that, with time, forest soil C content

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will ultimately return to pre-disturbance levels. In contrast to the conclusions of Johnson and Curtis (2001), previous studies that quantified the temporal response of total soil C to either fire or harvest disturbance in pine ecosystems failed to present a uniform story. Norris et al. (2009) suggested that in jack pine (Pinus banksiana Lamb.) ecosystems, for example, soil C levels returned to pre-disturbance levels after about 30 years. As suggested by Yanai et al. (2003), the small number of samples in terms of forest type representation and variation in site conditions was not sufficient to support the wide application of the Covington model. Independent of sampling problems, it is likely that the availability of uncertainty estimates would have been useful for anyone who used the Covington model to better interpret the relevancy of its application for the specific conditions studied.

When models are used to simulate carbon dynamics over large forest and agricultural regions, the uncertainty associated with the spatial variability can be extremely high. The USGS Carbon Trend project was proposed to provide more accurate carbon estimation for the contiguous United States by using the General Ensemble Biogeochemical Modelling System (GEMS) (Reiners et al., 2002; Liu et al., 2004). GEMS was designed to assimilate dynamic land use and land cover change (LUCC) data and perform ensemble simulations to incorporate uncertainties of input data. For forest systems, the model can generate initial forest age and biomass and schedule a forest cutting event based on inventory data and LUCC maps. For agricultural systems, GEMS can generate crop compositions and crop rotations based on census data and prepare various soil input data for biogeochemical simulations. The Monte Carlo method was used to: (a) select a random value between 0 and 1 linked with the cumulative probability of age class distribution in the forest inventory data, (b) determine crop composition, based on state-level averages of agricultural census data, and (c) assign each simulation unit a set of specific soil property values, such as soil type and drainage class based on area weights of different soil types. Each single simulation of an individual unit was partly determined by its random forest age, crop species, and soil properties downscaled from regional-level data. Therefore, a single simulation for an individual unit might produce highly biased output. Under this situation, a decision maker will naturally think that ‘every simulation unit is highly uncertain’ even though individual errors may cancel each other out over a large region. It was necessary to do ensemble simulations of each unit to incorporate the variability of input data and to average the outputs with associated variation. Averages of the ensemble simulations became more stable as the number of repeat runs increased. For example, when the ensemble simulation number reached 20, the error in net primary productivity output due to soil, forest age, or crop composition data was reduced to 2%. This reduced uncertainty range of an individual simulation might convince a decision maker that issues of input data uncertainty are well resolved (at the simulation unit level). The GEMS model application on a regional scale still gives large variations due to the sampling block approach. However, the variation among the 10 x 10 km sample blocks is an artifact of the spatial variability of the landscape, not the simulation uncertainty of individual units within any of the sample blocks. Decision makers may therefore understand the higher model accuracy at the local scale due to Monte Carlo ensemble simulation and the high spatial variability at the regional level. If decision makers want to further reduce risk in decision making, they have an indication of the degree of magnitude with which to expand the number of sample blocks. Zhang et al. (2008) compared five carbon (C) and nitrogen (N) cycling models (FLDM, CENTURY, SOMM, DOCMOD, CANDY) for their ability to quantify C dynamics across a wide range of litter types and climates. These models differed in their structure and assumptions, litter and litter component representations, and assumptions and formulations about litter decomposition and N mineralization, predictor variables and parameters. Fig. 1 illustrates the black spruce litter total mass remaining and N concentrations from 1992 to 2042 predicted by each model. Analysis established that all five models generated fairly similar trends for remaining mass, while predicting different N concentrations for the decayed black spruce litter at the end of the simulation period. SOMM predicted N concentrations above 3%, while FLDM and CANDY predicted N concentrations at about 1.5%, and DOCMOD predicted N concentrations at about 3% (Fig. 1). With CENTURY, N concentrations built up quickly and then remained constant. These differences in simulated N concentration were in part due to the different model requirements for fixed (CENTURY, DOCMOD, CANDY, SOMM) or flexible (FLDM) C/N ratios within the humified litter pools, and also in part to the rather slow estimates for the decay of some of the non-humified litter pools (e.g. lignocellulose) that are ‘over-parameterized.’ This tends to occur when pools, processes and parameters are: too closely linked or complementary to one another (either directly or indirectly through feedback loops), or when the available data do not represent the ranges and scales of the particular pools and

Fig. 1. Fifty-year projections obtained from the models FLDM, CENTURY, SOMM, DOCMOD, CANDY for organic matter and N concentrations remaining in black spruce (Picea mariana [Mill.] B.S.P.) CIDET litter bags (10 g) at the Morgan Arboretum in Quebec. (Data were obtained from Zhang et al. (2008).)
processes targeted by the model. These results clearly show that models with many pools and processes (i.e., CENTURY, DOCMOD, SOMM) are not necessarily better than models with few pools and processes (i.e., FLDM, CANDY) when it comes to predicting long-term C and N dynamics. In general, more complex models require greater model formulation, initialization and parameter estimation efforts and may create greater uncertainty associated with model structure. In particular, satisfactory convergence towards precise and unambiguous parameter values cannot be achieved when the models are ‘over-parameterized.’

It is likely that the application of model evaluation approaches described in the previous section would have been useful in the case studies reviewed. For instance, sensitivity or identifiability analysis or Bayesian inference could have contributed to detecting over-parameterization problems or providing guidance to simplify the representation of some processes. Uncertainty analysis, such as Monte Carlo, would have been useful to evaluate if the predictions of different models were significantly different, which would have had an implication on the interpretation of the comparisons. There are examples in the ecosystem modelling literature that examined and compared the outputs of various models relatively similar in concept. For example, Ryan et al. (1996a,b) compared seven models of ecosystem element cycling. Following a description of the basic features of each model, they compared model predictions against field data from two experimental sites for different climate change scenarios. Dealing with so many different predictions was a challenging task and the authors insisted on the necessity to improve comparison methods. The importance of uncertainty estimates was not mentioned, but it is likely that computing uncertainty would have had an influence on the conclusions drawn by the authors. For instance, if large overlaps had been obtained between the errors or confidence limits among the predictions of some models, it is possible that Ryan et al. (1996a,b) would have lessened the importance of the differences among the models and focused more on explaining why some models had predictions differing considerably from others. This could allow them to better highlight differences in model specific structures and better focus on the identification of research needs. The same observation can be made for the comparison exercises conducted by Smith et al. (1997), Price et al. (1999) and Luckai and Larocque (2002).

4. Analytical support framework to address user needs

The analytical support framework reported here consists of five main components: 1) defining the boundaries of the problems addressed, 2) identifying models and possible alternatives, 3) dealing with data quality, 4) organizing the analysis of the outputs of several models and 5) interpreting the uncertainty associated with different model outputs. The fact that models consist of imperfect representations of reality is well recognized in the modelling community. Insufficient or incomplete data associated with several processes for the majority of forest ecosystems may partially explain this situation. More importantly, model development is still limited by the lack of understanding of several factors that affect the processes within forest ecosystems. For reasons that may be related to cultural or professional background, it is not necessarily easy for model users to fully understand the scope of model limitations or conceptualize knowledge gaps (see Parker et al., 2002; Argent, 2004; McIntosh et al., 2007). Therefore, there is a danger that model users will lose confidence in models if their limitations are not well explained. Good communication and knowledge transfer practices usually help resolve this issue (see Argent, 2004; McIntosh et al., 2007).

We propose an analytical framework that highlights processes to deal with the output originating from several models that are similar in concept, each one having uncertainty associated with their predictions. In real-world situations, the level of complexity and difficulty of problems being addressed has continually increased over time. As a result, there has been a corresponding increase in the level of model complexity (Maier et al., 2008). Independently of the computation of uncertainty estimates, the comparison of the performance of different models is not an easy task. Mentioning that it would be far more difficult for model users without formal training in modelling is also not an overstatement. However, the task of model users may become less cumbersome by using an appropriate decision flow chart as a guide during the decision-making process (Fig. 2). An orderly application is important to ensure that model users do not get lost in the process or focus on less important details. Step 1 consists in identifying the problems or questions and defining the objectives. This is often the most difficult step because it requires a clear understanding of the problems or the issues involved. If the problem identification exercise is undertaken by a group of people, this step may even become more difficult, particularly if the group is interdisciplinary. The term “group” in this case means experts or non-experts with different organizational affiliations, disciplinary backgrounds, or cultural preferences who form a group to develop policies. It may also refer to a team involved in the decision-making process on specific issues related to the management of natural resources. The next step involves identifying possible models (Step 2). The group may consult experts, conduct a literature search or browse the Internet. Once potentially useful models are identified, requirements pertaining to the data required (quality and availability), the
temporal and spatial scales, the user interfaces and the program-
ning language need to be evaluated (Step 3) because these factors have a direct impact on the efficiency of the process. Even though computing power constantly increases, there will always be a computational capacity limit since support tools become more complex as the number of numerical methods used increases (Maier et al., 2008). Thus, it is also important to have professional programmers who can understand the most recent developments on algorithmic methods that improve computational efficiency. Maier et al. (2008) identified three specific areas that need improvements: algorithms for Monte Carlo methods, development of innovative sensitivity analysis methods and use of metamodels. Regarding applicability by non-modellers, it is essential to develop consistent user-friendly graphic interfaces to facilitate the efficient use of models. This is particularly important for the examination of model outputs. When predictions are made for long periods, model developers and users prefer to use graphics to observe the long-term patterns of change over time in the variables of interest instead of columns of numbers. Also, graphical user interfaces must be carefully designed. Even though they may increase the accessibility of decision support tools to many users, they may also induce incorrect application or fail to communicate the appropriate information to users (Mcintosh et al., 2008).

For models requiring considerable data input to initialize the state variables and provide basic parameter values, model users should be able to process data input easily. Thus, it is essential to pay attention to the amount and details of data required and develop sub-programs that verify potential errors, problems or inconsistencies in the data. Dealing with data quality (i.e., the capability of data to be used effectively, economically and rapidly to inform and evaluate decisions (Karr et al., 2006)) is a sub-step that must not be underestimated in environmental and ecological decision making. The problem of data quality can be approached from two angles. The first is to improve the data using specific data processing techniques (e.g. various data mining methods); the second is to evaluate the uncertainty of the data and use error propagation equations (IPCC, 2006) to estimate the impacts of data quality on model outputs. Decision support tools capable of performing data and model uncertainty analyses are more robust for decision making.

While valuable methods and techniques exist for assessing the quality of data in hand, it is also important to consider the strategy of acquiring new data, if necessary. When dealing with data uncertainty, managers must indeed ask themselves questions such as those posed by Karr et al. (2006): What costs are needed to achieve a specified level of data quality? What are the financial benefits of improved data quality and what are the costs of poor data quality? A balance must thus be obtained between the cost of obtaining more precise information, if possible, with the cost of making a poor decision. To accomplish this task, Reed and Jones (2003) argue that decision makers must function as risk managers, not just risk avoiders. With sampling decisions, the cost-plus-loss method (Cochran, 1977) may help the decision maker balance the cost of installing n samples with the expected loss due to the uncertainty associated with a sample size of n (Reed and Jones, 2003). The method allows the user to take into account not only the costs of implementing a particular option, but also the fact that there are risks of poor performance associated with an option and the fact that there are often opportunity costs associated with foregoing the same option. It is important to keep in mind that technological advances may have created a false sense of security (Karr et al., 2006). As a consequence, it is imperative that decisions based on forest ecosystem model predictions be made using the best overall tools available for extracting knowledge and for assisting in the quantification of data uncertainties. Also, because decisions are of two kinds, i.e., those based on the data and those about the data, managers should also take into account the context in which information will be used to support decision making (Reed and Jones, 2003). This is a necessary step to ensure that the information available at hand is adequate and relevant.

The identification of alternatives includes several tasks (Step 4). For the selection of assessment criteria, the group must define common ground that will be used to evaluate the models. This could be how closely the models simulate the dynamics of known ecosystem dynamics using historical datasets. Are the predictions realistic, precise, or both? Comparing the performance of the models by analyzing their predictions under hypothetical scenarios could be another criterion. In this step, the acceptable error level for the comparison of the models can also be decided. Sensitivity analysis can also be undertaken to identify the parameters that have a strong influence on the performance of the models. This step may lead to the identification of constraints that are specific to each model. The modellers’ task (Step 4.3) includes the duties normally associated with the usual model development process. Once they are well calibrated, the models are executed, and preferably, the output will include uncertainty estimates.

Uncertainty estimates can be in the form of estimated percent errors, standard deviations, confidence belts, or any other relevant coefficient. Two options are possible for the computation of these estimates. The first one consists in developing and integrating the appropriate code directly into the model. In order to facilitate the uncertainty analysis, the algorithms should aim at automating the numerical analysis procedures by developing applications based on the integration of mathematical rules and sets of logical inferences (Larocque et al., 2008). The second option is to use applications that were designed to simplify uncertainty analysis. For instance, GEM-SA was developed for this purpose (Kennedy et al., 2006). An example of application for a forest carbon accounting model may be found in White et al. (2008). Both options have advantages and disadvantages. The first option requires considerable programming time to develop and debug the code. If methods such as Monte Carlo analysis are used, execution time can be considerable. Even though alternative methods, such as Bayesian statistical methods, may improve computational efficiency, the execution time may appear too long if time constraints are important. On the other hand, if well developed, it is possible to let the models run without user intervention, which may reduce the possibility of human error. For the second option, there is no programming required and considerable time can be saved in the execution. However, user intervention is much more frequent, which may result in increasing human errors, and the application of the types of uncertainty analytical methods is limited to those included with the application selected. In summary, it is up to the group to consider the different options and select what they consider the most appropriate method. Ideally, this decision should be made in Step 3.

The review and selection of relevant output consists in identi-
yzing the results that are intimately linked to the questions or objectives that were defined. For the majority of ecosystem models, the output can be quite considerable. Thus, not all the variables may be needed to meet the objectives. Sensitivity analysis can help to identify the most relevant factors. The output assessment step is where model outputs and their uncertainty are analyzed on the basis of the criteria that were defined in Step 4.1 (Fig. 2). For instance, the group evaluates the extent to which the errors from the models are sufficiently high or not as to limit model usefulness. Indices such as
mean average differences or distance coefficients may be derived. If it is concluded that the differences among the model outputs are not pronounced, the group may decide that the modelling exercise meets the expectations originally defined. If differences are significant, the group may decide to perform a systematic examination of the extent of the variation in model structures. The examination of variation consists in comparing model properties that may explain the causes of variability. For instance, can differences be explained by heterogeneity or linkages among model components (Brugnach et al., 2008)? If differences in model structures that cause differences in the predictions cannot be associated with a lack of biological consistency in the representation of processes, it is appropriate to consider different interpretations of the predictions in the development of the decision-making process. If there are irreconcilable biological inconsistencies, major ambiguities or severe knowledge conflicts, the group may decide to remove one or more models because they realize that the representation of some processes is inadequate for the conditions that were simulated. At this point, it is preferable to repeat the processes in Step 4. Once there is a consensus on the results of the model evaluation process, the group may move to the selection of plausible alternatives by reviewing and confirming the decision criteria, employing adaptive management approaches, or conducting a risk assessment on the basis of the model results and uncertainties (Step 5, Fig. 2). The outcomes of both methods are intimately linked to the existence of uncertainty. For instance, adaptive management usually includes an iterative process based on uncertainty and analysis of consequences that is flexible enough to modify management alternatives over time (Failing et al., 2004; Gregory et al., 2006).

5. A case study to illustrate a decision making application

An on-going exercise that aims to develop silvicultural guidelines for forest operations in Ontario², Canada, can be used to illustrate the analytical framework shown in Fig. 2. The goal is to link the results of modelling with the development and modification of forest management planning and policy. In this case, project participants wished to determine the effects of constraining the type of vegetation management treatment to a future forest condition. Specifically, what happens to the presence and growth of crop trees (often conifers such as jack pine and black spruce) when herbicides and/or mechanical cleaning are either removed from the forest manager’s toolkit or reduced due to cost or public pressure. As shown in Fig. 2, the exercise consists of the following steps:

• Step 1: At the outset, the initial research committee identified potential problems associated with the withdrawal of certain silvicultural techniques, but the specific objectives were not fully defined until a broader working group, including the specialists responsible for forest management and modelling within the partner companies, was convened.

• Step 2: A workshop was held to identify the suitability and availability of models for addressing the project objectives.

• Step 3: The task of selecting the actual models for use was simplified because the provincial government recommends only one (aspatial) management planning model while cost and complexity of available spatial models usually restricts companies to one option. The spatial model, Patchworks³, is a multiple objective optimization model while the aspatial model Sustainable Forest Management Model (SFMM)⁴ is based on linear programming. Because our private sector partners were very familiar with the models chosen, the acquisition of information for model calibration and parameterization was relatively straightforward. Exceptions to this included succession rules (i.e., how a forest moves from one serial state to another), growth curves reflecting the impact of various silvicultural treatments and the incorporation of output from the aspatial model to the spatial one.

• Step 4.1: In this example, the selection of assessment criteria was done by the research committee, which included representatives of both private sector partners.

• Step 4.2: Constraints on the models included costs, cost of individual treatments, response of species to treatment, planning targets including area/volume of mature forest (by species) and wildlife habitat. For the aspatial model, constraints can be identified as either binding or non-binding. In the case of the latter, the model can return an “infeasible” solution but a feasibility analysis option can assist users in identifying conflicting, impractical or improbable inputs. The spatial model attempts to achieve target values (as specified by the modellers and/or the aspatial model). However, if the solution is not straightforward, the modeller must choose to conclude the scenario.

• Step 4.3a: At this point, the task of obtaining output was taken up by the modelling specialists who were situated in three different organizations. Close coordination and cooperation were therefore critical. As noted previously, important calibration data was either already available or designed (e.g., succession rules, growth curves).

• Step 4.3b: Neither model includes uncertainty analyses so an independent approach (such as GEM-SA) must be applied. Given that both models can easily run for several hours before a solution is achieved, this additional investment of time must be justified especially if the uncertainty analysis requires many runs of the model.

• Step 4.3c: Depending upon whether objectives have been reached (i.e., the solution is feasible), the research committee will select from over 200 outputs for assessment purposes. Even if a solution is achieved, a range of output variables will be considered in order to ensure consistency in the results.

• Step 4.3d: For this exercise, the project participants wish to determine whether or not conifer stand types can be maintained on the boreal landscape and at what cost. Final assessment of the output requires not only the values generated by the models but also their interpretation within policy and economic contexts by the research committee. For example, if volumes are achieved but critical wildlife habitat is lost, managers may choose another course of action.

• Step 4.3e: Upon completion of all scenarios, the research committee will use the output to address concerns over the withdrawal of silvicultural tools such as herbicide spraying, cleaning using brushsaws and/or planting.

• Step 5: Ideally, a matrix of options, based on efficacy and cost, will be available to assist forest managers to achieve stocking and stand type objectives that fulfill economic, ecological and social concerns. However, should this matrix not exist, adjustments to policy, societal expectations, regeneration and tending strategies will have to be made.

6. Conclusions

The role of both decision makers and ecosystem modellers is critical in the process of making flexible, low risk, near optimal decisions. It is, therefore, essential that they have the opportunity

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² See www.forestresearch.ca for more details.
³ See www.spatial.ca/products for more information.
⁴ See www.sfmmstuff.com for more information.
to use standard procedures that can help them organize, verify and adjust the model evaluation process. The key concept of introducing model uncertainty to decision makers is that deterministic model predictions are usually incomplete and non-flexible. Future model predictions have to provide measures of errors, risks, or extreme scenarios. The analytical methods of deriving model uncertainty can help identify the source and magnitude of uncertainties so that efforts are directed at reducing those sources that have the greatest impact on output uncertainty. At least, awareness of the major uncertainty source and magnitudes will be a factor in a decision maker’s evaluation equation.

Support tools are needed to facilitate model uncertainty evaluations and model comparisons. The analytical framework we have discussed provides an outline that requires the interaction of decision makers and modellers. Modellers will need to build, in addition to the development of background ecosystem models, the interface that will effectively link or communicate with the decision makers.

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