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What has been accomplished twenty years after the Oreskes et al. (1994) critique? Current state and future perspectives of environmental modeling in the Great Lakes

"*…Complete [model] confirmation is logically precluded by the fallacy of affirming the consequent and by incomplete access to natural phenomena. Models can only be evaluated in relative terms, and their predictive value is always open to question. The primary value of models is heuristic…*"

[Oreskes et al. (1994)]

With well over 1000 citations, the Oreskes et al. (1994) paper stands out as one of the classical critiques of the veracity of the scientific methodology of models in earth sciences, arguing that the validation of models that deal with natural systems is inherently impossible. Going beyond the controversy of the "technical versus philosophical" meaning of validation, this viewpoint reflects the important notion that model outputs should be viewed through the prism of the underlying assumptions and that good model performance in one or more settings is not evidence for general applicability, but rather the start of a perpetual race for predictive confirmation. While the Oreskes et al.'s (1994) critique has been a defining moment of the broader appreciation of the challenges surrounding a model validation exercise the documented inadequacy of many models to address important societal issues reflects the fact that the field has advanced without the healthy dose of introspection required to obtain good science. An evidence of the latter assertion is the inconsistency that still characterizes the environmental modeling practice with respect to the methodological steps typically followed (Arhonditsis and Brett, 2004; Arhonditsis et al., 2006; Stow et al., 2009; Robson, 2014; Wellen et al., submitted for publication). After more than four decades of active modeling in the context of environmental management and policy analysis, many of the published aquatic ecosystem and watershed modeling studies still fail to report the results of predictive confirmation, goodness of fit statistics, and uncertainty analysis in the broader sense (Fig. 1a).

Indicative of the lack of rigor characterizing the field, with respect to model confirmation, is also the fact that the methodological consistency does not seem to be playing any role in regard to the impact (as expressed by their citation frequency) of the published modeling papers (Figs. 1b–g). Although watershed studies that follow more closely the typical methodological protocol during the model development tend to receive higher citations, the general appreciation is that the recognition of a modeling paper is predominantly determined by the questions being asked or the popularity of the topics addressed (Arhonditsis et al., 2006). On a positive note though, there are several excellent examples of highly cited modeling studies that offered novel insights into the ecosystem functioning or introduced technical advancements, and thus produced knowledge that has profound influence to other cognitive disciplines. Two characteristic examples are the seminal plankton food web model by Fasham et al. (1990) and the landmark study by Beven and Binley (1992), that first presented the Generalized Likelihood Uncertainty Estimation methodology (Figs. 2a,c). The articles citing these two papers were classified in more than 30–35 different disciplines. Several of these disciplines (e.g., astronomy, computer science, software engineering, plant sciences, life sciences and biomedicine) had no apparent association with process-based environmental modeling, which is probably another indication that this field produces scientific knowledge (e.g., methodological advancements for system analysis, ecological questions addressed) that can have broader application and assist quite different subject areas. Classified in more than 100 scientific disciplines, the breakdown of the second-generation of citations paints an even more favorable picture about the potential influence of modeling as a scientific enterprise (Figs. 2b,d).

In the Great Lakes area, the growing appreciation of the complex policy decisions required to restore and maintain the ecosystem integrity along with the need to address the cumulative effects of numerous tightly intertwined stressors has triggered a shift from the historical water quality/fisheries exploitation paradigms to the ecosystem management paradigm (Minns and Kelso, 2000). Rather than narrowly focusing on the loss of beneficial uses stemming from water quality problems, the ecosystem approach aims to integrate across a wide range of issues associated with fisheries management, sustainable economic development, habitat conservation and restoration, exotic species introductions, land-use planning, biodiversity, human behavior and education. However, while the concept of a holistic ecosystem management makes sense as a pragmatic means to address the multifaceted environmental problems, skeptical viewpoints caution that this approach entails an accommodation of the ecological complexity through a multi-causal way of thinking which, in turn, exposes the lack of robust methodologies for eliciting the straightforward scientific answers required from the regulatory agencies to address the provisions of the Great Lakes Water Quality Agreement. Specifically, the 2012 Great Lakes Water Quality Protocol directs Canada and the United States to develop numerical targets or "substance objectives" as a tool to manage pollutant inputs into the Great Lakes (Great Lakes Water Quality Protocol, 2012). Thus, the demand for attractive and powerful methodological tools is more pressing than ever before.

The emergence of the ecosystem approach has also shaped the contemporary mathematical modeling practice, increasing the demand for more comprehensive (and thus more complex) ecosystem models. The evolution of models should ideally follow the improvement of our understanding of the major ecosystem processes underlying the

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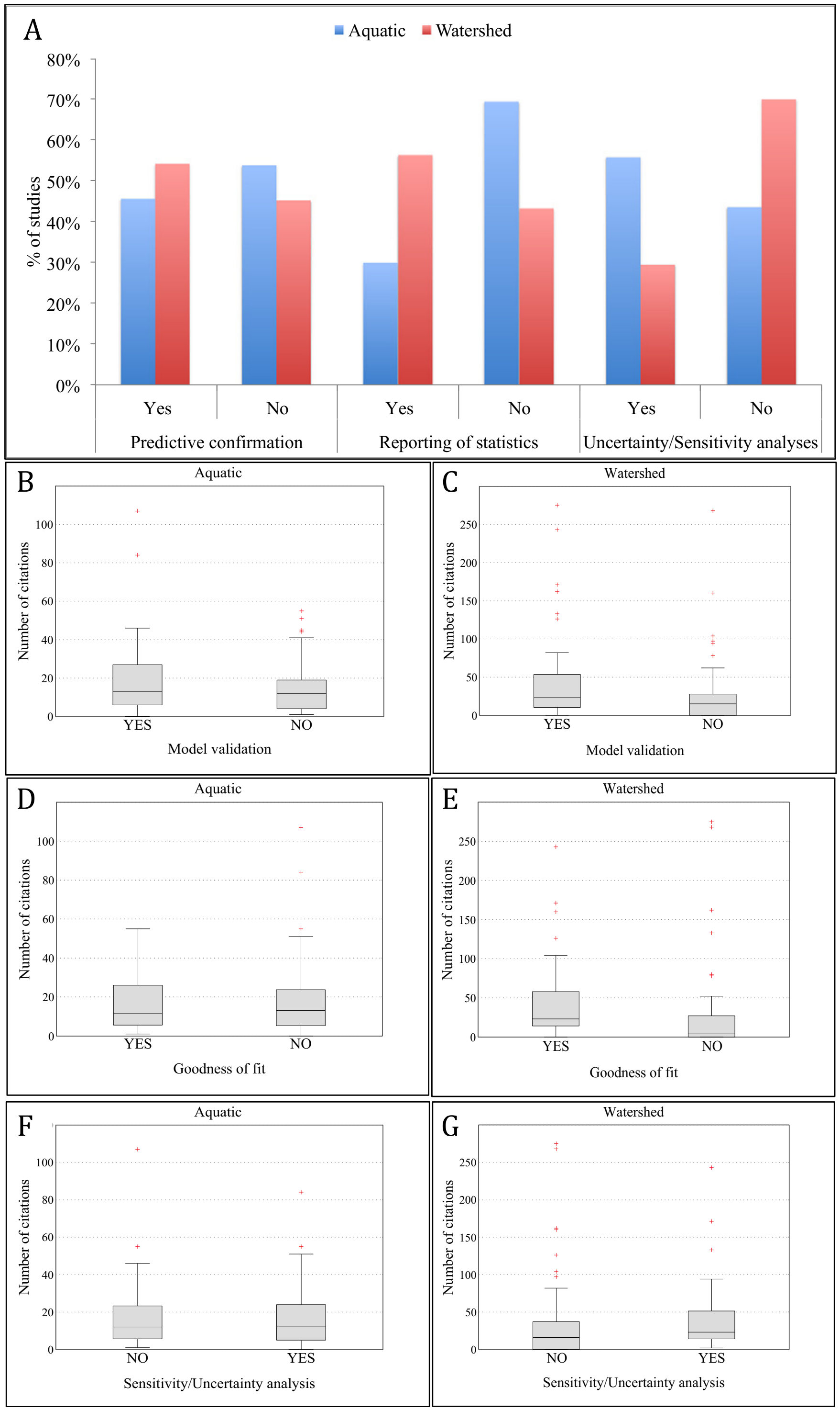

Fig. 1. (A) Portion of aquatic and watershed modeling studies that performed validation in its broader sense (Predictive confirmation), reported goodness of fit (Reporting of statistics), and conducted sensitivity and/or uncertainty analyses (Uncertainty/Sensitivity analyses). Citations frequency based on whether (or not) the original aquatic and watershed modeling studies reported results of (B) validation, (C) goodness of fit, and (D) sensitivity/uncertainty analyses. Results adapted from Arhonditsis and Brett (2004), Arhonditsis et al. (2006), and Wellen et al. (2014-submitted for publication).

environmental problems in a particular system. When the necessary data to parameterize the key causal ecological linkages are lacking, it is unreasonable to expect that more complex (and over-parameterized) model structures will improve the credibility of our forecasting tools (Fig. 3). Current challenges make compelling the development of more realistic modeling platforms: (i) to elucidate causal mechanisms, complex interrelationships, direct and indirect ecological paths of the Great Lakes basin ecosystem, (ii) to examine the interactions among the various stressors (e.g., climate change, urbanization/land-use changes, alternative management practices, invasion of exotic organisms), and (iii) to assess their potential consequences on the lake ecosystem functioning (e.g., food web dynamics, benthic–pelagic coupling, fish communities). This special issue aims to provide insights into the current state of the field, and also highlights the major challenges and future directions of research. Special emphasis is placed on studies that address topics, such as novel uncertainty analysis techniques, Bayesian inference methods, proper representation of plankton functional types, effective integration of physics with biology, accommodation of the interplay between inshore and offshore areas, and strategies to improve modeling in the context of fisheries.

How close are we to achieve reliable ecological forecasts in Lake Erie? Lake Erie is the smallest and shallowest system of the Great Lakes; and therefore, it is the most susceptible to nutrient-driven water quality issues. Recent evidence suggests that rapid ecological changes are occurring in the ecosystem, driven by a complex and often poorly understood interplay among many factors related to the lake's chemical, physical and biological characteristics (Michalak et al., 2013). A variety of data-oriented and process-based models have been in place to understand ecological interactions and to predict the response of Lake Erie to external nutrient loading changes. In this regard, Kim et al. (2014-in this issue-a) examined the strengths and weaknesses of the different modeling strategies, their adequacy in representing the processes underlying plankton dynamics, and their ability to reproduce the spatio-temporal variability in hypoxia or harmful algal blooms. According to Kim et al. (2014-in this issue-a), we are still not in a position to draw credible predictive statements and meaningfully support environmental management. The existing models have mainly offered heuristic tools for examining different ecological hypotheses and dictating future

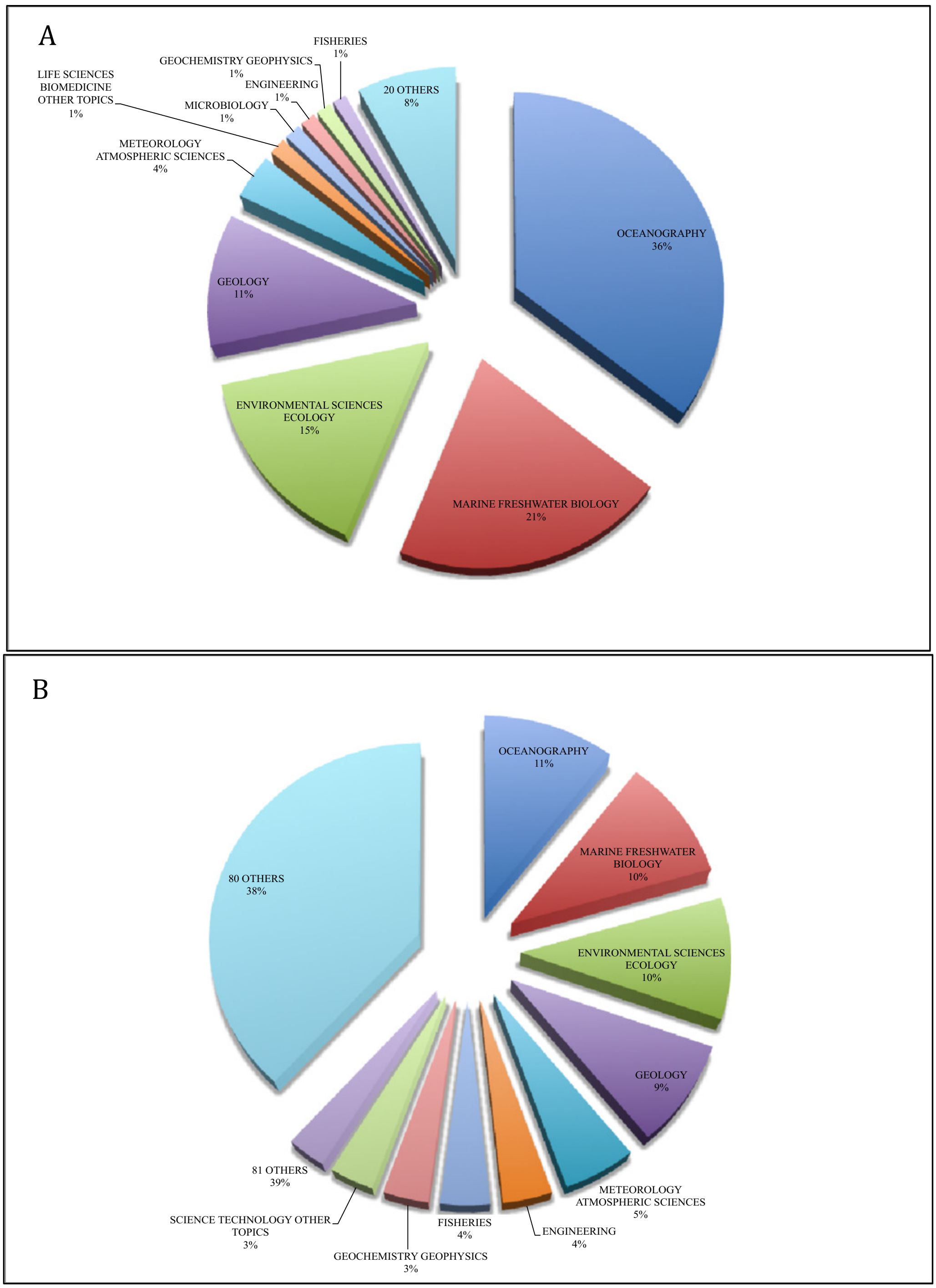

Fig. 2. (A) Breakdown of scientific disciplines for papers citing Fasham et al. (1990). (B) Breakdown of scientific disciplines for second-generation citations of Fasham et al. (1990). (C) Breakdown of scientific disciplines for papers citing Beven and Binley (1992). (D) Breakdown of scientific disciplines for second-generation citations of Beven and Binley (1992).

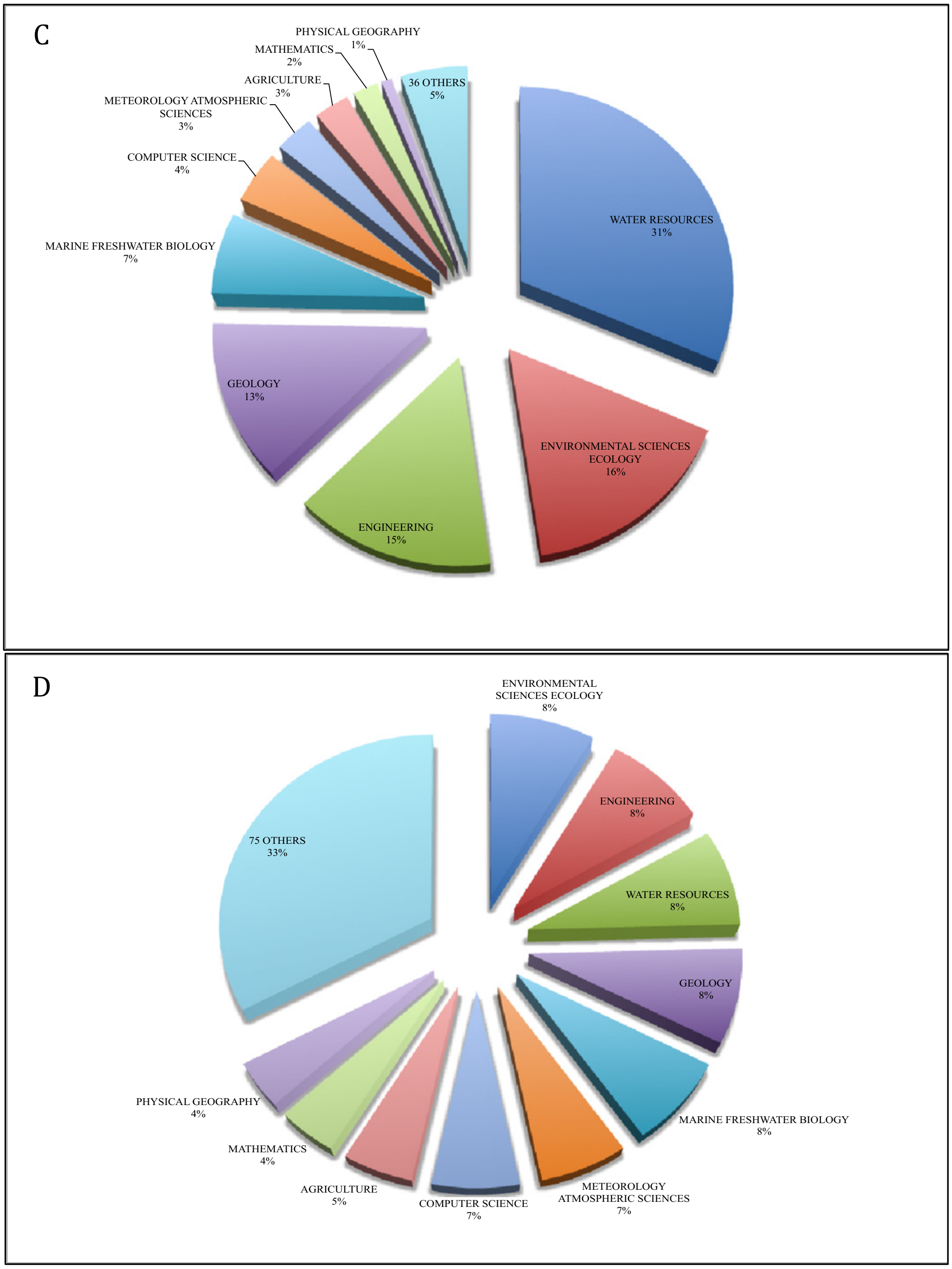

Fig. 2 (*continued*).

data collection efforts. Given that a single "correct" strategy does not exist, the same study advocates the standpoint that the local efforts should strive for a synthesis of multiple modeling approaches that can contribute to an integrative view of the functioning of the system.

Hypoxia in the deeper regions of Lake Erie is a lingering concern after decades of remediation efforts. Rucinski et al. (2014-in this issue) set out to model the relationship between external phosphorus loading, and hypolimnetic dissolved oxygen concentrations. The authors coupled a hydrodynamic model with a eutrophication model aiming to reproduce the summer stratified period in the central basin of Lake Erie. Their model accounted for temporal trends in chlorophyll *a* and phosphorus concentrations, zooplankton biomass, and both temporal and vertical trends in dissolved oxygen concentration. To assist eutrophication management in a meaningful way, the authors established response curves accounting for the inter-annual variability in physical conditions, driven by the meteorological forcing. In a similar study, Oveisy et al. (2014) coupled an explicit three-dimensional hydrodynamic model with a water quality model to reproduce the eutrophication problems in Lake Erie. In particular, the authors were concerned with the relationship between winter ice cover and the development of hypoxia later on in the growing season. This study suggested that phytoplankton biomass in winter, under conditions of low light and low temperatures, may still be comparable to summer-time concentrations. The authors concluded that ice cover dynamics

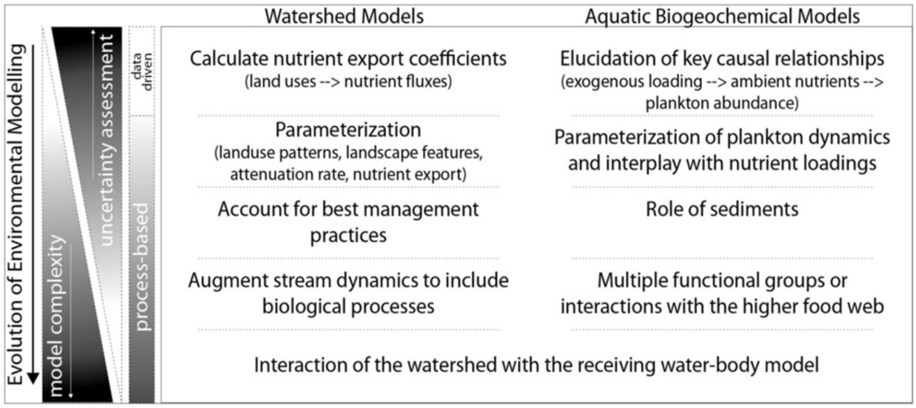

Fig. 3. Evolutionary progression from simple data-driven watershed and aquatic ecosystem models to more complex process-based models, terminating in an integrated watershed-receiving water body model.
Conceptual diagram adapted from Kim et al. (2014-in this issue-a).

(e.g., thickness and duration) will likely influence winter algal productivity, effectively highlighting the importance of modeling ice cover in hydrodynamic models.

Why Bayesian? Bayesian inference provides a convenient methodology in which past knowledge along with present ecological information form the basis for more accurate predictions of future ecosystem responses. The rigorous assessment of uncertainty in model predictions, the optimization of the sampling design of monitoring programs, and the alignment with the policy practice of adaptive management are some of the advantages of the Bayesian approach that are particularly useful for stakeholders and policy makers when making decisions for sustainable environmental management (Arhonditsis et al., 2007). In this context, Stow et al. (2014-in this issue) presented a Bayesian hierarchical model that was used to support management decisions by assessing the exceedance frequency and confidence of compliance with different water quality standards. Using data from Saginaw Bay in Lake Huron, the study illustrated the capacity of this framework to represent spatial and temporal domains of particular interest, such as spring mean conditions in a certain area, and to allow the transfer of information in space, thereby enabling regions with sparse data and high uncertainty to "borrow strength" from data-rich locations. The latter feature of the Bayesian hierarchical proposition is highly relevant to the conservation practices of countries like Canada, containing a high number of freshwater resources for which complete datasets could never be practically collected.

Based on the Hamilton Harbour Area of Concern (AOC), Wellen et al. (2014-in this issue) and Kim et al. (2014-in this issue) offered two additional case studies to illustrate the benefits of Bayesian analysis in the context of model-based environmental management. One of the challenges of the contemporary modeling practice is the development of calibration techniques that can effectively accommodate the behavior of watersheds during extreme events, given that the frequency of such events is expected to increase if the current urbanization and climate change trends continue. To achieve this objective, Wellen et al. (2014-in this issue) introduced a novel Bayesian framework postulating two distinct states with respect to the watershed response to precipitation; that is, precipitation depth above a certain threshold triggers an extreme state, characterized by a qualitatively different response of the watershed to precipitation. The integration of this calibration framework with the SWAT (Soil–Water Assessment Tool) model offered promising results in that the state-specific parameters were coherently identified, while the extreme state of the watershed was characterized by a higher propensity for runoff generation. Along the same line of thinking, Kim et al. (2014-in this issue-b) presented a network of models that aims to connect the watershed processes with the dynamics of the receiving waterbody in the Hamilton Harbour. The novel features of this Bayesian framework include the development of a downscaling algorithm that transforms the annual phosphorus loading estimates of the SPARROW (SPAtially Referenced Regressions On Watershed attributes) model to daily inputs for the eutrophication model; and a neural network that emulates the posterior linkages between model parameters/phosphorus loading inputs and the predicted total phosphorus, chlorophyll *a* concentrations, and zooplankton abundance. The same study used this network of models to gain insights into the ecological factors that modulate the current water quality conditions and may determine the success of the on-going restoration efforts in the area.

Other modeling advancements (surface waves, sediment transport, phytoplankton functional groups, and oil spills): The advent of fast computing and the greater data availability have fundamentally shifted the field of environmental modeling in the last two decades. This shift has allowed researchers to focus on larger-scale problems (e.g., three dimensional models) with finer ecological detail (e.g., the incorporation of functional groups in food web models). These advancements are a great boon to the effective management of complex ecological systems, such as the Laurentian Great Lakes hub — vital to both shipping and industry. In this context, McCombs et al. (2014-in this issue) presented a novel integrated modeling system, consisting of a spectral wave model coupled to a depth averaged hydrodynamic model, which was used to simulate the wave and flow conditions in the Kingston Basin of Lake Ontario during winter storm events. Flows throughout the basin showed a complex circulation pattern that is composed of several wind-driven gyres, magnified during storm events. Based on the successful reproduction of the waves and currents in eastern Lake Ontario, the proposed modeling tool can be particularly useful for engineering studies, such as offshore wind farm impact assessment. In an attempt to address the challenges pertaining to the validation of distributed hydrodynamic sediment transport models, Büttner et al. (2014-in this issue) introduced a new method that relies on the linear relationship between sedimentation and heavy metal concentrations in the topsoil of riverine floodplains. The tracer method was tested in the heavily contaminated 45 km^2 floodplains of River Mulde near Bitterfeld (Germany) where sediment deposition during flood events was simulated using the hydrodynamic and sediment transport model Telemac2D. The study reported a monotonic increase in median cadmium (Cd), zinc (Zn), and arsenic (As) concentrations of the topsoil with increasing simulated sediment deposition classes, which was consistent with the available empirical evidence from the study site.

The incorporation of hydrodynamics into lake ecosystem models is an exciting area of study, offering an increased articulation level into the simulations of real world dynamics. Driven by this motivation, Frassl et al. (2014-in this issue) modeled phosphate uptake by phytoplankton with a spatially explicit model for Lake Constance. They examined two phytoplankton cellular strategies (i.e., static vs. dynamic cellular stoichiometry) within this framework and found minor discrepancies in model performance, but strong differences in spatial phosphate depletion. The more complex (and more realistic) depiction of phytoplankton with dynamic cellular stoichiometry was able to correctly reproduce vertical nutrient distributions. With this modeling exercise, Frassl et al. (2014-in this issue) effectively illustrated the macroscopic ramifications of microscopic dynamics. To this end, Reynolds et al. (2014-in this issue) studied the sensitivity and predictive power in phytoplankton simulations when accommodating morphological and physiological traits. Using the PROTECH (Phytoplankton RespOnses To Environmental CHange) model, they were able to successfully reproduce the phytoplankton succession patterns across various scenarios and delineate ecologically beneficial traits. Namely, large cell size is a trait often associated with vertically migrating species that are unpalatable for zooplankton. Reynolds et al. (2014-in this issue) also found larger cells with oblong morphologies to be very competitive, as they can maintain high surface area to volume ratios, maximizing incoming solar radiation and surficial nutrient dynamics. This latter trait can also be associated with smaller algal species, which however are highly sensitive to zooplankton grazing. Thus, the effects of overlooked microscopic details (tradeoff between realism and model feasibility) can permeate to the macroscopic level, and have a wide array of management implications.

While there is a considerable amount of effort being put into incorporating hydrodynamics into water quality models, Perhar and Arhonditsis (2014-in this issue) reviewed an area, where they call for the reverse: the incorporation of ecological dynamics into hydrodynamic models of petroleum hydrocarbon spills. The authors reviewed the oil spill modeling literature, and found the majority of models to be driven almost exclusively by abiotic factors, such as temperature, wind speed, water turbulence, and evaporation rate. In the few cases where a biotic compartment was considered, it was more as an afterthought than a fully integrated module. Building on this idea, the authors conducted a comprehensive review of the ecological impacts of hydrocarbon toxicity on various trophic levels. They found a substantial wealth of knowledge that has not been incorporated into oil spill modeling efforts. As such, they proposed a framework that aims to fill the gap of biology and ecology in contemporary oil spill models, using data collected from high profile events, such as the Exxon Valdez tanker spill, and the British Petroleum underwater blowout.

Topics in fish modeling (larval fish patterns, fish tumors, catch curve models): Larval fish abundance can offer insights into early life history dynamics and provide critical information that shapes habitat protection and restoration strategies. However, the high spatial and temporal variability driven by stochastic environmental conditions, the time and location of spawning as well as their larval behavior pose significant challenges when quantifying larval fish abundance. To address some of the problems related to sampling and data analysis, DuFour et al. (2014-in this issue) presented a Bayesian (hierarchical and state-space modeling) framework combined with spatiotemporally distributed sampling for ichthyoplankton which was used to partition variance and offer abundance and mortality estimates of larval walleye (*Sander vitreus*) in the Maumee River in northwestern Ohio. The DuFour et al. (2014-in this issue) study showed that most of the variability is encountered in finer spatial (within site) and time (day-to-day) scales while the Bayesian state-space modeling can offer a meaningful management tool by improving estimates and properly accounting for the underlying uncertainty.

Another difficult issue in fisheries is the establishment of proper delisting criteria for the “fish tumors and other deformities” BUI (Beneficial Use Impairment), given that the characterization of non-impairment in a particular location requires the fish tumor incidence rates to not exceed rates at control sites. To overcome the ambiguity surrounding the selection of “unimpacted” sites, Mahmood et al. (2014-in this issue) presented a Bayesian modeling framework that is founded upon the explicit consideration of the sampling bias in tumor observations as well as the causal association between important covariates (age, fork length, liver weight, and gonad weight) and tumor incidence. The same study introduced a new criterion that stipulates the likelihood of tumor occurrence for each individual to be lower than 10% for a certain fraction (or greater) of the fish samples collected from a particular location. The proposed criterion may be a more reliable way to characterize the prevailing conditions in potentially impacted sites while avoiding the – oftentimes – controversial delineation of reference conditions. In the context of fisheries, Doll and Lauer (2014-in this issue) presented an interesting comparison between frequentist and Bayesian inference approaches using catch curve modeling. Based on long term monitoring data of yellow perch (*Perca flavescens*) from southern Lake Michigan, this analysis showed that both mean estimates and associated uncertainty bounds were similar between the two strategies. Nonetheless, according to Doll and Lauer (2014-in this issue), the Bayesian approach resulted in lower error than its frequentist counterpart with increasing variability in the datasets, and also demonstrated greater flexibility when conducting multiple comparisons.

The Great Lakes community has been at the forefront in the development and application of models to guide environmental management actions. Phosphorus targets under the 1978 Great Lakes Water Quality Agreement were developed using an ensemble of models of differing scope and complexity, an approach generally regarded as the “gold standard” for addressing complex environmental problems. More recently, the updated 2012 GLWQA has endorsed the Adaptive Management concept, a framework in which models, process-based research, and long-term monitoring are used in concert to inform decision-making. Adopting this approach constitutes recognition that the Great Lakes will continue evolving into the future, as they respond to a changing, often unanticipated, assemblage of stressors. Developing a coherent strategy to operationalize the Adaptive Management concept, with the ideas articulated by Oreskes et al. (1994) in mind, offers the opportunity for the Great Lakes community to continue leading in this area.

References

Arhonditsis, G.B., Brett, M.T., 2004. Evaluation of the current state of mechanistic aquatic biogeochemical modeling. Mar. Ecol. Prog. Ser. 271, 13–26.

Arhonditsis, G.B., Adams-VanHarn, B.A., Nielsen, L., Stow, C.A., Reckhow, K.H., 2006. Evaluation of the current state of mechanistic aquatic biogeochemical modeling: citation analysis and future perspectives. Environ. Sci. Technol. 40, 6547–6554.

Arhonditsis, G.B., Qian, S.S., Stow, C.A., Lamon, E.C., Reckhow, K.H., 2007. Eutrophication risk assessment using Bayesian calibration of process-based models: Application to a mesotrophic lake. Ecol. Model. 208, 215–229.

Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrol. Process. 6, 279–298.

Büttner, O., Schulz, M., Rode, M., 2014. A new semi-quantitative tracer approach for the validation of a two dimensional sediment transport model. J. Great Lakes Res. 40 (Supplement 3), 8–18 (in this issue).

Doll, J.C., Lauer, T.E., 2014. Comparing Bayesian and frequentist methods of fisheries models: hierarchical catch curves. J. Great Lakes Res. 40 (Supplement 3), 41–48 (in this issue).

DuFour, M.R., Pritt, J.J., Mayer, M.C., Stow, C.A., Qian, S.S., 2014. Bayesian hierarchical modeling of larval walleye (*Sander vitreus*) abundance and mortality: accounting for spatial and temporal variability on a large river. J. Great Lakes Res. 40 (Supplement 3), 29–40 (in this issue).

Fasham, M.J.R., Ducklow, H.W., McKelvie, S.M., 1990. A nitrogen-based model of plankton dynamics in the oceanic mixed layer. J. Great Lakes Res. 48, 591–639.

Frassl, M.A., Rothhaupt, K.O., Rinke, K., 2014. Algal internal nutrient stores feedback on vertical phosphorus distribution in large lakes. J. Great Lakes Res. 40 (Supplement 3), 162–172 (in this issue).

Great Lakes Water Quality Protocol, 2012. Protocol amending the agreement between the United States of America and Canada on Great Lakes Water Quality, 1978, as amended on October 16, 1983 and on Nov. 18, 1987. http://www.epa.gov/greatlakes/glwqa/20120907-Canada-USA_GLWQA_FINAL.pdf.

Kim, D.K., Zhang, W., Watson, S., Arhonditsis, G.B., 2014. A commentary on the modelling of the causal linkages among nutrient loading, harmful algal blooms, and hypoxia patterns in Lake Erie. J. Great Lakes Res. 40 (Supplement 3), 117–129 (in this issue).

Kim, D.K., Zhang, W., Hiriart-Baer, V., Wellen, C., Long, T., Boyd, D., Arhonditsis, G.B., 2014. Towards the development of integrated modelling systems in aquatic biogeochemistry: a Bayesian approach. J. Great Lakes Res. 40 (Supplement 3), 73–87 (in this issue).

Mahmood, M., Blukacz-Richards, A., Baumann, P.C., McMaster, M., Hossain, M., Arhonditsis, G.B., 2014. A Bayesian methodological framework for setting fish tumor occurrence delisting criteria: a case study in St. Mary's River area of concern. J. Great Lakes Res. 40 (Supplement 3), 88–101 (in this issue).

McCombs, M.P., Mulligan, R.P., Boegman, L., Rao, Y.R., 2014. Modeling surface waves and wind-driven circulation in eastern Lake Ontario during winter storms. J. Great Lakes Res. 40 (Supplement 3), 130–142 (in this issue).

Michalak, A.M., Anderson, E., Beletsky, D., Boland, S., Bosch, N.S., Bridgeman, T.B., Chaffin, J.D., Cho, K.H., Confesor, R., Daloğlu, I., DePinto, J., Evans, M.A., Fahnenstiel, G.L., He, L., Ho, J.C., Jenkins, L., Johengen, T., Kuo, K.C., Laporte, E., Liu, X., McWilliams, M., Moore, M.R., Posselt, D.J., Richards, R.P., Scavia, D., Steiner, A.L., Verhamme, E., Wright, D.M., Zagorski, M.A., 2013. Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions. Proc. Natl. Acad. Sci. U. S. A. 110, 6448–6452.

Minns, C.K., Kelso, J.R.M., 2000. NO! It is time for a Great Lakes Ecosystem Management Agreement that SUBSUMES the Great Lakes Water Quality Agreement. J. Great Lakes Res. 26, 1–2.

Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, validation, and confirmation of numerical models in the earth sciences. Science 263, 641–646.

Oveisy, A., Rao, Y.R., Leon, L.F., Bocaniov, S.A., 2014. Three-dimensional winter modeling and the effects of ice cover on hydrodynamics, thermal structure and water quality in Lake Erie. J. Great Lakes Res. 40 (Supplement 3), 19–28 (in this issue).

Perhar, G., Arhonditsis, G.B., 2014. Aquatic ecosystem dynamics following petroleum hydrocarbon perturbations: a review of the current state of knowledge. J. Great Lakes Res. 40 (Supplement 3), 56–72 (in this issue).

Reynolds, C.S., Elliott, J.A., Frassl, M.A., 2014. Predictive utility of trait-separated phytoplankton groups: a robust approach to modeling population dynamics. J. Great Lakes Res. 40 (Supplement 3), 143–150 (in this issue).

Robson, B.J., 2014. State of the art in modelling of phosphorus in aquatic systems:review, criticisms and commentary. Environ. Modell. Softw. 61, 339–359.

Rucinski, D.K., DePinto, J.V., Scavia, D., Beletsky, D., 2014. Modeling Lake Erie's hypoxia response to nutrient loads and physical variability. J. Great Lakes Res. 40 (Supplement 3), 151–161 (in this issue).

Stow, C.A., Jolliff, J., McGillicuddy, D., Doney, S., Allen, J.I., Friedrichs, M., Rose, K., Wallhead, P., 2009. Skill assessment for coupled biological/physical models of marine systems. J. Mar. Syst. 76, 4–15.

Stow, C.A., Cha, Y.K., Qian, S.S., 2014. A Bayesian hierarchical model to guide development and evaluation of substance objectives under the 2012 Great Lakes Water Quality Agreement. J. Great Lakes Res. 40 (Supplement 3), 49–55 (in this issue).

Wellen, C., Arhonditsis, G.B., Long, T., Boyd, D., 2014. Accommodating environmental thresholds and extreme events in hydrological models: a Bayesian approach. J. Great Lakes Res. 40 (Supplement 3), 102–116 (in this issue).

Wellen, C., Kamran-Disfani, A., Arhonditsis, G.B., 2014. Evaluation of the current state of distributed watershed-water quality modeling, (submitted for publication).

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