

1 Reviewing uncertainty in bioenergetics and food web models to project invasion impacts: four
2 major Chinese carps in the Great Lakes

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32 **Abstract**

33 Bioenergetics and food web models are tools available for understanding and projecting the
34 impacts of aquatic species invasions on food web structure and energy allocation of an
35 ecosystem. However, uncertainty is inherent in modeling the impact of invasive species in novel
36 ecosystems, as assumptions must be made about physiological responses to novel environments
37 and interactions with existing (native and non-native) species. Here we use the four major
38 Chinese carps (FMCC) in the Laurentian Great Lakes as a case study to categorize and describe
39 the suite of uncertainties inherent in projecting the impact of invasive species with bioenergetics
40 and food web models. We approach this case study in a decision analytic framework, describing
41 structural uncertainties, environmental variation, partial observability, partial controllability, and
42 linguistic uncertainty. Finally, we review and give suggestions for how the use of methods
43 including adaptive management, scenario planning, sensitivity analyses, and value of
44 information, as well as efforts to ensure clarity in language and model structure, can enable
45 modelers and managers to reduce and account for key uncertainties and make better decisions for
46 the control of invasive species.

47

48 Keywords: Asian Carp; Ecopath with Ecosim; invasive species risk assessment; Laurentian
49 Great Lakes; ecological modeling

50 **Introduction**

51 Understanding how ecosystems might change following the establishment of invasive
52 species is a core component of invasive species risk assessment and necessary to decide whether
53 species management (i.e., prevention, eradication, or control) is warranted. The predominant
54 mechanism by which invasive species exert effects on other species appears to be predation and
55 competition for prey resources (Mills et al., 1993; Sturtevant et al., 2019; Zhang et al., 2019). At
56 the extreme, species invasions can drastically change food web structure and function (e.g.,
57 Willson et al., 2011). Therefore, methods to identify the ecological impact of invasive species
58 must be capable of determining how species assimilate prey in new environments and the
59 impacts of this consumption on the food web as a whole.

60 The ecological impacts of invasive species are often evaluated after invasions have
61 occurred, which hinders preventative decision making. Forecasting tools are urgently needed to
62 gauge how the recipient community could change in response to a new invader, which would
63 help to prioritize management responses and resources. Two major approaches to forecasting
64 ecological impacts of invasive species are to: (1) project individual or population level
65 consumption by the invader on existing prey species (Cooke and Hill, 2010; Dick et al., 2014;
66 Jackson et al., 2015) and (2) project direct and indirect effects of the invader on existing species
67 by accounting for predator–prey interactions in the food web (Zhang et al., 2019).

68 Bioenergetics (Kitchell et al., 1974; Ney, 1993; Winberg, 1956) and food web models
69 (Zhang et al., 2019, 2016) describe the flow of energy (consumption and growth) between
70 species and their environment under different ecological conditions. In particular, bioenergetics
71 models estimate how much somatic growth can be supported by thermal conditions and prey
72 availability and may therefore help determine whether sufficient prey exists to support an
73 invasive species, as well as the consequences of consumption on prey resources (Johnson et al.,
74 2005). Food web models explain how changes in consumption and trophic relationships shift
75 energy flows within a community, allowing the direct and indirect impacts of invasive species to
76 be better understood (Kao et al., 2018, 2016, 2014; Zhang et al., 2019). Using these two tools
77 may therefore provide a comprehensive evaluation of potential invasions. However, both
78 bioenergetics and food web models are complex, leading to considerable uncertainty in
79 parameterization and interpretation.

80 When dealing with potential invasions, uncertainty can hinder our understanding of the
81 probable effects of species on the ecosystem, as well as our ability to make decisions about how

82 to minimize these effects via prevention or control (Robinson et al., this issue). Most uncertainty
83 is attributed to our limited knowledge about the invasive species and their adaptive potential in
84 new environments. To fundamentally reduce uncertainty, modeling should be carried out with
85 input from and feedback to field studies and invasive species managers. This review will serve as
86 a way for modelers to communicate with biologists and managers by classifying and
87 summarizing uncertainties associated with ecological models.

88 Efforts to project the potential impacts of the four major Chinese carps (hereafter FMCC;
89 bighead carp [*Hypophthalmichthys nobilis*], silver carp [*H. molitrix*], black carp
90 [*Mylopharyngodon piceus*], and grass carp [*Ctenopharyngodon idella*]) on food webs of the
91 Laurentian Great Lakes illustrate how reducing and accounting for critical uncertainties will
92 increase the utility of the models for understanding potential effects and making informed
93 decisions. The FMCC present high invasion risk to the Great Lakes (Cudmore et al. 2017, 2012;
94 Drake et al., 2020), with grass carp already extant and reproducing in the Lake Erie basin
95 (Embke et al., 2016). FMCC have invaded the Mississippi River system with silver carp
96 becoming a dominant species in many river reaches (see Chapman et al., this issue for a review
97 of the status of each species in North America). Species-specific bioenergetics and food web
98 models have been developed, or are under development, to estimate the ecological dynamics of
99 FMCC in the Great Lakes basin and account for the different trophic positions and feeding
100 strategies (planktivorous, herbivorous, molluscivorous) of each species. While current models
101 have provided significant insight, a more complete treatment of the uncertainty inherent in these
102 models is needed to evaluate model projections and prioritize future research needs. The FMCC
103 are an ideal example to emphasize the generality of uncertainty for any novel invader, as they
104 have similar life histories, but each species will capitalize on different prey resources, and thus,
105 pose different food web impacts. Determining how uncertainties within the models change
106 projections within the recipient community is urgently needed to refine the scope and scale of
107 potential ecological effects.

108 Model uncertainty is complex and includes numerous components. We first describe a
109 typology of uncertainties that can influence bioenergetics and food web models. This framework,
110 which is rooted in decision analysis, lends structure to delineating uncertainties in terms of
111 reducibility, system understanding, inaccuracies in observation, and incomplete influence of
112 control actions on an invader. We then review and give suggestions for how efforts to evaluate
113 these uncertainties in terms of value of information, scenario planning, and sensitivity analyses

114 can highlight key uncertainties that must be reduced to increase the utility of models for decision
115 support and risk assessments. Throughout, we use projecting the ecological effects of FMCC in
116 the Great Lakes as a case study to demonstrate model uncertainties and how they may be
117 handled; however, these generalities are pertinent for how we handle modeling of new species in
118 new environments.

119

120 **Typology of Uncertainties in Bioenergetics and Food Web Modeling**

121 There are five components of a decision analytic framework that can be used to
122 categorize uncertainties in bioenergetics and food web modeling. Williams (1997) describes four
123 uncertainties related to information used to model population processes when making harvest
124 management decisions: structural uncertainty, environmental variation, partial observability, and
125 partial controllability. In addition, Regan et al. (2002) included another common and important
126 type of uncertainty: linguistic uncertainty. Categorizing uncertainties in this manner can help to
127 identify general solutions for similar types of uncertainties. Below we describe each of the five
128 categories of uncertainty in bioenergetics and food web modeling for the risk assessment of
129 FMCC in the Great Lakes and discuss whether they can be resolved with more research effort
130 (i.e., epistemic uncertainties) or are unresolvable and can only be accounted for (i.e., aleatory
131 uncertainties). The information we describe is summarized in Table 1.

132

133 *Structural Uncertainty*

134 Structural uncertainty, or process uncertainty, refers to uncertainty regarding the
135 biological and ecological processes of the system being modeled (Peterman, 2004; Williams,
136 1997). Structural uncertainty can be expressed as either functional uncertainty, in which discrete
137 models describe different hypotheses about states of knowledge, or parametric uncertainty, in
138 which there is a large range of potential parameter values. Both of these forms of structural
139 uncertainty are important in bioenergetics and food web models, particularly for invasive species
140 like the FMCC, for which there are limited data to predict their behavior and effects in a new
141 habitat. Functional uncertainties exist with regard to the effects of anthropogenic and
142 environmental drivers in the present and future, such as climate change and land use change, as
143 well as trophic interactions among the FMCC and between the FMCC and existing species.
144 Parametric uncertainties exist in myriad forms for both food web and bioenergetics models,
145 stemming from a lack of information about basic parameters for all species and uncertainty about

146 parameter estimates for invasive species in novel habitats. Below we describe several aspects of
147 these uncertainties for the FMCC in the Great Lakes, focusing on climate change, land use
148 change, trophic interactions, and general parametric uncertainties for the two model types.

149

150 Effects of climate change

151 Climate change is expected to make the Great Lakes' thermal environment more
152 favorable for the survival and establishment of FMCC (Alsip et al., 2020; Coulter et al., 2018).
153 However, the influence of these large lakes on regional climate (Notaro et al., 2013), with their
154 high interannual meteorological variation and complex hydroclimatic linkages (Gronewold et al.,
155 2015; Lenters et al., 2013; Xue et al., 2017), can hinder projection of the effects of climate
156 change at time scales relevant for the ecological modeling of FMCC establishment and impacts.
157 Effects of climate change on Great Lakes aquatic habitats may result in a deeper thermocline,
158 warmer surface waters, a longer period of summer stratification, and milder winters (Brandt et
159 al., 2002; Brooks and Zastrow, 2002; Collingsworth et al., 2017; McCormick and Fahnenstiel,
160 1999); these changes would provide favorable thermal habitat for the growth of FMCC. To date,
161 several bioenergetics models indicate growth potential, overwinter survival, and consumption
162 rates of bighead, silver, and grass carps will increase under warming scenarios if food is not
163 limiting (Alsip et al., 2020; Coulter et al., 2018; van der Lee et al., 2017). Thus, accounting for
164 and, if possible, reducing the uncertainty in climate warming effects on the thermal environment
165 is important to projecting FMCC growth dynamics for a given year in the near to distant future.

166 Changes to the thermal environment and precipitation and wind patterns under a
167 projected future climate may change the species composition and productivity of primary and
168 secondary producers across the Great Lakes (Brinker et al., 2018; Mandrak, 1989; Reavie et al.,
169 2017). These projected changes in prey availability may differentially affect consumption and
170 growth of FMCC and should be accounted for in modeling efforts. Bighead and silver carp,
171 together known as the bigheaded carps, primarily feed on both phytoplankton and zooplankton,
172 grass carp feed on benthic macrophytes, and black carp are primarily molluscivorous but also
173 feed on other benthic organisms. Therefore, we expect each FMCC species to respond differently
174 to changes in productivity related to climate change. For example, in oligotrophic areas,
175 increased temperature could increase macrophyte growth, but in more eutrophic areas shading by
176 algae may reduce light penetration and macrophyte growth, leading to site-specific differences in
177 grass carp population dynamics. Similarly, increases in temperature and precipitation may also

178 increase the relative abundance of cyanobacteria biomass and the magnitude and frequency of
179 harmful algal blooms (HABs) in eutrophic areas like Western Lake Erie or Green Bay, Lake
180 Michigan (Michalak et al., 2013; Paerl and Huisman 2008). Increases in cyanobacteria may
181 provide more food for bigheaded carps but would reduce mussel filtration (Vanderploeg et al.,
182 2009), and thus may indirectly affect black carp by reducing dreissenid mussel biomass (Drake
183 et al. 2020). In future modeling efforts, reducing structural uncertainty regarding climate effects
184 on primary and secondary production in different habitats of the Great Lakes and the consequent
185 effects on FMCC energetics will improve understanding of when and where ecological impacts
186 will be greatest, and help prioritize prevention and control efforts.

187 In addition to the FMCC, other invasive species may be affected by climate change,
188 resulting in greater uncertainty in bioenergetics and food web model outcomes. In the absence of
189 HABs, increases in water temperature will increase filtration rates of dreissenid mussels, which
190 could decrease available biomass of phytoplankton and zooplankton, thereby decreasing
191 potential production of bigheaded carps while providing increased biomass of dreissenid mussels
192 for black carp production. Conversely, filtration by bigheaded carps could reduce plankton
193 biomass before it becomes available to dreissenid mussels. Alsip et al. (2020) used a biophysical
194 model linked to a bioenergetics model to project that climate warming, by extending the
195 stratification period, would reduce the time that dreissenid mussels could access prey throughout
196 the whole water column, increasing the length of the growing season of bigheaded carps in Lake
197 Michigan. Increases in water clarity and light resulting from dreissenid mussel filtration would
198 stimulate the growth of aquatic plants, benefitting grass carp growth in nearshore habitats.

199 Uncertainty in range expansion of other aquatic invasive species may have unknown or
200 uncertain effects on the establishment of FMCC. For example, in northern areas of the Great
201 Lakes, climate change has the potential to increase the abundance and food consumption of
202 parasitic sea lamprey (*Petromyzon marinus*), as well as thermal habitat overlap between sea
203 lamprey and the FMCC, potentially resulting in greater predation rates on FMCC adults. In
204 southern areas of the Great Lakes, effects of climate change on sea lamprey are less certain, as
205 temperatures may become unfavorable for its reproduction or growth (Lennox et al., 2020).
206 Although future species invasions are difficult to predict, a better understanding of potential
207 interactions among the FMCC and existing invasive species in the Great Lakes, similar to the
208 work of Alsip et al. (2020), will reduce some of this structural uncertainty.

209

210 Land use change

211 Modeling physiological, community, or ecosystem responses to land use change is often
212 obscured by uncertainties about the progression of the rate and type of change, and the resulting
213 effects on the biophysical environment that drive modeled processes. Using information from
214 land use and human population models to inform ecological models can help resolve
215 uncertainties in the aquatic ecosystem response to changes in land use and land management.
216 Understanding how changes in land use will affect the availability of food or alter the thermal
217 environment is necessary to project habitat quality and FMCC bioenergetics into the future. For
218 example, annual US phosphorus loads are forecasted to increase by 3.4–5.8% from 2010 to 2040
219 without accounting for the effect of climate change on hydrology (LaBeau et al., 2014), which
220 could increase the frequency of large runoff events and thereby increase annual loads even more
221 (Bosch et al., 2014; Michalak et al., 2013). This is particularly important for the planktivorous
222 bigheaded carps for which simulation studies have demonstrated that growth is notably
223 responsive to differences in phosphorus loads under different scenarios for Lakes Michigan
224 (Alsip et al., 2020) and Erie (Zhang et al., 2016). In contrast, increases in large runoff events and
225 urbanization that lead to increased sedimentation and turbidity in nearshore waters might
226 negatively affect the biomass or quality of macrophytes and mussels as food for grass and black
227 carps. Finally, an increase in frequency of runoff events may increase spawning success for all
228 FMCC (Kolar et al., 2007; Kočovský et al. 2012), resulting in increased recruitment and
229 population growth. Therefore, isolating the different effects of land use change (e.g., increased
230 phosphorus loads, sedimentation, changes to water temperature and hydrology) on survival,
231 growth, and establishment of each carp species can improve understanding of how expected
232 changes in land use could influence invasion risk.

233

234 Trophic interactions

235 Uncertainty about the diet of invaders in novel environments also presents a challenge for
236 improving model projections. Planktivorous bigheaded carps are capable of surviving on diets
237 dominated by detritus or cyanobacteria, including *Microcystis* (Anderson et al., 2016; Vörös et
238 al., 1997; Zhang et al., 2016), making them highly adaptable to new environments. Accounting
239 for this dietary breadth in modeling efforts demonstrated a > 4-fold increase in the volume of
240 suitable habitat available for bigheaded carps compared to when they were restricted to feeding
241 on phytoplankton alone (Alsip et al., 2019). Food items previously incorporated into models for

242 bigheaded carps include detritus/dreissenid biodeposits, *Microcystis*, green algae, and
243 macrozooplankton (Alsip et al., 2019; Anderson et al. 2017, 2015; Cooke and Hill, 2010). Future
244 models of bigheaded carps should also include microzooplankton (e.g., rotifers, copepod nauplii,
245 and dreissenid veligers) in carp diets as they made up about 74% of total zooplankton biomass in
246 Lake Michigan (Thomas et al., 2017).

247 There is general uncertainty about whether or how black and grass carps will show
248 preference for prey based on the quantity and quality of food items in the Great Lakes. For
249 bioenergetics model simulations, reliable prey abundance estimates are necessary to develop
250 credible projections of carp biomass and impact. Although estimates for benthos biomass are
251 available for the Great Lakes, macrophyte biomass and species composition are poorly sampled,
252 which could ultimately affect decisions for the control of these species (Robinson et al., this
253 issue). In addition, uncertainty about black carp prey preferences has implications for the
254 response of the food web components that are consumed (Smyth et al., 2020).

255 Whether the FMCC consume fish larvae also is highly uncertain. Although there are no
256 field observations of the FMCC eating fish eggs or larvae, these invasive carps would occupy
257 areas that are spawning and nursery habitats for many native fishes. Moreover, black carp have
258 been observed to consume larval fishes in controlled laboratory experiments, although there is no
259 conclusive evidence they will consume larval fishes in natural environments (Hung et al., 2014).
260 Alewife (*Alosa pseudoharengus*) serve as an example of the potential for invasive species to
261 have unanticipated effects on larval fishes. Alewife were not reported to consume larval fishes in
262 their native habitat, but in the Great Lakes, their consumption of larval fishes can significantly
263 decrease the recruitment of many fish species (Mason and Brandt, 1996; Dettmers et al., 2012;
264 Kao et al., 2014; Madenjian et al., 2008). Incorporating potentially novel foods, such as larval
265 fishes (e.g., Zhang et al., 2016), into future models is needed to evaluate the implications of these
266 uncertainties on the establishment and impact of FMCC in the Great Lakes.

267 In addition to consumption of existing prey species by non-native species, the adaptation
268 of existing predators to new prey resources also affects the potential abundance of non-native
269 species. Uncertainty in this adaptation, however, obscures projections related to the probability
270 and rate of proliferation of a new invader. Existing predators first must recognize the new species
271 as prey, which creates a time lag between invader establishment and the onset of predation by
272 existing species. The length of this time lag depends on the behavior of the new species, its
273 abundance relative to existing prey, and detection by the predator (Abrams and Matsuda, 2004).

274 Moreover, predators switching their diet to the FMCC may facilitate co-existence of some
275 competing species, such as bigheaded carps and existing planktivores (Abrams and Matsuda,
276 2004; Murdoch, 1969; Murdoch et al., 1975).

277 Uncertainty in occurrence and strength of these trophic interactions is most important for
278 models that attempt to project FMCC population growth, asymptotic population size, and effects
279 on Great Lakes food webs. For example, many piscivores in Lake Erie are generalists and
280 opportunists (Johnson et al., 2005). The reproducing population of grass carp in western Lake
281 Erie (Embke et al., 2016) may constitute a new prey source for these predators, as has been
282 observed for round goby (*Neogobius melanostomus*; Foley et al., 2017). However, the rapid
283 growth in body size of FMCC juveniles creates uncertainty in the potential for similar changes in
284 Great Lakes piscivore diets (see Cudmore et al., 2017, 2012; Drake et al., 2020). In addition,
285 some predators are known to feed on bigheaded carps in their introduced range of the Illinois and
286 Upper Mississippi Rivers. Mesocosm studies indicate largemouth bass (*Micropterus salmoides*)
287 preferred bighead carp over silver carp or native prey fishes (Sanft et al., 2018), while additional
288 predator diet studies and mesocosm experiments suggest silver carp is less preferred than native
289 prey fishes (Wolf and Phelps, 2017). Adult bigheaded carps have been found in stomachs of
290 large blue catfish (*Ictalurus fircatus*; Locher, 2018), whereas several smaller native predators
291 such as white bass (*Morone chrysops*), shortnose gar (*Lepisosteus platostomus*), and flathead
292 catfish (*Pylodictis olivaris*) will readily consume juvenile silver carp when they are abundant
293 (Anderson, 2016). Reducing uncertainty associated with predation on FMCC by Great Lakes
294 species would improve our understanding of the degree to which predation affects establishment
295 probability and the levels of achievable FMCC biomass.

296 Modeling bioenergetics of invasive species and their impacts on food webs requires
297 accounting for indirect trophic interactions and cascading effects in a large, complex ecosystem,
298 which leads to highly uncertain outcomes. Managers must account for these uncertainties when
299 considering methods to control and mitigate the effects of these species. For example, grass carp
300 will consume aquatic macrophytes that provide spawning or nursery habitat for native species
301 like centrarchids, esocids, percids, and numerous imperiled species (Cudmore et al., 2017; van
302 der Lee et al., 2017). These effects would be most severe in wetland habitats such as Lake St.
303 Clair and other large, shallow embayments that currently support macrophytes and wetland
304 fishes. Dead benthic macrophytes are an important source of detritus for benthic invertebrates in

305 nearshore habitat, so grass carp expansion could lead to bottom-up control on the production of
306 benthos that may serve as prey for benthivores.

307 If bigheaded carps are introduced to the Great Lakes, their consumption could reduce the
308 biomass and size of zooplankton prey for planktivorous larval, juvenile, and adult fishes (e.g.,
309 alewife), thereby reducing their growth and recruitment (Minder and Pyron, 2018; Sampson et
310 al., 2009). A decrease in alewife would negatively affect biomass of Chinook salmon
311 (*Oncorhynchus tshawytscha*), which rely on alewife for prey (Dettmers et al., 2012; Kao et al.,
312 2016, 2018). Alewife also prey on fish early life stages (Mason and Brandt, 1996) and cause
313 thiamine deficiency syndrome, which leads to early life mortality in lake trout (*Salvelinus*
314 *namaycush*; Czesny et al., 2009). If competition for plankton by bigheaded carps causes a
315 decline in alewife populations, recruitment of some predator species, such as lake trout and
316 walleye (*Sander vitreus*), could increase. However, bigheaded carps had only minor negative
317 effects on native age-0 fish in the Illinois River, perhaps because abundant age-0 bigheaded
318 carps might release age-0 native fish from predation pressure (DeBoer et al., 2018).

319 The FMCC have complementary diets, and in China, are raised together in aquaculture
320 ponds where they feed on different prey types, at different depths, and thus avoid competition
321 (Lin, 1982). However, interactions among these species in introduced habitats present potential
322 uncertainties. The bigheaded carps feed on plankton, but finer gill raker spacing of silver carp
323 relative to bighead carp allow it to access smaller particles (Kolar et al., 2007). In North
324 American rivers, silver carp appear to be in better condition and more abundant than bighead
325 carp where the two co-occur in high densities, implying that silver carp are a superior competitor
326 for plankton in mesotrophic and eutrophic riverine ecosystems (DeBoer et al., 2019). However,
327 silver carp's higher energy density requires them to consume more energy than bighead carp to
328 achieve similar growth. This implies that, all else being equal, silver carp need to consume more
329 per gram body weight to grow than do bighead carp (Alsip et al., 2019). In food-rich
330 environments, this would be a successful strategy as prey abundance would not limit silver carp
331 growth. However, in the food-limited habitats of the Great Lakes, fishes that can survive on less
332 food would likely be more successful. Furthermore, typical species-specific differences in gill
333 raker morphology among the bigheaded carps may change when bighead x silver carp hybrids
334 are produced in the wild. Resulting hybrids can exhibit significant differences in gill raker
335 morphology (Mozsár et al., 2017) that could affect foraging efficiency and, thus, add an
336 additional layer of uncertainty.

337 The interactions between black carp and other FMCC could be affected by the ability of
338 black carp to consume dreissenid mussels (reviewed in Nico et al. 2005). Black carp
339 consumption of large numbers of dreissenid mussels could increase the availability of primary
340 production, which is now sequestered by the mussels, to zooplankton and would benefit
341 bigheaded carps. Such consumption by black carp is unlikely to occur at a lake-wide scale
342 because of cold bottom temperatures in some lakes, but it could occur in isolated patches of
343 warmer preferred temperatures (Drake et al., 2020; Smyth et al., 2020). On the other hand,
344 reduced dreissenid filtration could result in decreased light availability for benthic macrophytes,
345 which would limit food availability to grass carp. Potential interactions between grass and black
346 carps may be weaker when benthic macrophytes are abundant, but then may intensify after
347 benthic macrophytes are greatly reduced and grass carp begin to consume an increasing
348 proportion of the benthos. These uncertainties should be accounted for in bioenergetics modeling
349 efforts, as these potential interspecific interactions could affect FMCC performance in new
350 environments.

351

352 Parametric uncertainty in food web models

353 A food web model can potentially include hundreds of parameters. As such, the largest
354 source of uncertainty in these models involves estimating parameters such as biomass,
355 consumption rate, and diet composition (e.g., Christensen and Walters, 2004). For example,
356 uncertainties in fish biomass estimates could include estimating abundance from catch-per-unit-
357 effort data, converting fish abundance into biomass with averaged individual weight, spatial and
358 temporal averages, and fishing gear catchability. Sensitivity analyses could be conducted to
359 determine the effect of parametric uncertainty on model outputs and to understand where efforts
360 are best placed to reduce parametric uncertainty.

361 Recently, Rutherford et al. (in press) used Ecopath with Ecosim (EwE) food web models
362 (Christensen and Walters, 2004; Heymans et al., 2016) to investigate potential food web effects
363 of bigheaded carps across habitats in Lakes Michigan, Huron, and Erie. The simulated effects of
364 bigheaded carps were highly sensitive to the values set for prey vulnerability, a parameter in the
365 EwE model which integrates many characteristics of the recipient ecosystem that may affect prey
366 consumption by predators. These characteristics include restrictions of predator or prey
367 spatiotemporal distributions through predation avoidance, habitat limitations, agonistic behavior,
368 and physical transport (Ahrens et al., 2012). Prey vulnerability is difficult to measure in the field

369 and tends to be a calibrated parameter. Rutherford et al. (in press) borrowed values of plankton
370 prey vulnerability from reference planktivorous fishes in the model ecosystem, which likely
371 underestimated prey availability to bigheaded carps because invasive species tend to have better
372 feeding efficiency (Cuthbert et al., 2019). Thus, studies that compare feeding efficiency between
373 the FMCC and their food competitors in the same environment would improve estimation of
374 vulnerability and, consequently, biomass and food web impact of the FMCC.

375

376 Parametric uncertainty in bioenergetics models

377 In bioenergetics models, parametric uncertainty has largely resulted from a lack of
378 species-specific parameters and physiological functions. Compared with well-established
379 bioenergetics models (e.g., lake trout; Stewart et al., 1983), current bioenergetics models of
380 bigheaded carps lack species-specific parameters for egestion, excretion, and specific dynamic
381 action (Alsip et al., 2019; Anderson et al., 2017, 2015). Parameter borrowing is a common
382 approach when species-specific information is not available, but finding bioenergetics model
383 parameters of a surrogate fish can be difficult (Ney, 1993). For example, allometric relationships
384 of egestion and excretion for bioenergetics models of bigheaded carps were borrowed from
385 brown trout (*Salmo trutta*; Elliot, 1976), which can be problematic as bigheaded carps do not
386 have true stomachs like brown trout (Kolar et al., 2007). For the grass carp bioenergetics model
387 that includes more species-specific parameters, van der Lee et al. (2017) used a Monte Carlo
388 approach to investigate effects of parametric uncertainty and found that consumption estimates
389 were particularly sensitive to variation in parameters associated with respiration and egestion.

390 Further investigation of respiration parameters is warranted to reduce uncertainty in
391 FMCC bioenergetics models, as respiration accounts for a species' greatest energetic loss, and
392 consumption requirements for bigheaded carps, and likely other FMCC, are quite sensitive to
393 adjustments in respiration parameters (Cooke and Hill, 2010). While there are numerous reports
394 on grass carp oxygen consumption and derived allometric relationships for respiration (reviewed
395 in van der Lee et al., 2017), there is only one set of reported respiration parameters and
396 allometric relationships for each of bighead and silver (Hogue and Pegg 2009), and black carps
397 (Lv et al. 2018; Smyth et al. 2020). Comparing respiration parameters for FMCC between
398 studies can help resolve uncertainties in metabolism. Further, reducing uncertainty in activity
399 costs could refine understanding of the ability of FMCC to maintain weight while moving
400 through colder and less productive regions in the Great Lakes.

401 There also is great uncertainty in the parameters describing foraging and filtration
402 efficiency for FMCC in the Great Lakes. For example, parameters in the model currently used to
403 approximate bighead and silver carp filtration rate as a function of fish weight were derived from
404 juvenile bigheaded carps (Smith, 1989). Recent bioenergetics models have extrapolated this
405 relationship to project growth potential of adult bigheaded carps (4.35–5.48 kg) in Great Lakes
406 habitats (Alsip et al., 2020, 2019; Anderson et al., 2017, 2015; Cooke and Hill, 2010).
407 Additionally, prey- and size-specific foraging rates and filtration efficiencies have not been
408 incorporated into bighead and silver carp bioenergetics models, but experimental work that
409 estimates retention efficiencies, like that of Smith (1989), could be useful. Measuring filtration
410 and retention efficiencies, along with evaluating the effect of size-specific foraging rates on
411 growth potential, should be included in future bioenergetics modeling efforts for bigheaded
412 carps. This is particularly important for reducing uncertainties in growth potential in open water
413 habitats of the Great Lakes where bigheaded carps will be more food limited.

414 The large geographic ranges of the FMCC lead to wide ranges of parameter values
415 reflecting their broad physiological tolerances and plasticity, as well as the various methods and
416 motivations that were behind the research reporting these values (Cooke, 2016). With
417 increasingly wide ranges for parameter values, parameter estimation becomes more uncertain. To
418 address this, Cooke (2016) stated that researchers should account for genotypic variation and
419 phenotypic plasticity among geographically distinct populations. For example, bighead and silver
420 carp spawning patterns in the Wabash River, Indiana, differed from other parts of the world
421 (Coulter et al., 2013). Recent evidence also suggests that genetic variation and differential gene
422 expression can occur at even finer spatial scales (Jeffrey et al., 2019; Stepien et al., 2019).
423 Therefore, the improvement of future models of the FMCC used for Great Lakes risk
424 assessments is dependent on parameter refinement that focuses on deriving physiological
425 parameters from North American populations.

426

427 *Environmental Variation*

428 Environmental variation, also described as natural variation (Peterman, 2004), includes
429 variation in any abiotic and biotic component and/or ecosystem process that is external to FMCC
430 modeling but can theoretically influence model outcomes. Variations in the abiotic environment,
431 including episodic changes in weather (e.g., random variation in climate, in contrast to long-term
432 climate change) and heterogeneity in the aquatic habitat (e.g., lake bottom features or water

433 temperature), may influence variation in the biotic environment, and both can directly influence
434 FMCC modeling. For example, episodic changes in temperature can directly influence FMCC
435 physiological processes, whereas the heterogeneity of light penetration may indirectly affect
436 FMCC model outcomes by altering the distribution and abundance of prey. Although this type of
437 uncertainty cannot be reduced, it must be accounted for in modeling efforts (Williams, 1997).

438 Environmental variation involves temporal or spatial differences in ecosystem
439 components (e.g., distribution of animals and water temperatures) or processes (e.g., predation
440 and consumption; nutrient and energy cycles) and depends on the spatial and temporal scale of
441 observation. Most ecosystem components and processes underlying bioenergetics and food web
442 models exhibit some form of environmental variation, including temperature, primary
443 production, prey availability and energy density, consumption, and trophic transfer efficiency
444 (e.g., Smyth et al., 2020; van der Lee et al., 2017). Therefore, the ability of bioenergetics and
445 food web models to reflect current conditions and project future conditions depends on the
446 degree of environmental variation within an ecosystem, the extent to which models can account
447 for such variation, and whether future conditions will exhibit the same type of variation.

448 Several authors have shown that the projected establishment and impact of the FMCC in
449 the Great Lakes are influenced by environmental variation. The temperatures experienced by the
450 FMCC will differ based on the location of an introduced population, the behavioral
451 thermoregulation of each species, as well as randomness in thermal regime, all of which will
452 drive the timing and intensity of life history processes. Among-year and spatial climate
453 variability will influence temperature-dependent processes in grass and black carps, including the
454 onset of spawning; young-of-year recruitment, growth, and overwinter survival; and, the length
455 of the cold-water period over which grass and black carps limit consumption (Jones et al., 2017;
456 Smyth et al., 2020). Therefore, accounting for temporal and spatial variation in realized thermal
457 use, and other temperature-dependent processes, could be an important source of uncertainty
458 when projecting FMCC impacts in the Great Lakes (e.g., van der Lee et al., 2017).

459 Environmental variation can also manifest as spatial and temporal differences in the
460 availability of prey, with implications for the consumption and impact of FMCC in different
461 habitat areas. For example, the area of food availability provided to bigheaded carps by
462 cyanobacteria blooms in Lake Erie could encompass several hundred to several thousand
463 kilometers, depending on the year of observation (Anderson et al., 2015). These differences,
464 combined with increasing phytoplankton availability during the study period, suggested that a

465 small adult bighead carp could attain 20–81% of body weight in a year based on consumption in
466 open waters of the western basin (Anderson et al., 2015). Phytoplankton availability also has
467 been shown to differ between open waters and coastal embayments in Lake Michigan, raising
468 uncertainty about the ability of bighead carp to maintain weight in the open waters of Lake
469 Michigan (Anderson et al., 2017). The potential for bighead carp to exhibit positive growth in
470 open-water areas of the Great Lakes will differ among lake basins, with positive growth expected
471 in some, but not all, open water environments of the Great Lakes (Anderson et al., 2017, 2015).
472 However, these analyses considered phytoplankton or *Microcystis* as the sole prey resource
473 (Anderson et al., 2017); the availability and use of other planktonic food items, such as
474 dreissenid veligers or detritus (e.g. Alsip et al., 2019) could bolster prey availability.

475 Not all forms of environmental variation can be effectively considered within
476 bioenergetics and food web models. Often, assumptions are made that homogenize model inputs
477 or models are built at such coarse scales that such variability becomes less important (e.g.,
478 Mason and Brandt, 1996). However, to address the critical role of environmental variation
479 (chiefly temperature and food availability) on model outcomes, many authors have favored a
480 simulation approach, whereby the key sources of environmental variation are tested within the
481 modeling effort (e.g., temperature effects in van der Lee et al., 2017; prey utilization in Zhang et
482 al., 2016). As with any modeling effort, it is necessary to communicate the forms of
483 environmental variation being considered and their implications on system dynamics. Effectively
484 accounting for environmental variation within bioenergetics and food web models requires that
485 the temporal and spatial variability of relevant environmental components and processes be well
486 understood before decisions are made regarding model development.

487

488 *Partial Observability*

489 Partial observability (or observation error; Peterman, 2004) results from an imperfect
490 ability to observe true system dynamics (Williams, 1997). There are three aspects that contribute
491 to this uncertainty related to invasive species. First is uncertainty about the ecosystem into which
492 the species will arrive. This can result from monitoring programs that are not adequately
493 designed to detect the information needed to consider invasive species effects, or from a lack of
494 precision in the actual tools and methods used for observation. Second is uncertainty about the
495 invasive species. This is related to parametric uncertainty (see above) and the fact that
496 predictions about ecological impacts will frequently involve extrapolation to new or projected

497 environmental conditions and borrowing parameter values from related species. Finally, there is
498 uncertainty about how a species will interact with a novel ecosystem. Cooke and Hill (2010)
499 were the first to develop a bioenergetics model to assess whether bigheaded carps could survive
500 and grow in the Great Lakes. While some of their model parameters were informed by both
501 existing and new research, they needed to use parameter values from other species (partial
502 observability from extrapolation) and a sample of offshore sites to represent ecosystem
503 conditions (partial observability from existing monitoring programs). They concluded that
504 bigheaded carps could only survive in restricted eutrophic areas of the Great Lakes (e.g., western
505 Lake Erie or Green Bay, Lake Michigan). Anderson et al. (2015) built upon the Cooke and Hill
506 (2010) model by updating it with some species-specific parameter values and used satellite
507 imagery of chlorophyll-*a* to broaden the coverage of ecosystem conditions. Reducing these
508 observation uncertainties resulted in an expanded area of suitable habitat projected for bigheaded
509 carps. Focusing on Lake Michigan, Alsip et al. (2019) evaluated surface and subsurface biomass
510 inputs for three different types of prey (phytoplankton, zooplankton, and detritus), and projected
511 a much larger area of suitable habitat than was projected by Anderson et al. (2017). Contrary to
512 the expectation that uncertainty will expand the possible outcomes from models making them
513 less useful, this example demonstrates that partial observability can underestimate invasion risk.

514

515 *Partial Controllability*

516 Partial controllability (or implementation uncertainty; Peterman, 2004) results from the
517 differences between intended and realized outcomes of management actions (Williams, 1997).
518 Any action for prevention and control can vary in its effectiveness based on unexpected events,
519 catchability of the species, potential errors in predicting the effectiveness of actions, human
520 error, or lack of human willingness to follow management regulations. Some aspects of invasive
521 species management should be under greater control than is faced by natural resource
522 management because more of the actions are carried out by the management agencies. For
523 example, unlike sport or commercial fishing regulations (e.g., catch limits) that rely on
524 stakeholder compliance, invasive species removal efforts are largely enacted by agency staff,
525 leading to less uncertainty related to predicted versus realized effects of the removal action. This
526 should reduce partial controllability associated with a willingness to follow regulations (human
527 nature). However, prevention is also targeted with public outreach and changes in human
528 behavior designed to reduce the risk of moving invasive species (e.g., bait releases, cleaning

529 boats, etc.), which rely on human willingness to apply these actions and would be associated
530 with greater implementation error (Drake et al., 2015). To date, partial controllability has not yet
531 been considered when planning management strategies for FMCC.

532

533 *Linguistic Uncertainty*

534 Linguistic uncertainty, which is a hindrance to biological understanding, includes
535 categories such as vagueness, context dependence, ambiguity, indeterminacy of theoretical
536 terms, and underspecificity (Regan et al., 2002). Many of the efforts at modeling bioenergetics
537 and food web effects of the FMCC on the Great Lakes require diverse teams of researchers. In
538 any team setting, these categories of linguistic uncertainty must be guarded against, such that all
539 members of the research team have complete clarity about model structure, parameter values and
540 descriptions, and other aspects of the model, like spatial and temporal scale. Even in the
541 development of this manuscript, substantial effort was spent by the authors to arrive at a common
542 set of terms. In addition, communication of modeling outcomes to managers and stakeholders
543 requires ensuring that terms are fully understood and agreed upon. Many of these linguistic
544 uncertainties are also related to risk assessment, including discussions around terms such as the
545 “impact” of an invasive species (e.g., ecological impact of grass carp; Cudmore et al., 2017), or
546 how to best define establishment of an invasive species (Kočovský et al., 2018b). In addition,
547 changes in the ecosystem related to invasion risk should be discussed in terms of values and
548 objectives, as modelers and managers may have different perspectives on the effects of different
549 magnitudes of change in a system. For example, a change in fish biomass within the large
550 bounds of uncertainty in a food web model may seem insignificant to a modeler but may be quite
551 concerning to a manager. Finally, the terminology related to FMCC can be confusing for
552 stakeholders and the general public, which can lead to misunderstandings related to model
553 outputs and risk assessments. Kočovský et al. (2018a) described myriad linguistic uncertainties
554 with using the term “Asian carp”, including confusion among the public and professionals about
555 which species are being discussed, confusion in translation to Chinese and other languages, and
556 miscommunication among cultures. Although linguistic uncertainty is not quantified in
557 bioenergetics and food web models, the related confusion can have lasting effects on
558 development of these models and communication of results.

559

560 **Accounting for Important Uncertainty**

561 We have used a decision analytic framework to describe and categorize the uncertainties
562 inherent in modeling the bioenergetic and food web effects of the FMCC on the Great Lakes
563 ecosystem. The list of uncertainties is long, but we argue that there are approaches that can be
564 used to account for and, when possible, reduce these uncertainties. We describe methods for
565 determining how to allocate research effort to most benefit risk assessments and management
566 decisions, as well as approaches to account for irreducible uncertainties in modeling efforts. In
567 all cases, we provide guidance and suggestions (see Table 1 for synthesis) but acknowledge that
568 at times the way to account for these uncertainties is less clear.

569

570 *Structural Uncertainty*

571 Research efforts to reduce or resolve structural uncertainties, such as adaptive
572 management, will likely be part of FMCC control plans in the Great Lakes moving forward (see
573 Robinson et al., this issue and Herbst et al., this issue for an example with grass carp). However,
574 as is the case with most aspects of invasive species control, we have described many sources of
575 structural uncertainty that could be reduced. We suggest that these structural uncertainties could
576 be considered in terms of their ultimate effects on decisions. Those uncertainties that affect a
577 control and prevention decision, and that can be reduced (“important uncertainties”), could then
578 be prioritized for further research and adaptive management efforts (Runge et al., 2011).

579 Determining the value of gathering information about a particular uncertainty can aid
580 biologists and managers in ascertaining the important uncertainties for invasive species impacts,
581 and related aspects of control and prevention. A suite of calculations, known as expected value
582 of information, provides a method for elucidating these important uncertainties (Runge et al.,
583 2011). This method describes the value of gathering new information in terms of the difference
584 between enacting a management or control action after gathering new information and enacting
585 the action without the new information (Raiffa and Schlaifer, 1961; Runge et al., 2011). By
586 calculating the value of new information in terms of gains in outcomes from management
587 actions, research and monitoring efforts can be directed at those uncertainties that have the
588 greatest value of information.

589 Three value of information measures are relevant for bioenergetics and food web
590 modeling of FMCC: expected value of perfect information (EVPI), partial expected value of
591 information (EVPXI), and expected value of sample information (EVSI). Each of these measures
592 provide an understanding of how resolving structural uncertainty, such as what we describe for

593 FMCC, might lead to better overall management and control responses. Expected value of
594 perfect information describes how important a gain in information is to improving the
595 performance of the control or management action (Runge et al., 2011). In cases like FMCC in
596 the Great Lakes, EVPXI highlights how reductions in various components of uncertainty, like
597 particular effects of climate change, can improve management actions, whereas EVSI can
598 indicate how gathering a sample of information, rather than completely resolving an uncertainty,
599 can improve management outcomes (Runge et al., 2011). Each of these measures can be used to
600 inform bioenergetics and food web modeling for FMCC, but they will require the elucidation of
601 specific objectives for control decisions, description of formal models of system uncertainties,
602 and a set of control actions designed to achieve the objectives (Runge et al., 2011).

603 In addition to value of information, scenario planning (Peterson et al., 2003) can be
604 useful for understanding the effects of uncertainties related to climate or land use change on
605 FMCC and their effects on the Great Lakes. By creating plausible scenarios of future climate or
606 land use, researchers can evaluate the relative differences in model outputs under different
607 scenarios. For example, recent work on scenarios of phosphorus loading in Lake Michigan
608 indicated that the growth potential of bigheaded carps is especially responsive to this variable
609 (Alsip et al., 2020). Describing multiple future scenarios and related predictions for ecosystem
610 change is also known as predictive control (Allen and Gunderson, 2011; Game et al., 2014).

611 Although tools like value of information and scenario planning are helpful for elucidating
612 important uncertainties, accounting for all parametric uncertainty in bioenergetics and food web
613 models can be onerous. Sensitivity analyses for these models are difficult to perform and can be
614 resource intensive, but we suggest it is paramount to understand how parameters affect the
615 results of the models. As an example, the Pedigree routine in Ecopath documents the confidence
616 levels of input data based on their origin (Christensen et al., 2008). The uncertainty related to
617 these parameter estimates in Ecopath was evaluated using a Monte Carlo algorithm in the
618 Ecoranger module in earlier model versions (Stewart and Sprules, 2011; Currie et al., 2012).
619 Although the Ecoranger module could provide a heuristic uncertainty analysis for Ecopath input
620 parameters, it was rarely used in published studies owing to a very data intensive task to describe
621 the probabilistic distributions for all input parameters (Christensen et al., 2008). This module was
622 removed in more recent versions of the model but is proposed to be included in future versions.
623 The probabilistic distributions of model parameters associated with FMCC could be identified by
624 a structured expert judgment process, which weights and aggregates expert knowledge on key

625 uncertainties of invasion risk and quantifies uncertainty in a stochastic manner (Wittman et al.
626 2015; Zhang et al. 2016). Concerted efforts to evaluate sensitivity to parametric uncertainty,
627 similar to these examples, will enable researchers to begin to focus on uncertainty reduction.
628 Furthermore, innovative adaptations of tools like structured expert judgement that are common in
629 other disciplines should be explored as a means of addressing uncertainties in FMCC risk
630 assessments.

631

632 *Environmental Variation*

633 Environmental variation can be accounted for at the data gathering and modeling stages.
634 Environmental monitoring can provide modelers with better information about the range of
635 anticipated variation in a system (Williams, 1997), which can enable better control responses for
636 invasive species like the FMCC. For example, when considering the variation in spatial and
637 temporal availability of prey items, monitoring programs can be implemented to identify how
638 prey density varies within the ecosystem. Accounting for this uncertainty in model inputs can
639 ensure that the range of possible outcomes is projected (Nichols et al., 2011). This can be
640 accomplished implicitly, by incorporating the range of potential values for environmental state
641 variables, or explicitly, by linking environmental variables with vital rates through functional
642 relationships, such as a relationship between temperature and survival (Nichols et al., 2011).

643 Earlier we acknowledged structural uncertainty related to climate change and defined
644 environmental variation as any naturally occurring variation unrelated to climate change.
645 Environmental variation includes random variation in climate, which typically occurs at temporal
646 or spatial scales that are finer than those needed to evaluate climate change signals. However,
647 these two sources of uncertainty become more difficult to dissociate when confronting how
648 climate change is presumed to affect environmental variation. Data collected for deriving inputs
649 of ecological models are often assumed to represent stationary processes, but a changing climate
650 will lead to mischaracterization of future environmental variation when using historical data
651 (Johnson et al., 2015; Milly et al., 2008; Nichols et al., 2011). In the face of climate change,
652 Nichols et al. (2011) suggested that models for making management decisions should be
653 developed to incorporate changing probabilistic distributions of environmental variables over
654 time. In addition, models that update probabilistic distributions of environmental variables by
655 more heavily weighting recent monitoring data can begin to account for the future effects of
656 climate change on environmental variability (Johnson et al., 2015). Accounting for projected

657 future changes in environmental variation through evolving probabilistic distributions of external
658 inputs of forcing, or changing the weighting schemes for monitoring data, could be incorporated
659 into bioenergetics and food web models, allowing for shifts in ranges of environmental variables
660 and their ecological effects.

661

662 *Partial Observability*

663 Uncertainty related to partial observability is reducible through increased monitoring
664 efforts and incorporating a diversity of habitats and long-term assessments that can lead to more
665 precise estimates of variables and better information about habitat (Williams, 1997). This is
666 particularly salient when projecting the ecological impacts of invasive species like the FMCC in
667 a novel ecosystem. As with many uncertainties, collecting more data can help to reduce partial
668 observability. For example, the studies described above of increasing habitat information, such
669 as chlorophyll-*a* coverage (Anderson et al., 2015) and depth (Alsip et al., 2019), show how
670 inclusion of more and better data can provide a more accurate projection of habitat suitability for
671 bigheaded carps. If more data can be collected to reduce observation error in parameters that
672 affect the projection of ecological impacts and the decision-making process for control or
673 prevention, then we believe this is the best option available. However, identifying the key
674 uncertainties related to partial observability will often require a value-of-information analysis to
675 first understand where to allocate efforts to reduce these uncertainties. Therefore, it is paramount
676 to account for these uncertainties in predictive models, especially when working with invasive
677 species. When applying a modeling exercise, partial observability can be included by (1)
678 considering alternative model structures, (2) considering the full range of possible states and
679 implications for the assessment of risk or management actions, and (3) fully considering the tails
680 of parameter distributions and the potential for surprises (e.g., Hilborn, 1987). These
681 considerations will enable researchers and managers to understand where to direct efforts for
682 increased monitoring to reduce partial observability, which requires iterative interactions among
683 researchers, managers, and modelers.

684

685 *Partial Controllability*

686 Quantifying uncertainty is a common best practice, and applies to partial controllability.
687 Both the expectation (mean) and distribution of the uncertainty should be specified and could be
688 improved by including covariates that affect the uncertainty. For example, the willingness of

689 individuals to apply control actions may be affected by local conditions. The full range of
690 compliance may span from low to high, but if it is dependent on local conditions, the
691 probabilistic distribution may actually be bimodal. Ultimately, a true understanding should
692 consider the constraints or limitations of management or control actions, as well as policies.

693 By incorporating bioenergetics and food web modeling into a larger decision analysis
694 framework (e.g., structured decision making or adaptive management), ecologists can work with
695 social scientists, decision makers, and managers to understand the full set of management actions
696 and their implementation capacity when building predictive models of ecological impacts.
697 Although predicting human behaviors related to management actions is difficult, including a
698 suite of experts and stakeholders can reduce the uncertainty surrounding the implementation of
699 control actions (Robinson et al., 2019). Models then can be used to evaluate how management
700 strategies are affected by partial controllability. This can be accomplished by building scenarios
701 (e.g., Lauber et al., 2016) that consider the range of events and implementation of management
702 actions, assessing how robust management actions are to implementation uncertainty, and
703 evaluating if managers need multiple tools to manage the consequences of partial controllability
704 (e.g., Coulter et al., 2018).

705

706 *Linguistic uncertainty*

707 Regan et al. (2002) described five sources of linguistic uncertainty and potential means to
708 reduce it. In general, these methods include specifying the context of discussions, clarifying
709 meanings of ambiguous words, narrowing the bounds as much as possible for underspecified
710 data, and using tools for defining borderline cases for vague terms. Linguistic uncertainty causes
711 difficulties in all aspects of decision making and risk assessment, in part because of the range of
712 expertise required for invasive species management, including ecologists, statisticians, managers,
713 stakeholders, and social scientists. The bioenergetics and food web models that project
714 ecological impacts of invasive species provide needed clarity to the decision-making process and
715 can serve as a tool for reduction of linguistic uncertainty (Irwin et al., 2011). By assigning
716 numerical ranges to model parameters and state variables, terms related to the ecological impacts
717 of invasion are clearly defined. Overall, groups involved in assessing risk and making decisions
718 for the control of invasive species like the FMCC must be aware of the potential effects of
719 linguistic uncertainty and make every effort to account for these effects.

720

721 **Conclusions**

722 Multiple types of uncertainty exist when projecting the ecological effects of invasive
723 species in novel habitats like the FMCC in the Great Lakes (Table 1). In this review, we identify
724 uncertainties within bioenergetics and food web models, classify these into an existing typology
725 (Peterman, 2004; Regan et al., 2002; Williams, 1997), and provide tools to account for and
726 reduce key uncertainties. Together, we hope this review will spur continued development and
727 application of broad solutions for these types of uncertainties, thereby improving an
728 understanding of the ecological impacts of FMCC in the Great Lakes basin. Although the scope
729 of this paper was applied to the FMCC and their projected effects on the Great Lakes ecosystem,
730 the typology of uncertainties described herein, and the methods and tools suggested, can be
731 applied to invasive species in almost any aquatic ecosystem (e.g., grass carp in the Colorado
732 River [Brandenburg et al., 2019] or snakehead species in North America [Herborg et al., 2008]).

733 Despite the seemingly overwhelming uncertainties, the models used to make these
734 projections are necessary tools for helping managers and decision makers understand the
735 potential establishment and ecological impacts of invasive species following their introduction
736 because of their ecological realism and ability to account for several aspects of species
737 assimilation within the ecosystem. They also inform a range of critical management questions,
738 such as how reducing abundance of an invasive species can prevent various food web changes.
739 For example, the results of bioenergetics (van der Lee et al., 2017) and population (DuFour et al.,
740 this issue) models for grass carp in Lake Erie informed a subsequent decision analysis to
741 determine optimal actions for grass carp control and key uncertainties for implementation of
742 adaptive management (Robinson et al., this issue).

743 Targeted approaches to reducing identified uncertainties exist and have been reviewed
744 extensively in this paper (Table 1). We do not advocate for a different set of tools to address
745 establishment and impact questions, but rather a refinement of current tools using existing
746 solutions. It is our hope that the synthesis presented here will clarify the range of uncertainties
747 that exist and motivate future research effort towards addressing the unanswered questions
748 related to survival, establishment, and impact of not only the FMCC in the Great Lakes, but
749 aquatic invasive species in general.

750

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762

763 **Literature Cited**

- 764 Abrams, P. A., Matsuda, H. 2004. Consequences of behavioral dynamics for the population
765 dynamics of predator-prey systems with switching. *Popul. Ecol.* 46, 13-25.
- 766 Ahrens, R. N. M., Walters, C. J., Christensen V., 2012. Foraging arena theory. *Fish Fish.* 13, 41–
767 59.
- 768 Allen, C.R., Gunderson, L.H., 2011. Pathology and failure in the design and implementation of
769 adaptive management. *J. Environ. Manage.* 92, 1379–1384.
- 770 Alsip, P.J., Zhang, H., Rowe, M.D., Mason, D.M., Rutherford, E.S., Riseng, C.M., Su, Z., 2019.
771 Lake Michigan's suitability for bigheaded carp: the importance of diet flexibility and
772 subsurface habitat. *Freshw. Biol.* 64, 1921-1939.
- 773 Alsip, P.J., Zhang, H., Rowe, M.D., Rutherford, E., Mason, D.M., Riseng, C., Su, Z., 2020.
774 Modeling the interactive effects of nutrient loads, meteorology, and invasive mussels on
775 suitable habitat for Bighead and Silver Carp in Lake Michigan. *Biol. Invasions* 22, 2763–
776 2785.
- 777 Anderson, C., 2016. Diet Analysis of Native Predatory Fish to Investigate Predation of Juvenile
778 Asian Carp. Western Illinois University.
- 779 Anderson, K.R., Chapman, D.C., Hayer, C.-A., 2016. Assessment of dreissenid biodeposits as a
780 potential food resource for invasive Asian carp. *BioInvasions Records* 5, 251-257.
- 781 Anderson, K.R., Chapman, D.C., Wynne, T.T., Masagounder, K. and Paukert, C.P., 2015.
782 Suitability of Lake Erie for bigheaded carps based on bioenergetics models and remote
783 sensing. *J. Great Lakes Res.* 41, 358-366.

784 Anderson, K.R., Chapman, D.C., Wynne, T.T., Paukert, C.P., 2017. Assessment of
785 phytoplankton resources suitable for bigheaded carps in Lake Michigan derived from remote
786 sensing and bioenergetics. *J. Great Lakes Res.* 43, 90-99.

787 Bosch, N. S., Evans, M.A., Scavia, D., Allan, J.D., 2014. Interacting effects of climate change
788 and agricultural BMPs on nutrient runoff. *J. Great Lakes Res.* 40, 581-589.

789 Brandenburg, W.H., Francis, T.A., Snyder, D.E., Bestgen, K.R., Hines, B.A., Wilson, W.D.,
790 Bohn, S., Harrison, A.S., Clark Barkalow, S.L., 2019. Discovery of grass carp larvae in the
791 Colorado River arm of Lake Powell. *North Am. J. Fish. Manag.* 39, 166–171.

792 Brandt, S.B., D.M. Mason, M.J. McCormick, B. Lofgren, and T.S. Hunger. 2002. Climate
793 Change: Implications for fish growth performance in the Great Lakes. *Am. Fish. Soc. Symp.*
794 32, 61-76.

795 Brinker, S.R., Garvey, M., Jones, C.D., 2018. Climate change vulnerability assessment of species
796 in the Ontario Great Lakes basin. Ontario Ministry of Natural Resources and Forestry,
797 Science and Research Branch, Peterborough, ON. Climate Change Research Report CCEE-
798 48. 85 p. + append.

799 Brooks, A., Zastrow, J., 2002. The potential influence of climate change on offshore primary
800 production in Lake Michigan. *J. Great Lakes Res.* 28, 597–607.

801 Chapman, D.C., Benson, A.J., Embke, H.S., King, N.R., Kočovský, P.M., Lewis, T.D., Mandrak,
802 N.E., This issue. Status of the major aquaculture carps of China in the Laurentian Great
803 Lakes Basin. *J. Great Lakes Res.* This issue.

804 Christensen, V., Walters, C. J., 2004. Ecopath with Ecosim: methods, capabilities and
805 limitations. *Ecol. Model.* 172, 109–139.

806 Christensen, V., Walters, C. J., Pauly, D., Forrest, R., 2008. Ecopath with Ecosim Version 6.
807 User Guide. Vancouver, University of British Columbia.

808 Collingsworth, P.D., Bunnell, D.B., Murray, M.W., Kao, Y.-C., Feiner, Z.S., Claramunt, R.M.,
809 Lofgren, B.M., Höök, T.O., Ludsins, S.A., 2017. Climate change as a long-term stressor for
810 the fisheries of the Laurentian Great Lakes of North America. *Rev. Fish Biol. Fish.* 27, 363–
811 391.

812 Cooke, S. L., 2016. Anticipating the spread and ecological effects of invasive bigheaded carps
813 (*Hypophthalmichthys* spp.) in North America: a review of modeling and other predictive
814 studies. *Biol. Invasions* 18, 315-344.

815 Cooke, S. L. Hill, W.R., 2010. Can filter-feeding Asian carp invade the Laurentian Great Lakes?
816 A bioenergetics modelling exercise. *Freshw. Biol.* 55, 2138-2152.

817 Coulter, A.A., Keller, D., Amberg, J.J., Bailey, E.J., Goforth, R.R., 2013. Phenotypic plasticity
818 in the spawning traits of bigheaded carp (*Hypophthalmichthys* spp.) in novel ecosystems.
819 *Freshw. Biol.* 58, 1029–1037.

820 Coulter, D. P., MacNamara, R., Glover, D. C., Garvey, J.E., 2018. Possible unintended effects of
821 management at an invasion front: reduced prevalence corresponds with high condition of
822 invasive bigheaded carps. *Biol. Cons.* 221, 118-126.

823 Cudmore, B., Mandrak, N.E., Dettmers, J., Chapman, D.C., Kolar, C.S., 2012. Binational
824 Ecological Risk Assessment of Bigheaded Carps (*Hypophthalmichthys* spp.) for the Great
825 Lakes Basin. DFO Can. Sci. Advis. Sec. Res. Doc. 2011/114. vi + 57 p.

826 Cudmore, B., Jones, L.A., Mandrak, N.E., Dettmers, J.M., Chapman, D.C., Kolar, C.S, Conover,
827 G., 2017. Ecological Risk Assessment of Grass Carp (*Ctenopharyngodon idella*) for the
828 Great Lakes Basin. DFO Can. Sci. Advis. Sec. Res. Doc. 2016/118. vi + 115 p.

829 Currie, W. J. S., Cuddington, K. M. D., Stewart, T. J., Zhang, H., Koops, M. A., 2012. Modelling
830 Spread, Establishment and Impact of Bighead and Silver Carps in the Great Lakes. Canadian
831 Science Advisory Research Document 2011/113. 74 pp. www.dfo-mpo.gc.ca/csas-sccs.

832 Cuthbert, R. N., Dickey, J. W. E., Coughlan, N. E., Joyce, P. W. S., Dick, J. T. A. 2019. The
833 Functional Response Ratio (FRR): advancing comparative metrics for predicting the
834 ecological impacts of invasive alien species. *Biological Invasions* 21(8):2543-2547.

835 Czesny, S., Dettmers, J. M., Rinchar, J., Dabrowski, K., 2009. Linking egg thiamine and fatty
836 acid concentrations of Lake Michigan lake trout with early life stage mortality. *J. Aquat.*
837 *Anim. Health* 21, 262-271

838 DeBoer, J.A., Anderson, A.M., Casper, A.F., 2018. Multi-trophic response to invasive silver carp
839 (*Hypophthalmichthys molitrix*) in a large floodplain river. *Freshw. Biol.* 63, 597–611.

840 DeBoer, J. A., Whitten, A. L., Lubinski, B. J., Chick, J. H. 2019. Long-term Survey and
841 Assessment of Large-River Fishes in Illinois, 2018. Illinois Natural History Survey Technical
842 Report 2019 (15).

843 Dettmers, J.M., Goddard, C.I., Smith, K.D. 2012. Management of Alewife using Pacific Salmon
844 in the Great Lakes: whether to manage for economics or the ecosystem? *Fisheries* 37(11):
845 495-501.

846 Dick, J.T.A., Alexander, M.E., Jeschke, J.M., Ricciardi, A., MacIsaac, H.J., Robinson, T.B.,
847 Kumschick, S., Weyl, O.L.F., Dunn, A.M., Hatcher, M.J., Paterson, R.A., Farnsworth, K.D.,
848 Richardson, D.M., 2014. Advancing impact prediction and hypothesis testing in invasion
849 ecology using a comparative functional response approach, *Biological Invasions* 16, 735-
850 753.

851 Drake, D.A.R., Baerwaldt, K., Dettmers, J.M., Nico, L.G., Chapman, D.C., 2020 Ecological Risk
852 Assessment of Black Carp (*Mylopharyngodon piceus*) for the Great Lakes Basin. DFO Can.
853 Sci. Advis. Sec. Res. Doc. 2018/nnn. vi + 186 p.

854 Drake, D.A.R., Mercader, R., Dobson, T., Mandrak, N.E. 2015. Can we predict risky human
855 behaviour involving invasive species? A case study of the release of fishes to the wild.
856 *Biological Invasions* 17, 309-326.

857 DuFour M., Robinson, K.F., Jones, M.L., Herbst, S., This issue. A matrix population model to
858 aid grass carp (*Ctenopharyngodon idella*) management in the Great Lakes Basin – Lake Erie.
859 *J. Great Lakes Res.* This issue.

860 Elliot, J. M., 1976. The Energetics of Feeding, Metabolism and Growth of Brown Trout (*Salmo*
861 *trutta* L.) in Relation to Body Weight, Water Temperature and Ration Size. *J. Anim. Ecol.*
862 45, 923-948.

863 Embke, H.S., Kočovský, P.M., Richter, C.A., Pritt, J.J., Mayer, C.M., Qian, S.S., 2016. First
864 direct confirmation of grass carp spawning in a Great Lakes tributary. *J. Great Lakes Res.* 42,
865 899-903.

866 Foley, C. J., Andree, S. R., Pothoven, S. A., Nalepa, T. F., Höök, T. O. 2017. Quantifying the
867 predatory effect of round goby on Saginaw Bay dreissenids. *J. Great Lakes Res.* 43:121–131

868 Game, E.T., Meijaard, E., Sheil, D., McDonald-Madden, E., 2014. Conservation in a wicked
869 complex world; challenges and solutions. *Conserv. Lett.* 7, 271–277.

870 Gronewold, A. D., Clites, A. H., Smith, J. P., Hunter, T. S., 2015. Impacts of extreme 2013–2014
871 winter conditions on Lake Michigan’s fall heat content, surface temperature, and
872 evaporation. *Geophys. Res. Lett.* 42, 3364–3370.

873 Herborg, L.M., Mandrak, N.E., Cudmore, B.C., MacIsaac, H.J., 2008. Comparative distribution
874 and invasion risk of snakehead (Channidae) and Asian carp (Cyprinidae) species in North
875 America. *Can. J. Fish. Aquat. Sci.* 29, 1723–1735.

876 Herbst, S.J., Nathan, L.R., Newcomb, T.J., DuFour, M.R., Tyson, J., Weimer, E., Buszkiewicz,
877 J., Dettmers, J.M., This issue. An adaptive management approach for implementing multi-
878 jurisdictional response to grass carp in Lake Erie. *J. Great Lakes Res.* This issue.

879 Heymans, J.J., Coll, M., Link, J.S., Mackinson, S., Steenbeek, J., Walters, C., Christensen, V.,
880 2016. Best practice in Ecopath with Ecosim food-web models for ecosystem-based
881 management. *Ecol. Modell.* 331, 173–184.

882 Hilborn, R., 1987. Living with uncertainty in resource management. *N. Am. J. Fish. Manag.* 7, 1-
883 5.

884 Hogue, J. L., Pegg, M. A., 2009. Oxygen consumption rates for bighead and silver carp in
885 relation to life-stage and water temperature. *J. Fish Biol.* 24, 535-543.

886 Hung, N. M., The, D. T., Stauffer, J. R., Madsen, H. 2014. Feeding behavior of black carp
887 *Mylopharyngodon piceus* (Pisces: Cyprinidae) on fry of other fish species and trematode
888 transmitting snail species. *Biol. Control* 72, 118-124.

889 Irwin, B.J., Wilberg, M.J., Jones, M.L., Bence, J.R., 2011. Applying structured decision making
890 to recreational fisheries management. *Fisheries* 36, 113–122.

891 Ivan, L.N., D.M. Mason, D.M., Zhang, H., Rutherford, E.S., Hunter, T. 2020. Potential
892 establishment and ecological effects of bighead and silver carp in a productive embayment of
893 the Laurentian Great Lakes. *Biol Invasions*. doi: 10.1007/s10530-020-02263-z

894 Jackson, M.C., Ruiz-Navarro, A., Britton, J.R., 2015. Population density modifies the ecological
895 impacts of invasive species. *Oikos* 124, 880-887.

896 Jeffrey, J.D., Jeffries, K.M., Suski, C.D., 2019. Physiological status of silver carp
897 (*Hypophthalmichthys molitrix*) in the Illinois River: An assessment of fish at the leading edge
898 of the invasion front. *Comp. Biochem. Physiol. - Part D Genomics Proteomics* 32, 1–12.

899 Johnson, F.A., Boomer, G.S., Williams, B.K., Nichols, J.D., Case, D.J., 2015. Multilevel
900 Learning in the Adaptive Management of Waterfowl Harvests: 20 Years and Counting.
901 *Wildl. Soc. Bull.* 39, 9–19.

902 Johnson T. B., Bunnell, D. B., Knight, C. T., 2005. A potential new energy pathway in central
903 Lake Erie: the round goby connection. *J. Great Lakes Res.* 31, 238–251.

904 Jones, L.A., Drake, D.A.R., Mandrak, N.E., Jerde, C.L., Wittmann, M.E., Lodge, D.M., van der
905 Lee, A.S., Johnson, T.B., Koops, M.A., 2017. Modelling survival and establishment of grass
906 carp, *Ctenopharyngodon idella*, in the Great Lakes Basin. Ottawa, Canada.

907 Kao, Y.-C., Adlerstein, S.A., Rutherford, E.S., 2014. The relative impacts of nutrient loads and
908 invasive species on a Great Lakes food web: An Ecopath with Ecosim analysis. *J. Great*
909 *Lakes Res.* 40, 35–52.

910 Kao, Y.-C., Adlerstein, S.A., Rutherford, E.S., 2016. Assessment of top-down and bottom-up
911 controls on the collapse of alewives (*Alosa pseudoharengus*) in Lake Huron. *Ecosystems* 19,
912 803–831.

913 Kao, Y.-C., Rogers, M.W., Bunnell, D.B., 2018. Evaluating stocking efficacy in an ecosystem
914 undergoing oligotrophication. *Ecosystems* 21, 600–618.

915 Kitchell, J.F., Koonce, J.F., Magnuson, J.J., O’Neill, R. V., Shugart, H.H., Booth, R.S., 1974.
916 Model of fish biomass dynamics. *Trans. Am. Fish. Soc.* 103, 786–798.

917 Kočovský, P.M., Chapman, D.C., McKenna, J.E., 2012. Thermal and hydrologic suitability of
918 Lake Erie and its major tributaries for spawning of Asian carps. *J. Great Lakes Res.* 38, 159–
919 166.

920 Kočovský, P.M., Chapman, D.C., Qian, S., 2018a. “Asian Carp” is societally and scientifically
921 problematic. Let’s replace it. *Fisheries* 43, 311–316.

922 Kočovský, P.M., Sturtevant, R., Schardt, J., 2018b. What it is to be established: Policy and
923 management implications for non-native and invasive species. *Manag. Biol. Invasions* 9,
924 177–185.

925 Kolar, C. S., Chapman, D. C., Courtenay, J. W. R., Housel, C. M., Williams, J. D., Jennings, D.
926 P., 2007. Bigheaded carps: a biological synopsis and environmental risk assessment. Special
927 Publication 33. American Fisheries Society, Bethesda.

928 LaBeau M.B., Robertson D.M., Mayer A.S., Pijanowski, B.C., Saad, D.A., 2014. Effects of
929 future urban and biofuel crop expansions on the riverine export of phosphorus to the
930 Laurentian Great Lakes. *Ecol. Modell.* 277, 27–37.

931 Lauber, T.B., Stedman, R.C., Connelly, N.A., Rudstam, L.G., Ready, R.C., Poe, G.L., Bunnell,
932 D.B., Höök, T.O., Koops, M.A., Ludsin, S.A., Rutherford, E.S., 2016. Using scenarios to
933 assess possible future impacts of invasive species in the Laurentian Great Lakes. *N. Am. J.*
934 *Fish. Manag.* 36, 1292-1307.

935 Lennox, R.J., Bravener, G.A., Lin, H., Madenjian, C.P., Muir, A.M., Remucal, C.K., Robinson,
936 K.F., Rous, A.M., Siefkes, M.J., Wilkie, M.P., Zielinski, D.P., Cooke, S.J., 2020. Potential
937 changes to the biology and challenges to the management of invasive sea lamprey
938 *Petromyzon marinus* in the Laurentian Great Lakes due to climate change. *Glob. Chang.*
939 *Biol.* 1–20. <https://doi.org/10.1111/gcb.14957>

940 Lenters, J. D., Anderton, J. B., Blanken, P. D., Spence, C., Suyker, A. E., 2013. Assessing the
941 impacts of climate variability and change on Great Lakes evaporation: Implications for water
942 levels and the need for a coordinated observation network. *Great Lakes Integrated Sciences*
943 *and Assessments Center Project Rep.*, 11 pp.

944 Lin, H-R., 1982. Polycultural system of freshwater fish in China. *Can. J. Fish. Aquat. Sci.* 39,
945 143–150.

946 Locher, T.W., 2018. Blue catfish (*Ictalurus furcatus*) piscivory on invasive bigheaded carps in
947 the Mississippi River Basin. Western Illinois University.

948 Lv, X., Xie, H., Xia, D., Shen, C., Li, J., Luo, Y. 2018. Mass scaling of the resting and maximum
949 metabolic rates of the black carp. *J. Comp. Physiol. B* 188, 591-598.

950 Madenjian, C.P., O’Gorman, R., Bunnell, D.B., Argyle, R.L., Roseman, E.F., Warner, D.M.,
951 Stockwell, J.D., Stapanian, M.A., 2008. Adverse effects of alewives on Laurentian Great
952 Lakes fish communities. *N. Am. J. Fish. Manage.* 28, 263–282.

953 Mandrak, N.E. 1989. Potential invasion of the Great Lakes by fish species associated with
954 climatic warming. *Journal of Great Lakes Research* 15(2): 306-316.

955 Mason, D. M., Brandt, S. B. 1996. Effect of alewife predation on survival of larval yellow perch
956 in an embayment of Lake Ontario. *Can. J. Fish. Aquat. Sci.* 53, 685-693.

957 McCormick, M. J., Fahnenstiel, G. L., 1999. Recent climatic trends in nearshore water
958 temperatures in the St. Lawrence Great Lakes. *Limnol. Oceanogr.* 44, 530–540.

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

966 Mills, E.L., Leach, J.H., Carlton, J.T., Secor, C.L., 1993. Exotic species in the Great Lakes: a
967 history of biotic crises and anthropogenic introductions. *J. Great Lakes Res.* 19, 1–54.

968 Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier,
969 D. P., Stouffer, R. J. 2008. Stationarity is dead: whither water management? *Science.* 319,
970 573–574.

971 Minder, M., Pyron, M., 2018. Dietary overlap and selectivity among silver carp and two native
972 filter feeders in the Wabash River. *Ecol. Freshw. Fish* 27, 506–512.

973 Mozsár, A., Specziár, A., Battonyai, I., Borics, G., Görgényi, J., Horváth, H., Présing, M., G.-
974 Tóth, L., Vitál, Z., Boros, G., 2017. Influence of environmental factors and individual traits
975 on the diet of non-native hybrid bigheaded carp (*Hypophthalmichthys molitrix* × *H. nobilis*)
976 in Lake Balaton, Hungary. *Hydrobiologia* 794, 317–332.

977 Murdoch, W.W. 1969. Switching in general predators: Experiments on predator specificity and
978 stability of prey populations. *Ecological Monographs* 39, 335-354.

979 Murdoch, W.W., Avery, S., Smyth, M.E.B. 1975. Switching in predatory fish. *Ecology* 56, 1094-
980 1105.

981 Ney, J. J., 1993. Bioenergeticss modeling today: growing pains on the cutting edge. *Trans. Am.*
982 *Fish. Soc.* 122,736– 748

983 Nichols, J.D., Koneff, M.D., Heglund, P.J., Knutson, M.G., Seamans, M.E., Lyons, J.E., Morton,
984 J.M., Jones, M.T., Boomer, G.S., Williams, B.K., 2011. Climate change, uncertainty, and
985 natural resource management. *J. Wildl. Manage.* 75, 6–18.

986 Nico, L.G., Williams, J. D., Jelks, H. L., 2005. Black Carp: biological synopsis and risk
987 assessment of an introduced fish. *Am. Fish. Soc. Spec. Publ.* 32. Bethesda. MD. 337 p.

988 Notaro, M., Homan, K., Zarrin, A., Fluck, E, Vavrus, S., Bennington, V., 2013. Influence of the
989 Laurentian Great Lakes on regional climate. *J. Climate* 26, 789-804.

990 Paerl, H. W., Huisman, J., 2009. Blooms like it hot. *Science* 320, 57-58.

991 Peterman, R.M., 2004. Possible solutions to some challenges facing fisheries scientists and
992 managers. *ICES J. Mar. Sci.* 61, 1331-1343.

993 Peterson, G.D., Cumming, G.S., Carpenter, S.R., 2003. Scenario planning: a tool for
994 conservation in an uncertain world. *Conserv. Biol.* 17, 358–366.

995 Raiffa, H., Schlaifer, R.O., 1961. *Applied Statistical Decision Theory.* Graduate School of
996 Business Administration. Harvard University, Cambridge, MA, USA.

997 Reavie, E.D., Sgro, G.V., Estepp, L.R., Bramburger, A. J., Shaw, V. L., Chraïbi, Pillsbury, R.
998 W., Cai, M, Stow, C.A., Dove, A., 2017. Climate warming and changes in *Cyclotella sensu*
999 *lato* in the Laurentian Great Lakes. *Limnol. Oceanog.* 62, 768–783.

1000 Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A taxonomy and treatment of uncertainty for
1001 ecology and conservation biology. *Ecol. Appl.* 12, 618–628.

1002 Robinson, K.F., DuFour, M., Jones, M., Herbst, S., Newcomb, T., Boase, J., Brenden, T.,
1003 Chapman, D., Dettmers, J., Francis, J., Hartman, T., Kočovský, P., Locke, B., Mayer, C.,
1004 Tyson, J., This issue. Using decision analysis to collaboratively respond to invasive species
1005 threats: A case study of Lake Erie grass carp (*Ctenopharyngodon idella*). *J. Great Lakes Res.*
1006 <https://doi.org/10.1016/j.jglr.2020.03.018>, This issue

1007 Robinson, K.F., Fuller, A.K., Stedman, R.C., Siemer, W.F., Decker, D.J., 2019. Integration of
1008 social and ecological sciences for natural resource decision making: challenges and
1009 opportunities. *Environ. Manage.* 63, 565–573.

1010 Runge, M.C., Converse, S.J., Lyons, J.E., 2011. Which uncertainty? Using expert elicitation and
1011 expected value of information to design an adaptive program. *Biol. Conserv.* 144, 1214–
1012 1223.

1013 Rutherford, E.S., Zhang, H., Kao, Y-C, Mason, D.M., Shakoor, A., Bouma-Gregson, K., Breck,
1014 J., Lodge, D., Chadderton, W.L. In press. Potential effects of bigheaded carps on four Great
1015 Lakes food webs. *N. Am. J. Fish. Manag.*

1016 Sampson S.J., Chick J.H., Pegg M.A., 2009. Diet overlap among two Asian carp and three native
1017 fishes in backwater lakes on the Illinois and Mississippi rivers. *Biol. Invasions* 11, 483–496.

1018 Sanft, E., Parkos, Jr., J. J., Collins, S. F., Porreca, A. P., Wahl, D. H., 2018. Vulnerability of
1019 juvenile bighead and silver carps to predation by largemouth bass. *Trans. Am. Fish. Soc.* 147,
1020 1207–1214.

1021 Smith, D. W., 1989. The feeding selectivity of silver carp, *Hypophthalmichthys molitrix* Val. *J.*
1022 *Fish Biol.*, 34, 819–828.

1023 Smyth, E.R.B., Drake, D.A.R., Koops, M.A., van der Lee, A.S., Hossain, M. M., Morris, T.J.,
1024 Woolnough, D.A., Barbati, J., 2020. Modelling arrival, establishment, spread, and ecological
1025 impacts of black carp, *Mylopharyngodon piceus*, in the Great Lakes Basin. *DFO Can. Sci.*
1026 *Advis. Sec. Res. Doc.* 2018/nnn. vi + 253 p.

1027 Stepien, C.A., Snyder, M.R., Elz, A.E., 2019. Invasion genetics of the silver carp
1028 *Hypophthalmichthys molitrix* across North America: Differentiation of fronts, introgression,
1029 and eDNA metabarcoding detection, PLoS ONE. <https://doi.org/10.1371/journal.pone.0203012>
1030 Stewart, D.J., Weininger, D., Rottiers, D.V., Edsall, T.A., 1983. An energetics model for lake
1031 trout, *Salvelinus namaycush*: application to the Lake Michigan population. Can. J. Fish.
1032 Aquat. Sci. 40, 681-698.

1033 Stewart, T. J., Sprules, W. G., 2011. Carbon-based balanced trophic structure and flows in the
1034 offshore Lake Ontario food web before (1987–1991) and after (2001–2005) invasion-induced
1035 ecosystem change. Ecol. Modell. 222, 692–708.

1036 Sturtevant, R.A., Mason, D.M., Rutherford, E.S., Elgin, A., Lower, E., Martinez, F., 2019.
1037 Recent history of nonindigenous species in the Laurentian Great Lakes; An update to Mills et
1038 al., 1993 (25 years later). J. Great Lakes Res. 45, 1011–1035.

1039 Thomas, S. C., Chick, J. H., Czesny, S. J., 2017. Underestimation of microzooplankton is a
1040 macro problem: One size fits all zooplankton sampling needs alterations. J. Great Lakes Res.
1041 43, 91–101.

1042 van der Lee, A.S., Johnson, T.B., Koops, M.A., 2017. Bioenergetics modelling of grass carp:
1043 estimated individual consumption and population impacts in Great Lakes wetlands. J. Great
1044 Lakes Res. 43, 308-318.

1045 Vanderploeg, H. A., Johengen, T. H., Liebig, J. R., 2009. Feedback between zebra mussel
1046 selective feeding and algal composition affects mussel condition: did the regime changer pay
1047 a price for its success? Freshw. Biol. 54,47-63.

1048 Vörös, L., Oldal, I., Présing, M., Balogh, K.V., 1997. Size-selective filtration and taxon-specific
1049 digestion of plankton algae by silver carp (*Hypophthalmichthys molitrix* Val.). Hydrobiologia
1050 342, 223-228.

1051 Williams, B.K., 1997. Approaches to the management of waterfowl under uncertainty. Wild.
1052 Soc. Bull. 25, 714-720.

1053 Willson, J.D., Dorcas, M.E., Snow, R.W., 2011. Identifying plausible scenarios for the
1054 establishment of invasive Burmese pythons (*Python molurus*) in Southern Florida. Biol.
1055 Invasions 13, 1493–1504.

1056 Winberg, G. G., 1956. Rate of metabolism and food requirements of fishes. Fisheries Research
1057 Board of Canada, Translation Series 194, Biological Station, Nanaimo, British Columbia,
1058 Canada.

1059 Wittmann, M. E., Cooke, R. M., Rothlisberger, J. D., Rutherford, E. S., Zhang, H., Mason, D.
1060 M., Lodge, D. M., 2015. Use of structured expert judgment to forecast invasions by bighead
1061 and silver carp in Lake Erie. *Cons. Biol.* 29,187–197.

1062 Wolf, M. C., Phelps, Q. E., 2017. Prey selectivity of common predators on silver carp
1063 (*Hypophthalmichthys molitrix*): controlled laboratory experiments support field observations.
1064 *Env. Biol. Fish.* 100, 1139–1143.

1065 Xue, P., Pal, J. S., Ye, X. Lenters, J. D., Huang, C., Chu, P. Y., 2017. Improving the simulation
1066 of large lakes in regional climate modeling: two-way lake–atmosphere coupling with a 3D
1067 hydrodynamic model of the Great Lakes. *J. Clim.* 30, 1605-1627.

1068 Zhang, H., Rutherford, E.S., Mason, D.M., Beck, J.T., Wittmann, M.E., Cooke, R.M., Lodge,
1069 D.M., Rothlisberger, J.D., Zhu, X. and Johnson, T.B., 2016. Forecasting the impacts of
1070 silver and bighead carp on the Lake Erie food web. *Trans. Am. Fish. Soc.* 145, 136-162.

1071 Zhang, H., Rutherford, E.S., Mason, D.M., Wittmann, M.E., Lodge, D.M., Zhu, X., Johnson,
1072 T.B., and Tucker, A., 2019. Modeling potential impacts of three benthic invasive species on
1073 the Lake Erie food web. *Biol. Invasions* 21, 1697-1719.

1074 Table 1. Summary of the five types of uncertainty covered in this paper including their definitions, relevance to models of the four
 1075 major Chinese carps (FMCC), techniques for addressing, research needs for reducing, and examples of relevant references.
 1076

Type of Uncertainty	Description	Relevance to FMCC modeling	Techniques for addressing uncertainties	Research needs to reduce or account for uncertainty	Examples of relevant references
Structural	An epistemic uncertainty related to biological and ecological processes of the modeled system; classified as either functional or parametric.	<ul style="list-style-type: none"> • Effects of environmental drivers and trophic interactions on FMCC (Functional) • Lack of information on certain bioenergetics or food web model parameters (Parametric) 	<ul style="list-style-type: none"> • Sensitivity analysis to identify priority parameters where efforts to reduce parametric uncertainty would be best focused • Monte Carlo analysis to quantify parametric uncertainty • Institute measures of value of information • Scenario planning • Structured expert judgement • Adaptive management 	<ul style="list-style-type: none"> • Resolving uncertainty related to climate change effects on prey biomass and trophic interactions • Narrowed estimates of recruitment for FMCC • Reliable prey biomass estimates and evaluation of potentially novel foods • Predator adaptability to FMCC as prey • Interactions among FMCC • Species-specific bioenergetics parameters • Foraging efficiency of adult FMCC 	<p>Alsip et al. (2020)</p> <p>Coulter et al. (2018)</p> <p>Ivan et al. (2020)</p> <p>Robinson et al. (this issue)</p> <p>Wittman et al. (2015)</p> <p>Zhang et al. (2016)</p>
Environmental variation	An aleatory uncertainty dependent on scale of observation; includes random variation in weather and	<ul style="list-style-type: none"> • Affects all stages of model development, parameterization, validation, and forecasting • Underlying processes and ecosystem 	<ul style="list-style-type: none"> • Model probabilistic distributions of potential values for environmental state variables • Account for predicted future changes in environmental 	<ul style="list-style-type: none"> • Establishment of long-term monitoring programs can provide better information about the anticipated variation in a system 	<p>Alsip et al. (2020)</p> <p>Jones et al. (2017)</p> <p>Smyth et al. (2020)</p> <p>van der Lee et al. (2017)</p>

spatiotemporal heterogeneity in aquatic systems.

components in models are affected by variation in temperature and aquatic habitat, which influences primary production, prey availability, energetic quality of prey, consumption and trophic transfer efficiency

variation (rather than assuming stationarity in environmental processes) through evolving probabilistic distributions, allowing for shifts in ranges of environmental variables

- Link environmental variables with vital rates through functional relationships, such as a relationship between temperature and survival

<p>Partial observability</p>	<p>An epistemic uncertainty resulting from our imperfect ability to observe true system dynamics</p>	<ul style="list-style-type: none"> • Lack of adequate monitoring programs tracking recipient ecosystem components • Lack of data on FMCC ecology and physiology leads to extrapolating from other species • No information on how FMCC interact with a given novel environment 	<ul style="list-style-type: none"> • Consider alternative model structures • Consider the full range of possible states and implications for risk assessment or management actions • Consider the tails of parameter distributions and the potential for surprises 	<ul style="list-style-type: none"> • Implementation of a value of information analysis to identify where and how best to allocate monitoring efforts • Establishment of monitoring programs tracking relevant ecosystem components 	<p>Alsip et al. (2019)</p> <p>Anderson et al. (2017, 2015)</p> <p>Cooke and Hill (2010)</p>
<p>Partial controllability</p>	<p>Uncertainty resulting from differences in intended and</p>	<ul style="list-style-type: none"> • The realized effects of management decisions informed by models may 	<ul style="list-style-type: none"> • Specify the expectation and probabilistic distribution of the uncertainty 	<ul style="list-style-type: none"> • Increased understanding of the range of possible 	<p>Coulter et al. (2018)</p> <p>Drake et al. (2015)</p>

	realized outcomes	differ from the predicted efficacy on prevention and control strategies due to human behavior, unexpected events, catchability of a species, prediction error, or human error	<ul style="list-style-type: none"> • Identify important covariates that affect uncertainty • Consider constraints of management or control actions • Incorporate modeling into larger decision analytic framework 	events and management actions <ul style="list-style-type: none"> • Assessment of the effect of robust management actions on implementation uncertainty 	<p>Lauber et al. (2016)</p> <p>Robinson et al. (2019)</p>
Linguistic	Limitation of biological understanding due to vagueness, context dependence, ambiguity, indeterminacy of theoretical terms, and underspecificity	<ul style="list-style-type: none"> • “Asian Carp(s)” is a term used to describe four ecologically distinct species • What constitutes an ecosystem impact? • How do we define establishment? • How do managers and modelers value projected model outputs? 	<ul style="list-style-type: none"> • Specify context of discussions, clarify meanings of ambiguous words, and use tools for defining borderline cases for vague terms • Clarify model parameters related to ecological consequences in an intelligible manner for managers and stakeholders • When not collectively referring to all FMCC, specify the distinct species in scientific publications and all communications 	<ul style="list-style-type: none"> • Identification, review, and synthesis of potentially problematic terms • Diverse input to modeling exercises 	<p>Kočovský et al. (2018a)</p> <p>Kočovosky et al. (2018b)</p>