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11 3 **The confluences of ideas leading to, and the flow of ideas emerging from, individual-based**
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13 4 **modeling of riverine fishes**
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4 22 **Abstract**
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7 23 In this review article, we trace the history of events leading to the development of individual-based
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9 24 models (IBMs) to represent aquatic organisms in rivers and streams. As a metaphor, we present this
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11 25 history as a series of confluences between individual scientists sharing ideas. We describe contributions
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13 26 of these models to science and management. One iconic feature of river IBMs is the linkage between
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15 27 flow and the physical habitat experienced by individuals, and the first model that focused on this linkage
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17 28 is briefly described. We continue by reviewing the contributions of riverine IBMs to eight broad areas of
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19 29 scientific inquiry. The first four areas include research to understand 1) the effects of flow regimes on
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21 30 fish populations, 2) species interactions (e.g., size-mediated competition and predation), 3) fish
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23 31 movement and habitat selection, and 4) contaminant and water quality impacts on populations. Next,
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25 32 we review research using IBMs 5) to guide conservation biology of imperiled taxa through population
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27 33 viability analysis, including research 6) to understand fragmentation and reconnection, 7) to understand
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29 34 genetic outcomes for riverine metapopulations, and 8) to anticipate the future effects of temperature
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31 35 and climate change. This rich body of literature has contributed to both theoretical insights (e.g., about
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33 36 animal behavior and life history) and applied insights (e.g., population-level effects of flow regimes,
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35 37 temperature, and the effects of hydropower and other industries that share rivers with aquatic biota).
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38 38 We finish by exploring promising branches that lie ahead in the braided channel that represents future
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40 39 river modeling research.

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43 42 We dedicate this paper to Dr. Webster Van Winkle, who passed away March 29, 2018. Webb was a
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45 43 facilitator of, and pioneer in, IBM modeling and coauthor of the first IFIM-type river IBMs.

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4 44 **1. Individual confluences passing streams of memes**
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7 45 Ideas in science rarely emerge intact. Rather the conditions leading to new ideas or 'memes' spring up in
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9 46 different places and follow independent paths that then converge, merge, and spread. This was true for
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11 47 individual-based modeling (IBM), and later, the development of IBMs for biota in rivers and streams.
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14 48 Ideas flowing out of tributaries carried advances in computer science, theoretical ecology (e.g., optimal
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16 49 foraging theory), forest-gap modeling, and physical modeling of dynamic stream habitat.
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20 50 These ideas co-mingled to generate a diverse, braided complex of downstream channels that continues
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22 51 to bring new insights (Figure 1). These downstream channels are different in size. A large productive
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24 52 inSTREAM modeling community of users is an important example. In addition, the initial EPRI models fed
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26 53 into genetic IBMs (IBM+G) and other variants and these have been used to address a wide variety of
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29 54 basic and applied scientific questions.
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33 55 [Figure 1]
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36 56 The use of individual-based modeling in ecology, as depicted in Figure 1, emerged initially at the
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38 57 confluence between silvicultural problems (one tributary branch) and technological progress (another
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40 58 tributary) in the early 1970's. The technological advance was the increasing power of computers, while
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42 59 the motivating problems involved how to optimize planted forests; e.g., what trees to plant, and how to
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44 60 space them (Shugart et al., 2018; Shugart and Woodward, 2011). Computational power allowed Yale
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46 61 ecologist Daniel Botkin to model a forest in the way that he thought it really worked mechanistically.
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49 62 Working with James Wallis and James Janak of IBM's Thomas J. Watson Research Center, Botkin
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51 63 simulated the growth of individual trees of different species as accurately as possible, given their basic
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54 64 traits and local soil and climate conditions, and then let trees from different species interact on a small
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57 65 plot through mutual competition for light. This general type of model was termed an 'individual-based
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60 66 model', or, coincidentally, IBM.
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4 67 JABOWA was called a 'gap-phase replacement' model because the spatial area simulated was about the
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6 68 size of a gap left by the death of a large canopy tree (Botkin et al., 1972). JABOWA predicted the
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8 69 successional dynamics of tree communities in a New Hampshire forest so well that forest ecologists such
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10 70 as Bormann and Likens (1979) used it to derive their ideas about biomass accumulation in aggrading
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12 71 forests. Hank Shugart and Darrell West, then research ecologists at Oak Ridge National Laboratory, soon
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14 72 developed a version of a gap-phase replacement IBM named FORET (Shugart and West, 1977) and other
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16 73 models followed, as reviewed by Bugmann (2001). By now scores of different forest simulation
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18 74 platforms with a high degree of detail and sophistication exist and are applied world-wide.
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24 75 Two factors made fish the next candidate for extensive application of individual-based modeling. The
25
26 76 first factor is that individual size is an important characteristic for piscivorous fish, as it was for trees. As
27
28 77 gape-limited predators, size influences the foraging success of fish and their ability to escape predation
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30 78 by other fishes. Individual differences in size within a cohort could therefore influence the dynamics of
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32 79 that cohort. DeAngelis et al. (1980) demonstrated this for a cohort of young-of-the-year largemouth
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34 80 bass (*Micropterus salmoides*) in an aquarium. Depending on the initial size distribution, varying degrees
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36 81 of cannibalism could occur within the cohort, leading to a final number of surviving fish after a couple of
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38 82 months. The IBM, which followed every fish in the cohort through time, was able to predict the
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40 83 outcomes of two successive aquarium experiments surprisingly well.
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46 84 The second factor favoring development of IBMs for fish was the need to understand the effects of
47
48 85 mortality of fish though entrainment and impingement by nuclear power plant cooling systems (Figure
49
50 86 1). A key question was to what extent compensatory mechanisms in the fish populations could mitigate
51
52 87 the loss of perhaps billions of eggs, larval, and other early life-stage fish. At high densities, few offspring
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54 88 of such species survive to adulthood due to density-dependent mortality. The loss of some fish by non-
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56 89 natural factors such as power plants increases resources available to others. Therefore, increased
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4 90 mortality imposed by anthropogenic sources was proposed by some scientists to have little net effect on
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6 91 recruitment to the adult stage.
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10 92 To understand and quantify how such compensatory mechanisms work in fish populations, the Electric
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12 93 Power Research Institute (EPRI) funded a 10-year project, "Compensatory Mechanisms in Young-of-the-
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14 94 Year Fish", at Oak Ridge National Laboratory (ORNL), which already had a long history of studying the
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16 95 effects of power plants on fish (Barnthouse et al., 1984; Boreman et al., 1981; Coutant, 1971). The
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18 96 project, led by Dr. Webster Van Winkle and stimulated by the success of IBM forest simulations by
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20 97 colleagues at ORNL, used the IBM approach to try to understand the complex processes of growth and
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22 98 mortality of young-of-year (YOY) fish of species potentially impacted by nuclear power plants. At
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24 99 universities across North America, PhD students funded by EPRI developed such models, in the process
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26 100 training a generation of fish ecologists in modeling. Following the 'Wisconsin' school of fish modeling,
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28 101 the bioenergetics of each fish was modeled in these IBMs, and large numbers of young-of-year fish were
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30 102 simulated, along with food resources and predation, to estimate the effects of power plants and other
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32 103 mortality factors. Early papers were published by DeAngelis et al. (1990), Madenjian et al. (1991), and
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34 104 Deangelis et al. (1991) for fish in lakes. DeAngelis et al. (1993) predicted patterns of recruitment vs. egg
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36 105 density and the transition from density-dependent to density-independent mortality in YOY fish that
37
38 106 agreed well with empirical patterns. Scheffer et al. (1995) introduced the key IBM modeling technique of
39
40 107 'super individuals' to efficiently simulate huge numbers of YOY, most of which die in the first year of life.
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42 108 Applications of IBMs to fishes were reviewed by (VanWinkle et al., 1993) and more recently by Sibly et
43
44 109 al. (2013). The growth in IBMs during the late 1980s in all areas of ecology and across taxa stimulated
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46 110 both a review paper of individual-based modeling in general (Huston et al., 1988) and a workshop at the
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48 111 University of Tennessee in 1990, published as a proceedings (DeAngelis and Gross, 1992, editors). In a
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50 112 subsequent review, (DeAngelis and Mooij, 2005) counted over 900 manuscripts using IBMs, over 100 of
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4 113 which were applied to fish, though these numbers were surely underestimates. The monograph of
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6 114 Grimm and Railsback (2005) advanced the theoretical foundations for individual-based modeling.
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10 115 Modeling of individual activities was influenced by bioenergetics modeling (e.g., the 'Wisconsin' school
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12 116 for fishes, mostly centered on lake fishes), optimal foraging theory, and theories related to habitat
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14 117 selection and movement (Figure 1). These component sub-models used to represent individual activities
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16 118 formed the backbone of IBMs. Other early papers described IBMs of riverine populations. (Petersen and
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18 119 Deangelis, 1992) simulated northern pike fish (formerly squawfish, *Esox lucius*) predation on juvenile
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20 120 salmon, addressing the question of how schooling of downstream swimming smolts reduced predation
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22 121 risk in a Columbia River reservoir, and Rose and Cowan (1993) simulated striped bass in the Potomac
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24 122 River.
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27 123 Arguably, river IBMs differ from those applied to organisms in other ecosystems because the dynamic
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29 124 and directional changes in river habitat are such an important influence on species' life histories. Thus,
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31 125 the ability to simulate population-level responses to flow as an outcome of individual behaviors is a
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33 126 defining characteristic, and development of river IBMs depended on the convergence of two tributary
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35 127 ideas. One tributary carried the biological IBM and the other carried the Instream Flow Incremental
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37 128 Methodology or IFIM (Orth and Maughan, 1982). Used to establish minimum flows for fishes below
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39 129 dams in the United States, the IFIM has two components; (1) physical habitat modeling (for the variables
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41 130 depth, velocity, and cover) and (2) representation of species preferences for these three habitat
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43 131 variables (Bovee, 1982; Thomas and Bovee, 1993). Because preference curves are not flow-invariant and
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45 132 do not necessarily reflect a species' habitat requirements over time well, the IFIM generated
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47 133 controversy from its inception (Mathur et al., 1985; Railsback, 2016). In the confluence of the 1980s, Dr.
48
49 134 Mike Sale, a recently-hired environmental engineer, brought his experience with IFIM models to Oak
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51 135 Ridge, where he recognized the potential for applying IBMs in river ecosystems. The confluence of ideas
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53 136 among theoretical modelers, environmental engineers, and aquatic ecologists in East Tennessee

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4 137 spawned many uses of IFIM models using IBMs to study riverine fishes. These tools have produced
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6 138 numerous insights, not just in understanding flow responses by fishes and reducing uncertainty in
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8 139 instream-flow standards (VanWinkle et al., 1997), but also in understanding biological processes. Below
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10 140 we will highlight aspects specific to lotic habitats.
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15 141 Over the years, individual- or agent-based modeling has evolved (DeAngelis and Grimm, 2014). For
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17 142 example, computation times were reduced through the use of various 'cloning' methods for
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19 143 representing meta-individuals started to be used (Rose et al., 1993). An attractive feature of IBMs as
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21 144 mechanistic process-based models is the ability to 'validate-by-parts' and to compare against
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23 145 intermediate outputs. New techniques were adopted for model-data comparison. One is to compare
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25 146 patterns produced by the model against those observed (e.g., the use of pattern-oriented model
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27 147 evaluation (Grimm and Railsback, 2012; Grimm et al., 2005), which is similar to 'functional validation'
28
29 148 (Jager et al., 2000). The pattern-oriented approach can be used to select among alternative model
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31 149 structures that differ in complexity. A protocol for documenting IBMs was developed (Grimm et al.,
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33 150 2010). In addition, significant advances have been made in developing new methods for incorporating
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35 151 historical data and producing a distribution of model outcomes from a likelihood-weighted joint
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37 152 distribution of input parameters [e.g., approximate Bayesian computational methods (Piou et al., 2009)].
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39 153 Developments specific to riverine IBMs include alternative approaches to representing dynamic stream
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41 154 habitat (hydrodynamics, stream temperature and water quality), simulation of animal movement in a
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43 155 directional flow environment, and models that use network theory as a basis for representing dendritic
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45 156 riverine metapopulations. These advances are described in the sections below.
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54 157 In this paper, we trace the ideas leading to modeling of river fish populations using IBMs, we highlight
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56 158 some of the key contributions IBMs have made to understanding aquatic populations in river habitat,
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58 159 and we suggest future opportunities for new discoveries.
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4 160 **2. Headwaters of riverine IBMs**
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7 161 One of the first IBMs applied to riverine populations in the early 1990's sought to understand the effects
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9 162 of regulated flow regimes on fish in the North Anna River, Virginia, USA. The model, focused on
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11 163 smallmouth bass (*M. dolomieu*), was published in the journal, *Rivers*, that is no longer in existence (Jager
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13 164 et al., 1993)(see Supplemental Information). This model evolved from a version developed by Deangelis
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15 165 et al. (1991) for lakes (Figure 1). The lake model simulated gape-limited optimal foraging on a spectrum
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17 166 of invertebrate (e.g., zooplankton) prey, ontogenetic size-based shifts in optimal diet, smallmouth bass
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19 167 bioenergetics, as well as nesting and reproduction.
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25 168 To represent fish in a river environment, other processes became important to include. Representation
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27 169 of physical habitat linking time series of flow and temperature to 2-dimensional fields of depth and
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29 170 velocity, and the responses of each biological process to those fields is depicted in Figure 2 and
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31 171 described below.
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35 172 [Figure 2]
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38 173 *Physical habitat.* Flow is such an important driver of habitat for fishes and other river biota that much
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40 174 more attention to dynamic simulation of habitat was required. This was achieved by coupling hydraulic
41
42 175 simulation portion of the Physical Habitat Simulation System (PHABSIM) directly with an individual-
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44 176 based model for nesting, reproduction, and YOY dynamics (Figure 2). To represent hydrodynamics, the
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46 177 data requirements were significantly higher than those of previous IBMs. PHABSIM relies on
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48 178 measurements of depth and velocity along fixed transects at different flows, as well as substrate and
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50 179 cover. A representative stream reach was partitioned into spatial cells containing measurement stations
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52 180 from a PHABSIM survey of the reach. The model required daily predictions of average depth and velocity
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55 181 for each grid cell in the representative reach as a function of daily average flow (Figure 2). In later
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4 182 models, changes in velocity with depth and presence of cover were represented as well (Van Winkle et
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6 183 al., 1998). Water temperature was also simulated, influencing fish growth and development.
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10 184 *Movement.* The smallmouth bass IBM uses departure rules to simulate fish movement (Jager and Tyler,
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12 185 2001). Each individual fish's growth over time is tracked. In a time-for-space substitution, movement is
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14 186 initiated when growth falls below the fish's long-term expectation.
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18 187 *Foraging.* Foraging differs substantially in flowing rivers compared with lentic habitats. Regeneration of
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20 188 prey is affected by flow, and by the local habitat's carrying capacity, setting an upper limit on standing
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22 189 biomass. Larger invertebrate prey items and crayfish are simulated because these can be important in
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24 190 streams, especially for larger bass. The model was able to reproduce fish growth in the North Anna
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27 191 River.
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31 192 *Mortality.* Mortality factors in rivers and streams differ from those in lakes because of the risk of being
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33 193 swept away by high flows or dewatered during non-mobile life stages (i.e., eggs and larvae during
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35 194 nesting). One insight produced from this river IBM is a recognition that non-mobile life stages are the
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37 195 most vulnerable when examining responses to disturbance regimes.
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41 196 *Reproduction.* Reproduction and early development are affected by different abiotic effects in rivers
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43 197 than they are in lakes. Nesting and guarding of nests by males were represented in both the lake and
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45 198 versions of the model. However, to understand nesting success in dynamic rivers, it is important not
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47 199 only to simulate disturbance of nests by flow extremes (e.g., floods or dewatering), but also to provide
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51 200 the opportunity for renesting if disturbance is early in the season. We compared simulated reproductive
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53 201 success and first year growth with field observations from the North Anna River in Virginia. The timing of
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55 202 nesting was well-simulated based on water temperature (see Supplemental Information), and renesting
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57 203 occurred on three occasions in 2-year simulations.
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4 204 In summary, this first IBM linking river habitat dynamics to fish populations explored previously
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6 205 unappreciated facets of riverine fish responses and adaptation to flow. But more importantly, it laid the
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8 206 groundwork for subsequent modeling efforts to evaluate the influence of alternative flow regimes, as
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10 207 the authors continued to deploy river IBMs, with the next applications focused on trout (Van Winkle et
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12 208 al., 1998) and Chinook salmon (Jager et al., 1997), as well as numerous others reviewed below.
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17 209 **3. How have river IBMs contributed to ecology?**
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20 210 Since the early models described above, river IBMs have fanned out to address a varied set of questions,
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22 211 illustrated by the braided channel in Figure 1, yielding different kinds of insights. Spatially explicit IBMs
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24 212 are well-suited for many questions involving aquatic populations in river habitats for several reasons.
25
26 213 First, as noted by Anderson et al. (2013b) properties that emerge from transient, non-equilibrium
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28 214 dynamics are particularly important in disturbance-dominated ecosystems like rivers (Strange et al.,
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30 215 1993). Second, risks are dependent on attributes of individuals. In addition to size-dependent predation
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32 216 risk, in regulated rivers, entrainment and survival of turbine passage both depend on fish size.
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37 217 HIJ conducted a Web of Science search of “individual-based model” in the title and (‘river’ OR ‘stream’),
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39 218 which found 54 publications, with an average of 25 citations per publication. When ‘individual-based’
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41 219 was not required to be in the title, and extraneous topics were excluded, just under 200 papers were
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43 220 identified between 1992 and 2018 and these produced an average of 36.2 citations per item. The
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45 221 number of publications increased near-linearly over time. Many of these publications were produced by
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47 222 a few individuals (Dr. Steve Railsback, with coauthor Dr. Brett Harvey authored 8.2 and 7.1% of papers
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49 223 based on the InSTREAM model). Other authors represented many countries, with more than half from
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51 224 the USA, roughly 10% each from England, Canada, and France, followed by Germany, the Netherlands,
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53 225 China, Japan, and Norway and twelve other countries. Papers were published in the journal Ecological
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55 226 Modeling (16%), fisheries journals (28%), and general ecology and conservation journals (16%),
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4 227 especially PLOS One and Ecological Applications, with the remaining journals represented by fewer than
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6 228 two papers each. Two studies were published in the Proceedings of the National Academy of Sciences,
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8 229 USA.
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12 230 Processes in rivers, as in most ecosystems, span multiple scales (Anderson et al., 2005). Likewise,
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14 231 riverine IBMs with different purposes fall along a range of scales from a focus on spatial questions
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16 232 related to fish responses to flow- and temperature-mediated variation in habitat (lower left in Figure 3)
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18 233 to questions related to metapopulation dynamics in river networks (upper right in Figure 3).
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23 234 [Figure 3]
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26 235 The specific questions which river IBMs have been used to address (Figure 5) have evolved over time,
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28 236 but at least one general purpose (e.g., understanding the effects of river regulation) has remained an
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30 237 active area of research throughout. One significant shift in emphasis has been from models to manage
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32 238 stream habitat for fisheries to Population Viability Analysis (PVA) models designed to guide recovery of
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34 239 rare species of high conservation concern. Below, we briefly discuss four categories of IBM studies
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36 240 focused on single tailwaters or reaches in which higher spatial resolution is used (bottom left in Figure 3)
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38 241 and four categories of IBM modeling studies involving long-term projections of meta-populations over
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40 242 broader spatial scales (upper right portion of Figure 3). These studies relate to the questions depicted in
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42 243 Figure 4.
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49 244 [Figure 4]
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52 245 **3.1 Research to understand the effects of flow regimes on fish populations**
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55 246 Understanding how flow regimes influence fishes is a fundamental area of river research has been, and
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57 247 continues to be, explored by IBMs (Figure 6a). From an early emphasis on determining 'how much flow a
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59 248 river needs' through setting minimum flow standards, to the more-recent emphasis on flow variability, a
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4 249 mechanistic understanding of the linkages between flow regimes is needed, and spatially explicit IBMs
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6 250 provide this capability. Some of the more recent research is described in section 3 under 'Research to
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8 251 understand habitat selection and movement'. The purpose of early river IBMs was to improve the 'fish
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10 252 preference' curves used in IFIM. Although IFIM is typically used in a regulatory context to set minimum
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12 253 flows, IBMs made it possible to address questions about flow regimes. For example, optimization flow
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14 254 releases from reservoirs was used to benefit downstream fishes, such as Chinook salmon (*Oncorhynchus*
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16 255 *tshawytscha*) (Jager and Rose, 2003). A key finding has been that thermal effects tend to have more
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18 256 biological importance than those of flow alone (Jager et al., 1997) (Tyler and Rutherford, 2007; Xu et al.,
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20 257 2010). In addition, IBMs have enabled researchers to evaluate the mechanisms behind ecological
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22 258 riverflow (i.e., properties of flow regimes including variation in flows) that benefit tailwater fish
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24 259 populations (Tyler and Rutherford, 2007) as well as ways in which 'natural flows' can be improved on.
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30 260 For example, one [non-IBM] study found that timing of releases earlier in spring than the natural snow-
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32 261 melt pulse produced floodplain inundation that allowed juvenile salmon to grow faster and exit the
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34 262 system before river temperatures became dangerously warm (Jager, 2014). Thus, an 'unnatural' flow
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36 263 regime performed better than the way that the river was historically regulated, which usually produced
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40 264 suboptimal flows for fishes.
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43 265 [Figure 5]
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46 266 Moving from an initial focus on setting minimum flow regulations, river managers now also focus on
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48 267 understanding elements of flow regimes that have high ecological value, and these are often the
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50 268 seasonal pulse flows (for example produced by snowmelt) to which native species are adapted in
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52 269 temperate rivers. In regulated rivers, flow augmentation ensures that high flows are available to
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54 269 downstream biota when needed. These pulse flows may facilitate migration and improve temperatures
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56 270 below dams. For example, cold, augmentation flows from Dworshak Reservoir are an important part of a
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4 272 strategy to facilitate salmon and steelhead migration through the hydrosystem of the lower Columbia
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6 273 River in spring. Augmentation may also be needed to provide flow in cases of extreme dewatering. In a
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8 274 more-arid climate, Pine et al. (2017) used a population viability analysis (PVA) IBM model to evaluate the
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10 potential benefits of augmenting flows to two federally-listed fish species in an arid New Mexico, USA
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12 275 stream.
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17 277 Another important research area for regulated rivers is to understand trade-offs between operating in
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19 278 'peaking' or 'load-following' mode, whereby flows are released when electricity demand (and value) is
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21 279 high. Rapid fluctuations in flow can have adverse effects on biota, and these can be modeled by IBMs
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23 280 that simulate influences on bioenergetics and on non-mobile life stages. For example, an IBM of the
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25 Green River below Flaming Gorge Dam predicted the effects of flow fluctuations on nursery habitats of
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27 281 the Colorado pikeminnow (*Ptychocheilus lucius*) (Grand et al., 2006).
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32 283 **3.2 Research to understand species interactions**
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35 284 IBMs can be used effectively to study species interactions (Figure 6b). For example, the spread of
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37 285 invasive aquatic species is a significant threat to native species worldwide, and one associated with
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39 286 human activity (Leprieur et al., 2008). Stream IBMs can be used to understand biologically mediated
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41 287 invasion dynamics. For example, topological properties of river networks and the spatial distribution of
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43 288 larval habitat within them controlled the spread of sea lamprey (Neeson et al., 2012).
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47 289 The use of an IBM is particularly important when individual characteristics influence the outcome of
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49 290 such interactions. For example, representing individual size differences among fishes was an early
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51 291 emphasis because it highlighted the role of size-based (gape-limited) predation (Rice et al., 1993). Size
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53 292 was also the focus of the first application of an IBM to fish stocking, as resource managers became
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55 293 aware that releasing fish at a larger size could enhance survival (Madenjian et al., 1991). In situations
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57 294 when spatial resources can be defended (e.g., drift-feeding territories, high-quality spawning habitat),
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4 295 size-based competition for space occurs. This has been represented in models for salmonids. Similarly,
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6 296 competition for mates and female fecundity are functions of size or condition (Van Winkle et al., 1998).
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10 297 The need to grow beyond a certain size prior to a stressful period (e.g., winter), and the population
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12 298 resilience created by 'contest' competition and compensatory (density-dependent) mortality were two
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14 299 insights gained through individual-based modeling (DeAngelis et al., 1993). In rivers, the first application
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16 300 with a focus on size-mediated effects simulated predation on migrating salmon smolts (Petersen and
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18 301 Deangelis, 1992, 2000). These size-based algorithms were later incorporated into models of bass
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20 302 predation on salmon juveniles in rivers, particularly deep pools (Jager et al., 1997). The interaction
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22 303 between warming rivers and predation by warm-water fishes on cold-water salmonids remains an
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24 304 important concern for species listed under the Endangered Species Act in rivers of the western US.
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30 305 Trophic dynamics in rivers have been represented by IBMs (Anderson et al., 2012; Giacomini et al., 2009;
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32 306 Railsback and Harvey, 2013; Robson et al., 2017). Simulating predation required some changes when
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34 307 applied to species in flowing rivers. In lentic habitats, modelers typically assume that the geometry
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36 308 defined by the reaction distance of the fish and its speed define a cylindrical volume of pelagic prey, or a
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38 309 truncated volume of benthic prey, available to foraging fishes. In rivers, a strategy of 'sit-and-wait' drift
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40 310 feeding becomes possible (Fausch, 2014). Therefore, at low and high velocities, individuals are predicted
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42 311 to adopt a search strategy, whereas at intermediate velocities, profitability of a drift-feeding strategy is
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44 312 higher (Van Winkle et al., 1998). Another consideration is the relationship between flow and turbidity
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46 313 for visual-feeding fishes. Increased turbidity can lead to reduced feeding and subsequent starvation
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48 314 (Harvey and Railsback, 2009).
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55 315 **3.3 Research to understand fish movement and habitat selection**
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58 316 One of the most important reasons for adopting an individual-based approach is the need to represent
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60 317 movement at a relatively fine resolution (i.e., multiple reaches or patches within reaches versus a few
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4 318 different habitats). Understanding animal behavior (Figure 6c), including movement and habitat
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6 319 selection, has been studied by postulating and testing movement rules (Rohlf and Davenport, 1969), and
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8 320 this was greatly facilitated by using IBMs. This research was initially influenced by the wealth of
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10 literature in ecology on optimal foraging theory and decision rules for switching prey and habitat
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12 321 departure. Economic concepts, such as the marginal value theorem, were used in deciding when model
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14 322 organisms should leave a patch when searching for food (or other resource) (Rashleigh and Grossman,
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16 323 2005; Tyler and Brandt, 2001). Early stream IBMs partitioned the day into resting and foraging portions,
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18 324 based on reaching a maximum daily ration within daylight hours (Van Winkle et al., 1998). An
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20 325 individual's departure from a patch was simulated to occur when its expectation of a higher ratio of
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22 326 growth to predation risk (or product of growth and survival) exceeded the value in the current stream
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24 327 cell (Jager et al., 1993; Railsback and Harvey, 2002; Van Winkle et al., 1998). Later models have
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26 328 identified situations in which the distribution of individuals does not reflect the fitness landscape, as is
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28 329 expected under an 'ideal-free distribution' produced by departure rules that optimize fitness (Railsback
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30 330 et al., 2003). The limited perceptual ability of individuals to sense conditions beyond their current
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32 331 location is one factor that can negatively influence the ability of a population to produce a distribution
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34 332 that tracks the fitness landscape (Jager and Tyler, 2001; Pe'er and Kramer-Schadt, 2008; Railsback et al.,
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36 333 1999, 2001).
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45 335 Understanding movement is not merely a theoretical exercise. The use of spatially explicit IBMs can help
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47 336 resource managers by providing more-sophisticated movement algorithms to understand how
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49 337 management decisions influence fish populations (Railsback, 2016). In one example, simulation of flow
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51 338 responses by two carp species in China suggested relatively little effect of regulation, but did suggest
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53 339 improved timing of reservoir water releases during spring (Li et al., 2010). Understanding the effects of
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55 339 dams on downstream migration by juvenile salmon has been a strong area of applied research in the
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57 340 Columbia River Basin, where a large proportion of US hydropower is generated. Computational fluid
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4 342 dynamics has been used to understand juvenile salmonid movements through passage facilities (Gao et
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6 343 al., 2016; Romero-Gomez and Richmond, 2014; Weber et al., 2006). Typically, a combined Eulerian-
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8 344 Lagrangian-Agent (ELAM) approach (i.e., fish trajectories modeled through a fixed gridded physical
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10 345 habitat representation of a river) is employed (Goodwin et al., 2006). A hypothesis to explain the
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12 346 navigation of juvenile salmonids downstream through surface collectors and other devices at dams was
13
14 347 the strain-velocity-pressure hypothesis, whereby juveniles are assumed to minimize total hydraulic
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16 348 strain (Nestler et al., 2008). This hypothesis has since been supplanted, as water acceleration alone
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18 349 appears to do a better job of predicting the movements of salmon. The resulting models simulate the
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20 350 ability of salmon to navigate safely through passage routes at large dams by modulating their swimming
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22 351 orientation and speed to water acceleration (Goodwin et al., 2014). The ELAM model differs from earlier
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24 352 PHABSIM models in that fish are simulated on a dynamic habitat represented by high-resolution
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26 353 computational fluid dynamics models (Weber et al., 2006).
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34 354 The approaches above make sense for animals that can control movements. However, for some species
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36 355 and life stages, movement is passive and determined by flow fields. Fonseca (1999) used an IBM to
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38 356 examine the consequences of movement rules related to drift of blackfly larvae in a fluid medium and
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40 357 was able to reproduce spatial patterns of settling in depositional zones. In fragmented rivers,
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42 358 downstream drift of larvae was found to be an important effect on upstream population persistence.
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44 359 Thus, the most vulnerable life stages are those that are incapable of directed movement, whether
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46 360 because they are sessile (eggs, mussels) or because they lack apparatus for swimming well.
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51 361 One situation where IBMs suggest that passive drift can be important is in coastal rivers, where salinity
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53 362 can play a role in movement and survival of early life stages that are not-yet salt-water tolerant (Jager et
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55 363 al., 2013a; Rose et al., 2014). Premature exposure to salinity was a leading cause of mortality for juvenile
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57 364 shortnose sturgeon (*Acipenser brevirostrum*) in an IBM for a river in coastal, Georgia, USA (Jager et al.,
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4 365 2013a). If confirmed by fieldwork, this risk will increase as sea level rises. Canals and water diversions
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6 366 can also influence exposure to high salinity in coastal rivers, as can intrusion of saltwater due to
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8 367 excessive groundwater pumping.
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12 368 **3.4 Research to understand contaminant and water quality impacts**
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15 369 One important ecosystem service provided by rivers is to transport and purify waste water from
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17 370 watersheds that support human activities. Riverine populations are affected along the way, and the
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19 371 population-level effects of individual exposure to contaminants and poor water quality have been
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21 372 quantified by using IBMs (Figure 6d). As stochastic models, IBMs represent realistic variation in
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23 373 exposure. Research in this area involves linking IBMs with dynamic and spatial models of water quality,
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25 and past examples have focused on reservoirs. For example, in the US, particle-based (Lagrangian)
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27 374 approaches have been used to simulate fish movements in a 2-dimensional reservoir (Nestler et al.,
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29 375 2002; Scheibe and Richmond, 2002). Blueback herring, *Alosa aestivalis*, were simulated in Strom
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31 376 Thurmond Reservoir in the southeastern US by using rules to simulate swimming in the direction of
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33 377 optimal habitat quality (Nestler et al., 2002). Reservoir habitat was represented by a laterally averaged
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35 378 CE-QUAL-W2 model of hydrodynamics, temperature, and dissolved oxygen (Nestler et al., 2002). Nestler
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37 379 et al. (2002) adjusted the parameters of conditional movement rules to produce reasonable seasonal
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39 380 responses. In another particle-based model, a vertically-averaged representation of a reservoir was used
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41 381 to evaluate exposure of juvenile salmon to dissolved gases while migrating near the water's surface
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43 382 through dams on the Columbia River (Scheibe and Richmond, 2002). Sullivan et al. (2003) used a
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45 383 Eulerian approach to simulating movements of white sturgeon, *A. transmontanus*, in response to
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47 384 dissolved oxygen and temperature in the bottom layer of a Snake River reservoir. Two studies of fish
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49 385 movements have pointed to interactions between predation and dissolved oxygen. In one study,
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51 386 juveniles were spatially concentrated and therefore increasingly vulnerable to predation (Breitburg et
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53 387 al., 2003). Another study of simulated movement indicated how, depending on its location, hypoxia can
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4 389 create a barrier in reservoirs, as well as an 'ecological sink' for scavengers attracted to carcasses
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6 390 (Sullivan et al., 2003). Survival estimates for individuals produced by these IBMs can then be used to
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8 391 project population-level responses.
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12 392 A handful of studies have used IBMs to evaluate contaminant effects at the population level and a few
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14 393 examples pertain to rivers. Salice et al. (2011) evaluated alternative strategies for Polychlorinated
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16 394 Biphenyl (PCB) cleanup on mink. The study determined that early cleanup was the best option. A study
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18 395 to rank threats to shortnose sturgeon used an IBM to evaluate risk from mercury (Jager et al., 2013b).
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21 396 Recently, Dohmen et al. (2016) compared toxicity from farm chemicals in ditches at the edge of a field
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23 397 using models representing hydrodynamics as a moving stream versus a deep pool. In shallow waters,
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25 398 toxicity was found to be higher primarily because of higher temperatures. Another comparison found
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28 399 drift in flowing waters to have an influence on population recovery (Van den Brink et al., 2007). In
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30 400 another recent example, Brito et al. (2017) evaluated sewage treatment options to select one most
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32 401 likely to protect the silver catfish (*Rhamdia quelen*).
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37 402 The considerable research on contaminant transformation, fate and transport within rivers, floodplains,
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39 403 and reservoirs has not been married with the mechanistic power of river IBMs to aggregate individual-
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41 404 level exposure and effects to the population-level for riverine species. The studies above did not
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43 405 simulate detailed adverse outcome pathways experienced by individuals. To this end, a working group
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45 406 hosted by the National Institute for Mathematical and Biological Synthesis is currently evaluating ways
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47 407 to combine Dynamic Energy Budget (DEB) models with IBMs to scale the effects of contaminant
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49 408 exposure to understand effects at the population-level (Forbes et al., 2016).
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55 409 **3.5 Research to understand the conservation biology of rare fishes and other taxa**
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57 410 Perhaps it is ironic that understanding density dependence and compensatory mechanisms led to the
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59 411 development of IBMs for fish populations, because applications to understand threats to rare or
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4 412 endangered species are now more prominent (Peterseni et al., 2008). At the low end of the population
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6 413 density spectrum, Allee effects are as important as compensatory effects at high densities when
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8 414 developing IBMs for small populations. In conservation biology, questions about minimum population
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10 sizes for persistence emerge, and this is related to the question of whether there is sufficient habitat to
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12 415 support a viable population. In advective river environments, downstream drift is a dominant feature
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14 416 that influences population persistence (Kolpas and Nisbet, 2010). Generally speaking, species evolve
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16 417 spatial life histories that counteract this tendency. Fragmentation by dams can interrupt 'conveyer-belt'
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18 418 life histories characteristic of rivers and prevent access to the variety of habitat required to sustain
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20 419 viable populations. Therefore, assessing long-term viability involves understanding spatial
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22 420 metapopulation structure and mechanisms by which genetic structure is maintained.
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29 422 An important use of PVAs is to rank threats to small populations (Caughley, 1994)(Figure 6e). IBMs used
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31 423 for PVA accomplish this by comparing scenarios with different assumptions about potential threats
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33 424 (Loos et al., 2010; Peterseni et al., 2008). The response variables in PVA's are those associated with
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35 425 population recovery; i.e., the likelihood of extirpation (or persistence), population trends, spatial
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37 426 diversity, and genetic diversity. Therefore, genetic models are appropriate. For example, an IBM+G PVA
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39 427 model was developed to rank risks linked to white sturgeon (*A. transmontanus*) populations in the
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41 428 middle Snake River (Jager et al., 2007). PVA studies typically require summarizing results from a large
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43 429 number of replicate [meta]populations and projecting many generations into the future. The
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45 429 combination of simulating many individuals and running Monte Carlo simulations is a significant
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47 430 computational challenge.
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54 432 Applications of IBMs in conservation biology is especially important for river species because freshwater
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56 433 ecosystems contain some of the most imperilled taxa (Dudgeon et al., 2006; Jelks et al., 2008; Johnson
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58 434 et al., 2013; Richman et al., 2015; Warren and Burr, 1994). Freshwater mussels are a particularly
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4 435 vulnerable group that provides important water-filtration services (Layzer et al., 1993). In addition to
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6 436 being sessile, and therefore unable to move to avoid disturbance, many mussels depend on fishes to
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8 437 colonize new sites. As larvae (glochidia), they attach to the gills of a host fish, where they develop during
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10 438 transport to a new site. In rivers, upstream colonization is particularly important for these taxa (Terui et
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12 439 al., 2014). Lee and DeAngelis (1997) developed a structured model to study the spatial spread of mussel
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14 440 populations. The model showed that colonization patterns resembled a traveling wave front, with a
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16 441 faster velocity for mussel species maturing at an earlier age (Lee and DeAngelis, 1997). Understanding
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18 442 colonization rates is important to predicting recovery from disturbances, such as dredging,
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20 443 sedimentation, or chemical spills. In a subsequent paper, Lee et al. (1998) evaluated metapopulation
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22 444 dynamics of various Unionid mussels. A key result was that mussel species associated with a fish host
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24 445 having a restricted movement range require a high success rate of finding fish host to achieve at least an
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26 446 intermediate level of abundance. Mussel species with fish hosts having a limited range, coupled with a
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28 447 low success rate of finding a host, tend to be rare in numbers and sparsely distributed (Lee et al., 1998).
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36 448 **3.6 Research to understand the effects of river fragmentation and reconnection**
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39 449 IBMs have been used to understand the potential costs and benefits of reconnection options, including
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41 450 translocation and passage (Figure 6f). One result is that fish in upstream reaches are more likely to
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43 451 experience higher risk of extirpation than those in downstream reaches when barriers prevent upstream
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45 452 movement (Harvey and Railsback, 2012). An important finding is that export of larvae from short
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47 453 segments to downstream reaches can deplete upstream segments, a general result in physical systems
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49 454 where migration is asymmetric (Jager et al., 2001). These results emphasize the general idea that
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51 455 upstream recolonization is a fundamental problem for organisms in directional, advection-dominated
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53 456 systems.
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4 457 A series of simulation experiments to compare reconnection options were conducted with an IBM of
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6 458 white sturgeon in the Middle Snake River. Translocation was found to be most successful when adults
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8 459 were transported upstream as far as possible to a reach with good habitat conditions (Jager, 2006b). In
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10 460 addition, a strategy of screening upstream reaches to prevent downstream movement was shown to be
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12 461 successful for simulated white sturgeon (Jager, 2006b). Conditions under which passage (Jager, 2006a)
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14 462 and translocation (Jager, 2006b) were beneficial depended on whether the recipient was upstream,
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16 463 having sufficiently large amount of habitat, and whether screening by trash racks to prevent large
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18 464 objects (including sturgeon) from entering turbine intakes was sufficiently narrow to prevent
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20 465 entrainment into turbines during downstream migration. Thus, mortality risk during migration through
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22 466 dams is an important consideration. In another study, a PVA model was used to evaluate the benefits of
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24 467 translocation for the humpback chub (*Gila cypha*) in the Colorado River, USA (Pine et al., 2013). The
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26 468 success of translocation depended on the relative survival in the donor and recipient reaches (Pine et al.,
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28 469 2013).
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36 470 **3.7 Research to understand genetics in riverine metapopulations**
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39 471 Simulating population and metapopulation (spawning populations linked by infrequent migration)
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41 472 genetics is an important reason for choosing to use IBMs (Figure 6g). Although substantial literature
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43 473 exists that uses non-IBM models, these typically require either an assumption of two important alleles
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45 474 or many alleles with small effects (i.e., statistical models that rely on a normal distribution of trait
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47 475 values). The earliest IBMs were more akin to genetic algorithms, motivated by the need to examine
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49 476 mutation effects (e.g., mutation meltdown) in small populations (Gabriel et al., 1993; Lynch et al., 1995).
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51 477 These models, used in conservation biology, focused strictly on neutral inheritance and not on selection
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53 478 resulting from decisions or activities of organisms.
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4 479 The first genetic IBM (IBM+G) model was applied to the question of selection on fish size due to fishing
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6 480 (Martinez-Garmendia, 1998). In rivers, the first IBM+G quantified the effects of population isolation of
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8 481 white sturgeon between dams in the Snake River (Jager, 2001). These models simulated both selection
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10 482 and neutral genetics. They have many advantages over non-IBM population genetic models, including
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12 483 the flexibility to represent different genetic systems (e.g., polyploidy), intermediate numbers of alleles,
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14 484 interactions among loci, control genes, and effects of mating systems and other behaviors (e.g., homing
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16 485 migration) (Jager, 2001).
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22 486 In many cases, IBM+Gs are used to understand the genetic effects of anthropogenic influences (e.g.,
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24 487 harvest size selection, hatchery operation, fragmentation by dams, reconnection, climate change).
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27 488 Models of hatchery influences, for example, have shown that supplementation of lake sturgeon had
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29 489 little effect on allele retention and inbreeding (Schueller and Hayes, 2011). Modifying the numbers
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31 490 released to reduce selection was shown not to be effective. Once introduced to a growing population
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33 491 (such as one supported by supplementation), a few 'alien' alleles can quickly increase in frequency until
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35 492 they reach an equilibrium (Jager, 2005). Results from these IBM+Gs confirm that ensuring demographic
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37 493 health of populations often alleviates genetic concerns. Another purpose has been to explore the risk of
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39 494 hybridization, for example between pallid (*Scaphirhynchus albus*) and shovelnose sturgeon (*S.*
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41 495 *platyrhynchus*) (Jager unpublished data).
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47 496 One exciting research direction is to understand how dendritic network properties influence riverine
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49 497 metapopulations. This has been explored using IBM+Gs (Labonne et al., 2008; Landguth et al., 2014). In
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51 498 one case, the combined effects of asymmetric dispersal along river networks, combined with overland
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53 499 movement (e.g., for amphibians or for fishes transported through floodplain inundation or being carried
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55 500 by non-aquatic organisms), was considered (Chaput-Bardy et al., 2009). The role played by traits that
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57 501 control homing behavior and spawning fidelity have not been fully explored. However, studies that
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4 502 simulate selection and genetic adaptation have been performed. These have shown that local
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6 503 adaptation can 'rescue' isolated populations in stream networks (Coombs et al., 2010; Letcher et al.,
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8 504 2007). Network properties were found to influence Chinook salmon growth in warmer thermal regimes
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10 505 (Fullerton et al., 2017). Juveniles in the least complex network grew faster and were ready to smolt
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12 506 earlier than those in more complex river networks (Fullerton et al., 2017). Other studies using IBM+G
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14 507 models to explore the ability of fishes to adapt to climate warming are discussed in the section below.
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20 508 **3.8 Research to understand the effects of warming and flow shifts under climate change**
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23 509 Modeling research using IBMs has addressed the potential effects of warming stream temperatures, as
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25 510 well as the effects of shifts in hydrology and timing of flows. A hypothesis has been that populations
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27 511 would shift toward cooler headwaters in response to warming, and concerns have been raised about
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29 512 barriers (e.g., dams) preventing such movements.
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33 513 One study of potential effects of climate change evaluated interactions between shifts in flow (early
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35 514 snowmelt) and warming on a fall- and a spring-spawning trout (Jager et al., 1999) (Figure 6h). An
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37 515 unexpected result was earlier maturation of the spring spawning rainbow trout life history under
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39 516 warming. Similar results have been observed in currently forested streams where wildfire has removed
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41 517 canopy cover and warmed stream temperatures (Rosenberger et al., 2015). Simulating interactions
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43 518 between warming and changes in flow can produce complex effects. For example, brown trout, a fall
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45 519 spawning species, was not impacted as expected by scouring of redds (nests) when high flows shifted
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47 519 from spring to winter. Warming benefited both species in the upstream, but not the downstream reach.
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49 520 This supports the idea that climate warming will cause movement toward cooler headwaters (Jager et
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51 521 al., 1999). This result was also produced by a study of brook (*S. fontinalis*) and rainbow trout (*O. mykiss*)
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53 522 in the Appalachian Mountains, USA (Clark et al., 2001). More recently, an IBM+G developed from
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55 523 inSTREAM determined that declines in biomass and extinction risks were substantially larger under
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57 524 inSTREAM determined that declines in biomass and extinction risks were substantially larger under
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4 525 combined warming and flow reduction scenarios, despite stronger evolutionary responses (Ayllon et al.,
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6 526 2016). The traits that varied in this study were size at emergence and maturity size threshold (Ayllon et
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8 527 al., 2016).

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12 528 Ultimately, it will be important to use IBM+Gs to address questions about adaptation to climate change.
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15 529 For example, climate adaptation via plasticity in growth has been explored for Atlantic salmon
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17 530 populations (Piou and Prevost, 2012, 2013). In another study, Anderson et al. (2013a) simulated
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19 531 phenotypic plasticity in adapting to shifts in seasonal events using an IBM. Model results suggested that
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21 532 population extinction can occur if the rate of change in the bioclimatic envelope exceeds the rate that
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23 533 the population's phenology can change, or if the variability in the envelope exceeds the population's
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25 534 inherent capacity for withstanding climate variability. The perceptual abilities of individuals again play a
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27 535 role in framing the ability of populations to adapt. For example, a population with migration timing cued
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29 536 by photoperiod exhibited weaker phenotypic plasticity than one cued by temperature (Anderson et al.,
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31 537 2013a). Anderson et al. also found that a threshold leading to population extinction was foreshadowed
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33 538 by increased variability in average individual condition across years.

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36 539 One concern is that climate change will have a 'bottleneck' effect on populations whereby decreased
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38 540 population size and the associated decrease in genetic diversity will prevent adaptation. A landscape-
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40 541 genetics IBM of bull trout (*Salvelinus confluentus*) model suggests that populations isolated by low flows
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42 542 under climate warming will face a risk of losing genetic diversity (Landguth et al., 2014).

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45 543 Not all studies using IBMs to simulate population-level responses to climate change have predicted large
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47 544 effects. For example, Clark et al. (2001) found that species differences in fecundity explained their
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49 545 competitive outcomes better than the influence of climate. Another notable feature of that study was
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51 546 the use of a geographic information system to allow the model to be distributed across streams in a
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53 547 large region. More recently, an IBM was used to examine interactions between forest harvest and

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4 548 climate change in the Pacific Northwest, USA (Penaluna et al., 2015). Individual- and population-level
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6 549 responses were variable. In some cases, forest harvest countered the effect of climate change through
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8 550 increased summer flow. The most consistent response was earlier emergence of fry, but this change in
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10 551 timing did not necessarily result in population-level differences (Penaluna et al., 2015).
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15 552 **4. Where will the flow of ideas go next?**
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18 553 Dendritic networks, one-directional flows, and adaptations to predictable and unpredictable features of
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20 554 flow (and temperature) are defining characteristics of river habitats used by aquatic biota. Increasingly,
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22 555 questions about the viability of fish and mussel populations in river networks are being asked (Thomaz
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24 556 et al., 2016), and riverine IBMs are a logical tool to apply. Advances in network theory and modeling
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26 557 tools, used in conjunction with IBMs, can be used to understand basic questions, e.g., “How organisms
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28 558 maintain distributions in river networks?” and applied questions, e.g., “What is the optimal placement
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30 559 and management of dams?” Clearly, the mechanisms by which riverine metapopulations in dendritic,
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32 560 directional networks recolonize tributaries are fundamental to understanding river ecology and
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34 561 integrating network modeling frameworks with IBM+Gs will be required to address these questions.
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40 562 The literature reviewed here reveals a strong bias toward IBMs describing fishes. Few examples exist of
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42 563 IBMs applied to aquatic species at risk other than fishes, suggesting an opportunity for future modeling
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44 564 research to rank threats and guide restoration efforts for mussels, gastropods, crayfishes, and other
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46 565 imperiled taxa (Jelks et al., 2008; Johnson et al., 2013; Richman et al., 2015). We see opportunities to
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48 566 help evaluate strategies for conserving non-fish imperiled taxa as well, and the ability to represent
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50 567 species interactions that may depend on species densities and individual encounters in flowing media
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52 568 (e.g., those between mussels broadcasting glochidia and their migrating fish hosts).
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57 569 A strength of IBMs is the ability to simulate the decisions by individual organisms in response to the
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59 570 environment and each other. Capitalizing on this strength, we see considerable opportunity for
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4 571 implementing IBM algorithms for movement in robotic fishes used for research to understand the
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6 572 effects of hydropower and other industries that rely on rivers (Garcia-Magarino et al., 2017). By applying
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8 573 our knowledge about animal and group social behavior, motivation and responses to environmental
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10 574 fields, and our understanding of animal perceptual limitations and capabilities (which are often different
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12 575 from ours) (Pe'er and Kramer-Schadt, 2008), we see opportunities for advancement in this area.
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17 576 On a related theme, integration between social agent-based models for human actors and IBMs for the
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19 577 riverine biota that are affected by their decisions is another frontier in applied research. Agent-based
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21 578 modeling has been used to allocate waste loads and water. Models fully integrating human decision
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23 579 makers with animals in downstream ecosystems have not been explored. We see this as part of a
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25 580 general trend toward integrating human and societal systems with ecological systems.
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30 581 Finally, a frontier of research that remains is to integrate individual-based models with biogeochemical
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32 582 models and functionally-defined ecosystem states requiring mass balance (Grimm et al., 2017). This
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34 583 challenge is starting to be addressed by merging IBMs with dynamic ecosystem models (Strauss et al.,
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36 584 2017). The science to understand carbon and nutrient dynamics is increasingly focusing on the incidence
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38 585 of 'hot spots and hot moments' at the terrestrial-aquatic interface. Although biotic processes strongly
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40 586 mediate biogeochemical cycles at the terrestrial-aquatic interface, the challenge of developing hybrid
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42 587 models that combine these conceptually distinct approaches remains for our metaphorical
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44 588 'downstream' researchers.
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50 589 These are a few examples of many possible future directions, or unwinding braids, in the channel of
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52 590 riverine ecology aided by IBMs. Undoubtedly many others will emerge (Figure 1).
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4 915 **6. List of Figures**
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7 916 Figure 1. Ideas originating in upstream tributaries merge at river confluences representing interactions
8
9 917 among scientists bringing together ideas that influenced the development of river IBMs. Downstream,
10
11 918 multiple channels represent downstream opportunities for future research. Motivating questions or
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14 919 topics are indicated by questions in italics and methodological influences and advances are in bold.
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17 920 Figure 2. Schematic of a model for stream populations of fishes illustrating linkages between physical
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20 921 Habitat Simulation (PHABSIM) as a function of flow and an individual-based model (IBM) of processes
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22
23 922 (reproduction, growth, movement, and mortality) that regulate each life stage. Population responses are
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25 923 illustrated for smallmouth bass, as simulated by (Jager et al., 1993).
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28 924 Figure 3. Stommel diagram showing the range in spatial and temporal scales addressed by spatially
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31 925 explicit river IBMs. On the left, we indicate the reasons for adopting a spatially-explicit model and
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33 926 reasons for using an IBM.
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36 927 Figure 4. Research questions addressed by riverine IBMs include those to understand a) population-level
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39 928 effects of flow regimes, b) species interactions, c) fish movement, and d) contaminant exposures. Other
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42 929 questions concern e) the conservation biology of imperiled riverine taxa including f) the effects of river
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44 930 fragmentation and reconnection, g) population-level genetic outcomes of management decisions, and h)
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46 931 future effects of global climate change.
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Figure 1

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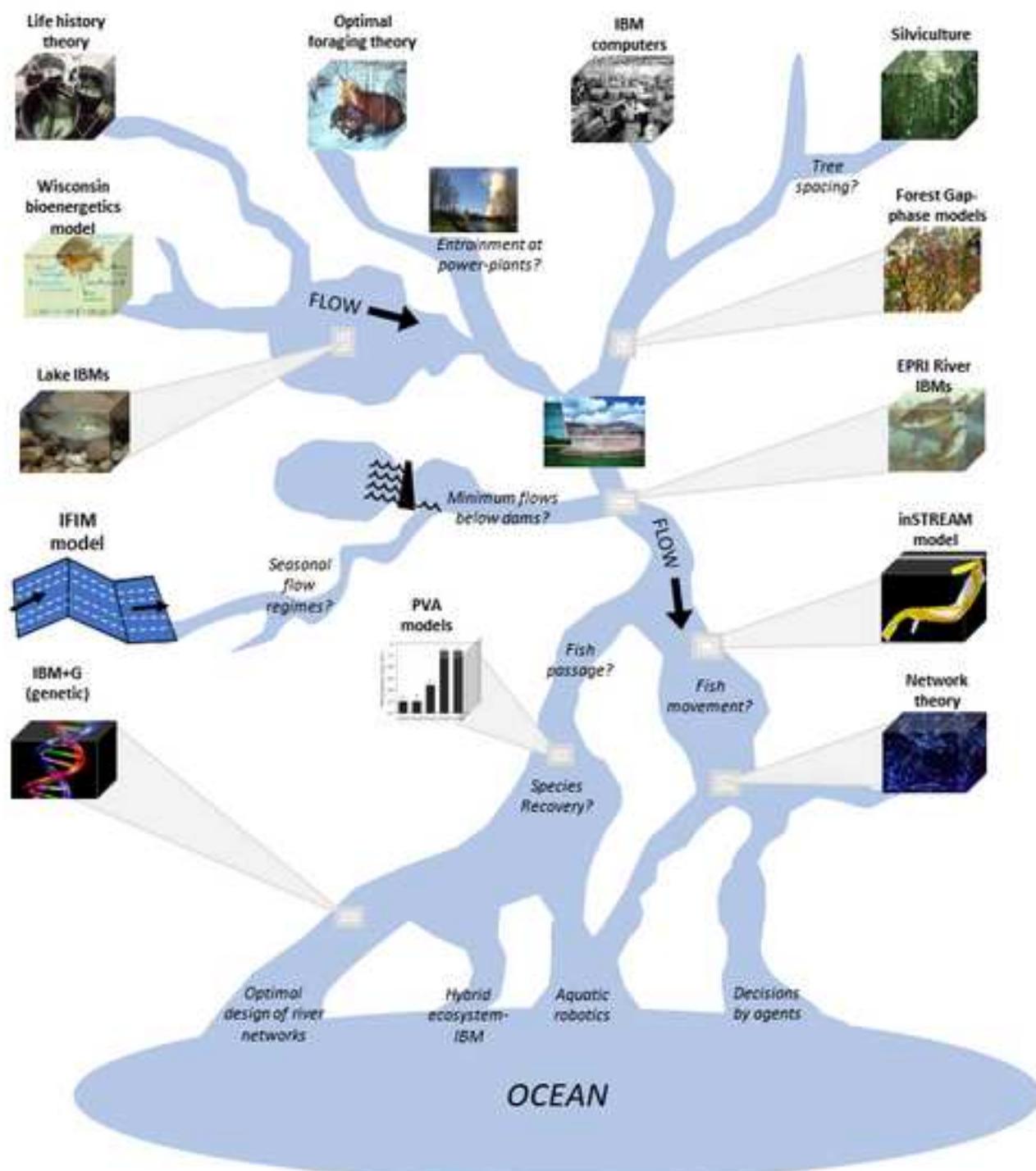


Figure 2

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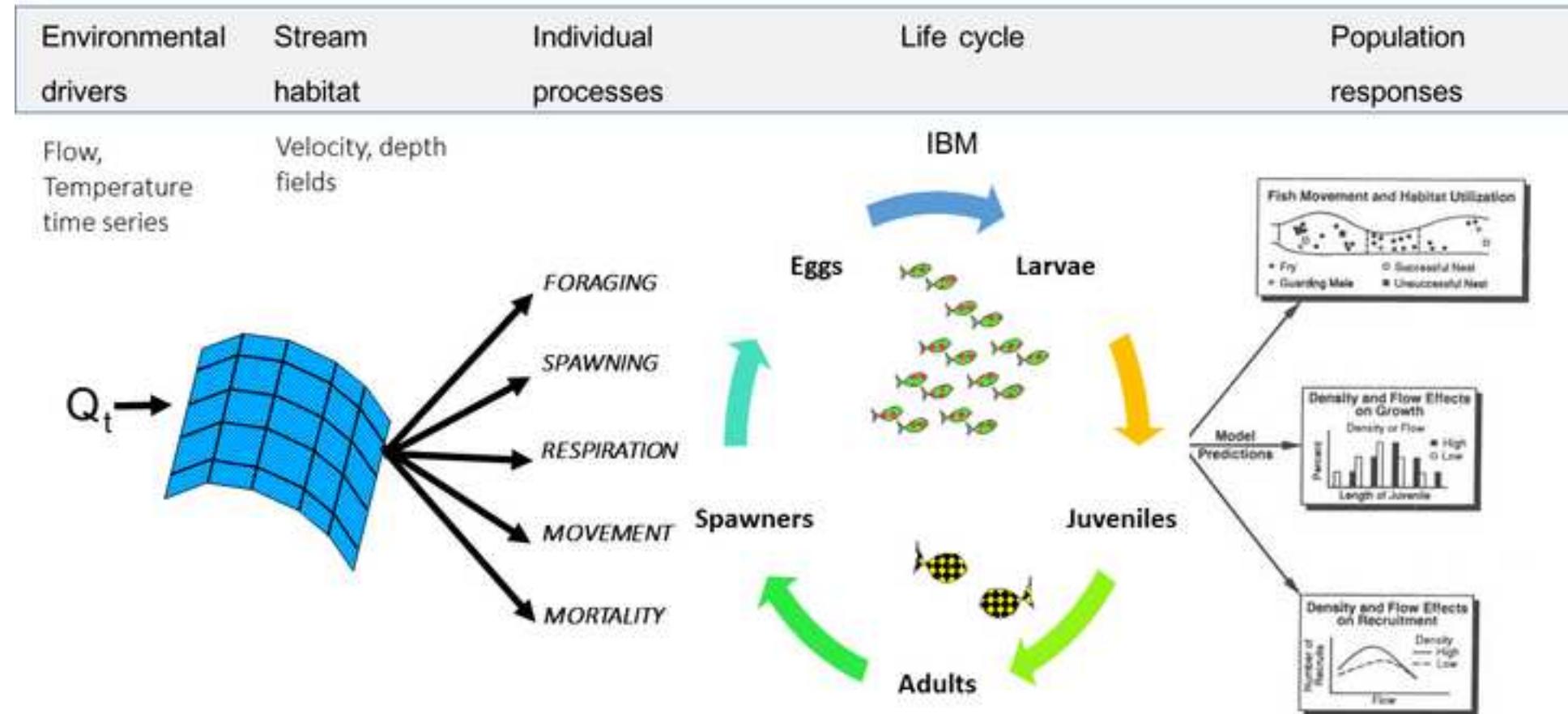


Figure 3

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Individual-based:

- Is movement important?
- Are genetic endpoints of interest?
- Are risks strongly dependent on individual attributes?
- Are population responses to disturbance important?

Spatially explicit:

- Is fish response to heterogeneous habitat important?
- Is movement risk important?

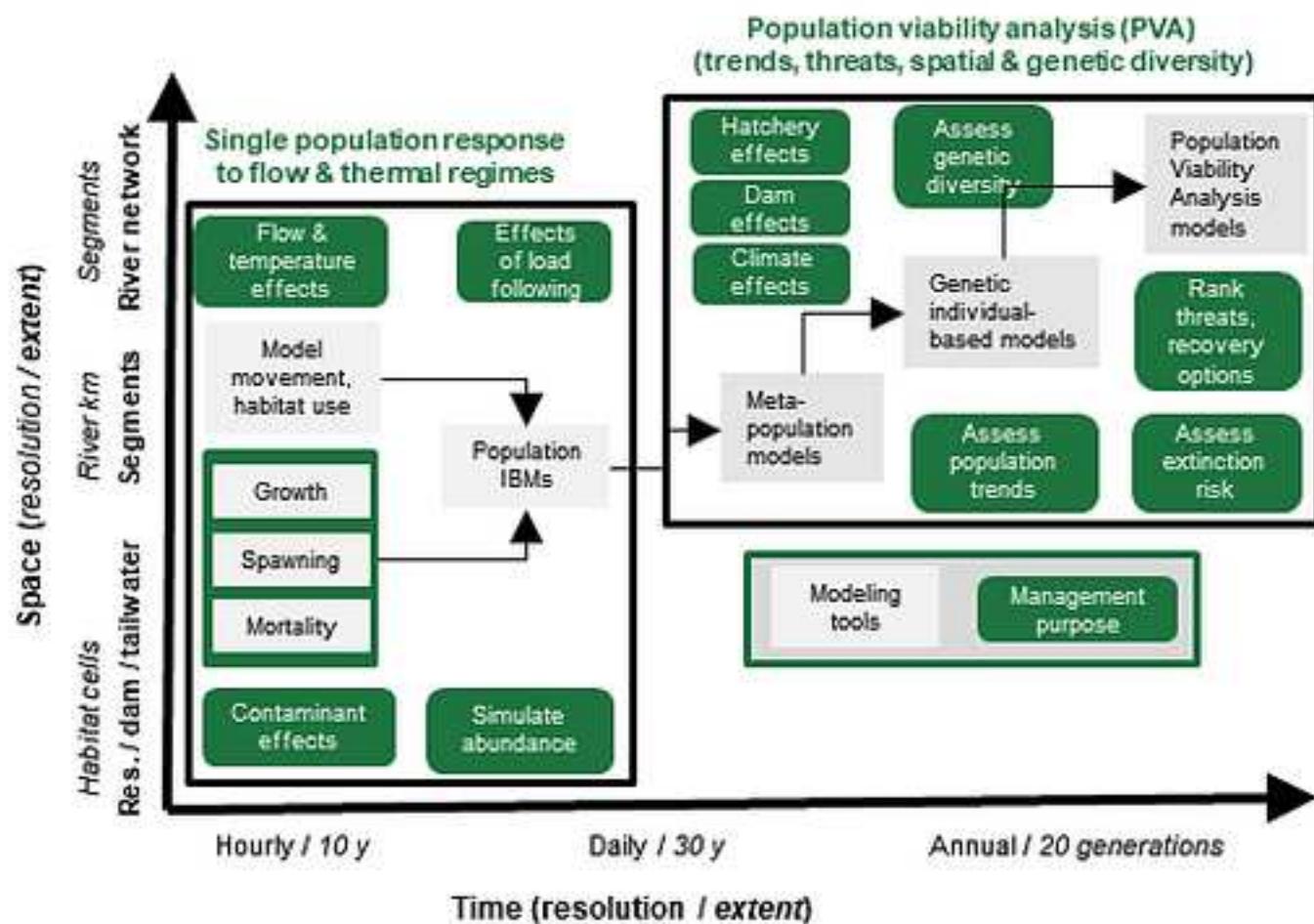


Figure 4

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