

1 **Title:** Linking Model Design and Application for Transdisciplinary Approaches in Social-Ecological
2 Systems

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42 **Abstract:**

43 As global environmental change continues to accelerate and intensify, science and society are
44 turning to transdisciplinary approaches to facilitate transitions to sustainability. Modeling is
45 increasingly used as a technological tool to improve our understanding of social-ecological systems
46 (SES), encourage collaboration and learning, and facilitate decision-making. This study improves
47 our understanding of how SES models are designed and applied to address the rising challenges of
48 global environmental change, using mountains as a representative system. We analyzed 74 peer-
49 reviewed papers describing dynamic models of mountain SES, evaluating them according to
50 characteristics such as the model purpose, data and model type, level of stakeholder involvement,
51 and spatial extent/resolution. Slightly more than half the models in our analysis were participatory,
52 yet only 21.6% of papers demonstrated any direct outreach to decision makers. We found that SES
53 models tend to under-represent social datasets, with ethnographic data rarely incorporated.
54 Modeling efforts in conditions of higher stakeholder diversity tend to have higher rates of decision

55 support compared to situations where stakeholder diversity is absent or not addressed. We discuss
56 our results through the lens of appropriate technology, drawing on the concepts of boundary
57 objects and scalar devices from Science and Technology Studies. We propose four guiding
58 principles to facilitate the development of SES models as appropriate technology for
59 transdisciplinary applications: (1) increase diversity of stakeholders in SES model design and
60 application for improved collaboration; (2) balance power dynamics among stakeholders by
61 incorporating diverse knowledge and data types; (3) promote flexibility in model design; and (4)
62 bridge gaps in decision support, learning, and communication. Creating SES models that are
63 appropriate technology for transdisciplinary applications will require advanced planning, increased
64 funding for and attention to the role of diverse data and knowledge, and stronger partnerships
65 across disciplinary divides. Highly contextualized participatory modeling that embraces diversity in
66 both data and actors appears poised to make strong contributions to the world's most pressing
67 environmental challenges.

68 **Keywords:** Dynamic modeling; knowledge co-production; mountain social-ecological systems;
69 mutual learning; transdisciplinarity; science and technology studies

70 1. Introduction

71 Social-ecological systems (SES) are facing unprecedented challenges from global environmental
72 change (Turner et al. 2007). Responding to these changes is a central challenge for the management
73 of sustainable ecosystems, with far-reaching consequences for human well-being (Lambin et al.
74 2001; Carpenter et al. 2009; DeFries et al. 2012). SES are characterized by complex processes with
75 nonlinear dynamics, indirect effects and feedbacks, emergent properties, and heterogeneous links
76 that extend across spatial and temporal scales (Liu et al. 2007). These characteristics can cause
77 unanticipated outcomes that make environmental management difficult, particularly as decisions
78 are often made in the context of limited data and high uncertainty (Polasky et al. 2011). Due to the
79 complexity of SES, understanding global environmental change is critical for developing effective
80 responses (Ostrom 2007, Turner et al. 2007, Lambin & Meyfroidt 2010).

81 As global environmental change continues to accelerate and intensify, science and society are
82 turning to transdisciplinary approaches to facilitate transitions to sustainability (Lang et al. 2012;
83 Brandt et al. 2013). Transdisciplinarity is a reflexive approach that brings together actors from
84 diverse academic fields and sectors of society to engage in co-production and mutual learning, with
85 the intent to collaboratively produce solutions to social-ecological problems (Cundill et al. 2015;
86 Lemos et al. 2018; Wyborn et al. 2019; Norström et al. 2020). Such collaboration enables problems
87 to be understood from multiple perspectives, and can expand the scope of potential solutions
88 (Tengö et al. 2014; Hoffman et al. 2017; Chakraborty et al. 2019; Steger et al. 2020). This diversity
89 also contributes to the perceived credibility, salience, and legitimacy of results (Cash et al. 2003;
90 Cundill et al. 2015), empowering participants to take ownership of products and apply new
91 knowledge to sustainability challenges on the ground (Lang et al. 2012; Balvanera et al. 2017).

92 Modeling is increasingly used by academics and development experts to encourage collaboration
93 and learning among diverse groups to facilitate decision-making (Bousquet and Le Page 2004;
94 Barnaud et al. 2008; Verburg et al. 2016; Voinov et al. 2018; Schlüter et al. 2019). While modeling
95 may refer to any kind of qualitative or quantitative system representation used to identify and
96 understand patterns or processes, in this study we explicitly focus on dynamic models showing
97 change over time. Designing models that capture the complexity of SES while yielding useful
98 information at relevant scales for management remains conceptually and methodologically
99 challenging (Elsawah et al. 2019). SES modeling is often criticized for failing to address broader
100 contexts: operating at too large a scale (O’Sullivan 2004; Mahony 2014), not representing or
101 arbitrarily reducing complex processes to abstract quantities (Taylor 2005; Hulme 2011; Dempsey
102 2016; O’Lear 2016), or overlooking end-users’ interests and capabilities (Rayner et al. 2005; Nost
103 2019). These critiques highlight the need for more widespread integration of transdisciplinary and
104 co-production processes into SES modeling. Researchers have begun to formulate conceptual
105 guides for transdisciplinary applications of SES models (Schlüter et al. 2019), though gaps remain in
106 the development of theoretical and practical recommendations.

107 The purpose of this study is to understand how SES models are being designed and applied to the
108 challenges of global environmental change and to develop guiding principles for transdisciplinary
109 SES modeling. To limit the scope of the review, we analyzed 74 peer-reviewed papers describing
110 applications of SES models in mountain areas. Mountains are a representative system for modeling
111 dynamic processes in complex SES as they have high spatial and temporal heterogeneity and attract
112 diverse actors with often conflicting worldviews and agendas (Klein et al. 2019; Thorn et al. 2020).

113 To analyze the design and application of SES models, we turn to Science and Technology Studies
114 (STS) to conceptualize models as scientific artifacts (Latour 1986). The field of STS has long
115 advanced the social study of science, illustrating how material devices (Latour 1986), embodied

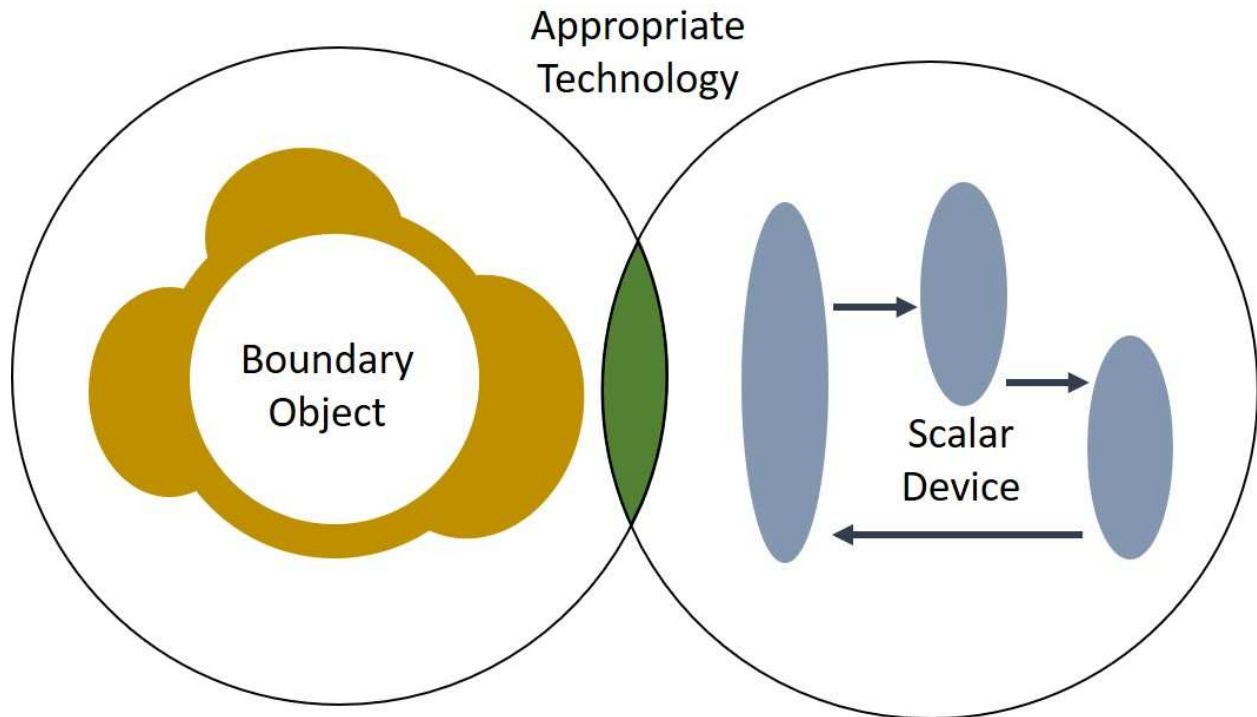
116 practices (Haraway 1988), and infrastructures (Bowker and Star 1999) shape knowledge
117 production. Here, we focus on models as knowledge infrastructures, which Edwards et al. (2013)
118 define as “robust networks of people, artifacts, and institutions that generate, share, and maintain
119 specific knowledge about the human and natural worlds” (p. 23). We draw on three concepts
120 related to knowledge infrastructures to analyze the design and application of SES models:
121 appropriate technology (Fortun 2004), boundary objects (Star and Griesemer 1989), and scalar
122 devices (Ribes 2014). We use these concepts to explore how SES models influence collaboration
123 around environmental problems (Taylor 2005; Sundberg 2010; Landström et al. 2011), shaping the
124 production of new knowledge, relationships, and decisions.

125 **1.1 Conceptual framework: SES models as appropriate technology for transdisciplinary** 126 **applications**

127 Scholars are calling for a more reflexive consideration of models’ embeddedness in socio-cultural
128 contexts and relevance for particular places and problems (Taylor 2005; Crane 2010). The concept
129 of appropriate technology broadens our view beyond the technical correctness of models, towards
130 this more societal focus. Appropriate technology emerged from alternative technology movements
131 of the mid-twentieth century, and refers to tools, techniques, and machinery used to address
132 livelihood and development problems in ways that are sensitive to place-based needs, as opposed
133 to one-size-fits-all solutions. STS researchers have applied the concept to other contexts, such as
134 questioning how scientists acquire “the right tools for the job” (Clarke and Fujimura 1992; de Laet
135 and Mol 2000). Following Fortun (2004), an SES tool such as simulation modeling could be
136 considered appropriate technology when it is “designed in a way attuned to the material, political,
137 and technological realities with which it works, and to the social actors who will be its users” (p.54).
138 For example, Fortun (2004) describes the development of a publicly-available pollution database
139 and website in the early 2000s, which allowed the public to search for toxic releases by company

140 name and to learn about subsequent risks to human and environmental health. This website was
141 appropriate technology for the time given that key aspects to US environmentalism were open
142 source technologies, corporate transparency, and complexity science.

143 In this paper, we examine whether SES models are appropriately designed for contemporary
144 transdisciplinary applications that aim to understand and overcome the challenges presented by
145 global environmental change. These challenges demand societally-relevant integration of data and
146 stakeholder perspectives across spatial and temporal scales, yet this is difficult to accomplish due
147 to: (1) diverse and sometimes contradictory stakeholder objectives and worldviews (Etienne et al.
148 2011; Etienne 2013; Lade et al. 2017), including epistemological rifts between the socio-cultural
149 and computational sciences that prevent detailed representations of social processes in SES models
150 (Taylor 2005; Crane 2010; Verburg et al. 2016; Voinov et al. 2018); and (2) mismatching scales of
151 social and ecological processes and associated data (Zimmerer and Basset 2003; Cumming et al.
152 2006; Bakker and Cohen 2014; Rammer and Seidl 2015; Lippe et al. 2019). By employing the
153 conceptual framework of models as “appropriate technology,” our evaluation focuses on how SES
154 models span social boundaries and spatial scales. We use the concepts of “boundary objects” and
155 “scalar devices” to explore how SES models bring together diverse groups of people with the aim of
156 improving understanding and management of SES (boundary objects, section 1.1.1), and how SES
157 models can help understand cross-scale and cross-level dynamics (scalar devices, section 1.1.2). We
158 propose that SES models that achieve these dual objectives can best function as appropriate
159 technology (Figure 1).



160

161 **Figure 1.** Conceptual relationship between boundary objects and scalar devices, indicating that SES
 162 models may function as appropriate technology for transdisciplinary applications when they
 163 simultaneously span social boundaries and spatial scales (green area).

164 1.1.1 Models as boundary objects

165 Traditionally, model design has been the purview of scientific research communities. However,
 166 recent attempts to incorporate more diverse stakeholder perspectives have led to the co-design of
 167 SES models, allowing for different understandings, values, and worldviews to be elicited, visualized,
 168 and negotiated in the pursuit of a shared “boundary object” or system representation (Zellner
 169 2008; Etienne et al. 2011; Etienne 2013; Edmonds et al. 2019). Boundary objects are conceptual or
 170 material items that emerge through collaboration, remaining both adaptable to local needs yet
 171 “robust enough to maintain a common identity” across different groups (Star and Griesemer 1989,
 172 pg. 393). Stakeholders can hold different, sometimes conflicting, ideas about boundary objects yet
 173 still collaborate through them. One example, described by Star and Griesemer (1989), includes a

174 bird in a natural history museum: the specimen carried different value and meaning to amateur
175 bird watchers, professional biologists, and taxidermists, who worked together using the boundary
176 object while maintaining different epistemic perspectives. In this way, boundary objects enable
177 people to work together across knowledge systems despite syntactic and semantic differences in
178 understanding (Carlile 2002), illustrating how collaboration can occur without requiring
179 consensus.

180 The boundary object concept has been widely applied outside STS given its utility in understanding
181 the process of collaboration in inter- and trans-disciplinary settings (Clark et al. 2011; Steger et al.
182 2018). Here, we examine how SES models can function as boundary objects for transdisciplinary
183 work, exploring how a model can span multiple social worlds beyond one system or knowledge
184 type (Clarke and Star 2008).

185 **1.1.2 Models as scalar devices**

186 A core challenge of modeling SESs is the scalar mismatch (Zimmerer and Bassett 2003) occurring
187 between social and ecological processes and the data that represent them (Walker et al. 2004;
188 Cumming 2006; Rammer and Seidl 2015). For example, models that forecast regional climate
189 change may not have adequate spatial resolution to incorporate local level human drivers like land
190 use change, yet it is the combination of these multi-scalar drivers that could pose the highest risk
191 and uncertainty for the system (Altaweel et al. 2009). Efforts to address these scalar issues are
192 limited by computing power, data availability, and the ability to make inferences from highly
193 complex or complicated models (Kelly et al. 2013; Verburg et al. 2016; Lippe et al. 2019). Here, we
194 examine how models are used as “scalar devices” to conceptually shift between temporal or spatial
195 scales, thus aiding users in overcoming this scalar mismatch.

196 Ribes (2014) proposed the ethnography of scaling as a methodological approach for studying long-
197 term scientific enterprises, where scalar devices are the tools and practices researchers use to
198 represent, understand, and manage large-scale objects or systems that cross multiple levels of
199 organization (Ribes and Finholt 2008). For example, Ribes examines how scientists used agendas,
200 slides, and notes as scalar devices to summarize current and future disciplinary needs across
201 multiple scales when creating the geosciences network known as GEON. These tools condensed
202 months of work across disparate groups of scientists into concrete objects and representations that
203 could be examined and questioned within the same room at the same time, thus translating a large
204 and complex system into a more approachable format. Scalar devices can also refer to social
205 activities such as all-hands meetings that bring together networks of people to deliberate and
206 communicate about large-scale spatial and temporal dynamics. In this paper, we conceptualize SES
207 models as scalar devices to understand how they are used to isolate certain components and
208 feedbacks in SES so that these systems might be more clearly understood, predicted, and managed
209 across scales.

210 Below, we describe patterns in how SES models are designed and used to address cross-
211 disciplinary and cross-scalar processes. We draw on these results to re-examine our conceptual
212 framework (Figure 1) that places appropriate technology for SES modeling at the intersection of the
213 boundary object and scalar devices concepts. In light of these results, we propose a set of guiding
214 principles to facilitate the development of SES models as appropriate technology for
215 transdisciplinary applications.

216 **2. Materials and Methods**

217 **2.1 Search strategy**

218 We reviewed literature employing dynamic social-ecological models in mountain systems,
 219 searching combinations of keywords in the search engine Google Scholar (model*; ‘coupled human
 220 natural systems’ or ‘coupled natural human systems’; ‘social-ecological systems’ or ‘socio-ecological
 221 systems’; ‘change’; ‘management’; ‘mount*’ or ‘highland’ or ‘alpine’). Keywords were compiled
 222 during meetings with experts from the Mountain Sentinels Collaborative Network
 223 (mountainsentinels.org), a group of researchers and other stakeholders working towards mountain
 224 sustainability worldwide. We expanded this search by following references included in these
 225 papers to other studies and via consultations with experts. All papers published in English prior to
 226 August 2017 were considered for inclusion if they contained one overarching modeling effort,
 227 which in some cases consisted of multiple modeling approaches either integrated or presented
 228 alongside one another. To be included, models needed to be dynamic (showing change over time)
 229 and include both social and ecological components. Although this search was not systematic, the 74
 230 papers we reviewed represent a significant proportion of the literature available.

231 **2.2 Data collection**

232 Each of the 74 papers (Appendix A) was coded independently by two team members according to a
 233 codebook developed and tested on five papers. Differences were discussed and resolved by a third
 234 reviewer as needed. We operationalize the concept of appropriate technology by assessing
 235 characteristics of SES model design and application, including the model purpose, stakeholder
 236 involvement, and spatial extent/resolution (Table 1). We use these codes as “sensitizing concepts”
 237 (Blumer 1954) to guide our exploratory analysis and to conceptually bridge between measurable
 238 SES modeling characteristics and the relative ambiguity of the STS concepts we described above.

Design codes	Description	Measurement	Appropriate Technology
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Model purpose (intended)	System understanding; prediction and forecasting; decision support; and communication/learning (Kelly et al. 2013)	Not addressed / secondary purpose / primary purpose	Scalar devices Boundary objects
Model specificity	Level of context-specificity and level of generalizability	None/low/medium/high	Scalar devices
Model orientation	Level of scientific orientation and level of societal orientation	None/low/medium/high	Boundary objects
Model types	Agent-based, integrated simulation, systems dynamics, Bayesian Network, cellular automata, mathematical, statistical, or GIS	Present or absent	Scalar devices Boundary objects
Data types	Biophysical (e.g. climatic, ecological, hydrological, geologic/topographic) Social (e.g. economic, political, demographic, ethnographic) Social-Ecological (e.g. land use or livelihoods)	Present or absent	Boundary objects Scalar devices
Model extent	Social	The broadest organizational level addressed: individual, household, community,	Scalar devices

	Spatial	region, nation, multi-nation, or global The size of the study area (e.g., km ²) where available	
Model resolution	Social Spatial	The narrowest organizational level addressed: individual, household, community, region, nation, multi-nation, or global The size of the smallest pixel or modeling unit (e.g., km ²) where available	Scalar devices
Public participation	Whether or not non-researchers were involved in modeling	Present or absent	Boundary objects
Stakeholder diversity	What level of stakeholder diversity was present in the system being modeled	Not mentioned/none/low/high	Boundary objects
Application codes			
Model purpose (achieved)	System understanding; prediction and forecasting; decision support; and communication/learning (Kelly et al. 2013)	Not addressed / secondary purpose / primary purpose	Scalar devices Boundary objects
Policy or planning outreach	Whether or not modeling results were communicated to	Present or absent	Boundary objects

	decisionmakers (e.g., policy makers, planners, managers)		
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239 **Table 1.** Codebook organization.

240

241 Design codes focused on the methods used to build the models. Model types included eight non-
 242 mutually exclusive categories each study could include: agent-based, integrated simulation, systems
 243 dynamics, Bayesian network, cellular automata, mathematical, statistical, and GIS. We also noted
 244 whether toy models or role-play games were used to engage participants. Data types were coded
 245 into: “biophysical”, “social”, or “social-ecological” categories, which were further specified into sub-
 246 categories (Table 1). We drew on the data types used to understand how models act as boundary
 247 objects by integrating diverse perspectives through data, and what kinds of data are most
 248 frequently applied to model cross-scale dynamics. See Appendix B for detailed definitions of data
 249 and model types.

250 Coders identified information on the social and spatial scale of the models, which we used to assess
 251 how models function as scalar devices. We divided these data into extent (broadest level) and
 252 resolution (narrowest level). We classified social scale according to the organizational or
 253 administrative levels addressed in the model (Gibson et al. 2000; Cash et al. 2006; Preston et al.
 254 2015), organizing them into seven qualitative and hierarchical categories: individual, household,
 255 community, region, nation, multi-nation, or global. We determined whether a model considered
 256 cross-scale processes by calculating the number of social levels crossed between the extent and
 257 resolution of the model. For example, a model that crossed two scales might go from a regional-
 258 level extent to a household-level resolution. We also recorded the quantitative size of the study area
 259 (extent) and the size of the smallest pixel or unit of the model (resolution), when available.

260 The level of model specificity was assessed via two questions regarding the degree of a) contextual
261 understanding and b) general, transferable understanding emphasized in the model development
262 and application. Contextual and general understanding were ranked independently of one another
263 (Table 1; none/low/medium/high), contributing to our understanding of how SES models act as
264 scalar devices. A highly contextual model presented a detailed description of the study site and
265 clarified how this context influenced model design and application, while a highly generalizable
266 model explicitly and repeatedly emphasized how their modeling effort was relevant to other
267 systems. Similarly, the theoretical orientation of the model was assessed via two questions (ranked
268 independently) regarding the advancement of a) theoretical/scientific knowledge and b) societal
269 goals/processes. According to our rubric, a highly scientifically-oriented model clearly advanced
270 some research field or theory, while a highly societally-oriented model supported a social objective
271 or laid the foundation for locally-relevant decision-making (e.g., policy making, management action,
272 planning processes, educational tools). Thus the orientation of the model sheds light on how these
273 models function as boundary objects. These four questions allow us to determine which models
274 were both highly contextual and also highly generalizable to other systems, or which models
275 managed to achieve high scientific as well as high societal relevance.

276 Coders extracted all textual references to public participation, which included the involvement of
277 any non-researcher stakeholder group. These data were categorized into a binary participatory or
278 non-participatory variable. Any level of engagement with the public - from model
279 conceptualization, design, development, or implementation - was considered participatory.

280 Stakeholder diversity was another variable that was either not mentioned in the paper, or coded as
281 none, low, or high levels of diversity. Together these variables clarify the diversity of people
282 involved in the modeling activity, an important criteria for functioning as a boundary object.

283 Model purpose refers to the goals of the modeling work and were adapted from Kelly et al. (2013)
284 to include: system understanding, prediction/forecasting, decision support, and
285 learning/communication (see Appendix B). We define the learning/communication purpose as a
286 contribution towards “the capacity of a social network to communicate, learn from past behaviour,
287 and perform collective action” (Kelly et al. 2013, pg. 161), which distinguishes it from more general
288 system understanding. Models designed for decision support include a wide variety of decision
289 contexts, including multi-criteria analyses, trade-offs in decision-making, land use planning, and
290 management actions. Coders recorded the intended model purpose and classified whether each
291 intention and outcome was addressed as a primary or secondary purpose of the project. We used
292 quotations from the text to resolve any differences between coder ranking. Due to this potential
293 subjectivity, and sometimes small sample sizes, we treated the model purpose variables as binary
294 Yes (primary or secondary purpose) or No (not addressed) in most of our analyses. Finally, coders
295 extracted all references to policy and planning outreach, which we translated into a binary code
296 indicating whether or not the model or study results were directly communicated to decision
297 makers.

298 **2.3 Analysis**

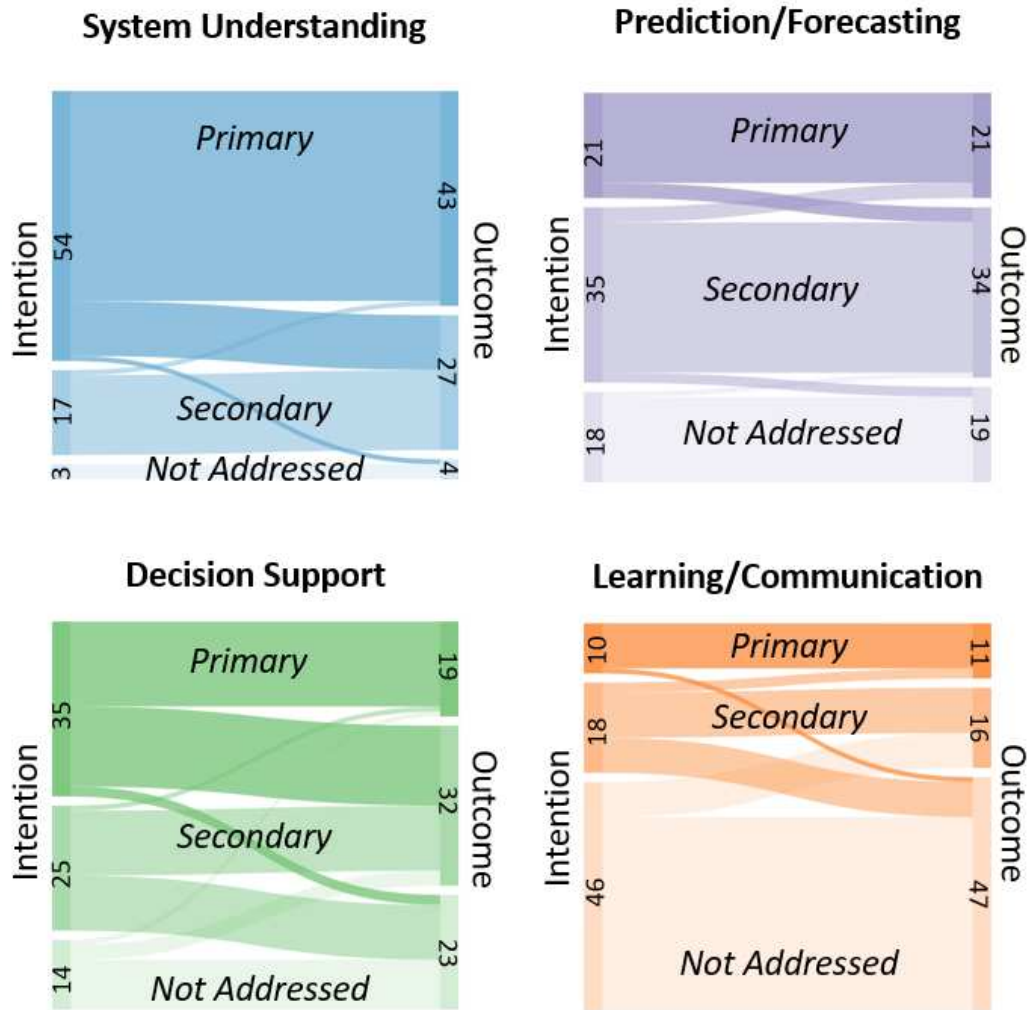
299 We present summary statistics that describe trends in SES modeling design and application. We use
300 chi-square or Fisher’s exact tests and t-tests as relevant to look for associations between model
301 purpose outcomes and the various design codes described above. For all tests, we consider $p < 0.05$
302 to be statistically significant.

303 **3. Results**

304 **3.1 Model purpose: Intention vs. outcome**

305 Many studies successfully achieved the outcome they intended (Figure 2). Almost three-quarters
306 (73%) of the papers intended system understanding to be a primary purpose of the model (n=54),
307 yet only 57% (n=42) achieved it as a primary outcome. Instead, most of these papers achieved
308 secondary system understanding outcomes. Prediction/forecasting was not a frequent primary
309 model purpose (n=21, 28%), but was commonly considered a secondary model purpose (n=35,
310 47%). There was little difference between intentions and outcomes for the prediction/forecasting
311 purpose, indicating these SES models generally achieved their intended purpose. These model
312 purposes require integrating information about the world across different geographic levels and
313 multiple time horizons, thus aligning with the scalar devices concept.

314 There was considerably greater difference between intentions and outcomes for both decision
315 support and learning/communication model purposes (Figure 2), indicating that SES models may
316 face barriers when created for these purposes. Decision support was commonly intended as a
317 primary model purpose (n=35, 47%). However, almost half of the papers that intended decision
318 support as a primary purpose instead achieved it as a secondary purpose (n=16), and 44% of the
319 papers that intended it as a secondary purpose failed to report any successful decision support
320 outcomes (n=11). Most papers we reviewed did not consider learning/communication to be an
321 intended model purpose (n=46, 62%). Nevertheless, 39% of the papers that intended it as a
322 secondary purpose failed to report any learning/communication outcomes (n=7), while the same
323 number of papers discovered unexpected learning outcomes despite having no intention of it.
324 These results point to gaps in the ability of SES models to contribute to decision support outcomes,
325 and a general inattention to learning/communication model purposes. These model purposes are
326 aligned with the boundary object concept as they typically rely on significant stakeholder
327 engagement. The fact that their intended use fell short of their realized use suggests critical gaps in
328 the role of SES models as boundary objects.



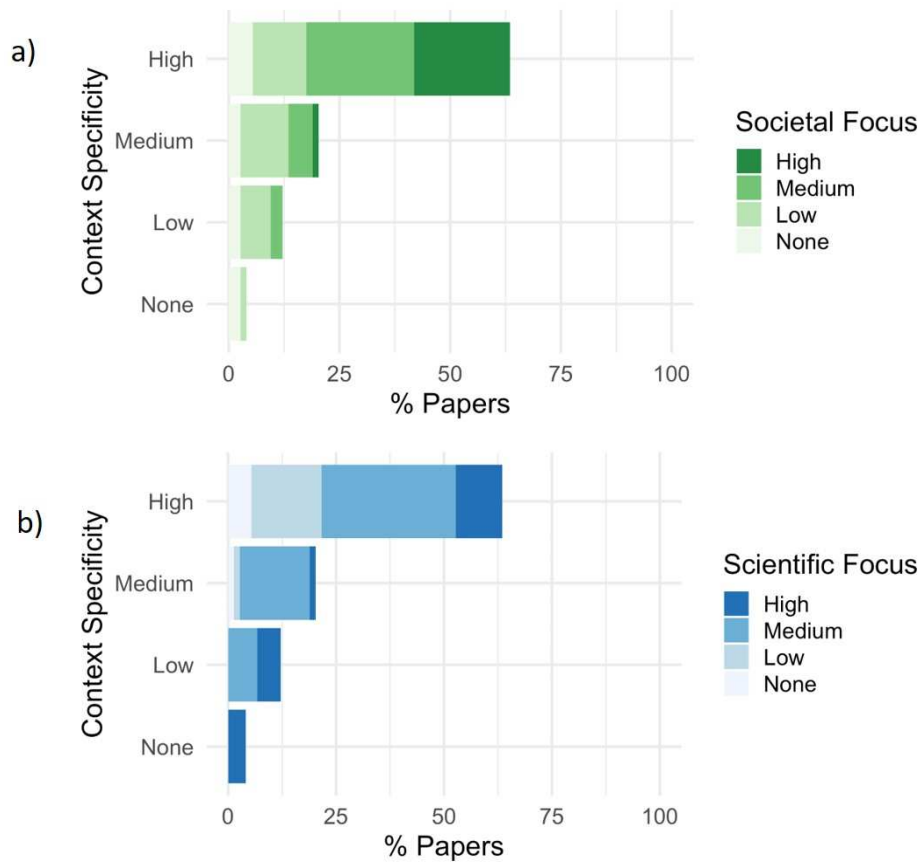
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330 **Figure 2.** Number of papers per model purpose, for both intentions and outcomes.

331 **3.2 Model specificity and orientation**

332 Most models (n = 47, 63.5%) had a highly context-specific focus, while only 10.8% (n=8) were
 333 considered highly generalizable, illustrating a preference for SES models to focus on particular
 334 places and their relevant scales of operation rather than generic systems or processes. Most models
 335 (n=40, 54%) were also classified as having medium scientific orientation. While scientific or
 336 theoretical advancement was a common goal of SES modeling efforts, there was less consistency for
 337 societal goals, as models were roughly evenly distributed across low, medium, and high levels of

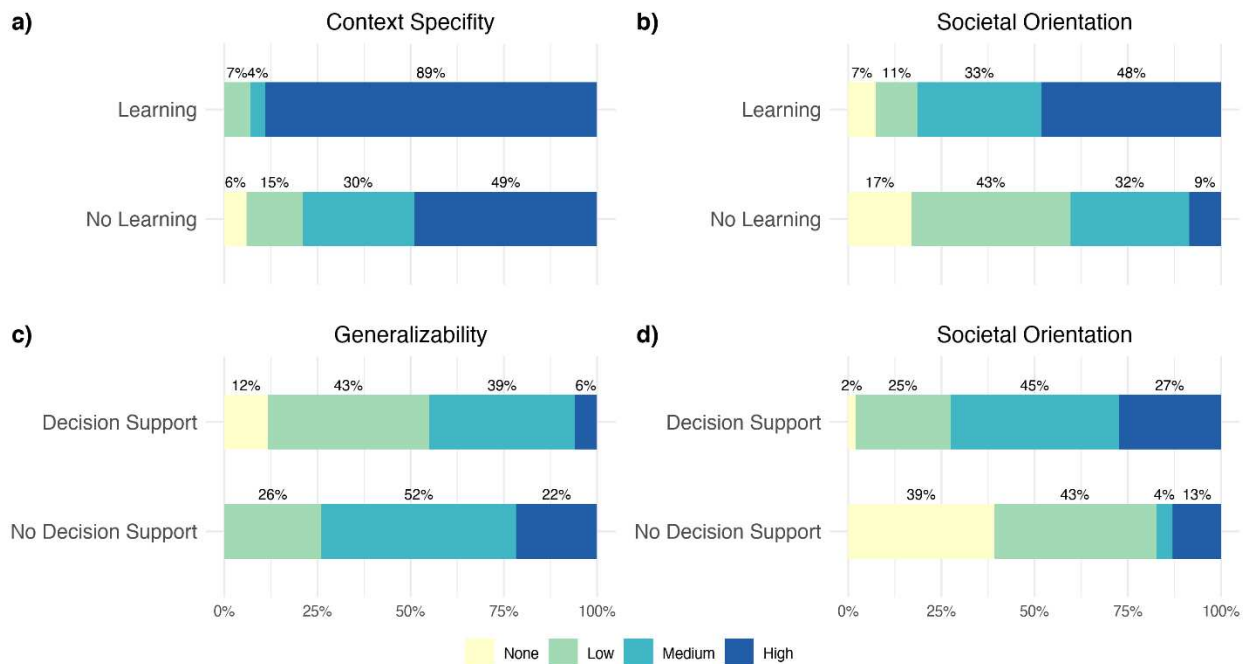
338 societal orientation. These results again highlight potential gaps in how SES models are used as
 339 boundary objects. When analyzing the relationship between model specificity and orientation, our
 340 results indicated that SES models used to advance societal goals also tended to be highly context
 341 specific ($p < 0.01$; Figure 3a), while scientific goals appeared to be advanced even at low or
 342 nonexistent levels of system-specific context ($p = 0.02$; Figure 3b). This points to potential synergies
 343 between the STS concepts, where SES models are more likely to function as boundary objects (i.e.,
 344 by advancing societal goals) when they are created at scales relevant to a particular context.



345

346 **Figure 3.** Percent of papers per level of context-specificity, according to a) societal orientation and
 347 b) scientific orientation.

348 We found significant associations between learning/communication outcomes and context-
 349 specificity ($p < 0.00$), where most models with learning outcomes were also highly context-specific
 350 ($n=24, 89\%$; Figure 4a). This indicates that context specificity is an important characteristic of SES
 351 models that function as boundary objects, perhaps by enabling stakeholders to recognize and relate
 352 to the system represented. Learning outcomes also occurred with more regularity across medium
 353 to high levels of societal orientation ($p < 0.00$; Figure 4b), supporting the idea that societally-
 354 oriented models are more likely to function as boundary objects. Decision support outcomes were
 355 highest at low to medium levels of generalizability ($p = 0.04$; Figure 4c) and almost non-existent
 356 when the models lacked societal orientation ($p < 0.00$; Figure 4d). This suggests there was some
 357 flexibility in achieving decision support outcomes; if modeling efforts included a modest degree of
 358 generalizability and societal focus, decision support outcomes tended to occur. However, both
 359 learning and decision support outcomes were most common at medium to high levels of societal
 360 orientation, indicating that the pursuit of these model purposes may promote the use of SES models
 361 as boundary objects.



362

363 **Figure 4.** Model purpose outcomes were significantly associated with the context-specificity,
364 generalizability, and societal-orientation of the models.

365 **3.3 Model types**

366 Of the eight model types, agent-based models (ABM) were the most frequently used (n = 48,
367 64.8%), followed closely by cellular automata models (n = 46, 62.1%). In fact, ABM and cellular
368 automata models were used together in almost half the studies (n = 36, 48.6%), though decision
369 support outcomes were more common when cellular automata models were absent (p = 0.02).
370 Mathematical models were also relatively common (n=34, 45.9%). Learning outcomes were
371 significantly higher when toy models or role-play games were used (p < 0.01), indicating that
372 models built with stakeholder involvement in mind tended to function as boundary objects. No
373 other model types were associated with higher model purpose outcomes.

374 Studies used one modeling approach (n =11, 14.8%), or combined two (n=30, 40.5%), three (n=21,
375 28.3%), or four (n=12, 16.2%) modeling approaches to represent and scale the system in different
376 ways. When only one modeling approach was used, system dynamics and mathematical models
377 were most frequent. When multiple approaches were used, ABM and cellular automata models
378 were most frequent. We did not find any associations between model purpose outcomes and the
379 number of modeling approaches used.

380 We did not find significant associations between model type and scientific orientation, though
381 mathematical models and system dynamics models do have significant associations with societal
382 orientation. Specifically, mathematical models were more likely than non-mathematical models to
383 have intermediate (low or medium) levels of societal orientation (p<0.00). We also observed a
384 higher proportion of system dynamics models with high societal orientation (71%), compared to
385 only 18% of non-system dynamics models (p=0.01). This suggests that system dynamics and

386 mathematical models tend to be used as boundary objects. We did not find any associations
387 between model type and model specificity, indicating that the type of modeling approach is
388 unrelated to the context-specificity or generalizability of the model. Together, these results
389 demonstrate that the question of model type is related more to the role of the model as a boundary
390 object rather than as a scalar device.

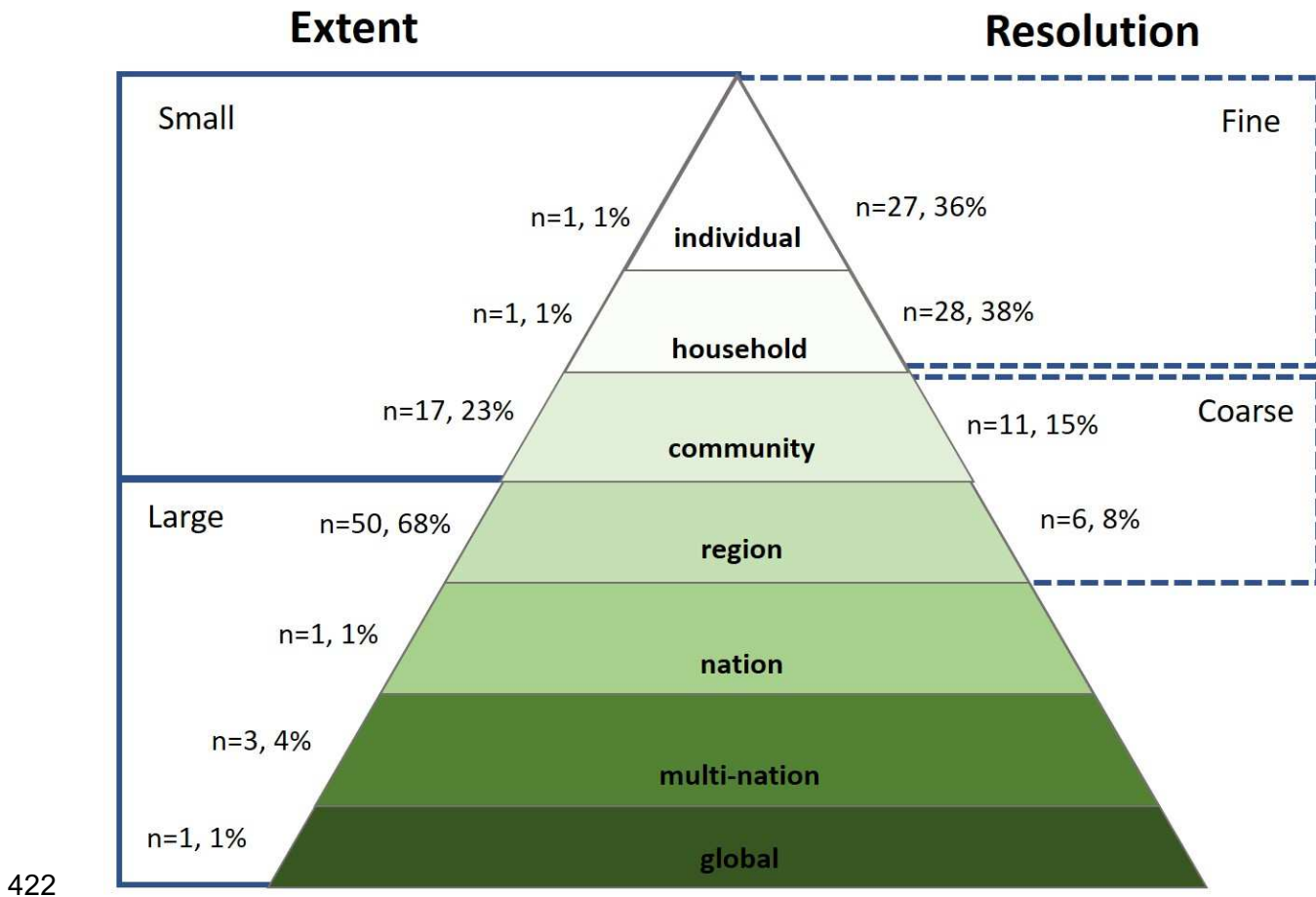
391 **3.4 Data types**

392 We found that SES models tend to under-represent social datasets, and are more likely to rely on
393 pre-existing datasets. Models used significantly higher numbers of biophysical ($\mu = 5.0$, $SE \pm 1.2$, $p <$
394 0.00) and social-ecological ($\mu = 4.3$, $SE \pm 0.9$, $p = 0.04$) datasets compared to social datasets ($\mu = 3.4$,
395 $SE \pm 0.8$). The similar number of biophysical and social-ecological datasets suggests these data types
396 are roughly equally valued for representing dynamic SES. However, the relative lack of social
397 datasets may point to gaps in how SES models span multiple social worlds. For all data types,
398 secondary datasets (e.g., from the literature or published data) were significantly more common
399 than primary datasets collected from the study site. The most common datasets were ecological
400 (median = 2), followed by land use (median = 1.5) and demographic, economic, climatic,
401 geologic/topographic, and SES livelihood datasets (median = 1). Meanwhile political, ethnographic,
402 and hydrologic datasets were infrequently included in models (median = 0).

403 Our results point to potential tradeoffs between the number of biophysical datasets used and model
404 purpose outcomes related to system understanding and learning/communication. Models with
405 system understanding outcomes used significantly higher numbers of biophysical datasets ($u = 5.1$)
406 than those without understanding outcomes ($u = 2.8$, $p < 0.02$). However, models with learning
407 outcomes used significantly fewer biophysical datasets ($u = 3.7$) compared to those without
408 learning outcomes ($u = 5.7$, $p < 0.00$).

409 3.5 Extent and resolution

410 Most models had social extent at the regional and community levels and social resolution at either
411 the household or individual level (Figure 5). No models had coarser than a regional resolution. We
412 grouped models according to small or large social extent as well as fine or coarse social resolution,
413 and found no association with model purpose outcomes. We examined patterns between social and
414 spatial scale, finding that regional-level extent corresponded to an average study area of 10,815
415 km² (SE± 4,855 km²) and community-level extent had an average study area of 385 km² (SE± 348
416 km²). We also found the average resolution was 0.54 km² (SE± 0.31 km²) for household-level
417 models, and 0.22 km² (SE± 0.09 km²) for individual-level models. However, quantitative
418 information was only provided by 69 papers (93%) for spatial extent and 56 papers (76%) for
419 spatial resolution. These results shed light on how SES models act as scalar devices by integrating
420 information across different geographic scales into more compressed representations of the
421 system.

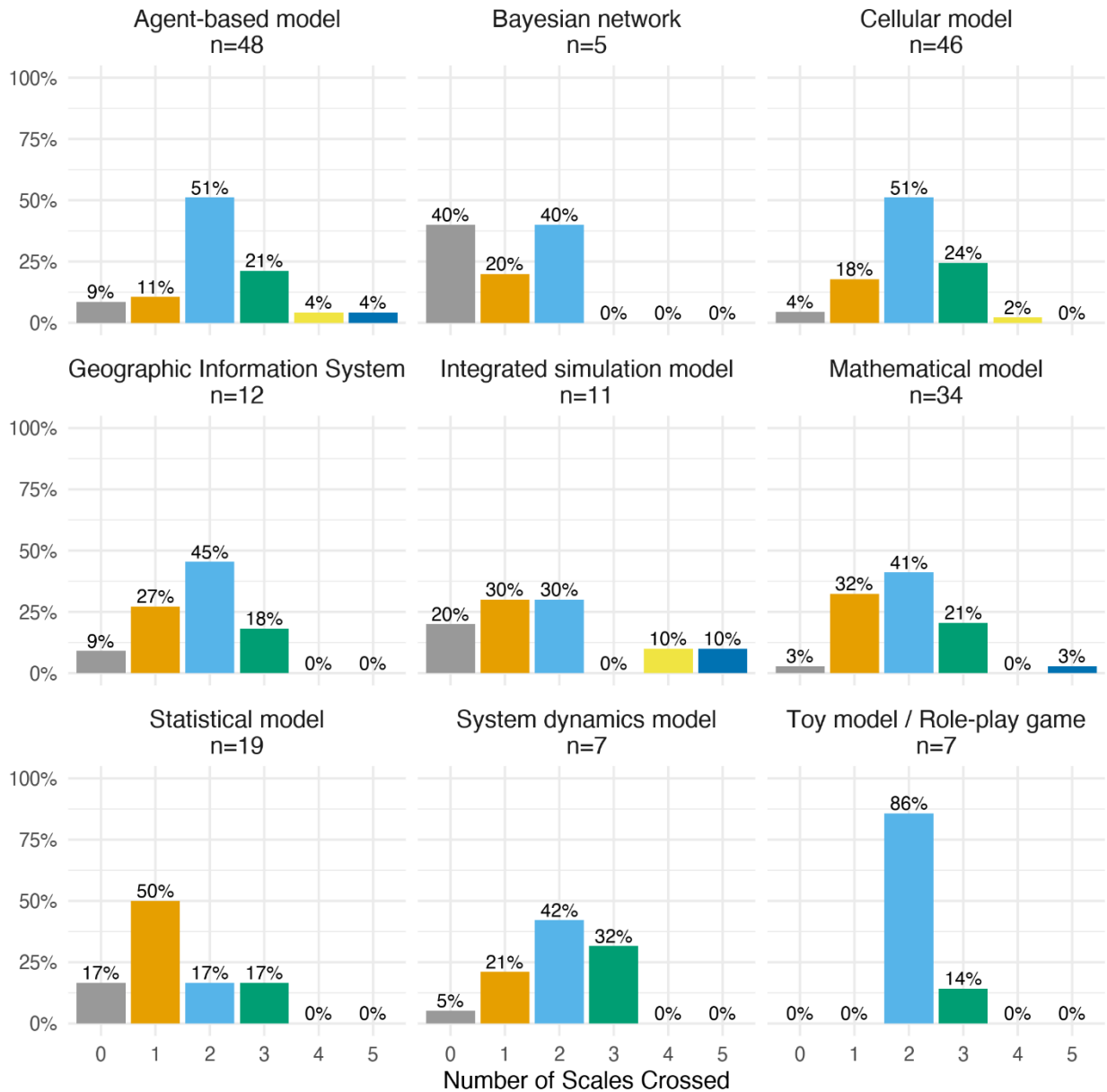


422
423 **Figure 5.** The number and percentage of models at each extent and resolution level.

424

425 Only seven models in our review focused on a single scale (i.e., had the same extent and resolution),
 426 and these were found across all model types except toy models (Figure 6). Models crossed either
 427 one (n=17, 23.0%), two (n=31, 41.9%), three (n=13, 17.6%), four (n=2, 2.7%), or five (n=2, 2.7%)
 428 scales. Bayesian networks tended to maintain the same extent and resolution (i.e., were not cross-
 429 scalar), and system dynamics models were most likely to cross just a single scale. Of all the model
 430 types, only ABMs, ISMs, and mathematical models were observed to cross five spatial scales
 431 between their extent and resolution. We examined whether the number of scales crossed between
 432 extent and resolution impacted model outcomes, but found no significant associations. These

433 results indicate that certain model types may be more useful than others for representing highly
 434 cross-scalar dynamics. However, the number of scales crossed is not by itself an adequate measure
 435 of what constitutes a scalar device, because a higher number of scales crossed does not appear to
 436 support higher model purpose outcomes.



437

438 **Figure 6.** The proportion of each model type according to the number of scales crossed.

439

440 **3.6 Public participation, stakeholder diversity, and policy or planning outreach**

441 Roughly half the models in our analysis were participatory (n = 38, 51.4%). However, only 21.6% (n
442 = 16) demonstrated any direct outreach to decision makers (e.g., through a presentation of results
443 or workshop). We found higher learning outcomes in participatory models (p < 0.00) and models
444 with policy or planning outreach (p < 0.00). While not significant, decision support outcomes were
445 also more likely with participatory models (n=30, 79%) compared to non-participatory models
446 (n=21, 58%). Perhaps unsurprisingly, we found a strong association between decision support
447 outcomes and models with policy or planning outreach (p < 0.00). Finally, we found a significant
448 association between outcomes of decision support and levels of stakeholder diversity, indicating
449 that modeling efforts where stakeholder diversity is present tend to have higher rates of decision
450 support compared to situations where stakeholder diversity is not present or not addressed.
451 Together, these results support our characterization of SES models as boundary objects that invite
452 successful collaboration (i.e., learning or decision support) between diverse actors who may not
453 otherwise agree.

454 **4. Discussion**

455 This study improves our understanding of how SES models are designed and applied to address the
456 rising challenges of global environmental change, using mountains as a representative system. In
457 this section, we discuss the results outlined above by drawing on the concepts of boundary objects
458 and scalar devices to understand how SES models operate as appropriate technology (Table 1,
459 Figure 1). While we initially proposed that appropriate technology for SES modeling would sit at
460 the intersection of boundary objects and scalar devices, our results stress the importance of SES
461 models functioning as boundary objects for effective transdisciplinary work to occur. Meanwhile,

462 crossing multiple temporal and spatial scales was less critical for appropriate SES modeling, and we
463 encourage modelers to instead remain flexible and sensitive to end user needs and contexts when
464 designing models. We propose four guiding principles to facilitate the development of SES models
465 as appropriate technology for transdisciplinary applications: (1) increase diversity of stakeholders
466 in SES model design and application for improved collaboration, (2) balance power dynamics
467 among stakeholders by incorporating diverse knowledge and data types, (3) promote flexibility in
468 model design, and (4) bridge gaps in decision support, learning, and communication.

469 **4.1 Increase diversity in SES model design and application for improved collaboration**

470 We found that models incorporating diverse stakeholders through public participation and policy
471 outreach act as transdisciplinary boundary objects by supporting higher learning and decision
472 support outcomes. For example, Anselme et al. (2010) used an agent-based model to better
473 understand and manage high biodiversity habitats threatened by shrub encroachment in the
474 French Alps. Through this collaborative process, a forest manager came to appreciate the need for
475 genetic diversity in the forest stands he was managing, leading him to support the development of a
476 “genetic quality index” to better enable managers and scientists to work together. Despite strong
477 learning outcomes, stakeholders in this process remained skeptical about their ability to influence
478 policy formation at higher levels. Smajgl and Bohensky (2013) took a more targeted approach to
479 influencing policy in their spatial modeling of poverty in East Kalimantan, Indonesia. They worked
480 directly with government decision-makers to determine the optimal level for petrol prices that
481 would enable more citizens to engage in high-income, petrol-dependent livelihoods like fishing and
482 honey collection. While both of these participatory examples had high outcomes of both decision
483 support and learning/communication, they differed in the degree to which they targeted specific
484 policy decisions - indicating that policy outcomes are not necessary for SES models to function as
485 boundary objects.

486 Models used in conditions of high stakeholder diversity tended to yield higher decision support
487 outcomes compared to models where stakeholder diversity was not present or not addressed.
488 While it might be expected that situations bringing together people from diverse backgrounds and
489 perspectives would be a source of conflict, examining these results through the lens of boundary
490 objects highlights how SES models can work across scientific and social worlds to promote
491 collaboration without requiring consensus. For example, Barnaud et al. (2013) examined an agent-
492 based model in the context of conflicting ecological, economic, and social interests among
493 stakeholders involved in land management in Northern Thailand. The collaborative modeling
494 process encouraged stakeholders to reframe their approach to the conflict and “move from a
495 distributive to an integrative model of negotiation” (pg. 156) by setting aside the question of park
496 boundaries for a time and instead focusing on a more integrated understanding of the system as
497 represented through the model. This enabled them to find potential synergies rather than focusing
498 on the conflicting interests of the different groups, suggesting the process of creating and using
499 models as boundary objects can encourage diverse stakeholders to move past underlying
500 disagreements and develop workable solutions.

501 Overall, participatory models were strongly represented in our review, indicating that these
502 approaches are no longer on the periphery of SES modeling practice in mountains. We find similar
503 patterns throughout the literature (Voinov and Bousquet 2010; Gray et al. 2017; Jordan et al. 2019),
504 indicating that the field of participatory modeling is maturing rapidly in non-mountain systems as
505 well. Whether by design or not, some SES models have functioned as boundary objects by enabling
506 the integration of diverse perspectives without sublimating them. Diverse perspectives are at the
507 core of transdisciplinary work, as multiple viewpoints, epistemologies, and values are needed to
508 holistically understand complex SES problems and devise solutions with high relevance (Bernstein
509 2015; Hoffman et al. 2017; Norström et al. 2020). Diversity has also been shown to increase the
510 likelihood of innovation in collaborative processes (Paulus and Nijstad 2003). As SES modeling

511 continues to gain traction as a tool for promoting transdisciplinary co-production processes, we
512 urge modelers not to lose sight of the need for diverse perspectives in the design, evaluation, and
513 application of the model so that they can act as boundary objects, and thereby enable broader
514 participation and understanding.

515 **4.2 Balance power dynamics by incorporating diverse knowledge and data types**

516 While models with diverse participants were more likely to facilitate learning and cooperation, this
517 did not necessarily translate to more diverse types of knowledge populating the models themselves.
518 The knowledge infrastructure that supports SES modeling currently favors quantitative data and
519 modeling approaches over qualitative forms (Elsawah et al. 2019). In fact, there are pervasive
520 epistemological gaps regarding what is even considered “data” across the natural and social
521 sciences, much less how to analyze or validate them (Verburg et al. 2016; Chakraborty et al. 2019).
522 Our results confirm this gap by showing that scientists frequently try to understand SES through
523 the use of pre-existing datasets, the majority of which are biophysical rather than social. By not
524 integrating social data, these models are less likely to reach across multiple social worlds and thus
525 less likely to function as boundary objects. One reason for this might be the perception that
526 qualitative data are exorbitantly expensive in terms of the time and cost of data collection and
527 processing (Alexander et al. 2019; Elsawah et al. 2019). This may reflect a broader SES modeling
528 epistemology that seeks to predict and generalize to other systems rather than engage in expensive
529 and time-consuming processes at local scales that lack transferability to other sites or systems
530 (O’Sullivan et al. 2016). Another reason may be that quantitative data are easier to incorporate into
531 computer-based models. Indeed, we find that quantitative demographic and economic data are the
532 most commonly used social datasets in SES models, while ethnographic, descriptively rich data are
533 incorporated into very few studies. However, it is possible that modelers may be using qualitative

534 data without reporting it in their papers - for example, to conceptualize (rather than parameterize)
535 the model.

536 There is clear evidence that qualitative data can help place modeling results in a broader context,
537 thus enhancing a models' ability to function as a scalar device. For example, Altaweel et al. (2009)
538 demonstrated that Arctic peoples' decisions about where to source their water impacted their
539 perceptions of system-wide ecological change, which could in turn support or restrict their ability
540 to adapt to climate change in a timely manner. Including qualitative data can also help overcome
541 widely acknowledged shortcomings of SES models, such as the lack of adequate complexity in
542 representing individual decision-making and behavior (Müller et al. 2013; Brown et al. 2013;
543 Preston et al. 2015; Schlüter et al. 2017; Groeneveld et al. 2017) and the ways in which subjective
544 processes associated with human agency and intentionality (i.e., culture and politics) drive the
545 evolution of social rules and positions (Manuel-Navarrete 2015). There is some evidence from our
546 analysis to support this. For example, Rogers et al. (2012) used ethnographic understanding of
547 Mongolian pastoral kinship affinities to demonstrate that weather impacts (both snowstorms and
548 drought) nearly double in severity due to strained social relationships under conditions of
549 restricted movement. Without this detailed understanding of social networks and pressures, their
550 model likely would have underestimated the impact of extreme weather events on the well-being of
551 pastoral communities. Ethnographic and narrative studies of life trajectories can thus help clarify
552 how humans construct their identities and social positions over time, encouraging SES models to
553 move away from purely structural or static rule-based interactions among model agents (Manuel-
554 Navarrete 2015). Qualitative descriptions can also aid in the communication of SES model results,
555 as narratives have been shown to foster greater appreciation of simulation models by non-
556 modelers when compared to aggregated, statistical summaries (Millington et al. 2012).

557 We also found that models using higher numbers of biophysical datasets were associated with
558 higher system understanding outcomes but lower learning/communication outcomes. For example,
559 Briner et al. (2013) found that biological interdependencies were the most influential factor causing
560 trade-offs between ecosystem services in the Swiss Alps, acknowledging that economic and
561 technological interdependencies were under-represented in their analysis and would benefit from
562 further exploration. They articulated how this improved system understanding could theoretically
563 benefit management and policy, but fell short of describing any clear learning outcomes
564 experienced by practitioners on the ground.

565 Still, our analysis shows that biophysical datasets are a common and useful tool for understanding
566 cross-scale processes in SES models. Yet, as Callon and Latour (1981) note, scale is not just about
567 moving across space and time - it is also about translation and power. Our review of SES models
568 then raises the question - whose system understanding is being (re)produced by SES models with
569 high biophysical focus? And who is benefitting? An example from Alaska (not included in our model
570 review) illustrates that while participants in a modeling workshop collaborated through
571 engagement with a largely biophysical model, there was a lack of formal avenues for incorporating
572 different observations or data types deemed valuable by local and Indigenous residents into the
573 model (Inman et al. in review). While public participation in the modeling process may have
574 encouraged learning about scientific concepts and collaboration through the model as a boundary
575 object, this would be a unidirectional form of learning as scientists were less likely to incorporate
576 other types of data or knowledge into the model. This unidirectional learning is problematic given
577 the historical tendency for scientists to attempt to validate other forms of knowledge without
578 respecting their unique epistemologies (Agrawal 1995; Nadasdy 1999; Latulippe 2015;
579 Chakraborty et al. 2019). Therefore, SES models that bring diverse people together while still
580 representing only a narrow fraction of the knowledge types involved are not functioning as
581 appropriate technology.

582 Local ecological knowledge can provide highly detailed understanding to overcome barriers in
583 understanding and representing social processes in SES models. Local knowledge may be
584 particularly useful in data-poor regions around the world, including mountains (Ritzema et al.
585 2010). For example, Lippe et al. (2011) used qualitative expert knowledge to parameterize a land
586 use model in Northwest Vietnam, enabling a more accurate portrayal of farmers' cropping choices.
587 Moreover, local knowledge itself can act as a scalar device, as knowledge that is transmitted across
588 generations can enhance system understanding across temporal scales (Moller et al. 2004; Gagnon
589 and Berteaux 2009). Though not a modeling study, Klein et al. (2014) found that Tibetan
590 pastoralists who travel further from their home base to higher elevations while herding showed
591 more consensus around climate change and added valuable spatial data beyond what was available
592 from the scant meteorological stations in the region.

593 It is not yet clear whether more balanced inclusion of social data and local knowledge could resolve
594 the apparent trade-off between system understanding and learning/communication, or whether
595 learning is more dependent on the modeling *process* regardless of the datasets and knowledge
596 types used. It is also not yet clear how to integrate different knowledge types into models without
597 privileging certain ways of knowing. We encourage future research into these questions, and urge
598 modelers to remain cognizant of biases towards disciplinary datasets and of power imbalances in
599 the types of knowledge used and how these might impact participant learning. Studies that examine
600 the kinds of learning experienced by participants are needed to ensure that learning occurs as a
601 mutual and reflexive process among the diverse groups of people involved (Keen et al. 2005; Reed
602 et al. 2010; Fernández-Giménez et al. 2019). Qualitative social science approaches play a powerful
603 role in understanding not just what people want or what they value, but who they are (Callon and
604 Latour 1981), and should therefore be granted a more central role in transdisciplinary SES
605 modeling design and application.

606 **4.3 Promote flexibility in model design**

607 Modelers make a distinction between “complicatedness” and “complexity” in SES models (Sun et al.
608 2016). When model structures have large numbers of variables or when processes are represented
609 by highly detailed rules and/or equations, these models are said to have high complicatedness (Sun
610 et al. 2016). Meanwhile, model complexity refers to the simulated behaviors that emerge at the
611 system level through application of the model, which can occur even from quite simple models
612 (Conway 1970; Schelling 1971). The aim is for all SES models to mimic some degree of real-world
613 complexity (Balbi and Guipponi 2010). However, modelers still debate how complicated a model
614 needs to be in order to facilitate this emergent complexity and support decision-making outcomes.

615 Typically, modelers seek the benefits of highly stylized models for testing theories and yielding
616 generalizable results, while highly detailed models are praised for their utility in supporting
617 decision making in complex, real-world situations (Smajgl et al. 2011). Parker et al. (2003)
618 distinguishes between highly stylized simple “Picasso” models and highly detailed empirical
619 “photograph” models, while others describe them as the “KISS: Keep it Simple, Stupid” (Axelrod
620 1997) versus the “KIDS: Keep it Descriptive, Stupid” approaches (Edmonds and Moss 2004). Some
621 modelers and decision-makers prefer ensemble modeling, integrating multiple diverse models,
622 algorithms, and datasets to produce a single set of recommendations (Elder 2018). In short, there
623 are modelers who believe the more complicated a model is, the better it can be used for decision
624 support and stakeholder learning (Barthel et al. 2008).

625 Yet, our results do not support these distinctions in disparate benefits from different levels of
626 model complicatedness, and challenge the idea that a model needs to be highly complicated in
627 order to advance societal objectives. Fine-scale SES models in our review were not more likely than
628 coarse-scale models to report greater model purpose outcomes. Furthermore, we found that
629 models that represent processes occurring across multiple scales were not more likely to support

630 higher outcomes than those focusing on processes operating at a single scale. We found no evidence
631 of improved or diminished decision support when higher numbers of modeling approaches were
632 used concurrently in the same study (as in ensemble modeling), or when more datasets were used.

633 These results further support our assertion that in order to function as appropriate technology in
634 transdisciplinary applications, SES models ought to be designed as boundary objects to address a
635 specific information need presented by a societal problem. We recommend that modelers
636 repeatedly reflect on the needs of their system and diverse end users when considering the scale
637 and choice of modeling approach, rather than assuming finer-scale or highly complicated models
638 will necessarily yield superior results. Viewing these results through the lens of scalar devices, we
639 encourage SES modelers to remain flexible in the ways they represent cross-scalar processes in
640 their models, and to consider in advance how their choice of scale might enable or constrain
641 collaboration among participants - that is, how scale itself functions as a boundary object.

642 Researchers are still in the early stages of empirically measuring how the design and application of
643 modelling and data visualization tools relate to non-technical stakeholders' capacity to contribute
644 meaningfully to collaborative planning processes (Zellner et al. 2012; Radinsky et al. 2017). There
645 is some indication that models and tools that encourage active, energetic dialogue without
646 overwhelming participants with information (Pelzer et al. 2015) are best suited for these
647 applications. Recent research has shown that participatory modelers often use the modeling
648 approaches they are most familiar with, rather than objectively selecting "the best tools for the job"
649 (Voinov et al. 2018). Our results seem to confirm this, as we do not see any evidence of a particular
650 modeling type or scale yielding higher model purpose outcomes. For example, our analysis
651 demonstrates systems dynamics models usually have high societal orientation, but not necessarily
652 the high learning and decision support outcomes proposed by other reviews (Schlüter et al. 2019).
653 Our finding that decision support outcomes are higher when cellular automata models are not used

654 aligns with previous insights into the limited utility of these approaches for certain contexts (NRC
655 2014). Yet, nearly half the models in our review were a combination of agent-based models and
656 cellular automata models, highlighting the popularity and flexibility of these particular model types
657 for representing complex SES - something anticipated nearly two decades ago (Parker et al. 2003;
658 Verburg et al. 2004). Additional empirical studies are needed in the context of SES models for
659 transdisciplinary applications to clarify whether particular modeling approaches or scales can best
660 function as boundary objects.

661 These findings contribute to ongoing debates about the level of complicatedness needed for SES
662 models to support learning and decision making. Multiple modeling paradigms have emphasized
663 the benefits that emerge from achieving an intermediate level of model complicatedness. Grimm et
664 al. (2005) present this as the “Medawar zone,” describing that models are most useful when design
665 is guided by multiple patterns observed at different scales and hierarchical levels. Meanwhile,
666 members of the Companion Modeling network have articulated a “KILT: Keep It a Learning Tool”
667 approach that advocates for slightly less complicated models than the Medawar zone in order to
668 allow diverse stakeholders to connect with the system on their own terms (Le Page and Perrotton
669 2018). O’Sullivan et al. (2016) have similarly argued that mid-range complicatedness is often the
670 optimal or appropriate level. Yet, our results do not necessarily support these hypotheses in all
671 circumstances. For example, we find that highly context-specific models lead to higher learning
672 outcomes, but this does not necessarily mean finer-scale data or model resolution are required.
673 Meanwhile, decision support seems to be best supported at intermediate (not low or high) levels of
674 generalizability. We encourage more explicit attention to the assessment of participant learning and
675 decision support in future modeling efforts to help resolve these debates and advance our
676 understanding of the role of scale in SES models functioning as appropriate technology.

677 **4.4 Bridge institutional gaps for decision support, learning, and communication**

678 For SES models to act as appropriate technology for transdisciplinary work, they must support
679 decision-making processes and learning for real-world applications. This can be accomplished by
680 ensuring that models act as transdisciplinary boundary objects and facilitate cross-scalar learning
681 as scalar devices. Our review revealed considerable gaps between the intentions and outcomes of
682 SES models for these purposes. The gap in decision support stemmed from failing to achieve or
683 report outcomes that matched the intended model purpose, while learning/communication
684 outcomes were rarely even intended by most models in our review. While interviews with
685 modelers themselves may help us better understand these gaps, integrating societal goals into
686 model design and application could be one approach to improving transdisciplinary applications of
687 SES models. Yet, this may be difficult for modelers to achieve due to the current knowledge
688 infrastructure surrounding the modeling process. One issue is the stigma sometimes attributed to
689 “applied” research, or the false dichotomy between “applied” and “basic” research that seems to
690 resist simultaneous advances in theoretical and pragmatic fronts (Stokes 1997). Indeed, we did not
691 find any models in our review that supported high scientific as well as high societal orientation -
692 although Brunner et al. (2016a) and Smajgl and Bohensky (2013) came close to achieving this. Both
693 modeling efforts incorporated and explored specific policy interventions while advancing theory
694 and methodologies in the field of SES modeling, indicating a path forward for joint basic and applied
695 research in SES modeling.

696 Another infrastructural barrier is that some modelers do not appreciate the value of investing time
697 and money in knowledge co-production processes, particularly if their funding mechanisms and
698 career advancement do not reward this kind of engagement with stakeholders. There is some
699 evidence that this is changing, as large-scale funding initiatives such as the Global Challenges
700 Research Fund, the Belmont Forum, and Future Earth require close partnerships between
701 researchers and decision or policy-makers (Mauser et al. 2013; Suni et al. 2016). Researchers also
702 typically operate on slower time scales than societal problems, which may be a source of frustration

703 for communities experiencing severe economic and ecological consequences from global
704 environmental change. These barriers require institutional changes to facilitate and reward
705 modelers' engagement with societal challenges, and we encourage modelers to begin making
706 incremental changes towards this goal within their own projects and institutions.

707 **5. Conclusions**

708 This study improves our understanding of how SES models can be more appropriately designed
709 and applied to fit transdisciplinary approaches, both in mountains and other SES. First, we found
710 that diversity among the participants involved in modeling can lead to improved collaboration and
711 cooperation for real-world problem solving. As global environmental change increases the need to
712 collaborate across diverse groups for sustainable outcomes in SES, we encourage modelers to take
713 the time to build stronger relationships across academic disciplines and social worlds. Second, we
714 found that diverse participation does not necessarily translate into diverse knowledge and data
715 being incorporated into the model. This suggests that modelers must pay closer attention to issues
716 of power when using SES models as boundary objects, and specifically how diverse perspectives are
717 translated and incorporated into the final model product, or excluded from it. Third, we find that
718 flexibility in model design is a key element for employing SES models as scalar devices in
719 transdisciplinary applications, as the context of the modeling effort is of greater consequence than
720 the technical complicatedness of the model. As STS scholars continue to develop the scalar devices
721 concept into an analytical tool, we encourage more explicit engagement with questions of
722 knowledge translation and power. Finally, we highlight some institutional barriers that may be
723 inhibiting SES modelers from long-term, place-based engagement in societal issues. Creating SES
724 models that are appropriate technology for transdisciplinary applications will require advanced
725 planning, increased funding and attention to the role of diverse data and knowledge, and stronger
726 partnerships across disciplinary divides. Highly contextualized participatory modeling that

727 embraces diversity in both data and actors appears poised to make strong contributions to the
728 world's most pressing environmental challenges.

729

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