POLICY AGGREGATION AND HETEROGENEITY IN NORTHERN WISCONSIN FISHERIES: AN AGENT-BASED APPROACH

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Abstract. Lake-rich landscapes operate as socio-ecological systems (SESs), with complex interactions between humans and fish populations which present a variety of unique problems from the perspective of recreational fishery management. Management and regulation are moving from one-size-fits-all (OSFA) to aggregated management, where similar lakes share the same policy (Ostrom 2009). However, the criteria for effectively sorting and sizing aggregated policies have not been fully considered. To explore the differences in utility of small-scale and OSFA management policies, an agent-based model was implemented to compare the performance of different aggregations at increasingly variable angling pressure and intrinsic growth rates. Instead of simulating policies as a static submodel, agents make flexible, reactive policy decisions. Along with simple equations, the model accurately reflects patterns observed in lake-rich landscapes. Simulations suggest individual-level management consistently performs better than all aggregation setups as intrinsic growth rates vary. However, aggregates and individual-level management unexpectedly reached optimal levels of performance at different variabilities of angling mortality. Although the results may be influenced by artifacts within the model, these simulations present a novel way to approach modeling recreational fisheries policy.

INTRODUCTION

With rapid changes in carbon emissions, human populations, and pollution, effective policies are necessary to maintain sustainable use of common pool resources. Understanding the proper management of harvesting common pool resources from socio-ecological systems is a critical aspect of developing environmental policy and will frame societal attitudes towards common pool resources in the near future (Ostrom 2007). However, common pool resources are often socially, spatially, and temporally complex enough to create challenges in sustainable management (Ostrom et al. 1994, Solomon et al. 2016).

Recreational fisheries in lake-rich landscapes are a common pool resource with significant value. They can be the economic backbone of towns and cities that rely on anglers to generate revenue for local businesses (Liddle 1997). Recreational fisheries can also be a great cultural influence and recreational fishing can be an important activity for leisure and community building (Carpenter and Brock 2004, Solomon et al. 2016). Although recreational fisheries possess great societal value, governance is difficult given their open-access and common pool nature.

Proper governance poses such a challenge because lake-rich landscapes are SESs with nuanced heterogeneous ecological interactions. The high mobility of humans between lakes links these ecosystems together, altering the catchable populations of fish across lake districts (Solomon et al. 2016). Lake districts face environmental pressure from lakeshore development and recreational angling, but the magnitude of these impacts can vary across the landscape (Ziegler et al. 2017). Combined with the limited budget of managers to maintain sustainable fish populations, the predatory behavior of anglers, and disrupted food webs, the continued instability of recreational freshwater fisheries seem far less surprising (Post et al. 2002).

Although recreational fisheries have been managed in one-size-fits-all (OSFA) policies, where every lake in a system is managed in an identical way, modern management has emphasized creating policies at a smaller scale. One of Wisconsin's primary fisheries research goals includes developing a methodology to classify lakes, which encourages flexibility in policy implementation (Wisconsin DNR 2007). Likewise, Minnesota set evaluating experimental and special regulations as a high priority for fisheries management (Minnesota DNR 2005). The movement towards more specialized policy makes sense in the context of recreational fisheries. Lakes within a lake-rich landscape may have variable rates of recruitment and fecundity in their catchable fish populations, providing initial conditions for how quickly a lake's population can be exploited. Consequently, this can influence where anglers with different preferences choose to fish, and how angling pressure varies across the landscape (Carpenter and Brock 2004). This heterogeneity in biological and recreational factors means that OSFA policies are not able to adequately manage lake-rich landscapes to maximize fishing opportunity across all lakes, and that the management policies of lakes will need to be dynamic. Therefore, the best management policy would be to scale effort to the biological productivity and angling pressure of individual lakes within a lake-rich landscape (Post and Parkinson 2012).

However, individual-level management policies may not be feasible in many circumstances, especially under limited funding. Lake-by-lake management can be overwhelming for fisheries managers and confusing for anglers. Tightening restrictions on one lake could also cause a shift in angling pressure across the landscape, which can be spatially and temporally unpredictable. Additionally, more complex regulations could increase individual costs on anglers, decreasing the total number of anglers and negatively impacting local economies that rely on recreational fishing (Lester et al. 2003, Carpenter and Brock 2004). Ideally, a balance could be struck between maximizing the fishing potential of every lake while limiting the number of unique policies to reduce costs for managers and anglers. As grouping lakes into aggregation may be the best compromise between OSFA and individual-level management, determining these aggregations should be assembled according to how heterogeneous recreational fisheries are in these respects may determine the optimum amount of policy aggregation for the given lake-rich landscape.

No prior research has looked into the degree of heterogeneity in a lake-rich landscape to optimize different scales of policy aggregation. Realistic agent-based models have been used in recreational marine fisheries to determine optimum policies, but have a greater focus on the heterogeneity of angler distribution and effort instead of fish population productivity (Gao and Hailu 2012, 2013, 2018). Other work has been guided by a greater focus on demonstrating the utility of active management of recreational fisheries and how angler decisions shape fish populations on landscapes (Schuhmann et al. 2001, Beard et al. 2003, Cox et al. 2003, Post and Parkinson 2012, Stoeven 2014, Askey 2016, Dabrowksa et al. 2017). More specific studies have looked deeper into specific interactions between human and natural systems in lake district SESs (Ziegler et al. 2017). Current work is being done to fully explore the socio-ecological dynamics of freshwater recreational fisheries to further develop SES theory (Solomon et al. 2016).

To analyze the degree of aggregation needed to best manage lake districts of varying heterogeneity, an agent-based model (ABM) will be implemented. ABMs provide abstractions of complex systems by utilizing independently acting agents that make decisions based on their perception of the environment around them. An agent-based approach is ideal for representing management behaviors and incorporating stochasticity to examine the heterogeneity of a lake district SES and emerge landscape-level responses to policy aggregation. How will the heterogeneity of intrinsic growth rates and angler effort on a lake-rich landscape for aggregated management to be beneficial?

METHODS

Overview and Rationale

This model is designed to explore how heterogeneous must the productivity and angler effort on a lake-rich landscape be to encourage higher policy disaggregation. The objective of lake associations in the model is to maintain their fish populations at the biomass that produces maximum sustainable yield (MSY) through stocking fish and improving aquatic habitat. MSY was chosen as the measure of performance for associations because it is an ideal goal for a harvest-based recreational fishery, which is the case for panfish and perch-related species, and MSY matches the overall complexity of the parameters and functions of the model.

The model can be broken into 3 interacting submodels. A fish population submodel uses a modified Gordon-Schaeffer biomass model to describe the dynamics of the fished population and the abundance of fish at a particular moment. An angling submodel is a simple equation to scale the number of fish removed from a lake by population size and catch per unit effort (CPUE). Lastly, a management submodel simulates adaptive and cooperative management through evolutionary programming techniques to determine policies for the next time step.

Fish Population Dynamics

A change in the fish population for each association will be calculated through a modified Gordon-Schaeffer biomass equation that represents simplified dynamics of fish populations observed in recreational fisheries (Solomon et al. 2016).

$$N = r_{max}\frac{(K-N)}{K}N + S + M_A$$

Where r_{max} is maximum growth rate, K is carrying capacity, S is the number of fished stocked, and M_A is mortality due to angling. Since the equation is based on logistic growth, fish populations are ultimately self-regulating. However, the management submodel can augment the population by stocking, which directly adds fish to the population, and improving habitat, which increases the r_{max} value. Improving habitat has been shown to increase the resiliency of fish populations to larger shocks (Carpenter and Brock 2004). For the sake of simplicity, this habitat effect works differently within the model, as improving habitat acts to increase the intrinsic growth rate of fish populations. The angling submodel interacts with the population through the angling mortality term.

Initial r_{max} values are determined by random number selections from normal distributions. These normal distributions can be manipulated to replicate the dynamic nature of lake-rich landscapes and allow the model to determine effective aggregate policies for different levels of heterogeneity in the productivity of a fish population.

The carrying capacity for each lake initialized as a random value between 50 – 75% larger than the starting population. Assuming all lakes start below carrying capacity is not greatly consequential, as the model has a burn-in period before it reaches a stable state. Initializing the carrying capacity in a more complex manner would only change conditions during the burn-in period, but not have any effect on the results.

Angling

The angling submodel is represented by the following equation adapted from code:

$$M_A = N * (randomNormal(CPUE\ Scaling\ Factor, CPUE\ Variability))$$

Where randomNormal represents a function that generates a normal distribution with a mean and standard deviation of the two parameters. CPUE Scaling Factor is a range from 0 to 1, representing what proportion of fish anglers catch for a given time-step. CPUE Variability functions as the standard deviation for the distribution and denotes how variable the anglers' harvest will be from time-step to time-step. The normal distributions are dynamic, as the fish population changes at every time-step.

Management Submodel

Management: Population Estimations and Comparisons

Initially, associations will estimate the population of fish in their respective lakes. Estimates will be drawn from a normal distribution with the mean value being the actual fish population and a standard deviation that will determine the accuracy of the estimation. If a simulation includes aggregates, a mean estimated population will be calculated from these estimates for each aggregation to inform their management decisions. Once the estimates have been made for each association, the associations will determine how close they are to their objective, which is to manage their fish populations at maximum sustainable yield (0.5 * carrying capacity) as closely as possible, referred to as their objective population. Given the fishing culture of lakes in the U.S., this would be a reasonable management goal for some fish species that are harvested regularly, like crappie, walleye, and perch. Their closeness to MSY for a given time step is found through an equation that yields an index:

$$index = \frac{objective\ population - estimated\ population}{objective\ population}$$

This index will be used to determine the intensity of management for the next time step, as well as how much the management policy will change moving forward.

- At index = 1, the estimated population is near 0 and likely to collapse.
- At index <= -1, the estimated population is much higher than the objective population.
- At index = 0, the objective population equals the estimated population and the lake is perfectly managed.

If the simulation is using aggregates, indices will be averaged for all associations in an aggregate for later changes in management policy.

Management: Point Allocation and Spending

The index is used to determine how many "policy points" an association will have to work with. Policy points act as a discrete currency that can be used for stocking fish or improving aquatic habitat, which are management actions that can be taken by associations (Solomon et al. 2016). How much each policy point is "worth" will depend on the species being stocked. For example, the Wisconsin DNR stocks about 132 largemouth bass per month in Vilas County. If using a system of 100 maximum policy points per association on a monthly time step, then it may be reasonable to have 1 point = 1 stocked largemouth bass. However, it is difficult to quantify the impact of a discrete improvement of aquatic habitat on a population's intrinsic growth rate. In a system of 100 maximum points per association, having 1 point = 0.00001 increase in the intrinsic growth rate produces reasonable results.

The policy point system allocates a maximum of 100 points to each association, since the associations will spend all of their allocated policy points per time step. This means an association may have considerably less points depending on their index. This allows policy points to act as a simplified management budget by making some assumptions about how associations/agencies spend their money to manage lakes. If a lake's fish population is near collapse (index = 1), the association/manager will likely want to spend as much money as possible to stock fish, improve habitat, and change policy. Conversely, if a lake is overpopulated with fish (index <= -1), or are close to MSY (index = 0), the association/manager will not spend any money to stock fish, improve habitat, or change policy, since angling mortality will bring the estimated population closer to the objective population, or the association is already meeting their goal.

An association's index can be used to determine how many policy points they are allocated:

$$Policy\ Points = 50(index) + 50$$

Once the associations are allocated their policy points, they will spend their points based on their policy. Policies are implemented as the proportion of points spent towards stoking fish and improving habitat.

Management: Altering Policies

An association's policy will change depending on their index from the current time-step. The policy will change depending on where the index falls into various intervals (Figure 1). A randomly determined change in policy represents experimentation in management technique. Although there is more to experimental management than random decisions, this was the most accurate way to represent this in the model. A change in policy to partially copy the best performing association could represent larger scale shifts in management practices and the adoption of best practices.

As an association strays further from MSY, they make greater changes to their policy (Table 1). This simulates collaborative and active management as associations that perform poorly adopt a large portion of policy from the best performing association. Regardless of performance, all associations have some random element in their policy to represent active, experimental management.

Parameters and Simulation Procedure

All simulations were run with the nominal values unless otherwise noted (Table 2). Every set of parameters was simulated 30 times to ensure patterns were consistent and to reduce standard error.

RESULTS

Model Function

This primary simulation demonstrates basic interactions between the angling and fish dynamics submodels, as well as limitations in the management submodel. With all stochastic elements removed from the model, it performs as anticipated. When the mean angling mortality was at the low end of the parameter range, lake associations performed poorly (Figure 2). At low mean angling mortality, the intrinsic growth rate of the fish population is greater than the rate of angling mortality, so the population reaches and maintains carrying capacity. At high mean angling mortality, the fish were removed faster than they are replaced by stocking and natural reproduction, and the populations crashed initially. However, managers were able to develop policies to combat the high angling pressure over time. These responses mirror the interactions between fish populations and anglers in reality, but the model produces a more variable response in the moderate range of angling mortality where fish are removed at a rate close to the intrinsic growth rate. Managers create policies to maintain an equilibrium the populations but are unable to move the population towards the optimal size for maximum sustainable yield (MSY). The stability in the objective indices shows that the model does not encourage boom-bust management, as the objective indices hardly fluctuate over time. However, it also shows that the managers do not have the means to influence the populations effectively, as they only receive enough policy points to reach an equilibrium with the intrinsic growth rate and angling mortality.

A moderate variation in angling mortality yields the best performance from managers (Figure 3). As in the first simulation, managers were unable to attain optimal populations due to drawbacks of the management submodel. At low CPUE variabilities, managers are changing their policies too quickly and are more apt to overshoot or undershoot their management. Conversely, at high CPUE variabilities the fish population changes too quickly for managers to keep up with implementing appropriate policies. The best performance comes from moderate variability, where the speed at which managers change their policies and fish populations change reach an equilibrium. This partially validates the logic of the fish population dynamics model. As any managed resource becomes more variable, management will become less beneficial. Additionally, implementing policies at too fine of a scale will lead to poor management. The managers' faulty performance at low CPUE variability can be explained by the faults in the management submodel, where managers are only allowed to make policy decisions according to the previous time-step instead of long-term trends.

Detail of Angling Submodel

In early iterations of the model, it was assumed that angling mortality was random, due to the numerous factors that could go into an angler's catchability at any given time-step. However, this produced results that were contrasted existing findings, as the most aggregated form of policy outperformed completely disaggregated policy at high angling mortality (Figure 4). The assumption of random angling allowed aggregates to manage their individual populations as one combined population. The angling mortality is not tied to any lake-level variable, so the angling mortality from one lake becomes interchangeable with the angling mortality from any other lake under the same management.

The angling submodel was changed to establish a relationship between angling mortality and the size of the fish population for each individual lake. This caused the model produces more intuitive results (Figure 5). The parameter on the x axis has changed to accommodate the updated submodel, but "Mean Angling Mortality" and "CPUE Scaling Factor" function in the same manner, as they indicate the magnitude of angling pressure. Aside from the results of the two lowest CPUE scaling factors, which can be accounted for by model artifacts explained in Figure 1, the new angling submodel shows individual-level policies significantly outperforming all higher levels of aggregation as the scaling factor is incremented.

Results significantly improved by adding more detail to the angling submodel, which shows that understanding how anglers affect with fisheries with greater depth is an important aspect of how this system functions.

Optimum Aggregation for Across Levels of Heterogeneity

As the range of aggregations remained reasonable consistent as r_{max} varied more, individual-level management performed noticeably better in every case (Figure 6). Considering the random grouping of associations into aggregations, the close means of all aggregates makes sense. Regardless of the number of associations in an aggregate, the variability of r-max will be consistent across aggregations, due to the normal distribution that was used to assign initial r_{max} values to the associations. This means that overarching policies used in aggregates will be equally ineffective regardless of aggregate size. Individual-level management works best in this scenario as policies will not have to make compromises to account for any variability in r_{max} values.

As the CPUE scaling factor becomes more variable, individual-level management and high aggregations reach points of optimization at different levels of variability (Figure 7). Individual-level management optimizes sooner due to having a smaller total fish population to manage compared to higher aggregations. Small populations are more sensitive to changes in angling mortality and their policies follow trends in population size more closely than high aggregations, which use the average population sizes to inform their policy.

This difference in how often policies change in high and low aggregations is illustrated by the standard deviations (Figure 8). High aggregations have lower standard deviations because they manage for the larger mean population of many lakes that exhibit a less drastic response under increased variability of angling mortality. This is detrimental at low variability because high aggregations lack the sensitivity in their management to follow small-scale fluctuations in populations. As a result, high aggregations perform sub-optimally at low variability, but are more consistent at high variability. Alternatively, individual-level management performs better at low variability, but quickly break down at high variability. Individual-level management has a higher sensitivity for variability in angling mortality due to managing smaller populations than their high aggregation counterparts. This sensitivity allows them to make more effective policies at low variabilities because they can create more precise policies without being negatively impacted by a change in the size of their population from a high angling mortality event. The same sensitivity and precision in policy is what causes individual-level management to perform poorly at high variability. Individual-level management is constantly overcompensating in policy when variability in angling mortality is too high. Managers in the model only access information from the last time-step to create new policies. Since managers are limited in their information, new policies are implemented without considering long-term trends and can be vary greatly.

DISCUSSION

This work shows the effectiveness of different recreational fisheries aggregations under variable parameters. Although OSFA management has long been known to be ineffective at preserving recreational fisheries, this model also demonstrates that even smaller sized aggregations may provide much of an improvement as the natural productivity and angling mortality vary (Cox et al. 2003, Carpenter and Brock 2004). Individual-level management, although optimal within this model, may not be logistically feasible to implement on large-scale landscape. A new idea for management, referred to as “buffet-style”, may provide a compromise between the extreme ends of aggregation by grouping lakes into managing lakes for specific classes of anglers (Van Poorten and Camp 2019).

However, the buffet-style model did not incorporate elements of adaptive and collaborative management, which seem to be predominant concepts in modern natural resources management. This current model demonstrates that ideas from adaptive and collaborative management can be implemented fairly simply when used in an agent-based context. One drawback of implementing these management ideas is the lack of empirical studies to understand how these kinds of management should be implemented in a model. Adaptive and collaborative management resulted in high standard deviations to the outputs of the model, as thresholds for when policies should change and how often managers should communicate were assumed to be arbitrary.

Model Limitations and Areas for Improvement

This model, as well as others like it, must formulate a quantitative management objective (Johnston et al. 2010). This can be problematic for models as there are many different factors that may guide management objectives. Likewise, simplifications of how lake-rich landscapes function were made to better understand model outputs, but details like ecological interactions, motivations of different angler classes, and management funding certainly play a role determining the effectiveness of aggregation. As interpreted in this model, management only occurs at the association level through actions that associations can take. These actions, stocking and improving habitat, are methods for managing fish populations and do little by way of managing anglers.

Refining the management submodel would yield the greatest improvements for the model's performance. Specifically, determining thresholds for how often management should adapt and associations should communicate would provide more validity towards the model's logic. Another shortcoming lies within the policy point system. As a basic economic system, it is difficult to quantify the monetary cost of management in terms of policy points. This caused trouble, especially as managers could have the proper policy needed to correctly alter their fishery but did not have the necessary funding to make those changes. Requiring managers to spend all of their policy points every time step may be too rigid and could be implemented as an additional adaptive behavior for associations.

Future Research

There are a variety of options for future research from this model. Using the same model, adaptive and cooperative management could be more fully explored, such as determining how often managers should share information, how often policies should adapt, and how experimental management should be to yield the best outcomes. Interesting findings could come from grouping associations into aggregations based on varying criteria to determine the best way to create aggregations, and how well their performance compares to individually managed lakes. More interesting ideas could come from incorporating anglers as agents, to represent various classes of anglers that can move around the landscape. Additionally, the model could be spatially explicit to see how angler mobility and accessibility contribute to management.

Conclusion

Recreational fisheries are in a widespread collapse as angler catch rates have fallen significantly over time (Post et al. 2002). As biological and ecological systems move at their own slow pace, short-term fixes will likely not be enough to restore these recreational fisheries. Novel, thoughtful changes to how we manage this resource will need to be made to see a resurgence of healthy recreational fisheries, for the sake of the communities that rely on these fisheries. Greater effort must be made in modelling to best understand the theoretical backing for the new ideas in fisheries management and assist in carefully transitioning recreational fisheries to a better, sustainable future.

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APPENDIX

TABLE 1. The ranges of objective indices, or association performance, and how they relate to dynamic policy changes. Worse performing associations copy more of their policy from the best performing associations. The best performing associations retain more of their policies, with minor variations to emulate experimentation.

Range of Objective Index	Redistribution of Policy Proportions
1.0 – 0.75	50% Best Practice, 50% Random
0.74 – 0.50	25% Current Policy, 50% Best Practice, 25% Random
0.49 – 0.25	80% Current Policy, 20% Random
0.24 – 0.05	90% Current Policy, 10% Random
0.04 – 0.00	95% Current Policy, 5% Random

TABLE 2. Nominal values and explanations for model parameters.

Variable	Explanation	Value
Num-associations	Number of associations	12
Num-aggregates	Number of aggregates	12
Mean-starting-fish-pop	Average starting fish population	500
St-dev-starting-fish-pop	Variability of starting population from lake-to-lake	0
Mean-r-max	Average intrinsic growth rate	0.40
St-dev-r-max	Variability of intrinsic growth rate from lake-to-lake	0
CPUE-scaling-factor	Proportion of fish removed from a population	0.3
CPUE-variability	Variability in the proportion of fish removed from a population	0
Num-months	Number of time-steps/duration of simulation	600
Ticks-per-new-policy	How many time-steps are between each policy update	1

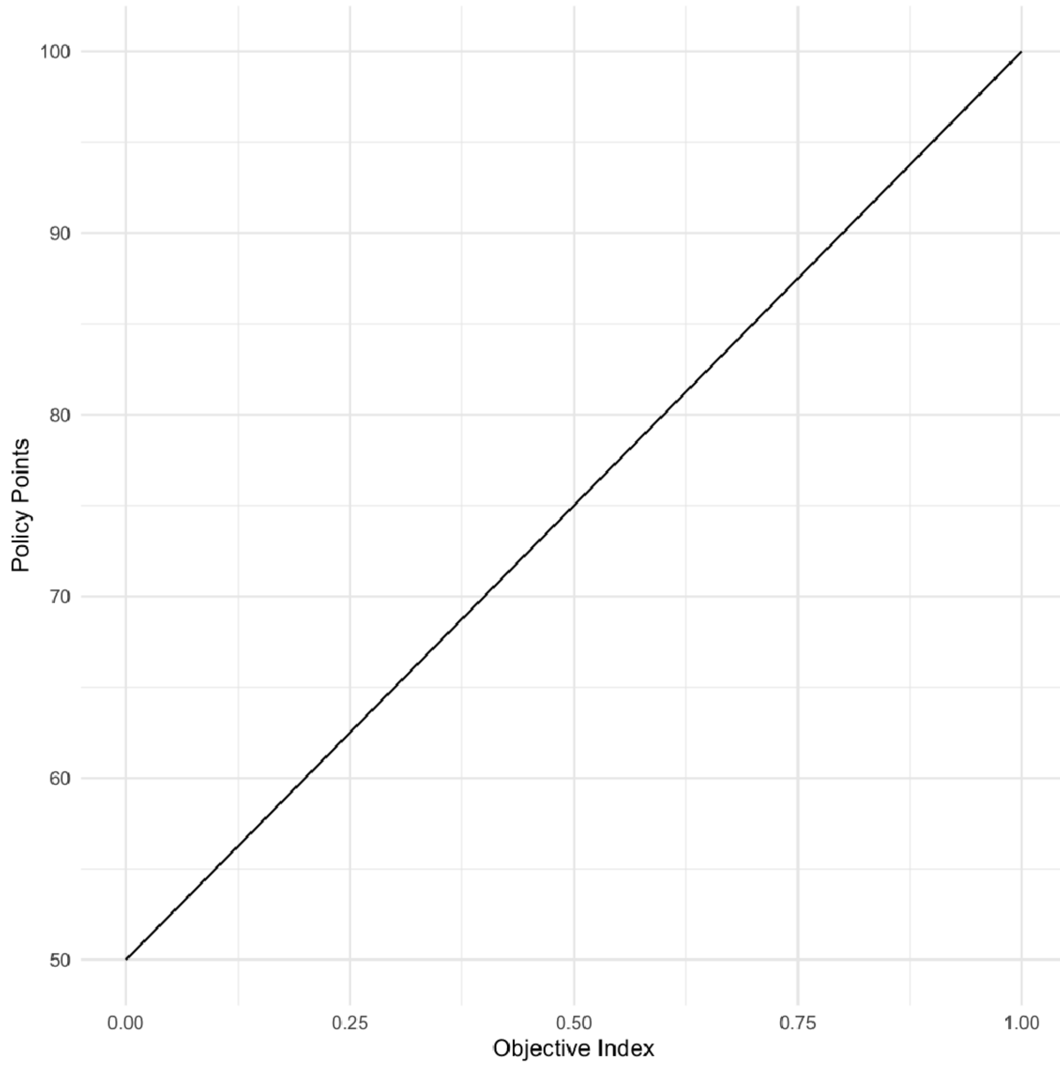

FIGURE 1. How policy points, or the means to enact policy, an association receives for a time-step is related to their objective index, how well the association currently performs. The objective index also determines how their policy will change moving forward. As associations perform worse and their objective indices increase, they have more means to implement their policies.

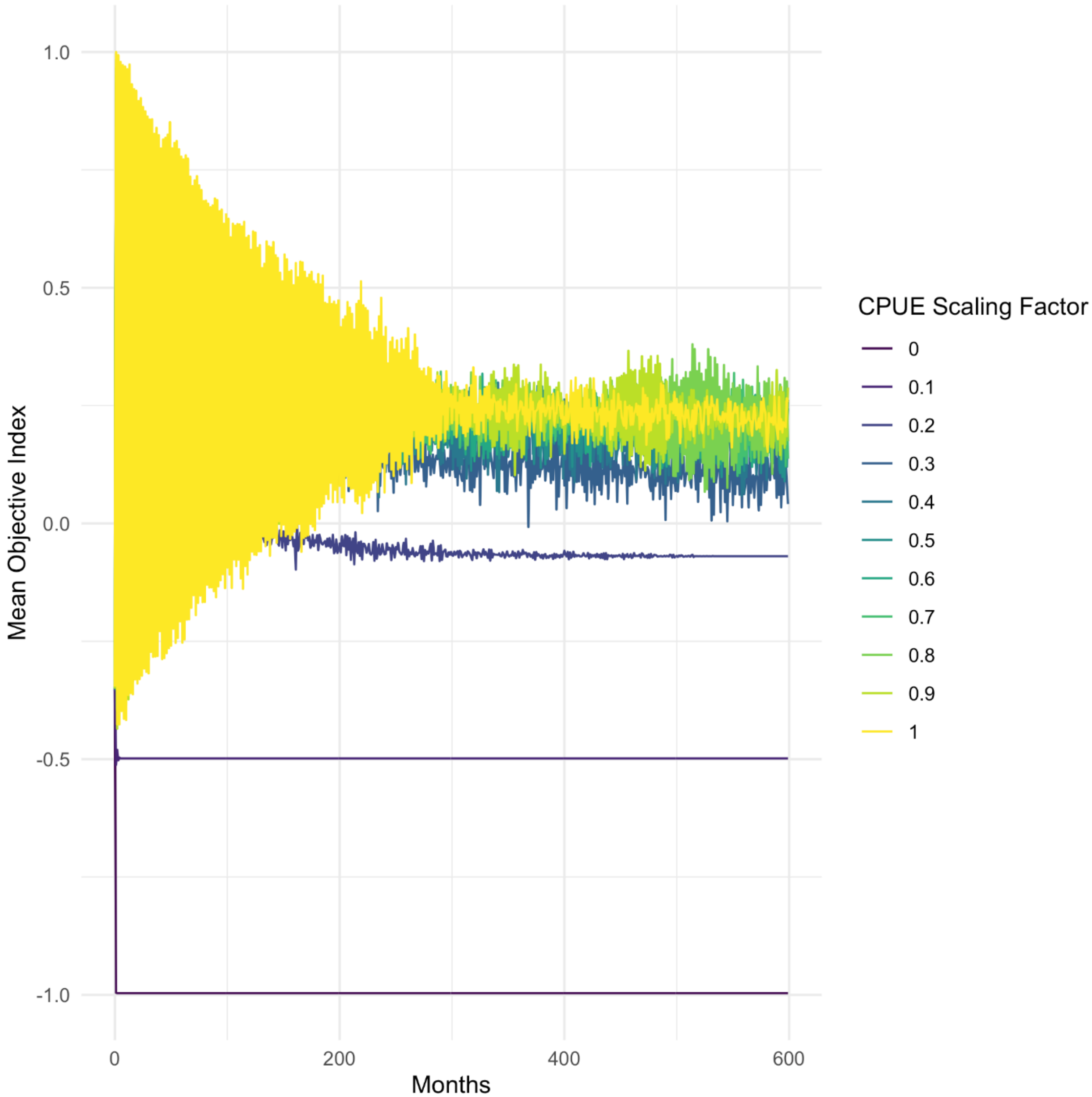

FIGURE 2. When the CPUE scaling factor is high, meaning anglers remove fish very effectively, associations performed fairly well, maintaining an objective index that is close to zero. At lower levels of the CPUE scaling factor, fish populations grew too large and association performance worsened.

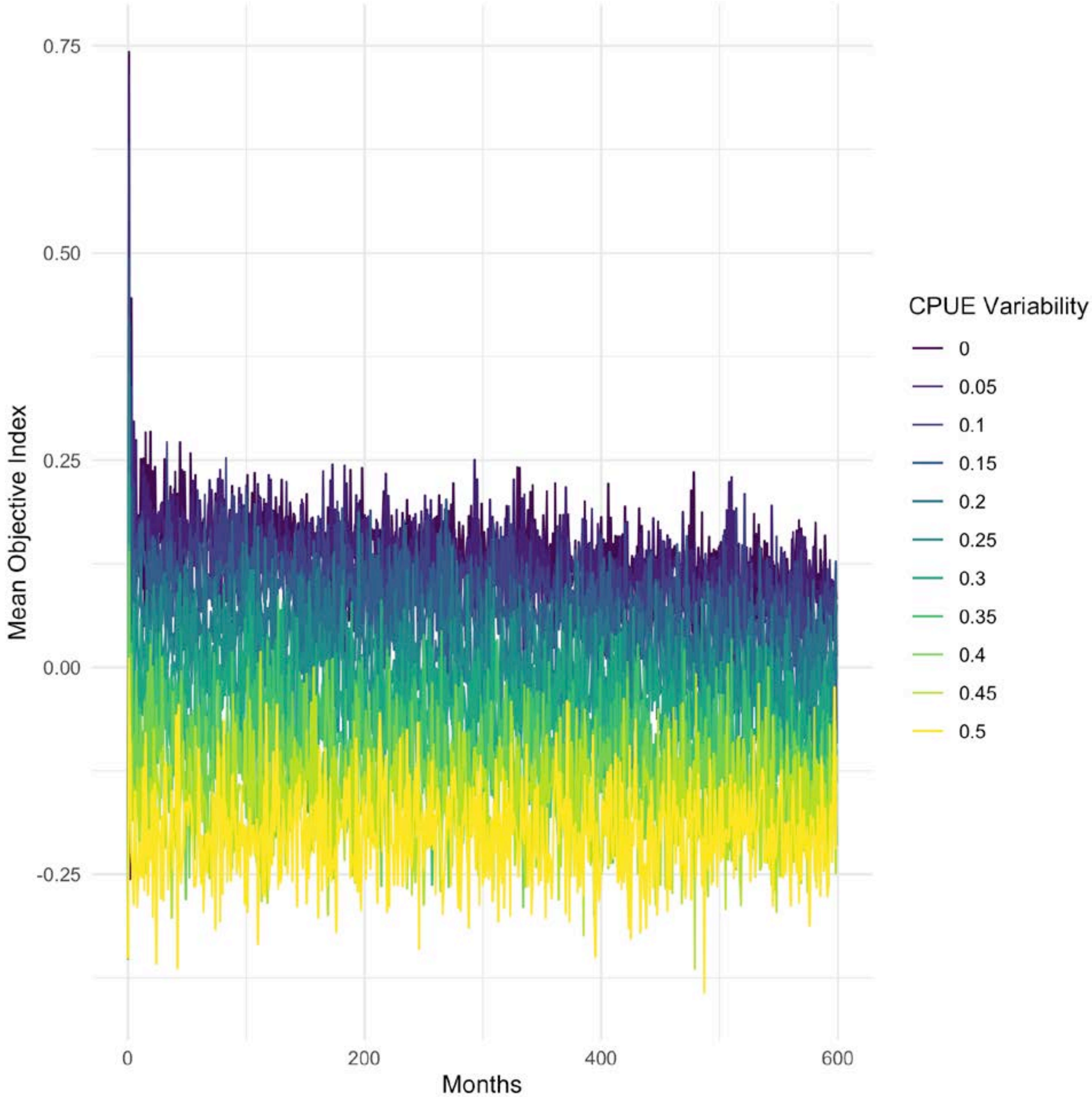

FIGURE 3. At moderate levels of CPUE variability, or how variable the proportion of fish removed from a population, associations performed best, maintaining an objective index close to zero.

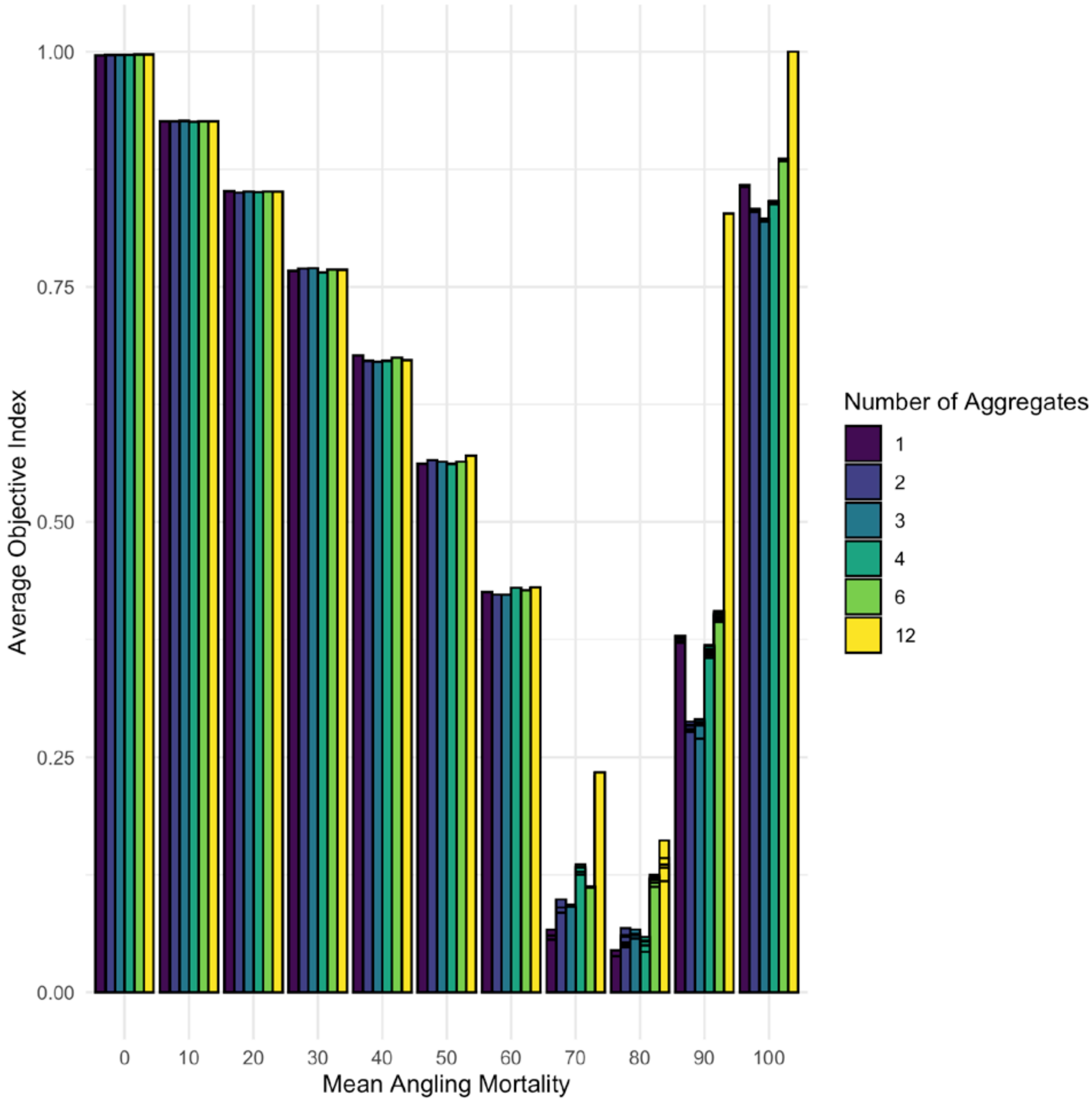

FIGURE 4. In preliminary versions of the model, angling mortality was random and average objective indices, how the associations performed, were illogical. Higher numbers of aggregates, meaning smaller groupings of associations, should perform better across all levels of mean angling mortality. Error bars omitted and absolute values for objective indices used for clarity.

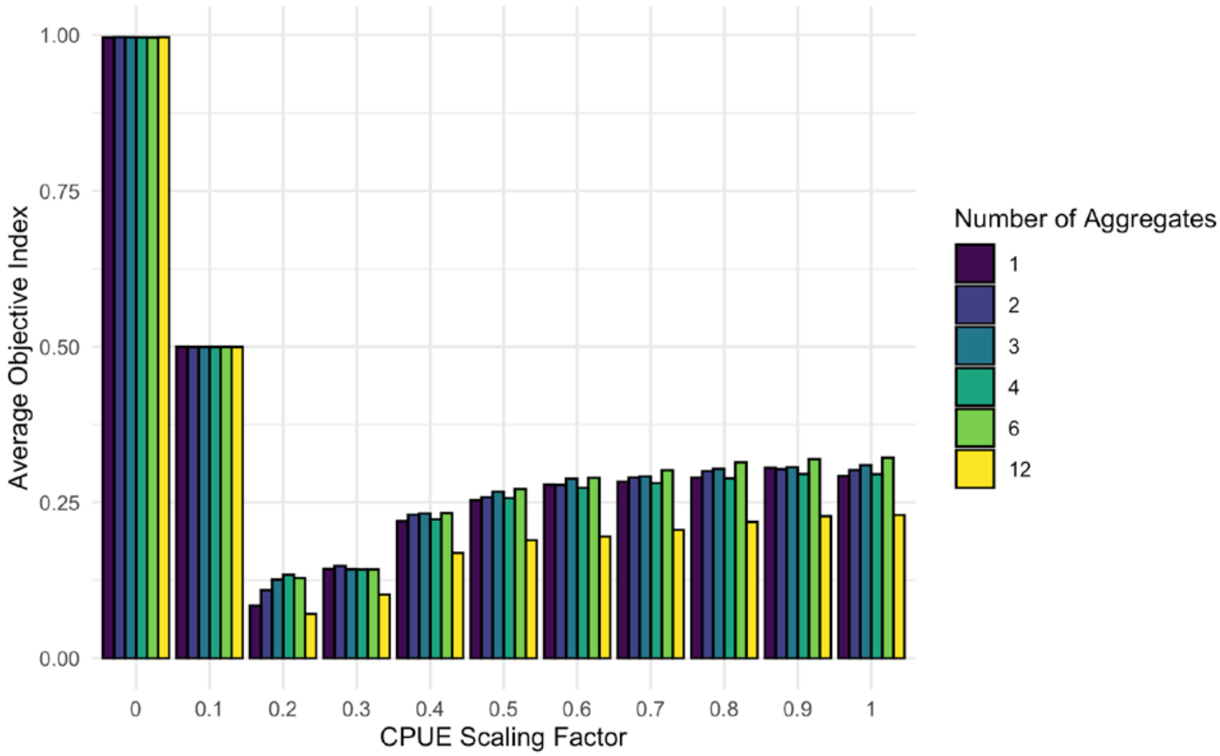

FIGURE 5. Response of associations when angling mortality was linked to fish population size (the current version of the model). Here, the model shows a more intuitive response. Across nearly all levels of the CPUE scaling factor, the proportion of fish removed from a population, the highest number of aggregates (smallest grouping of associations) performs consistently better. Error bars omitted and absolute values for objective indices used for clarity.

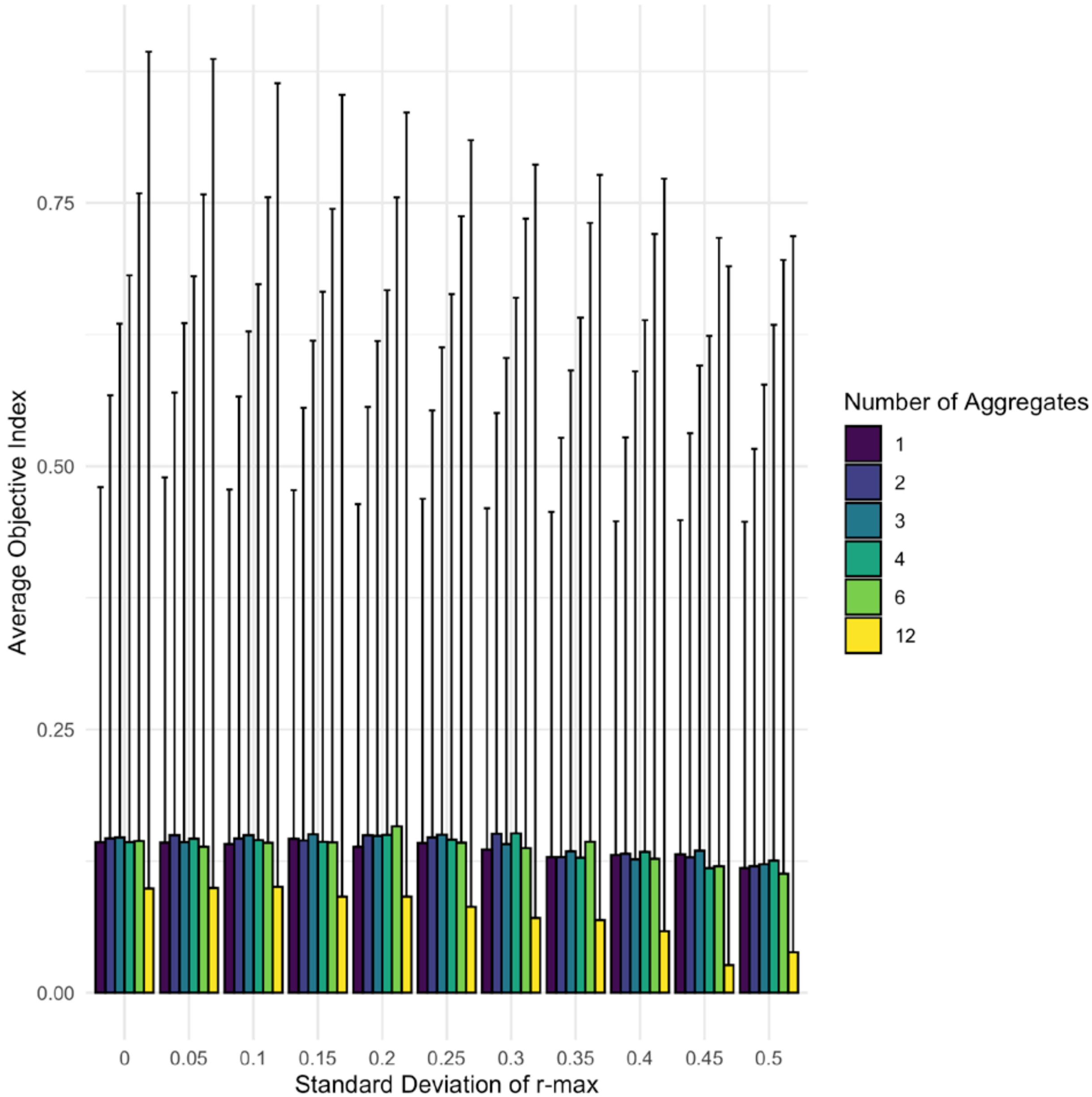

FIGURE 6. Across all levels of variability in r_{max}, the highest number of aggregates had the lowest objective index and performed best.

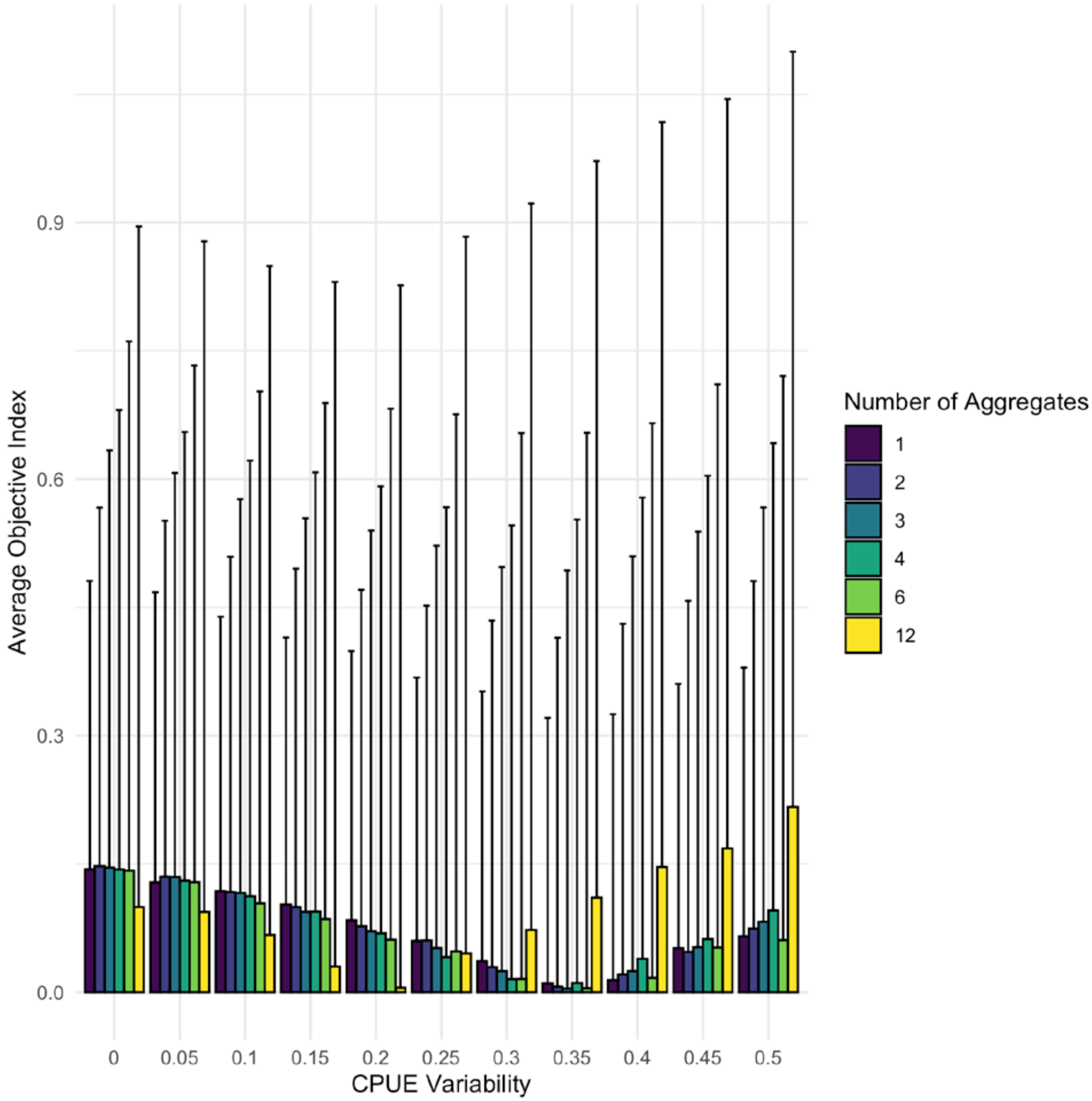

FIGURE 7. At low CPUE variability (low variability in the number of fish removed) the highest number of aggregates had a lower objective index, outperforming the other groups, until a threshold in variability was met.

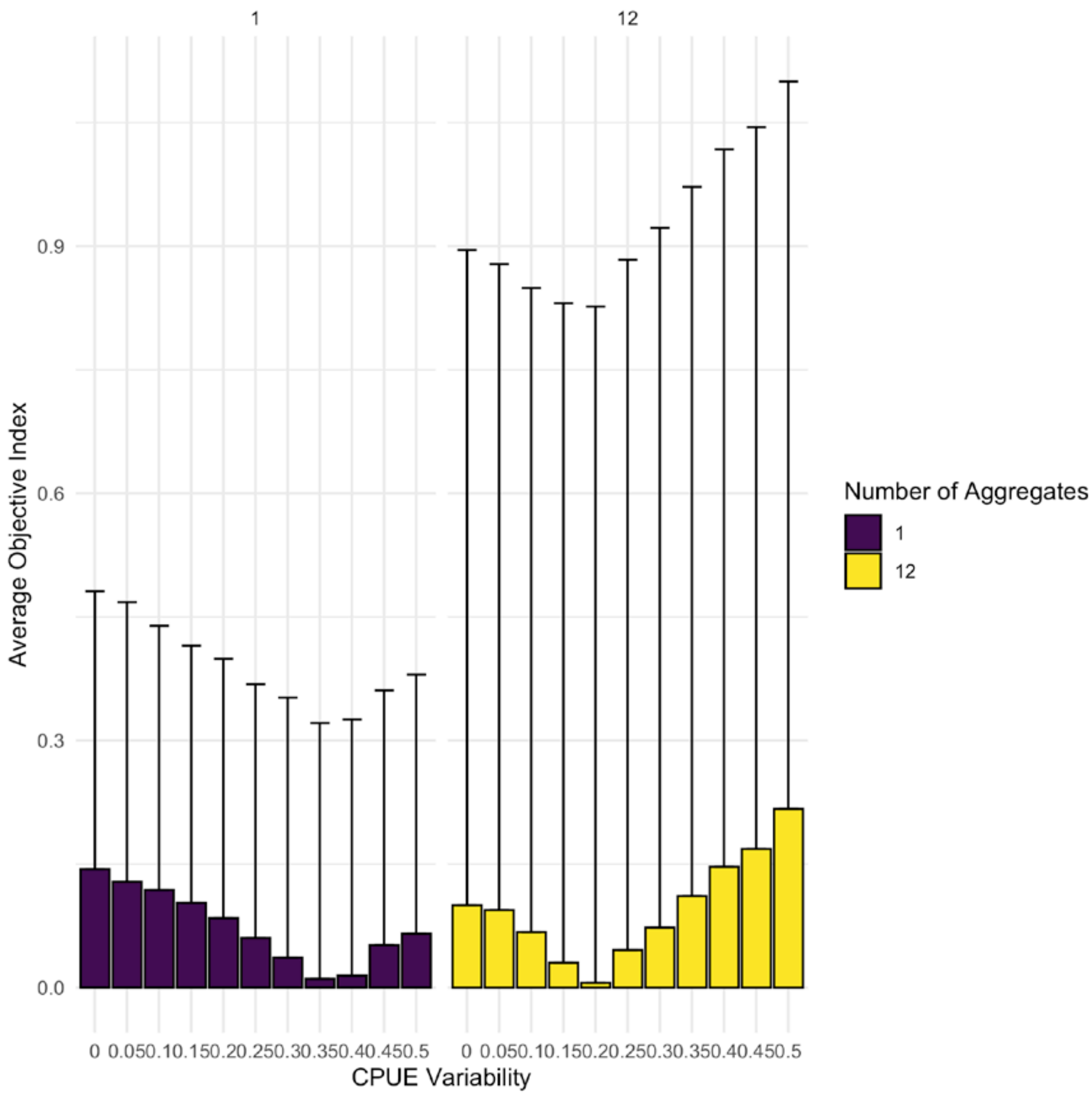

FIGURE 8. Comparing the objective index, or performance, of the highest and lowest number of aggregates. The lowest value for the objective index, indicating the best performance, for each group depends on the CPUE variability, or how variable the proportion of fish removed from a population. Each group performs best at different levels of variability, suggesting that a higher number of aggregations may be a better management choice in certain situations.