Hydrologic controls on abundance and distribution of the endangered Rio Grande Silvery Minnow in the Middle Rio Grande

by

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August 5, 2020

Report to:

U.S. Department of the Interior, Bureau of Reclamation, Albuquerque Area Office

Preface

To determine how the Rio Grande Silvery Minnow (RGSM) population of the Middle Rio Grande (MRG) responds to interannual hydrologic variation, the U.S. Fish and Wildlife Service conducted a hydrobiological analysis (HBO) as part of a Biological Opinion regarding management of water resources (U.S. Fish and Wildlife Service 2016). These analyses determined RGSM populations correlate strongly with many hydrologic indices of the magnitude and duration of both high and low flows. An external review of the HBO identified several opportunities refining and expanding the analyses (Budy and Walsworth 2019), particularly focusing on improving the statistical appropriateness and biological realism of the models explored. Here, we incorporate many of the suggested changes based on collaborator and internal Reclamation review of that report to the HBO analyses to explore (1) how RGSM abundance in the MRG responds to changes in annual hydrologic conditions, (2) how RGSM relationships with hydrologic conditions differ spatially in the MRG, and (3) what hydrologic conditions would need to be present for managers to expect to meet recovery thresholds. In the future, the results of these analyses can be used in the development of an adaptive management strategy aimed at managing the trade-offs between off-stream water use and conservation of the RGSM.

Executive Summary

Increasing water demand, water development, and on-going climate change have driven extensive changes to the hydrology, geomorphology and biology of arid-land rivers globally. As many native desert fishes have experienced dramatic declines, there is an increasing need to understand how annual hydrologic conditions affect the distribution and abundance of their populations. We analyzed the relationship between annual hydrologic conditions (i.e., spring high flows, summer drying) and the distribution and abundance of the endangered Rio Grande Silvery Minnow in the Middle Rio Grande. We fit a twenty-five year data set (1993-2017) of sampling site catch-per-unit-effort to hurdle models predicting both the presence and density of Rio Grande Silvery Minnow as a function of annual hydrologic metrics. Both presence and density were positively related to spring high flow magnitude and duration and negatively related to summer drying. Additionally, when we included a latent trend in the presence model component, we observed evidence suggesting the strong influence of an unobserved driver operating on a decadal scale periodicity, potentially representing regional climatic variation or spawner-recruit dynamics. The results of our simulation models suggest hydrologic conditions at or near the wettest observed in the data set would be required to produce sufficient Rio Grande Silvery Minnow to meet recovery goals (> 5 RGSM per 100m^2) with 95% confidence in a single year in all reaches. As recovery goals require sustaining these higher densities, such large runoff events would need to recur across multiple years. However, the self-sustaining population target (> 1 RGSM per 100m^2) is likely to be met at more modest flows near the median observed in the dataset. The results of these analyses both inform current management actions and can be used to explore alternative water management approaches in a simulation framework while considering trade-offs between recovery and other management goals.

Introduction

Freshwater ecosystems are home to a disproportionate degree of global biodiversity. While freshwater habitats cover less than 1% of the Earth's surface, they contain nearly 9.5% of the planet's animal species (Dudgeon et al. 2006; Balian et al. 2008; Reid et al. 2019). However, freshwater biodiversity has also experienced a greater rate of decline than that of other biomes (Ricciardi and Rasmussen 1999; Sala et al. 2000; Reid et al. 2019). Rivers are frequently altered to reduce risks to human infrastructure and settlements (e.g., flood control), reduce temporal variation in water availability (e.g., storage), and derive additional benefits from the available water (e.g., irrigation water, hydroelectric power, creation of recreation opportunities). However, hydrologic alterations aimed at achieving social and economic goals often present substantial challenges to native aquatic biota (Poff et al. 1997; Olden and Poff 2005). As native biodiversity is increasingly valued by societies (e.g., U.S. Endangered Species Act, Canadian Species at Risk Act), counteracting the impacts of habitat alterations has become an important focus of research and management efforts (Soule 1985). However, for conservation efforts to be successful, we must identify the most limiting factors and the actions with the greatest potential benefit given logistical feasibility (e.g., Budy and Schaller 2007; Budy et al. 2015; Walsworth and Budy 2015; Mantyka-Pringle et al. 2016).

Fishes native to desert rivers are particularly susceptible to the challenges presented by hydrologic alterations (Minckley and Deacon 1991; Olden and Poff 2005). Lacking sufficient precipitation, human settlements in arid climates frequently rely on diversions of water from rivers for agriculture, and large storage or flood control dams are often constructed to reduce the uncertainty presented by flow variability within and among years, as well as mitigate flooding impacts. These modifications result in major changes to the hydrologic conditions of the river, which in turn can drive dramatic geomorphic and biological changes (Poff et al. 1997; Schmidt et al. 2001; Schmidt and Wilcock 2008). Storage and flood control dams reduce the magnitude and duration of spring runoff flows, limiting the availability of high flows responsible for the creation and maintenance of complex in stream habitats, as well as reducing lateral connectivity between channel and floodplain (Junk et al. 1989; Poff et al. 1997; Naiman et al. 2008). However, storage and flood control dams generally increase the magnitude of summer flows, as they release water stored during high flow periods during typically low flow periods. Water withdrawals can reduce the quantity and quality of in-stream habitats available to aquatic species (Xenopoulos et al. 2005; Benejam et al. 2010; Matthaei et al. 2010). As a result of these changes to the hydrology and physical habitat, most native desert fishes have experienced dramatic declines in range and abundance (Minckley and Deacon 1991; Olden and Poff 2005; Budy et al. 2015).

Once distributed in high densities and across nearly the entire extent of the Rio Grande, the Rio Grande Silvery Minnow (*Hybognathus amarus*; hereafter “RGSM”) is currently restricted to the 240 km of the Middle Rio Grande (New Mexico, USA; hereafter “MRG”; Cowley 2006). The MRG has a long history of human settlement and alteration, and large-scale modifications to habitat and flow throughout the watershed have led to major changes in the fish community (Calamusso and Rinne 1999; Cowley 2006). The Rio Grande Silvery Minnow has declined by an estimated 95% in range and abundance (Bestgen and Platania 1991) and is listed as endangered under the U.S. Endangered Species Act (U.S. Fish and Wildlife Service 1994).

The primary threats to RGSM persistence are alteration of the natural hydrograph and resultant changes in geomorphology, driven by development of water infrastructure for flood control and irrigation withdrawals, as well as long-term climatic changes (U.S. Bureau of Reclamation 2016; Stone et al. 2017; Blythe and Schmidt 2018). Hydrologic and geomorphic changes have reduced the quantity, quality and heterogeneity of habitats available (e.g., Swanson et al. 2010; Magaña 2012; Archdeacon 2016). Combined with large interannual variation in precipitation (i.e., snowpack), the geomorphic and hydrologic changes have reduced the frequency at which suitable spawning and rearing conditions exist, as well as increasing the frequency and extent of summer channel drying (Blythe and Schmidt 2018). The interannual variability in snowpack alongside limited storage capability, obligations to private water rights holders, and interstate water compacts complicate the ability of managers to address the hydrologic changes negatively affecting RGSM in the MRG (Hill 1974; O'Connor 2002; Kelly et al. 2007). Nonetheless, exploring and implementing habitat restoration, fish propagation and water management alternatives to promote the persistence and recovery of RGSM is a top priority for the many state and federal agencies operating in the MRG (U.S. Fish and Wildlife Service 2016).

Given substantial uncertainty regarding the conditions most limiting to RGSM persistence and recovery, including the potential for hydrologic-based recovery options, there is a need to characterize the relationship between annual hydrologic conditions and RGSM abundance and distribution (U.S. Fish and Wildlife Service 2016). The U.S. Fish and Wildlife Service conducted initial analyses of the hydrologic drivers of RGSM abundance in the MRG as part of a biological opinion on the effects of U.S. Bureau of Reclamation water management activities. Following an external review of the statistical approach used those analyses (Budy and Walsworth 2019), we were contracted to incorporate the analytical changes suggested therein.

Our goals were to explore (1) how RGSM abundance in the MRG responds to changes in annual hydrologic conditions, (2) how RGSM relationships with hydrologic conditions differ spatially in the MRG, and (3) what hydrologic conditions would need to be present for managers to expect to meet different management and recovery targets. The results of these analyses and the models developed herein can be used in an adaptive management framework aimed at managing the trade-offs between off-stream water use, dam operations, and the conservation and recovery of RGSM in the MRG. Further, the framework developed for these analyses can be applied to examine the relative conservation potential of alternative management actions targeting other imperiled fishes globally.

Methods

Study Site

The Rio Grande flows from the Rocky Mountains of southern Colorado, through central New Mexico, before forming the border between the United States of America and Mexico along the southern border of Texas and discharging into the Gulf of Mexico. The MRG extends from Cochiti Dam on the upstream end to the upstream extent of Elephant Butte Reservoir on the downstream end in central New Mexico. The MRG is delineated into four reaches separated by diversion dams: (*upstream to downstream*) Cochiti (36.2 river km), Angostura (65.6 river km), Isleta (85.5 river km), and San Acacia (102.3 river km). Due to limits to Tribal land access, RGSM have not been surveyed in the Cochiti reach since 1994 (U.S. Fish and Wildlife Service 2016). Therefore, we restricted our analyses to the three downstream reaches for which data have been regularly collected. The number of sample sites per reach has varied and generally increased throughout the period of observation, with lower, less consistent effort before 2001 (number of sites per reach ranged from 2 to 8, with most effort in the San Acacia reach), consistent effort between 2001 and 2016 (5 sites in the Angostura reach, 6 sites in the Isleta reach, and 9 sites in the San Acacia reach), and further increased effort beginning in 2017 (a total of 10 sites in each reach; Dudley et al. 2018).

Data

The fish community of the MRG has been sampled multiple times annually since 1993 (Dudley et al. 2018; data used in this study extend through 2017), with the exception of 1998 and 2011. Samples collected in October have been the most consistent across the period of data collection and are the values examined for meeting conservation targets. As such, we limit our analyses to using the October sampling data. Newly recruited age-0 RGSM have survived the harshest summer drying conditions, flow variability is lowest, and are available for capture by sampling crews. The fish community is sampled via seining different habitats within a sample site, with the total area seined recorded for each haul. We pooled all October seine hauls within a sampling site for each year and divided by the total area seined to generate a site-specific index of RGSM density (# of RGSM per 100m^2), which reflects the metrics used in RGSM conservation and recovery goals.

The hydrobiological (HBO) analyses contained in the 2016 biological opinion (U.S. Fish and Wildlife Service 2016) incorporated many hydrologic metrics in their regressions of RGSM densities, including mean daily discharge, total discharge, number of days above or below different threshold discharge levels, and channel inundation area. Additionally, we calculated and explored the explanatory power of a metric of peak spring high flow timing, defined as the

Julian day of year with the greatest 5-day moving average discharge in May and June. All discharge data used in this analysis were from the Albuquerque Central gage (U.S. Geological Survey gage 08330000).

In addition to high flow metrics, the HBO incorporated several metrics of summer drying conditions, including number of days the gages were less than different threshold discharge levels correlating with the onset of river drying. Such metrics are insufficient for delineating between extreme drying seasons, as a year with 10 days at 99 cfs discharge will have the same number of days below a threshold of 100 cfs as a year with 10 days at 0 cfs, for example. The habitat conditions experienced by RGSM under these two hypothetical scenarios will be vastly different, yet the conditions are identical by the threshold metric. As such, we developed an alternative metric of drying which would account for both the extent and duration of drying within each reach. Using data of the location of drying in the MRG from the "RiverEyes" program (U.S. Bureau of Reclamation), we calculated the number of mile-days dry per reach per year, by adding the number of miles dry per day across the season. While this metric provides a useful index of summer drying, it does not indicate the actual length and duration of drying. As daily drying data are only available from 2002 to present, we estimated the extent of drying in the preceding years by fitting a linear regression between the square root of mile-days dry from the "RiverEyes" data to the area of the MRG channel that was inundated during the low flow period from July through October (U.S. Fish and Wildlife Service 2016). We fit separate regressions for each reach (San Acacia r^2 =0.47, Isleta r^2 = 0.30), resulting in unique drying indices for each reach in each year. The Angostura reach never experienced a measurable degree of drying during the period of "RiverEyes" monitoring, and we thus assumed it did not run dry throughout the extent of the RGSM monitoring data.

Pairwise comparisons revealed that many of these flow and drying metrics were highly correlated (Budy and Walsworth 2019), severely limiting the ability to ascribe importance to any single metric. To address this challenge, we conducted a principal components analysis (PCA) incorporating all of the metrics used in the HBO to describe the major axes of variation between years (*additional details and examples in Appendix A*). We subsequently used the first two principal components resulting from this PCA as our integrated flow metrics predicting RGSM distribution and density.

Catch Model

We developed a mixed-effects hurdle model incorporating a random-walk latent (unobserved) trend to predict the probability of encountering RGSM during sampling as well as the density of RGSM (catch per 100m^2 sampled; hereafter *"CPUE"*) given they were encountered. The random effects (i.e., baseline probability of presence in the hurdle component and asymptotic maximum expected CPUE in the catch model) describe unique responses to environmental predictor variables in each reach, generating spatially-heterogeneous predicted RGSM CPUE. Additionally, the model assumes a random capture probability as a function of environmental conditions, reflecting the patchy distribution of RGSM observed in the dataset.

Our model incorporated a hurdle component determining whether any RGSM were encountered at a sampling site during October sampling:

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta_p}\boldsymbol{\varphi_{ry}} + w_y \qquad (1a)$$

$$w_y \sim N(w_{y-1}, \sigma_w^2)$$

$$w_{y=1} \sim N(0, \sigma_w^2)$$

$$\alpha_r \sim N(\mu_\alpha, \sigma_\alpha^2)$$

$$I(C_{ry} > 0) \sim Bernoulli(p_{ry}) \qquad (1b)$$

where p_{ry} is the probability of encountering RGSM (i.e., catch is greater than zero) at a sample site in reach *r*, year *y*, α_r is the reach-specific random effect baseline logit-capture probability, $\boldsymbol{\beta_p}$ is a vector of estimated parameters, $\boldsymbol{\varphi_{ry}}$ is a vector of environmental predictor variables (i.e., principal component scores), w_y is the random walk time series component, μ_α is the global mean baseline logit capture probability, σ_α^2 is the among reach variance in baseline logit capture probability, and C_{ry} is the CPUE sampled at site *r*, year *y*. This formulation assumes that if any RGSM are present at the site, at least one will be captured. While the probability of capturing RGSM likely varies among mesohabitats (due to depth, velocity, connectivity), this model does not explicitly account for this variation as mesohabitat samples are combined by site in our analysis. Any variation in capture probabilities among mesohabitat types or differences in mesohabitat composition among sites will be accounted for in the variance of p_{ry}. Low flow variation in October allows us to assume that the probability of encountering RGSM will not be substantially affected by discharge, though any discharge effect that remains will be accounted for in the variance of p_{ry}.

The catch component of the model incorporates a Gompertz function with gamma distributed errors to predict October RGSM CPUE in each reach (given CPUE is greater than zero):

$$C_{ry} = K_r e^{-\beta_o e^{-\boldsymbol{\beta_c}\boldsymbol{\delta_{ry}}}} \tag{2a}$$

$$K_r \sim N(\mu_K, \sigma_K^2)$$

$$\sigma_{ry} = cv \times C_{ry} \tag{2b}$$

$$\theta_{ry} = \frac{C_{ry} + \sqrt{C_{ry} + 4\sigma_{ry}^2}}{2\sigma_{ry}^2}$$

$$\gamma_{ry} = 1 + \theta_{ry} C_{ry}$$

$$(C_{ry} | C_{ry} > 0) \sim \Gamma(\gamma_{ry}, \theta_{ry}) \tag{2c}$$

where K_r is the asymptotic maximum expected CPUE in reach *r*, which is normally distributed with an among reach mean of μ_K and variance of σ_K^2, β_o and $\boldsymbol{\beta_c}$ are estimated parameters, $\boldsymbol{\delta_{ry}}$ is a vector of environmental variables predicting CPUE, σ_{ry} is the residual standard deviation in CPUE, *cv* is the coefficient of variation of CPUE, θ_{ry} and γ_{ry} are the gamma distribution rate and shape parameters.

Importantly, our model assumes that capture probability and catch rates are not impacted by discharge at the time of sampling. Low flows during sampling may concentrate RGSM in easily sampled habitats, while higher flows may spread RGSM more broadly. Explicitly acknowledging CPUE metrics as indices of relative abundance and not linearly-related proportions of total abundance when interpreting model results limits the potential management pitfalls from violating the assumption of equal catchability across all flow conditions during sampling (Budy and Walsworth 2019).

In addition to the base model described above, we explored three model structures which altered the base model in minor but meaningful ways: one model removed the hurdle component, one model removed the latent trend estimation, and a third modeled age-0 RGSM abundance only and included an effect of the previous year's total RGSM CPUE. These models and their results are described more fully in Appendix B, but the broad results and management implications of all of the models are comparable to the base model reported in the main document.

We fit the hurdle models in a Bayesian hierarchical framework, with 3 Markov Chain Monte Carlo (MCMC) chains, a burn-in period of 150,000 samples, a monitoring period of 150,000 samples, and a thinning rate of 150. We considered models to have reached convergence if all parameters had an "Rhat" value less than 1.1, (Gelman and Hill 2007). We fit all models using the Just Another Gibbs Sampler (JAGS) software (Plummer 2003) with uninformative priors (Table 1), implemented through the R Statistical Computing Environment (R Core Team 2018).

Simulation Model

To examine the probability of meeting conservation targets under different hydrologic scenarios, we simulated RGSM CPUE from 10 sample sites (i.e., 10 random draws from the model predicted distribution of CPUE) in each reach across a range of hydrologic conditions (i.e., integrated flow metric values) using parameter values drawn from the posterior distribution of MCMC samples from the best fitting model. We then calculated the proportion of simulated years in which recovery targets were met for each reach individually, as well as across all reaches.

Additionally, we examined the probability of individual reaches achieving a range of CPUE targets for five consecutive years under contemporary hydrologic conditions. We randomly selected five hydrologic years observed in the data set, five consecutive random walk values from the presence model component output, and examined whether the individual reaches or MRG as a whole met a range of CPUE thresholds from 0 to 5 RGSM per $100m^2$. We conducted the simulation analyses in the R Statistical Computing Environment (R Core Team 2018).

Results

Environmental Factors

The first principal component of the PCA of hydrologic predictors used in the HBO explains 70.4% of the variation in the data. Years with large spring flows and less summer drying are characterized by positive values on this axis, while years with small spring flows and more summer drying are characterized by negative values (Figs. 1, 2). We used the scores on the first principal component as our integrated annual "hydrologic index", broadly characterizing wet years from dry years. As this hydrologic index accounted for over 70% of the annual variation in hydrologic conditions, we used this as the hydrologic predictor variable for both density and presence in our models. The second principal component explained an additional 16.9% of the variation in the annual hydrologic conditions. Years with early spring flow peaks and more summer drying are characterized by positive PC2 values, while years with late spring peak flows and less summer drying are characterized by negative PC2 scores (Figs. 1, 2). The scores on the second principal component served as an additional integrated flow metric, characterizing years with delayed spring flows and limited drying from years with early spring flows and more drying, and can be considered a "*flow timing index*". While we examined a model incorporating both the hydrologic and flow timing indices simultaneously as predictors for both presence and density of RGSM, that model had much lower support by WAIC (Watanabe 2010; Gelman et al. 2014). As such, we focus on the model incorporating only the hydrologic index in the main document (*hereafter*, the "base model"), while presenting the model incorporating both indices along with other alternative model results in *Appendix B*.

Catch Models

From the base model, we predicted the CPUE of RGSM sampled in October would increase with greater values of our annual hydrologic index (i.e., higher spring flows and less summer drying; Fig. 3a). The probability of encountering RGSM was also positively related to the annual hydrologic index (Fig. 3b). The three reaches of the MRG demonstrated substantial overlap in estimated baseline encounter probabilities (Fig. 4ac) and asymptotic maximum CPUE estimates (Fig. 4bd), though the San Acacia reach demonstrated the highest values for both parameters (4ef) and Isleta demonstrated a significantly greater baseline probability of presence than Angostura (4f). The latent trend impacting encounter probabilities demonstrated an approximately decadal periodic pattern (Fig. 3c), with a low period in the late 1990s and early 2000s, as well as during the early 2010s, with periods of higher values intervening.

Based on Model 1 predicted CPUEs matched field observations very well (Fig. 5), with only 11 out of 413 observations (2.7%) falling outside of the predicted ranges. For each reach and year, the model predicts many sites will have low CPUE, with smaller probabilities of large capture events occurring. The model also recreated the general patterns of encounter probabilities well for all reaches (Fig. 6), though, unsurprisingly given the relatively small number of sample sites in each reach, the observed proportion of sample sites with non-zero catch sometimes fell outside of the 95% credible intervals for predicted probabilities.

Simulation Model

Model simulations suggest hydrologic conditions near the median of those observed during the monitoring period are required for there to be a 95% chance of mean CPUE within and among reaches to be greater than 1 (Fig. 7a), the "self-sustaining population" threshold for the RGSM population, with the exception of in the San Acacia reach. The Angostura reach would require an annual hydrologic index slightly above the median observed value to have a 95% probability of having CPUE greater than 1. Angostura has the lowest probability of meeting the CPUE threshold of the three reaches because the majority of site-specific CPUE values are predicted to be small, even during above average flow years (Fig 7b). The Isleta reach is predicted to have larger site-specific CPUE during modest flow years than the Angostura reach (Fig. 7c), and thus is predicted to have a reach-level CPUE greater than 1 with 95% probability during years with hydrologic indices slightly below the observed median values. The San Acacia reach has a 95% of having a mean CPUE greater than 1 under hydrologic indices greater than approximately the 25^{th} percentile, as large (>20 RGSM per $100m^2$) CPUE at individual sampling sites is predicted to occur sporadically even during modestly low flow years (Fig. 7d).

As expected, the probability of meeting CPUE targets across five consecutive years declines with increasing CPUE targets (Figure 8). While none of the reaches are likely to exceed the published down-listing criteria of CPUE >5 RGSM/100m^2 for five consecutive years, lower targets commonly used for management are more likely to be met. The San Acacia reach is more likely to achieve CPUE targets than the other two reaches across all thresholds explored and is more likely to achieve CPUE targets than the MRG average for threshold greater than ~0.6 RGSM per 100m^2. San Acacia reach has a high probability of meeting current "self-sustaining population" targets of 1.0 RGSM per 100m^2 for five consecutive years, exceeding this threshold in approximately 60% of simulations. However, both Isleta (~40%) and Angostura (~25%) have much lower exceedance probabilities.

Discussion

Successful conservation of imperiled species occupying rivers with highly altered hydrographs will often require a return to more natural flow regimes (Poff et al. 1997; Dudgeon et al. 2006; Reid et al. 2019), but contemporary constraints may require a focus on ecological principles and creative management (Thorpe and Stanley 2011). Here, we demonstrate how the Rio Grande Silvery Minnow (RGSM) is predicted to respond positively in both distribution and abundance to wetter conditions across both spring and summer. Years with larger spring high flow events and less summer drying demonstrated a greater probability of RGSM being captured at each sampling site, as well as higher expected densities when they were encountered. These results support previous assessments of RGSM population responses to hydrologic changes in the MRG (Archdeacon 2016; Dudley et al. 2018; USFWS 2016), but also incorporate a model structure accounting for spatially-heterogeneous relationships, sampling variability, and a more robust presentation of prediction uncertainty. These results can ultimately guide explorations of future management options aimed at providing sufficient habitat conditions to allow persistence and growth of the RGSM population, as well as meet the needs of off-stream water users.

Inundated floodplain habitats during spring runoff historically provided RGSM with low velocity spawning habitats and productive rearing habitats for juveniles to grow rapidly (Medley and Shirey 2013), and these habitats may still attract spawning RGSM when available (Hutson et al. 2018; Valdez et al. 2019). Water development and levee construction throughout the basin has reduced the magnitude, extent and duration of spring high flow events, such that floodplains are inundated less frequently and for shorter periods of time (Stone et al. 2017; Blythe and Schmidt 2018), limiting the quantity and quality of available rearing habitat. These changes have combined to reduce the frequency and magnitude of RGSM recruitment events. Additionally, the effect of increased flows on CPUE is stronger for the San Acacia reach than the Isleta reach, which responds more strongly than the Angostura reach, a pattern potentially explained by the different discharges required to inundate floodplain habitats in the three reaches (Tetra Tech 2014). Our model results suggest years with smaller spring high flows produce smaller recruitment classes and, thus, lower catch rates in the fall. Similar patterns have been observed in other desert rivers globally (e.g., Propst and Gido 2004; Balcombe and Arthington 2008; Van Haverbeke et al. 2013; Budy et al. 2015).

Arid land rivers have experienced increased intermittency in recent decades due to over-allocation of water and drought, with major consequences for native biota not adapted to intermittent conditions (e.g., Gleick 2003; Datry et al. 2014; Allen et al. 2019). In our study, intermittent, but extensive, channel drying in summer also appears to be driving reduced distribution and densities of RGSM in the MRG, as drying metrics loaded strongly onto our integrated annual hydrologic index. Increased extent of drying will reduce the total amount of habitat available to RGSM, potentially increase competition for resources, as well as strand individuals as isolated pools dry up, collectively resulting in both indirect and direct mortality (Lake 2003). While it is difficult to tease apart the effect of spring flows from summer drying in the available dataset due to high correlation between the hydrologic metrics, our model suggests efforts to reduce the amount of drying in the summer would benefit RGSM populations. The extent of drying that needs to be avoided or mitigated in order to maintain conservation targets will likely depend on the magnitude and duration of spring flow events, because lower spring flows produce very weak recruitment, which can then be exacerbated by extensive drying further reducing abundance. Additionally, our modeling results suggests that were extensive drying to occur in the MRG following a large spring high flow event, the benefits realized from a large and successful spawning event would be diminished (*see also results of base model incorporating both the hydrologic and flow timing indices in Appendix B*). However, given the data available, the trade-offs between mitigating summer drying conditions versus promoting spring high flows remain uncertain.

The ideal, though logistically and socially challenging, approach to teasing apart the effect of summer drying from the magnitude and duration of spring high flows would be multiple adaptive management based experimental manipulations of flows, such as allowing extensive drying following a large spring flow event, or maintaining relatively high flows during summer following a relatively small spring high flow event. The existing observed data provide initial glances into the different effects of spring high flows and summer drying on RGSM. First, RGSM CPUE was very low (zero in Angostura and Isleta, 0.8 in San Acacia) in 2000 after managers maintained in-stream flows despite a small (only 1 day with flows >1500cfs) spring runoff. Additionally, the Angostura reach does not experience drying (during the time frame examined here), yet the CPUE trends in this reach match those of the other two reaches experiencing summer drying. While this pattern may suggest a stronger influence of spring high flows than of drying, the available data provide no information about how much lower CPUEs would have been had Angostura experienced drying. Until sufficient data become available to discriminate the effects of summer drying from spring high flows at the population level, basic biological principles suggest reducing the amount of drying will benefit RGSM summer survival. Nonetheless, our model results highlight the need to manage water across years to cope with variable hydrology across years and the life history of the RGSM, a challenging but not insurmountable concept given the way the MRG is currently operated (e.g., Stanford et al. 1996; Rood et al. 2005).

Despite the substantial changes to the river's hydrology and floodplain habitats, our model results suggest, in years with large spring flows and limited summer drying (or when water releases are managed for RGSM spawning; Valdez et al. 2019), the remaining habitat in the MRG is sufficient to produce enough recruits to meet management and recovery targets (>1 RGSM per m^2 for self-sustaining population target; > 5 RGSM per m^2 for downlisting target). However, sufficient hydrologic conditions to meet downlisting targets have occurred only sporadically during the period examined here and would need to occur more frequently and across multiple years if recovery goals were to be met. More modest management targets currently in use to avoid extinction are much more likely to be met under the current range of hydrologic conditions. The relationship between annual flows and RGSM density demonstrates a non-linear pattern, indicating increasing CPUE response rates across lower hydrologic indices, while simultaneously suggesting eventual diminishing returns of increasing hydrologic indices given the current configuration of channel and floodplain habitats (i.e., how high flows interact with local geomorphology and levees to inundate floodplain habitats). While these non-linearities are driven by the model formulation and available data here, the process makes intuitive biological sense in the MRG and other large rivers (e.g., Tetra Tech 2014; Robertson et al. 2018). High flows do not inundate valuable floodplain rearing habitats until surpassing bank heights dependent on local geomorphology, and increasing flows once floodplains begin to be inundated will increase the amount of productive rearing habitat available for RGSM (Junk et al. 1989; Tetra Tech 2014). However, under current conditions, if flows were to reach the levees, further increased flows would no longer inundate additional, historical floodplain rearing habitats, making existing inundated areas deeper instead. As these hypothetical capacities exist under flow conditions well beyond those observed in the recorded data, their estimated values should be considered with caution. Floodplain restoration activities aimed at increasing the amount of available habitat at lower flow levels should increase RGSM production during years with smaller spring runoff events (Widmer et al. 2010; Valdez et al. 2019). However, the scale of habitat restoration necessary for population level impacts may be extensive (Opperman et al. 2010) and would likely require considerable active maintenance if the natural processes creating and maintaining these habitats are not restored (Beechie et al. 2010).

Species which are more widely distributed across the landscape are less sensitive to local disturbances (Hanski 1998), as populations can remain productive despite poor conditions at a subset of locations (Schindler et al. 2010; Schindler et al. 2015). Rio Grande Silvery Minnow recovery targets focus not only on catch rates, but also on their distribution across habitats, requiring RGSM to be present at 75% of sampling sites for 5 consecutive years (USFWS 2016). The probability of encountering RGSM at each sampling site was greater in years with greater hydrologic indices, suggesting a broader spatial distribution in these years. This pattern may be driven by several potential (though not mutually exclusive, nor exhaustive) mechanisms. Higher spring flows will inundate the floodplain across a greater percentage of the length of the MRG, thus producing recruits in more locations. Alternatively, the increased abundance of RGSM after large flow years causes RGSM to occupy more locations to find sufficient resources (Fretwell and Lucas 1970; Rosenzweig 1991). At low abundances, RGSM should occupy only the best habitats for growth and survival opportunities. As those habitats become increasingly crowded at larger abundances, the per capita growth and survival opportunities decline, and individuals should seek out alternative habitats (e.g., Fausch 1984; Hedger et al. 2005; McMahon and Matter 2006). Increased abundance should thus increase the spatial distribution of RGSM in the MRG as sequentially less beneficial habitats become occupied. Further, years with higher hydrologic indices also generally have less summer drying, which should allow RGSM to maintain their distribution without having to disperse in the face of drying. While any of these processes would result in RGSM being encountered at more locations during years with higher hydrologic indices, they are not the only possible drivers, and the uncertainty of additional stressors presents a valuable opportunity for future studies (Göthe et al. 2019).

Incorporating latent trends into time-series analyses can not only explain additional variance not described by measured predictor variables, but also help identify unmeasured drivers of the dynamics of interest, highlighting avenues of future research and adaptive management (e.g., Mills et al. 2013; Cline et al. 2017). The latent trend in our model of RGSM presence demonstrates a periodic pattern to RGSM presence, where years with higher probability of presence than expected from hydrology alone are likely to be followed by years of higher than expected presence, for example. The trend we observed demonstrates periodicity at approximately decadal scales, thus possibly being driven by decadal scale regional climate variation (e.g., Pacific Decadal Oscillation; Mantua and Hare 2002). Alternatively, this pattern could potentially be explained by survival from the previous year (potentially including stocked individuals) impacting the current year's RGSM population. Indeed, the alternative model structure examining the response of age-0 RGSM density to both hydrologic indices and the previous year's abundance found a negative effect of very low previous abundance on the probability of presence at any given site, though the effect diminished as abundance in the preceding year increased (*see Appendix B*). While we have not explored the impact of augmentation activities on RGSM CPUE dynamics, the results of our age-0 model suggest that any stocking effect would be primarily important when abundance in the preceding year is very low. When RGSM occupy a large proportion of their habitats in one year, they may continue to occupy a larger than expected proportion of habitats the next year even in the presence of relatively poor hydrologic conditions. Similarly, if RGSM are restricted to a small proportion of habitats, one year of favorable hydrologic conditions may not restore them to all possible habitats, and thus they may remain at fewer habitats than would be otherwise anticipated. King et al (2015) similarly observed that both concurrent and antecedent flow conditions were important for many species, with the best outcome resulting from an increase in the magnitude of smaller high flow events following lower antecedent flow conditions in the Murray River, Australia. Future research which would complement our study results could explore the environmental or biological conditions which may be driving the latent trend identified in this study. However, the highly managed hydrograph of the Rio Grande from its headwaters through the MRG could make this challenging, as in many years, river flows are decoupled from environmental conditions in the basin due to upstream and local storage and diversion, as well as inter-basin water transfers (Blythe and Schmidt 2018; Budy et al. 2018).

While the hydrology of the contemporary MRG is highly altered from the historic conditions to which RGSM have adapted their life history (Cowley 2006; Medley and Shirey 2013; Blythe and Schmidt 2018), conditions suitable to producing large recruitment events still occur intermittently. Indeed, our simulations suggest that local RGSM densities can be anticipated to be at or above the target threshold with 95% probability under hydrologic conditions relatively common to the MRG during the period of observation, particularly in the San Acacia reach. While wetter hydrologic conditions would be required to achieve targets in the Isleta and Angostura reaches, as well as for the full MRG segment of the Rio Grande, these flows have been observed in the period of record and could potentially occur more frequently under alternative water management strategies. These results suggest managing the water in the MRG to achieve conservation goals may be attainable under current hydrologic conditions, though doing so will be complicated by the ability to manage flows across multiple years, periodic conditions of multi-year drought, legal barriers presented by local and inter-state water agreements, and changing climatic conditions over longer time frames (Hill 1974; O'Connor 2002; Kelly et al. 2007). Using the model developed herein (along with the alternative models presented in *Appendix B*) to explore alternative management approaches can highlight options that have an opportunity to succeed which can then be assessed for their feasibility (*see example in Appendix A Figs. S5-8)*, an approach which has been applied in other river systems. For example, Zarri et al. (2019) recently used a similar hydrologically driven optimization approach to determine the best strategy to manage dam releases for multiple species with different temperature requirements in the Sacramento River (California, USA). Given that management and conservation resources are limited, future work also complementary to our study could incorporate the costs of management actions in feasibility assessments to aide in sound conservation planning (Evans et al. 2015; Walsh et al. 2020).

Understanding how sensitive species respond to changes in their environment allows managers, stakeholders and policymakers to consider the trade-offs of multiple ecosystem goals when setting management plans (e.g., Halpern et al. 2013; Redpath et al. 2013; Song et al. 2019). Many biological, social, and economic goals are being pursued simultaneously in the MRG, often by different agencies operating different control levers. The relationships between RGSM abundance, distribution and MRG hydrology identified in this study provide a valuable framework for stakeholders to explore trade-offs between RGSM conservation and fulfilling obligations to off-stream water users. By exploring trade-offs presented by different water management strategies under future hydrologic scenarios, approaches that provide positive outcomes for multiple management goals may be identified and implemented in an adaptive management framework (Walters and Hilborn 1978; Walters 1986). Explicitly considering the trade-offs between multiple management goals will allow stakeholders in the MRG to make more informed decisions about managing the ecosystem for multiple benefits, including the conservation of endangered species.

Acknowledgments

This study was funded by the U.S. Bureau of Reclamation – Albuquerque Area Office and the U.S. Geological Survey – Utah Cooperative Fish and Wildlife Unit (in-kind). We would like to thank Kenneth Richard, Ashlee Rudolph, and Mark McKinstry for project logistical support. Joel Lusk did a tremendous amount of work compiling and cleaning the data and on valuable preliminary analyses and provided extensive constructive review of previous drafts of this report. Charles Yackulic, Kevin McDonnell, Rich Valdez, Joel Lusk, Eric Gonzalez, Ashlee Rudolph, Mickey Porter, and David Gensler provided valuable feedback on a previous version of this report. No new data were collected as part of this study. Any use of trade, firm or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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Tables and Figures

Table 1. Prior distributions used in the RGSM catch model.

Parameters	Prior
β_c β_p	N(0,1000)
β_0 $ln(cv)$	N(0,100)
μ_k	N(0,10) T(0,5)
μ_p	N(0,10)
σ_k σ_α σ_w	U(0,10)

Figures

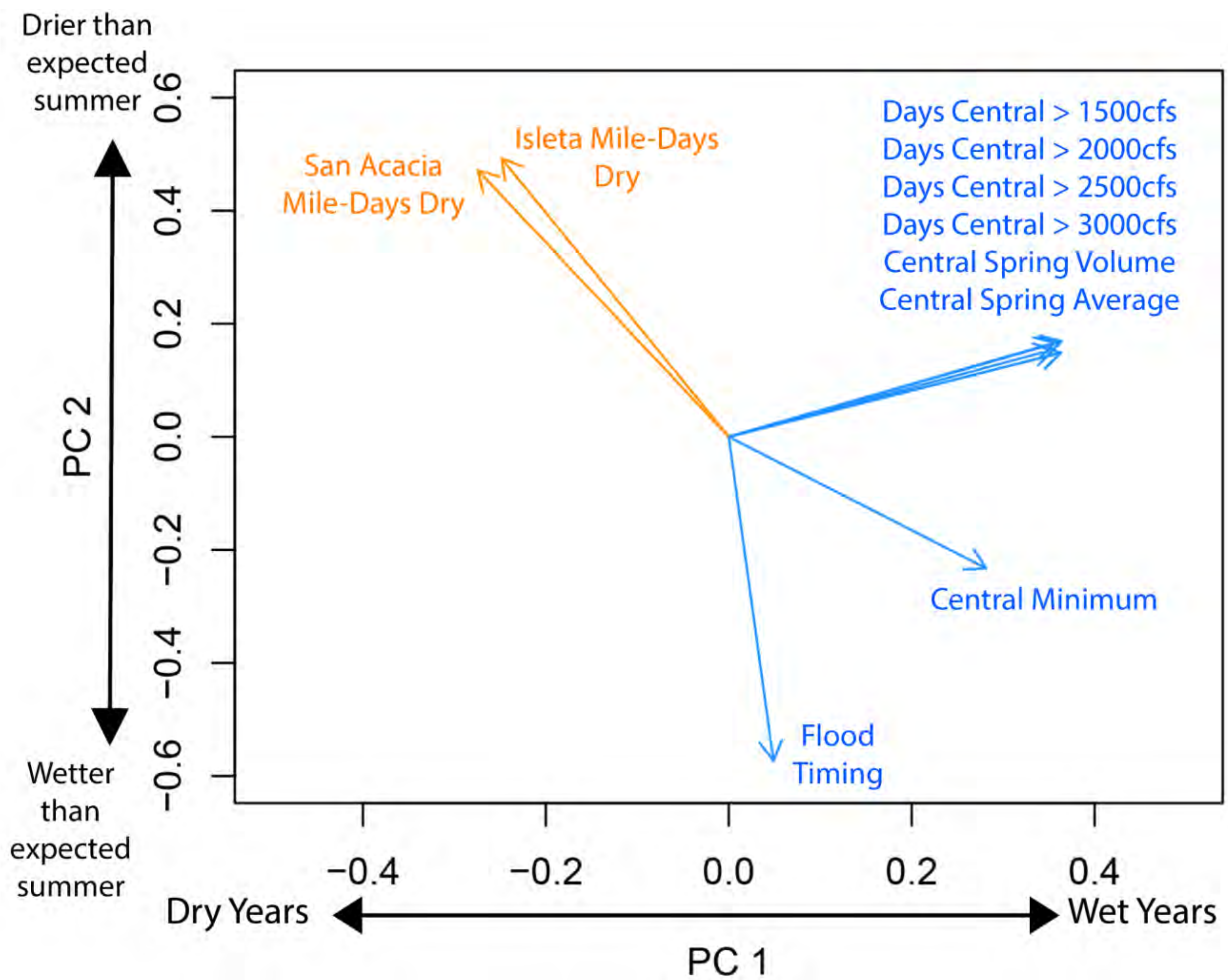

Figure 1. Biplot of the first and second principal components of the hydrologic predictors used in the HBO analysis. Arrows indicate the direction and magnitude of the predictor variable vectors. Blue (orange) arrows represent predictor variables related positively (negatively) to wetter conditions. The first principal component explains 70% of the observed variation in hydrologic predictor variables across years.

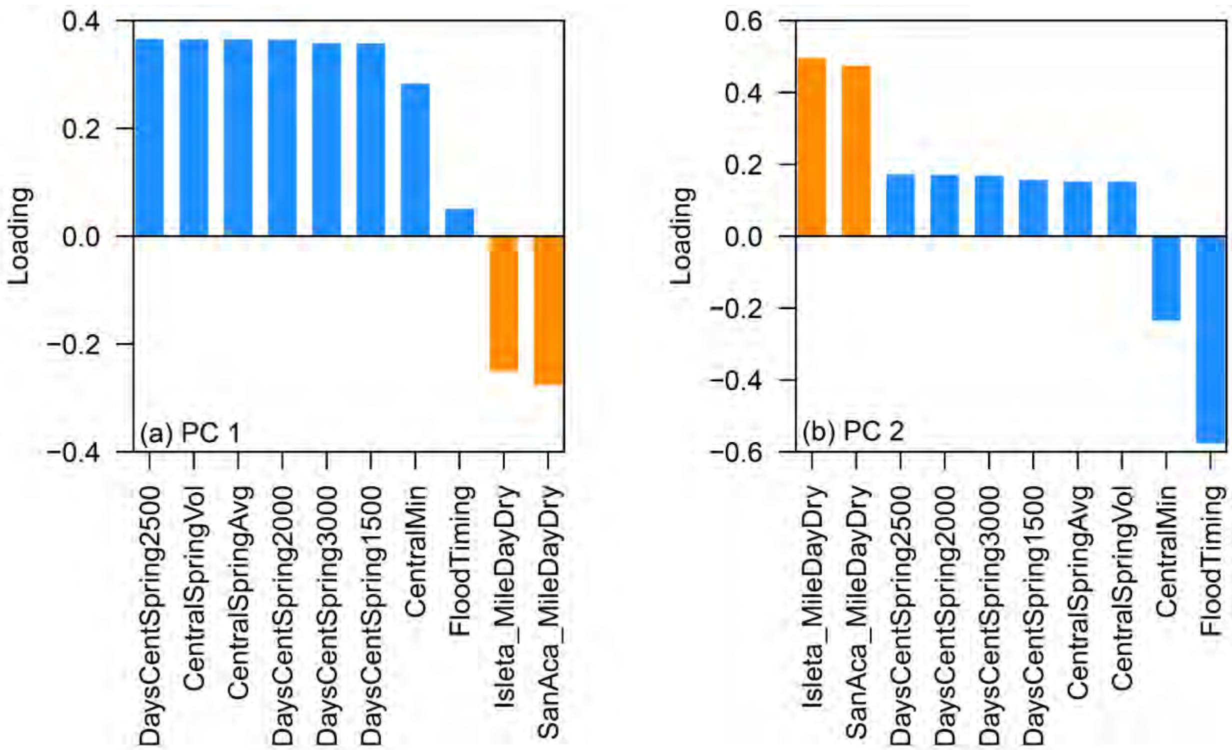

Figure 2. Principal component loadings for the first two principal components of our PCA. Blue (orange) bars represent predictor variables related positively (negatively) to wetter conditions.

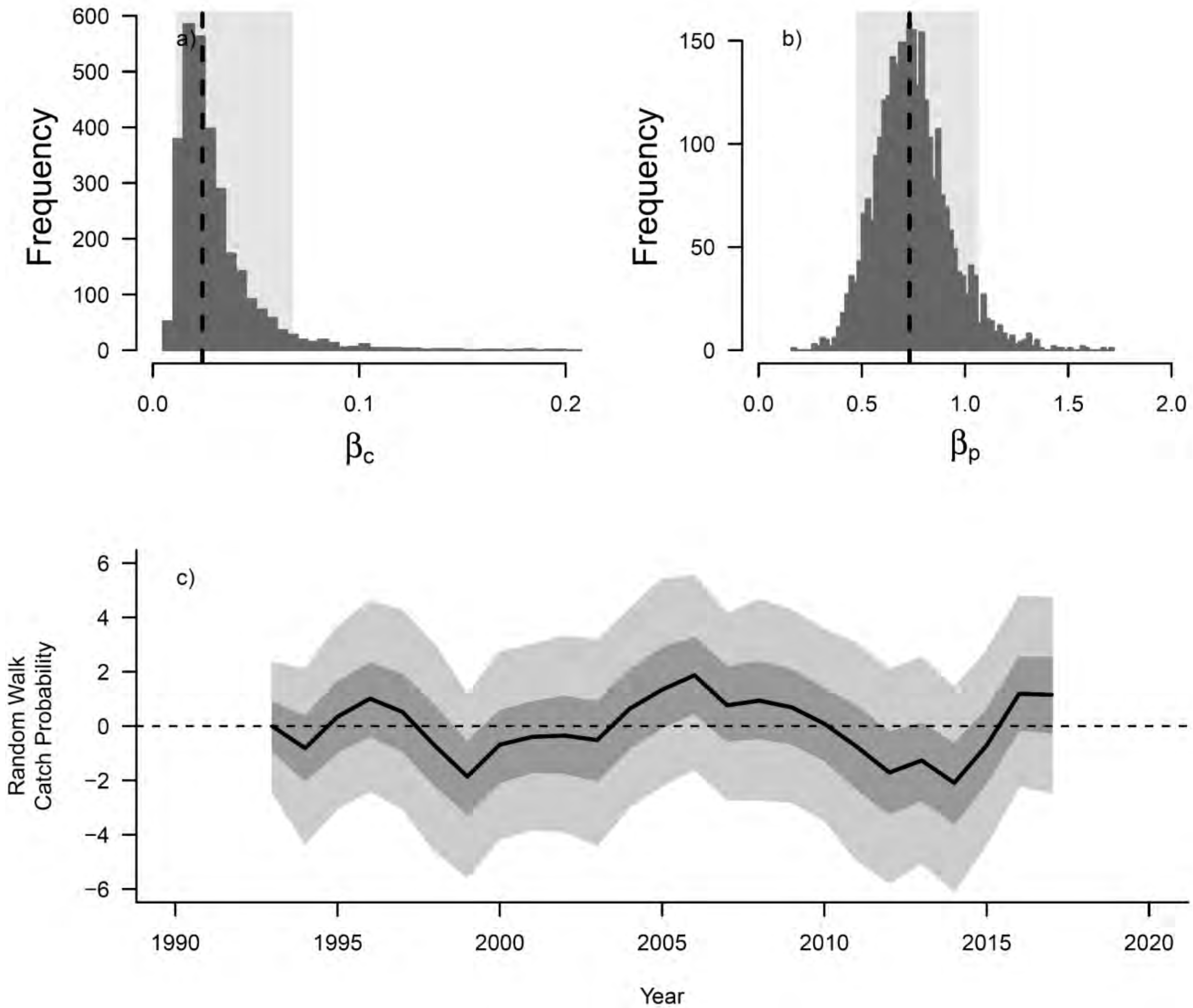

Figure 3. Posterior distributions of parameter estimates for the effect of hydrologic index on catch (a) and encounter probability (b), and the random walk latent trend impacting encounter probabilities (c). The light grey box indicates the 95% credible interval from the MCMC samples, and the vertical dashed line (a, b) indicates the median parameter estimate for panels (a,b). The light grey polygon and dark grey polygons indicate the 95% and 50% credible intervals, respectively, for MCMC samples of annual random walk values, and the solid black line indicates the median MCMC estimate.

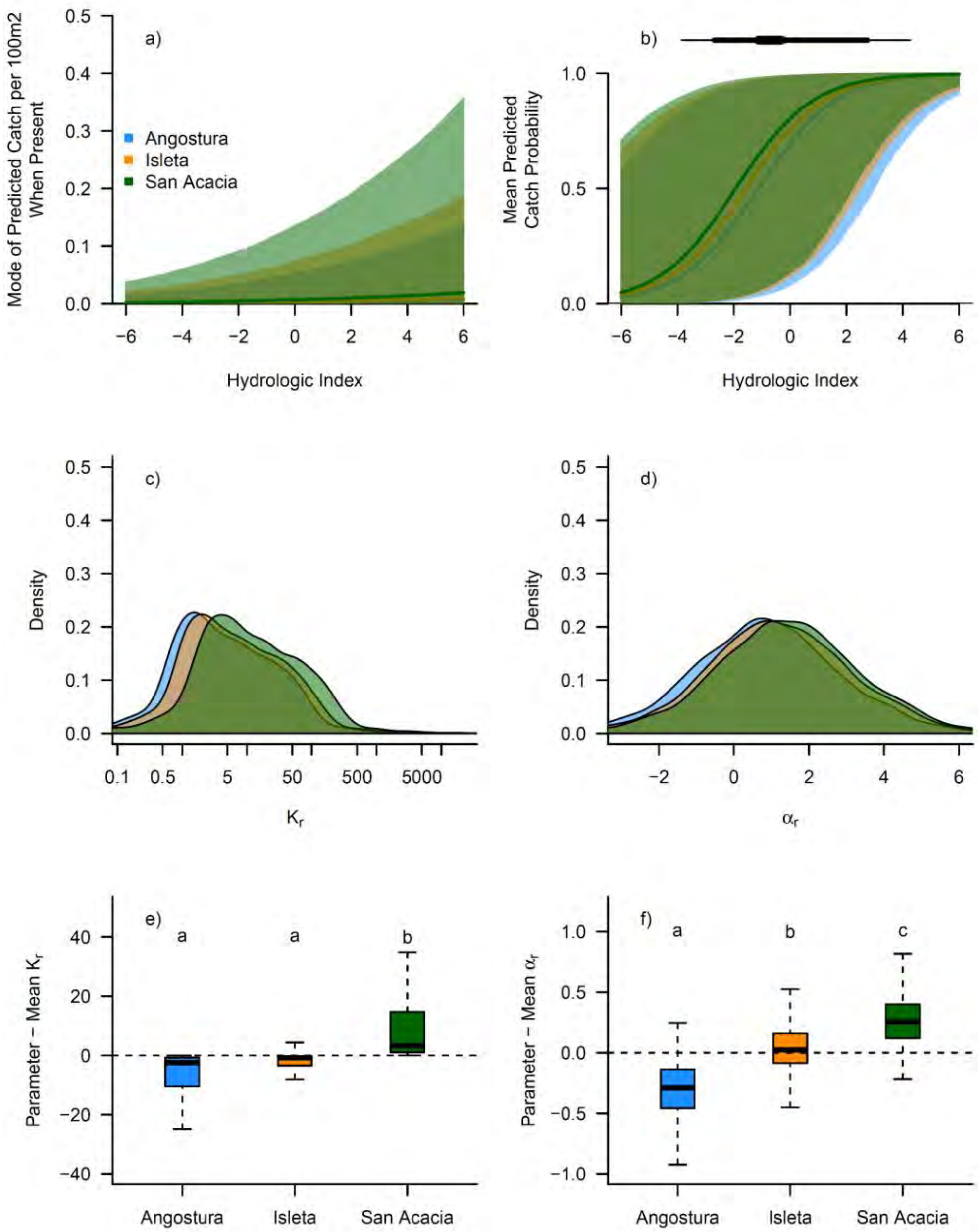

Figure 4. Predicted mode of reach-specific RGSM catch per 100m2 when they are present (a) and reach-specific probability of encountering RGSM (b) across a range of hydrologic index values (larger values indicate larger and longer duration spring high flows, and less summer drying), and the posterior distributions of MCMC samples for reach specific carrying capacity (c) and baseline encounter probability (d) parameters. Posterior distribution of reach specific differences in K (e) and α (f) from the global mean value. The horizontal boxplot above (a) and (b) indicates the 95%, 50% and 10% ranges of observed hydrologic indices magnitudes.

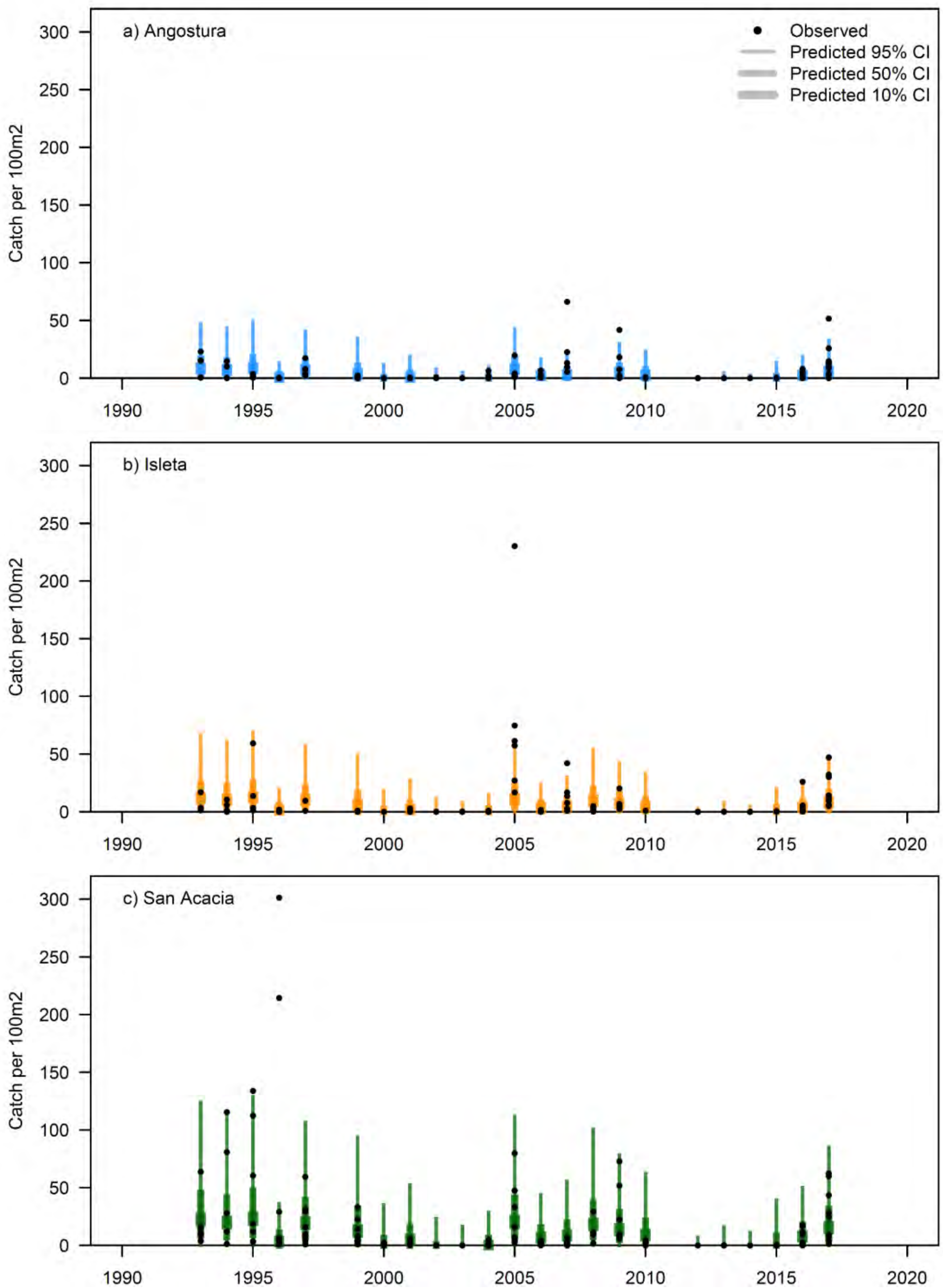

Figure 5. Predicted (boxplots) and observed (points) catch per $100m^2$ for Rio Grande Silvery Minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

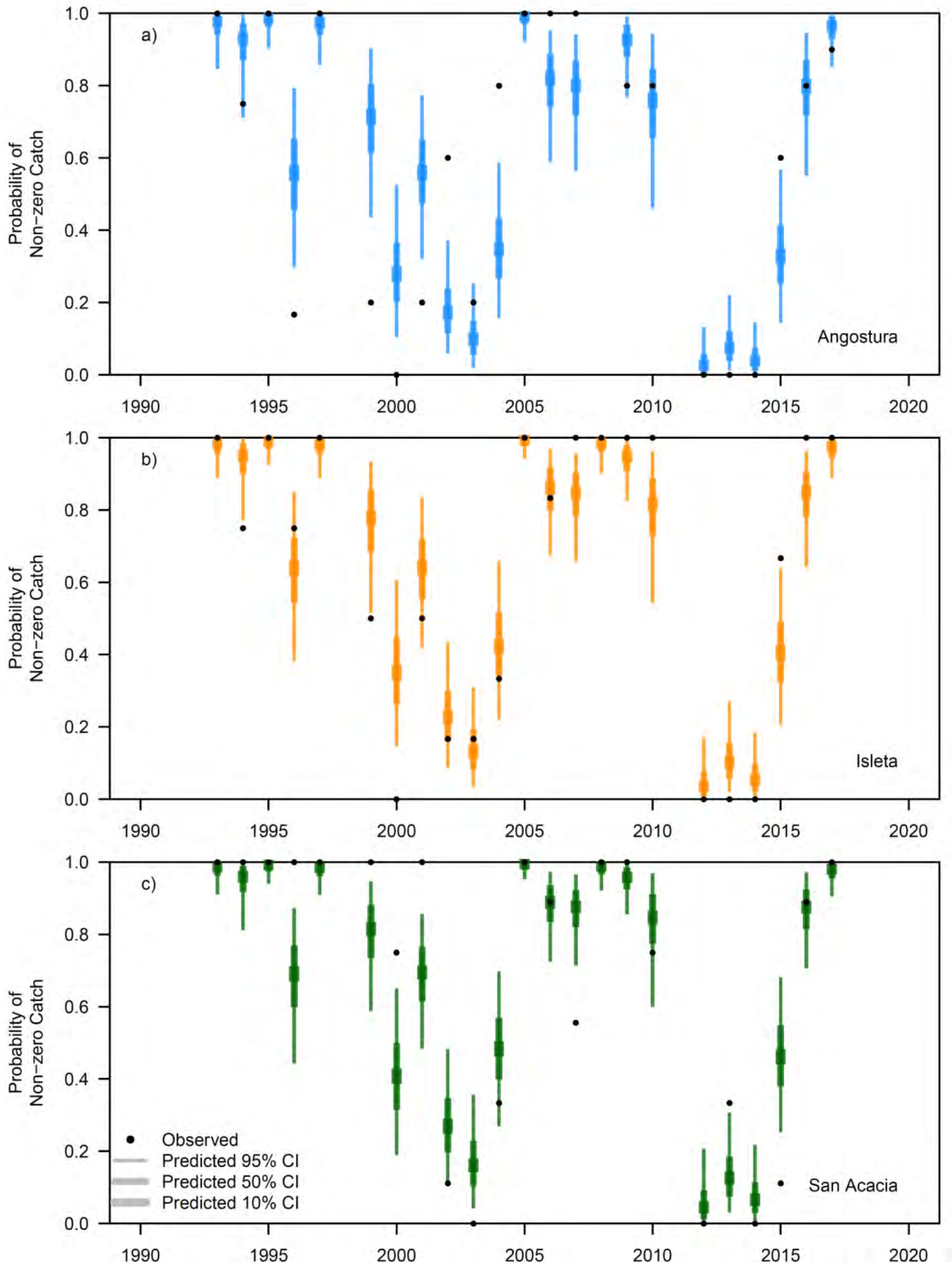

Figure 6. Predicted (boxplots) and observed (points) annual encounter probabilities for Rio Grande Silvery Minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

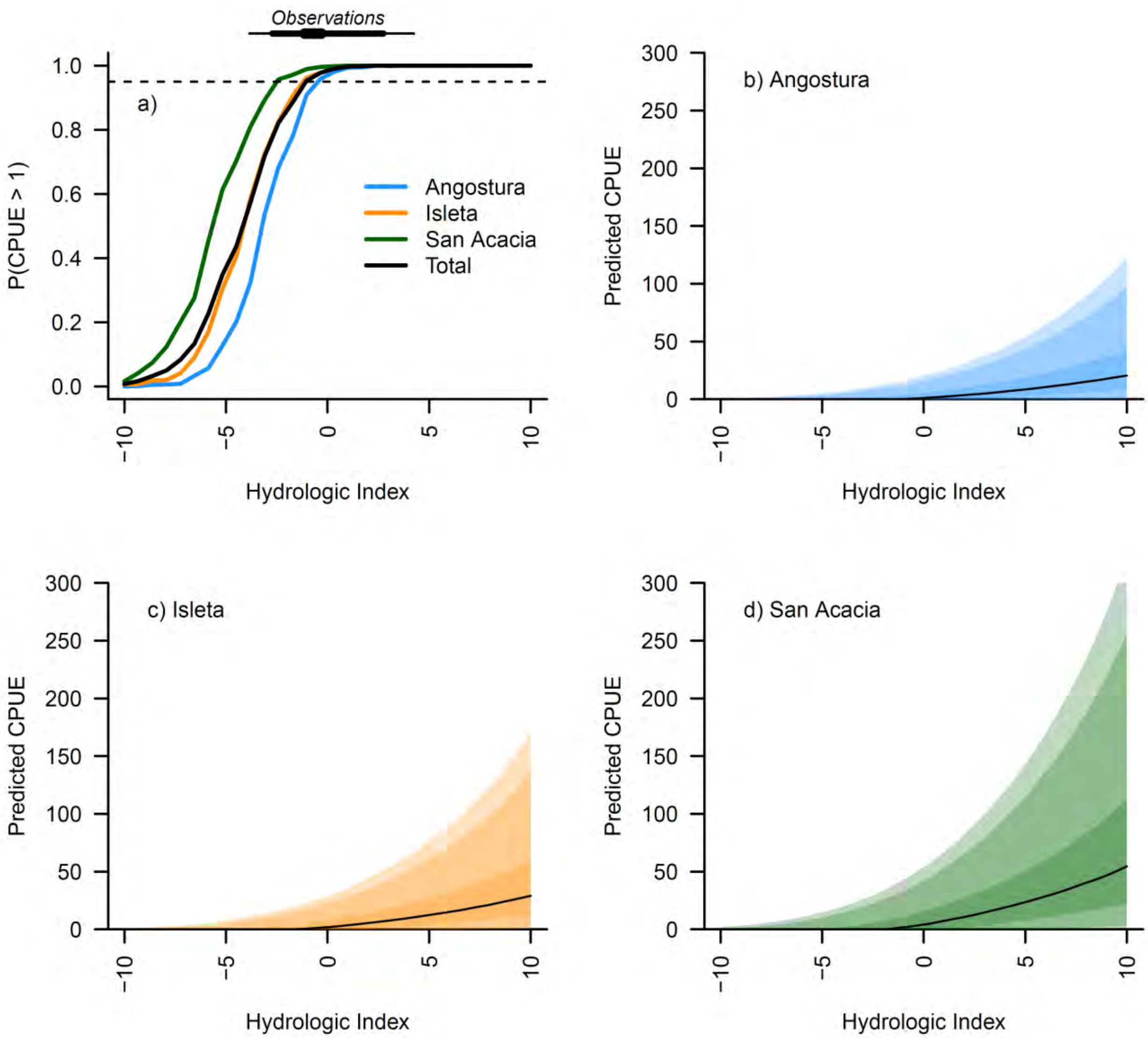

Figure 7. Probabilities of Rio Grande Silvery Minnow catch per 100m2 in each reach (colored lines) and across the whole MRG (black line) being greater than 1.0 across a range of hydrologic indices (a), and the predicted CPUE of Rio Grande Silvery Minnows at different hydrologic indices in the Angostura (b), Isleta (c) and San Acacia (d) reaches. The horizontal boxplot above (a) indicates the 95%, 50% and 10% ranges of observed hydrologic indices and the horizontal dashed line indicates a 95% threshold. The polygons in (b-d) indicate the 95%, 90% and 50% simulation intervals and the line indicates the median predicted CPUE.

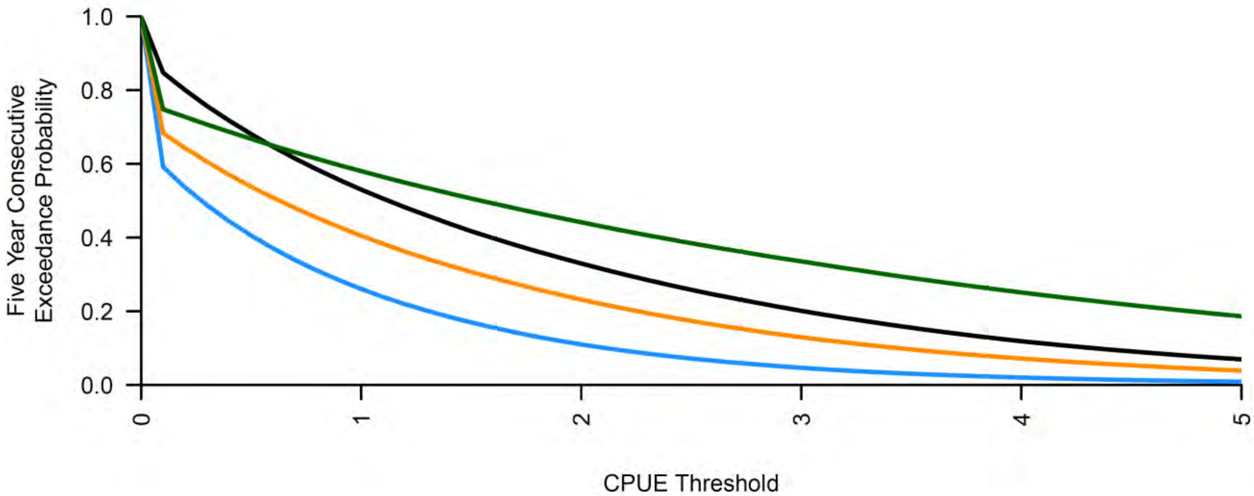

Figure 8. Simulated probability of RGSM catch per $100m^2$ exceeding different target thresholds for five consecutive years under the range of hydrologic conditions in the dataset.

Hydrologic controls on abundance and distribution of the endangered Rio Grande silvery minnow in the Middle Rio Grande

Appendix A: Principal Components Analysis to Generate Integrated Annual Flow Metric

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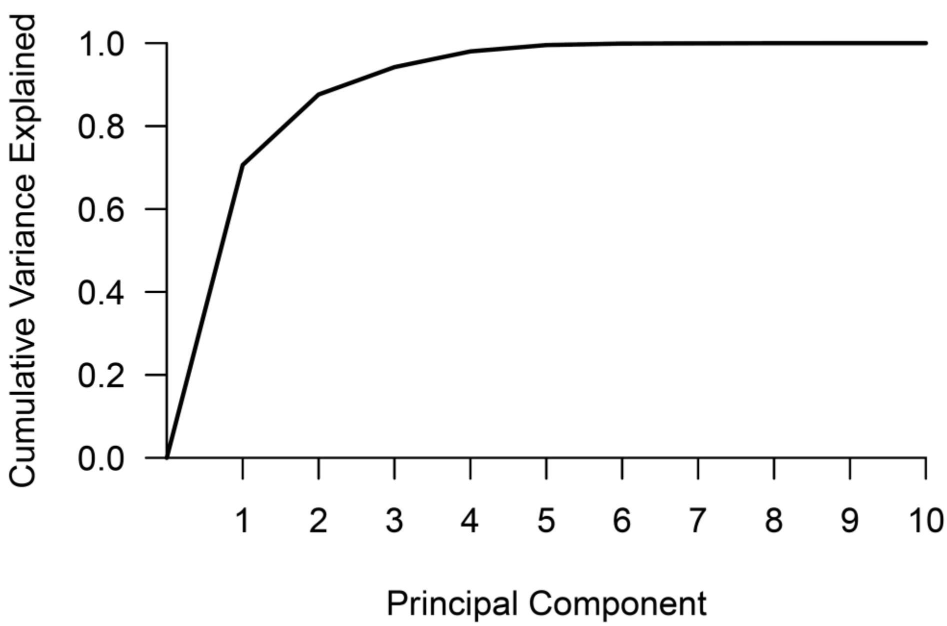
Principal Components Analysis Background

Exploratory analyses examining the relationship between a response variable and different environmental conditions are often presented with a large number of plausible driving factors to consider. Such high dimension datasets can be difficult to manage and efficiently explore. Additionally, many of the plausible predictor variables can be correlated, limiting the ability to differentiate between the effects of two potential drivers. Principal components analysis (PCA) is a method for generating orthogonal (perpendicular and uncorrelated) variables from a larger set of predictor variables, and are a valuable tool for reducing dimensionality of data sets (method developed by Pearson 1901; primer for use in ecology presented in Gotelli and Ellison 2004). The first principal component of a dataset is the linear combination of the original predictor variables describing the maximum variance in the data set. The second principal component is the linear combination of the original predictor variables which describes the maximum variance in the dataset after accounting for the first principal component. As the principal components are orthogonal and thus uncorrelated, each component provides distinct information.

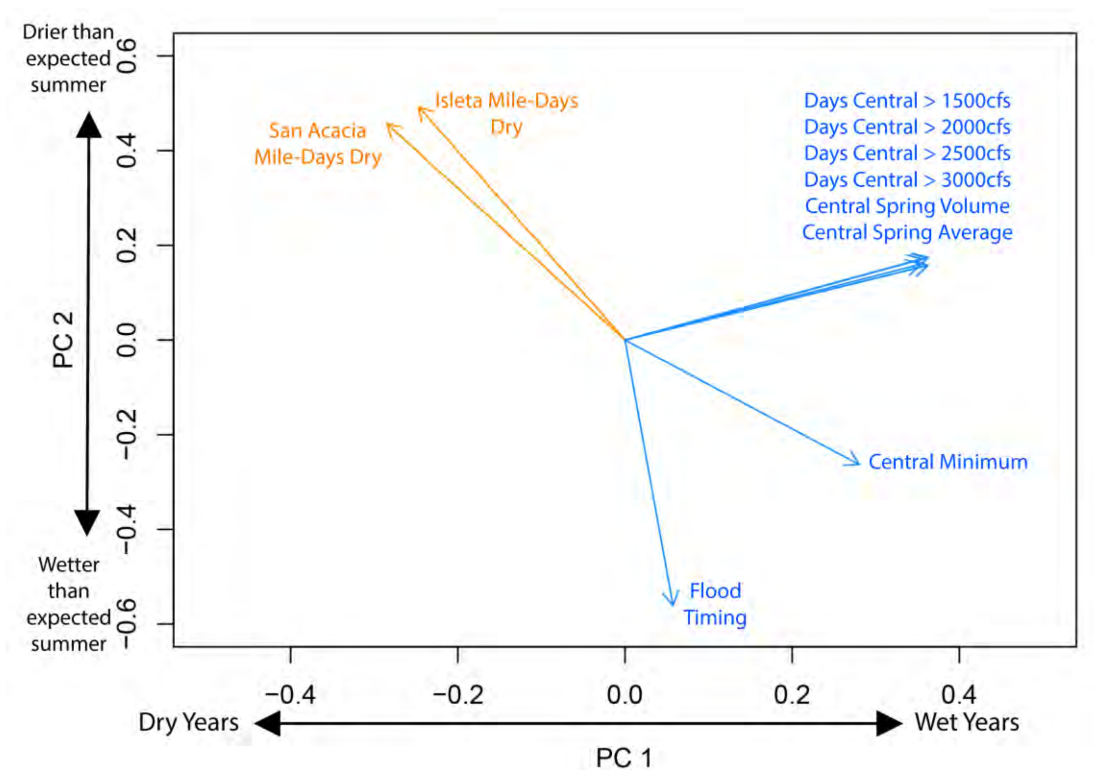
For our exploration of Rio Grande silvery minnow (RGSM) response to annual hydrologic conditions, we initially considered the large number of hydrologic metrics incorporated in the original HBO. These metrics ranged from spring flow volumes, to days with flow above a various threshold discharges, to summer minimum flow values and the extent of drying. Many of these hydrologic variables are highly correlated with one another, limiting our ability to disentangle the influence of multiple variables. Therefore, we applied a PCA to our predictor variables to produce two new, uncorrelated and integrated metrics of annual hydrologic conditions in the Middle Rio Grande.

The first principal component (PC1) explained over 70% of the interannual variance in hydrologic conditions (Fig. S1). Thus, by reducing the dimensionality of our hydrologic dataset to a single variable (PC1), we are still able to retain over 70% of the information contained in the original 15 predictor variables. The second principal component explains an additional 17% of the variance in the data (Fig. S1). Using only these two novel, uncorrelated integrated metrics of annual hydrologic conditions, we are able to retain 87% of the information contained in the original dataset and do not have to address issues of collinearity in our predictor variables, greatly simplifying our ultimate RGSM distribution and catch modeling efforts.

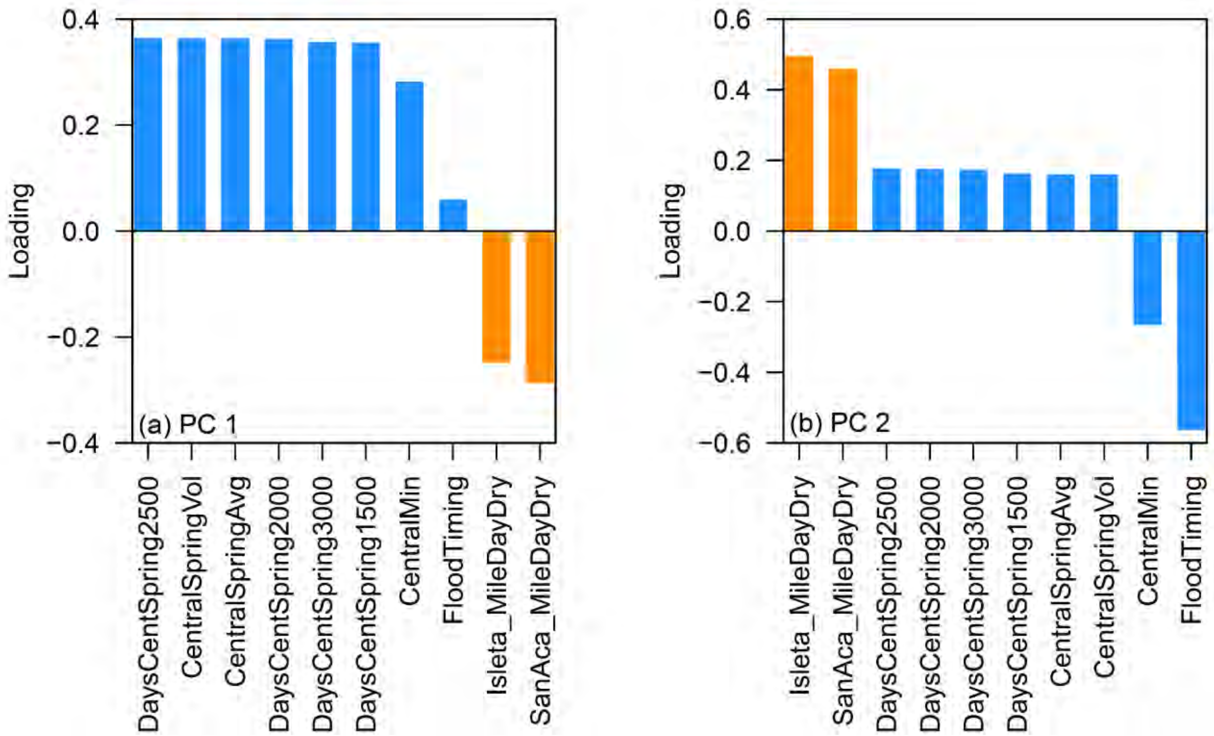


Supplemental Figure S1. Cumulative variance in interannual hydrologic conditions explained by principal components. The first principal component explains approximately 70% and the second principal component explains an additional 17% of the variance in the hydrologic data.

The first principal component generally separates wet years (those with larger spring flows and less summer drying; positive values on PC1) from dry years (with smaller spring flows and more summer drying; negative values on PC1; Figs. S2, S3a), and is referred to as the annual hydrologic index in the main document. The second principal component separates out those years with more summer drying than would be expected given large spring flows coupled with early spring peak flow timing (positive values on PC2) from those with less drying than would be expected given smaller spring flows coupled with late spring peak flows (negative values on PC2; Figs. S2, S3b), and is referred to as the flow timing index in the main document.



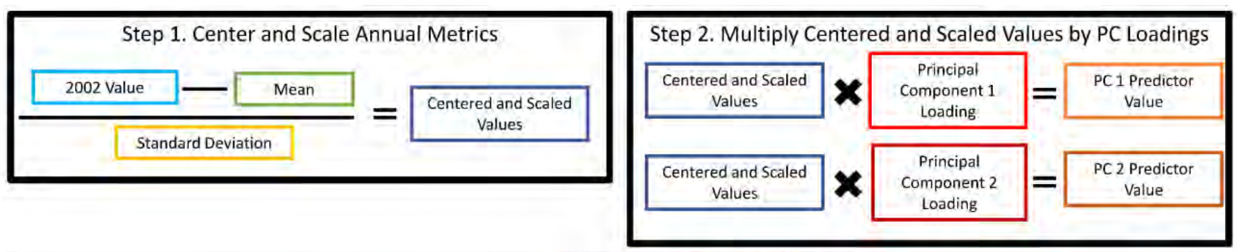
Supplemental Figure S2. Biplot of the first two principal components for the Middle Rio Grande annual hydrologic metrics. The first principal component generally separates wet years (those with large spring flows and less summer drying; positive values) from dry years (with small spring flows and more summer drying; negative values). The second principal component separates out those years with more summer drying than would be expected given large spring flows coupled with early spring peak flow timing (positive values) from those with less drying than would be expected given smaller spring flows coupled with late spring peak flows. Blue (orange) arrows indicate loadings for those predictor variables which respond positively (negatively) to wetter conditions.



Supplemental Figure S3. Predictor variable loadings for principal component 1 (a) and principal component 2 (b). Loadings represent the multipliers used in the linear combination of predictor variables (centered and scaled) used to calculate annual principal component scores. Blue (orange) bars indicate loadings for those predictor variables which respond positively (negatively) to wetter conditions.

Conducting a Principal Components Analysis

A principal components analysis requires predictor variables to be centered (i.e., subtract the mean from all values such that the mean of the centered data equals zero) and scaled (i.e., divide the centered data by the standard deviation of the data). Each predictor variable is centered and scaled individually. The matrix of centered and scaled predictor variables is then passed to a PCA function in a statistical computing environment (we used the function “prcomp” within the R Statistical Computing Environment; R Core Team 2018). The PCA function will calculate the principal component loadings (i.e., the linear contributions of each predictor variable to each principal component, representing eigenvectors which diagonalize the covariance matrix of centered and scaled predictor variables), the variance explained by each principal component, and the "scores" for each principal component for each year of data. Below, we provide an example of how these scores are calculated from the input data and the principal component loadings (Fig. S4).



Predictor Variable	2002 Values	Mean	SD	2002 Centered and Scaled, X	PC1 Loading, u_1	PC2 Loading, u_2	PC1 Predictor Value	PC2 Predictor Value
CentralSpringVol	82635.37	269081.82	193575.08	-0.96	0.36	0.16	-0.35	-0.15
CentralMin	115.00	242.08	135.86	-0.94	0.28	-0.26	-0.26	0.25
CentralSpringAvg	682.98	2223.97	1599.90	-0.96	0.36	0.16	-0.35	-0.15
DaysCentSpring1500	0.00	29.96	25.72	-1.16	0.35	0.16	-0.41	-0.19
DaysCentSpring2000	0.00	27.04	25.14	-1.08	0.36	0.17	-0.39	-0.19
DaysCentSpring2500	0.00	23.75	24.48	-0.97	0.36	0.17	-0.35	-0.17
DaysCentSpring3000	0.00	19.04	23.41	-0.81	0.35	0.17	-0.29	-0.14
SanAca_MileDayDry	872.00	509.81	495.47	0.73	-0.28	0.46	-0.21	0.33
Isleta_MileDayDry	201.00	112.65	176.45	0.50	-0.25	0.49	-0.12	0.25
FloodTiming	138.00	149.17	15.15	-0.74	0.06	-0.56	-0.04	0.41

Step 3. Add all PC Predictor Values for Annual PC Score

$$Annual\ PC\ Score = \sum \boxed{PC\ Predictor\ Values}$$

Annual PC1 Score	Annual PC2 Score
-2.78	0.25

Supplemental Figure S4. Conceptual description of how annual principal component scores are calculated. Metrics are color coded between the table and the step-by-step boxes.

Annual principal component scores are calculated by adding the linear combination of principal component loadings multiplied by the centered and scaled annual hydrologic conditions:

$$PC_{zy} = u_{z,1}X_{1,y} + u_{z,2}X_{2,y} + \cdots u_{z,n}X_{n,y} \tag{S.1}$$

where X_1, X_2, … X_n are the annual hydrologic metrics and $u_{z,n}$ are the principal component loadings for the z^{th} principal component and n^{th} predictor variable. In the case of our Middle Rio Grande hydrology PCA, the equation for principal component 1 is:

$$\begin{aligned} PC_{1,y} = 0.36 \times CentralSpringVol_y &+ 0.28 \times CentralMin_y \\ &+ 0.36 \times CentralSpringAvg_y + 0.35 \times DaysCentSpring1500_y \\ &+ 0.36 \times DaysCentSpring2000_y + 0.36 \times DaysCentSpring2500_y \\ &+ 0.35 \times DaysCentSpring3000_y - 0.28 \times SanAcaMileDayDry_y \\ &- 0.25 \times IsletaMileDayDry_y + 0.06 \times FloodTiming_y \end{aligned} \tag{S.2}$$

Supplemental Figure S1 provides a graphical walkthrough of the calculation of the annual PC1 and PC2 scores for the year 2002.

Simulating with Principal Component Metrics

In addition to generating scores for years which hydrologic observations are available, equation [S.1] can be used to generate principal components scores for hypothetical hydrologic conditions. With the exception of the mile-days dry in San Acacia and Isleta, all of the other predictor variables can be calculated off of a hydrograph, and the remaining drying metrics can be sampled with uncertainty given the other hydrologic conditions. Therefore, if a management agency generates a forecast hydrograph, with mean daily flows throughout the year, calculating PC1 and PC2 scores for the forecast year involves only calculating or estimating the predictor variables from that forecast hydrograph and using equation [S.1] to calculate an annual principal components score. This could similarly be done with a simulated hydrograph including alternative water management scenarios (e.g., storing water during the spring high flow period and releasing the stored water during the summer low flow period; Fig. S5). The resultant principal components scores (Fig. S6) can be used to predict RGSM distribution and density (Fig. S7), as well as the probability of achieving conservation targets (Fig. S8), with the model presented in this report. Ultimately, examining the predicted response of RGSM populations to alternative flow and management scenarios across multiple models can provide managers and stakeholders with a quantitative view of the trade-offs among the different options available to managing flows for RGSM in the MRG.

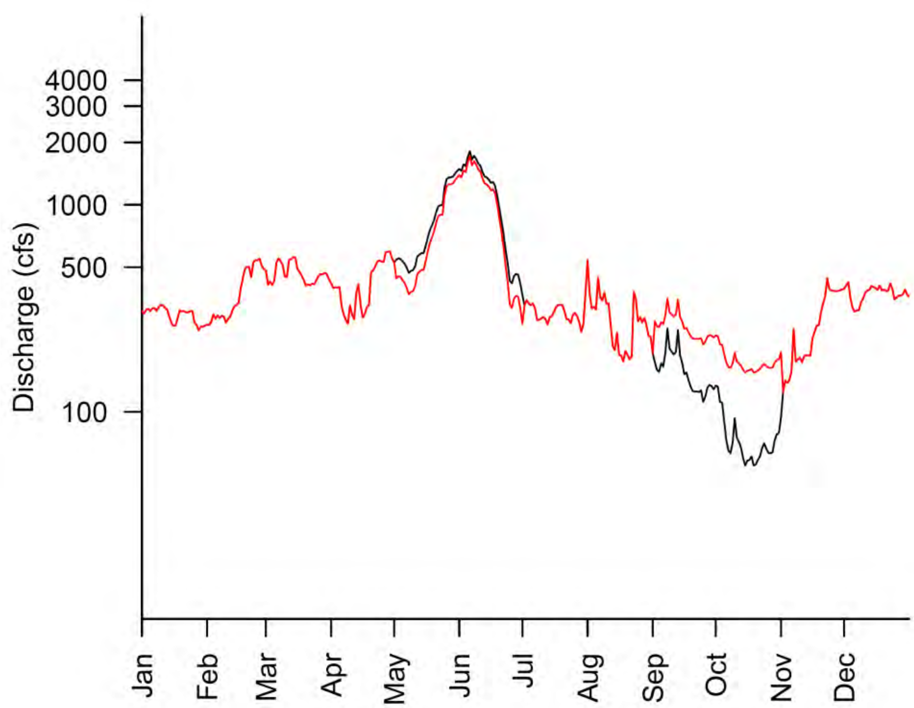


Figure S5. Examples of alternative water management strategies within a given water year. Here, the black line represents the "no action" hydrograph, while the redline represents the hydrograph when ~200 acre feet per day are stored during May and June, and subsequently released during September and October. Principal components scores can be calculated from these hydrographs to compare expected RGSM performance under the two strategies. Note the log-scaled y-axis.

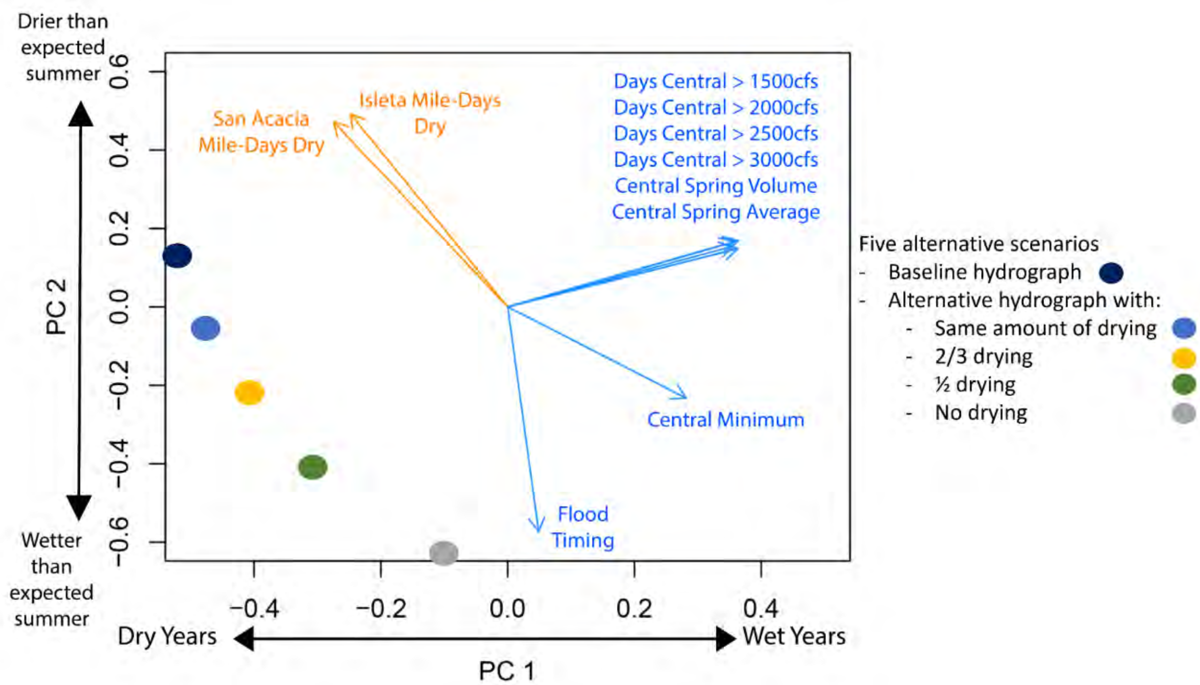


Figure S6. Example changes in PCA scores with alternative management strategies. Note that alternative scenario PCA scores are presented relative to each other and scaled to PCA loadings. Actual PCA scores have greater magnitude and have been compressed on x-axis to demonstrate relative changes (e.g., baseline PC1 = -1.18).

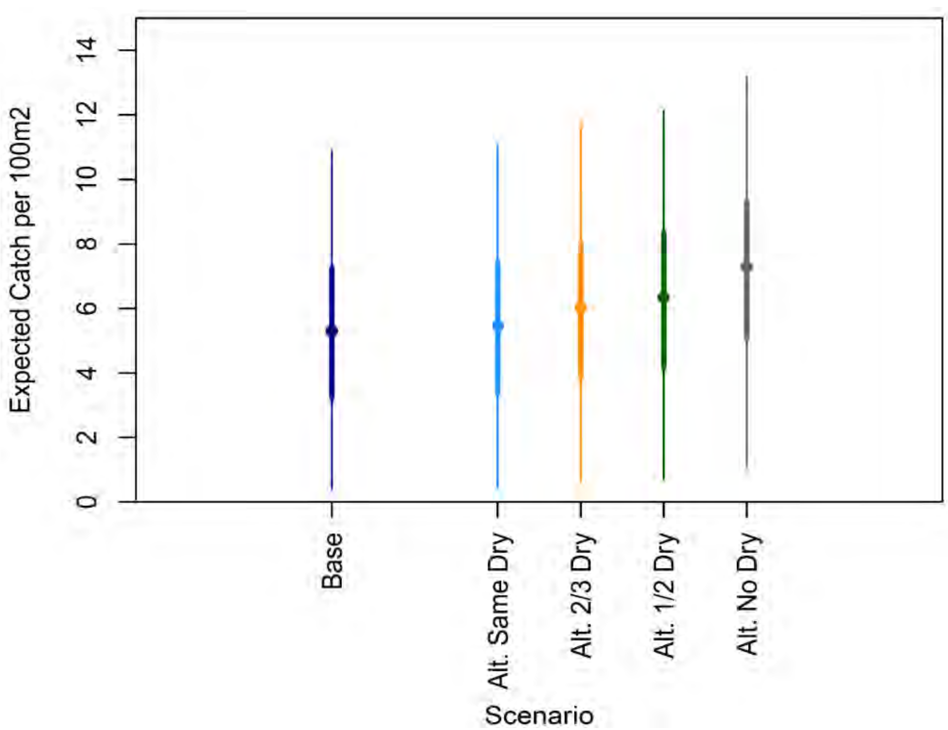


Figure S7. Expected catch of Rio Grande silvery minnow per 100m^2 sampled under alternative flow management scenarios from Fig. S5. Thin and thick lines represent the 95% and 50% prediction intervals, respectively. Points indicate the median predicted values.

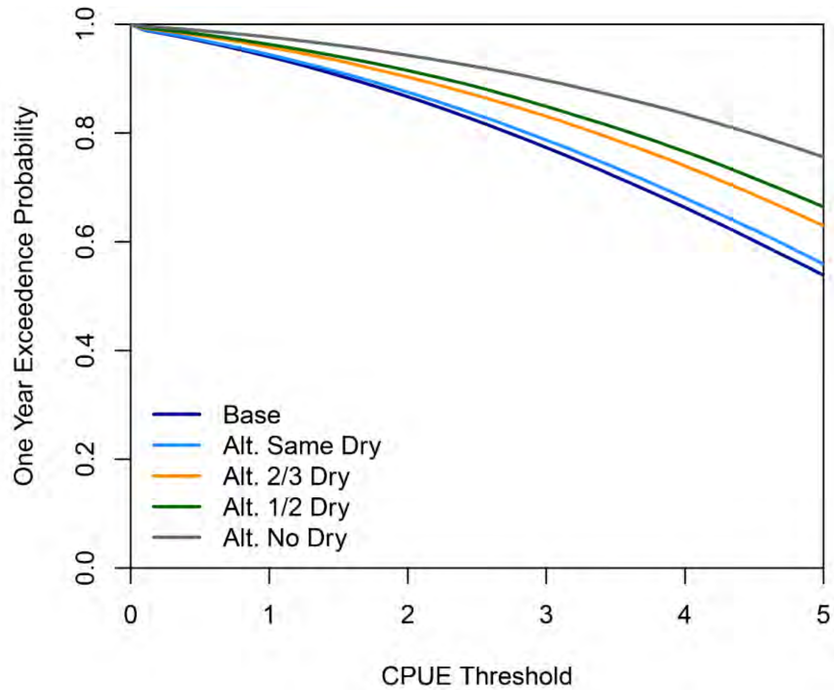


Figure S8. Simulated probabilities of meeting different target CPUE thresholds for Rio Grande silvery minnow in the Middle Rio Grande under alternative flow management strategies. Exceedance probabilities are reported for the full Middle Rio Grande only here, not for individual reaches.

Appendix References

Gotelli, N.J. and Ellison, A.M., 2004. *Primer of ecological statistics*. Sinauer Associates Publishers.

Pearson, K., 1901. Principal components analysis. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *6*(2), p.559.

R Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Hydrologic controls on abundance and distribution of the endangered Rio Grande silvery minnow in the Middle Rio Grande

Appendix B: Alternative models of the effect of annual hydrologic conditions on RGSM distribution and density

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Alternative Model Structures

In addition to the base model presented in the main document, we examined three alternative model structures. The alternative model structures include (1) the base model without the hurdle component, (2) the base model without the latent trend, and (3) the base model estimating CPUE of age-0 RGSM only with an additional effect of the previous year's RGSM CPUE on the probability of presence at a sampling site. Additionally, we examined a model with the same underlying structure as the base model, but with both the hydrologic and flow timing indices (i.e., principal components 1 and 2; *Appendix A*). In this appendix, we present the details of teach alternative model structure, their fits to the observed data, as well as the results of simulation experiments (described in the methods of the main document) predicting RGSM response to different hydrologic conditions. Despite the different model structures, each model predicted generally similar RGSM responses to changing hydrologic conditions. As such, incorporating all of these models as alternative "states of nature" in a decision support framework would likely provide very similar strategy recommendations, though some subtle and important differences may arise, warranting the inclusion of multiple models.

Catch-only Model (No Hurdle Component)

The alternative model structure without the hurdle component alters the base model by excluding equations [1a] and [1b], only using the Gompertz function [2a] and gamma likelihood [2b] and [2c]. However, as the gamma distribution is not defined at 0, a small constant value (0.01) was added to all site-specific CPUE observations.

The catch-only model also fit the observed data fairly well, though more of the observed CPUE values fell outside of the 95% credible intervals (3.9%; Fig. S2.1) than did for the base model. The model predicts less variation in predicted CPUE among years with relatively high densities than the base model as well.

Parameter estimates for the catch-only model were more certain than for the base model (Fig. S2.2). As with the base model, expected CPUE increased in years with greater hydrologic indices (i.e., wetter years; Fig. S2.2ab). Unlike in the base model, estimated "carrying capacity" for each reach was well constrained and predicted to occur at relatively low hydrologic indices (Fig. S2.2b). Similar to the base model, San Acacia was predicted to have the highest "carrying capacity", with Isleta expected to have a greater "carrying capacity" than Angostura (Fig. S2.2cd).

Simulation experiments predict all three reaches, as well as the MRG average, CPUE would meet recovery targets under below average hydrologic conditions from the period of record (Fig. S2.3a). This results from each reach being predicted to achieve its maximum expected catch under relatively modest flow conditions, with no benefit to increasing flows further (Fig. S2.3bcd). The range of predicted site-specific densities for each reach is much narrower than those predicted for the base model. Estimated probabilities of achieving lower CPUE targets for five consecutive years are lower and more similar among reaches than for the base model, but are greater than the base model for higher CPUE targets (Fig. S2.3e).

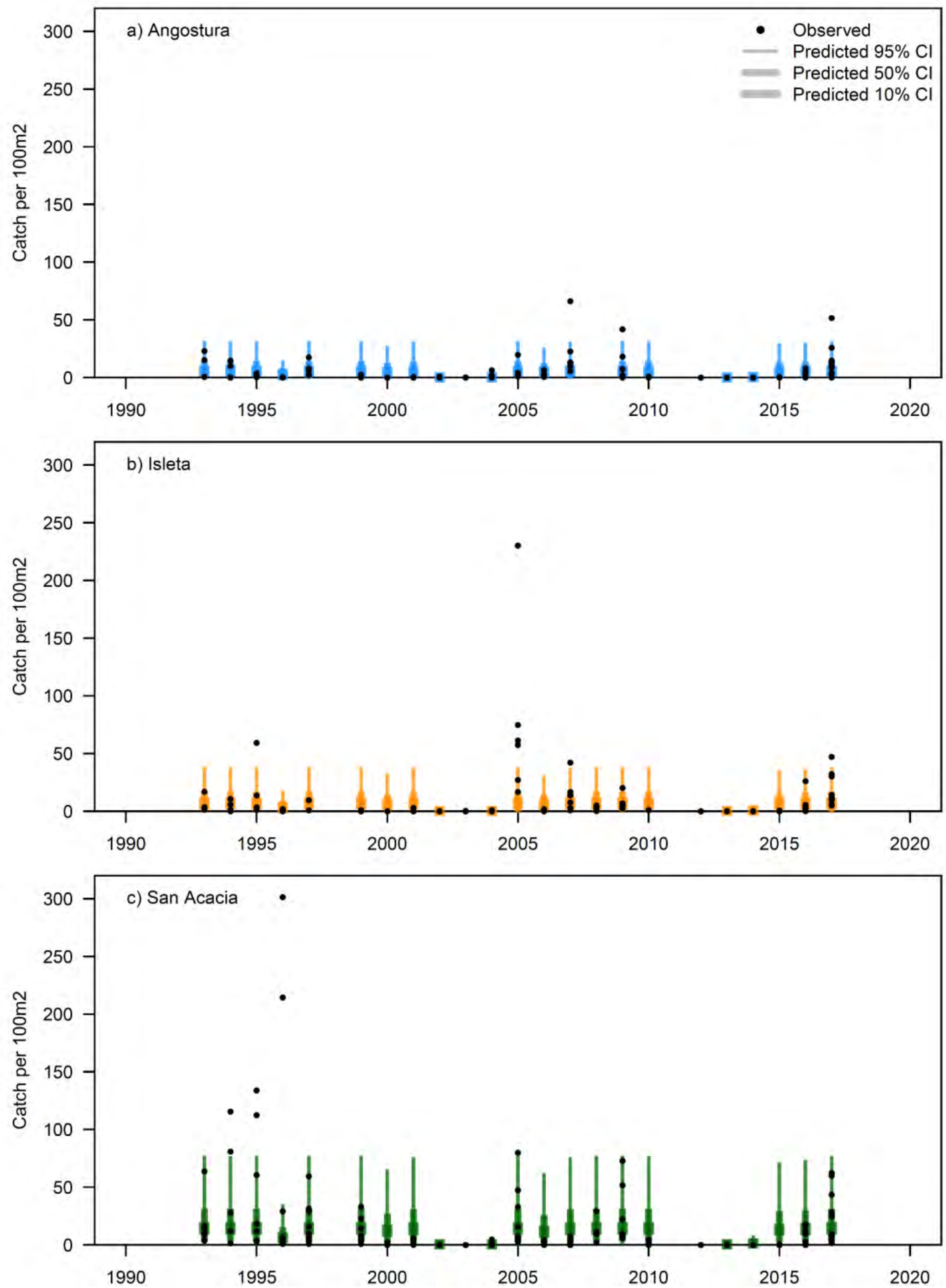

Figure S2.1. Predicted (boxplots) and observed (points) catch per 100m^2 for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the no hurdle component model. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

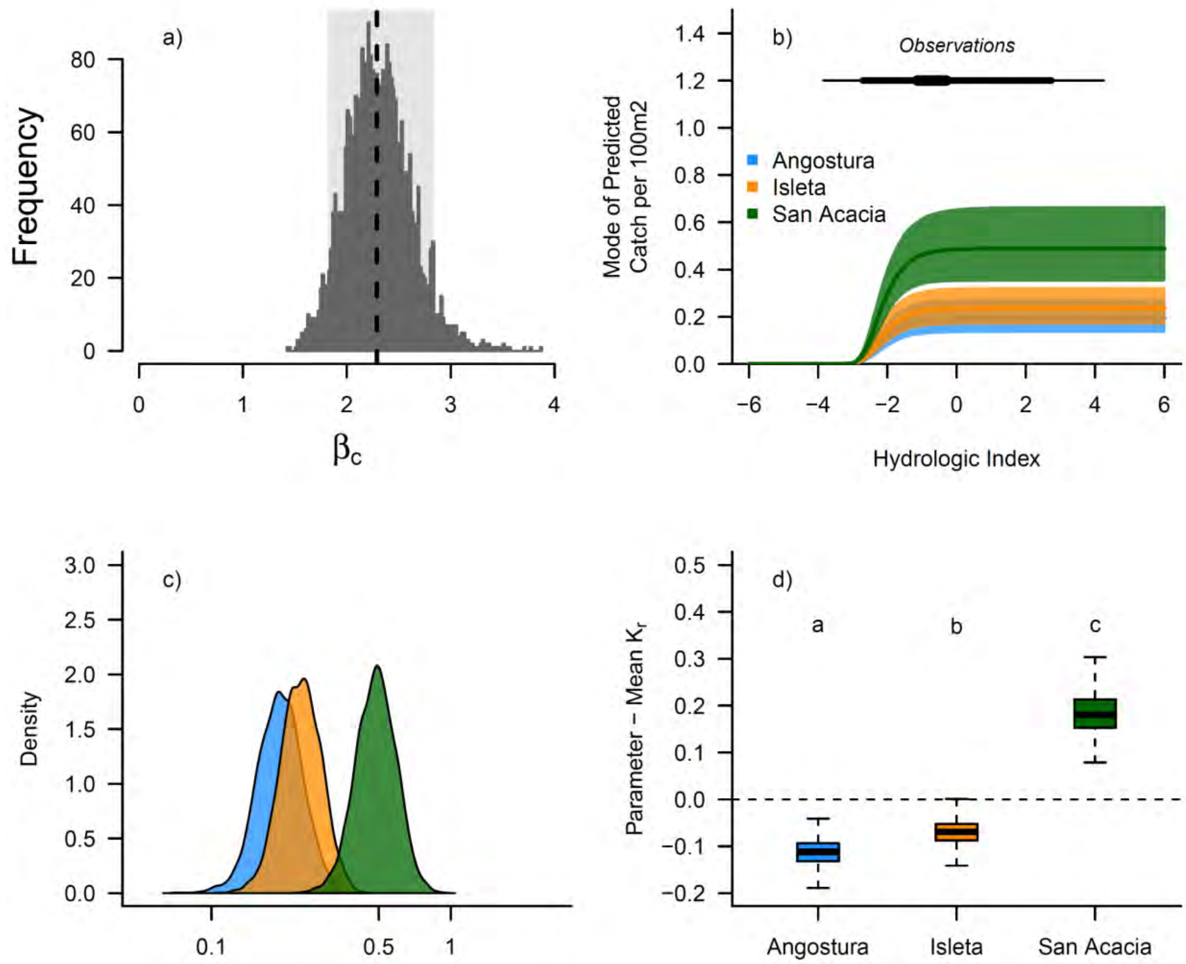

Figure S2.2. Posterior distribution of the effect of annual hydrologic index on expected catch (a), the predicted mode of reach-specific RGSM catch per 100m2 when they are present (b) across a range of annual hydrologic indices (larger values indicate higher spring flows and less summer drying), the posterior distributions of MCMC samples for reach specific carrying capacity (c), and the posterior sample differences between reach specific carrying capacity estimates and the global mean value (d) for the no hurdle component model. The horizontal boxplot above (b) indicates the 95%, 50% and 10% ranges of observed hydrologic indices. Letters above boxes in (d) indicate significant differences

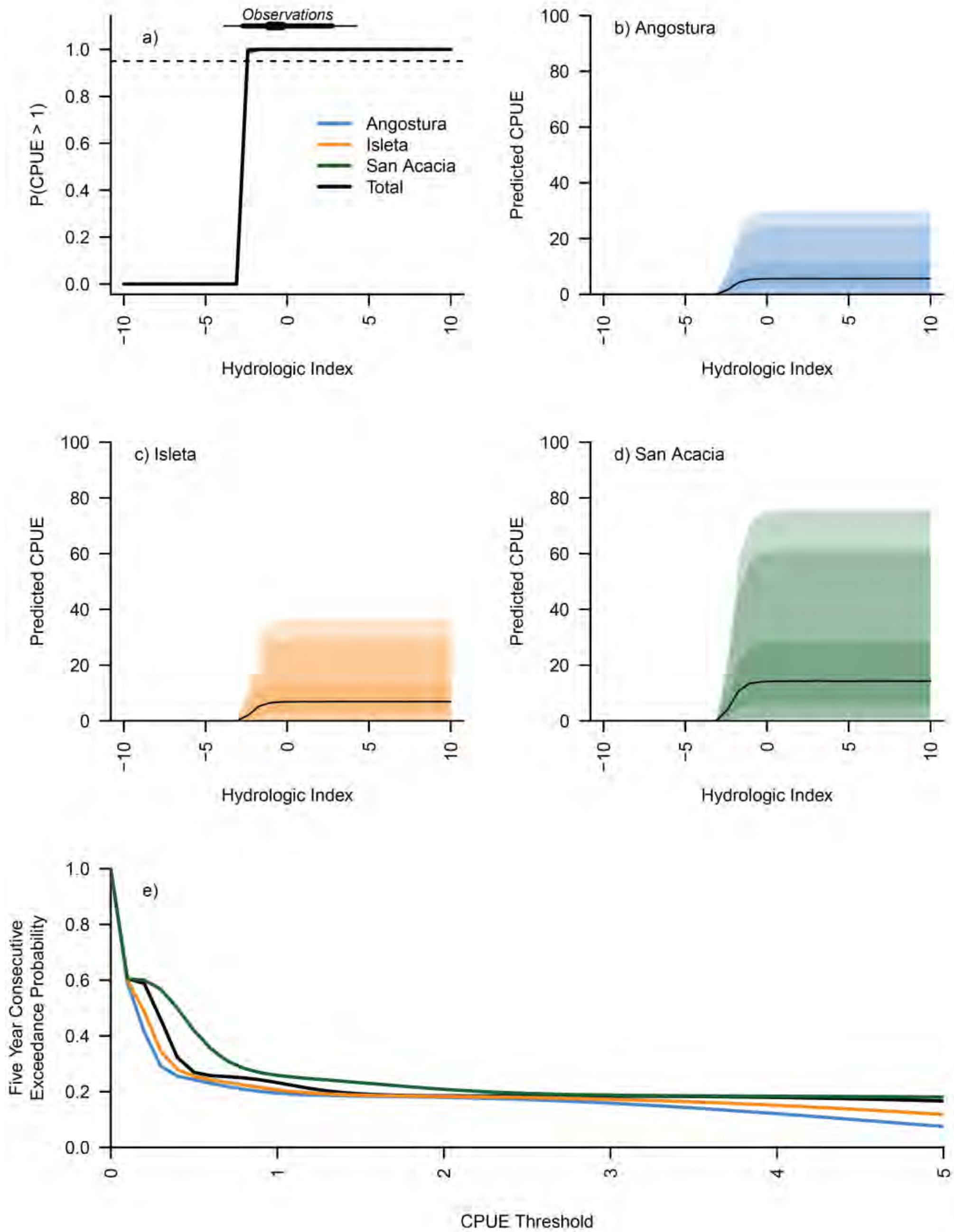

Figure S2.3. Probabilities of Rio Grande silvery minnow catch per 100m2 in each reach (colored lines) and across the whole MRG (black line) being greater than 1 across a range of annual hydrologic indices levels (a), and the predicted CPUE of Rio Grande silvery minnows at different hydrologic indices in the Angostura (b), Isleta (c) and San Acacia (d) reaches, and simulated probability of RGSM catch per 100m^2 exceeding different target thresholds for five consecutive years under the range of hydrologic conditions in the dataset for the no hurdle component model. The horizontal boxplot above (a) indicates the 95%, 50% and 10% ranges of observed hydrologic indices and the horizontal dashed line indicates a 95% threshold. The polygons in (b-d) indicate the 95%, 90% and 50% simulation intervals and the line indicates the median predicted CPUE. Vertical dashed lines indicate different management targets.

No Latent Trend Model

The alternative model structure without latent trend alters the base model by modifying equation [1a] to be:

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta_p \varphi_{ry}} \qquad (1a)$$

$$\alpha_r \sim N(\mu_\alpha, \sigma_\alpha^2)$$

all other model components are the same as in the base model.

The no latent trend model also fit the observed data well, capturing the same number of observed CPUE values within the 95% credible intervals (97.6%; Fig. S2.4) as the base model. The predicted distributions for annual site-specific CPUE are very similar to those from the base model. The no latent trend model predicted annual probabilities of presence with narrower credible intervals than did the base model, and the 95% credible intervals were less likely to include the observed values (Fig. S2.5).

Parameter estimates for the no latent trend model were similar for the catch component, but more certain for the hurdle component than for the base model (Fig. S2.6abcd). As with the base model, expected CPUE and expected probability of presence both increased in years with greater hydrologic indices (i.e., wetter years; Fig. S2.6ab). Estimated "carrying capacity" for each reach had similar levels of uncertainty to the base model (Fig. S2.6c). Estimates of the baseline probability of presence (in logit space) were more constrained in the no latent trend model than in the base model (Fig. S2.6d). Similar to the base model, San Acacia was predicted to have the highest "carrying capacity", with Isleta expected to have a similar value as Angostura (Fig. S2.6e). Additionally, San Acacia was estimated to have he greatest baseline probability of presence, while Isleta had greater probability of presence than Angostura (Fig. S2.6f)

Simulation experiments predict both San Acacia and Isleta, as well as the MRG average, CPUE would meet recovery targets under slightly below median hydrologic conditions from the period of record (Fig. S2.7a). Angostura is predicted to achieve the recovery threshold with 95% confidence only under slightly above median hydrologic conditions. The distribution of predicted CPUE values for each reach increases across the range of hydrologic conditions examined (Fig. S2.7bcd). The range of predicted site-specific densities for each reach is very similar to those predicted for the base model. Estimated probabilities of achieving CPUE targets for five consecutive years is also very similar to the base model (Fig. S2.7e).

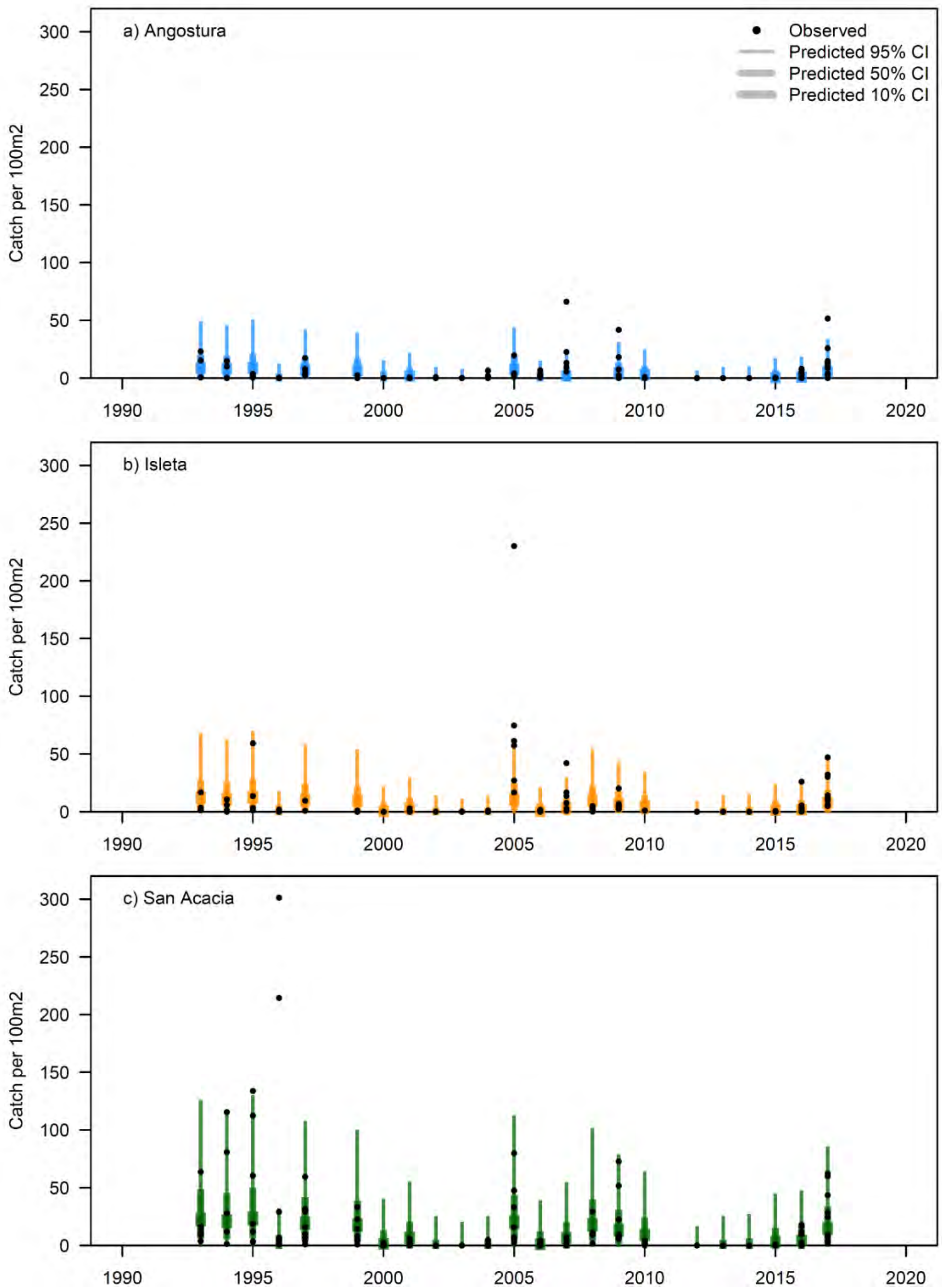

Figure S2.4. Predicted (boxplots) and observed (points) catch per $100m^2$ for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the no latent trend model. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

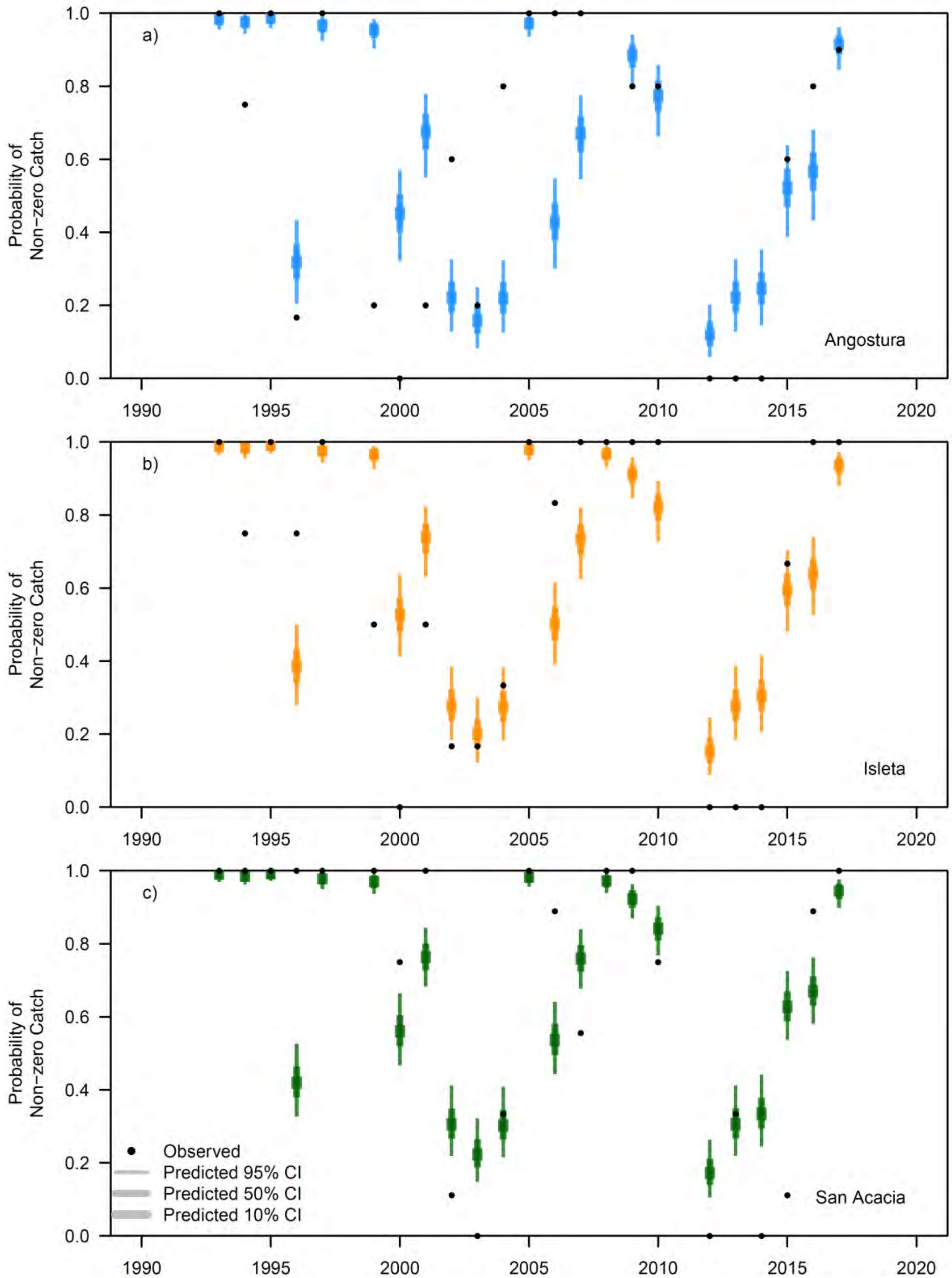

Figure S2.5. Predicted (boxplots) and observed (points) annual encounter probabilities for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the no latent trend model. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

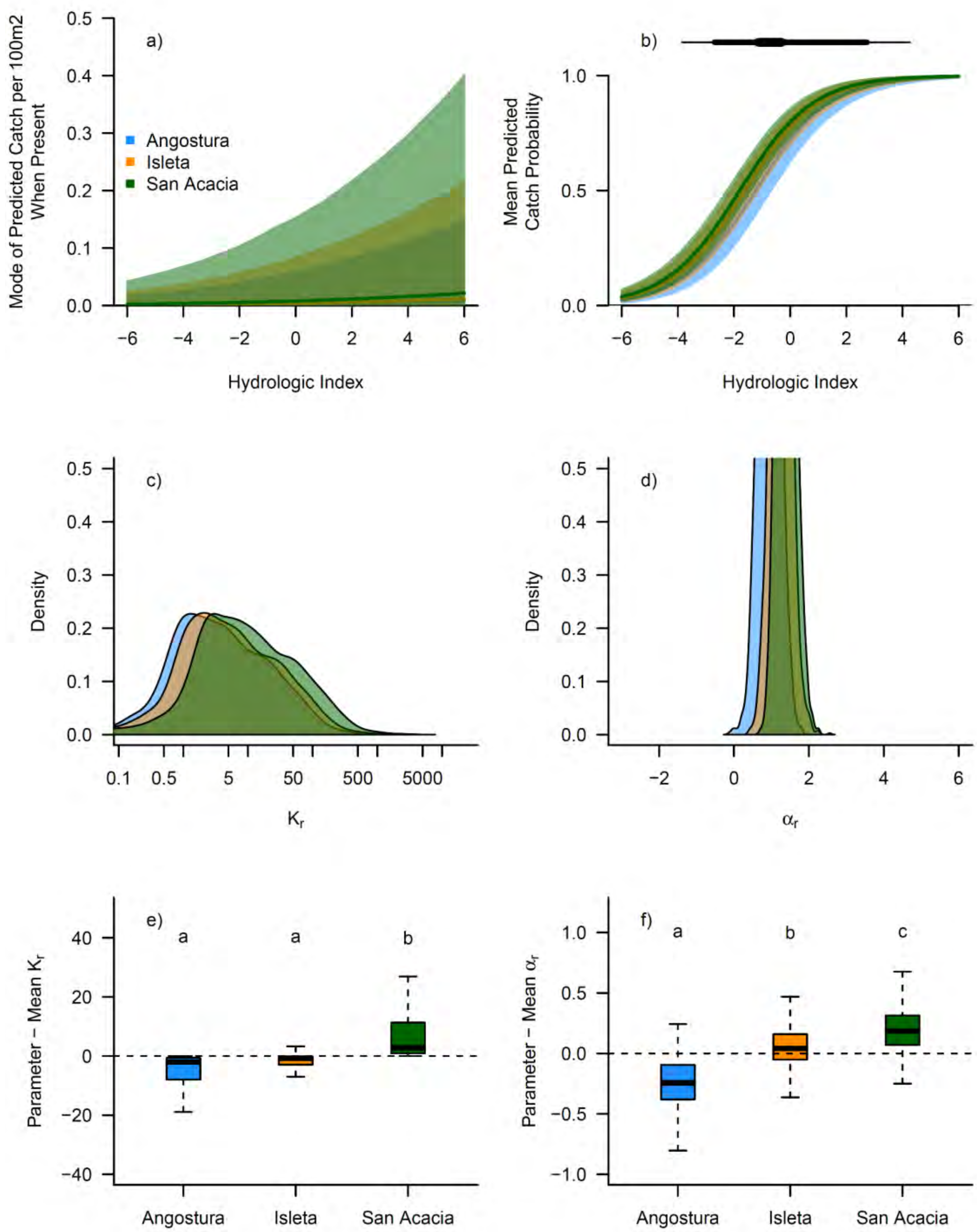

Figure S2.6. Predicted mode of reach-specific RGSM catch per 100m2 when they are present (a) and reach-specific probability of encountering RGSM (b) across a range of annual hydrologic indices (larger values indicate higher spring flows and less summer drying), and the posterior distributions of MCMC samples for reach specific carrying capacity (c) and baseline encounter probability (d) parameters for the no latent trend model. Posterior distribution of reach specific differences in K (e) and α (d) from the global mean value. The horizontal boxplot above (a) and (b) indicates the 95%, 50% and 10% ranges of observed hydrologic indices. Letters above boxes in (e) and (f) indicate significant differences.

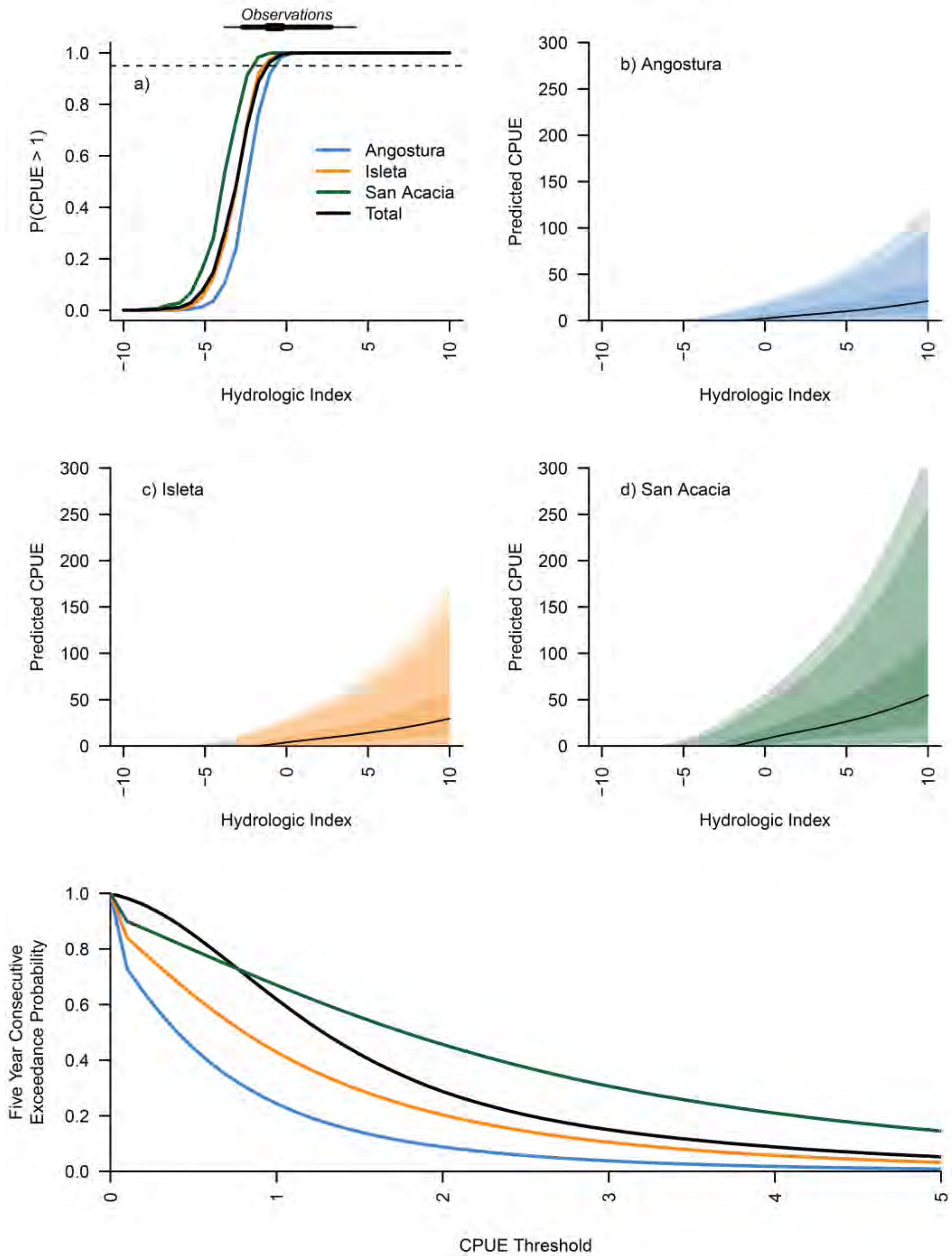

Figure S2.7. Probabilities of Rio Grande silvery minnow catch per 100m2 in each reach (colored lines) and across the whole MRG (black line) being greater than 1 across a range of annual hydrologic indices levels (a), and the predicted CPUE of Rio Grande silvery minnows at different hydrologic indices in the Angostura (b), Isleta (c) and San Acacia (d) reaches, and simulated probability of RGSM catch per 100m^2 exceeding different target thresholds for five consecutive years under the range of hydrologic conditions in the dataset for the no latent trend model. The horizontal boxplot above (a) indicates the 95%, 50% and 10% ranges of observed hydrologic indices and the horizontal dashed line indicates a 95% threshold. The polygons in (b-d) indicate the 95%, 90% and 50% simulation intervals and the line indicates the median predicted CPUE. Vertical dashed lines indicate different management targets.

Age-0 Model

The alternative model structure estimating age-0 RGSM abundance alters the base model by modifying equation [1a] to be:

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta_p \varphi_{ry}} + \frac{\beta_L}{L + .01} \quad (1a)$$

$$\alpha_r \sim N(\mu_\alpha, \sigma_\alpha^2)$$

where L is the mean CPUE for all RGSM in the October samples from the previous year, and β_L is an estimated parameter. Additionally, C_{ry} no longer represents the site-specific CPUE of all RGSM, but only the age-0 RGSM. All other model components are the same as in the base model.

The age-0 model also fit the observed data well, capturing the nearly same number of observed CPUE values within the 95% credible intervals (97.3%; Fig. S2.8) as the base model. The age-0 trend model predicted annual probabilities of presence with narrower credible intervals than did the base model, and the 95% credible intervals were less likely to include the observed values (Fig. S2.9).

As with the base model, expected CPUE and expected probability of presence for the age-0 model both increased in years with greater hydrologic indices (i.e., wetter years; Fig. S2.10ab). Estimated “carrying capacity” for each reach had similar levels of uncertainty to the base model (Fig. S2.10c). Estimates of the baseline probability of presence (in logit space) were more constrained than in the base model (Fig. S2.10d). Similar to the base model, San Acacia was predicted to have the highest “carrying capacity”, with Isleta expected to have greater “carrying capacity” than Angostura (Fig. S2.10e). Additionally, San Acacia was estimated to have the greatest baseline probability of presence, while Isleta had greater probability of presence than Angostura (Fig. S2.10f)

Simulation experiments from the age-0 model predict both San Acacia and Isleta, as well as the MRG average, CPUE would meet recovery targets under near median hydrologic conditions from the period of record (Fig. S2.11a). Angostura is predicted to achieve the recovery threshold with 95% confidence under slightly above average hydrologic conditions. The distribution of predicted CPUE values for each reach increases across the range of hydrologic conditions examined, though the rate of increase slows once annual hydrologic indices reach values greater than 1 (Fig. S2.11bcd). However, large uncertainties in the carrying capacity parameter estimates drive increasing variation in prediction intervals under higher hydrologic indices. The range of predicted site-specific densities for each reach is lower than those predicted for the base model. Estimated probabilities of achieving CPUE targets for five consecutive years is very similar to the base model, when assuming the previous year had average densities (Fig. S2.11e). However, when the previous year’s RGSM density was very low (i.e., zero), the probability of exceeding different target CPUE thresholds is reduced (Fig. 2.12). The effect of the previous year's CPUE rapidly diminishes as previous CPUE rises above zero.

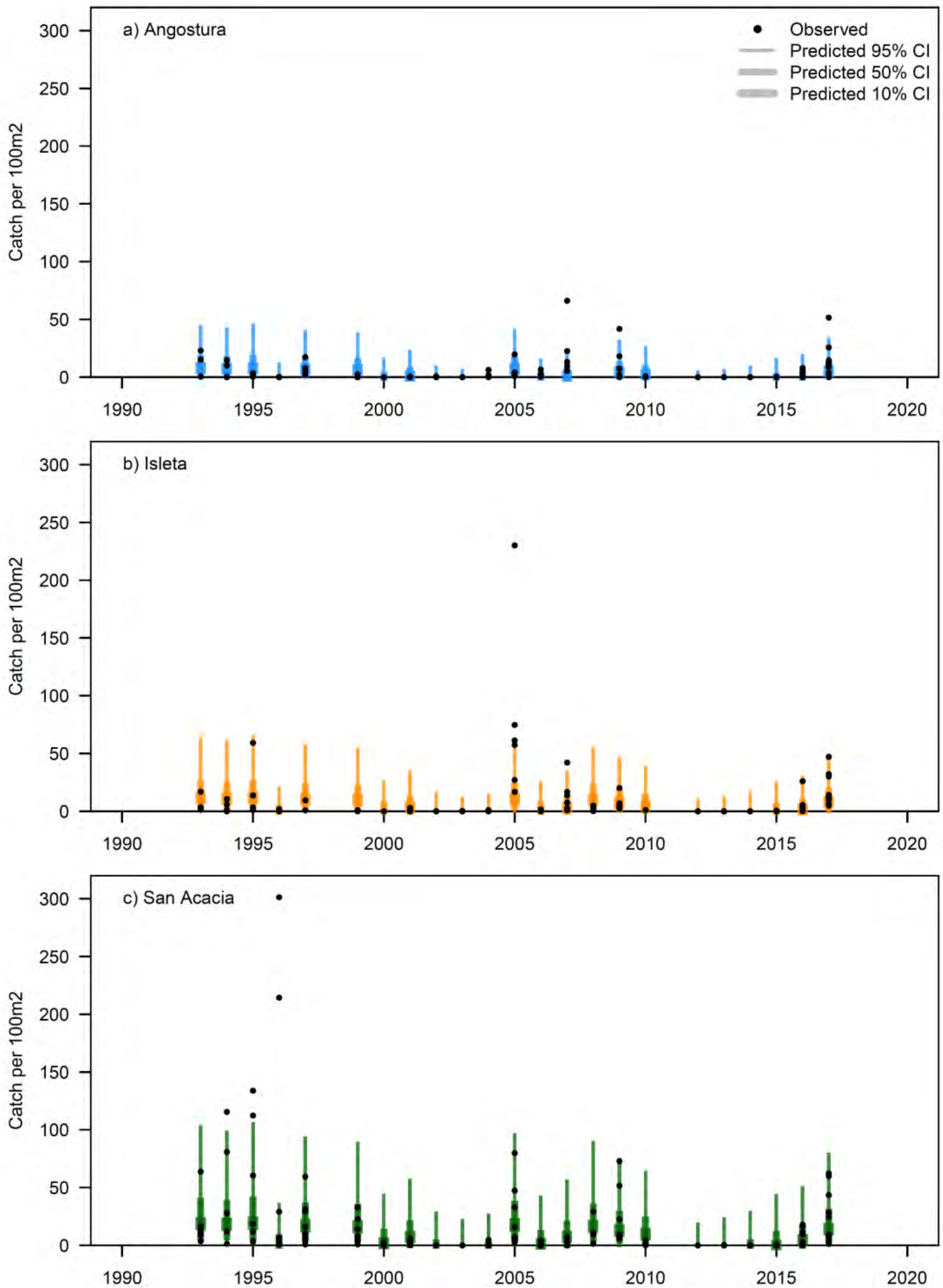

Figure S2.8. Predicted (boxplots) and observed (points) catch per 100m^2 for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the age-0 model. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

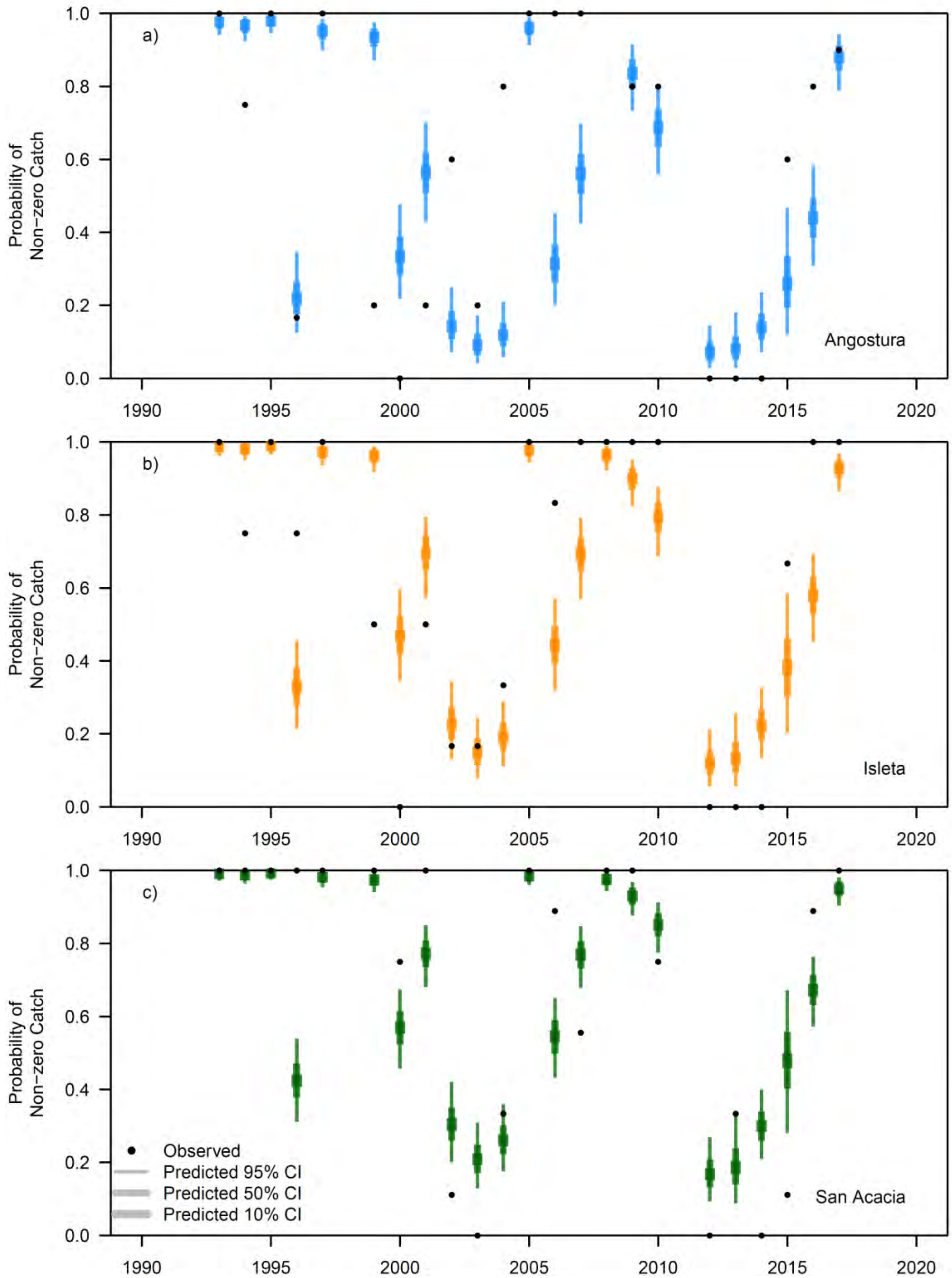

Figure S2.9. Predicted (boxplots) and observed (points) annual encounter probabilities for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the age-0 model. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

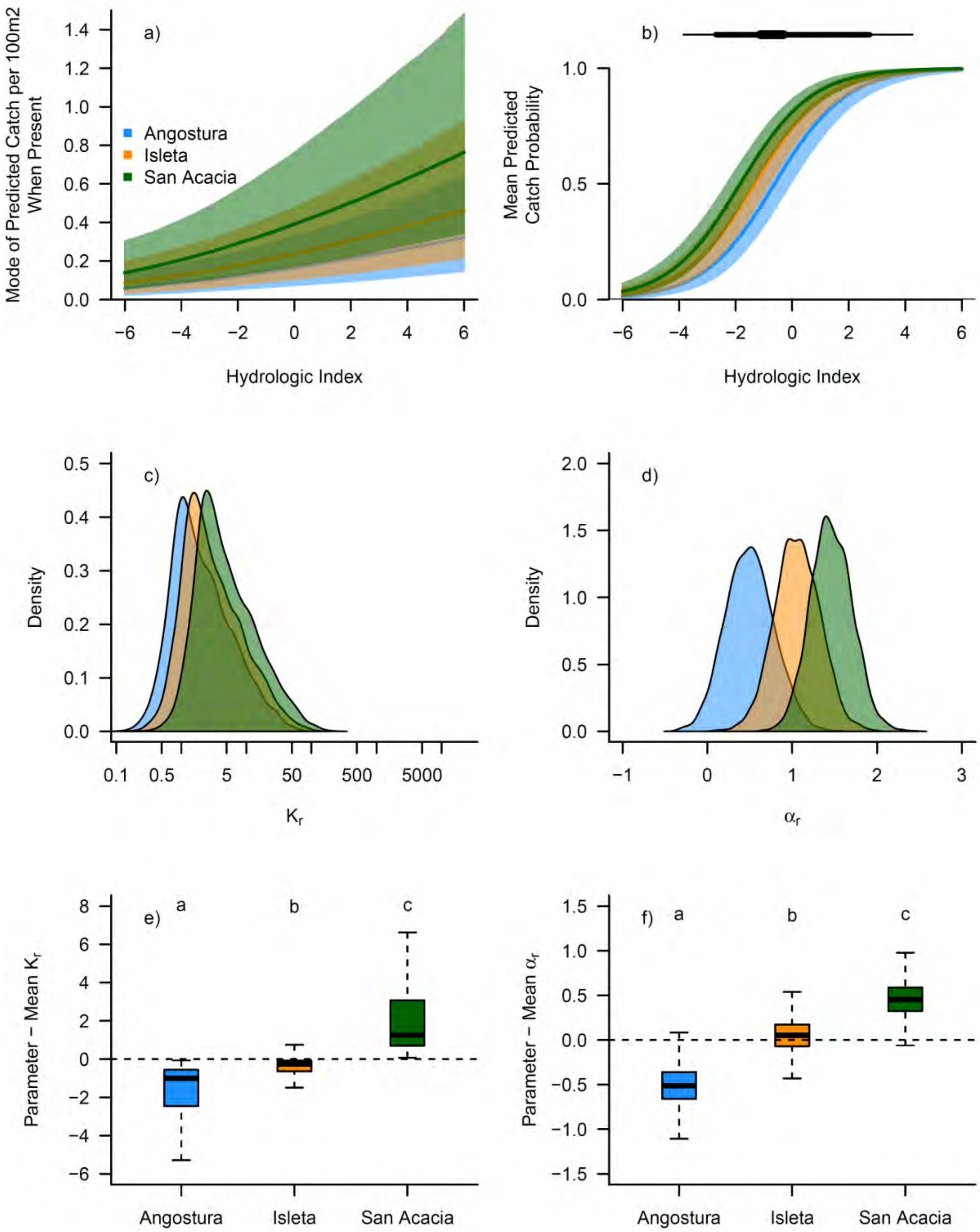

Figure S2.10. Predicted mode of reach-specific RGSM catch per 100m2 when they are present (a) and reach-specific probability of encountering RGSM (b) across a range of annual hydrologic indices (larger values indicate higher spring flows and less summer drying), and the posterior distributions of MCMC samples for reach specific carrying capacity (c) and baseline encounter probability (d) parameters for the age-0 model. Posterior distribution of reach specific differences in K (e) and α (d) from the global mean value. The horizontal boxplot above (a) and (b) indicates the 95%, 50% and 10% ranges of observed hydrologic indices. Letters above boxes in (e) and (f) indicate significant differences.

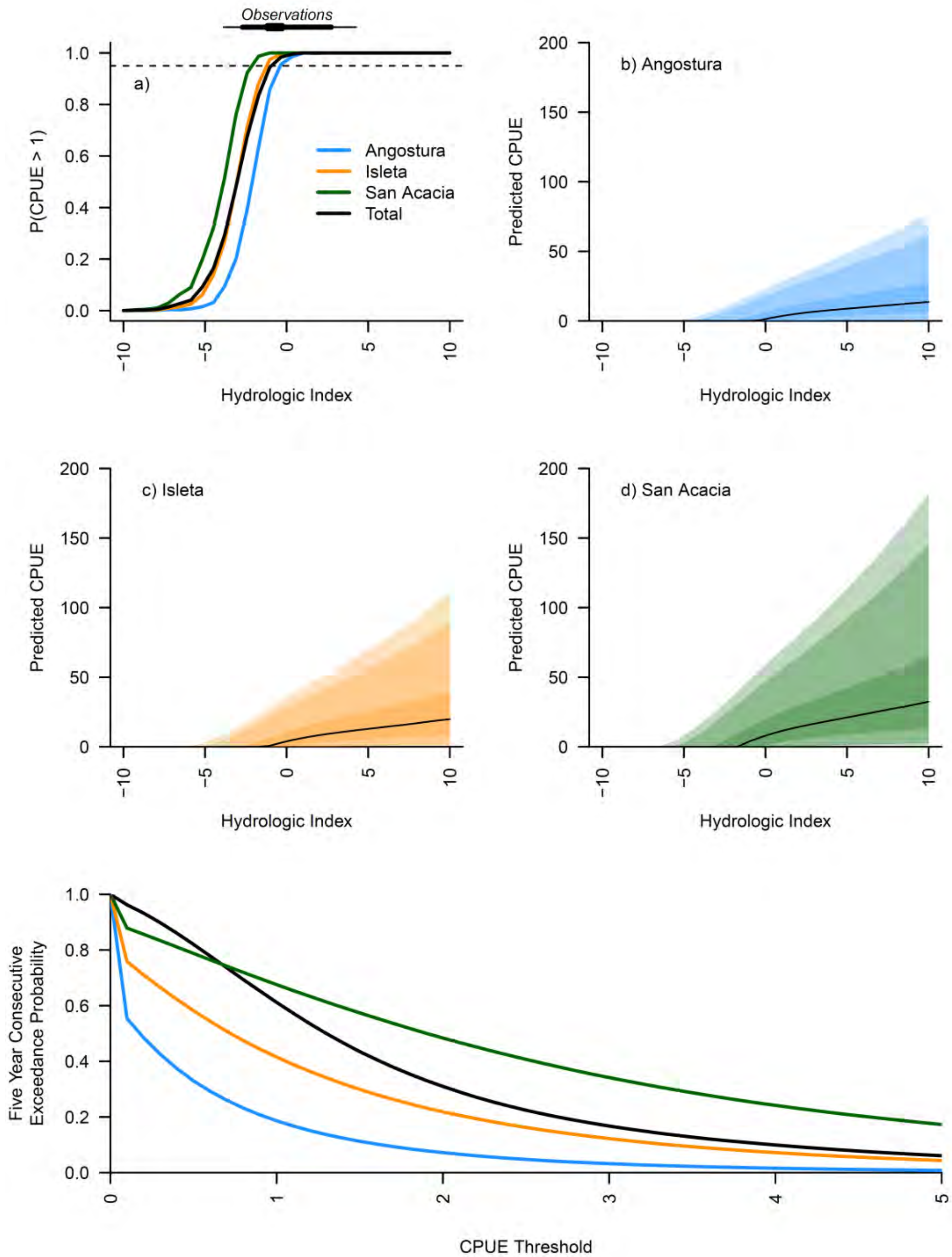

Figure S2.11. Probabilities of Rio Grande silvery minnow catch per 100m2 in each reach (colored lines) and across the whole MRG (black line) being greater than 5 across a range of annual hydrologic index levels (a), and the predicted CPUE of Rio Grande silvery minnows at different hydrologic indices in the Angostura (b), Isleta (c) and San Acacia (d) reaches, and simulated probability of RGSM catch per 100m^2 exceeding different target thresholds for three consecutive years under the range of hydrologic conditions (e) in the dataset for the age-0 model. The horizontal boxplot above (a) indicates the 95%, 50% and 10% ranges of observed hydrologic indices and the horizontal dashed line indicates a 95% threshold. The polygons in (b-d) indicate the 95%, 90% and 50% simulation intervals and the line indicates the median predicted CPUE. Vertical dashed lines indicate different management targets.

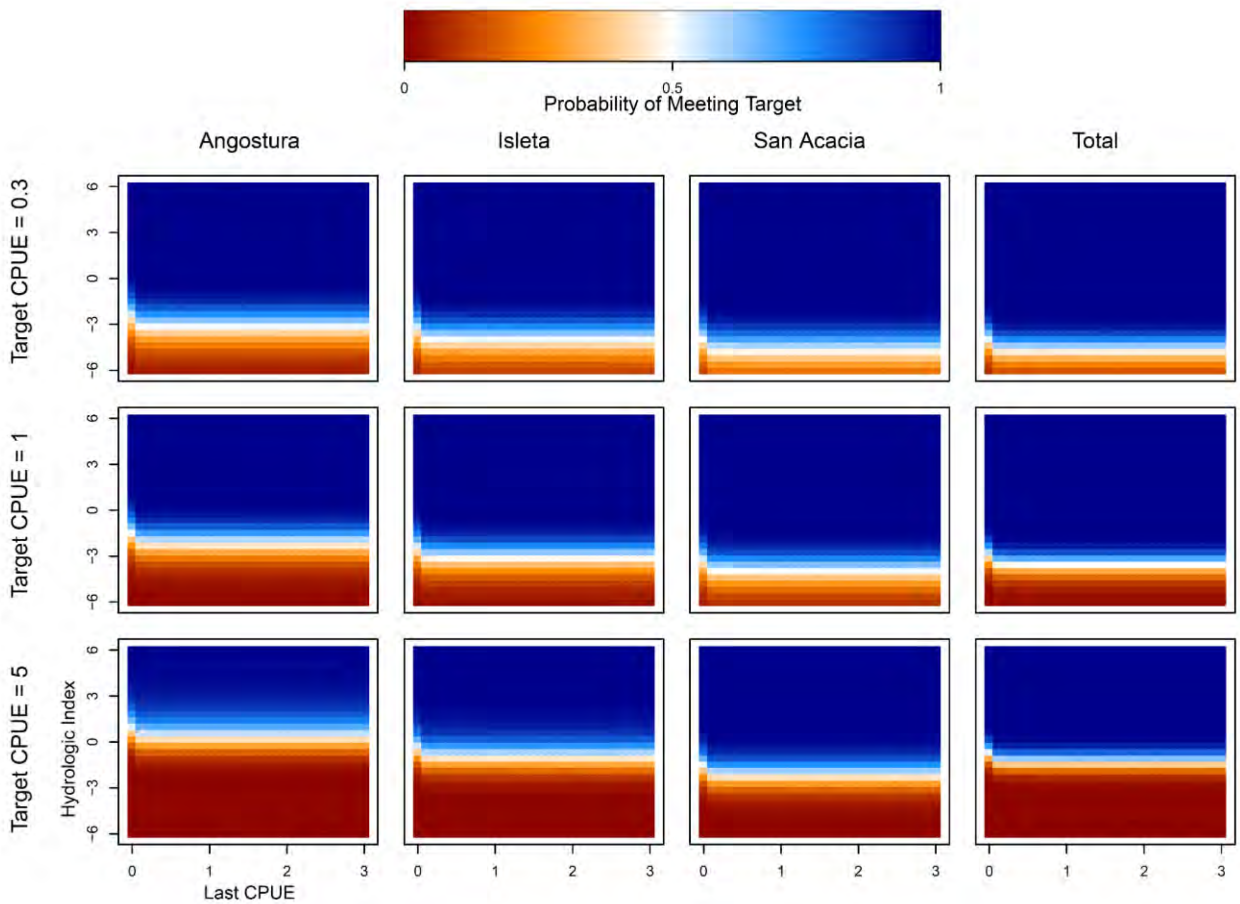

Figure S2.12. Filled contour plots of the probability of exceeding different target CPUE thresholds under different annual hydrologic indices (y-axes) and different densities of RGSM in the previous year (x-axes). Predictions for the different reaches are organized by column: Angostura (far left), Isleta (center left), San Acacia (center right), and total MRG (far right). Predictions for different CPUE targets are organized by row: target CPUE of 0.3 RGSM per 100m^2 (top), target CPUE of 1 RGSM per 100m^2 (center), and target CPUE of 5 RGSM per 100m^2 (bottom).

Base Model structure incorporating both the Hydrologic and Flow Timing Indices

The base model incorporating both the annual hydrologic and flow timing indices fit predicted very similar CPUE dynamics as the base model incorporating only the hydrologic index (Figs. S2.13 and S2.14), and the predicted site-specific CPUE distributions captured 97.3% of the observed CPUE values. The model estimated a positive effect of the annual hydrologic index and a negative effect of the annual flow timing index on both presence and density of RGSM (i.e., later spring high flow peaks and less summer drying result in increased expected RGSM CPUE; Fig. S2.15abcd). As in the base model, the latent trend demonstrated a roughly decadal periodic pattern (Fig. S2.15e).

Estimated reach-specific “carrying capacities” were smaller than those estimated in the base model (Fig. S2.16a), though estimated baseline probabilities of presence (in logit space) were similar to the base model (Fig. S2.16b). Additionally, San Acacia had a significantly greater “carrying capacity” and baseline probability of presence than the other two reaches, and Isleta had a significantly greater “carrying capacity” and baseline probability of presence than Angostura (Fig. S2.16cd).

The estimated probability of exceeding a range of CPUE targets across five consecutive years under hydrologic conditions drawn from the period of record was slightly lower than estimated for the base model, though the trends among reaches were very similar (Fig. S2.16e). The annual hydrologic index had a greater impact on the probability of meeting CPUE targets within a single year than did the flow timing index (Fig. S2.17), though both drivers caused substantial changes in exceedance probability. However, while we explored the same range of values across both indices in our simulations, the range of observed values on the flow timing index were narrower than for the hydrologic index and both were narrower than the range simulated.

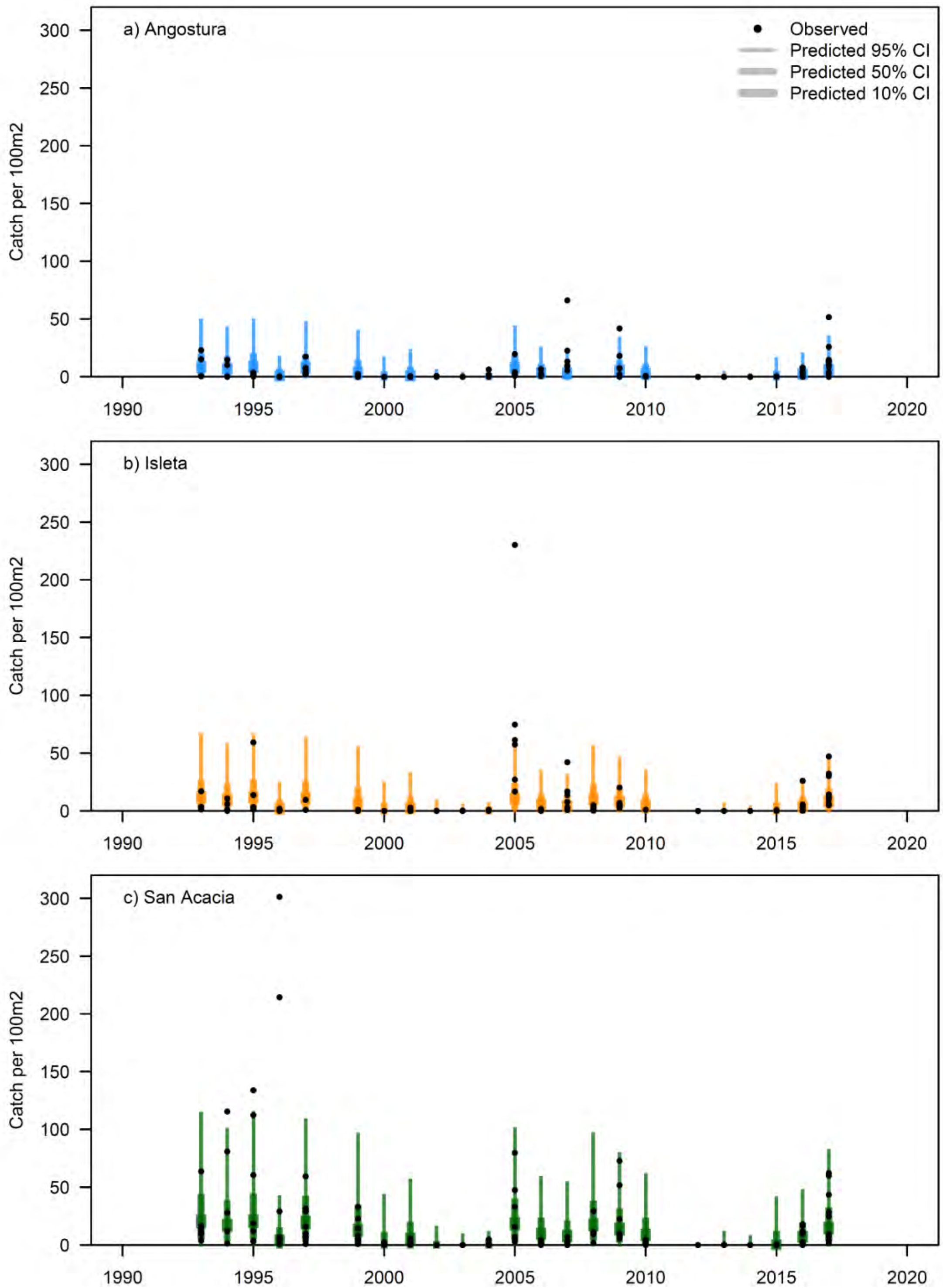

Figure S2.13. Predicted (boxplots) and observed (points) catch per 100m^2 for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the base model incorporating both the annual hydrologic and flow timing indices. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

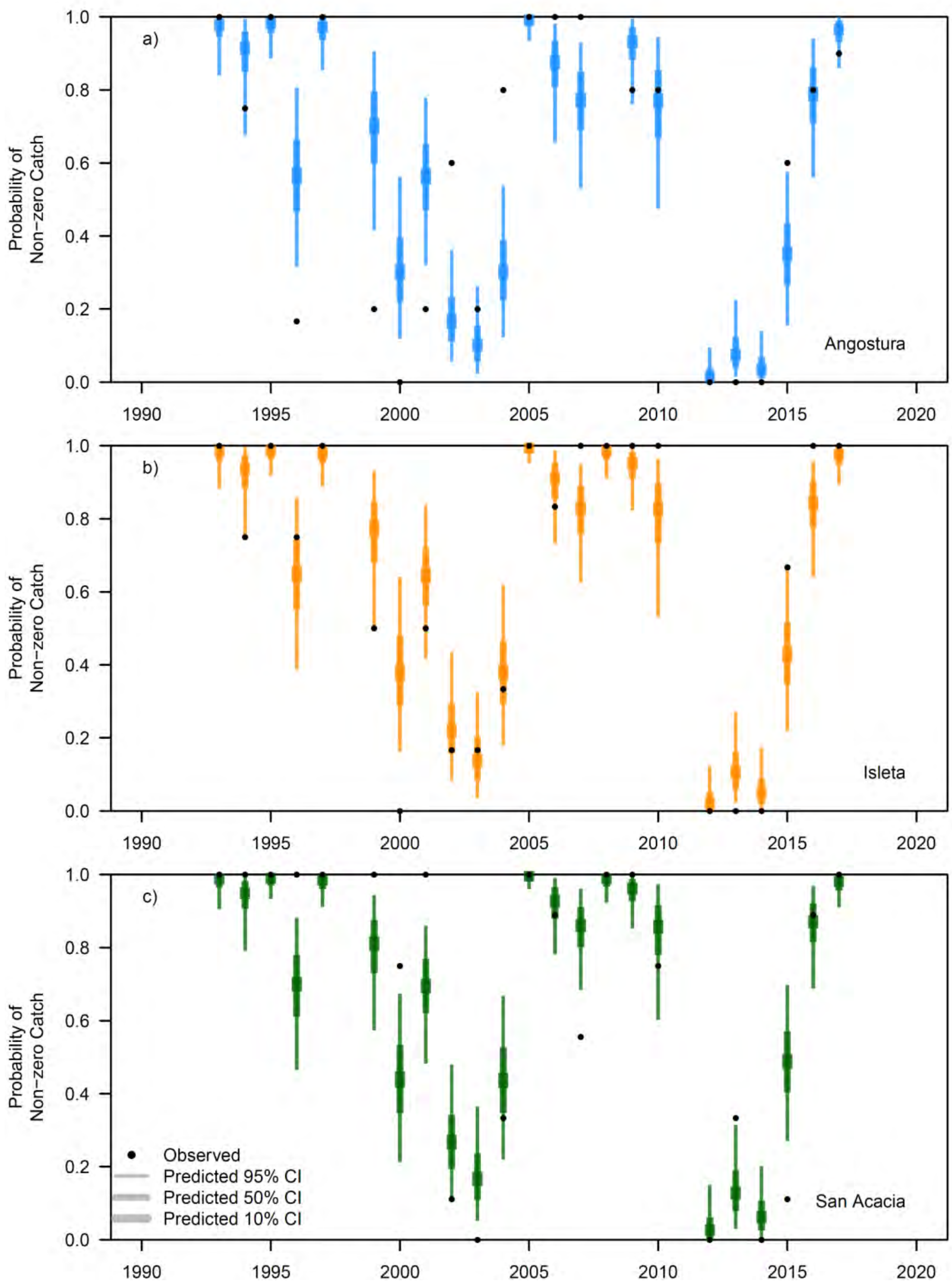

Figure S2.14. Predicted (boxplots) and observed (points) annual encounter probabilities for Rio Grande silvery minnow in the Angostura (a), Isleta (b) and San Acacia (c) reaches for the base model incorporating both the annual hydrologic and flow timing indices. The different widths of the boxplots represent the 95%, 50% and 10% prediction intervals.

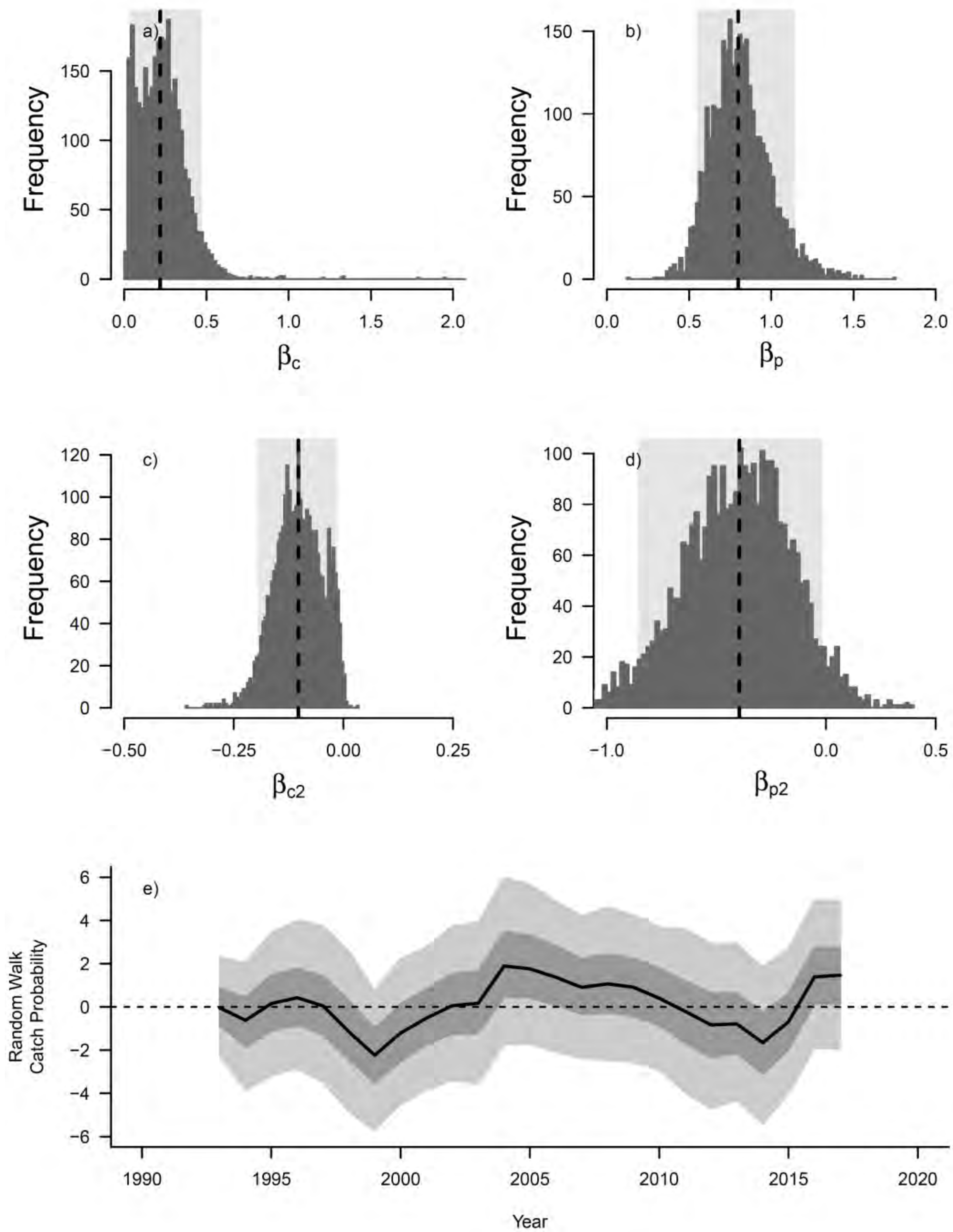

Figure S2.15. Posterior distributions of parameter estimates from the base model incorporating both the annual hydrologic and flow timing indices for the effect of the annual hydrologic index on density (a) and presence (b), the effect of the flow timing index on density (c) and presence (d), and annual values of the latent trend (e). Shaded grey boxes in panels a-d indicate the 95% credible intervals and the vertical dashed line indicates the median parameter estimate. For the latent trend, the light (dark) grey polygon indicates the 95% (50%) credible interval and the solid grey line indicates the median estimate.

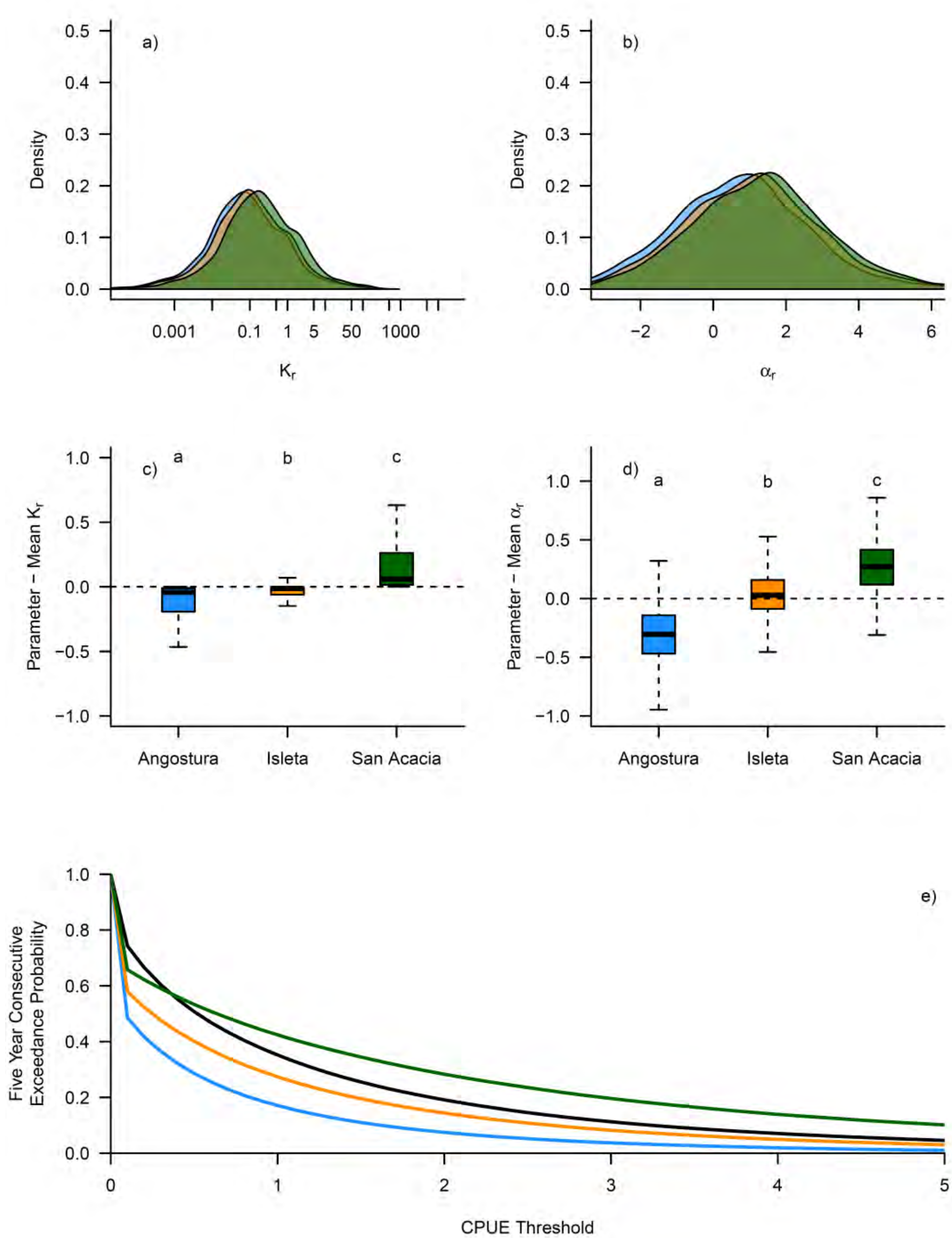

Figure S2.16. Posterior distributions of MCMC samples for reach specific carrying capacity (a) and baseline encounter probability (b) parameters for the base model incorporating both the annual hydrologic and flow timing indices, posterior distribution of reach specific differences in K (c) and α (d) from the global mean value, and simulated probability of RGSM catch per 100m^2 exceeding different target thresholds for five consecutive years under the range of hydrologic conditions (e) in the dataset for the base model incorporating both the annual hydrologic and flow timing indices. Letters above boxes in (c) and (d) indicate significant differences.

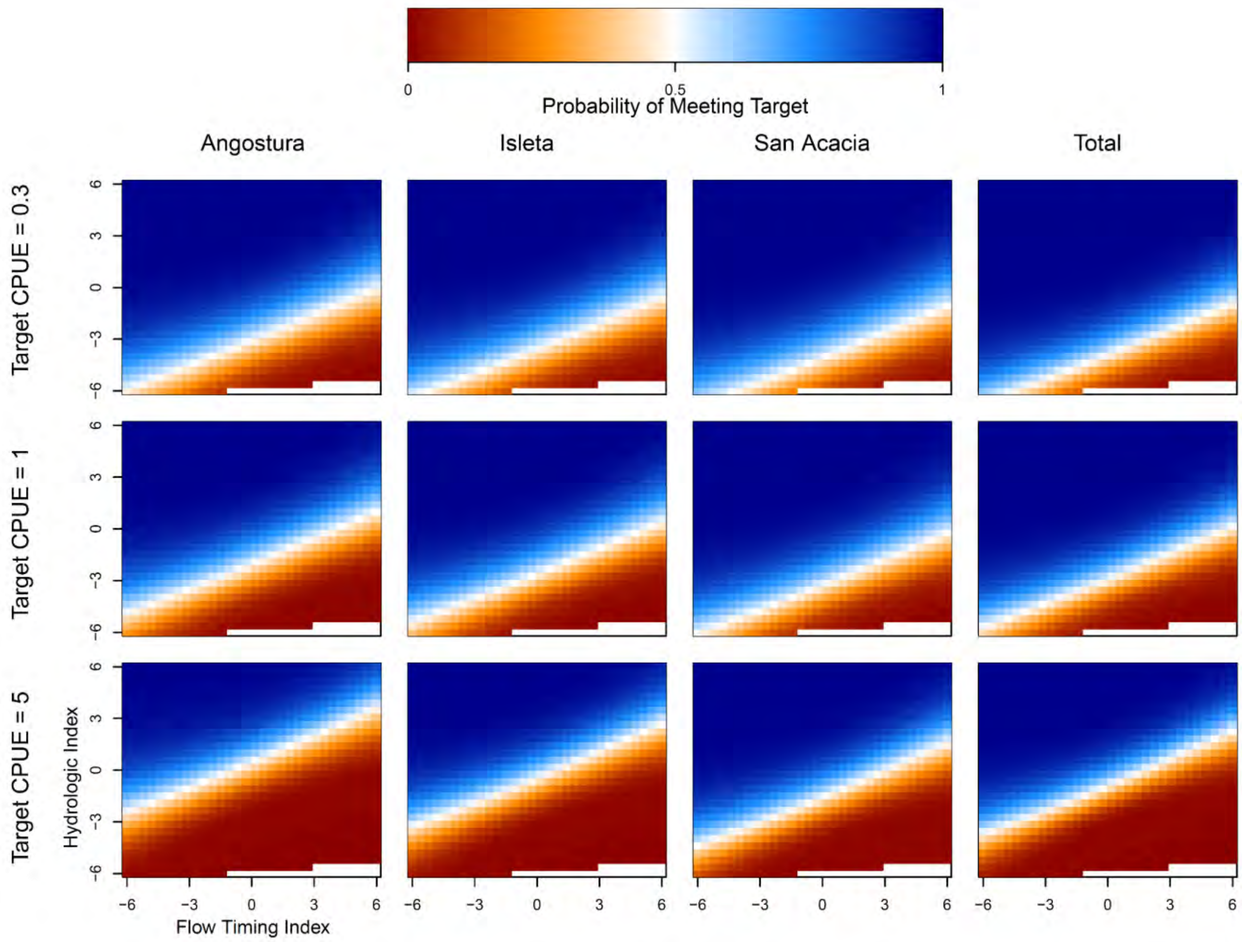

Figure S2.17. Filled contour plots of the probability of exceeding different target CPUE thresholds under different annual hydrologic indices (y-axes; positive values indicate larger spring high flow events and less summer drying) and annual flow timing indices (x-axes; positive values indicate earlier spring high flow peaks and more summer drying) from the base model incorporating both the annual hydrologic and flow timing indices. Predictions for the different reaches are organized by column: Angostura (far left), Isleta (center left), San Acacia (center right), and total MRG (far right). Predictions for different CPUE targets are organized by row: target CPUE of 0.3 RGSM per $100m^2$ (top), target CPUE of 1 RGSM per $100m^2$ (center), and target CPUE of 5 RGSM per $100m^2$ (bottom).

Response to Reviewer Comments on Draft Report

Hydrologic controls on abundance and distribution of the endangered Rio Grande silvery minnow in the Middle Rio Grande

Authors: Timothy E. Walsworth and Phaedra Budy

In May 2020, we submitted a second draft report of our analysis of the hydrologic controls on the abundance and distribution of Rio Grande Silvery Minnow in the Middle Rio Grande to the U.S. Bureau of Reclamation Albuquerque Office, which was shared with other stakeholders, management agencies and collaborators. We received valuable feedback from one reviewer, whose comments were very insightful and addressing their concerns has tightened our report.

Below, we address each of the reviewer's comments which required a response. Reviewer comments are presented as numbered items, followed by our response in bold.

<u>Reviewer Comments</u>

Thank you for the opportunity to review and provide comments on the Final Report "Hydrologic controls on abundance and distribution of the endangered Rio Grande silvery minnow in the Middle Rio Grande" by Drs. Timothy E. Walsworth and Phaedra Budy of Utah State University.

The comments provided below address the Phase 2 Final Report to the Bureau of Reclamation, dated May 8, 2020 (Walsworth and Budy 2020a), and the associated Appendix A (Walsworth and Budy 2020b) and Appendix B (Walsworth and Budy 2020c).

<u>General Comments:</u>

1. Drs. Walsworth and Budy have done an excellent job of developing a mathematical model that will help Reclamation and the Collaborative Program evaluate hydrologic control options for the Middle Rio Grande. The Final Report and associated appendices are very informative and will help stakeholders make decisions that better balance water management with conservation of the endangered Rio Grande Silvery Minnow.
2. The NMISC appreciates the through manner in which Drs. Walsworth and Budy have addressed our previous comments on the Draft Report, particularly the comment on timing of spring runoff. We note that PC2 is referenced as the "*flow timing index*" in the Final Report and further explained in Appendix A as a way to use the model to possibly evaluate the timing or spring runoff. We look forward to further evaluation of the timing, magnitude, and duration of spring runoff.
    a. **In addition to the description in Appendix A, we also explore the predictive ability of the flow timing index in Appendix B. As that model had much**

weaker support by WAIC, we focus the main document on the models incorporating only the hydrologic index.

3. The NMISC supports further development and implementation of this model, and continued collaboration with the "Integrated Population Model for Rio Grande Silvery Minnow" being developed by Dr. Charles Yackulic (2018).

4. This Final Report is a valuable document that is well written and well-reasoned. One over-riding concern that we have is use of the 5 fish/100 m^2 as the metric for species recovery. As noted in our earlier comments, this metric was not developed quantitatively or from a demographic modeling process. It was decided as a consensus of the authors of the 2010 Recovery Plan for the Rio Grande Silvery Minnow (USFWS 2010). The authors used a RAMAS Population Viability Analysis (PVA) to derive estimates of carrying capacity, but did not derive the 5 fish/100 m^2 from that PVA. It is unknown if the metric is a realistic index of population abundance necessary for recovery, and merits evaluation before it is further used in evaluating actions necessary for recovery.

    a. **We report the probabilities of meeting a range of October CPUE targets in subsequent figures. As we are not attempting to identify what CPUE targets would indicate recovery, but instead developing a model that can estimate under what conditions any given recovery target is likely to be met, we believe our analyses are highly valuable. We have shifted the focus of the analyses to the 1 RGSM per 100 m2 target, though we still discuss the recovery target. As this is the target set in the official recovery plan, we believe it deserves treatment in our analysis.**

5. The model examines the probability of individual reaches achieving a range of CPUE targets for three consecutive years under contemporary hydrologic conditions. The downlisting criteria for the Recovery Plan (USFWS 2010) specifies that the October CPUE from all monitoring sites within each reach should be > 5 fish/100 m^2 for "at least 5 consecutive years." If the model is to be used to evaluate the 5 fish/100 m^2 in the context of recovery, we suggest running the hydrology scenarios for 5 and not 3 years.

    a. **We thank the reviewer for the clarification. We re-ran this analysis for five consecutive years instead of three. The general patterns remained the same, though probabilities of exceeding the different management and conservation thresholds decreased, as expected. All figures and text have been updated.**

6. The model determined that 5 fish/100 m^2 for three consecutive years could be met in the San Acacia and Isleta reaches under a range of flows currently seen in the MRG. It would be helpful for water managers to have the flow index translated to a flow exceedance analysis to better understand the range of flows necessary to achieve the criteria. This should be done for five consecutive years.

a. **We agree that such a hydrologic analysis would be beneficial to managers, but it is beyond the scope of this report. It could potentially be incorporated into the third phase of this project.**

7. The prior report by Budy and Walsworth (2019) provided a comprehensive analytical review of the discharge to CPUE relationship used to derive the criteria for genetic viability (0.3 fish/100 m^2) and demographic self-sustainability (1.0 fish/100 m^2) for the RGSM. These criteria, as identified in Appendix A of the 2016 BiOp (USFWS 2016), are used as levels of "incidental take" not to be exceeded by the Proposed Action. These are the criteria that we would like to see evaluated, rather than the criteria of the Recovery Plan, which have no basis in development.

    a. **We have changed the figures to focus on the 1 RGSM per100 m2. We still reference multiple different targets in some figure panels and in the discussion, but the focus is now on the threshold of 1.**

8. The latent trend analysis showed the strong influence of an unknow and unobserved driver that may be related to regional climate variation or spawner-recruit dynamics. We hope that future evaluations with this model will help to identify and parse this driver, as either of the identified possible relations are important in the context of water and species management.

    a. **We would like to explore this further in future analyses (potentially in Phase 3). We have attempted to examine one of the possible drivers (spawner abundance/carryover) in Appendix B.**

<u>Specific Comments:</u>

1. On lines 159 and 160 of the Final Report, the statement is made that "Newly recruited age-0 RGSM become available to capture in the fall and summer low flow conditions have generally abated by this time." This sentence is confusing, as the age-0 RGSM first recruit into the seine gear in June or July, as can be seen in the database.

    a. **We thank the reviewer for the suggestion and have changed this sentence to "Newly recruited age-0 RGSM have survived the harshest summer drying conditions, flow variability is lowest, and are available for capture by sampling crews."**

2. Between lines 173 and 191, it should be clearly stated that the drying metric used is an index of drying and not a reflection of actual length and duration of drying.

    a. **We have added a sentence "While this metric provides a useful index of summer drying, it does not indicate the actual length and duration of drying."**

3. On lines 207 and 208, it is unclear if the capture probability corresponds to actual p-hat or to the occurrence of RGSM in mesohabitats. Low occurrence and CPUE of RGSM

from runs and riffles may be more of a reflection of numbers of fish present in those habitats, rather than capture probability.

   a. **We have added a sentence to the end of this paragraph "While the probability of capturing RGSM likely varies among mesohabitats (due to depth, velocity, connectivity), this model does not explicitly account for this variation as mesohabitat samples are combined by site in our analysis. Any variation in capture probabilities among mesohabitat types or differences in mesohabitat composition among sites will be accounted for in the variance of p_{ry}."**

4. In lines 226 to 228, it would be helpful to point out that the analysis was done for only October samples, a time when flow variability is the lowest. The assumption that catch rate and capture probability are not impacted by discharge at the time of sampling would not apply to other months of the year.

   a. **We have clarified that we are modeling October CPUE. Additionally, we now describe the benefits of low flow variability in the previous paragraph, and that any remaining effect of discharge on capture probability will be accounted for in the parameter variance.**

5. On lines 368 to 370, an important part of water management in the MRG will be to reconcile where to put water--in the spring for higher or longer runoff, or in summer to reduce rate, extent, and duration of drying. It would be helpful if future modeling exercises could include this analysis, as it is probably one of the most important aspects of water management in the MRG.

   a. **We agree that this will be an important part of water management decisions and fully intend to incorporate this trade-off as part of the analysis in Phase 3. We describe the benefits of exploring alternative management scenarios in the final two paragraphs of the discussion.**

6. On lines 380 to 384, the idea of large-scale experimentation may be possible in a system with hydrological flexibility, but this is not likely in the MRG. Instead of designed experiments, the better approach will be condition-dependent experiments.

   a. **We plan to explore both condition-dependent and large-scale experimental approaches in Phase 3 of this project. If simulations identify a large-scale experimental approach that is logistically challenging but expected to provide benefits for both RGSM populations and off-stream water users, managers and stakeholders can then determine if they want to attempt such an experiment.**

7. On lines 388 to 390, comparing the Angostura Reach with the other reaches during drying is an interesting way to look at the reaches. Another important consideration is the offsetting effect that habitat restoration in the Angostura Reach could have on CPUE.

a. **As we have not modeled habitat restoration explicitly in our models we do not discuss it here, though the reviewer is correct that habitat restoration may allow Angostura to produce more RGSM than it currently does under the same hydrologic conditions. However, the scale at which such restoration would be required to elicit a population level response is potentially very large.**

8. On lines 407 to 411, the finding that CPUE and annual flows are non-linear is important given that better water management options may be available within the range of observed discharges. We look forward to further evaluation of this aspect of water management.

    a. **We agree that this is an important result and it will be on of the foci of our Phase 3 analyses.**