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Evaluating Multisystem Length Limits for Inland Fisheries

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By

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Multisystem length limits are a popular output control implemented to regulate harvest of many gamefishes. Evaluating the direct effects of length limits is crucial in selecting a regulation, but to my knowledge, no formal methodology exists to model length limits for multiple systems. Without a formalized process, complexities associated with multisystem scales of management can preclude effective communication and interpretation of information. I created a quantitative decision model as an approach for comparing length limits applied to multiple systems. This approach combined an extension of the Beverton-Holt yield-per-recruit function and an additive utility function to compare multisystem length limits. I also conducted a sensitivity analyses to clarify the effect of input parameters and uncertainty on the expected utility, and on performance metrics. This approach provides a consistent methodology for evaluating multisystem length limits, and as a decision support tool, can improve transparency of the length-limit-selection process.

DEDICATION

To my uncle Richard Challen, who instilled in me the value of science.

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CHAPTER I

EVALUATING MULTISYSTEM LENGTH LIMITS FOR INLAND FISHERIES

Introduction

Harvesting fish is among the most diverse and impactful forces in fisheries. People harvest fish in many ways, and for many purposes including food, commerce, and cultural identity (Clark 1886; Bosworth 1995; Moffitt et al. 2010). Declining fishing success and fish-population-dynamics research support the perception that harvest can affect the sustainability of aquatic resources (Quinn 2003). Natural resource agencies often regulate harvest because of the power of fishing harvest to affect the sustainability of fisheries (Bowen 1970; Isermann and Paukert 2010) and in some cases to follow mandates to manage public trust resources (Craig 2010).

A harvest regulation is a management action that limits the way people take fish from a fishery in order to achieve management objectives like maximizing and sustaining the utility of resources. Fisheries managers can use harvest regulations to define where, when, what, and how much people harvest from a fish stock. Often, the objectives set by agencies warrant the use of multiple regulation types such as permit requirements, as well as catch, gear, and seasonal restrictions (Isermann and Paukert 2010). Managers commonly use length-based harvest restrictions, or length limits, as a means for regulating harvest.

Length limits are a type of output control that limits the size of fish harvested. Managers most commonly define legal harvest size with a minimum length limit (MLL) or a slot length limit (SLL) (Isermann and Paukert 2010). An MLL restricts harvest to individuals above a specified size, while an SLL can either protect all fish within a distinct length range (protected slot) or restrict harvest to fish within that length range (harvest slot) (Gwinn et al. 2015). Less frequently used is the maximum length limit, which defines legal fish as below a specific length. Managers may also enact length-based creel limits to regulate the number of fish of a certain length that anglers can harvest. Length-based creel limits are a combination of a length limit and a bag limit, and can be used to limit the take of larger fish (Paukert et al. 2003).

The process of selecting length limits, or any other harvest regulation, starts with perceived problems about the fishery from available biological, sociological, and ecological data. After identifying problems in the fishery, management goals and objectives are then considered (Powers et al. 1975). Managers then enact regulations to achieve management objectives. Some decisions on regulations have a scientific basis, informed by data and facts from the fishery. Others may have an ad hoc approach, where decisions lack input from data and may only consider angler and management goals before selecting a regulation (Goeman 1995; Johnston and Martinez 1995; Radomski et al. 2001).

Managers have many justifications for using length limits and may choose specific length limits depending on biological, sociological, or ecological circumstances. From a biological perspective, managers consider harvest regulations when a sportfish population is suspected to be at risk for growth overfishing, and sometimes recruitment overfishing (Colvin 1991b; Maceina et al. 1998; Fayram et al. 2001; Stone and Lott 2002; Scholten and Bettoli 2005). Evidence from empirical and simulated data also supports the use of MLLs for increasing yield and size structure, although slower growth rates or high natural mortalities may inhibit MLLs from achieving management objectives (Novinger 1987; Colvin 1991a; Colvin 1991b; Allen and Miranda 1995). Webb and Ott (1991) found that MLLs increased yield for crappies *Pomoxis spp.* on all three of their study sites, and improved size structure of crappies in systems where growth overfishing occurred. Beamesderfer and North (1995) found that MLLs for largemouth bass *Micropterus salmoides* and smallmouth bass *Micropterus dolomieu* reduced yields in systems with high natural mortality, and can reduce size structure in populations with low or stunted growth. A protected SLL may prevent stunting by allowing anglers to harvest smaller fish, and let bigger (more desirable) fish stay in the system longer (Eder 1984; Novinger 1990; Isermann and Paukert 2010). In fisheries with higher growth rates and a class of large females, a harvest SLL can provide anglers harvest opportunity while also protecting smaller fish and the larger, more fecund individuals (Scarnecchia et al. 1989; Gwinn et al. 2015).

Ecological knowledge such as habitat factors or species interactions are less frequently considered but can be important factors in establishing regulations (Johnson and Martinez 1995; Link 2002). Length limits can protect the spawning segment of a population (Scarnecchia et al. 1989; Munger et al. 1994; Paukert et al. 2001) and restore predator-prey balance, such as that between largemouth bass and bluegill (Rasmussen and Michaelson 1974). Angler perceptions of fishing quality, such as catch rate, harvest allowance, and opportunities for trophy fish may also drive managers to regulate harvest

(Hess 1991; Johnson and Martinez 1995; Radomski and Goeman 1996; Radomski et al. 2001).

Managers may incorporate fisheries data in predictive models to evaluate the potential for a proposed regulation to achieve management objectives (Allen and Miranda 1995; Scholten and Bettoli 2005; Colvin et al. 2013). One such predictive model is the yield-per-recruit (YPR) model, which provides insight on how a cohort from a fish population may respond to various harvest regulations given assumptions (Beverton and Holt 1957). This type of model works by predicting harvest yield from a simulated cohort, and can evaluate different length limits by comparing yield from the cohort under different times and levels of exploitation. The YPR model also can generate output for other variables of interest, such as the average weight of each fish harvested and number harvested (Allen and Hightower 2010).

Beverton and Holt's YPR model is a first-order differential equation that evaluates a single cohort and describes the cohort's yield to fishing over the course of its existence, given biological assumptions. It describes individual growth with an age-length relationship developed by Brody and Bertalanffy (Ricker 1975). From von Bertalanffy's length-at-age growth curve, weight-at-age can be estimated with a weight-length relationship. The Beverton-Holt model (Beverton and Holt 1957) assumes isometric growth, meaning that all parts of the fish grow at the same rate (i.e. retains a fixed body shape) (Ricker, 1975). The remaining components are the number of recruits (R) and instantaneous mortality (Z). R can be arbitrarily set, because the model defines yield as relative to recruitment (thus the name yield-per-recruit). Z consists of fishing mortality (F) and natural mortality (M), and estimates can come from several estimation methods, such as catch-curve analysis. In a catch-curve analysis, instantaneous mortality (*Z*) is the slope of the regression line of the natural logarithm of catch-at-age data. Catch-curve models assume constant recruitment, equal survivability at each age, constant gear selectivity on the descending limb, and a representative sample of the population. Mark-recapture models are additional methods for estimating *F* and *M* (Miranda and Bettoli 2006; Kerns et al. 2015). With all parameters defined, the cohort's total yield is the area under the yield curve. This area can be found by integration, solving either by closed form, approximate, or numerical methods.

Several other equations have been developed for modeling yield-per-recruit. Thompson and Bell (1934) and Botsford (1981) both developed age-structured models instead of a cohort analysis, and thus their models require age-specific values of mortality. These age-structured models have more biological realism but require more data than a cohort model. Baranov's (1918) method is a cohort analysis similar to Beverton and Holt (1957), and assumes isometric scaling of weight with length, and constant rates of fishing and natural mortality (Ricker 1975). The Jones (1957) modification of the Beverton-Holt yield equation (Ricker 1975) relaxes the assumption of isometric growth by using the incomplete beta function to calculate the area under the yield curve. The equation's versatile and simple integration technique, incorporation of allometric growth, and its use in fisheries-modeling software (FAMS; Slipke and Maceina 2010) make the Jones (1957) modification a more prominent method for evaluating length limits of inland fisheries.

The Jones (1957) modification of the Beverton-Holt equilibrium yield equation (Ricker 1975) still has biological assumptions that may limit the scope of its use.

Specifically, the model assumes that *F* and *M* are constant rates across all age groups and that *F* is additive to *M*. However, assuming additive mortality could overestimate yield at low levels of exploitation if mortality was compensatory (Anderson and Burnham 1976; Allen and Miranda 1995). Assuming constant *F* and *M* can limit the model from simulating more complex harvest regulations, such as an SLL or a length-based creel limit, with only one function. Additionally, the Jones (1957) approximation can only predict total biomass yield, and not yield that accounts for harvesting lucrative fish tissues like roe or liver oil (Scholten and Bettoli 2005; Colvin et al. 2013). Despite limitations to the Beverton-Holt yield-per-recruit model, only one adaptation has been used that can relax the assumptions of when fishing and natural mortality are applied (Colvin et al. 2013). Colvin et al. (2013) solved for yield using numerical integration, which combines one-dimensional evaluations of the integrated function. Because numerical solutions do not require a closed-form solution or approximation, this adaptation could relax some of the biological assumptions found in the Jones (1957) approximation.

Software packages that use yield-per-recruit models are popular resources for evaluating length limits. Programs such as the Generalized Inland Fishery Simulator (GIFSIM; Taylor 1981), MOCPOP (Beamesderfer 1991), Fishery Analyses and Simulation Tools (FAST; Slipke and Maceina 2001), and Fishery Analyses and Modeling Simulator (FAMS; Slipke and Maceina 2010) allow for efficient length limit modeling, making yield-per-recruit functions accessible with a user-interface that managers can use to evaluate a length limit. These types of software can model the response of any fish population to a length limit, yet they do not have a straightforward approach to model a length limit that applies to multiple waterbodies (hereafter known as multisystem length limits). Managers often enact multisystem length limits, and although many studies make reference to such regulations (Terre and Zerr 1994; Novinger 1990; Wilde 1997; Isermann et al. 2002; Hupfeld et al. 2016), none focus on standardizing an approach to evaluating multisystem length limits. Modifying the Beverton-Holt YPR to include multiple systems, with different growth and mortality rates, could satisfy a solution to this limitation. A standard approach for modeling multisystem length limits, accessible with a simple user-interface, would allow managers to evaluate multisystem length limits in an efficient and repeatable process.

Assessing multisystem length limits needs a formalized approach for three reasons. First, a region of water bodies may have sportfish populations with a variety of growth and mortality dynamics, and an angling community that has multiple desires (Edison et al. 2006). Without a standard procedure to follow, the complexity of handling multiple water bodies could allow for inconsistent approaches that are harder to repeat or compare. A formal process to evaluate alternative harvest regulations can account for heterogeneity in fish population and angler characteristics that may exist across multiple water bodies, which reduces the subjectivity of decision making (Clemen 1996). Second, it is not practical to obtain detailed information on every water body in a region (Shuter et al. 1998; Isermann et al. 2002), necessitating managers to generalize model parameters. Since many water bodies in a given area may lack relevant information to decide on regulations, sensitivity analysis can clarify the effect parameter uncertainties have on the utility of the regulation (Majkowski 1982; Bain 1987; Peterson and Evans 2003). Managers can use such analysis to look at risk of alternative decisions. For example, Peterson and Evans (2003) found that a 305-mm MLL for largemouth bass in West Point Reservoir would result in highest angler satisfaction, but a sensitivity analysis revealed that the 356-mm MLL was more likely the safer decision given uncertainty around fishing mortality. Sensitivity analysis can also help direct monitoring efforts to reduce uncertainty when resource limitations inhibit monitoring all systems in a region. Isermann et al. (2002) mention time and budget as factors limiting the amount of available data to estimate dynamic rates in their assessment of Tennessee's statewide crappie regulations. Studying the effect of each parameter in their predictive model could help identify sampling priorities to effectively monitor system responses to the regulation. Third, current models could misrepresent the decision framework for a multisystem length limit because they lack outputs relevant to regional objectives.

A regional objective is measured by aggregating utilities for a single system. For instance, if an objective for a single water body is to maximize a harvest rate, quantified by the number of fish harvested per hour by anglers, that same objective for a region of lakes would expand to maximizing the average harvest rate of all the systems. Other objectives could revolve around the distribution of utility values across the management area. Regional objectives may measure the proportion of systems where a certain outcome occurred. If a manager wants to maximize opportunity to harvest fish (hereafter referred to as harvest opportunity), the objective would be that anglers can harvest fish on all water bodies, and the proportion of systems where harvest occurred would be the metric that quantifies the objective. Regional objectives may also contain multiple criteria (ways to measure an objective), which if not handled consistently, could weaken the scientific support for the selection of a length limit (Keeney 1976; Bain 1987;

Peterson and Evans 2003). Angler-satisfaction criteria (e.g. yield, average weight, harvest rate) have different units of measurement, but need a common scale to be components in the objective to maximize angler satisfaction. A consistent process allows the science to inform how well a decision may achieve objectives without overlooking or underrepresenting any components within the decision framework (Conroy and Peterson 2013).

Given the complexity associated with the number of water bodies, agency objectives, and angler-satisfaction criteria, multisystem length limits are a good candidate for evaluation with a decision support tool as part of a structured-decision-making (SDM) process. An SDM process organizes decision making into three parts: establishment of quantifiable objectives, management alternatives, and models to predict how well a management alternative may achieve objectives (Conroy and Peterson 2013). Such a decision support tool would satisfy the 3rd part (i.e. predictive modeling) of the SDM process.

The objectives of this study were to (1) develop a model that simultaneously predicts the effects of a length limit for multiple waterbodies, (2) evaluate the sensitivity of the model outputs to inputs, and (3) demonstrate the use of the model as a decision support tool. To this end, I developed a YPR model that parameterizes multiple cohorts to represent water bodies with similar population and fishery dynamics. To apply my model, I compare a 254-, 279-, and 304-mm MLLs on a hypothetical lake region and identify the optimal MLL given two objective-weighting schemes: one with harvest-oriented objective weights and one with objective weights focused on catching larger fish (quality oriented). In these, I compare the MLLs with weighted utility scores calculated using an additive utility function. For each weighting-scheme I also conduct a sensitivity analysis on the expected utility of the optimal decision to the parameter groups. I then conducted a sensitivity analysis of each model output to the parameter groups.

Methods

I distinguish 3 steps necessary to achieve the three objectives. In step 1 I expanded the Beverton-Holt equilibrium-yield model to predict yield for multiple systems given a distribution of parameter inputs and varying minimum length limits. In step 2 I used the model to simulate 3 MLLs on a hypothetical lake region supporting crappie recreational fisheries. I evaluated each MLL in terms of achieving 5 management objectives, which were quantified as performance metrics. The performance metrics were combined into a single utility using 2 weighting schemes, reflecting a harvest oriented or a quality fishery. I then identified the optimal MLL under each of the 2 objective-weighting schemes. In step 3, I conducted sensitivity analyses. First, I evaluated how uncertainty in model inputs influenced the expected utility using a one-way sensitivity analysis. Then I evaluated the effect of input parameters on the performance metrics. I expand on each of these 3 steps in the subsections below.

Step 1 – Expanding Beverton-Holt equation

To simulate a multisystem length limit, I expanded on the equilibrium yield model, developed by Beverton and Holt (1957), to include multiple cohorts (each cohort reflects a water body), with each containing cohort-specific growth and mortality parameters. Total yield for multiple cohorts was calculated as

$$Yield = \sum_{i=1}^{n} \int_{t_{r,i}}^{t_{\lambda,i}} [C(t)_i W(t)_i] dt, \quad (1)$$

where i indexed each cohort (total of *n* cohorts per simulation). Total yield for each cohort i was the sum of catch-at-age $C(t)_i$ times weight-at-age $W(t)_i$, multiplied by step widths dt, starting at age of recruitment to the fishery ($t_{r,i}$) and ending at the maximum age (t_λ). Each cohort's catch-at-age function $C(t)_i$ calculated the number of harvested fish at age-*t* from the *i*th cohort as

$$C(t)_i = F_i \bullet R \bullet e^{-(M_i \bullet t_{r,i})} \bullet e^{-(M_i + F_i)(t - t_{r,i})}, \quad (2)$$

where F_i was cohort *i*'s instantaneous fishing mortality, R was the number of fish that are recruited to the cohort, and M_i is the *i*th cohort's instantaneous natural mortality rate. The model allows each cohort to have varying ages of recruitment to the fishery ($t_{r,i}$), depending on growth parameters as

$$t_{r,i} = \left(\frac{\ln\left(1 - \left(\frac{MLL}{L_{\infty,i}}\right)\right)}{-k_i} \right) + t_0, \quad (3)$$

where $L_{\infty,i}$ was the asymptotic length for cohort i, k_i was the ith cohort's Brody growth coefficient, t_0 was the theoretical age at length-0, and *MLL* was the minimum length a fish could be harvested. The cohort-specific weight-at-age function $W(t)_i$ estimated the average weight of the fish at age-*t* through fitting the weight-length relationship calculated as

$$W(t)_i = a \bullet L(t)_i^{\,b_i}, \qquad (4)$$

where a was the intercept of the weight-length relationship, b_i was the cohort-specific slope of the weight-length relationship, and $L(t)_i$ was length at age for cohort i. Length-at-age was predicted from a cohort-specific von Bertalanffy growth function (VBGF) as

$$L(t)_i = L_{\infty,i}\left[1 - e^{-k_i(t-t_0)}\right], \qquad (5)$$

where all parameters are as defined in equation 3.

Step 2 – Adaptation of the model to simulate applications

I demonstrated the use of the model to compare a 254-, 279-, and 304-mm (i.e. 10-, 11-, and 12-in) minimum length limit on crappies for a hypothetical region of 100 lakes, with two different weighting schemes. To conduct this analysis, I created 200,000 stochastic simulations of 100 cohorts with unique values of growth function, weight-length relationship, and mortality parameters, as described in Table 1.1. I assigned R = 1000 individuals per cohort in accordance with past studies (Allen and Miranda 1995; Colvin et al. 2013), and t_λ = 10 years for the maximum age of each cohort. I also fixed t_0 and a for all simulations (Table 1.1). I predicted the Brody growth coefficient *k* from L_∞ (Table 1.1), which comes from regression analysis on 57 populations of black crappie

Pomoxis nigromaculatus and white crappie *Pomoxis annularis* (Miranda 2002). Ranges for mortality parameters *F* and *M* were adapted from values found in Allen et al. (1998). I described parameters L_∞, *b*, *F*, and *M* using uniform distributions, which selected any parameter value between their ranges with equal probability. I used uniform distributions to reflect minimal certainty of parameter estimates.

I evaluated each MLL by how they achieved 7 management objectives, where each objective was quantified by a performance metric (Table 1.2). After calculating outputs for each performance metric, I then calculated the utility for each output by converting the outputs to a common scale (using a proportional scaling equation) from 0 (least desirable output) to 1 (most desirable output). The overall utility of a length limit was calculated as the weighted sum of performance metric utilities, specified under two different objective weighting schemes.

To measure how well a length limit achieved the 5 management objectives (Table 1.2), I adapted the yield equation (1) to calculate 5 performance metrics: total yield, average weight, total harvest, total harvest ≥304-mm, and growth overfishing severity. The yield model (equation 1) for each stochastic simulation *rep* with equations 3, 4, and 5 plugged in was

$$Yield_{rep} = \sum_{i=1}^{n} \int_{t_{r,i}}^{t_\lambda} \begin{pmatrix} F_i \bullet R \bullet e^{-(M_i \bullet t_{r,i})} \bullet e^{-(M_i+F_i)(t-t_{r,i})} \\ \bullet\, a\{L_{\infty,i}[1-e^{-k_i(t-t_0)}]\}^{b_i} \end{pmatrix} dt, \qquad (6)$$

where all parameters are previously defined. Average weight was calculated by dividing total yield (equation 6) by the integral of catch-at-age (equation 2), expressed as

$$Average\ Weight_{rep} = \frac{\sum_{i=1}^{n} \int_{t_{r,i}}^{t_\lambda} [C(t)_i \bullet W(t)_i] dt}{\sum_{i=1}^{n} \int_{t_{r,i}}^{t_\lambda} [C(t)_i] dt}, \qquad (7)$$

where all parameters are as previously defined. Number of fish harvested was calculated by taking the integral of equation 2 and dividing it by the time-period in which each cohort is harvested $(t_\lambda - t_{r,i})$, expressed as

$$Total\ Harvest_{rep} = \sum_{i=1}^{n} \frac{\int_{t_{r,i}}^{t_{\lambda,i}} (F_i \bullet R_i \bullet e^{-(M_i \bullet t_{r,i})} \bullet e^{-(M_i + F_i)(t - t_{r,i})}) dt}{(t_{\lambda,i} - t_{r,i})}, \qquad (8)$$

where all parameters are as previously defined. The calculation for total harvest ≥304-mm was the same as equation 8, except age-at-recruitment $(t_{r,i})$ within the numerator of the equation 8 was replaced by an age-of-interest $(t_{q,i})$. The age-of-interest in my application reflects when fish reach 304-mm, but could be assigned to any desired length. The full equation for size-specific harvest is

$$Total\ Quality\ Harvest_{rep} = \sum_{i=1}^{n} \frac{\int_{t_{q,i}}^{t_\lambda} (F_i \bullet R \bullet e^{-(M_i \bullet t_{q,i})} \bullet e^{-(M_i + F_i)(t - t_{q,i})}) dt}{(t_\lambda - t_{r,i})}, \qquad (9)$$

where the denominator reflects the same length of time as in equation 8, to normalize the two harvest rates for comparison and all parameters are as previously defined. Equations 6 through 9 were solved numerically with the Adams-Bashforth method of integration.

I calculated growth overfishing potential for each simulation by first comparing each cohort's difference in total yield *i* (equation 6) from F_i-0.02 to F_i. I arbitrarily selected F_i-0.02 to establish a difference in fishing mortality. The severity in growth overfishing for each cohort *i* was then expressed as

$$\Psi_i = \begin{cases} Yield_{i,(F_i-0.02)} - Yield_{i,F_i} & if \ Yield_{i,(F_i-0.02)} - Yield_{i,F_i} > 0 \\ 0 & if \ Yield_{i,(F_i-0.02)} - Yield_{i,F_i} \leq 0 \end{cases}, \quad (10)$$

where Ψ_i takes a value of the difference of total yield from F_i-0.02 to F_i if that difference is positive, and 0 if the difference in yield is ≤ 0. A positive difference indicates that growth overfishing occurred in the *i*th cohort, since the *i*th cohort has a greater yield at a reduced exploitation. A negative or null difference in yield indicates that no growth overfishing occurred in the *i*th cohort. The average growth overfishing severity among cohorts in a simulation was calculated as

$$Growth\ Overfishing_{rep} = \frac{\sum_{i=1}^{n} \Psi_i}{n}, \quad (11)$$

where *n* represents the number of cohorts in each simulation.

I also calculated the proportion of water bodies within each simulation where harvest occurred as

$$Harvest\ Opportunity_{rep} = \frac{\sum_{i=1}^{N} [h_i]}{N}, \quad (12)$$

where h_i is an indicator variable that takes a value of 1 if the *i*th cohort has a total yield greater than 0 in the simulation, and a 0 if total yield equals 0. The opportunity to harvest fish of a specific length was calculated the same way as harvest opportunity (equation 12), except h_i was defined as a vector (0 to 1) indicating whether harvest occurred during the time period in which fish of the *i*th cohort are at or above a specific length ($t_{q,i}$ to $t_{\lambda,i}$).

My remaining two performance metrics were the dispersions of average weight (equation 7) and total harvest (equation 8). Dispersion was measured with the Gini coefficient, a measure of inequality among values in a frequency distribution, which was calculated using the reldist package (Handcock 2016) in R software (R Development Core Team 2017).

After calculating performance metrics, I then computed a utility for each metric. I scaled the performance metrics ($x_{j,rep}$) from each stochastic simulation on a common scale from 0 to 1 for each performance metric. The utility of each metric for a simulation, $U(x_{j,mll,rep})$, was calculated using proportional scaling and expressed as

$$U\left(x_{j,rep}\right) = \left(\frac{x_j - MIN(x_j)}{MAX(x_j) - MIN(x_j)}\right), \tag{13}$$

where $MIN(x_j)$ and $MAX(x_j)$ are the lowest and highest values of each output, respectively, among the stochastic simulations (Clemen and Reilly 2001). Equation 12 scales high output values to 1, and was used when a high value is the desired target for an objective. Conversely, if a low output value is the desired target for an objective, $U(x_j)$ was calculated as

$$U(x_{j,rep}) = \left(\frac{MAX(x_j)-x_j}{MAX(x_j)-MIN(x_j)}\right), \tag{14}$$

to scale low values to 1. The utility $U(x_{j,mll,rep})$ of performance metric outputs ranged from 0 (least desirable output value) to 1 (most desirable output value), and were then assigned a weight, w_j, based on the weights for each objective scheme (Table 1.2). Utility weights range from 0 to 1 which determine the relative importance of each performance metric when computing the utility for each length limit. The utility for a stochastic simulation was calculated as

$$Score_{mll,rep} = \sum_{j=1}^{n} w_j \bullet U(x_{j,mll,rep}) \, . \tag{15}$$

The expected utility of each length limit was calculated as the average score of the simulations that pertained to each length limit. The length limit with the highest expected utility was the optimal length limit.

Step 3 – Model sensitivity

I conducted a one-way sensitivity analysis for each objective-weighting scheme to compare the sensitivity of the expected utility of the optimal decision to the ranges of model parameters (Table 1.1). The results of the sensitivity analysis were then used to visually assess how the uncertainty of each parameter influences the expected utility of the optimal decision. I found the range of expected values for the optimal decision given the range of each model parameter (Table 1.1) by calculating the difference of the decision values between the lowest 10% and highest 10% of values of that parameter.

Using model parameter values from Table 1.1, I examined the sensitivity of the performance metrics (Table 1.2) to each model input parameter using multiple linear regression. The performance metrics that measure the Gini coefficient (i.e. dispersion of average weight and dispersion of total harvest) were not analyzed for sensitivity because they require a distribution of values for each parameter, and thus cannot be analyzed in the same way. A regression model was created for performance metrics, where the metric's output was the response variable, and model components (L_∞, b, F, and M) were the independent variables. I normalized each independent variable and response variable by centering the means to 0 and setting 1 and -1 as the 1st standard deviations above and below the mean. Normalizing independent and response variables put their values on a common scale, which allowed me to directly compare slope coefficients during analysis. The value of each coefficient represented the effect of changes in the normalized model output to changes in the normalized model parameters. I used analysis of variance to test the significance of each regressor variable, assuming α=0.05.

I also added a visualization of how the YPR model parameters affect model outputs by ordinating, with a principal coordinates analysis (PCO), a subset of the normalized stochastic simulations from Table 1.1 (same normalization as used in the regression models). For the PCO, I analyzed all possible combinations of 3 MLLs (254-,279-, and 304-mm), 2 (low and high) L_∞ values (310- and 390-mm), 3 (low, medium, and high) values of *b* (3.1, 3.25, 3.5), and 3 (low, medium, and high) values of *F* (0.25, 0.5, and 0.75) and *M* (0.3, 0.55, and 0.8).

Results

Model application

The averages of the performance metrics for the stochastically replicated simulations of 100 hypothetical crappie fisheries varied among the 250-, 279-, and 304-mm MLL simulated (Table 1.3). For the harvest-oriented objective scheme, the 279-mm MLL was optimal (Table 1.4), while the 304-mm MLL was optimal for the quality-catch objective scheme (Table 1.5). Although the 254-mm MLL has the highest expected utility in Table 1.4 (70.290), the 279-mm MLL has a similar score (65.252). The 279-mm MLL ranks higher than the 254-mm MLL for minimizing growth overfishing and shares the same score for harvest opportunity, but ranks lower for each other objective. The MLL's exhibit more separated scores in the quality-catch scheme than in the harvest-oriented scheme (Table 1.4). The 304-mm MLL was the optimal decision to maximize quality-oriented objectives, but ranks the lowest for dispersion of average weight (Table 1.5). The dispersion of total harvest (Table 1.4) and dispersion of average weight (Table 1.5) were minimized at the 254-mm MLL.

Model sensitivity

The one-way sensitivity analyses (Figures 1.1 and 1.2) show the relative influence each parameter group's uncertainty has on the expected utility for the harvest-oriented and quality-oriented objective schemes, respectively. *M* displays a high relative influence on the expected utility for the harvest- and quality-oriented objective schemes, and *F* has a smaller but similar importance on both objective schemes. L_∞ has the highest relative influence among parameters on the quality-oriented objectives but has almost no impact on the utility of MLL for harvest-oriented objectives. The parameter *b* has a higher influence on the decision for the quality-oriented objective weights than for harvest-oriented objective weights.

Coefficients from the multiple linear regression models (Table 1.6) differed among performance metrics. For yield, *M* has a large negative coefficient (-0.5830, $p<0.01$), suggesting that natural mortality has a large influence on reducing yield. Alternatively, weight-length slope *b*, and asymptotic length L_∞ can increase yield as evidenced by their positive coefficients (0.4496, $p<0.01$ and 0.2335, $p<0.01$). *F* has a smaller positive correlation ($p<0.01$) with yield. Average weight positively associates with increases in *b* and L_∞ and is negatively impacted by increases in *M* and *F*. Both total harvest metrics have strong negative associations with *M* and increase with *F* and L_∞. Total harvest also appears to have null relationships with *b*, as coefficients are close to 0. Growth overfishing potential reduces when *M* increases, and increases with larger values of *F*, *b*, and L_∞. Harvest opportunity had significant relationships with L_∞ (0.5176, $p<0.01$) and *M* (-0.0164, $p<0.01$), but not with *F* or *b*.

According to the principal coordinates analysis, higher values of L_∞ (Panel A, Figure 1.3) can be associated with higher yield and total harvest, and more differences in average weight. Lower L_∞ appears to inhibit the severity of growth overfishing, and smaller differences in average weight. Changes in *b* (Panel B, Figure 1.3) have a strong influence on average weight, and higher values of yield and growth overfishing are achieved as *b* increases. The value of *b* has no association with either total harvest or total harvest (≥304-mm). Changes in natural mortality (Panel C, Figure 1.3) show a strong influence on yield and harvest rates, and growth overfishing is more associated with low *M*. Increases in *F* (Panel D, Figure 1.3) can increase yield and total harvest, but shows a negative association with harvest rate ≥304mm when *M* is low. Fishing mortality is also positively associated with growth overfishing, especially as natural mortality decreases.

Changes in MLL (Figure 1.4) have different effects on model outcomes, depending on *b* and *M* (Panels B and C, Figure 1.3). Given the parameter values used in this analysis, MLLs increase harvest rates, yield, average weight, and can decrease vulnerability to growth overfishing when *M* is low (right half of Figure 1.4). At high *M* (left half of Figure 1.4), higher MLLs can still increase average weight, but decrease yield and have a close to null impact on harvest rates. When *b* is high (bottom half of Figure 1.4), MLL has a stronger influence on average weight.

Discussion

Together, my YPR model and utility function provide a decision support tool that managers could include as part of a SDM process or regulatory process for evaluating a multisystem harvest regulation for multiple systems. Where traditional YPR models can only identify which regulation maximizes values for one population, the multisystem approach advances the convenience of evaluating values for multiple populations. The flexibility added to the model by permitting dynamics for multiple systems can describe how a length limit performs within a distribution of system types. The model can also evaluate regional objectives, such as harvest opportunity and the equality of fishery responses (measured by dispersion). Understanding how parameter uncertainties can influence the YPR and utility function outputs can help prioritize data collection for monitoring efforts within the management region to improve parameterization of future evaluations.

The model application and sensitivity analysis reveal relationships between parameter values and system responses that are similar to previous evaluations. Natural mortality has the most influence in reducing the benefits of length limits, which makes sense as the more fish die naturally, fewer will be available for harvest (Reed and Davies 1991; Allen and Miranda 1995). With lower *M*, each model output becomes more sensitive to delaying exploitation by increasing MLL, which other studies find can improve yield, average weight, and reduce growth overfishing (Colvin 1991a; Webb and Ott 1991; Allen and Miranda 1995; Maceina et al. 1998). Isermann et al. (2002) reported that length limits could improve yield and size structure in crappie fisheries when conditional natural mortality was below 50%, and suggest that systems benefit more from lower length limits as natural mortality increases. Higher growth rates consistently improve the utility of length limits (Colvin 1991a; Allen and Miranda 1995; Isermann et al. 2002), which I expected because the faster fish reach harvestable size, the more fish are expected to be available for harvest.

Fishing mortality and the weight-length relationship have inconsistent effects on each utility of size limit success. *F* had a negative effect on average weight and can increase the severity of growth overfishing, but appears to improve yield and harvest rates. Other studies support these impacts of fishing mortality (Allen and Miranda 1995; Isermann et al. 2002; Isermann 2007). These findings make sense as increasing *F* increases the simulated catch, and increases the proportion of small fish in the catch which lowers average weight. Since the equation for average weight (7) contains catch-at-age in both the numerator and denominator, they cancel out, making the number of fish harvested irrelevant in average weight's determination. The slope of the weight-length regression, *b*, shows strong positive correlations with yield and average weight, but no significant relationship with either harvest rate. The null influence of *b* on harvest rates is consistent with the absence of *b* from the differential equations (8 and 9) that simulate harvest rates.

My ordination suggests populations with different characteristics may respond differently to the same MLL, with most influence dependent on *M*. While length limits appear to have a consistent relationship with average weight, changes in *M* can change the way length limits affect yield, harvest rates, and growth overfishing. Other studies support these findings, with Isermann et al. (2002) reporting that length limits could improve yield and size structure in crappie fisheries when conditional natural mortality was below 50%. Allen and Miranda (1995) found that length limits may reduce yield in crappie populations with high natural mortality, but increase the average weight of fish harvested regardless of natural mortality. Although changes in *b* do not affect the direction in which an MLL changes model outcomes, they do affect the magnitude of change. Considering how MLLs influences of outcomes depend on parameter combinations, and that populations characteristics can vary within regions (Guy and Willis 1995; Allen et al. 1998; Isermann 2007), selecting a harvest regulation for multiple systems should involve consideration on the distribution of parameter estimates.

The model's application shows the importance of understanding how different MLL's may be optimal depending on the objectives for a multisystem area, and how balancing objectives affects the optimal length limit. With the harvest-oriented objective scheme (Table 1.5), the objectives favored less restrictive length limits, while the quality-oriented objective scheme selected the most restrictive length limit (Table 1.6). Both objectives to minimize dispersion (i.e. fishery responses were most equal among multiple systems) scored higher with less restrictive length limits. If more diverse fishing opportunities (i.e. higher dispersion of fishery responses among multiple systems) were desired for a region, a more conservative length limit would score higher. Because the optimal MLL for the objective-weighting schemes lacked stochastic dominance for individual objectives, different objective weights could favor one MLL over the other.

With the characterization of system parameters, managers can use this decision support tool to explore how feasible it is to accomplish management objectives with length limits for a given management area. Past studies describe the biological and sociological limitations of length limits, citing that combinations of growth and mortality factors may inhibit managers from accomplishing objectives with length limits (Johnson and Martinez 1995; Radomski et al. 1996). For black crappie and white crappie in the Delaware Reservoir, Ohio, slow growth and natural mortality were cause for the failure of a 254-mm length limit on crappie to improve yield (Hale et al. 1999). In cases where a selected length limit compromises harvest opportunity, systems may lose fishing effort if angling expectations become too difficult to meet (Boxrucker 2002). Sometimes stakeholder differences cause different angler responses to a MLL among systems. In Illinois bluegill fisheries, angler support for length limits depended both on fish population characteristics and angler demographics such as experience or motivation for fishing (Edison et al. 2006). Changes in fishing habits such as the adoption of a catch-and-release ethic can also hinder length limits from reaching objectives (Miranda et al. 2017). As seen in the ordination, MLLs may not always affect different systems the same way. Thus, depending on the diversity of population and angler characteristics within a management area, a multisystem length limit may increase yield in some systems while reducing yield in others.

Previous studies caution that multisystem length limits may not be the best option for managing some species with high population or angling diversity (Allen and Miranda 1995; Guy and Willis 1995; Isermann et al. 2002). Systems with consistent sampling coverage may have enough information for optimal management as single systems but in many cases, managers lack the data needed to individually manage most water bodies for their region (Shuter et al. 1998). Knowing when to use a multisystem length limit is outside of the scope of this research, but evaluating how well a regulation achieves regional objectives (e.g. harvest opportunity, dispersion of fishery responses) may provide support for managers to make the determination. I suggest that in cases where data are limited, my evaluation procedure can allow managers to relax the assumption of homogenous system characteristics and instead simulate unique parameter values with a probability distribution, to gather more insight as to how a diverse region may respond to multisystem length limits.

Several assumptions that may bias my results include constant recruitment, additive mortality, and each cohort is from a population in equilibrium. Temporal data on populations often exhibit variable recruitment (Hooe 1991; Allen and Pine 2000), which may impact expected harvest rates beyond the ability of my model to capture. Simulations of length limit effects on recruitment with spawn-per-recruit models are often too confounded by environmental fluctuations to be depicted as anything more than a random effect (Slipke and Maceina 2000; Allen and Pine 2000). In their study, Slipke and Maceina found that environmental factors were much more influential to recruitment success than length limits. Knowledge of recruitment dynamics could help managers anticipate size and age structure fluctuations, and along with an understanding of local angler expectations could provide valuable guidance towards selecting an appropriate length limit (Boxrucker 2002). Analyzing the sensitivity of growth and mortality estimates to recruitment dynamics could further reduce the uncertainty of model components.

My model also assumes all parameter inputs are constant. While temporal variation in growth, recruitment, and mortality all influence length limit evaluations (Maceina et al. 1998, Allen and Pine 2000), the effect of spatially varying population dynamics is the focus of this model. Additionally, spatially fixed recruitment allows for a direct comparison of the effects of other population dynamics such as individual growth and mortality on different length limits. Some benefits of modeling temporal variation include enhanced biological realism in the evaluation procedure, such as predicting density-dependent effects a length limit may have on growth rate (Bister et al. 2002; Isermann et al. 2002). The assumption of additive mortality may sometimes inflate the simulations sensitivity to natural and fishing mortalities. Allen and Miranda (1995) discussed that in systems with compensatory mortality and low exploitation, a model that assumes additive mortality could overestimate yield. Completely additive mortality may be considered conservative regarding sustainability, which may make my model overestimate its calculation of the potential for growth overfishing and number of fish harvested per system.

Besides the multisystem length limit model, a process for evaluating multiple systems needs an approach for parameterization. The characterization of system parameters with uniform distribution used in the applied examples reflects minimal certainty of population characteristics. While the scope of this model does not contain methods for more refined parameter estimation across regions, such a process could be retroactively added. Future applications of this model could improve upon my characterization of population dynamic rates as I improve my models of parameter behavior throughout landscapes, and across waterbody morphologies. Spatial trends in biological and social characteristics of fisheries have been modeled using lake morphology and water chemistry (Shuter et al. 1998), latitudinal variation (Helser and Lai 2004; Kimura 2008), and reward tag systems (Meyer and Schill 2014; Kerns et al. 2015). Such methods could reduce uncertainty without requiring more data on all systems included under the regulation. Additionally, my one-way sensitivity analysis could help identify priorities for future monitoring and research efforts. If objectives for a region reflect the harvest-oriented scheme, estimation of natural mortality and exploitation rates should take precedence over length-at-age data. But if objectives seek to maximize quality size, accurate length-at-age models would be more beneficial in reducing decision uncertainty.

Model validation may not be possible in many situations, because of data requirements or temporal dynamics that go beyond the model predictions. Studies that review the effectiveness of length limits are often too short (Isermann 2007), and sometimes conclude that factors such as recruitment variation or low exploitation may confound the effects of regulation (Allen and Pine 2000; Fayram et al. 2001; Miranda et al. 2017). Understanding the model's sensitivity can help provide a useful prediction of stochasticity that may be observed in future monitoring. Monitoring should incorporate some way to reevaluate systems' responses to the length limit over a time period that would capture population stochasticity and cycles. Observing outcomes counter to model predictions does not invalidate the model, but it can reveal relationships outside of what the model incorporated. This can allow managers to improve their understanding of the management area and improve communications with stakeholders regarding what they could expect in a fishery.

Table 1.1 Parameter summary for model application and sensitivity analysis

Function	**Parameter**	**Units**	**Value(s)**	**Sampling method**
Von-Bertalanffy	L_∞	mm	300-400	uniform distribution
	k	years^{-1}	0.27-0.41	correlated with L_∞ ($k=e^{(6.62-1.32\bullet\ln(L_\infty))}$)
	t_0	years	0.21	fixed
Weight-Length	a	regression intercept	$10^{-5.6}$	fixed
	b	regression slope	3.10-3.50	uniform distribution
Mortality	M	years^{-1}	0.30-0.80	uniform distribution
	F	years^{-1}	0.25-0.75	uniform distribution

Summary of parameter inputs for model application and sensitivity analysis, based on minimal understand of population dynamics for crappie *Pomoxis* spp. in Mississippi.

Table 1.2 Objectives summary for model application

					Objective weighting schemes	
Objective	**Performance metric**	**Equation**	**Units**	**Scaling equation**	**Harvest oriented**	**Quality oriented**
Maximize yield	Yield	6	Kg.	12	0.2	0
Maximize size of fish in catch	Average Weight	7	Kg./fish	12	0	0.2
Maximize harvest	Total Harvest	8	# fish	12	0.2	0
Maximize harvest of ≥304-mm	Total Harvest (≥304-mm)	9	# fish	12	0	0.2
Minimize overfishing	Growth Overfishing	11	Δyield	13	0.2	0.2
Maximize harvest opportunity	Harvest Opportunity	12	%water bodies	12	0.2	0.2
Minimize harvest inequality	Dispersion (Total Harvest)	Gini Coef.	%water bodies	13	0.2	0
Minimize average weight inequality	Dispersion (Average Weight)	Gini Coef.	%water bodies	13	0	0.2

Summary of objectives and their relative importance in each weighting scheme.

Table 1.3 Performance metric outputs for model application

MLL (mm)	254	279	304
Yield (Kg)	20.976	16.859	10.928
Average Weight (Kg)	0.343	0.431	0.489
Dispersion Average Weight (Gini coefficient)	0.347	0.349	0.413
Total Harvest (# fish)	59.364	37.805	19.481
Dispersion Total Harvest (Gini coefficient)	0.409	0.476	0.605
Total Harvest ≥304-mm (# fish)	6.493	10.033	19.456
Harvest Opportunity (% water bodies)	1	1	0.906
Harvest Opportunity ≥304-mm (% water bodies)	0.893	0.9	0.905
Growth Overfishing (Δ yield)	0.222	0.078	0.014

Summary of performance metric outputs from the model application. Each value represents the average from 200,000 stochastic simulations of 100 crappie systems.

Table 1.4 Utility summary for the five non-zero harvest-oriented objective weights

MLL (mm)	254	279	304
Yield	***12.205***	8.995	4.373
Total Harvest	***14.656***	8.13	2.584
Dispersion Total Harvest	***15.878***	12.425	5.768
Harvest Opportunity	***20***	***20***	11.842
Growth Overfishing	7.55	15.7	***19.321***
Expected Utility	***70.29***	65.252	43.89

Summary of performance metric utilities and expected utility for each MLL under the harvest-oriented objective weights. Highest values are in bold.

Table 1.5 Utility summary for the five non-zero quality-oriented objective weights

MLL (mm)	**254**	**279**	**304**
Average Weight	4.513	9.354	***12.542***
Dispersion Average Weight	***14.087***	13.885	8.411
Total Harvest ≥304-mm	2.487	5.078	***11.975***
Harvest Opportunity	4.513	9.354	***12.542***
Growth Overfishing	7.55	15.7	***19.321***
Expected Utility	39.733	55.723	***64.396***

Summary of performance metric utilities and expected utility for each MLL under the quality-oriented objective weights. Highest values are in bold.

Table 1.6 Multiple linear regression coefficients for performance metrics

Performance Metric	**M**	**F**	**b**	**L_∞**
Yield	**-0.5830**	**0.0852**	**0.4496**	**0.2335**
Average Weight	**-0.0285**	**-0.0308**	**0.8543**	**0.1724**
Harvest Rate	**-0.7450**	**0.1455**	-0.0001	**0.2224**
Harvest Rate ≥304mm	**-0.5937**	**0.0314**	0.0005	**0.4162**
Growth Overfishing	**-0.2954**	**0.1119**	**0.3175**	**0.3322**
Harvest Opportunity ≥304mm	**-0.0164**	-0.0004	-0.0008	**0.5176**

Multiple regression coefficients, by performance metric, for parameters M, F, b, and L_∞. Significant (α=0.05) values are in bold.

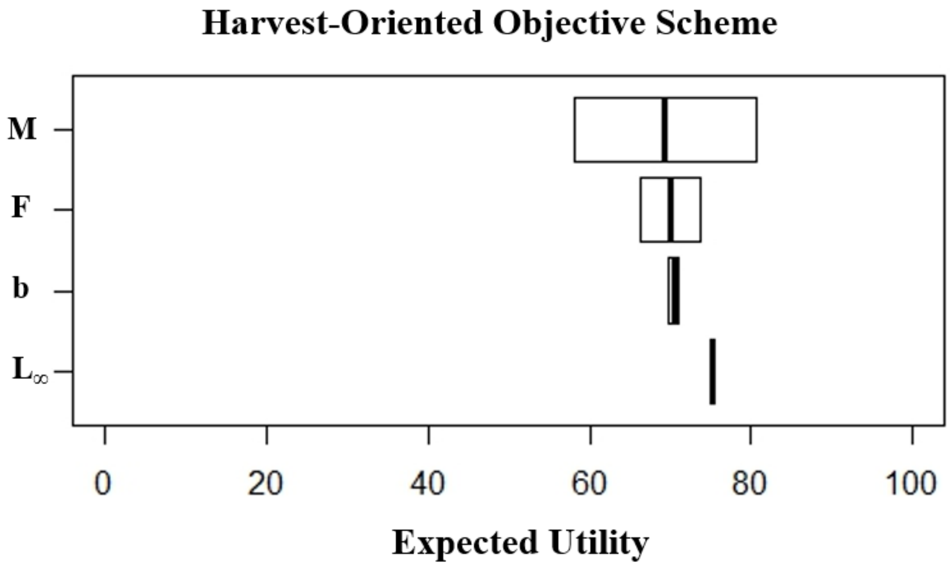

Figure 1.1 Tornado diagram for harvest-oriented objective scheme

Tornado diagram representing the one-way sensitivity analysis of the expected utility of the optimal MLL for the harvest-oriented objective scheme to variations in L_∞, b, M, and F.

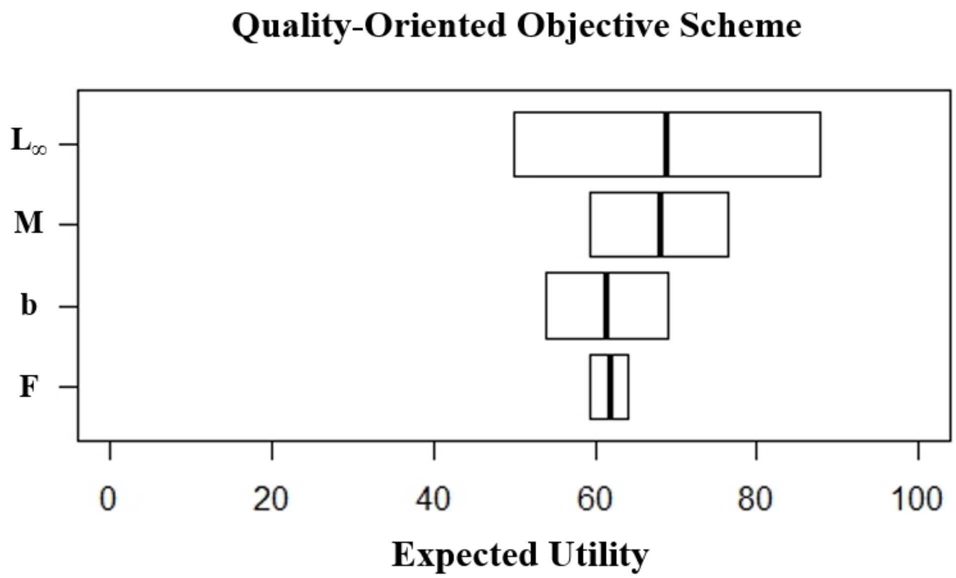

Figure 1.2 Tornado diagram for quality-oriented objective scheme

Tornado diagram representing the one-way sensitivity analysis of the expected utility of the optimal MLL for the quality-oriented objective scheme to variations in L_∞, b, M, and F.

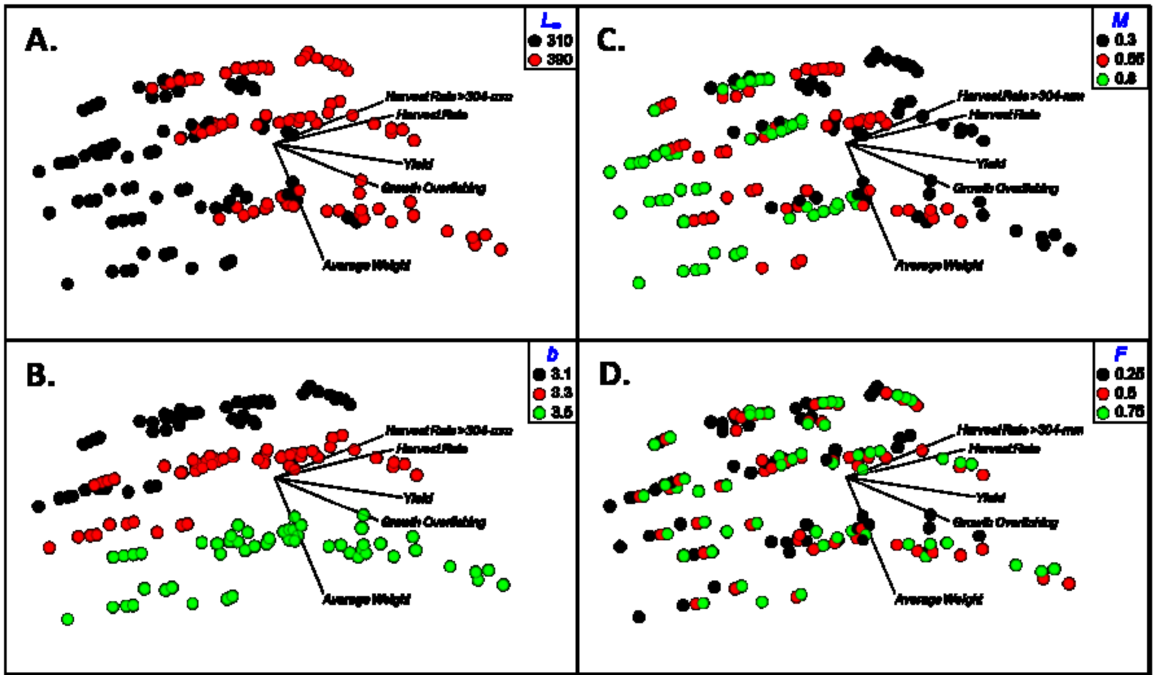

Figure 1.3 Principal coordinates analysis for model parameters

Principal coordinates analysis, with 162 unique parameter combinations selected from Table 1.1, showing how changes L_{∞}, b, M, and F associate with the performance metrics from Table 1.2.

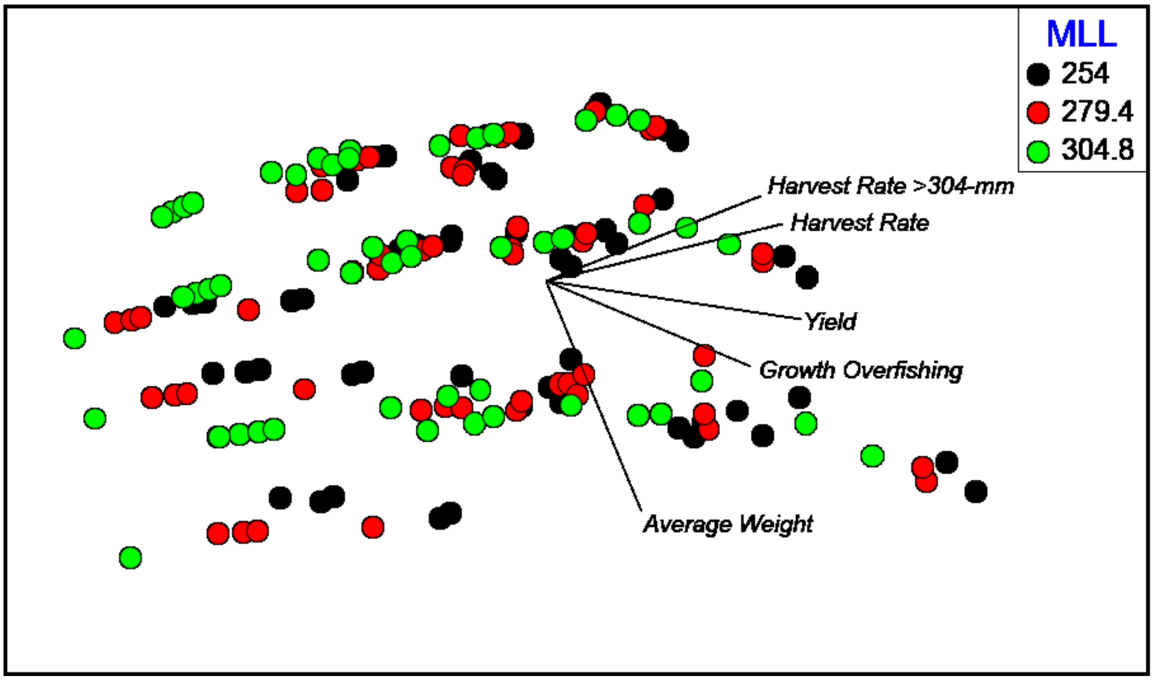

Figure 1.4 Principal coordinates analysis for MLL

Principal coordinates analysis, with 162 unique parameter combinations selected from Table 1.1, showing how changes in MLL associate with the performance metrics from Table 1.2.

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