Relationship Between Water Quality and Relative Weight of Four Sportfish Species in Oklahoma Impoundments

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Abstract: This project sought to classify 108 Oklahoma impoundments based on water quality as well as determine if water-quality parameters in these impoundments influenced the relative weight (W_r) of largemouth bass (*Micropterus salmoides*), white crappie (*Pomoxis annularis*) and black crappie (*Pomoxis nigromaculatus*), and channel catfish (*Ictalurus punctatus*). Agglomerative hierarchical clustering and subsequent discriminant analysis of seven water-quality parameters resulted in the grouping of impoundments into three classes. Chlorophyll-*a*, salinity, pH, and dissolved oxygen were the most important explanatory variables (83%) in impoundment classification. Class-1 impoundments (primarily located in east central and southeastern Oklahoma) had low salinity and pH values. Class-2 impoundments (spread statewide with a high concentration in the central part of the state) had mid-range pH and mid to low-range salinity values. Class-3 impoundments exhibited higher salinity and pH values. Mean W_r was relatively consistent among impoundment classes (largemouth bass = 92–98, crappie = 91–96, channel catfish = 86–92), but individual impoundment W_r ranged widely among classes (largemouth bass = 78–129, crappie = 66–139, channel catfish = 66–147), suggesting differences in fish condition among some impoundments. Multiple regression models found only a weak relationship among water-quality parameters and W_r, explaining no more than 11% of the variation among species, suggesting that additional research is needed before a solid model of lake classification can be suggested. Despite the lack of relation between W_r and water quality found in this study, other standard population metrics (e.g., size structure, age structure, and growth and mortality rates) may better characterize population health and therefore show a better correlation to limnological characters. Given the differences in water-quality parameters among impoundment classes noted in this study, a class-level goal for a particular metric might serve a better purpose and prove more beneficial to a manager than a statewide goal.

Fisheries management is primarily concerned with creating and/or maintaining sustainable fish populations to support recreational and commercial fisheries. Often, successful fisheries have fast growing, healthy sportfish populations; thus, fisheries biologists usually measure the body condition of fishes in waterbodies under their purview. One tool used to measure this is the relative weight (W_r) metric, which is a measure of an individual fish's health. It is determined by comparing the weight of an individual fish to a standard weight at the same length, calculated using an equation for each species that has been derived using length-weight data from a large number of populations across its range (Neumann et al. 2012). This value is given as a percentage of an individual fish's actual weight compared to its standard weight (Bolger and Connolly 1989). It is assumed that a healthy fish will weigh more than the average fish, and thus a high value for W_r equates to a fat, healthy fish, while a low W_r equates to a thin, malnourished fish (Wright 2000). Although other physiological based indices,

such as lipid content, exist to determine fish body condition, these analyses are expensive and require an advanced level of expertise to perform. For most applications, length and weight data provide adequate results for fish condition (Quist et al. 2009).

Various factors can mediate growth and body condition of fishes in aquatic systems. Landscape-scale factors such as geology and land uses can determine the availability and concentration of nutrients and other ions in the water. Trophic state of waterbodies can play a large factor in determining growth and ultimately body condition of fishes. For instance, Chu et al. (2015) examined fish W_r of up to 22 species in 693 Ontario lakes and found that W_r was higher for fish in eutrophic systems than those from oligotrophic and mesotrophic systems. Similarly, DiCenzo et al. (1995) noted that W_r of Alabama bass (*Micropterus henshallli*) in 10 Alabama reservoirs had a positive correlation to parameters including chlorophyll-*a*, drainage area, alkalinity, conductivity, and the morphoedaphic index, but had a negative correlation with Secchi disk

transparency. Most of these factors are correlated with trophic state, with eutrophic waters often having higher chlorophyll-*a*, alkalinity, and conductivity, but low Secchi disk transparencies. Although some of these variables are influenced by anthropogenic impacts such as sedimentation and non-point nutrient inputs, Chu et al. (2015) found that ecological (air temperature, precipitation, lake morphometry, and water quality) variables had a larger impact on fish condition than anthropogenic (human related watershed stress and angling pressure) variables in Ontario lakes. While eutrophication of a particular waterbody can initially result in increased W_r for a species, increased nutrients can result in the inhibition of natural reproduction and the eventual replacement of existing taxa by more tolerant species (Colby et al. 1972). This process has been observed within the Percidae family, where an initial increase in growth rate and production was followed by a large decline (Leach et al. 1977).

The W_r index has proven useful to evaluate population quality in terms of growth, individual fitness, density, and forage supply (Willis 1987, Guy and Willis 1995, Maceina and Grizzle 2006). Unlike age evaluations, length and weight data are commonly collected in the field, allowing easy calculation of W_r. Thus, data to calculate this index is often available over large geographic scales, allowing biologists to conduct regional evaluations of body condition across numerous systems of varying physical and chemical compositions. If W_r is related to these waterbody characteristics, it could afford biologists a tool to understand the potentials and limitations of these systems and offer a way of grouping them in terms of potential biologic productivity in lieu of simply close geographic proximity. Given that optimal chemical and physical characteristics of waterbodies differ among many popular sport fish species, the relationship between W_r and these characteristics are likely species specific. Quantifying these impacts would allow for more efficient management of aquatic systems and offer a tool for state agencies to engage the angling public to help them better understand how water-body characteristics and species biological requirements interact.

In order to understand whether Oklahoma impoundments could be grouped into similar classes based on routinely measured water-quality variables, we investigated the potential effect of water-quality parameters for 108 impoundments across the state on the mean W_r for largemouth bass (*Micropterus salmoides*), black crappie (*Pomoxis nigromaculatus*) and white crappie (*Pomoxis annularis*), and channel catfish (*Ictalurus punctatus*). These species were chosen due to their wide distribution across the state, their popularity among recreational anglers, and the large amounts of data available in comparison to other sportfish species. The objectives of this project were to: 1) determine if a correlation

exists between the mean W_r of the four study species and seven water-quality variables in 108 Oklahoma impoundments, and 2) classify these impoundments according to their water chemistry.

Study Area

The study area for this project encompassed 108 impoundments in Oklahoma. Impoundments with the largest surface areas are concentrated in the eastern portion of the state, with several smaller bodies of water located in the central and southwestern regions, decreasing in abundance moving northwest into the panhandle (Figure 1). This is mostly due to a significant variation in annual precipitation, which decreases from east to west across the state. Oklahoma's annual precipitation can vary from greater than 139 cm in the far southeast to less than 50 cm in the western Oklahoma panhandle (Mesonet 2017). As a result of regional precipitation differences, the dominant vegetation cover transitions from heavily timbered areas in eastern Oklahoma, to semiarid plains and Rocky Mountain foothill vegetation in the west. With a large portion of the state situated in the Southern Plains, Oklahoma experiences all seasons and has large daily temperature variation (Costa et al. 2007).

Ranching and agricultural land use is common throughout the state, particularly in the western half; whereas, forestry is common in the southeast. Some impoundments, such as Arcadia, Hefner, and Keystone are located adjacent to or within major population centers. Geologic factors, such as the contribution of salts to many western Oklahoma streams (the Cimarron River and Elm Fork of the Red River in particular) that drain the eastern edge of the Permian Basin likely contribute to high salinity levels in certain impoundments (Johnson 1981). Increased precipitation has been correlated to decreased salinity in some western Oklahoma streams (Pionke and Nicks 1970). The ranges of values for impoundment water-quality parameters (chlorophyll-*a*, average turbidity, average Secchi depth, salinity) are vast (Figure 1).

Methods

This project utilized three data sources. The Oklahoma Water Resources Board (OWRB) provided geospatial data for all the impoundments (OWRB 2016a). Water-quality data came from the Beneficial Use Monitoring Program (BUMP) of the OWRB (OWRB 2016b). Length (TL, mm), weight (g), and sampling data (gear type, unit of effort, date) for each study species were taken from the ODWC Standardized Sampling Procedures (SSP) dataset. This dataset contains abiotic, biotic, and descriptive data for all impoundments and species sampled and managed by the ODWC. Data were collected in accordance with the ODWC SSP Manual.
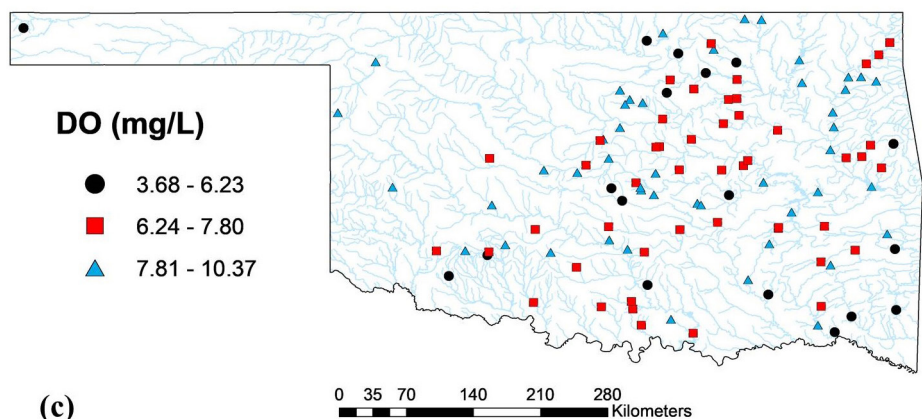
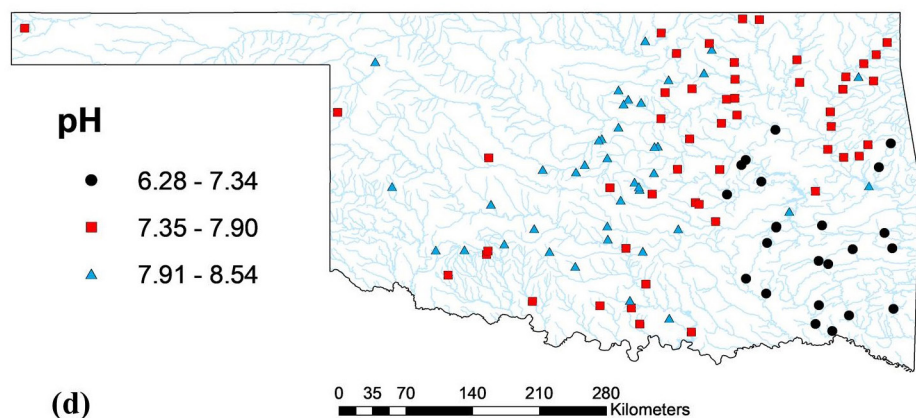The OWRB samples water quality in Oklahoma impoundments
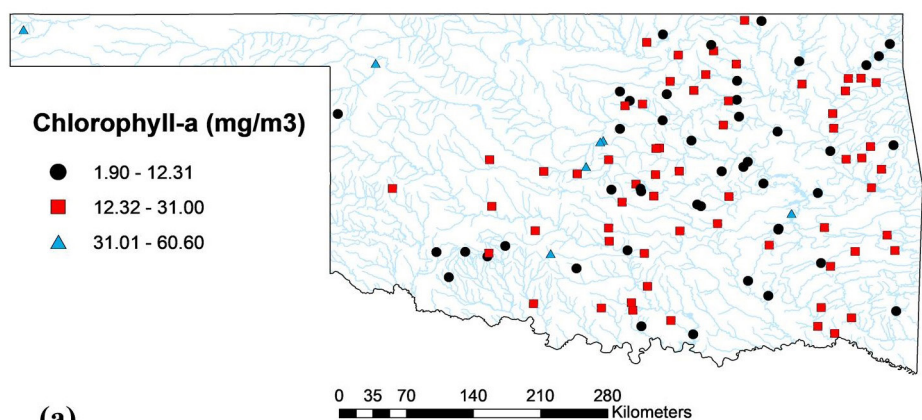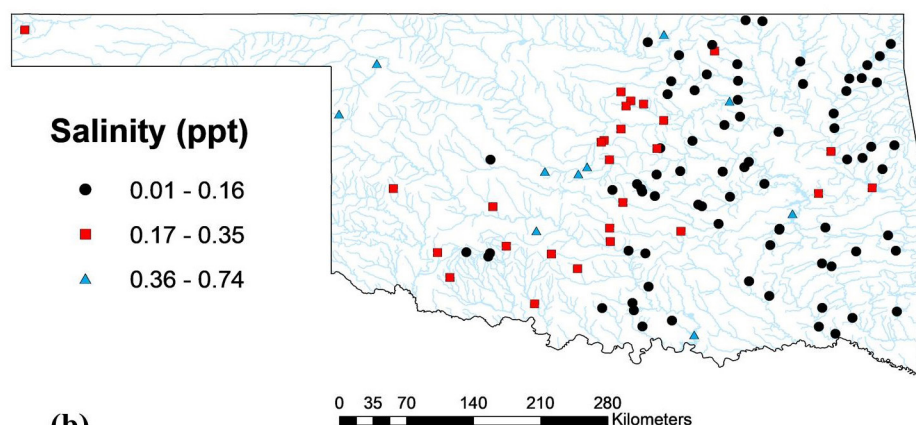
Figure 1. Chlorophyll-*a* (a), salinity (b), dissolved oxygen (DO) (c), and pH (d) range and location of study impoundments adapted from the Beneficial Use Monitoring Program Nutrient Status figure in Lakes of Oklahoma.

annually. Impoundments are sampled four times over a ten-month period (usually October through the following July) to account for seasonal variation. Either the Y.S.I. 6-series or the EXO² sonde (Yellow Springs Instruments, Inc., Yellow Springs, Ohio) was used to collect data for parameters including temperature, barometric pressure, dissolved oxygen (DO), DO percent saturation, pH, specific conductivity, salinity, depth, oxidation-reduction potential, total dissolved solids, and resistivity. Turbidity values were measured with a HACH 2100Q portable turbidimeter (Hach Co., Loveland, Colorado). Secchi depth measurements were taken using a Secchi disk. To determine cholorophyll-*a* concentrations, surface samples were collected, filtered, and ground at the OWRB laboratory according to their standard methods and sent to a contract laboratory for analysis (OWRB 2016b). Chlorophyll-*a* (mg m⁻³), average turbidity (NTU), average Secchi (cm), salinity (ppt), pH, oxidation-reduction potential (mV), and DO (mg L⁻¹) values were used for the purposes of this project. Specific conductivity was not used due to its high correlation ($r > 99\%$) with salinity. These data were available as a mean value for each impoundment, which was necessary to satisfy the design of this study's analysis. Acceptable ranges for the survival of most fish species include at least 2 mg L⁻¹ for DO and an optimal pH between 6.5 and 8.2 (MTU 2018). Turbidity and Secchi measurements can vary greatly between impoundments and seasons and can affect species differently depending upon a species reliance on sight versus other senses. Maximum salinity tolerance for largemouth bass, crappie, and channel catfish adults is approximately 12, 5, and 10 ppt, respectively (Stuber et al. 1982, Edwards et al. 1982, and McMahon and Terrell 1982).

Although the BUMP program monitors water quality at many of the study impoundments annually, some are not sampled as often, and BUMP data were available for each impoundment in the study from 2006 to 2016. Data for large impoundments were reported in regions, which were composed of multiple sampling sites. Available data were presented as an average for the impoundment (or region of the impoundment) dependent on size. In order to avoid calculating a total mean from these regional means, the furthest downstream (or dam adjacent) region was used on larger impoundments.

Mean W_r were calculated for each species by impoundment using the SSP dataset to identify any potential geographic trends in the data. Black crappie and white crappie were pooled into one category because both species are commonly managed as a group in Oklahoma. Largemouth bass were primarily sampled in the spring, whereas crappie and channel catfish were primarily sampled in fall and late summer, respectively. This could result in higher W_r means for largemouth bass due to the presence of enlarged gonads during the spawning season. Few publications address sample-size

requirements for calculating W_r estimates, but Quist et al. (2009) suggested a *n* of at least 100 individuals for the calculation of W_r when density data are not available. Wege and Anderson (1978) recommended a *n* of 10 to 20 largemouth bass in impoundments with densities greater than 50 bass ha⁻¹ and a *n* greater than 20 for impoundments with lower densities. Recommended minimum *n* for populations range from 5 to 50 (Brown and Murphy 1996, Brouder et al. 2009). For the Oklahoma SSP dataset, the *n* for some species were low (<20) for some impoundments, but due to the wide geographic scope of this project, all available data were used. Mean W_r was calculated for each fish greater than the minimum lengths for each species (150, 100, and 70 mm for largemouth bass, crappie, and channel catfish, respectively) recommended for the W_r equation by Neumann et al. (2012). Data for each species were not present for all study impoundments; largemouth bass data was present for 97 impoundments, crappie for 85 impoundments, and channel catfish for 77 impoundments.

Multivariate techniques have been used extensively to analyze water-quality data and can also aid in the determination of spatial differences due to natural and anthropogenic factors (Wunderlin et al. 2001, Singh et al. 2004, Shrestha and Kazama 2007, Shrestha et al. 2008). By using cluster analysis (CA) as an exploratory exercise, impoundments can be grouped into classes based on the similarities and differences of factors that relate to those impoundments (Singh et al. 2004). Discriminant analysis (DA) requires an initial number of groups and assigns objects into these pre-defined groups according to like properties (Wunderlin et al. 2001, Singh et al. 2004, Shrestha and Kazama 2007, Shrestha et al. 2008).

A combination of hierarchical agglomerative CA and DA techniques following Singh et al. (2004) were used to classify impoundments based on BUMP data. An outlier analysis was used to remove impoundments based on both water-quality parameters and mean W_r values, which addressed the problem of resulting CA classes with too few impoundments. Also, DA cannot be run if a grouping contains fewer objects than the total number of explanatory variables (in this case seven) (XLSTAT 2018). Cluster analysis was performed on standardized water-quality data using the Ward's method with Euclidian distance to measure dissimilarity (Singh et al. 2004). This evaluated distances between objects, grouping objects that minimized the agglomeration criterion until each of the objects were clustered. The resulting truncated dendrogram was used to determine the number of classes after truncation (XLSTAT 2018).

Spatial DA was then performed on raw water-quality data (composed of seven parameters) after grouping into three classes that were acquired through CA using the standard, forward, and backward stepwise modes. The class (clustered) was the grouping

(dependent) variable and the water-quality parameters were the independent variables (Singh et al. 2004). The analysis created a discriminant function for each group, using this equation:

$$f(C_i) = k_i + \sum\nolimits_{j=1}^{n} w_{ij} p_{ij}$$

where i is the number of classes (C), the constant for each class is k_i, the number of parameters used to classify a data set into a given class is n. In this case, n represented the number of parameters used to allocate a measure from an impoundment into a particular class. Discriminant analysis assigns the weight coefficient (w_j) to a given selected parameter (p_j) (Wunderlin et al. 2001, Singh et al. 2004). Discriminant analysis allows for considerable data reduction, retention of parameters with significant influence, and added information over factor analysis and principal components analysis when evaluating spatial differences between locations (Wunderlin et al. 2001, Singh et al. 2004, Shrestha et al. 2008).

Mean W_r was then regressed onto the DA factor axes to identify one or more factors from the DA that might facilitate the prediction of mean W_r for a given species within impoundments. This analysis used multiple explanatory variables from water-quality data to model a quantitative dependent variable (mean W_r), which allowed for the measurement of the explanatory power of water-quality parameters (Sliva and Williams 2001, XLSTAT 2018). Goodness of fit was evaluated by plotting values predicted against observed values (not shown). Significance for all statistical tests in the study was set at $P = 0.05$.

Results

Variation in mean W_r across the study area was not as high as expected (Table 1). Although means were consistent for each species, a high range was apparent for each class and statewide, suggesting there were differences in fish condition among some impoundments. The SD of W_r for largemouth bass was smaller among the three classes and statewide when compared to crappie and channel catfish (Table 1).

The CA resulted in assignment of each impoundment into one of three classes. In all three DA modes (standard, forward, and backward stepwise), chlorophyll-*a* (62%), salinity (68%), pH (74%), and DO (66%) exhibited strong positive correlation with the first axis (F1). Average secchi depth (-51%) was negatively correlated. Chlorophyll-*a* (-68%) had a strong negative correlation with the second axis (F2), while oxidation-reduction potential (52%) had a moderate positive correlation (Figure 2). Bartlett's test for eigenvalue significance showed that the first two axes were significant ($P < 0.001$), and the percentage of variance explained by those axes was 100% across all modes. In standard stepwise mode, F1 explained 83% of the classifications, while F2 encompassed the remaining 17% (Figure 2). There was minimal variation in the re-

Table 1. Summary statistics for the relative weight (W_r) of each study species (black and white crappie combined) according to discriminant analysis classifications for 108 Oklahoma impoundments.

| Class | n | Largemouth bass | | | Crappie | | | Channel catfish | | |
		min	Mean (SD)	max	min	Mean (SD)	max	min	Mean (SD)	max
1	41	78	92 (6)	107	80	94 (9)	120	81	92 (13)	147
2	58	80	97 (8)	129	82	96 (11)	139	66	88 (8)	104
3	9	92	98 (4)	107	66	91 (12)	105	76	86 (8)	98
All	108	78	95 (7)	129	66	94 (10)	139	66	89 (10)	147

classification of the impoundments and the percent correct of well classified impoundments (Table 2), with the same percent correct classification regardless of DA mode. Cross-validation resulted in 90% total correct classification across all modes, whereas 11 of 108 impoundments were reclassified. Forward and backward stepwise modes produced identical results. Summary statistics for each class and statewide for the four most influential water-quality parameters are found in Table 3.

Box and whisker plots of the four most influential discriminating parameters identified by DA (standard stepwise mode) were created to visualize patterns associated with variation in water quality between classes (Figure 3). A large increase was observed from classes 1 and 2 to class 3 for chlorophyll-*a* and salinity. Both DO and pH gradually increased progressing from classes 1–3.

Class-1 impoundments, which were located primarily in east central and southeastern Oklahoma, had some of the lowest salinities and pH values in the dataset. Class-2 impoundments were spread across the state, with the largest concentration in central Oklahoma. Mid-range pH and mid- to low-range salinity values best describe this class. Class-3 impoundments exhibited higher salinity and pH values (Figure 4). Salinity and pH appeared to be distributed on a southeast to northwest gradient (low to high) across the study area. The distribution of chlorophyll-*a* and DO was erratic and did not appear to have any resemblance to this pattern (Figure 1). Chlorophyll-*a* had the highest variance in SD between the classes (6.54–16.60), but the remaining variables showed little variation (Table 3). The cluster of Class-3 impoundments is well discriminated on the factor axes, while the class-1 and -2 clusters showed some overlap (Figure 5). All modes of DA indicated the importance of DO, pH, salinity, and chlorophyll-*a* in the classification of impoundments.

The multiple regression analysis resulted in low R^2 values for
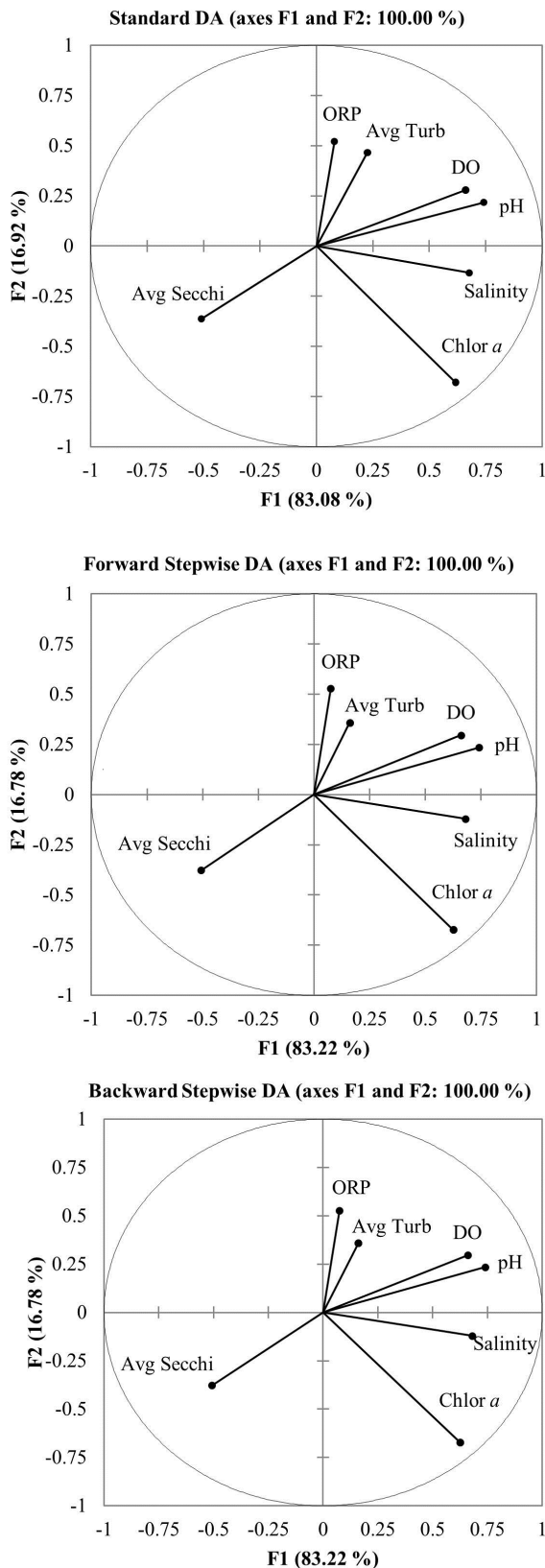
Figure 2. Ordination diagrams depicting results for the standard, forward stepwise, and backward stepwise discriminant analysis of water quality variables.

Table 2. Confusion and cross-validation matrix totals showing the percent correct classified observations for each type of discriminant analysis by class.

| Confusion matrix classes	1	2	3	Total	% correct
Standard DA mode					
1	38	5	0	43	88.37%
2	3	51	1	55	92.73%
3	0	2	8	10	80.00%
Total	41	58	9	108	89.81%
Stepwise (forward) DA mode					
1	38	5	0	43	88.37%
2	4	50	1	55	90.91%
3	0	1	9	10	90.00%
Total	42	56	10	108	89.81%
Stepwise (backward) DA mode					
1	38	5	0	43	88.37%
2	4	50	1	55	90.91%
3	0	1	9	10	90.00%
Total	42	56	10	108	89.81%

each species (0.02, 0.01, and 0.11 for largemouth bass, crappie, and channel catfish, respectively), indicating that the water-quality parameters used did not explain variation in W_r very well on their own. The only significant result for the standardized coefficients was for channel catfish (-0.25), although the effect of the F1 variable on channel catfish W_r was weak at best (Table 4).

Discussion

Studies have found that water-quality parameters can have an effect on mean W_r (e.g., Chu et al. 2015). However, we were unable to relate these differences to measurable changes in mean W_r of four sportfish species in Oklahoma impoundments despite water-quality differences found among the impoundments. The means for each species were relatively typical and fit well with the assumption that a fish with W_r of 90 or more is a healthy fish (Stahl and Harper 2008). Overall consistency in mean W_r for each species within an impoundment class may have contributed to the lack of relation found with water quality. Changes in spatial scale, evaluation of different size classes of the same species, or possibly the use of a species that exhibits higher mean variation could result in a more complete model. Additional explanatory variables are also likely needed to benefit any future work including land use/ land cover, surface geology, drainage basin size, variation in impoundment surface area, number and abundance of forage species present, angling effort, and habitat evaluation. Data representing many of these variables were not accessible to us or obtainable

Table 3. Summary statistics for the four most influential water quality parameters according to the discriminant analysis classifications for 108 Oklahoma impoundments.

Parameter	Classes (*n*)			
	1 (41)	**2 (58)**	**3 (9)**	**All (108)**
Chlorophyll-a (mg m^{-3})				
Min	1.9	3.0	15.6	1.9
Mean	12.9	14.2	38.8	15.8
(SD)	(8.5)	(6.5)	(16.6)	(11.0)
Max	45.0	31.0	60.6	60.6
Turbidity (NTU)				
Min	2	3	7	2
Mean	12	29	20	22
(SD)	(15)	(32)	(15)	(27)
Max	96	143	53	143
Secchi (cm)				
Min	26	8	19	8
Mean	101	56	48	72
(SD)	(51)	(34)	(25)	(46)
Max	240	195	98	240
Salinity (ppt)				
Min	0.01	0.02	0.29	0.01
Mean	0.10	0.17	0.51	0.17
(SD)	(0.11)	(0.11)	(0.18)	(0.16)
Max	0.71	0.58	0.74	0.74
pH				
Min	6.28	7.16	7.76	6.28
Mean	7.36	7.86	8.31	7.71
(SD)	(0.43)	(0.27)	(0.24)	(0.45)
Max	8.15	8.27	8.54	8.54
Oxidation reduction potential (mV)				
Min	44.1	173.1	149.9	44.1
Mean	283.7	345.8	286.4	317.3
(SD)	(106.8)	(61.5)	(79.8)	(87.8)
Max	450.0	471.0	422.2	471.0
Dissolved oxygen (mg L^{-1})				
Min	3.68	5.81	6.90	3.68
Mean	7.36	7.93	8.42	7.42
(SD)	(1.09)	(0.77)	(1.18)	(1.20)
Max	8.43	9.56	10.37	10.37
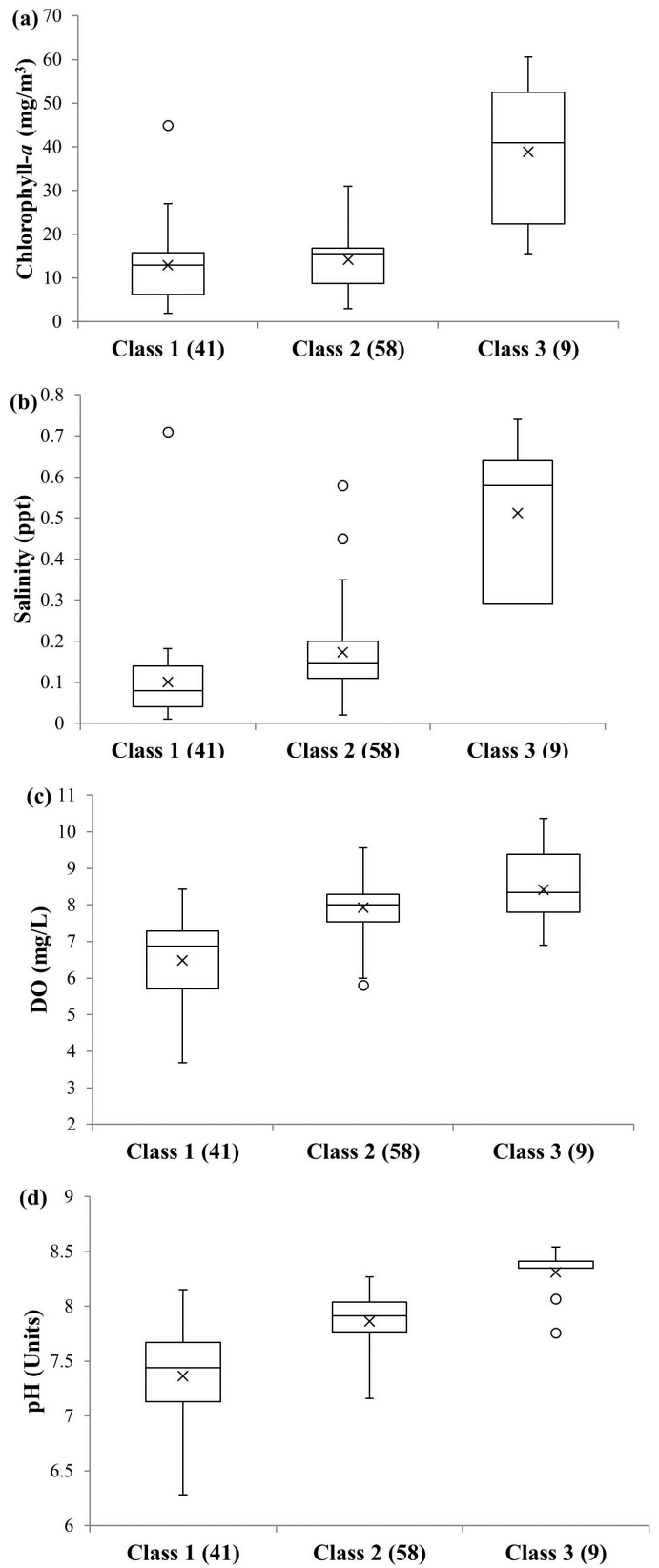
Figure 3. Spatial variations for the four most influential water quality parameters: Chlorophyll-*a* (a), salinity (b), dissolved oxygen (DO) (c), and pH (d) in Oklahoma impoundments. Total number of impoundments in each class are listed in parentheses.
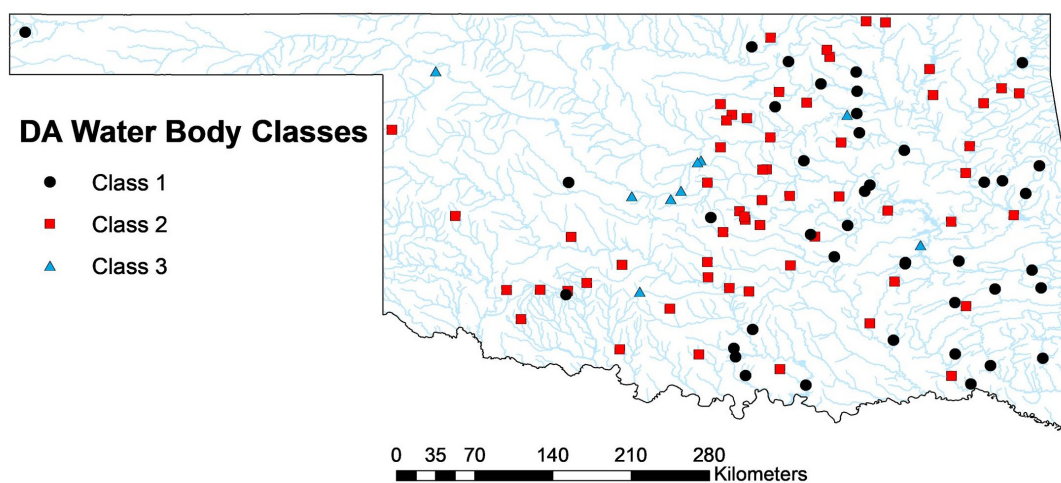
Figure 4. Spatial discriminant analysis classification of 108 Oklahoma impoundments.
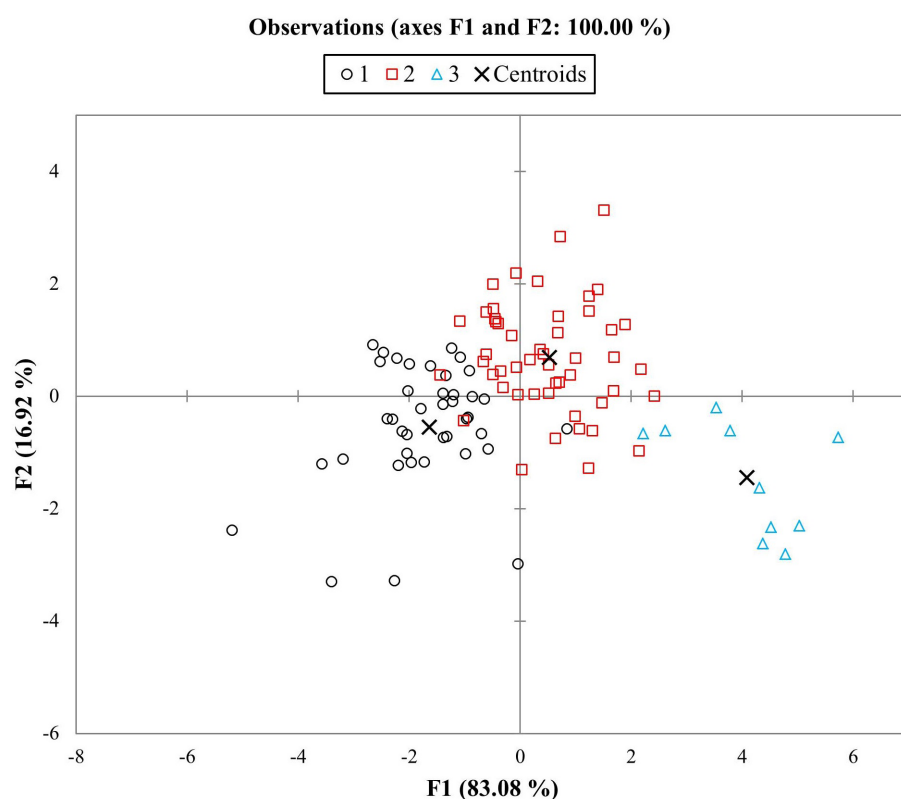
Figure 5. Impoundment class centroids and clusters with respect to discriminant analysis axes 1 and 2.

Table 4. Standardized coefficients (Std Coef), SE, and *P*-values (in parentheses) for the discriminant analysis factor axes by species.

	Bass		Crappie		Channel Catfish	
	Std coef	SE	Std coef	SE	Std coef	SE
F1	0.025	0.101 (0.802)	0.067	0.110 (0.546)	−0.253	0.110 (0.024)
F2	−0.146	0.101 (0.152)	−0.040	0.110 (0.716)	−0.204	0.110 (0.068)

within a timely manner due to the scale of the study area. Also, the methods used in this study would potentially need revision in order to accommodate additional explanatory variables due to the limitations of DA.

Modelling the potential link between water quality, additional explanatory variables, and mean W_r could inform decision-making for fisheries managers based on contributing explanatory factors rather than geographic location alone. For example, Lake Etling, located in far northwestern Oklahoma, clustered with impound-

ments in central and eastern Oklahoma based on water-quality parameters rather than other impoundments in western Oklahoma. This similarity is likely the result of geologic substrate, as Lake Etling is located on Paleozoic sandstones that lack halide deposits. It may be questioned, then, whether Lake Etling should be managed with the expectation of fish achieving a W_r akin to nearby impoundments or rather to eastern impoundments.

We approached this study as an exploratory exercise and believe the outcome, although not as successful as expected, still provides valuable information. This serves as a starting point for future work, helping to adjust and refine the approach and variables necessary for impoundment classification and its correlation to W_r. Even though W_r might not be the best differentiator of system productivity, ODWC managers could find utility in the comparison of other standard population metrics (such as length frequency, age and growth, and mortality) between impoundment classes. This would create the potential to base management strategies on a limnologic approach, rather than a geographic one. Artificial and often dynamic geopolitical boundaries have a tendency to influence management approaches by resource managers. Removing the geopolitical influence may allow for more ecological based management strategies to be utilized from a classification system like the one developed in this study. A class-level goal for a particular fisheries population metric might serve a better purpose and prove more beneficial to a manager than a statewide goal or benchmark (i.e., average statewide growth rate for channel catfish). Some examples that utilize study species include: a class of impoundment in which crappie growth could benefit from the introduction of saugeye *(Sander canadensis x S. vitreus)*, or differentiation between classes with impoundments that can sustain a higher stocking density of channel catfish while retaining adequate growth (Boxrucker 1992, Patterson 2014, Carl 2017). These impoundment classes could serve as a valuable tool for the continued evaluation of best management practices moving into the future.

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