State of California
Department of Fish and Wildlife

M e m o r a n d u m

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Subject: Predicting 2015 and 2016 White Sturgeon Year Class Index

I have attached the report detailing how we predict the 2015 and 2016 White Sturgeon Year Class Index (YCI) by modeling the relation of YCI as a function of Sacramento Valley Water Year Index. This memorandum serves as a formal way of documenting and preserving my work.

Predicting 2015 & 2016 White Sturgeon Year Class Index

Introduction

We can calculate a year class index (YCI) for White Sturgeon from Bay Study survey data (Fish 2010, Figure 1). This YCI is calculated using age-0 and age-1 fish and requires data over a 2-year span. Due to unforeseen circumstances, Bay Study fieldwork was markedly truncated in 2016 making it impossible to calculate a YCI for 2015 and 2016. Here we present an option for predicting the 2015 and 2016 White Sturgeon YCI by modeling the relation of YCI as a function of Sacramento Valley Water Year Index (SVWYI). I got the 1980-2015 SVWYI from http://cdec.water.ca.gov/cgi-progs/iodir/WSIHIST and a preliminary 2016 SVWYI from CDWR via Randy Baxter.

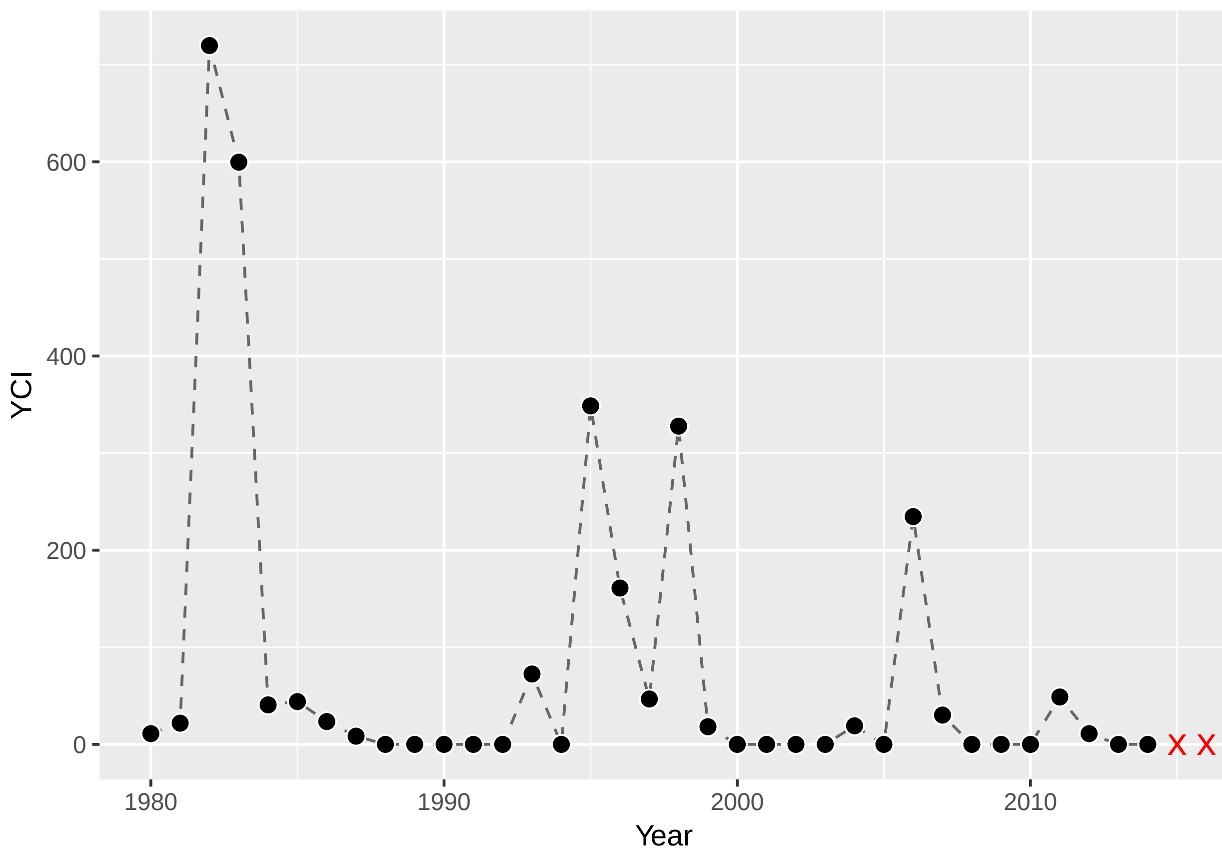

Figure 1: White Sturgeon Year Class Index 1980-2014 as calculated from Bay Study survey data. Red 'X' indicates values we wish to predict.

Relation of YCI on SVWYI

We used R software (R version 3.3.2 (2016-10-31)) to fit all models and to display data and model output. We used R packages `stats` (built-in) and `ggplot2` (installed).

We find the relation of YCI ~ SVWYI is positively correlated (r = 0.75, p = 0.00000019). Visually, the relation might be described as exponential (Figure 2).

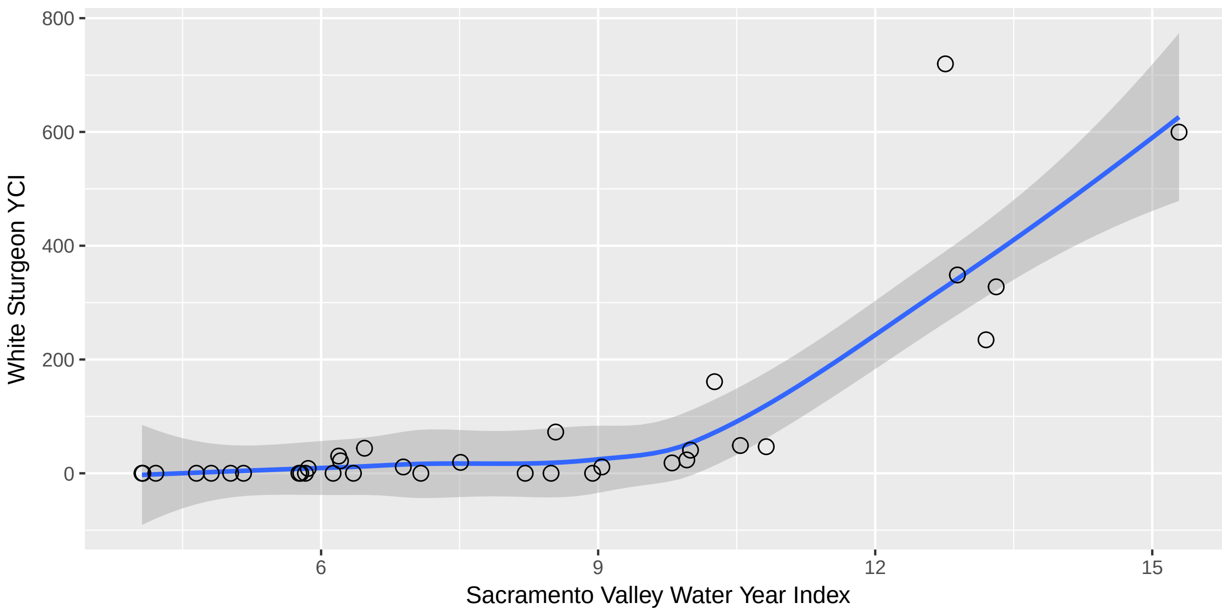

Figure 2: YCI as a function of SVWYI with loess line (blue) & 95% confidence interval (shaded), 1980-2014

We employ a linear model (with data transformation, equation 1) and a non-linear power model (`PWR`, equation 2, Crawley 2007). We fit linear models using `stats::lm()` and the power function using `stats::nls()`. Note: judging from the relation (Figure 2) applying a simple linear model (without data transformation) is obviously not appropriate, and so we opted not to fit this model.

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \tag{1}$$

$$y = ax^b \tag{2}$$

We estimate YCI ($\hat{y}$) using an exponential model (`LOG`, equation 3, natural log of YCI), and power function (`LLG`, equation 4, natural log of YCI and natural log of SVWYI). Note: when taking natural log of YCI, we added 1 to each YCI value due to the 0 values of YCI ($ln(YCI + 1)$). The non-linear power model (`PWR`) applies equation 2, where variable `y` and parameters `a` and `b` are now estimates (i.e., $\hat{y}$, $\hat{a}$, $\hat{b}$).

$$ln(\hat{y}) = \hat{\beta}_0 + \hat{\beta}_1 x \tag{3}$$

$$ln(\hat{y}) = ln(\hat{\beta}_0) + \hat{\beta}_1 ln(x) \tag{4}$$

Model Coefficients

Both linear models are comparable in terms of adjusted R^2 and residual standard error (RSE, Table 1). We obtain least-squares estimates (for parameters `a` & `b`) from our non-linear model, but only `b` is statistically significant (Table 2, see p-value in `Pr(>|t|)`, $p<0.05$). We will look into this further, but for this exercise we will visually compare the fit of this model with the two linear models.

Table 1: Results of fitting linear regression models to YCI as a function of SVWYI. 'Beta0' is intercept, and Beta1 is slope.

Model	Beta0	Beta1	RSE	FStat	AdjRsq	Df	PVal
Lin-Exp	-2.843751	0.6329178	1.300187	73.06902	0.6794540	33	p<0.05
Lin-Pwr	-7.853082	5.0049407	1.375299	61.79951	0.6413484	33	p<0.05

Table 2: Results of fitting non-linear regression model to YCI as a function of SVWYI.

	Estimate	Std. Error	t value	Pr(>|t|)
a	0.0024188	0.0043180	0.5601683	0.5791479
b	4.5964187	0.6804946	6.7545265	0.0000001

We can now add the estimated model parameters to our equations. Note: for linear models, we take the antilog of `Beta0` (e.g., $exp(\beta_0)$)

$$\hat{y} = 0.058207e^{0.6329178x} \quad \text{(linear exponential)}$$

$$\hat{y} = 0.0003885525x^{5.0049407} \quad \text{(linear power)}$$

$$\hat{y} = 0.00241881x^{4.5964187} \quad \text{(non-linear power)}$$

Plotting Model Fits

Visually, it appears the power function (`PWR`) fit with `stats::nls()` would yield a reasonable prediction (Figure 3). However, we would need to complete further testing to compare models and model fit.

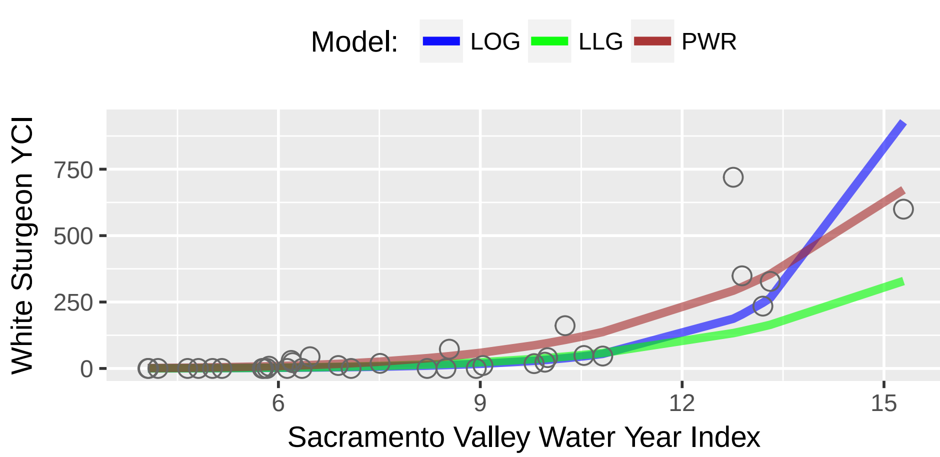

Figure 3: YCI as a function of SVWYI with lines of three model fits, 1980-2014.

Predict 2015 White Sturgeon Year Class Index

Given our models, we can now predict a 2015 and 2016 White Sturgeon YCI. The Sacramento Valley Water Year Index for 2015 was 4.01 and for 2016 was 6.7.

2015

$\text{YCI}_{\text{LOG}} = 0.7365707$
$\text{YCI}_{\text{LLG}} = 0.40565$
$\text{YCI}_{\text{PWR}} = 1.4318774$

2016

$\text{YCI}_{\text{LOG}} = 4.0422391$
$\text{YCI}_{\text{LLG}} = 5.2954773$
$\text{YCI}_{\text{PWR}} = 15.1560992$

References

Crawley MJ. 2007. The R Book. First Edition. John Wiley & Sons, Ltd., England. 942 p.

Fish MA. 2010. A white sturgeon year-class index for the San Francisco Estuary and its relation to delta outflow. Interagency Ecological Program for the San Francisco Estuary Newsletter 23(2). https://nrm.dfg.ca.gov/FileHandler.ashx?DocumentId=26542

R Core Team (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/

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CDFW Sportfish Unit