No. 142, Original

In the

Supreme Court of the United States

STATE OF FLORIDA,
Plaintiff,
v.
STATE OF GEORGIA,
Defendant.

Before the Special Master
Hon. Ralph I. Lancaster

UPDATED PRE-FILED DIRECT TESTIMONY OF FLORIDA WITNESS J. WILSON WHITE, PH.D.

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I. INTRODUCTION AND SUMMARY OF RESEARCH

1. My name is Will White and I am an Associate Professor at the University of North Carolina Wilmington (UNCW). I am an ecologist whose primary research focus is on the development of mathematical models to evaluate changes in populations of fish and other aquatic species, including oysters.

2. I was retained in this litigation to develop a computer model to examine changes in the oyster population of Apalachicola Bay to understand why that population crashed in 2012. I conducted research and development of the model in conjunction with Dr. David Kimbro, a fellow research ecologist with whom I have collaborated in other scholarly work.

3. My research also relies on particular input from another scientist, Dr. Marcia Greenblatt, who studies how patterns of freshwater flows from Apalachicola River influence environmental conditions in Apalachicola Bay.

4. Based on this research and analysis, I reached several conclusions.

5. First, the particular model I developed ‘fit’ actual observed data very well. Model ‘fit’ is a scientific research term that describes the degree to which a computer model or simulation matches observed data. The greater the degree of fit, the stronger the model is at predicting cause-and-effect relationships. In this case, the model I developed fit very well, and matched observed fluctuations in the Apalachicola Bay oyster population over 20 years.

6. Second, high salinity conditions associated with reductions of freshwater flow from Apalachicola River into Apalachicola Bay contributed to the oyster population crash in 2012. Salinity is the measure of all the salts dissolved in water. Salinity is commonly measured in parts per thousand (ppt). A salinity measurement of 35 ppt means that in every kilogram (1000 grams) of seawater, 35 grams are salt.

7. In determining that increased salinity was a principal contributor to the collapse, my model results reject the notion that over-harvesting caused the collapse. Specifically, harvesting pressure throughout the 2009-2012 time frame was not different from previous years, when the oyster fishery was extremely healthy.

8. Based on this analysis, I conclude that increased freshwater flows would improve conditions for the oyster population in Apalachicola Bay.

II. MY BACKGROUND

9. I am an Associate Professor at UNCW. I received a Ph.D. in Ecology, Evolution, and Marine Biology from the University of California Santa Barbara in 2007, and completed postdoctoral training in fisheries population modeling at the University of California Davis before joining the faculty at UNCW in 2010.

10. Since 2003 I have published more than 50 peer-reviewed journal articles on topics related to marine ecology, population modeling, and ecological statistics. My work has been funded by grants from the National Science Foundation, the U.S. Environmental Protection Agency, the North Carolina Division of Marine Fisheries, North Carolina Sea Grant, Florida Sea Grant, and California Sea Grant, among other sources. I am an internationally recognized expert in population dynamics, modeling, and management of marine species such as oysters.

11. As such, I have participated in scientific advisory panels and provided formal advice to resource managers in California, Oregon, North Carolina, the National Oceanic and Atmospheric Administration Southeast Atlantic Fishery Management Council, and British Columbia, and I have been invited to speak at both international and national scientific meetings and at a variety of research universities nationwide.

12. Other than this original action, I have never provided expert testimony in connection with litigation.

III. OBJECTIVES OF MY RESEARCH

A. Research Methodology

13. The objective of my work in connection with this original action was to collaborate with Dr. Kimbro to investigate the factors contributing to the cause of the oyster fishery collapse in Florida's Apalachicola Bay in 2012.

14. For this project, Dr. Kimbro and I took a three-pronged approach to identify causation. The three-pronged research methodology involved (**A**) monitoring of physical conditions and oyster populations in the Apalachicola Bay, to characterize patterns of variability in the system and suggest possible factors affecting population dynamics; (**B**) manipulative experiments, to establish cause-and-effect relationships for the various individual factors important to oysters in the Bay; and (**C**) population modeling, which links those individual factors and predicts their overall contribution to patterns of change in the oyster population. Dr. Kimbro was responsible for the monitoring and experimentation portions of this work, components **A** and **B** of the research approach; I developed and implemented the modeling, component **C**.

15. Employing a three-pronged approach is a useful strategy in pursuing research investigations in which observations were not made by the research team prior to or during the event of interest (oyster collapse). Such investigations are not uncommon in ecology.

16. One method to identify causation after the event of interest is to link the available data from before and during the event of interest with mathematical models. The models can then test hypotheses about the relative contribution of different factors to the event of interest.

17. For example, in 1998, well-respected scholars used such models to investigate the causes of historical population fluctuations in Canadian lynx and published their studies in the peer-reviewed *Proceedings of the National Academy of Sciences*. I have also used such models

in evaluating the cause of population changes in Pacific sockeye salmon and published my research in the peer-reviewed journal *Ecological Monographs* in 2015.

B. Selecting a Modeling Approach

18. The model I developed for this project is a state-space integral projection model (SSIPM). An SSIPM is a type of mathematical model designed to detect patterns of change in observed data that have a lot of natural variability. The model has two main components: state-space calculations, which are a way of identifying the underlying pattern in a dataset with a lot of variability, and integral projection calculations, which are a way of representing changes in the size distribution of an animal population. The size distribution is the summary of how many animals of each size are present in the population (e.g., 100 oysters less than 25 mm, 40 oysters between 25 mm and 30 mm, and so forth).

19. The 'state space' aspect of the model simply means that the model accounts for the two types of variability intrinsic to any physical or ecological system: measurement and process variability. 'Measurement' variability is the difference between a measured quantity and the actual, true state of the system. For example, an ecologist may estimate by sampling that there are 100 oysters on a bar, but the true value is 107.

20. 'Process' variability is natural variability in a system due to minor factors that are not directly accounted for in a model. For example, the average survival of oysters in a year could be 90 percent, but in any particular year the actual value could be 85 percent and in another year the value could be 95 percent.

21. A state-space model fits the data sequentially going through time (e.g., starting at the first, oldest data point and moving through time to the most recent data point). In doing so, based on repeated comparisons between the model prediction and the observed data, it

mathematically estimates both the measurement error and the process error, and accounts for them to estimate the 'true' state of the system.

22. 'Integral projection' refers to the way the model represents changes in the ecological population. An integral projection model keeps track of animals in terms of their size (in the case of oysters, their length). This means that the model can describe changes in the population due to the growth of oysters, as well as various factors that might depend on oyster size. For example, predators may focus on oysters of a particular size, and harvest is also restricted to oysters larger than a particular size.

23. Use of both state-space and integral projection approaches is well-known in research ecology. State-space techniques were developed in the 1960s and are also widely used in electrical engineering. The integral projection approach to population modeling was introduced in 2000 and has quickly become a standard method in ecology and conservation biology.

24. Recently, my colleagues and I published an article detailing how to develop an SSIPM and demonstrating the benefits of its use in a peer-reviewed journal. The article is called "Fitting state-space integral projection models to size-structured time series data to estimate unknown parameters," and was published online by the journal *Ecological Applications* in July 2016. This publication was the culmination of years of work and application of the SSIPM technique.

25. In selecting the SSIPM, I determined other modeling approaches were not suited to this particular research investigation. For example, matrix-based models could track oysters by age or stage, and then convert age to size to compare the model to data. This modeling approach is commonly used in fisheries management, but is problematic for several reasons, not

least because some model processes actually depend on size, not age (e.g., size limits for harvest). The SSIPM allowed me to more realistically model size-dependent aspects of oyster biology, and it was straightforward to match the model output with the available data, which counted oysters within size classes.

26. Additionally, other modeling techniques that are not state-space models do not directly account for measurement and process variability. Therefore they are not as reliable for detecting patterns and cause-and-effect relationships, because for example they may incorrectly assume that a change in the observed population due to measurement error represents actual fluctuations in the population. The SSIPM directly accounts for both types of variability in observed data.

C. Using Collected Data in the SSIPM

27. After selecting the right model to use, I evaluated how best to define the characteristics of the population (eastern oyster in Apalachicola Bay) which would be modeled by the SSIPM. This process of selecting appropriate characteristics is called ‘parameterization’ and simply involves choosing the right variable inputs for the model. There are two parts to this process.

28. First, there are model input parameters that describe different demographic processes in the oyster population (e.g., growth rate) that do not change over time. These values were obtained from observations and experiments conducted by Dr. Kimbro and from published, peer-reviewed literature sources.

29. Second, there are the observed data from the population of interest (in this case, 20 years of observations from Apalachicola Bay oyster reefs). The SSIPM is ‘fitted’ to these data, meaning that the model predictions for oyster abundance are compared to the observed data for that time period, and certain quantities in the model are adjusted so that there is a good match

(a good 'fit') between the model prediction and the observed data. The fitted model can then be used to deduce cause-and-effect relationships in the observed data. The quantities that are adjusted in the fitting process are termed the 'fitted' or 'estimated' parameters.

30. In performing this task, I relied on data collected by the Florida Department of Agriculture and Consumer Services (FDACS) from the Cat Point and Dry Bar oyster population. These were the observed data to which the model was fit. A map showing the major oyster bars in Apalachicola is shown below in Figure 1.

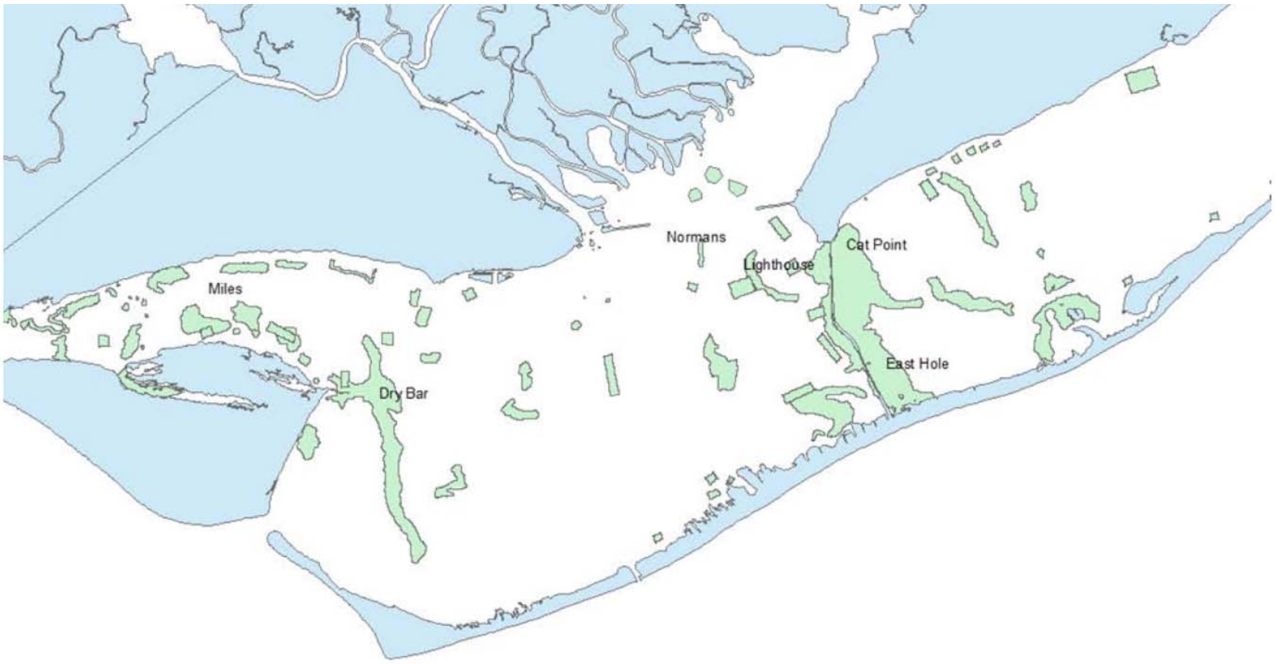

Figure 1. Map of Major Oyster Bars in Apalachicola Bay.

31. I fit the model to data from Cat Point bar for two main reasons.

32. First, that bar had the longest time series of data with very frequent sampling near the time period of greatest interest in 2009-2013, making it most suitable to obtain reliable model fits.

33. Second, it was one of the only bars in Apalachicola Bay that also had a continuous historical record of salinity collected by the Apalachicola National Estuarine Research Reserve (ANERR). Because various model processes depend on salinity, having a salinity record is necessary to fit the model. Therefore, the model primarily describes processes happening at Cat Point.

34. As a scientist, I am comfortable drawing broader conclusions about oyster populations throughout the Bay from these model results because the analysis was conservative as to harvest rate, the other parameter of interest in this study, as explained more fully below.

35. As additional support for my approach, I note that data collected from another bar in Apalachicola Bay, Dry Bar, also had a substantially robust fishery-independent dataset with corresponding salinity information.

36. The results from running the model on the Dry Bar dataset supports my conclusions based on the model run from Cat Point.

IV. OVERVIEW OF MY OPINIONS

37. After I constructed the model and checked that the model operated as expected, I fit the model to the Cat Point data as described above.

38. I then compared the pattern of population fluctuations predicted by the model to the actual population pattern of oysters in the Cat Point survey data collected by FDACS from 1992-2013.

39. The model faithfully captured major increases and decreases in the observed population abundance, and also produced size distributions that largely matched observed size distributions in the data. If the model had been formulated inappropriately or poorly parameterized, it likely would not recreate these aspects of the actual oyster population dynamics reflected in the FDACS survey data.

40. I therefore conclude the model fit the data very well.

41. The model also evaluated the impact of salinity on the Apalachicola Bay oyster population by examining how dynamics would change with alterations in salinity through increased freshwater flows from Apalachicola River.

42. I ran the SSIPM using salinity values for Cat Point derived from an alternative-flow scenario provided by Dr. Greenblatt (using the output of the hydrodynamic model described in her report) instead of actual historical salinity values.

43. I then compared the pattern of oyster abundance prior to and during the 2012 fishery collapse under this alternative scenario to the pattern obtained from fitting the model to the actual, historical pattern. Based on that comparison, I concluded that overall oyster abundance would have been higher if Apalachicola Bay had received additional freshwater during the crucial 2007-2012 period. Lack of freshwater heightened salinity levels and contributed to the oyster fishery collapse in Apalachicola Bay in 2012.

V. BASICS OF THE MODEL’S CONSTRUCTION

44. I will now summarize the basic formulation of the SSIPM. First, the SSIPM tracks the size distribution of the oyster population at each point in time. This is the number of oysters of each size (the model tracks oysters to the nearest millimeter, but converts those into 5-mm size categories to compare to the FDACS dataset).

45. The time step of the SSIPM was one week; that is, it calculates the population size distribution for every week of the SSIPM run from 1982-2013. This time interval is optimal for this system; it has enough fine-scale resolution to capture week-to-week variability in salinity and temperature (Dr. Kimbro’s experiments suggest that oyster drills respond to salinity changes on an approximately weekly time scale) and to match up to the timing of FDACS surveys (which happened at different times in different years) and changes in the oyster harvest season.

46. A finer scale (e.g., days) is computationally burdensome because it requires seven times more calculations. Even with a weekly time scale, a single computational run of the data-fitting SSIPM took approximately seven to eight days on a high-performance laboratory workstation.

47. At the most basic level, the SSIPM describes how the population size distribution changes from week to week. The population size distribution in one week is multiplied by an array of numbers, termed the ‘kernel,’ to obtain the size distribution in the following week. The kernel describes everything that can happen to an oyster in that week: it includes the probability of an oyster of a given size growing to any other size, and the probability that an oyster of a given size will die due to any of several causes. At certain times in the year, the SSIPM also includes oyster reproduction and the settlement of new spat.

48. I will explain each of these model components – growth, death, and reproduction – in turn.

A. Oyster Growth in the SSIPM

49. First, oyster growth was represented by what is known mathematically as a von Bertalanffy relationship, in honor of the Austrian biologist Ludwig von Bertalanffy who developed an equation that describes the growth of a biological organism with ‘indeterminate growth.’ Indeterminate growth refers to the increase in size of organisms that do not have a maximum size (like humans) but just keep getting bigger and bigger with age (like fish or oysters). In general organisms with indeterminate growth grow very quickly at first but then experience a slow-down in growth. Growth never quite stops in these organisms.

50. The von Bertalanffy relationship is used throughout fisheries and other population models. The shape of the growth curve is found by collecting a large number of organisms, aging them, and plotting their length versus their age.

51. The von Bertalanffy relationship has two parameters, the growth rate and the 'asymptotic maximum size.' The latter describes the average maximum size of very old individuals. Usually there is considerable spread around that 'maximum' value, with some individuals reaching larger or smaller sizes at old age. The degree of spread is also estimated from the data. Together those quantities are used to describe the probability of oysters of a particular size growing to different sizes in the next week.

52. To estimate the oyster growth curve for my model I used data collected by Dr. Kimbro, who placed juvenile oysters on experimental plots at various locations in Apalachicola Bay and tracked their growth over time. The values used in the model were updated in August 2016 based on the most recent growth data from Dr. Kimbro; those values were a growth rate of 0.01218 per week and an asymptotic maximum size of 120.35 mm. The spread was 25% of the predicted length at any given size.

B. Oyster Death in the SSIPM

53. The survival part of the kernel accounted for four possible ways an oyster could die: predators (the oyster drill), disease (Dermo), harvest, and natural mortality (excluding predation and disease). I will describe these in reverse order.

54. Natural mortality was estimated from caged oysters monitored in Dr. Kimbro's field experiments; those oysters were protected from predators and harvest, and did not exhibit Dermo disease. Those data showed that juvenile oysters (less than 15 mm) had a higher mortality rate than larger oysters, and I accounted for that difference in the SSIPM.

55. I understand that, under Florida state regulations, oysters from Apalachicola Bay may be harvested once they reached legal size, which is 76 mm (3 in). I allowed spread around this value with a standard deviation of 1 mm to account for some variation in the accuracy of sizing by harvesters.

56. In addition, regulations provide that oysters could only be harvested during legal harvest seasons. The historical schedule of oyster harvest seasons was included in the SSIPM, including the special open season in 2010 following the Deepwater Horizon disaster. The amount of harvest in a particular season was determined by a harvest rate parameter. I estimated this parameter the data, which is a process I describe in detail below (Section VIII.B).

57. Oysters could also die in the SSIPM due to infection with the Dermo pathogen. To account for Dermo infection, the SSIPM ran a secondary mini-model that tracked the abundance of Dermo due to temperature and salinity. That mini-model was based directly on equations developed by Dr. Eric Powell and Dr. Eileen Hofmann and their colleagues and published in peer-reviewed journals. Based on those relationships, once Dermo infection reached a certain point, it began to increase the oyster mortality rate.

58. Finally, the SSIPM accounted for predation, focusing primarily on the southern oyster drill, *Stramonita haemostoma*. The effects of the predator in the SSIPM were based on laboratory experiments conducted by Dr. Kimbro’s team. The mathematical relationship between drill abundance and oyster mortality was based on standard predator-prey equations (termed ‘functional responses’) used in the scientific literature.

59. However, using data from Dr. Kimbro’s experiments, I modified those equations from the literature to account for the following: (a) drill size preferences (drills of certain sizes prefer oysters of certain sizes; another example of the advantage of the size-based SSIPM approach); and (b) the effects of salinity and temperature on drill behavior. Drills are inactive at lower winter temperatures and low salinities, and are also temporarily inactivated by sudden drops in salinity.

C. Oyster Reproduction in the SSIPM

60. Reproduction in the SSIPM was a multi-step process. First, egg production was based on a published relationship with oyster size (larger oysters can spawn more eggs). Based on population genetics analyses conducted by Dr. Kimbro's lab, there is no evidence for substantial immigration of oyster larvae from other populations outside of Apalachicola Bay. Consequently, I only accounted for larvae produced in the Bay in the SSIPM.

61. Reproduction occurred in the SSIPM at two times: March and October. This frequency captures the general pattern of oyster reproduction or "recruitment" in the Bay, in which there are large pulses of new oysters or 'spat' in the spring and again in the fall.

62. Oyster larvae spend about two weeks in the plankton before settling back on the mass of stones, broken shells, and grit on which an oyster bed is formed. This mass is referred to as 'cultch.' During this larval period, they experience high mortality due to physiological stress, predation, and food limitation.

63. Because there existed no data on larval mortality available from studies in Apalachicola Bay, I relied on a 1958 peer-reviewed study by Davis which evaluated the Eastern oyster from Long Island, New York.[1] Davis presented the results of a variety of experiments investigating the relationship between salinity and egg and larval development, growth, and mortality in oysters. Focusing on his results for oyster larvae, he found that, over a series of experiments, the optimal salinity range for oyster larvae was somewhere in the 15 to 18 ppt range. Davis also determined that larval performance decreased as salinity moved away from that optimum.

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[1] Davis, H.C., 1958. Survival and growth of clam and oyster larvae at different salinities. Biological Bulletin 114: 296-307.

64. Davis did not perform any statistics on his data, so it is not possible to quantify the level of confidence or uncertainty in any particular value. Noting that his study used Long Island oysters and that oysters from different bays could have evolved slightly different salinity optima based on local conditions, I tried a range of different values for the optimum between 15 and 18 ppt. Using 15 ppt produced a good match between model and data, while using values greater than 15 ppt produced results in which the model occasionally deviated widely from the data. Therefore I used 15 ppt as the optimum in the model, with mortality increasing as salinity (averaged over the larval period) moved higher or lower.

65. The rate of increase in mortality as salinity moved away from the optimum was one of the variable parameters (labeled M_T) in the model that I estimated by fitting the model to the data.

66. Those oyster larvae that survived the larval stage were then allowed to settle into the model population. This process was limited by the availability of open space, i.e., dead shell cultch. The model accounted for dead shell cultch by tracking the mass of shells leftover from dead oysters in each time step (not counting the oysters that were harvested, for which the shell was assumed to be removed from the population). The dead shell thus gradually accumulated over time, but also gradually eroded using published literature estimates of the shell erosion rate in Apalachicola Bay.

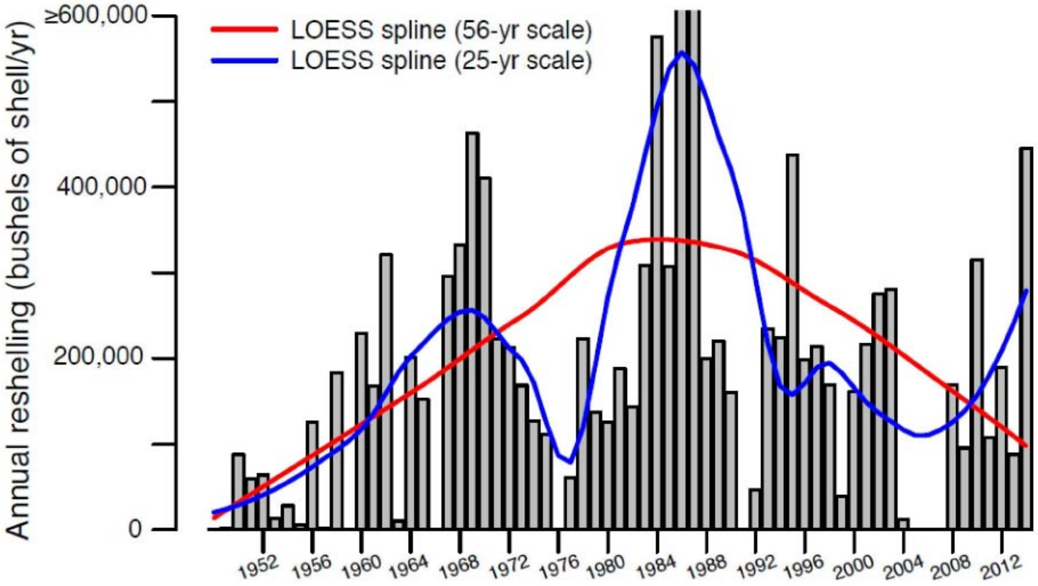
67. Larvae settled on the available shell substrate, competing for space according to mathematical relationships available in the published literature. The proportion of larvae that was not able to settle due to space limitations was assumed to die. The larvae that survived and settled entered the model population.

D. Properly Accounting for Shell Budget in the SSIPM

68. The SSIPM properly accounted for the dead shell cultch for the population at Cat Point sampled by FDACS. In particular, the model did not account for the re-shelling efforts by FDACS and any other agencies which added shell to empty, muddy areas in Apalachicola Bay in an effort to increase overall substrate availability. The active, living population at Cat Point would not have been re-shelled directly, so re-shelling would not affect the dead shell cultch budget in the model.

69. In performing my analysis, I disagree with the notion proposed by Georgia's expert, Dr. Romuald Lipcius, that reshelling efforts in Apalachicola Bay were steadily decreasing leading up to the 2012 collapse. In Figure 36 of his report, Dr. Lipcius presented a graph showing annual reshelling since the 1940s. Overlaid on that graph was a 'loess' curve he fit to the data. A loess curve is not a formal statistical analysis, rather it is a way to obtain a running average for a dataset, in order to smooth out small-scale variability. When constructing a loess fit, one has to specify the 'window' over which the running average is taken.

70. I was able to recreate Dr. Lipcius's analysis, and found that he chose a window corresponding to roughly 56 years. In other words, his 'trend' reflects changes over a 50-year time scale, and as a result it overemphasizes the extraordinary reshelling efforts in 1986-1987 following Hurricanes Elena and Kate. This creates the appearance that there has been a downward trend since that time. If you estimate the loess on a shorter, more realistic time scale, such as 25 years, the curve actually reveals an increase in shelling effort from 2003-2012, preceding the fishery collapse. The comparison between Dr. Lipcius's loess fit are depicted below in Figure 2.



Annual Reshelling in Apalachicola Bay from 1949 through 2013

Source: Shell1948to2013.csv (from Dr. Romuald Lipcius Expert Production)

Figure 2 (FX-437). Comparison of LOESS Curves for Apalachicola Reshelling Efforts in Florida. FX-437 is a true and accurate copy of a graph I created using generally accepted scientific principles and methodology, and it is an accurate representation of the shelling data Dr. Lipcius provided with his report.

71. FX-437 shows the red line that Dr. Lipcius used with a 56-year time averaging scale, and the blue line that I created with a 25-year time averaging scale. Thus while I agree with Dr. Lipcius that shelling is an important part of oyster management, I disagree with his assertion that Florida's shelling effort was declining before the 2012 oyster fishery collapse.

VI. INPUTS AND PARAMETERS OF THE SSIPM

72. As I mentioned above (Section III.C.), the SSIPM has two basic types of parameters: input parameters that I specified as known values, and fitted parameters that I estimated by fitting the model to the data. The input parameters include such things as growth rates, natural mortality rates, egg production, and so forth. Whenever possible I used values for these parameters derived from Apalachicola Bay (often from Dr. Kimbro's work). In some

cases, such as the larval mortality rate described above, I had to use parameters for the same species of oyster from other locations.

73. Below I begin with a discussion of what fitted parameters are generally and how they were used in this model. Following that discussion, I will detail all of the input parameters with the sources of data used for the model.

A. Fitted Parameters Estimated by the SSIPM

74. Fitted parameters were those for which no reasonable literature estimate was available. I estimated these by fitting the model to the data. In other words, I used a numerical routine to find the values for each of those parameters that provided the best fit of the model to the data. This routine starts with me specifying a ‘prior’ estimate of each parameter – essentially, a range of biologically plausible values. The model then produces a ‘posterior’ estimate of each parameter, meaning simply it is an estimate after the comparison of model to data. The posterior estimate is given as a point estimate and a confidence interval around that point estimate.

75. When developing a model, an important consideration is how many fitted parameters to try to fit. In general, one wants to have many fewer fitted parameters than there are data points. If a model has a large number of fitted parameters, relative to the number of data points, it will tend to ‘over-fit’ the data. In other words, the model will do a very good job of matching every tiny fluctuation in the data, so that it looks like there is a good match between model and data. The trade-off is that the model is then not very good at predicting what happens beyond the range of the data.

76. This technical point can be understood by way of analogy. Imagine a person describing how to travel between Washington, D.C. and New York City. They could offer a very specific description, including every bend in the highway, every lane change, and every exit

taken to refuel. This would be a very precise description of the path that they took, but it is not a very good way to explain to a visitor how to drive to New York because the visitor's path will have numerous deviations due to weather, traffic, or traveler preferences.

77. A better way is to simply say "take Interstate 95 north until you reach New York." The analogy illustrates that having a lot of fitted parameters (i.e., a lot of unnecessary details) in the model may just be fitting the noisy process variability in the data (e.g., individual lane changes), rather than capturing the actual dynamics of the system (e.g., drive north on the interstate). Of course if there are too few variable parameters, the model doesn't fit the data very well at all (e.g., suggesting the driver take I-95 without specifying north or south). The goal is to find a good balance between those extremes.

B. Choosing the Right Amount of Fitted Parameters

78. An example of a model that I consider to have too many fitted parameters and relevant to this original action is the model described by Dr. Bill Pine and colleagues in their 2015 publication "The curious case of eastern oyster *Crassostrea virginica* stock status in Apalachicola Bay, Florida," published in the electronic journal *Ecology and Society*.

79. In that paper, the authors fit a population model to the time series of oyster catch data in Apalachicola Bay from 1996 to 2014. In doing so, they estimated a separate recruitment rate for each year in the model, using nearly as many parameters as data points. This is a fundamentally flawed model design. As a result, the model appears to fit the data extraordinarily well, with the model curve hitting nearly every data point. However, the weakness of this is evident from the model prediction for 2015 (see Figure 5 in their paper, reproduced below as Figure 3): as the model moves beyond the range of the data, it immediately jumps up to the long-term average level of fishery yield rather than showing any sort of residual lag effect from the 2012-2014 decline, as I would expect from a properly constructed population model. Thus I

conclude that the Pine et al. model appears to be constructed in a way that does not properly represent realistic processes in oyster populations.

80. In other words, it does a good job of matching each tiny fluctuation in the data, but once it is no longer constrained to fit the data it does not appear to describe the way a real oyster population would be expected to behave. That is, the model does not seem to describe the actual processes underlying the Apalachicola Bay oyster population, but rather is just 'chasing the noise' in the data.

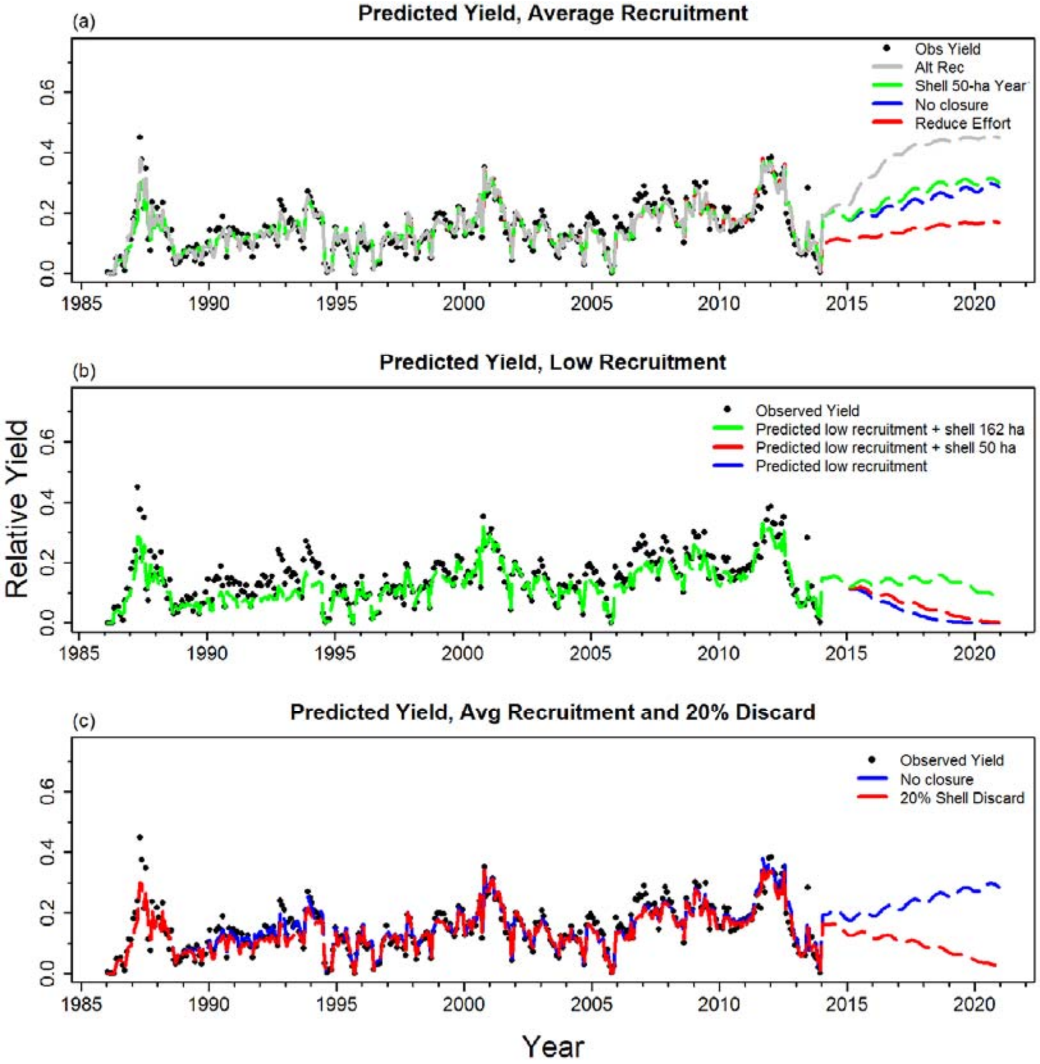


Figure 3. A True and Correct Copy of Figure 5 from the Pine et al. 2015 publication "The curious case of eastern oyster *Crassostrea virginica* stock status in Apalachicola Bay, Florida."

81. My SSIPM avoids this problem in two ways. First, by taking a state-space approach I explicitly account for the process and measurement variability in the system (the 'noise' that a non-state-space model like Pine et al.'s seems to over-fit). Second, I purposefully limited the number of parameters in the SSIPM to avoid over-fitting.

82. My model had eight fitted parameters that were estimated from the data. Five of these were harvest rates, each of which represented harvest for a particular time interval in the SSIPM. These time intervals were chosen to represent periods over which harvest could reasonably be expected to have been similar, and the breaks between the interval represent times when Florida instituted an important change in oyster harvest regulations. The model ran for 1982-2013, and the time periods for the fitted harvest rate parameter were 1982-1992 (the period prior to FDACS data collection which allowed the model to 'settle in'[2]), 1992-1999 (Florida instituted a bag limit in 1999), 1999-2005 (the bag limit was removed in 2005), 2005-2009 (the timing of the harvest season changed in 2009), and 2009-2013.

83. In the SSIPM, harvest is represented as a rate, with units of week^{-1}, that is, 'per week.' This is approximately equivalent to the proportion of oysters of legal size removed per week from Cat Point or Dry Bar, depending on the model run. While Florida collects data on oyster catches in Apalachicola Bay, these are bay-wide estimates, and thus cannot be translated directly into harvest effort on the model population at Cat Point or Dry Bar. Moreover, those data are fishery-dependent and thus subject to some forms of bias that I discuss later. Knowing that a topic of interest in this original action was the degree to which harvest had led to the 2012

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[2] Results from any model depend on the starting point. If the starting point (in this case, the number and size of oysters in 1992) is not known with perfect certainty, the solution is to start the model with an arbitrary number and size of oysters at some point well prior to 1992. I chose to start the SSIPM at 1982. Then the SSIPM runs forward and 'settles' in to appropriate values before the first comparison to data in 1992.

fishery collapse, I chose to take the more robust approach of estimating the harvest rate directly from the fishery-independent FDACS data to obtain an independent estimate of temporal patterns of harvest leading up to the collapse.

84. The other three parameters estimated by the model were the salinity effect on larval mortality (parameter M_T, which I described earlier) and two process variability parameters. I introduced process variability at two steps in the model: first, process variability was added to the number of new larvae settling in each settlement pulse (reflecting year-to-year variability in larval survival or other factors); second, a smaller amount of process variability was added to the number of oysters in the population at each time step (reflecting minor week-to-week variability in oyster survival). The standard deviations of those two process error terms were the final two fitted parameters estimated by the model. The values of each of the fitted parameters estimated by the model are given in Table 2, discussed in detail below. The harvest rates are the main fitted parameters of interest here, and I discuss my interpretation of these values later in this testimony.

C. Input Parameters and Data Used in Model

85. My overall goal in developing the model was to use data that, to the greatest degree possible, were obtained from Apalachicola Bay or Cat Point specifically. I will now describe the sources of my data.

86. First, the data to which I fit the SSIPM were the FDACS fishery-independent oyster population surveys at Cat Point and Dry Bar. These data are size-structured: the surveyors collected a sample of oysters from multiple points (0.25 m^2 quadrats) on each bar on the sample date, and count how many oysters fall into 5 mm size categories. That is, they counted how many oysters were less than 15 mm, greater than 15 mm but less than 20 mm, greater than 20 mm but less than 25 mm, and so forth up to greater than 105 mm. These data were collected intermittently at bars throughout the Bay, but the longest time series with the most frequent

sampling was at Cat Point, where data were available at least annually, and in some years much more frequently than that, from 1992-2013.[3] The oyster bar with the next longest time series of data was Dry Bar, which I also ran the model against.

87. Salinity and temperature data at Cat Point and Dry Bar were obtained from the long-term water quality monitoring data collected by ANERR. After obtaining these data I averaged them over one-week time steps to match the time step of the model. I used these data to represent water conditions in the model from 1992-2006 and the initial months of 2013 that were modeled.

88. To represent salinity and temperature in the model from 2007-2012, I used hydrodynamic model output created by Dr. Greenblatt. Dr. Greenblatt provided data from her hydrodynamic model output for the model node closest to the ANERR monitoring station. I used her hydrodynamic model outputs corresponding to the 'historical scenario' and alternative-flow scenarios in the SSIPM runs.

89. Although ANERR data was available from 2007-2012, I used Dr. Greenblatt's data to represent the historical scenario in order to facilitate direct apples-to-apples comparison between that historical and the alternative-flow scenario SSIPM runs. There was exceedingly strong correspondence between the modeled salinities for 2007-2012 and the actual salinities monitored by ANERR during that time, and I expect I would have obtained nearly identical results using the ANERR data in the historical scenario.

90. Many of the input parameters for the SSIPM were derived from Dr. Kimbro's field and lab experiments in Apalachicola Bay (all of the input parameters with their sources are

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[3] Although the FDACS data for Cat Point exists for 1990 and 1991, ANERR salinity data for Cat Point was not collected until 1992; thus, the SSIPM did not start fitting to the FDACS data until 1992.

listed on Table 1 on the following page). These included the parameters for oyster growth (the von Bertalanffy growth rate and asymptotic maximum size), obtained from Dr. Kimbro's long-term outplants[4] of juvenile oysters, and natural (non-predator, non-disease) mortality, obtained from the mortality rates of juvenile (less than 15 mm) and adult oysters (greater than 15 mm) outplanted in cages in the Bay.[5] Those outplants provided mortality rates over 12 weeks in the

Table 1: Revised Parameter Table. I created using generally accepted scientific principles and methodology, and it is an accurate representation of the input parameters used in my model.

Description	Symbol	Value	Source
IPM parameters			
Number of particles		50	
Mesh size (oyster)		250	
Mesh size (drill)		100	
Mesh limits (oyster)		0-150 mm	
Mesh limits (drill)		0-100 mm	
Oyster parameters			
Asymptotic maximum size	L_{inf}	120.35 mm	Kimbro Expert Report
Growth rate	K	0.01218 wk^{-1}	Kimbro Expert Report
Coefficient of variation in growth	CV_g	0.25	Kimbro Expert Report
Length-wet shell mass relationship	Mass = $5.77\text{x}10^{-4} \bullet L^{2.234}$ (g)		Kimbro Expert Report
Length-ash-free dry mass relationship	Mass = $5.09\text{x}10^{-5} \bullet L^{2.365}$ (g)		Kimbro Expert Report
Fecundity	$19.86\text{x}10^{6} \bullet (\text{Ash-free dry mass})^{1.17}$		Thompson et al. 1996
Size at maturation		40 mm	Thompson et al. 1996
Juvenile mortality rate	M_J	0.0186 wk^{-1}	Kimbro Expert Report (based on 80% survival over 12 weeks)
Size range experiencing juvenile mortality		0–15 mm	Based on expected size after 12 weeks' growth from spat

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[4] "Outplant" refers to the experimental procedure of attaching live oysters to ceramic tiles (or some other hard substrate) and mooring them at a fixed location in the field. Often these oysters are also protected by cages. Monitoring these outplanted oysters allows long-term monitoring of growth and mortality rates for oysters at particular sites in the field.

[5] The oyster growth parameters were updated in August 2016 from my initial report upon receiving additional data from Dr. Kimbro's continued research.

Adult mortality	M_A	0.0052 wk^{-1}	Kimbro Expert Report (based on 92% survival over 12 weeks)
Size limit for harvest	L_F	76 mm	3-inch harvest limit
Harvest selectivity		1 mm	
Mean spat size		2.5 mm	D. Kimbro (pers. obs.)
S.D. spat size		1 mm	D. Kimbro (pers. obs.)
Baseline larval mortality	M_0	7.8 (0.26 d^{-1} • 30 d)	Rumrill 1990, Morgan 1996
Oyster density-dependence		10^{-3}	Puckett and Eggleston 2012 (their Fig. 7)
Dead shell erosion rate	λ_{TAF}	0.0019 wk^{-1}	Powell et al. 2012
Drill parameters			
Crowley-Martin functional response			
Attack rate	A	3.8041 drill^{-1}wk^{-1}	
Handling time	H	1.1622 oyster^{-1}	
Predator interference coefficient	C	0.5203 drill^{-1}	
Drill size preference	39.33 + 0.367L_{pred} mm		Kimbro Expert Report
S.D. of drill size preference		3.92 mm	Kimbro Expert Report

field, which I converted to a weekly rate to match the SSIPM. Dr. Kimbro's observations were also the source of the mean spat size, standard deviation of spat size, and the relationships between oyster length and oyster mass used in the SSIPM.

91. Dr. Kimbro's observations and experiments also provided data for the southern oyster drill in the model. Because we did not have information on the reproductive patterns for that species, or long-term observations of drill abundance, and because we suspect that oyster drills move in and out of the Bay depending on salinity, we did not directly model the population dynamics of the drill. That is, we did not attempt to keep track of year-to-year fluctuations in drill numbers.

92. Instead we focused on the well-known pattern that oyster drills become more abundant and active in the Bay during periods of high salinity, and either leave the Bay, die, or become inactive during periods of low salinity (and low temperature). To represent this, I

modeled the drill as having a constant abundance and size distribution in the Bay, but its activity (i.e., the feeding rate on oysters) depended on the salinity and temperature in a given week. The baseline abundance and size structure were based on the number and size distribution of drills that Dr. Kimbro observed in his field surveys and field experiments. The feeding rate of the drill and the size preference the drill has for oysters were obtained from Dr. Kimbro's lab experiments. The effects of salinity on the drill feeding rate were also based on Dr. Kimbro's lab experiments.

93. Finally, some input parameters required by the model were not available from Dr. Kimbro's experiments and observations, so I relied on values reported in the published scientific literature. When possible I used values from studies conducted on eastern oysters elsewhere in the Gulf of Mexico, although this was not possible in all cases. The input parameters obtained from literature sources were: the size at maturity, the relationship between oyster mass and egg production, the baseline larval mortality rate (essentially this is the mortality rate at the optimal salinity; mortality was higher for other salinities, as I described above), the optimal salinity for larval survival, the rate of density-dependent competition among oyster spat, and the erosion rate for dead shell on the reef (all of these are also detailed, along with sources, in Table 1).

D. Avoiding Bias from Fishery-Dependent Data in the SSIPM

94. One important aspect of the FDACS survey data to which I fit the model is that they are so-called 'fishery *independent*' data. Fishery-independent data are those collected by an agency or research scientists, following a standardized protocol and using standardized methods and level of effort and so forth. By contrast, fishery-dependent data are obtained from the fishery itself.

95. Some examples of fishery-dependent data are landings data, number of fishing trips, or fishing licenses issued. These types of data are less reliable, because they are simply by-

products of the fishery – the harvesters' goal is to maximize profits, not to collect reliable, standardized data. Therefore fishery-dependent data is vulnerable to several types of bias. These include the fact that harvesting effort will depend not just on the abundance of the target species, but also other economic factors such as the price of fuel, market prices, and the availability of other economic opportunities (or other fisheries).

96. Additionally, harvest practices can cause fishery-dependent data to mask real patterns of decline in a fishery species. For example, harvesters will tend to focus effort on locations where the fishery species is abundant and easy to catch. As one spot becomes depleted, they shift their effort to other locations. Thus even if the harvest rate is unsustainable, the overall level of harvest may stay relatively constant (until the last location is depleted).

97. By contrast, fishery-independent data do not suffer from these problems because the data collection is not affected by economic factors. Thus, when available, fishery scientists prefer to rely upon fishery independent data, or possibly a mixture of both fishery-independent and fishery-dependent data. Even with fishery-independent data, manipulative experiments and modeling are required to develop causative theories as explained above.

98. The difference between fishery-independent and fishery-dependent data is an important distinction between my model and much of the data Dr. Lipcius relies upon for his opinion, including the data utilized by the model described in the Pine et al. publication that Dr. Lipcius cites. For example, oyster landings in Apalachicola Bay (and other bays) are fishery-dependent data. There is no way to determine from the landings data alone what part of the Bay was harvested (e.g., open bars, closed bars, private bars, or possibly other bays).

99. There is also no way to determine directly from landings what fraction of the oyster population in any given location is being harvested, or what the overall level of harvesting

effort is. Low landings could reflect either low oyster abundance or low harvesting effort due to market factors or other external factors.

100. Another example of fishery-dependent data used by Dr. Lipcius is commercial oyster fishing licenses. While the number of licenses is sometimes used as an indication of overall fishing pressure in this type of fishery, it can be a misleading indicator. This is because not all license holders spend the same amount of time on the water harvesting. Some license holders may operate in multiple fisheries (or have other non-fishery occupations), and only harvest oysters when it is profitable to do so.

101. Additionally, a well-known phenomenon is for non-harvesters to purchase fishing licenses as a rent-seeking strategy when there may be some kind of financial benefit to license holders, unrelated to being able to harvest. For example, in Apalachicola, the number of oyster fishery licenses spiked at the time of the Deepwater Horizon oil spill. It is presumed that this spike was in part due to some new licensees attempting to document a business hardship in order to pursue an economic damages claim against the BP Oil Spill Fund.

102. One of the main criticisms I have of Dr. Lipcius's study is the extent to which he relies upon fishery dependent data, including the two examples I just gave, to draw conclusions about the sustainability of oyster harvesting in Apalachicola Bay. Additionally, in his deposition, Dr. Lipcius stated that he relied upon Pine et al.'s model-based estimate of the annual exploitation rate in the Bay (Lipcius Dep. Tr. p. 458).

103. Aside from my previous criticism of that model for being over-parameterized and over-fitting the data, the data being fitted in Pine et. al's model were fishery-dependent landings data, and the harvest rates were derived from fishery-dependent reports of the number of fishing

trips made. Thus the model analysis is vulnerable to the issues I have raised with using fishery-dependent data.

E. Importance of Modeling Salinity Effects in the SSIPM

104. Salinity is an important aspect of the SSIPM. Most models of oyster population dynamics include some effect of salinity; for example, much of the modeling work published by Dr. Eric Powell and Dr. Eileen Hoffman include this effect. My SSIPM included explicit effects of salinity on most of the aspects of oyster biology known to be sensitive to salinity: larval survival, Dermo disease, and predation.

105. However, salinity effects are not always included in oyster population models. For example, the model described in Pine et al.'s 2015 publication does not have a salinity component, even though Pine et al. acknowledge in the report that salinity is an important factor in oyster recruitment and mortality ("The primary source of freshwater input into Apalachicola Bay is the Apalachicola River, and river discharge has a strong influence on the salinity, nutrient dynamics, and other aspects of the Apalachicola Bay ecosystem.").

106. Rather than include salinity directly as a factor affecting oyster populations within the model, Pine et al. attempted to test for salinity effects after the fact using their model output. They did this by averaging Apalachicola River flow rates over an entire year, and then compared annual mean river outflow to the annual oyster recruitment and oyster mortality estimated by their model. This is a seriously flawed approach, because averaging river flow over an entire year can totally obscure daily, weekly, or monthly variation in salinity that can be incredibly important to oyster populations.

107. For example, a year with extremely low summertime flows leading to high salinity and thus high mortality due to disease or predation could also have had extremely high

wintertime flows. The high winter flows would have little effect on the oysters because they did not occur during the stressful summer months when predators are active.

108. Pine et al.'s method would show this hypothetical year to have approximately average annual salinity despite a very dry, high-salinity summer. In their analysis, Dr. Pine and his coauthors did not find a statistically significant relationship between average river flow and either oyster recruitment or mortality.

109. Frankly, this is not surprising given that they have analyzed mean flow over such a long time scale that it is irrelevant to oyster biology. Nonetheless, they erroneously conclude: "We did not find correlations between Apalachicola River discharge measures (average monthly, total annual, total monthly, or coefficient of variation on annual discharge, mean seasonal, or total seasonal) and our estimated relative natural mortality rate (M) or oyster recruitment rates."

110. At the same time, Pine et al. acknowledge that the data they used was incomplete: "With the data currently available for Apalachicola Bay, we cannot be sure whether we are dealing with a small oyster population that has been subject to strong fishing impacts or a larger population that has been subject to strong environmental influences that have impacted the long-term carrying capacity." The SSIPM includes the rigorous analysis of salinity and size-dependent modeling relationships necessary to determine the effect of the environmental influences Pine et al. could not successfully analyze.

111. Dr. Lipcius bases his own conclusion that there is no evidence for river flows or low salinity contributing to the 2012 oyster collapse on the Pine et al. paper, so Dr. Lipcius's opinion in this matter is also flawed. To his credit, Dr. Pine and his coauthors acknowledge that more work is needed to test the effect of Apalachicola River flow on oyster populations: "The

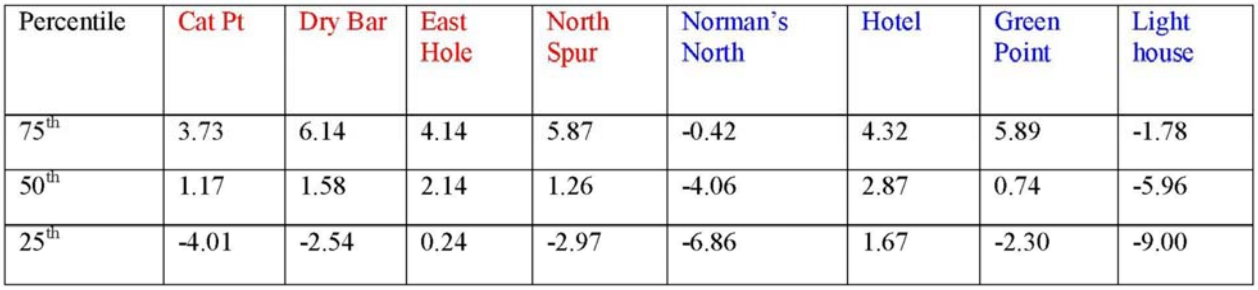
overall relationships between freshwater flows, drought frequency and severity, oyster recruitment, and harvest dynamics remain unclear, and this is an area of ongoing work."

112. The Pine et al. paper also acknowledges "Note that we did not study or reach any conclusions about any effect of water withdrawals affecting the Apalachicola River Basin or oyster populations in Apalachicola Bay. This is an area that warrants future research." Thus, the Pine et al. paper does not address the very issue involved in this original action. The work that Dr. Kimbro and I performed as part of work for this original action is precisely the type of research that the Pine et al. paper acknowledged as needed.

113. In contrast to the Pine et al. model, the SSIPM analysis directly accounted for salinity effects, and did so at a weekly time scale that better captures short-term within-season variations in salinity that field observations suggest are important to oyster populations.

114. Salinity also is important in regard to Dr. Lipcius's conclusions on harvesting pressures. I reviewed Dr. Lipcius's analysis of patterns of oyster decline on harvested and unharvested reefs in Apalachicola Bay and believe it is mistaken. Because the harvested reefs in his analysis are further from the mouth of the river than the unharvested reefs, differences in salinity among the reefs confounds and invalidates Dr. Lipcius's conclusions.

115. I made this determination by performing statistical analysis using salinity data contained in Dr. Greenblatt's report. A true and accurate copy depicting the analysis I performed using generally accepted scientific principles is below as Figure 4 and Figure 5, which correspond to FX-427 and FX-428.



Percentile	Cat Pt	Dry Bar	East Hole	North Spur	Norman's North	Hotel	Green Point	Light house
75th	3.73	6.14	4.14	5.87	-0.42	4.32	5.89	-1.78
50th	1.17	1.58	2.14	1.26	-4.06	2.87	0.74	-5.96
25th	-4.01	-2.54	0.24	-2.97	-6.86	1.67	-2.30	-9.00

Figure 4: FX-427. Salinity Anomalies for Eight Apalachicola Bay Oyster Bars Between July 2012 and December 2012.

116. Figure 4 shows the salinity trend for the last half of 2012 for each of the reefs in Dr. Lipcius's analysis. To create this figure, I calculated the average salinity across all eight reefs on each day. The figure shows the deviation from the average (the 'anomaly') for each of the eight sites. Values above zero are above-average salinity, values below zero are below-average salinity.

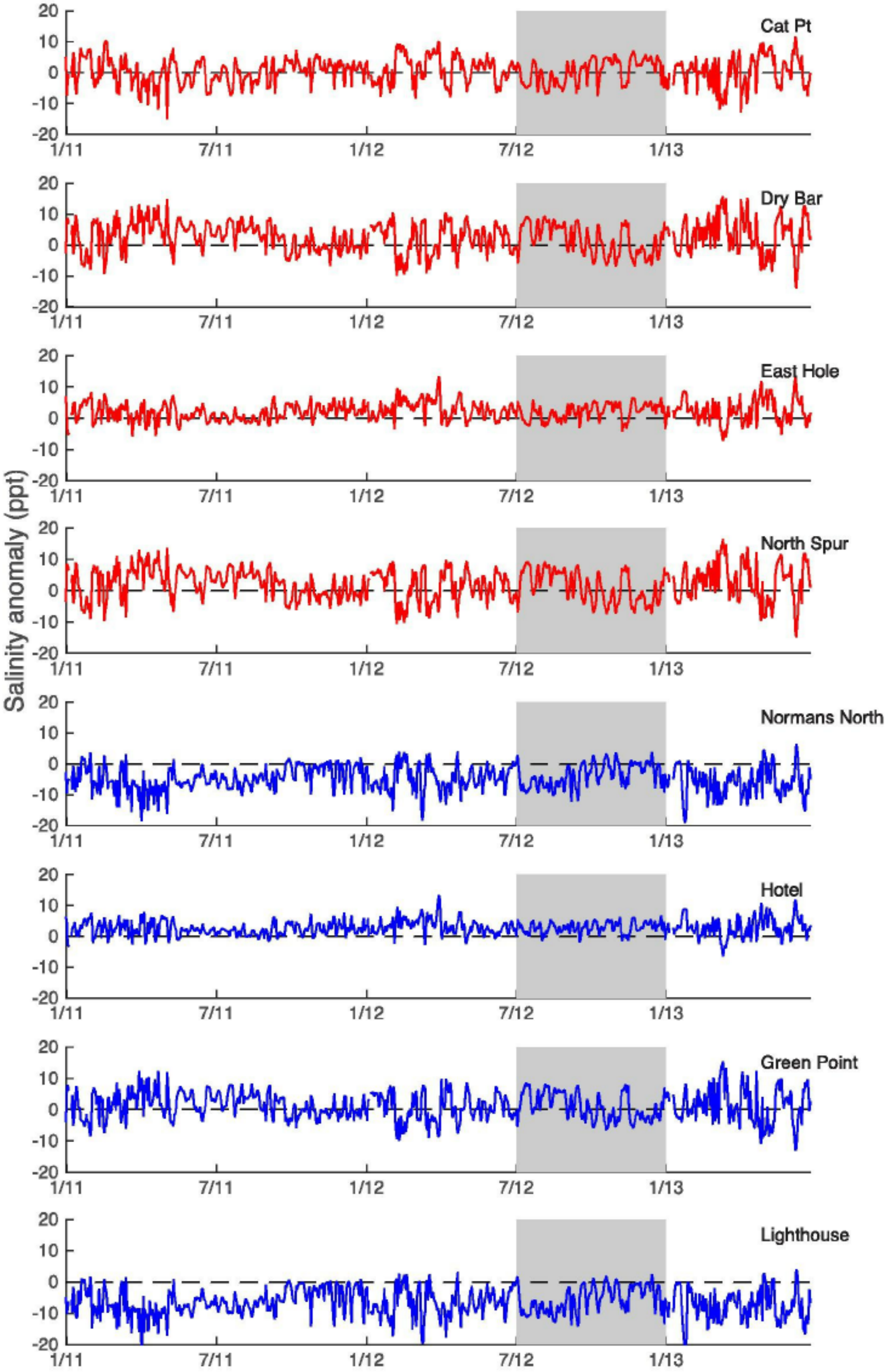


Figure 5. FX-428, Daily Salinity Anomaly for Eight Apalachicola Bay Oyster Bars During the 2011-2012 Period.

117. Figure 5 summarizes these results as percentiles of the anomaly data shown in Figure 4. It shows that overall, the harvested reefs had above-average salinities and the unharvested reefs had below-average salinities for this time period. Above-average salinities are associated with many factors causing reef decline, as explained in Dr. Kimbro's testimony; thus salinity, not harvest, can explain the pattern that Dr. Lipcius bases his conclusions on.

F. Extrapolation From Cat Point and Dry Bar to Bay-Wide Conclusions

118. I should note at this point that FDACS collected survey data on many of the other bars in Apalachicola Bay, not just Cat Point bar. I initially focused my analysis on Cat Point, because it had the longest continuous dataset, with sampling at least annually back to 1992 and particularly frequent sampling in the last five years of the dataset. Some earlier SSIPM simulations I conducted (reported in the White et al. 2016 paper) showed that accurate estimation of harvest rates from this type of data required long datasets.

119. Additionally, Cat Point is one of the only bars that also has an ANERR water quality monitoring station, which provided the requisite salinity and temperature data for the duration of the model simulations.

120. Moreover, when drawing inferences about larger patterns from a single set of observations, it is proper to consider whether those inferences will be conservative or not. By conservative I mean that one is likely to under-estimate, rather than over-estimate, the process or quantity of interest.

121. In this case, Cat Point is one of the most heavily fished bars in the Bay, so my estimates of harvest rates would be above average for the rest of the Bay. By contrast, Cat Point is further from the mouth of the river than some of the other important bars, so the effect of river outflow on salinity will be lower at Cat Point than at other bars. Thus by focusing on Cat Point, I was likely to over-estimate the role of harvest and under-estimate the role of river flow/salinity

on oyster population dynamics. Thus my conclusions will be conservative, rather than anti-conservative, with regard to the relative effects of flow on oysters.

122. Finally, the robustness of the conclusions I drew from Cat Point was supported by a second analysis at Dry Bar, another heavily fished bar.

123. One of the criticisms of the model by Georgia's expert, Dr. Lipcius, had to do with the model's sole focus on data from Cat Point. After Georgia released his expert report, I went back and used the model to analyze another oyster bar, Dry Bar, which was the only other oyster bar that had enough data over a long enough period of time to run the model and also had concurrent ANERR water quality sampling to provide temperature and salinity data.

124. The results from the Dry Bar run were consistent with what I had originally found with Cat Point in terms of the relative importance of harvest and upstream freshwater withdrawals on oyster population dynamics in the 2007-2012 period.

VII. MODEL FIT

A. Overview of Model Fit

125. Overall, the SSIPM fit the FDACS data from Cat Point and Dry Bar very well, capturing both multi-year and seasonal trends. Figures 6 and 7 are summaries of how the SSIPM fit the data at Cat Point and Dry Bar respectively.

126. For example, if you examine the years 1998 and 2007 on Figure 6 from Cat Point (the tick marks on the graph indicate January 1st of every other year), there are multiple observed data points (small circles) in both years. In both years there is a large spike in oyster abundance, corresponding to a large recruitment pulse, followed by a gradual decline due to mortality and harvesting until the next pulse. In both years the SSIPM fit the trend of the data well. Overall, the SSIPM captures the typical annual cycle of recruitment pulse and decline, as

well as interannual differences in overall abundance, such as the low abundances in 2005-2006 and 2008-2009 with high abundance intervening in 2007.

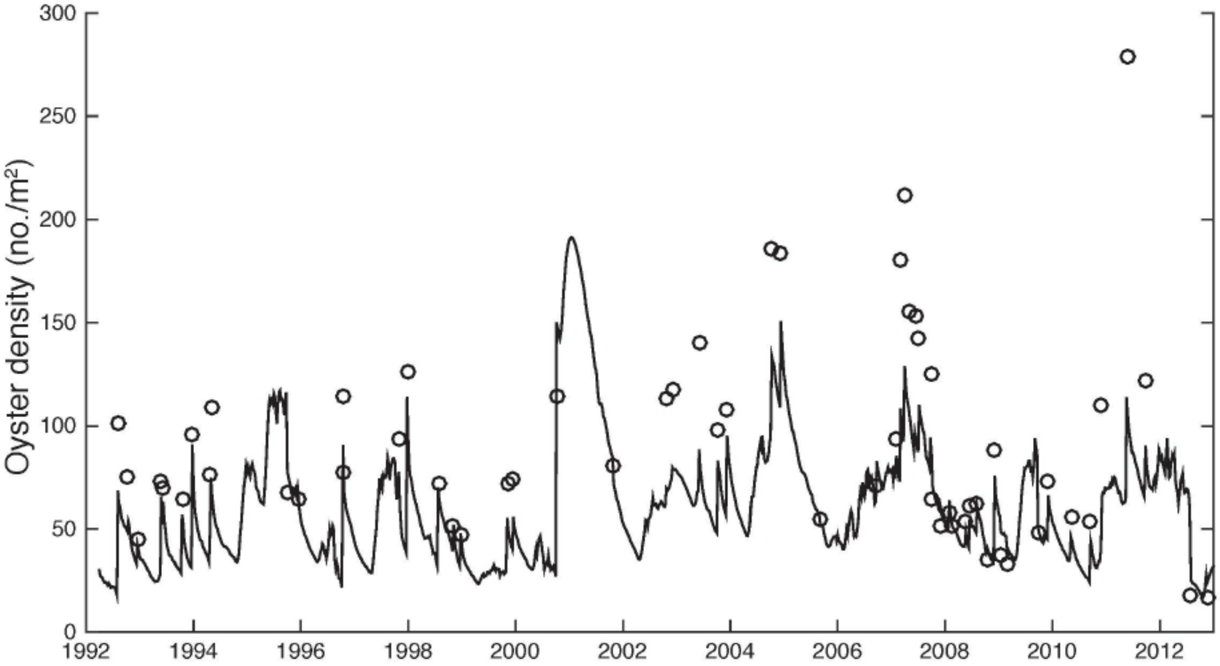


Figure 6 (FX-826a). SSIPM fit to FDACS Survey Data at Cat Point, Historical Flow Conditions, Model Run from 9/3/2016. FX-826a is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the FDACS Data compared to the SSIPM output.

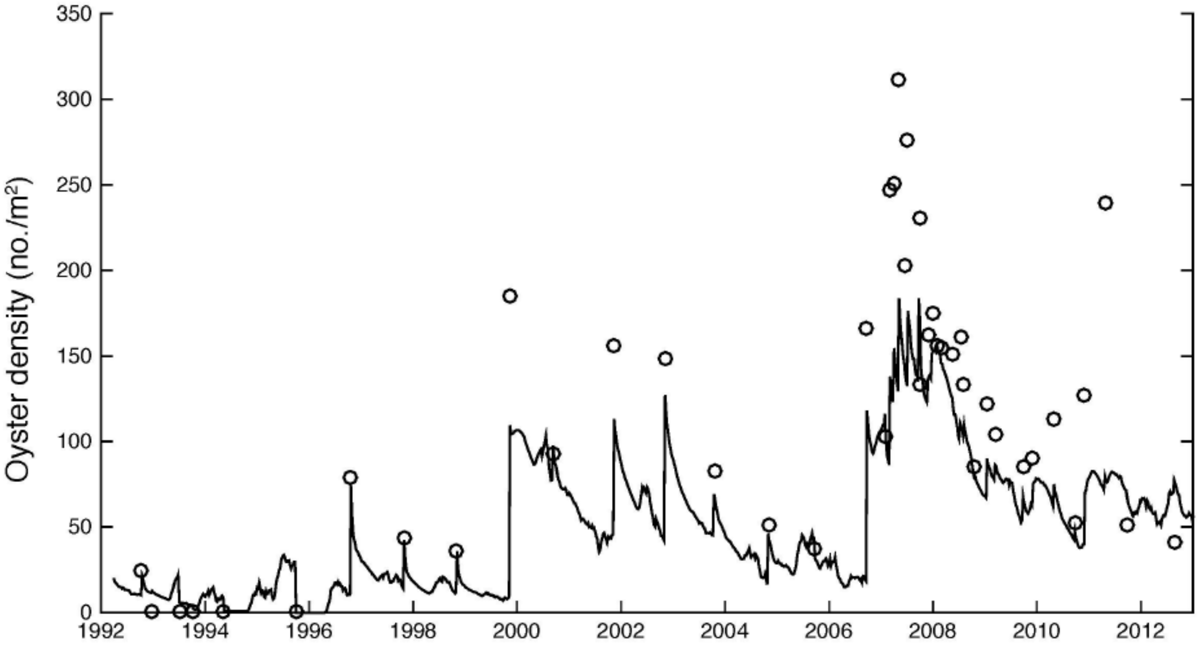


Figure 7 (FX-826b). SSIPM fit to FDACS Survey Data at Dry Bar by Year, Historical Flow Conditions, Model Run from 9/3/2016. FX-826b is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the FDACS Data compared to the SSIPM output.

127. Like any model of this type, the fit is better during time periods with more data. For example, data collection was less frequent in the late 1990s up to 2002 at Cat Point, which explains the relatively lower correspondence between the SSIPM and data at that time on Figure 6. Only four data points were collected between Jan 2000 and Jan 2002, so although the model continues to display the typical recruitment-pulse-followed-by-decline trend in that time period, it is less constrained by data.

128. Additionally, one aspect inherent to any state-space model is that it is intended to 'train' itself on the early portion of the data, allowing it to fit the later data points better. Essentially, with each additional data point, the SSIPM obtains a better estimate of the 'true' oyster population dynamics in Apalachicola Bay. As a result, the fit is much better for the later data points (2006 onwards) than for the initial data points in the mid-1990s. The SSIPM fit was

quite good in the period of interest, 2007-2012, when data were collected more frequently and after the SSIPM had run and developed the underlying process.

129. Regarding Figure 6, I have updated the version of the figure that was originally included in my expert report in February 2016 with a new version created in August 2016. This update was necessary because the original model run used data that contained an error, such that it included only some but not all of the FDACS data from 2009 and 2010. I fixed this error and reran the SSIPM so that it utilized all of the data from those years. The error was not so large that it changed the overall effect of salinity on the system or changed either of my opinions about model fit or causation of the oyster fishery collapse.

130. Additionally, after the original February 2016 SSIPM run, Dr. Kimbro completed additional analysis of oyster growth in Apalachicola Bay. This updated analysis led to revised estimates of the oyster growth parameters in the SSIPM; the revised SSIPM run and figures include these updated, improved parameter values.

B. Size-Structured Model Fit

131. In the actual underlying model calculations, the SSIPM was fitting itself to the size distribution of oysters corresponding to each data point. That is, the SSIPM was not simply trying to match up the total number of oysters it predicted to the total number of oysters counted by FDACS in a survey. Instead, the SSIPM was fitting itself to the number of oysters in each size class. This is depicted in Figure 8 below, in which I show the actual FDACS size distributions (blue) and the model prediction (orange) for a representative set of sample dates from 2006-2012.

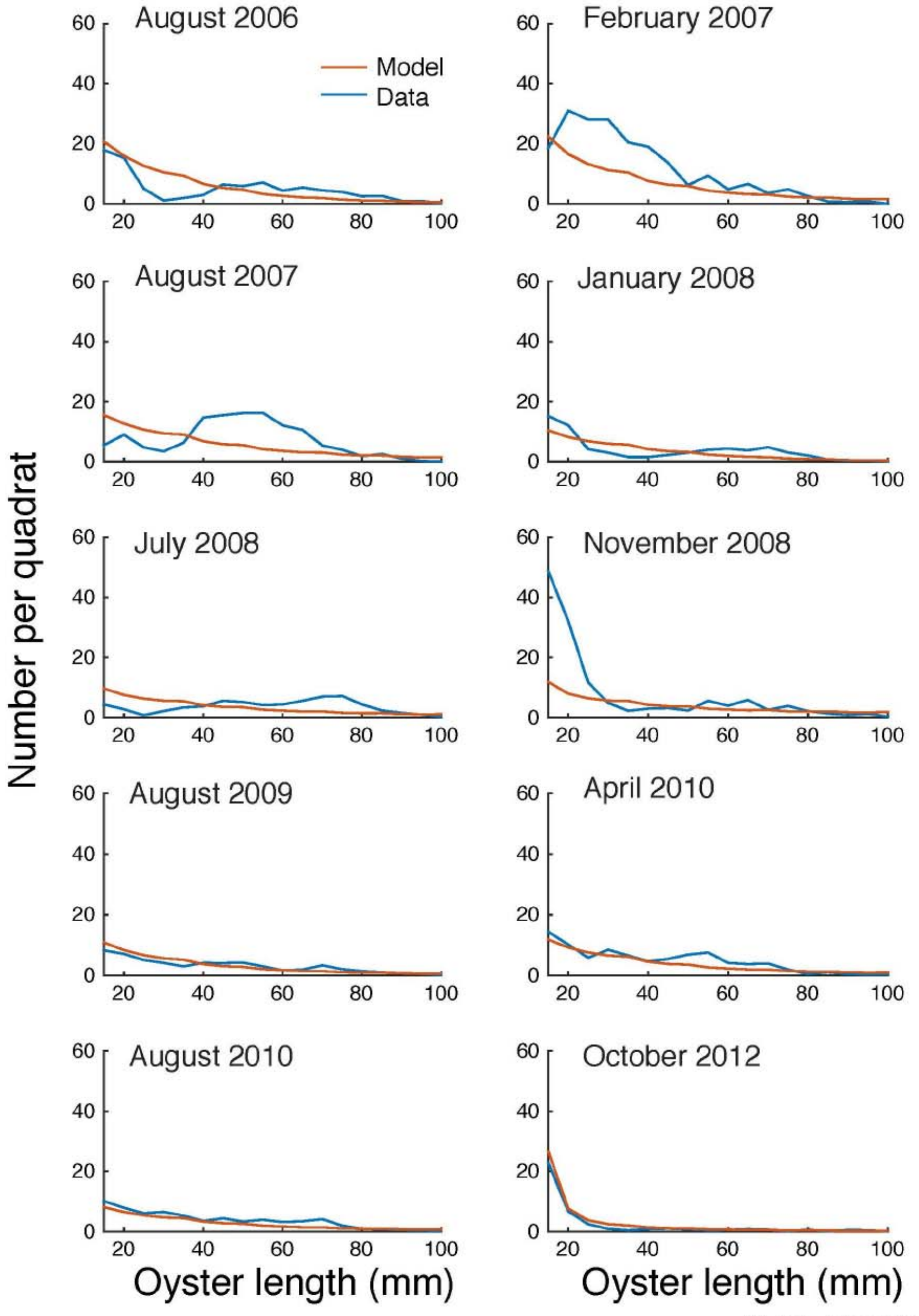
132. In these plots, it is further evident that the model captures some key aspects of the oyster population fluctuation, such as year-to-year variation in the number of larval recruits

compare August 2010 to October 2012 in the bottom panels; the latter year had more than twice the number of recruits.

133. The SSIPM also captures year-to-year variation in the number of oysters of harvestable size (greater than 76 mm); compare February 2007 or November 2008, when large oysters were relatively abundant, to October 2012 when there were essentially no oysters greater than 40 mm in the Cat Point surveys.

Example model fits to DACS size distribution data (Cat Point)

Source: State-space population model fit, run 3 Sept 2016



August 2006

February 2007

August 2007

January 2008

July 2008

November 2008

August 2009

April 2010

August 2010

October 2012

FL-ACF-04142976

Figure 8 (FX-828): Comparison Between SSIPM Predicted Oyster Size Distribution (Orange) to FDACS Data for Oyster Size Distribution (Blue). FX-828 is a true and accurate copy of a graph I created using generally scientifically accepted principles and

methodology, and it is an accurate representation of the FDACS Data compared to the SSIPM output.

C. The Importance of a Size-Structured Model

134. The model's fit to the size-structured data reveal an important strength of the SSIPM. The SSIPM separately accounts for processes affecting small oysters (e.g., effects of salinity on larval recruitment and predation) and processes affecting large oysters (e.g., harvest) as well as the link between small and large oysters (growth over time, as measured in the field). This allows the SSIPM to explicitly account for the interplay of all of the different factors affecting the oyster population, and estimate their individual influence.

135. One of the criticisms of my expert report (and Dr. Kimbro's) from Georgia's expert, Dr. Lipcius, was that sublegal and legal (defined as either less than or greater than 75 mm, respectively, in his report) oyster abundance declined simultaneously in 2012, which should not happen if the decline is caused by higher salinities due to freshwater withdrawals from Georgia. The logic he uses appears to be that this pattern of sublegal and legal oyster declines would only occur if legal-sized oysters were overharvested, which would then inhibit the recruitment of sublegal oysters. There are three flaws in this reasoning.

136. First, it is inappropriate to draw those type of causative theories without any manipulative experiments or modeling, as was done by Dr. Kimbro and me.

137. Second, other more plausible explanations exist for Dr. Lipcius's theories as to why legal and sublegal populations would decline simultaneously. While it is true that – over time – removal of adult oysters would lead to a decline in sublegal oysters, overharvest of adults would not lead to an instant loss of sublegal oysters; those that were already settled onto the reef would remain there. A simpler explanation is that some other factor (e.g., predation of both legal and sublegal oysters) caused both population subsets to decline simultaneously.

138. A third flaw in Dr. Lipcius's analysis is that he relied on the summary FDACS data, which obscures relevant information. The summary FDACS data groups the oysters into only three size classes: less than 25mm, greater than 50mm, and greater than 75mm. JX-135 is the FDACS summary data, which is a true and accurate copy of a spreadsheet prepared by DACS staff during the normal course of its operations and is maintained as an official record of the State of Florida. Dr. Lipcius apparently pooled the smaller two categories together to obtain his 'sublegal' data. However, the raw FDACS data has much more resolution, showing the number of oysters that are in every 5 mm increment from less than 15 mm up to greater than 105 mm. JX-166 is an example of the raw FDACS data, which shows survey data sheets from samples taken across Apalachicola Bay from 2013 to 2015.[6] JX-166 is a true and accurate copy of the data sheets created by DACS staff between 2013 and 2015 during the normal course of its operations and is maintained as an official records of the State of Florida.

139. The raw FDACS data shows important patterns that contradict the mechanism proposed by Dr. Lipcius. I graphed the raw FDACS data for Cat Point and Dry Bar for the years leading up to the collapse in Figures 9 and 10, corresponding to FX-425 and FX-426, respectively. This higher-resolution view sheds light on what actually occurred during the collapse.

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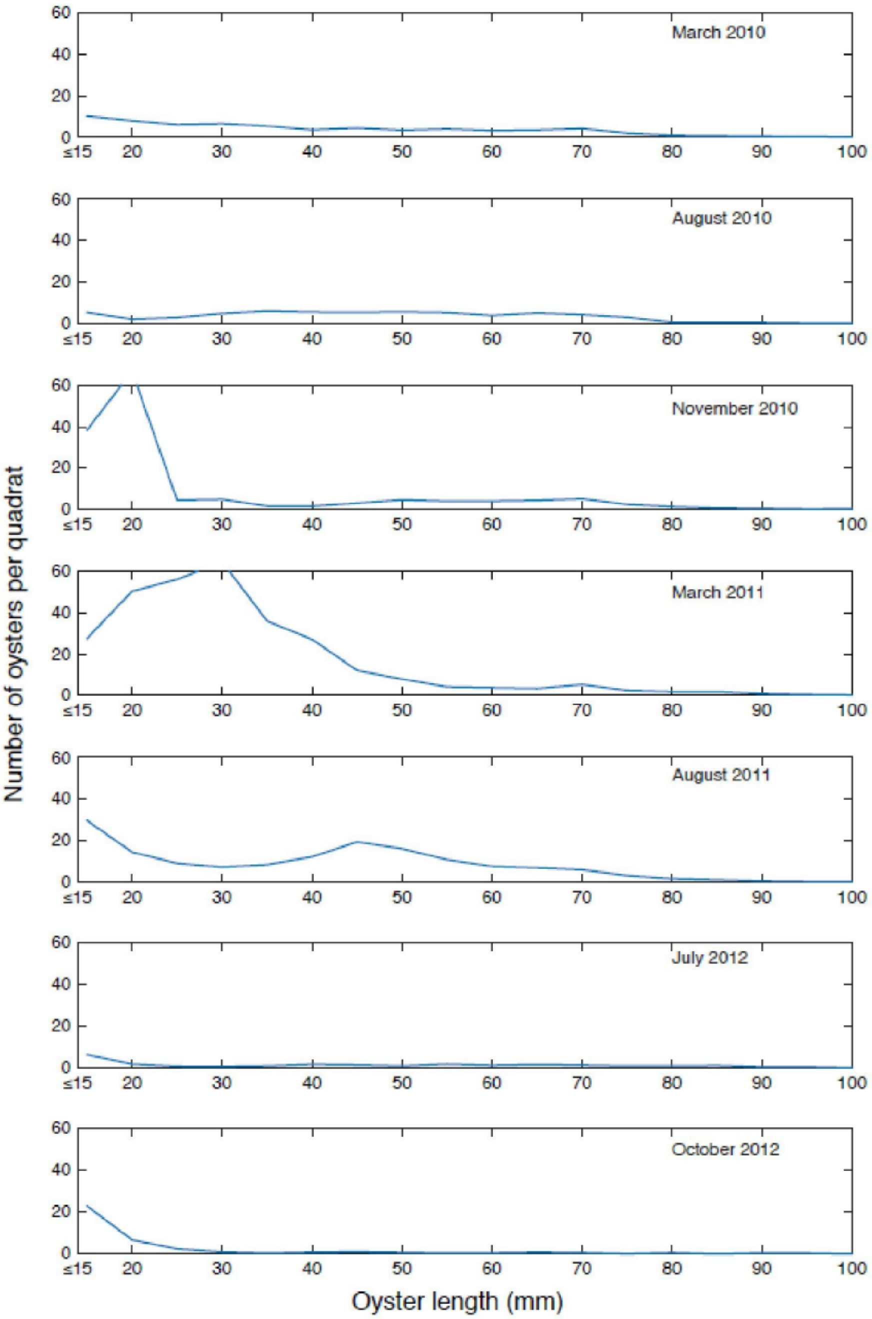
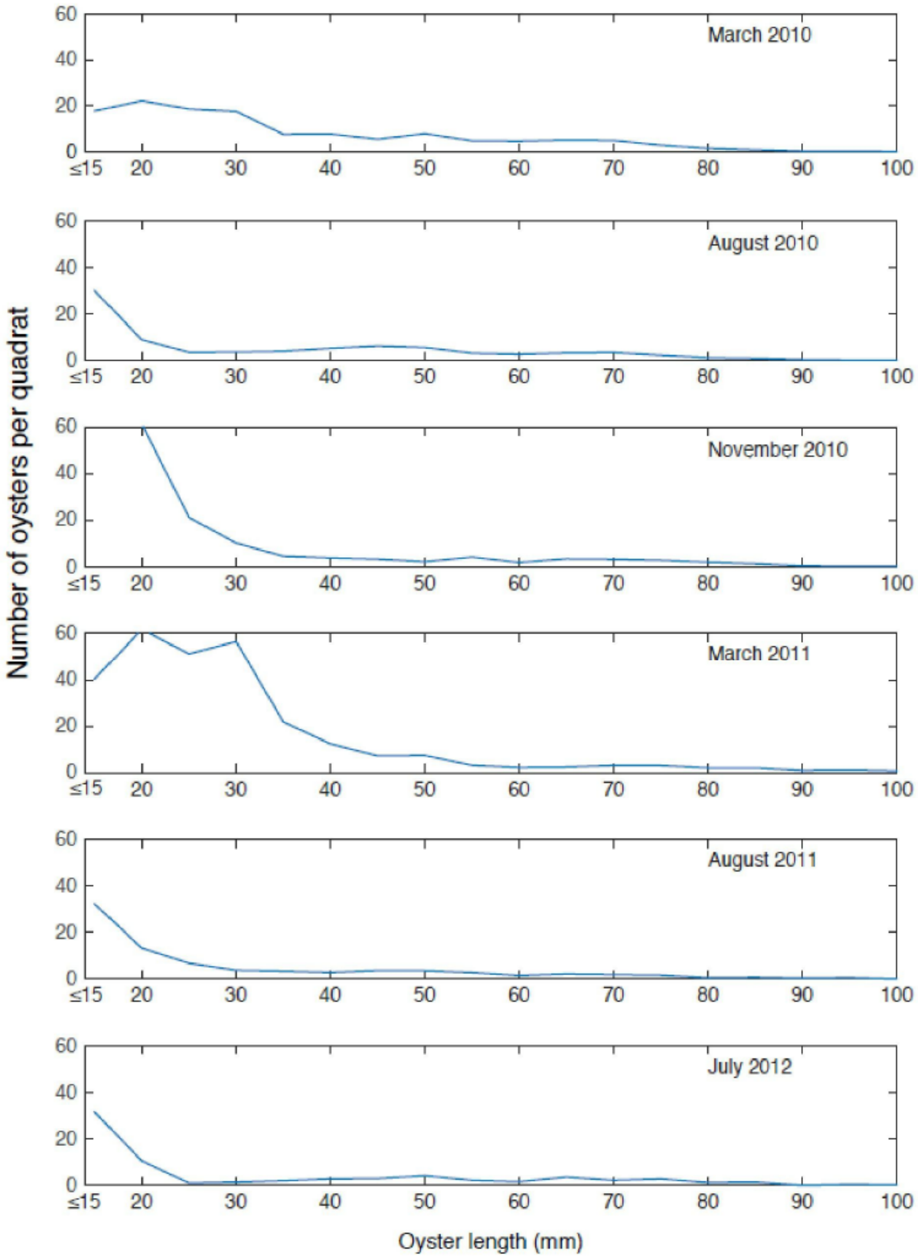
[6] An explanation of how FDACS collected the data is presented in FX-450 ("Explanation of FDACS Methodology"), a document prepared by FDACS in the normal course of its operations and produced to me in preparation of my expert report.



Source: FDACS Oyster Survey Data SAS Files (produced on February 11, 2015)

Figure 9 (FX-425). Size Distribution of Oysters in FDACS Surveys at Cat Point Bar. FX-425 is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the FDACS Data.



Source: FDACS Oyster Survey Data SAS Files (produced on February 11, 2015)

Figure 10 (FX-426). Size Distribution of Oysters in FDACS Surveys at Dry Bar. FX-426 is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the FDACS Data.

140. On both bars you can see typical dynamics of a healthy oyster reef in 2010 and early 2011. There was a large recruitment pulse into the population in late 2010, and that cohort

grew into larger size classes by March 2011. By August 2011 you can see considerable mortality of those very small size classes (particularly at Dry Bar), consistent with overall high mortality in the high-salinity conditions of summer 2011. In summer 2012 there continued to be high mortality across all size classes, though new recruitment in October 2012 was at a level similar to past years.

141. These patterns in 2011-2012 are consistent with a source of mortality that affected all size classes of oysters simultaneously in the summers of 2011 and 2012. The patterns are not consistent with the mechanism that Dr. Lipcius proposes: that overharvesting of legal and sub-legal size classes removed substrate and prevented subsequent recruitment of very small size classes.

VIII. MODEL SKILL ASSESSMENT

142. A straightforward and common way to assess how well a model performs and how much confidence one can place in the model's predictions is to run what is called a model skill assessment.[7] The basic procedure is to simulate model dynamics with *known* values for the variable parameters, and then use the model to estimate those parameters.

143. If the model estimates are close to the known simulated values, the model has high skill. In this case, the variable parameters to be estimated were the harvest rate, the salinity effect on recruitment (M_T, in the model notation), and the process variability and measurement variability parameters. Thus, I created simulated data with the harvest rate set to 0.2 per week and salinity effect on recruitment (M_T) set to 3.0 ppt^{-2} (these are the two parameters of greatest interest). The simulated data also included simulated process variability (i.e., random week-to-week fluctuations in oyster abundance).

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[7] A similar analysis of model skill is also included in the White et al. journal article published in July 2016 in *Ecological Applications*.

144. I created three separate simulated datasets with the same known parameter values. Each of these three had a different pattern of simulated process error, so the datasets were slightly different despite having the same known parameters – just like two different oyster populations could have the same external forces acting on them but differ significantly in abundance because of random year-to-year fluctuations. I then ran the model to fit it to each of the three simulated datasets to determine how well it could estimate those known values. The results of this skill assessment are shown in Table A1 of FX-493, shown below as Figure 11.

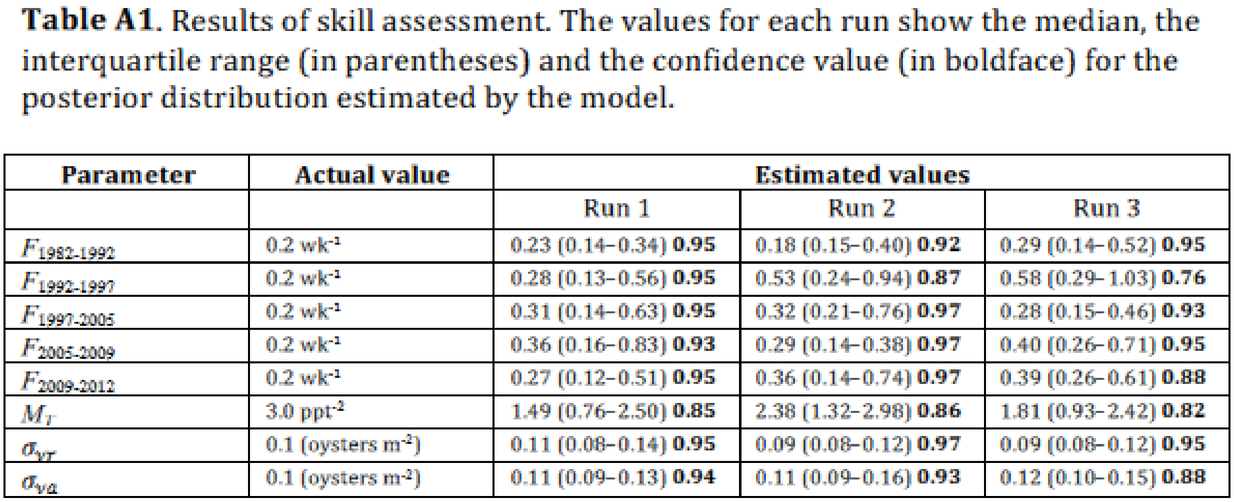


Table A1. Results of skill assessment. The values for each run show the median, the interquartile range (in parentheses) and the confidence value (in boldface) for the posterior distribution estimated by the model.

Parameter	**Actual value**	**Estimated values**		
		Run 1	Run 2	Run 3
$F_{1982\text{-}1992}$	0.2 wk^{-1}	0.23 (0.14–0.34) **0.95**	0.18 (0.15–0.40) **0.92**	0.29 (0.14–0.52) **0.95**
$F_{1992\text{-}1997}$	0.2 wk^{-1}	0.28 (0.13–0.56) **0.95**	0.53 (0.24–0.94) **0.87**	0.58 (0.29–1.03) **0.76**
$F_{1997\text{-}2005}$	0.2 wk^{-1}	0.31 (0.14–0.63) **0.95**	0.32 (0.21–0.76) **0.97**	0.28 (0.15–0.46) **0.93**
$F_{2005\text{-}2009}$	0.2 wk^{-1}	0.36 (0.16–0.83) **0.93**	0.29 (0.14–0.38) **0.97**	0.40 (0.26–0.71) **0.95**
$F_{2009\text{-}2012}$	0.2 wk^{-1}	0.27 (0.12–0.51) **0.95**	0.36 (0.14–0.74) **0.97**	0.39 (0.26–0.61) **0.88**
M_T	3.0 ppt^{-2}	1.49 (0.76–2.50) **0.85**	2.38 (1.32–2.98) **0.86**	1.81 (0.93–2.42) **0.82**
σ_{vr}	0.1 (oysters m^{-2})	0.11 (0.08–0.14) **0.95**	0.09 (0.08–0.12) **0.97**	0.09 (0.08–0.12) **0.95**
σ_{va}	0.1 (oysters m^{-2})	0.11 (0.09–0.13) **0.94**	0.11 (0.09–0.16) **0.93**	0.12 (0.10–0.15) **0.88**

Figure 11 Results of Model Skill Assessment Performed on the SSIPM. I created this table using generally scientifically accepted principles and methodology, and it is an accurate representation of the model skill assessment performed on the SSIPM.

145. Figure 11 shows that the model performed well with all confidence values greater than 75% and all but two were greater or equal than 85%. Most of the values were above 90%. This means that the model can estimate these unknown parameters – particularly the harvest rates – with very high confidence.

IX. MODEL RESULTS

A. The Effect of Georgia's Freshwater Withdrawals on Oyster Population

146. After fitting the model to the observed data from 1992-2012, I re-ran the model under an alternative salinity scenario: assuming Georgia removed no water from the system during 2007-2012. This is the so-called unimpacted flow scenario. To run this simulation, I relied upon Dr. Greenblatt's hydrology model, which predicted the change in salinity at different points in the Bay (including at Cat Point) that would be expected due to changes in the level of discharge of the Apalachicola River. FX-829a and FX-829b show the historical salinities and differences in salinities for the unimpacted flow scenario for Cat Point and Dry Bar, respectively, which were generated by me from the data obtained by Dr. Greenblatt, and are true and correct representations.

147. By running the model in the unimpacted flow scenario, I could determine how the oyster population on Cat Point and Dry Bar would have changed had Georgia not withdrawn water from the ACF watershed. The results of the unimpacted flow scenario are in FX-830a and FX-830b, which are shown below in Figures 12 and 13.

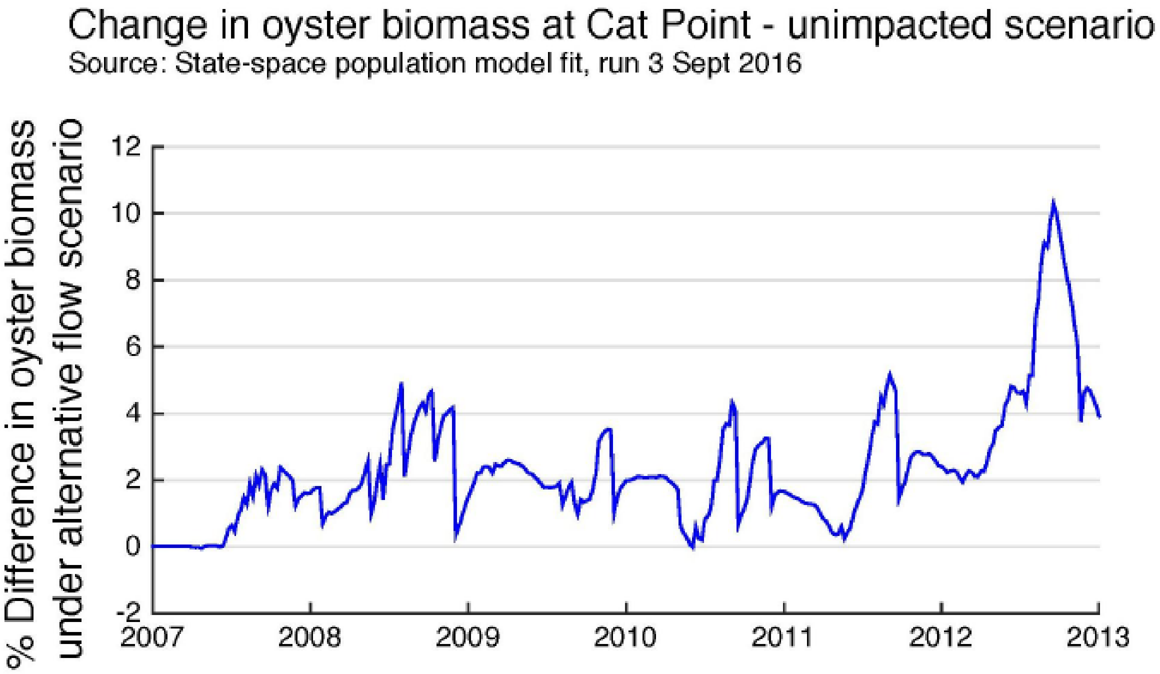


Figure 12 (FX-830a). Change in Oyster Biomass at Cat Point Under Unimpacted Scenario Salinity Conditions. FX-830a is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the change in oyster biomass at Cat Point.

148. The analysis summarized in the above Figure 12 shows that the salinity changes in Apalachicola Bay due to Georgia's freshwater consumption were responsible for up to 10% of the oyster biomass lost on Cat Point during the fishery collapse in 2012. In addition, oyster biomass would have been 2 to 4% higher in the years leading up to the collapse were it not for Georgia's upstream consumption.

149. The results for Dry Bar were similar, though they showed a greater effect of freshwater withdrawals over the entire 2007-2012 time period and slightly less in late summer 2012 than at Cat Point. These results are shown in the below Figure 13, which corresponds to FX-830b.

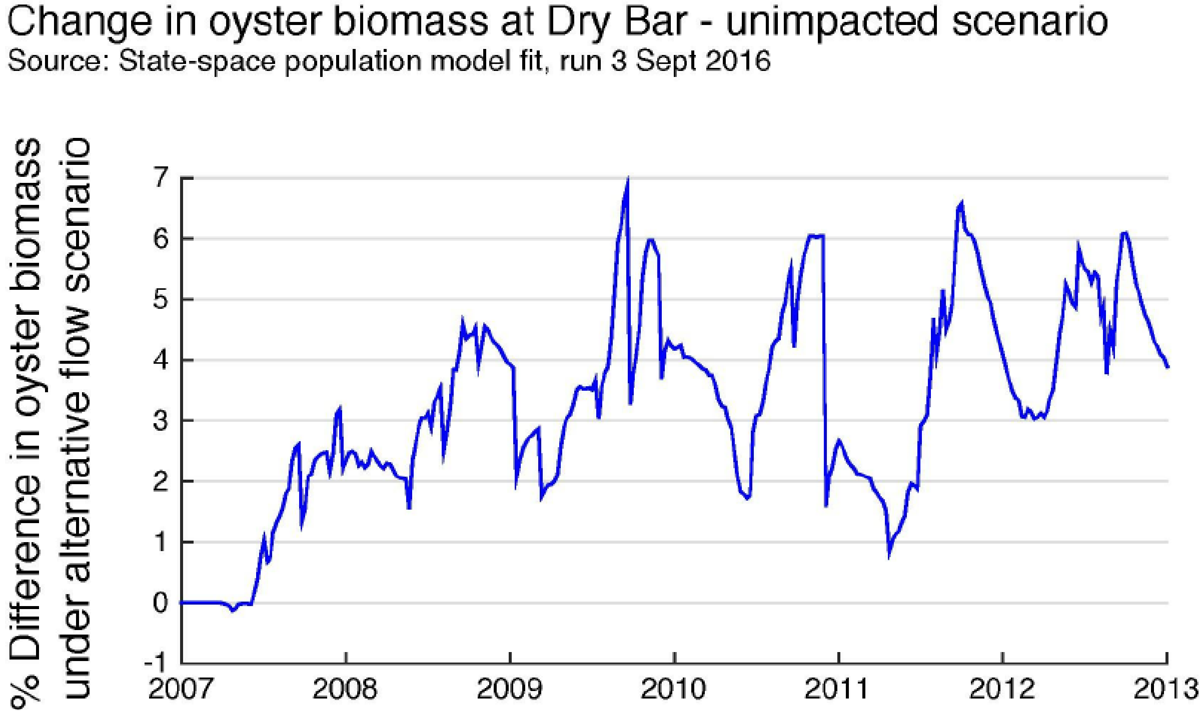


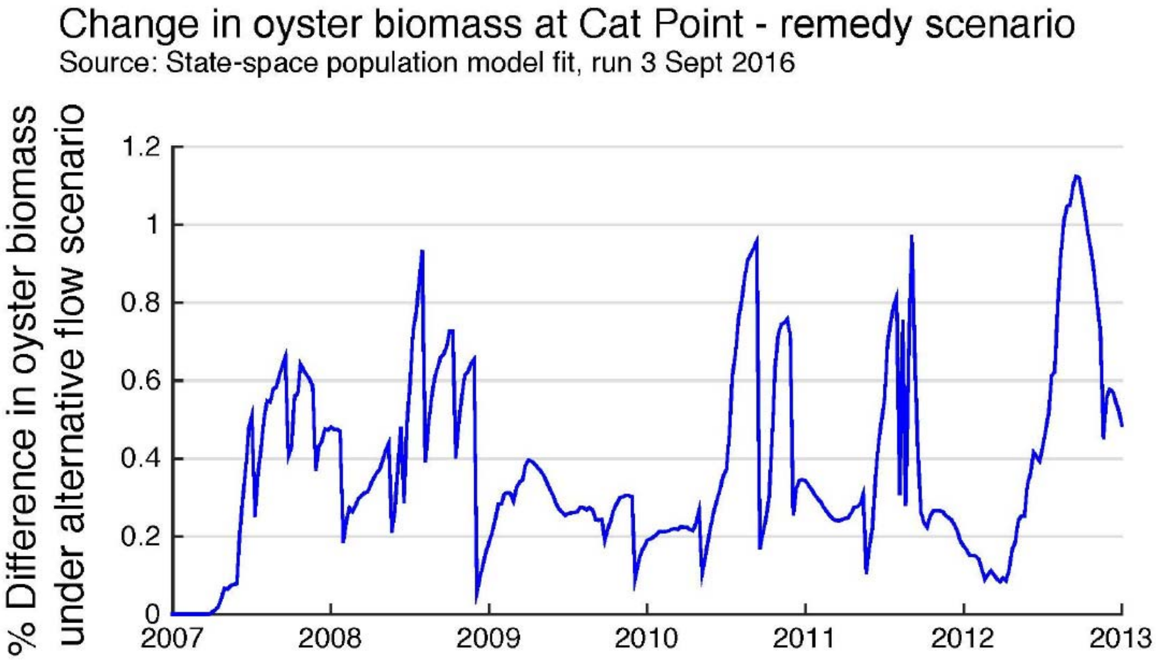
Figure 13 (FX-830b). Change in Oyster Biomass at Dry Bar Under Unimpacted Scenario Salinity Conditions. FX-830b is a true and correct copy of a graph I created using generally scientifically accepted principles and methodology, representing the change in oyster biomass at Dry Bar.

150. As such, it is my opinion that prolonged increases in salinity from Georgia freshwater withdrawals harm the oyster population in Apalachicola Bay, and any water Georgia could leave in the system to reach Apalachicola Bay would be beneficial. This benefit would be greater in periods of drought, such as the summer of 2012 because of the importance of variable salinity as shown by the model.

151. One of Dr. Lipcius's critiques of my model is that it was unrealistic because the only hypothetical flow scenario run was the unimpacted flow scenario. The unimpacted flow scenario is useful because it allows me to characterize the general dynamics of the system and rigorously test the effect of freshwater withdrawals on oyster populations.

152. Nonetheless, it is a valid critique from the standpoint that that Georgia would not completely cease all freshwater withdrawals. Therefore, after Dr. Lipcius submitted his report, I reran the model with a very conservative ‘remedy’ scenario similar to the relief that Florida is requesting in this original action. The salinity patterns associated with this remedy scenario were also generated by Dr. Greenblatt’s model. Attached to this testimony are FX-829c and FX-829d, which show the historical salinities and differences in salinities for the remedy flow scenario for Cat Point and Dry Bar, respectively, were generated by me from the data obtained by Dr. Greenblatt, and are true and correct representations.

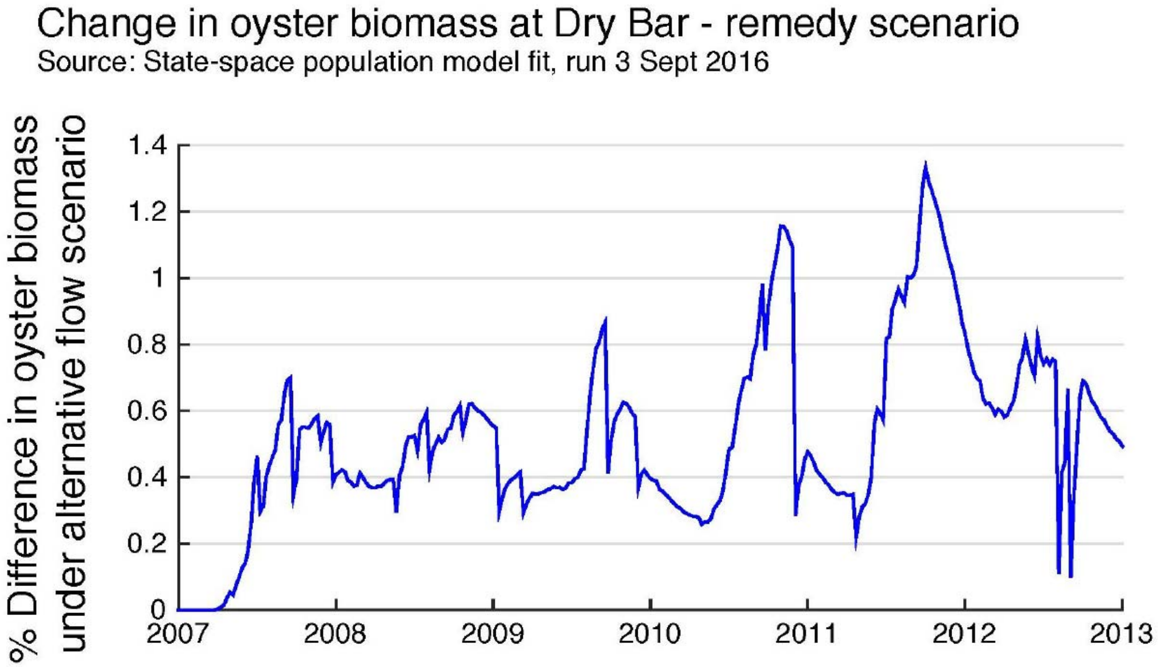
153. In general the results of this remedy scenario were consistent with the unimpacted flow scenario (Figure 14 – corresponding to FX-830c), but because the change in salinity was less, the overall benefit to the oyster population biomass was also less. However, the model still demonstrates that Georgia’s freshwater withdrawals exacerbated the natural low-salinity conditions in Apalachicola Bay, contributing to the oyster fishery collapse in Apalachicola Bay, and the situation would have been improved if Georgia had removed less water. The results for Dry Bar (Figure 15 – corresponding to FX-830d) under the remedy scenario were again similar to those for Cat Point.



Change in oyster biomass at Cat Point - remedy scenario

Source: State-space population model fit, run 3 Sept 2016

Figure 14 (FX-830c). Change in Oyster Biomass at Cat Point Under Remedy Scenario Salinity Conditions. FX-830c is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the change in oyster biomass at Cat Point.


Change in oyster biomass at Dry Bar - remedy scenario

Source: State-space population model fit, run 3 Sept 2016

Figure 15 (FX-830d). Change in Oyster Biomass at Dry Bar Under Remedy Scenario Salinity Conditions. FX-830d is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the change in oyster biomass at Dry Bar.

B. Insights on Harvesting From the Model

154. Another notable result of the model, aside from the predictions about salinity/flow effects, are the levels of harvest that the model estimated. The harvest rates for each of the five time periods are presented in Table 2 below, which has been revised and updated with the new data from those presented in Table 2 of my report.

Parameter	Description	Cat Point	Dry Bar
$F_{1982\text{-}1992}$	Harvest rate (wk^{-1})	0.256 (0.101-0.572)	0.063 (0.043-0.832)
$F_{1992\text{-}1997}$	Harvest rate (wk^{-1})	0.609 (0.384-0.910)	0.692 (0.453-0.723)
$F_{1997\text{-}2005}$	Harvest rate (wk^{-1})	0.302 (0.139-0.496)	0.087 (0.066-2.915)
$F_{2005\text{-}2009}$	Harvest rate (wk^{-1})	0.255 (0.123-0.457)	0.168 (0.024-0.169)
$F_{2009\text{-}2012}$	Harvest rate (wk^{-1})	0.239 (0.139-0.532)	0.356 (0.203-0.357)
M_T	Salinity effect on recruitment (ppt^{-2})	2.424 (2.090-3.326)	5.822 (5.484-5.997)
σ_{vr}	Process error in recruitment (oysters m^{-2})	34.867 (16.344-59.146)	18.101 (15.388-28.857)
σ_{va}	Process error in adult abundance (oysters m^{-2})	0.619 (0.350-1.083)	0.413 (0.413-0.426)

Table 2 (FX-831). Posterior estimates for parameters estimated by the model fit to data at Cat Point and Dry Bar. Values given are the median (interquartile range in brackets) for the posterior probability distribution for each parameter. FX-831 is a true and accurate copy of a graph I created using generally scientifically accepted principles and methodology, and it is an accurate representation of the fitted parameters obtained from the SSIPM.

155. Keep in mind that these rates are not expressed in terms of percent harvested; they have to be converted to percentages. The conversion for harvest rate x is $1 - e^{-x}$, where e is the base of the natural logarithm (about 2.718). So a harvest rate of 0.239 per week works out to about 21% harvest.

156. When interpreting these harvest rates, it is important to recall how harvesting is represented in the SSIPM. First, only legal-sized oysters can be harvested (with some variability around the size limit of 76 mm). Thus, the harvest rate only applies to those larger size classes, and recall from Figure 8 that the model generally predicted the abundance of those size classes quite well (lending confidence in the estimated harvest rates).

157. Second, new oysters are growing into the harvestable population every week. Thus, each week the legal-sized component of the population both loses some oysters to harvest and gains new ones from growth.

158. Third, the harvest rate (e.g., 21%) only applies to what is in the harvestable size range each week. That is, to estimate harvest over a four-week period you cannot simply multiply 21% by four to obtain 84% harvest. Each week's harvest is independent, so in general more oysters are taken at the beginning of the season and fewer later in the season, as the population is diminished before the next recruitment pulse – just like what happens in the real oyster fishery.

159. Fourth, the model accounts for the harvest seasons imposed by Florida fishery management authorities; thus there is no harvesting during the off-season in the model.

160. Fifth, these estimates of harvest are entirely based on the fishery-independent data in hand. That is, they are not influenced by other information regarding reported landings or number of commercial fishing licenses distributed. The estimate of harvest is based solely on what the size distribution of the oyster population looks like.

161. The harvest rates estimated by the model indicate the long-term pattern[8] of harvest in Apalachicola Bay. The most obvious pattern is the clear trend of declining harvest rates over time at Cat Point, from 0.609 per week in 1992-1999 to 0.255 per week in 2005-2009, to 0.239 per week in 2009-2012, the period of the fishery collapse.

162. Contrary to the analysis of Dr. Lipcius, which was based on fishery-dependent data, there is evidence that harvest rates at Cat Point (one of the most-harvested bars in the Bay) were well within historical norms during the critical period of 2009-2012. The SSIPM also shows that the fishery sustained consistently high harvest rates over several decades with harvest rates as high or higher than those in 2009-2012. This leads to the conclusion that overharvest, or dramatic increases in harvest rates, did not contribute to the fishery collapse in Apalachicola Bay in 2012.

163. The SSIPM analysis at Dry Bar supports these conclusions. For Dry Bar, the model estimated a higher harvest rate in 2009-2012 than during 2005-2009, but the 2009-2012 harvest rate was well within the historical range estimated for 1992-1999 and 1999-2005.

X. CONCLUSION

164. My model analysis shows that freshwater withdrawals by Georgia during a drought, which increased the salinity for prolonged periods of time, contributed materially to the

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[8] I do not focus on interpreting the results for 1982-1992 because that is the “settling in” part of the SSIPM run prior to the start of data collection.

2012 oyster fishery collapse in Apalachicola Bay. In general, if Georgia withdraws less water, particularly during drought periods, the Apalachicola Bay oyster population will benefit.

165. Furthermore, the levels of harvest estimated by the SSIPM – using reliable, fishery-independent data – show that harvest rates preceding and during the collapse were consistent with or lower than historical harvest rates. Thus the oyster fishery in Apalachicola can remain productive and sustainable with the level of harvest experienced during 1992-2012, so long as salinity is not increased by freshwater withdrawals for prolonged periods.