

Early Warnings of Regime Shifts: A Whole-Ecosystem Experiment

S.R. Carpenter^{1,*}, J.J. Cole², M.L. Pace³, R. Batt¹, W.A. Brock⁴, T. Cline¹, J. Coloso³, J.R. Hodgson⁵,
J.F. Kitchell¹, D.A. Seekell³, L. Smith¹, and B. Weidel¹

¹Center for Limnology, University of Wisconsin, Madison, WI 53706 USA

²Cary Institute of Ecosystem Studies, Millbrook, NY 12545 USA

³Department of Environmental Sciences, University of Virginia, Charlottesville, VA 22904 USA

⁴Department of Economics, University of Wisconsin, Madison, WI 53706 USA

⁵Department of Biology, St. Norbert College, De Pere, WI 54115 USA

*To whom correspondence should be addressed. Email: srcarpen@wisc.edu

Abstract

Catastrophic ecological regime shifts may be announced in advance by statistical early-warning signals such as slowing return rates from perturbation and rising variance. The theoretical background for these indicators is rich but real-world tests are rare, especially for whole ecosystems. We tested the hypothesis that these statistics would be early-warning signals for an experimentally-induced regime shift in an aquatic food web. We gradually added top predators to a lake over three years to destabilize its food web. An adjacent lake was monitored simultaneously as a reference ecosystem. Warning signals of a regime shift were evident in the manipulated lake during reorganization of the food web more than a year before the food web transition was complete, corroborating theory for leading indicators of ecological regime shifts.

23 Main Text

24 Massive ecosystem changes affect water supplies, fisheries, productivity of rangelands and
25 forests, and other ecosystem services (1, 2). Nonlinear regime shifts often come as surprises.
26 However, recent research has revealed statistical signals that precede some nonlinear
27 transitions, such as rising autocorrelation, steep increases in variance, extreme changes in
28 skewness and shift in variance spectra toward low frequencies (3-7). If the transition is
29 approached slowly and the right variables are sampled frequently, warnings may be evident
30 well before the regime shift is complete. Empirical evidence for early warnings of
31 environmental regime shifts comes from time series of major changes in paleoclimate (8),
32 spatial pattern of dryland vegetation during desertification (9), variability of exploited fisheries
33 (10, 11), and laboratory studies (12). Here we present a test of early warning indicators from a
34 large-scale multi-year field experiment using a manipulated and a reference ecosystem.

35 Gradual addition or removal of top predators destabilizes food webs, and extreme
36 manipulations of predators cause trophic cascades, a type of regime shift that alters food web
37 structure and ecosystem processes such as primary production, ecosystem respiration, and
38 nutrient cycling (13, 14). Predator-driven transitions in lakes involve nonlinear dynamics of fish,
39 zooplankton, and phytoplankton populations (15). Over three years, we gradually added a top
40 predator, largemouth bass (*Micropterus salmoides*), to a lake dominated by planktivorous
41 fishes to destabilize the food web and induce a trophic cascade leading to dominance of the
42 food web by piscivores (16). A nearby lake, dominated by adult largemouth bass, was not
43 manipulated and served as a reference ecosystem. The reference ecosystem allows us to
44 evaluate the possibility that responses were caused by external drivers rather than the
45 manipulation (15). Planktivorous fishes, zooplankton and phytoplankton were monitored daily
46 in both lakes for three years of summer stratification (2008-2010) (16).

47 Predicted responses of the food web follow from previous experiments in these lakes (15) and
48 an ecosystem model calibrated for the manipulated lake (17). Prior to manipulation, the
49 manipulated ecosystem was dominated by a variety of small fishes (hereafter planktivores, 16)
50 and largemouth bass were few. We expected that addition of largemouth bass would trigger
51 recruitment of juvenile bass that were planktivorous initially but become omnivorous, adding
52 benthos and fish to their diets, as they grew. Piscivory by largemouth bass would cause
53 planktivorous fishes to seek refuge from predation by occupying littoral refugia and shoaling
54 (aggregating). Eventually piscivory would drive planktivorous fishes to low densities. As
55 planktivory declined in the open water, larger-bodied zooplankton (including migratory
56 *Daphnia pulex*) would increase in relative abundance. Increased grazing would lead to cyclic
57 oscillations of zooplankton and phytoplankton biomass. Thus the food web transition would
58 exhibit a sequence of nonlinear changes due to shoaling and diel movements of consumers,
59 species replacement, and predator-prey cycles as the manipulated ecosystem became more
60 similar to the reference ecosystem. We hypothesized that dynamics during this transitional
61 period would generate early warning signals of a regime shift toward a piscivore dominated
62 food web.

63 Transitional dynamics of the food web were consistent with our expectations (Fig. 1). In the
64 manipulated lake, 39 adult largemouth bass were present at the beginning of the experiment.
65 We added 12 largemouth bass on day 193 of 2008, and 15 largemouth bass on each of days 169
66 and 203 of 2009. Enhancement of adult largemouth bass triggered a recruitment event in 2009,
67 leading to 1281 young-of-year largemouth bass (95% CI 1088-1560) by day 240 of 2009.
68 Numbers of this cohort (1+ in Fig. 1C) declined through 2010 while surviving individuals grew in
69 body mass and became piscivorous. Planktivore numbers in the manipulated lake declined
70 through the study as piscivory increased, and were similar to the reference lake by about day
71 230 of 2010 (Fig. 1F).

72 The spatial pattern of planktivores was occasionally patchy in 2008 and 2009, indicated by high
73 values in the discrete Fourier transform (DFT) of spatial data (16,18) (Fig. 2). Patchy
74 distributions were more frequent and of longer duration in 2010. Patchy distributions indicate
75 shoaling behavior – a likely response to predation risk.

76 Zooplankton biomass of the manipulated lake declined during the summers of 2008 and 2009
77 and became strongly oscillatory in 2010 (Fig. 1). Through 2009 and 2010, dominance of the
78 zooplankton shifted toward larger-bodied cladocerans, including *Daphnia pulex*, in the
79 manipulated lake [Fig. S1], consistent with previous whole-lake experiments in which body size
80 but not biomass of zooplankton responded to fish manipulations (15, 19). Phytoplankton
81 biomass as measured by chlorophyll *a* of the manipulated lake displayed strong oscillations in
82 2009 and the first half of 2010. By day 230 of 2010, manipulated and reference lakes were
83 similar in planktivore numbers, zooplankton biomass, and chlorophyll.

84 Modeling predicts that early warning indicators would appear after the largemouth bass
85 addition in 2008 and continue until stabilization of a new food web dominated by largemouth
86 bass (17). It is not necessary to observe complete convergence of the food webs, because in
87 order to be useful the early warnings must be seen before the food webs converge. Specifically,
88 after 2008 we expect periods of increased variability, return rates near zero, lag-1
89 autocorrelations near one, skewness far from zero, and shifts in variance spectra toward low
90 frequencies if the theory of early warning indicators is supported. We focused on chlorophyll
91 which responds strongly to food web fluctuations and can be measured at high frequency and
92 precision (20, 21). Chlorophyll variability was somewhat lower in the manipulated lake than in
93 the reference lake during the three years prior to manipulation (Table S2).

94 High frequency measurements of chlorophyll (every 5 minutes) had similar spectra in both lakes
95 in 2008 (Fig. 3). In 2009 and 2010, however, spectral power shifted to low frequencies in the
96 manipulated lake relative to the reference lake (yellow and tan colors in panels for 2009 and
97 2010, Fig. 3). This shift toward lower-frequency variance is characteristic of regime shifts (3),
98 including dynamics of chlorophyll in model simulations of trophic cascades in this manipulated
99 lake (17). Early warning indicators calculated for daily chlorophyll concentrations were
100 consistent with theoretical expectations (Fig. 4). In 2009 and 2010, there are times when the
101 variance was much higher in the manipulated lake than in the reference lake, and the return
102 time in the manipulated lake was close to zero. Variance was high in the manipulated lake for
103 most of 2009 and early 2010. The coefficient of variation (standard deviation / mean) was also

104 elevated in the manipulated lake through 2009 and early 2010 [Fig. S2]. The return rate was
105 close to zero in 2009 (days 185-210) and 2010 (until day 206) (Fig. 4). Autocorrelations near
106 one, which are also associated with near-zero return rates, occurred in the manipulated lake
107 from about days 180-215 of 2009 and until about day 210 of 2010 [Fig. S2]. Skewness, an
108 indicator of asymmetry associated with alternate states (6), reached high values in 2009, and
109 cycled from low to high values in 2010 (Fig. 4). These changes in skewness are consistent with
110 shifts between alternate states (6). The spectral ratio (16), a measure of the strength of the
111 shift in variance from high to low frequencies (22) was elevated in the manipulated lake in late
112 2008, much of 2009 and the first half of 2010.

113 Regime shifts are characterized by nonlinear dynamics. A conservative test for nonlinearity
114 (bootstrap BDS test on AR and GARCH residuals for daily chlorophyll data (16)) rejects the
115 hypothesis of linearity for the manipulated lake and does not reject the hypothesis of linearity
116 for the reference lake (23). This result is consistent with nonlinear dynamics due to a regime
117 shift in the manipulated lake but not the reference lake. Diverse nonlinear models have been
118 proposed for dynamics of plankton (24-28). The precise mechanism of the nonlinear transitions
119 is not known for our experiment; it could be one of the processes proposed in the literature, or
120 something else. These early warning signals are expected to occur for a wide class of nonlinear
121 transitions (7). Even though the mechanism is not known, manipulation of an apex predator
122 triggered a nonlinear food web transition that was signaled by early warning indicators more
123 than a year before the food web transition was complete. Thus the early warning indicators
124 appear to be useful even in cases where the form of the potential regime shift is not known.

125 This experiment created ideal conditions for detection of early warning indicators under field
126 conditions in a whole ecosystem. The regime shift was driven at a slow rate compared to the
127 frequency of sampling and the response rate of the plankton. A reference system was used to
128 assess the indicators in an unmanipulated system subject to the same weather and watershed
129 influences. Both the manipulated and reference ecosystems were sampled at high frequency
130 using identical methods, leading to relatively large datasets for evaluation of the indicators. In
131 other situations, it may be difficult to identify meaningful changes in the indicators. Modeling
132 studies have pointed out a number of limitations of these early warning indicators (7, 18, 22,
133 29, 30). False early warnings can be generated by aggregation of linear processes or by
134 exogenous shocks. Errors of this kind are not likely in our experiment because the regime shift
135 was induced experimentally, multiple indicators are consistent in the manipulated lake, the
136 reference lake shows no indications of exogenous shocks (e.g. regional weather events), and a
137 conservative statistical test is consistent with nonlinear dynamics in the manipulated but not
138 the reference lake. Early warnings, however, may fail in cases where the system is forced too
139 fast across a critical threshold, where observation errors are large, or where signals are
140 dampened by interactions among multiple nonlinear processes. Our experiment was designed
141 to minimize these limitations and thereby maximize the possibility of detecting early warnings.

142 Theory indicates that early warning signals should be discernible prior to regime shifts in
143 aquatic or terrestrial ecosystems as well as other types of nonlinear systems, even in cases
144 where the driver is not known (7). Spatial statistics may prove especially useful for terrestrial or
145 benthic habitats (7, 9, 17). Expanding availability of automated sensors and remote sensing

146 increases opportunities for measuring early warning signals. Comparison with a reference
 147 ecosystem was important for discerning changes in our experiment. Networks for long-term
 148 ecological observation, such as the US Long Term Ecological Research network
 149 (<http://www.lternet.edu/>) increase the possibility of detecting early warnings through
 150 comparisons across sites and among regions.

151 Early warning signals are potentially useful for managing ecosystem services that are subject to
 152 catastrophic change, such as unwanted shifts in freshwater quality or production of fisheries
 153 and rangelands. In our experiment early warnings were discernible while a transition was
 154 underway, but the experiment was not designed to assess if a regime shift could be reversed by
 155 intervention after detection. Modeling suggests that some but not all regime shifts can be
 156 reversed by prompt intervention after early warnings are detected (22, 31). Reversibility
 157 through detection of signals and subsequent intervention is a key question for future field
 158 experiments.

159 Ecosystems are subject to increasing human pressures that can lead to drastic changes
 160 including shifts to unwanted states (2). In this whole-lake field experiment early warnings were
 161 detected in a food web undergoing a regime shift. Statistical indicators related to variability,
 162 autocorrelation, and recovery time provide new tools for empirical studies of nonlinear
 163 dynamics in field studies of ecosystems or other complex systems. Thus our findings should
 164 prompt further field experiments to evaluate early warnings for massive change in ecosystems
 165 and other complex systems. This research could reveal new indicators of vulnerability to large
 166 environmental changes, and thereby improve ecosystem management in a rapidly changing
 167 and interconnected world.

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220 **staff of the University of Notre Dame Environmental Research Center for assistance.**
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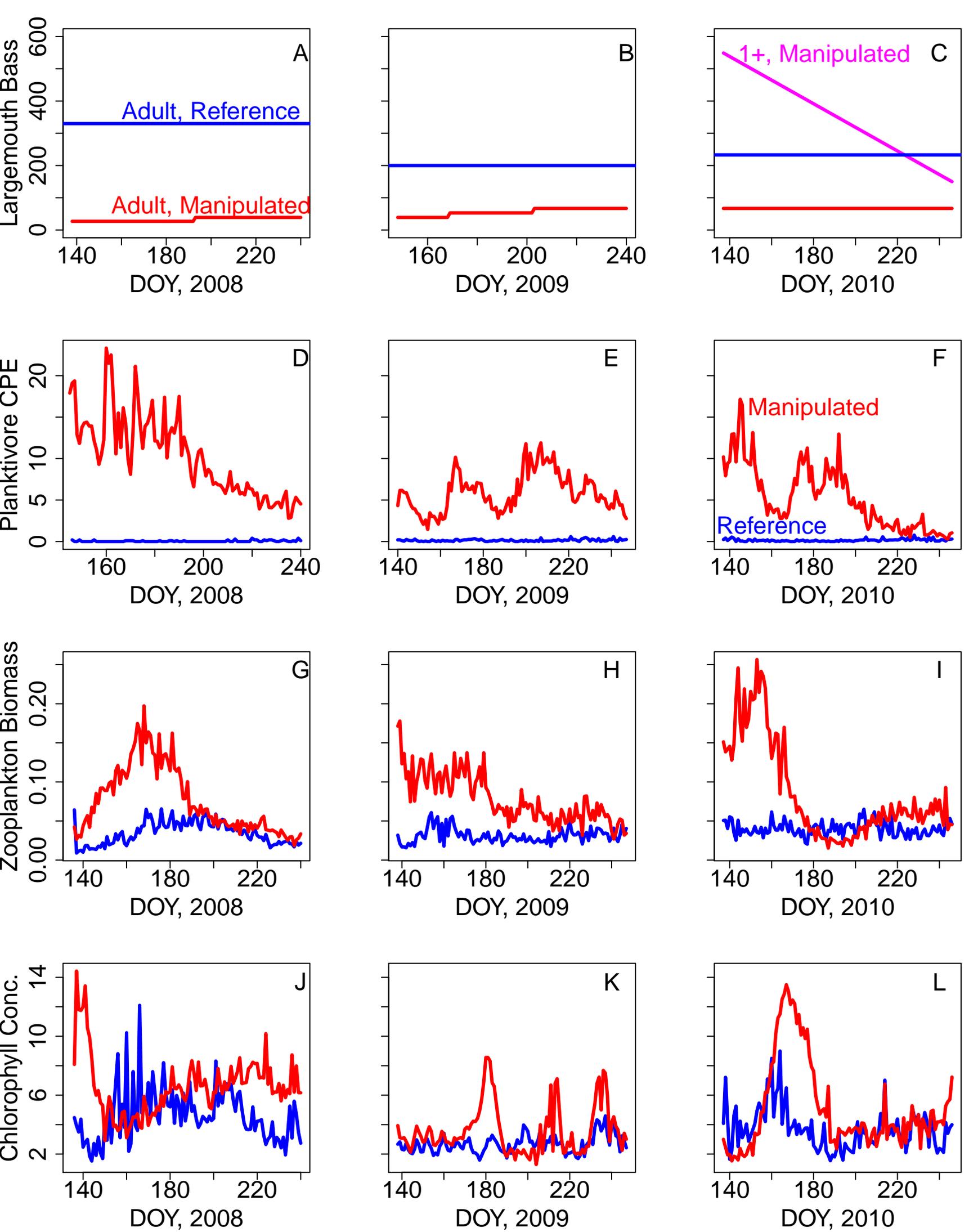
225 **Figure Captions**

226 Fig. 1. Time series of the food webs in manipulated (red) and reference (blue) lakes in 2008-
 227 2010 . A-C: Largemouth bass adult population (fish/lake) in each lake. For the manipulated lake
 228 in 2010, numbers of year 1+ bass (recruited in 2009) are shown in magenta. D-F: Planktivorous
 229 fish density (animals caught trap⁻¹ hour⁻¹) estimated as catch-per-effort in minnow traps
 230 deployed in the littoral zone. G-I: Zooplankton biomass (g m⁻²). J-L: Chlorophyll concentration
 231 (mg m⁻³) in the mixed layer.

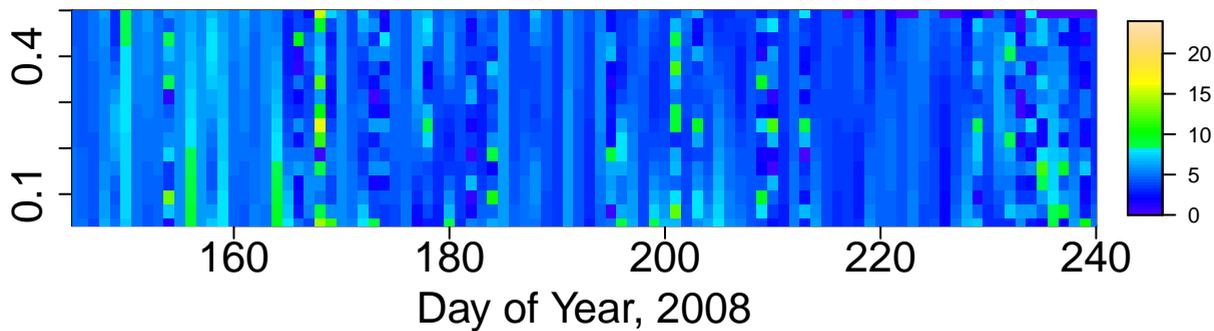
232 Fig. 2. Discrete Fourier transform (DFT) of the spatial sequence of minnow (planktivorous fish)
 233 trap catches around the perimeter of the manipulated lake on each day of sampling in 2008 (A),
 234 2009 (B) and 2010 (C). Spatial frequency (per trap) is plotted versus day of the year, with DFT
 235 ordinate (a measure of variance, 16) shown by colors (see legend). High ordinates indicate
 236 clustering of planktivores at a particular spatial frequency (18). Spatial frequency is inversely
 237 related to spatial extent; for example a frequency of 0.1 corresponds to once in 10 traps, or a
 238 total of 3 traps in our array of 30 traps. In the reference lake, catch numbers were too small to
 239 estimate the DFT.

240 Fig. 3. Difference between manipulated and reference lakes in spectra for high-frequency
 241 chlorophyll observations in 2008 (A), 2009 (B) and 2010 (C). On each date in each lake, spectra
 242 were computed for the preceding 7 days using observations recorded every 5 minutes by
 243 floating sensors (16). Frequency (per day, log₁₀ transformed) is plotted versus day of the year,
 244 with differences in spectra (log₁₀ transformed) indicated by colors (see legend). Green colors
 245 indicate little difference in spectral power between lakes, blue colors indicate that spectral
 246 power of the manipulated lake was lower than that of the reference lake, and yellow or tan
 247 colors indicate that the spectral power of the manipulated lake was greater than that of the
 248 reference lake. High spectral power at low frequencies is associated with nonlinear transitions
 249 (3, 17, 22).

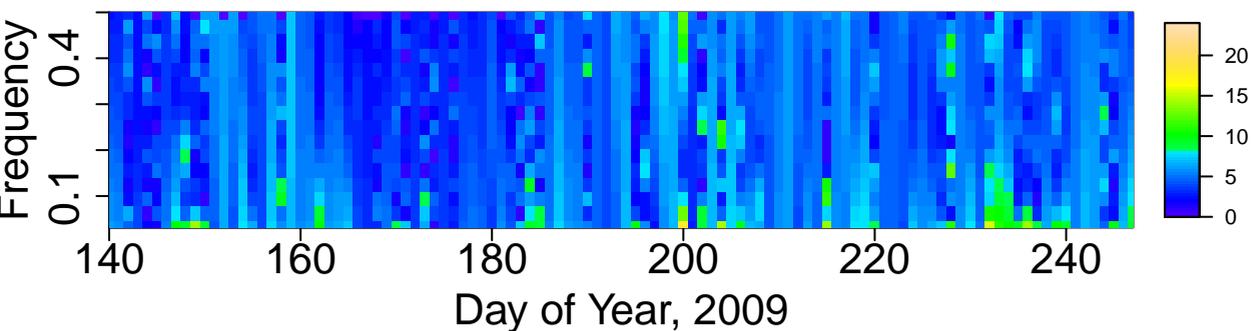
250 Fig. 4. Potential early warning indicators computed from daily chlorophyll time series in the
 251 mixed layer in the manipulated (red) and reference (blue) lakes in 2008, 2009 and 2010. On
 252 each date in each lake, statistics were computed for the preceding 28 days using daily
 253 observations (16). A-C: Variance; high values are associated with nonlinear transitions. D-F:
 254 Return rate from small perturbations computed by autoregressive modeling (16). Values near
 255 zero are associated with nonlinear transitions. G-I: Coefficient of skewness. Values far from 0
 256 (the value for a normal distribution) are associated with nonlinear transitions. J-L: Spectral
 257 ratio (log₁₀ transformed) of power at low frequencies (< once per day) to power at high
 258 frequencies (from once per three hours to once per 15 minutes) computed from chlorophyll
 259 measurements made every 5 minutes. High spectral ratios are associated with nonlinear
 260 transitions (22).



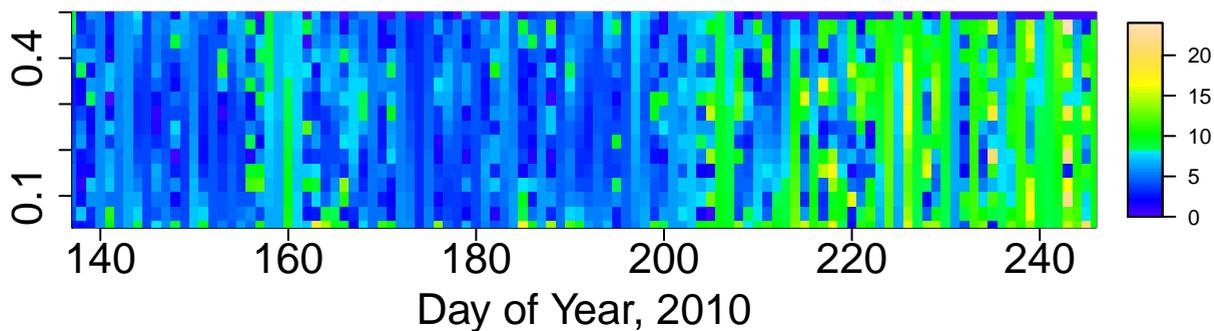
A. Planktivores, Manipulated Lake, DFT



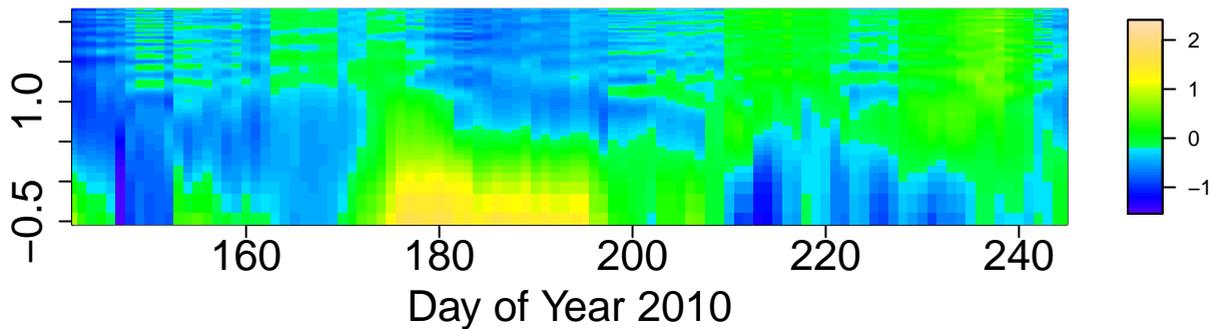
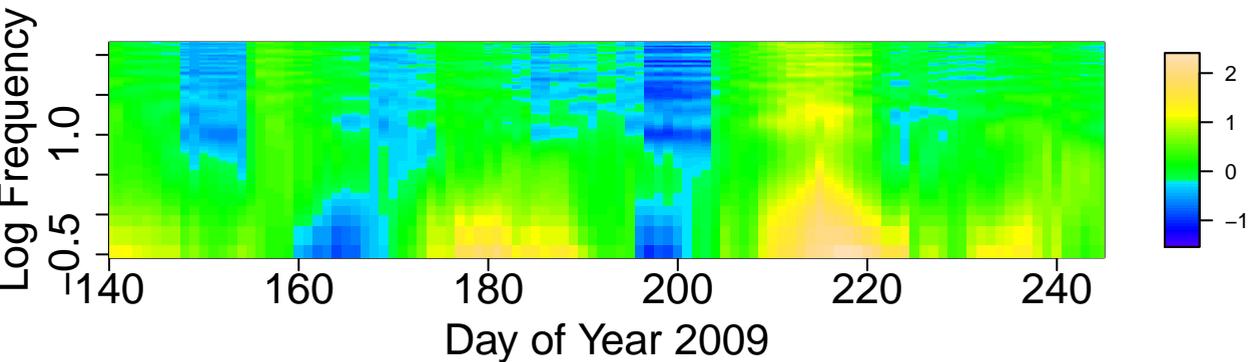
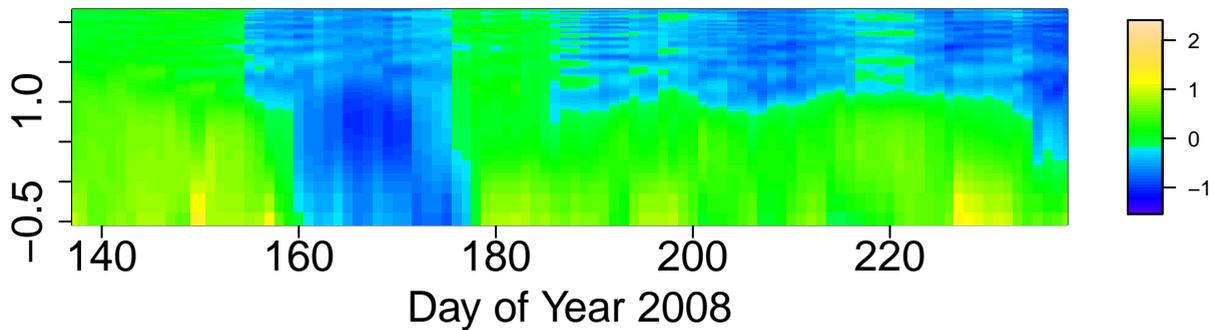
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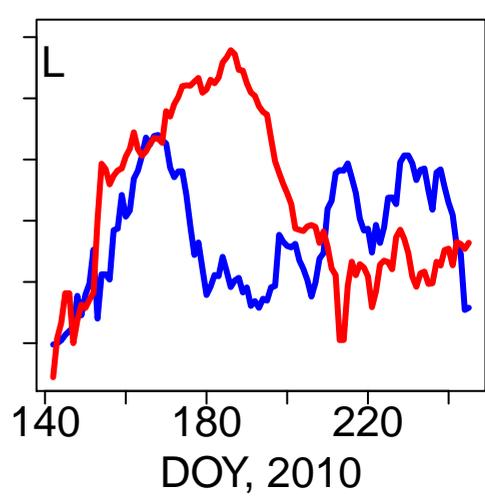
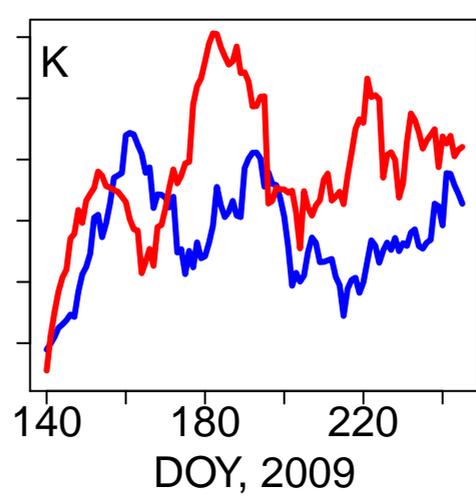
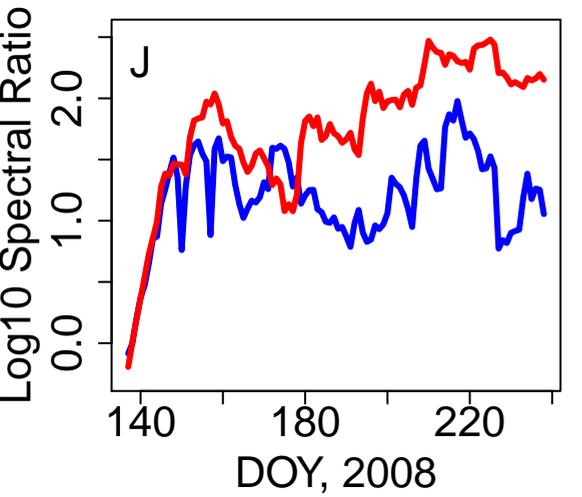
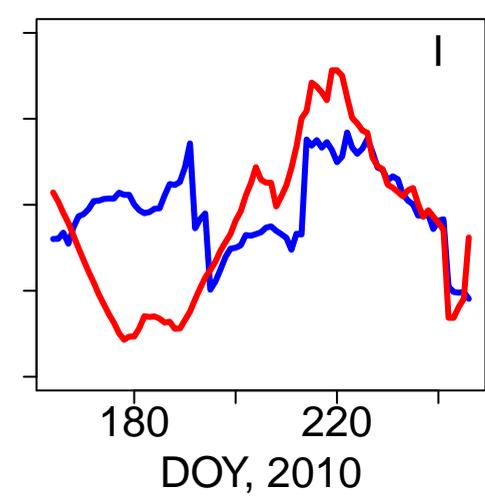
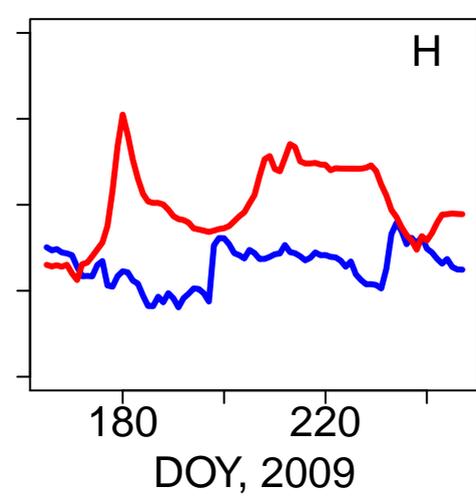
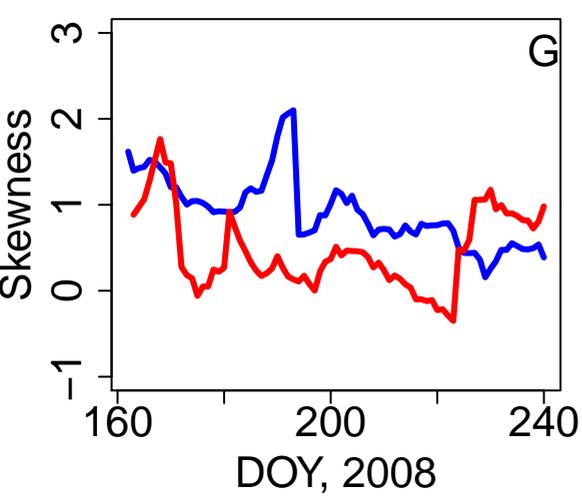
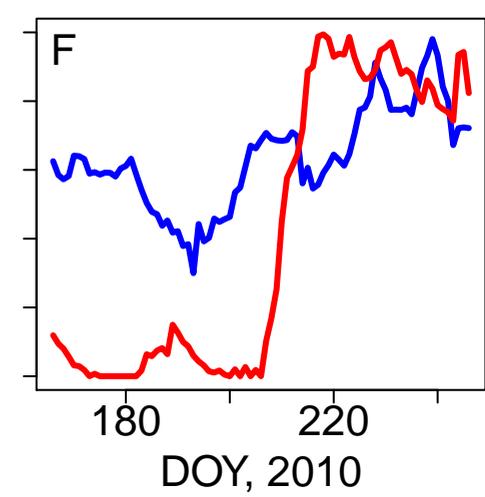
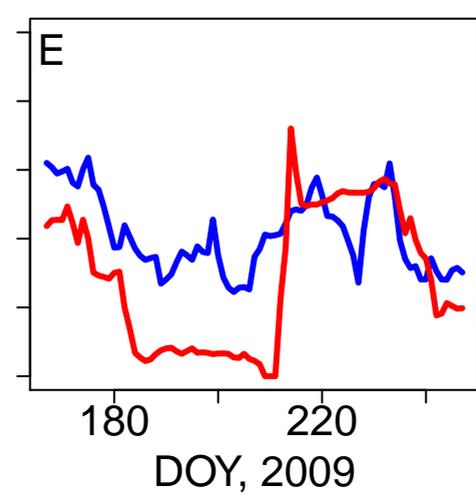
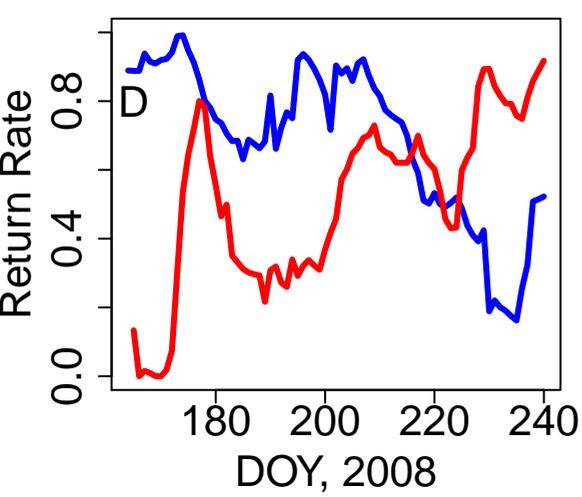
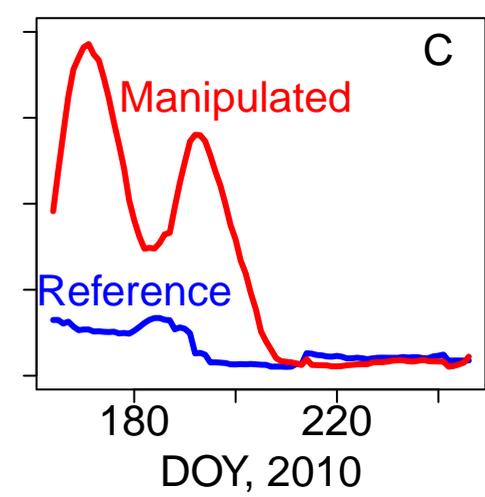
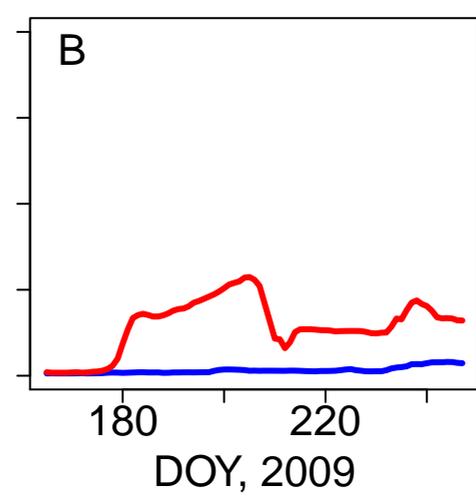
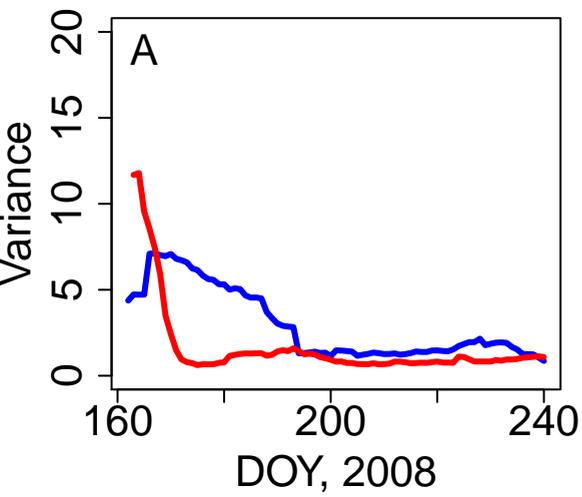


C. Planktivores, Manipulated Lake, DFT



Spectral Differences, Manipulated – Reference





Supporting Online Material for

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¹Center for Limnology, University of Wisconsin, Madison, WI 53706 USA

²Cary Institute of Ecosystem Studies, Millbrook, NY 12545 USA

³Department of Environmental Sciences, University of Virginia, Charlottesville, VA 22904 USA

⁴Department of Economics, University of Wisconsin, Madison, WI 53706 USA

⁵Department of Biology, St. Norbert College, De Pere, WI 54115 USA

*To whom correspondence should be addressed. Email: srcarpen@wisc.edu

This PDF file includes:

SOM Text:

Field and laboratory methods

Statistical analyses

Figures S1 to S4

Tables S1 and S2

Supporting online text

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Field and laboratory methods

Study Sites and Fish Community Structure - Paul and Peter Lakes, MI (89°32' W, 46° 13' N) located at the University of Notre Dame Environmental Research Center were used as the reference and manipulated systems in this study. The lakes are separated by an earthen dike, with Paul Lake lying slightly upstream of Peter Lake. The lakes have similar morphometry and limnology (15). Nutrient concentrations during this experiment are presented in Table S1.

During this study, the fish in the reference lake (Paul) were adult largemouth bass (*Micropterus salmoides*) and a smaller population of pumpkinseeds (*Lepomis gibbosus*). Average total abundance of adult largemouth bass in the reference lake ranged from 200 to 330 individuals over the period 2008 to 2010. At the outset of the study, the manipulated lake (Peter) was dominated by a variety of small-bodied fish species including pumpkinseeds (*Lepomis gibbosus*), golden shiners (*Notemigonus crysoleucas*), fathead minnows (*Pimephales promelas*), dace (primarily *Phoxinos eos* and *Phoxinus neogaeus*), brook stickleback (*Culaea inconstans*), and central mudminnow (*Umbra limi*). These fishes consume a mix of plankton and benthos. We focus here on their effect on chlorophyll through zooplanktivory, and refer to these fishes collectively as planktivores. On day 149 of 2008 we added 1200 golden shiners to Peter Lake to increase the dominance by planktivores. Approximately 39 largemouth bass were present in Peter Lake in early 2008. Over 2008-2010, biomass of largemouth bass increased as a result of our manipulations (see below) and a major recruitment event in 2009. As numbers of 1+ and adult largemouth bass increased, populations of small-bodied planktivorous fishes decreased (see main text).

Food web structure -- Adult largemouth bass, the apex predator in these lakes, feed on benthic invertebrates, zooplankton, terrestrial prey and smaller-bodied fishes, including young-of-year and juvenile largemouth bass. Planktivorous fishes in this experiment are listed above and feed on zooplankton as well as benthic invertebrates and in some cases young-of-year fishes. Importantly, planktivorous fishes move between littoral and pelagic habitats and engage in shoaling behavior in response to predation threats and food availability. Responses to bass predators thus diminish planktivory. Zooplankton feed on phytoplankton or in some cases on other zooplankton species. Large-bodied species of *Daphnia* are the most effective grazers in these lakes and are capable of diel vertical migration in the presence of planktivorous fishes. This paper focuses on the interactions of largemouth bass, the full set of planktivorous fishes, pelagic zooplankton and phytoplankton.

Bass addition and population sampling – Adult largemouth bass were added to the manipulated lake on day 193 of 2008, day 169 of 2009, and day 203 of 2009. Twelve largemouth bass were added in 2008 and fifteen were added on each of the two dates in 2009. Adult largemouth bass population size in the manipulated and reference lakes was estimated by mark/recapture sampling using electrofishing and angling (32, 33). Young-of-the-year and age 1+ largemouth

62 bass were sampled using a combination of traps and electrofishing (15). Population sizes of
 63 these age classes were also estimated in the manipulated lake as they became abundant.

64
 65 *Sampling of small fishes* – In the manipulated lake, we deployed a spatially distributed array of
 66 30 littoral and 30 pelagic minnow traps. In the reference lake, we deployed a spatially
 67 distributed array of 20 littoral and 20 pelagic minnow traps. Trap mesh size was 6 mm and trap
 68 opening diameters were 25 mm in all cases.. These traps were monitored daily in both lakes
 69 from late May to early September in each year of the study. The abundance of each species of
 70 fish collected in each trap was recorded daily.

71
 72 *Zooplankton biomass* – Four replicate vertical net hauls were made daily in each lake with a 153
 73 μm mesh net. Net haul samples were processed by filtering a sample through a 2 mm mesh to
 74 remove *Chaoborus* spp. and then concentrating the sample on a pre-weighed filter. The filter
 75 with zooplankton concentrate was dried and weighed to get a direct biomass measurement.
 76 Visual inspection of the zooplankton concentrate using a stereomicroscope confirmed that the
 77 samples were dominated by zooplankton. Further, phytoplankton biomass was a trivial
 78 component of total sample weight based on direct measures of chlorophyll in the concentrates.

79
 80 *Phytoplankton biomass* - We took daily water samples from 0.5 m in each lake to measure
 81 chlorophyll *a* as an indicator of phytoplankton biomass. We filtered 200 ml of water onto GF/F
 82 filters which were frozen and subsequently extracted in methanol. Chlorophyll *a* was measured
 83 using standard fluorometric methods (34). *In situ* chlorophyll measurements were also made at
 84 five minute intervals using a YSI 6600 V2 water quality sondes fitted with chlorophyll probes
 85 (model 6025). The probe sensors were calibrated and corrected for variations in fluorescence
 86 related to temperature.

87
 88 *Other limnological variables* – To characterize lake conditions and plankton communities we
 89 measured a variety of variables at a central station in the reference and manipulated lakes
 90 weekly from late May through August. Vertical profiles of dissolved oxygen and temperature
 91 were made at 0.5 meter depth intervals from surface to bottom at a central station. Light
 92 extinction was measured using a LiCor submersible meter. Chlorophyll *a* concentrations were
 93 measured at 100%, 50%, 25%, 10%, 5% and 1% light levels following the methods described
 94 above. Zooplankton were sampled using calibrated net hauls. Zooplankton were enumerated
 95 by taxa from preserved samples using a stereomicroscope. Body lengths of the dominant taxa
 96 of crustacean zooplankton were also measured and biomass estimated from length x weight
 97 regressions.

98
 99 ***Statistical Analyses***

100 *Daily time series autocorrelation, variance, CV, skewness and return rate* – Within each year in
 101 each lake, indicators presented in Figs. 4 and S2 were computed for each date as follows. Daily
 102 chlorophyll time series, x_t , were divided into sequential overlapping windows of length h days.
 103 For each date t , statistics were computed for the series $x_{t-h+1}, x_{t-h+2}, \dots, x_t$. Statistics were
 104 computed for each sampling day after h days of sampling had occurred. Thus each indicator is a

105 “leading indicator” based on data available prior to and including date t . Variance, coefficient of
106 variation, skewness, and lag-1 autocorrelation coefficient were computed using moment
107 functions in R (<http://www.r-project.org/>). Return rate was computed by linear regression of
108 the vector $[x_{t-h+2} \dots x_t]'$ on the vector $[x_{t-h+1} \dots x_{t-1}]'$. The slope b_1 is used to calculate the return
109 rate $1-b_1$ (35). We experimented with h values of 14 to 42 days. Higher h increases precision of
110 the estimates but decreases capacity to resolve events in the time series. We report results
111 based on $h=28$ days, a compromise between precision and resolution. The overall patterns
112 were similar for h values greater than 21 days. For h less than about 20 days, patterns were
113 noisy and precision was low, especially for autocorrelation and return rate estimators.

114 Several considerations affect selection of time windows for computing these early warning
115 indicators. Some of the methods used for early warning signals consider all possible windows
116 (e.g. spectral analysis, power laws). In some cases, it may be possible to use nonparametric
117 approaches and associated methods for choosing optimal bandwidths. In many ecological
118 cases, the most practical approach may be to consider a range of different windows, evaluate
119 the tradeoffs between precision and time-resolution of the signal, and consider whether the
120 outcome is sensitive to the choice of window length as we have done here.

121 *Spectral analysis of high frequency chlorophyll measurements* – Chlorophyll data measured at 5
122 minute intervals using sondes were analyzed in sequential overlapping windows of 7 days, the
123 duration of a sonde deployment. For each time window, variance spectra were computed using
124 the ‘spectrum’ function in R (<http://www.r-project.org/>). The spectrum was computed from the
125 autoregression function of optimal order selected by AIC. Thus in a year with n sampling dates
126 we computed $n-7+1$ spectra. These are plotted for each lake in each year in Figs. S3 and S4.
127 Prior to analysis, data points that were missing due to sonde malfunction were replaced with
128 randomly chosen values from the same lake the same year. Malfunction affected less than 0.6%
129 of the observations in the reference lake and less than 0.01% of the observations in the
130 manipulated lake. By replacing the missing observations with random observations from the
131 same lake and year, we maintain the continuity and variability of the time series.

132 Spectral differences (Fig. 3) were computed by subtracting the reference lake log spectral
133 density from the manipulated lake log spectral density on each date at each frequency. Because
134 differences were taken of log spectral densities, the values reported in Fig. 3 are equivalent to
135 the log of the ratio of spectral densities.

136 Spectral frequency ratios for each lake on each date were computed as the ratio of the mean
137 spectral density at low frequencies to the mean spectral density at high frequencies. Low
138 frequencies were all frequencies less than once per day. High frequencies were all frequencies
139 between once in 15 minutes and once in 3 hours.

140 *Discrete Fourier Transform of Planktivore Data* – In each lake, littoral minnow traps were placed
141 around the perimeter of the lake in a clock-like arrangement. This arrangement is equivalent to
142 a one-dimensional gradient in a closed loop. In this setting, changes in spatial pattern
143 consistent with shoaling of fishes or other nonlinear phenomena can be evaluated using the
144 discrete Fourier transform (DFT) (17). The DFT is a transformation of spatial data into the

145 frequency domain. Pattern is evaluated by plotting the DFT versus frequency, measured in units
146 of 1/trap in this study. A peak in the DFT at a particular frequency is associated with spatial
147 pattern at that frequency. We used the DFT as an indicator of shoaling by fishes (17). We
148 computed the DFT for littoral zone traps on each date in the manipulated lake. In the littoral
149 zone of the reference lake, and the pelagic zone of both lakes, the DFT was not computed
150 because catch rates were too often zero .

151 *Brock-Dechert-Scheinkman (BDS) Test for nonlinearity* – The early warning signals that we
152 studied are sensitive to nearby regime shifts in models of complex systems, but in field data
153 false signals can be generated by many linear processes that are unrelated to nonlinear
154 transitions. For example, autocorrelation can result from linear processes, and autoregressive
155 conditional heteroskedasticity can produce bursts of variance from linear processes.

156 Therefore, we tested the daily chlorophyll time series for potential effects of linear processes
157 masquerading as nonlinear ones (36). For each lake in each year, we fit an autoregressive
158 model to the time series, choosing the optimal order by AIC. We then fit the AR residuals to a
159 generalized autoregressive conditional heteroskedasticity (GARCH) model. In all cases the order
160 of the GARCH model was (1,1) and higher-order GARCH models did not improve the fit. AR, BDS
161 and GARCH statistics were computed by the corresponding functions in the ‘tseries’ module of
162 R (<http://www.r-project.org/>). The residuals of the GARCH model represent pattern that
163 cannot be explained by autoregressive or GARCH processes. Residuals of the GARCH models for
164 a given variate in a given lake were concatenated in a single series spanning all three years for
165 the BDS test (37). Concatenation was necessary because of the high sample size requirements
166 of the BDS test. The BDS statistic was referred to a null distribution computed by bootstrapping
167 10,000 random permutations of the GARCH residuals. For the reference lake, the p-value was
168 0.184. Thus we cannot reject the null hypothesis that the underlying dynamics are linear in the
169 reference lake. For the manipulated lake the p-value was 0.011. Thus the null hypothesis of
170 linearity is rejected for the manipulated lake.

171 We conclude that the early warning indicators in the manipulated lake cannot be explained by
172 linear processes, and are consistent with a regime shift caused by the manipulation. If a
173 regional driver of nonstationarity, such as variable plankton dynamics related to weather, were
174 involved in the behavior of the manipulated lake, then a similar signal would have been
175 expected in the reference lake, but the BDS test indicates this was not the case.

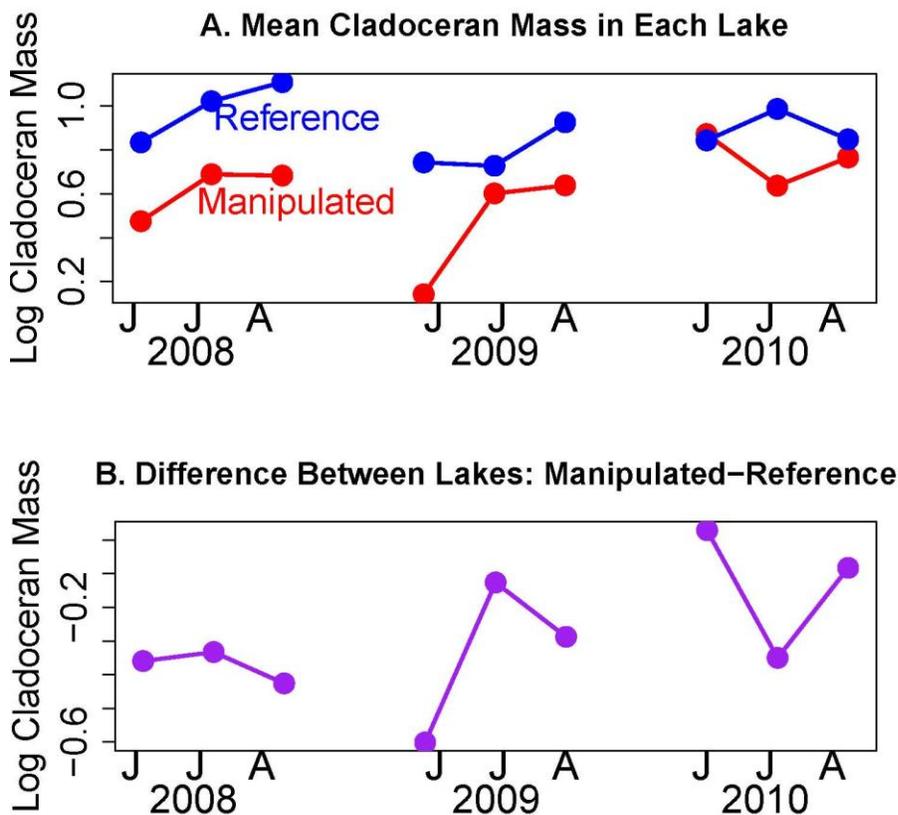
176

177 **Figure S1**

178 Cladoceran mass was computed from enumeration of zooplankton species in weekly samples.
 179 Measures of individual body sizes of cladocerans are effective indicators of lake food web
 180 structure and trophic cascades (15, 18). Plots of the log of body mass (which is linearly related
 181 to body length) in the reference lake illustrate the typical variability of a piscivore-dominated
 182 lake (Fig. S1A). Over time the manipulated lake became more similar to the reference lake (Fig.
 183 S1B). The low cladoceran mass in the manipulated lake June 2009 was due to high density of
 184 *Bosmina*, a small-bodied genus. Over the three years of the experiment, the mean length of
 185 *Daphnia* in the manipulated lake increased from about 0.8 mm to about 1 mm while no change
 186 was observed in the reference lake.

187 Fig. S1-A. Mean cladoceran mass (\log_{10} transformed) for each month of summer stratification in
 188 each lake, 2008-2010. In 2009, cladoceran mean mass was decreased by planktivory by young-
 189 of year largemouth bass.

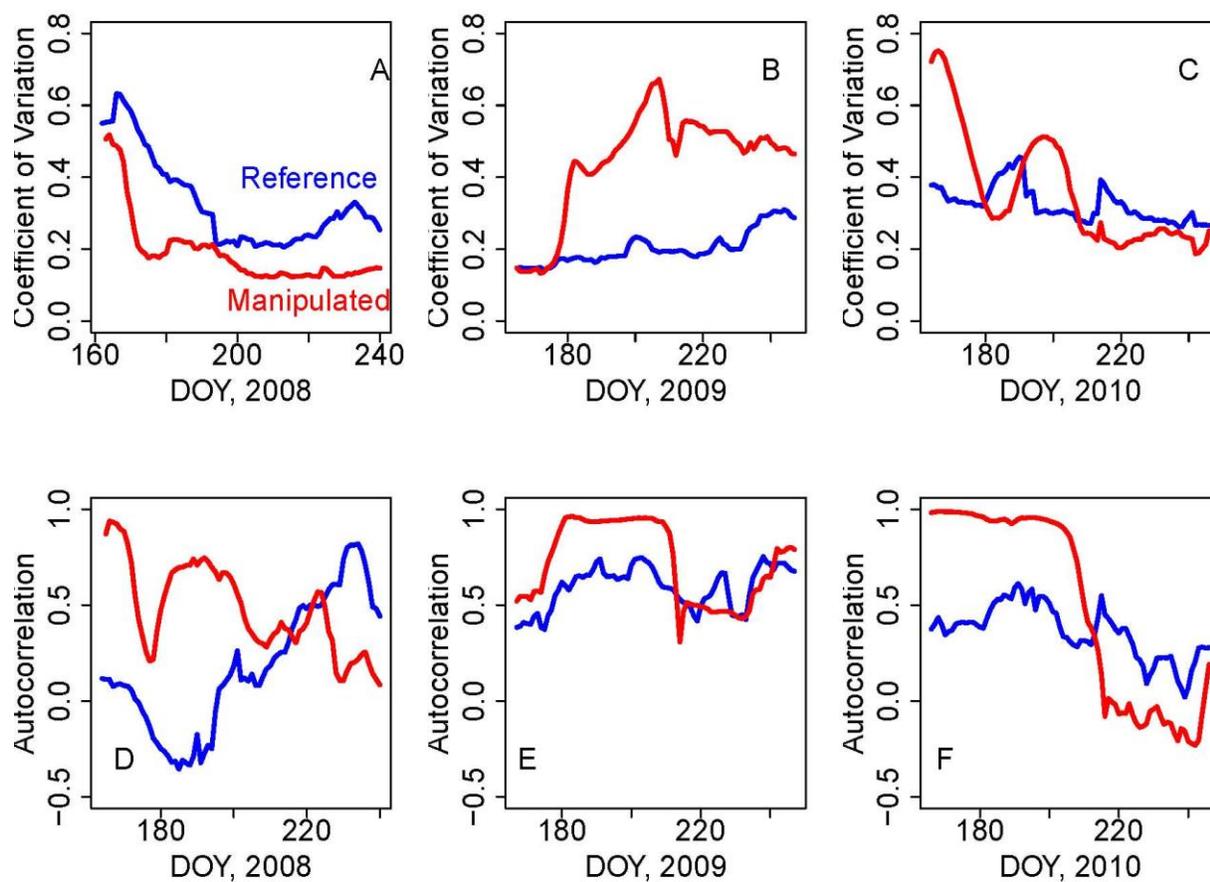
190 Fig. S1-B. Difference in mean cladoceran mass (\log_{10} transformed) between lakes (manipulated
 191 – reference values) computed from the data in panel A. Over the course of the experiment, the
 192 cladoceran mean mass in the manipulated lake became more similar to that of the largemouth-
 193 bass dominated reference lake.



195 **Figure S2**

196 The variance (Fig. 4 A-C) and return rate from small perturbations (Fig. 4 D-F) are closely related
 197 to the coefficient of variation and autocorrelation, respectively. The coefficient of variation
 198 (CV, standard deviation / mean) is a measure of variability that adjusts for possible correlation
 199 of the variance and mean. High values are associated with nonlinear transitions.
 200 Autocorrelation near one is widely used as a measure of slow return rate associated with
 201 nonlinear transitions (5). These additional early warning indicators are presented here.
 202 Expectations for early warnings in the manipulated lake are consistent with the high CV in 2009
 203 and early in 2010 and the intervals of autocorrelation near one in 2009 and early 2010.

204 Fig. S2. Potential early warning indicators computed from daily chlorophyll time series in the
 205 mixed layer of the manipulated (red) and reference (blue) lakes in 2008, 2009 and 2010. On
 206 each date in each lake, statistics were computed for the preceding 28 days using daily
 207 observations. Regime shifts are associated with high CV and autocorrelation close to one. A-C:
 208 coefficient of variation. D-F: autocorrelation.

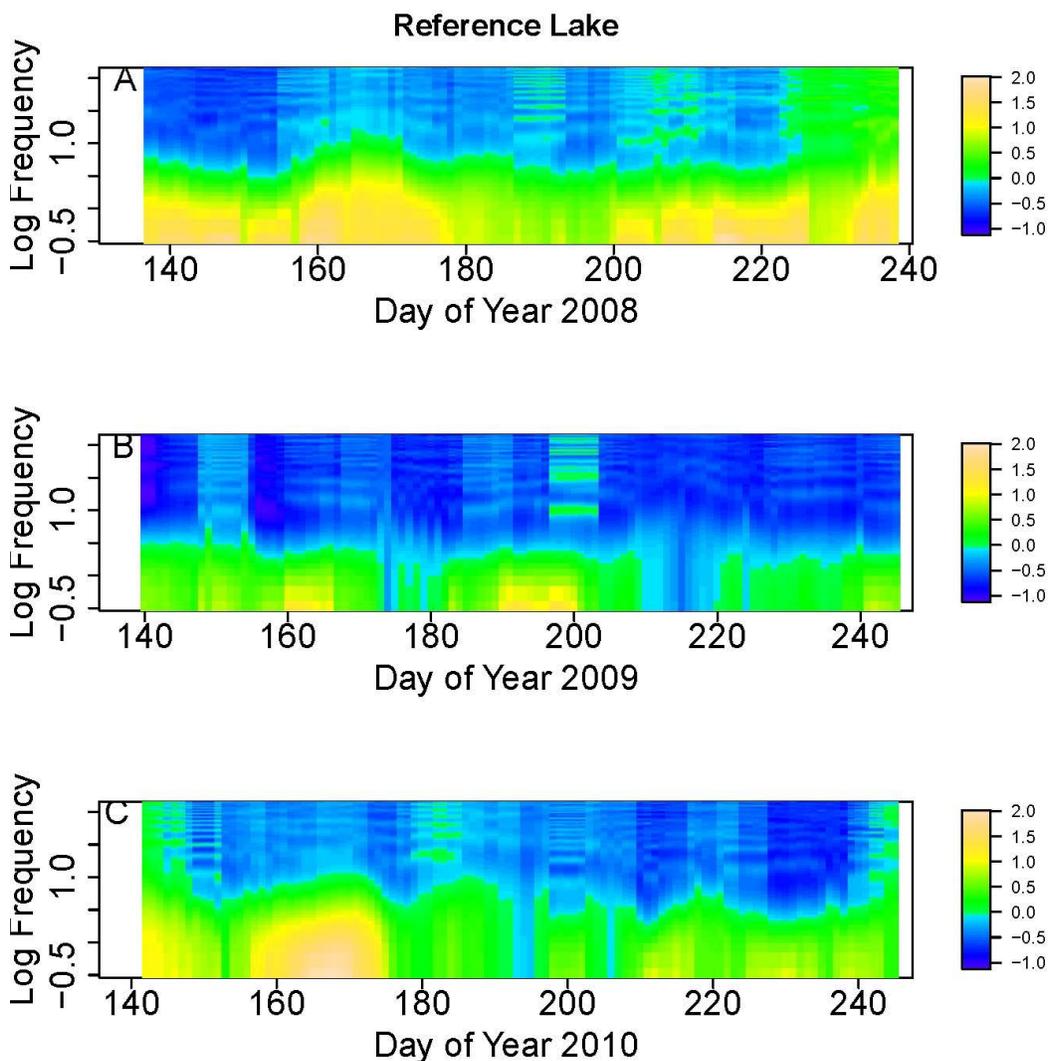


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211 **Figures S3 and S4**

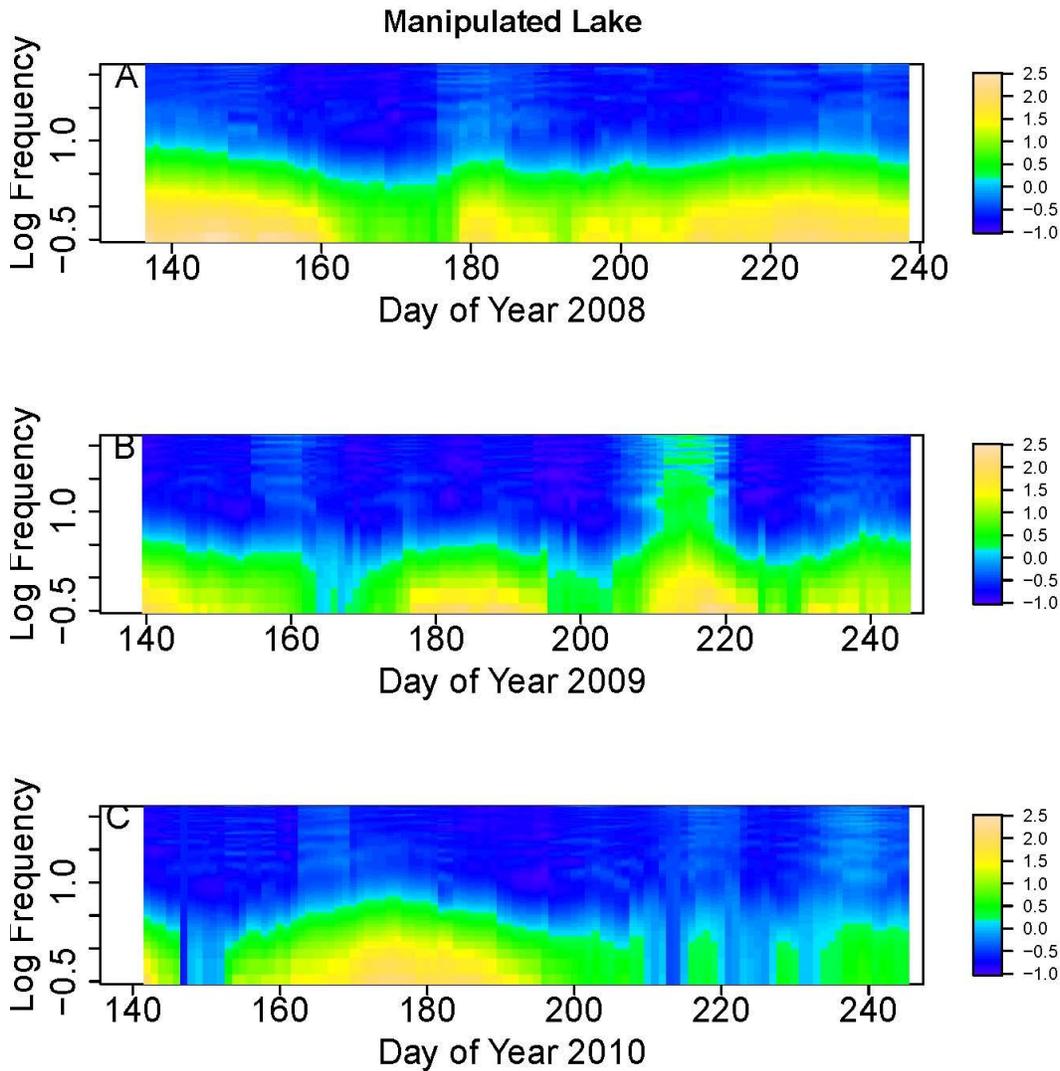
212 To assess changes in variance spectra of the manipulated lake versus the reference lake, we
 213 calculated differences in spectra based on high-frequency chlorophyll measurements (Fig. 3). To
 214 assess potential shifts in variance spectra toward low frequencies, we calculated spectral
 215 frequency ratios for both lakes (Fig. 4 J-L). Both of these indicators are based on the spectra for
 216 the individual lakes. We present these spectra in Figs. S3 and S4.

217 Fig. S3. Variance spectra for high-frequency chlorophyll observations from sondes in the
 218 reference lake. On each date, spectra were computed for the preceding 7 days using
 219 observations recorded every 5 minutes. Frequency (per day, \log_{10} transformed) is plotted
 220 versus day of the year, and spectral density (\log_{10} transformed) is indicated by the colors. High
 221 spectral density at low frequencies is associated with nonlinear transitions. A: 2008. B: 2009. C:
 222 2010.



223

224 Fig. S4. Variance spectra for high-frequency chlorophyll observations from sondes in the
225 manipulated lake. On each date, spectra were computed for the preceding 7 days using
226 observations recorded every 5 minutes. Frequency (per day, \log_{10} transformed) is plotted
227 versus day of the year, and spectral density (\log_{10} transformed) is indicated by the colors. High
228 spectral density at low frequencies is associated with critical transitions. A: 2008. B: 2009. C:
229 2010.



230

231 Table S1. Nutrient data for 2008-2010. Each value is based on 15 weekly samples during
 232 summer stratification from the epilimnion of each lake.

Year	Lake	Total P (mg m^{-3})		Total N (mg m^{-3})	
		Mean	SD	Mean	SD
2008	Ref	6.40	3.39	283	45.6
	Manip	6.67	2.79	344	47.7
2009	Ref	3.65	2.83	303	58.9
	Manip	5.60	2.57	353	41.0
2010	Ref	3.85	1.76	224	31.9
	Manip	4.37	2.04	302	39.6

233

234 Table S2. During three years prior to this experiment, chlorophyll concentration in the
 235 manipulated lake was less variable than chlorophyll concentration in the reference lake in two
 236 years out three based on standard deviation, and three years out of three based on
 237 coefficient of variation (SD/mean). However the differences between lakes in chlorophyll
 238 variability were small compared to those observed during the experiment in 2009 and 2010.
 239 The table below presents chlorophyll mean, standard deviation and coefficient of variation
 240 based on 15 weekly samples from the epilimnion during summer stratification in each of three
 241 years prior to manipulation, 2005-2007.

Year	Lake	Chl Mean (mg/m^3)	Chl SD	Chl CV
2005	Ref	3.16	1.94	0.613
	Manip	5.13	2.20	0.428
2006	Ref	4.20	2.44	0.580
	Manip	4.16	1.45	0.349
2007	Ref	4.17	1.54	0.369
	Manip	4.94	1.28	0.259

242