

# NTL\_LTER\_TR Case Study

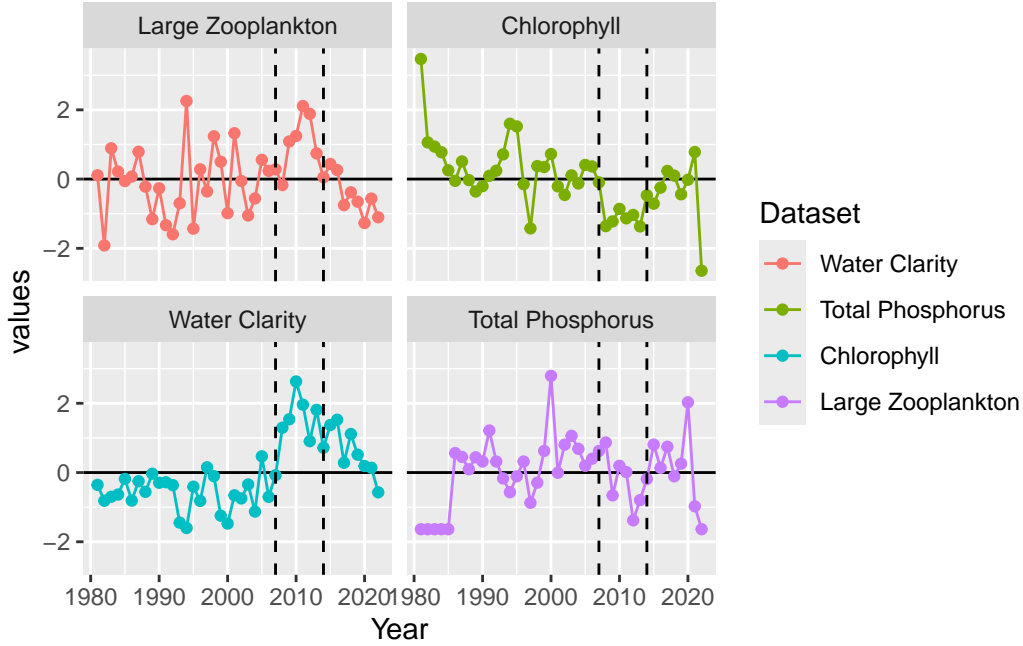
Approach for running LTER-NTL Trout Lake data using temporally structured GAMs and linear regression models with time periods defined a-priori.

First we start with looking at three time periods using linear regression models: 1. The historical regime with low water clarity 2. A clear water regime where the introduction of Lake Trout into the system from stocking in 2006. 3. A novel regime following the introduction of invasive, predatory water flea (*Bythotrephes*) in 2014 which lead to a reversion of water clarity to a less clear state.

To examine this we start by looking at a few key food web conditions using intercept only models through time: 1. Water clarity 2. Phosphorus - which impacts water clarity and is a common bottom-up process that could impact water clarity and we examine as an alternative hypothesis to the top down processes of Lake Trout and invasive speceis. 3. Abundance of large zooplankton *Daphnia* and *Calanoids* 4. Chlorophyll

Variable	No.Period.AIC	Period.AIC	Best.Model
Water Clarity	122.18	83.43	Period
Total Phosphorus	122.18	125.75	No difference
Chlorophyll	122.18	111.00	Period
Large Zooplankton	122.18	115.84	Period

Covariates	Period	Interaction
Chlorophyll	43.99	39.56
Total Phosphorus	44.45	46.31
Large Zooplankton	43.58	35.99



We approach this by fitting a linear model with the a priori time periods as a factor and compare AIC to a single intercept model for each variable.

We find that water clarity, chlorophyll, and large zooplankton abundance are all better explained by a model that includes a priori defined time periods improves model fit.

We have identified time-varying mean abundance or amount. We see that the relationship between large zooplankton and water clarity, and large zooplankton and chlorophyll, appears to be time-varying. Next we consider whether there are changing relationships between water clarity and these ecosystem dynamics by including a slope parameter and its interaction with time period.

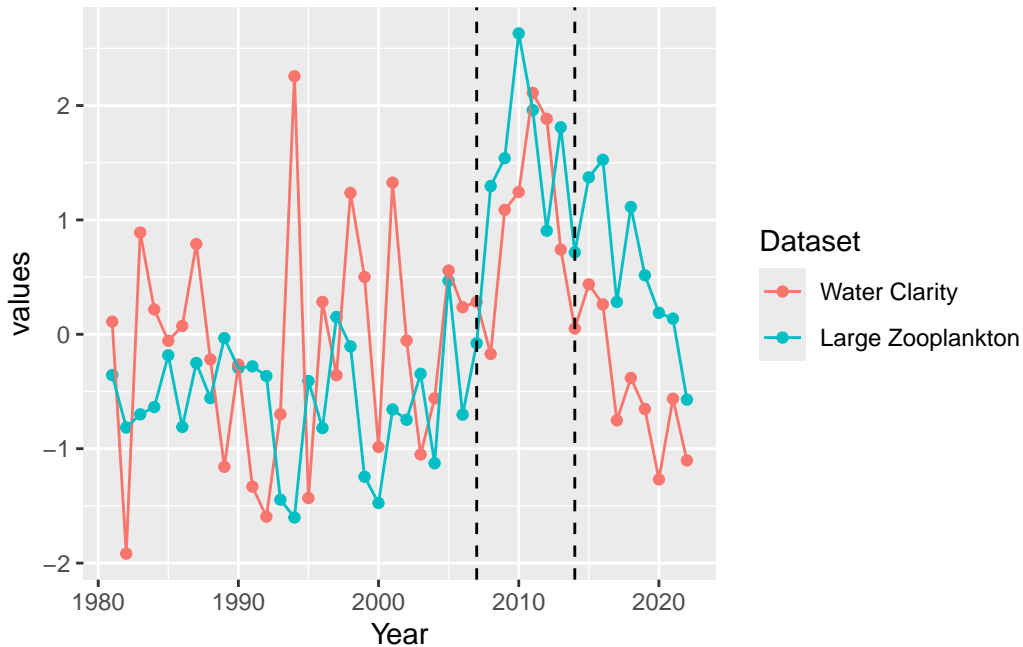
term	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	4.8349816	0.2528329	19.1232307	0.0000000
mean_chl	-0.0782362	0.0788946	-0.9916537	0.3279853
as.factor(period)2	2.2005743	0.5785710	3.8034645	0.0005327
as.factor(period)3	0.1117831	0.4101245	0.2725590	0.7867496
mean_chl:as.factor(period)2	-0.6484809	0.3038817	-2.1339917	0.0397262
mean_chl:as.factor(period)3	0.2348195	0.1514716	1.5502543	0.1298281

term	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	4.6974936	0.1973695	23.8005078	0.0000000
Large	-0.0440188	0.0789582	-0.5574951	0.5806395
as.factor(period)2	0.0552649	0.6211177	0.0889765	0.9295938
as.factor(period)3	-0.8929801	0.5510514	-1.6205024	0.1138523
Large:as.factor(period)2	0.3623181	0.1945706	1.8621421	0.0707613
Large:as.factor(period)3	0.7863286	0.2594449	3.0308115	0.0044983

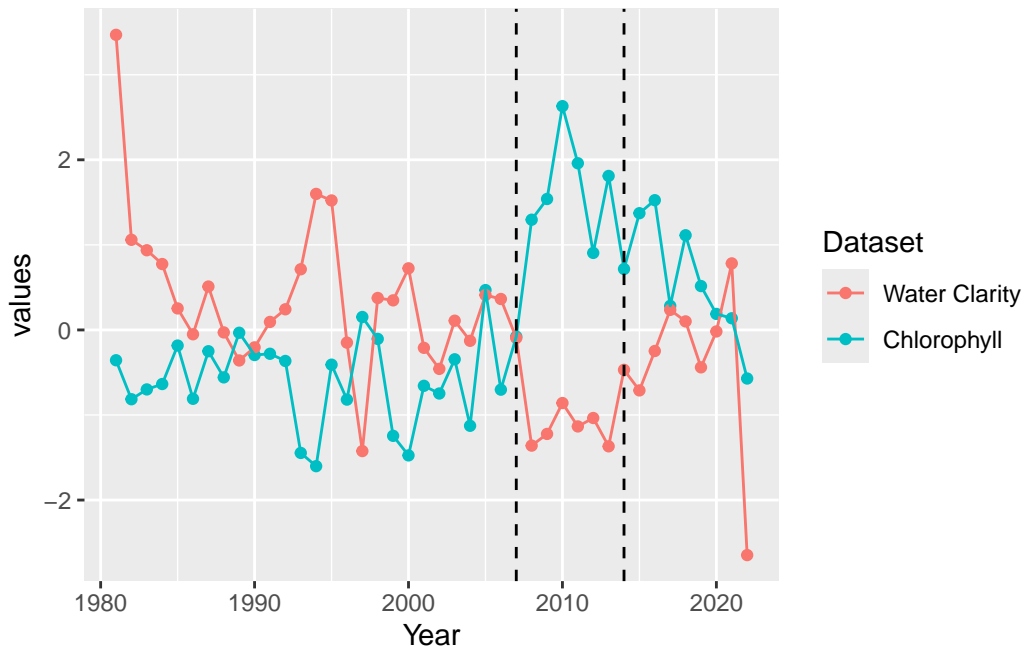
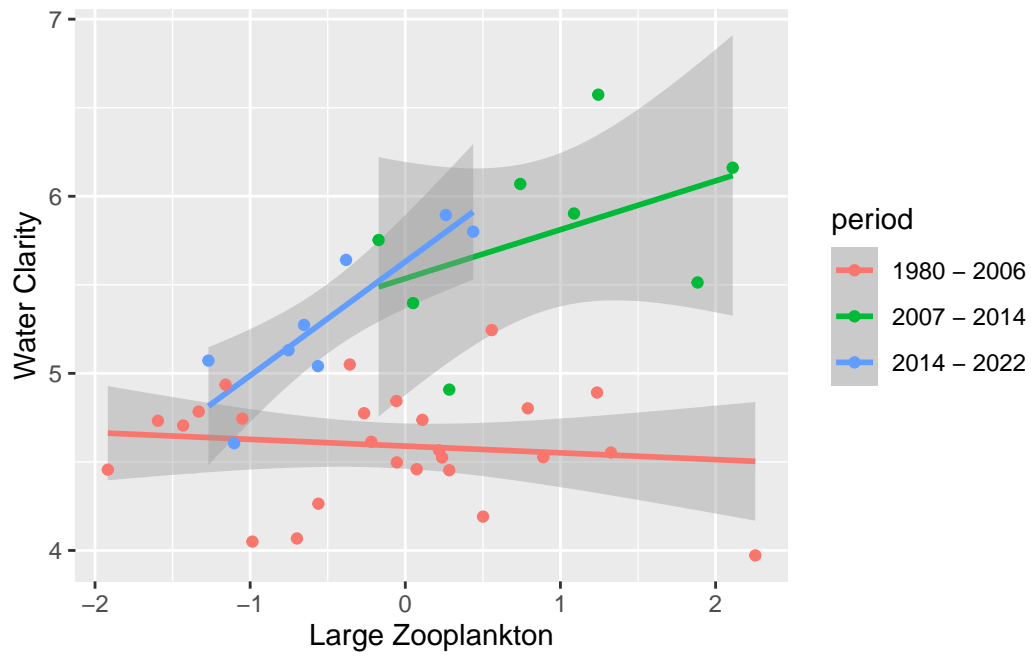
Both Chlorophyll and Large Zooplankton best explain water clarity with a time varying relationship. We examine how these relationships change through time.

[1] "Chlorophyll"

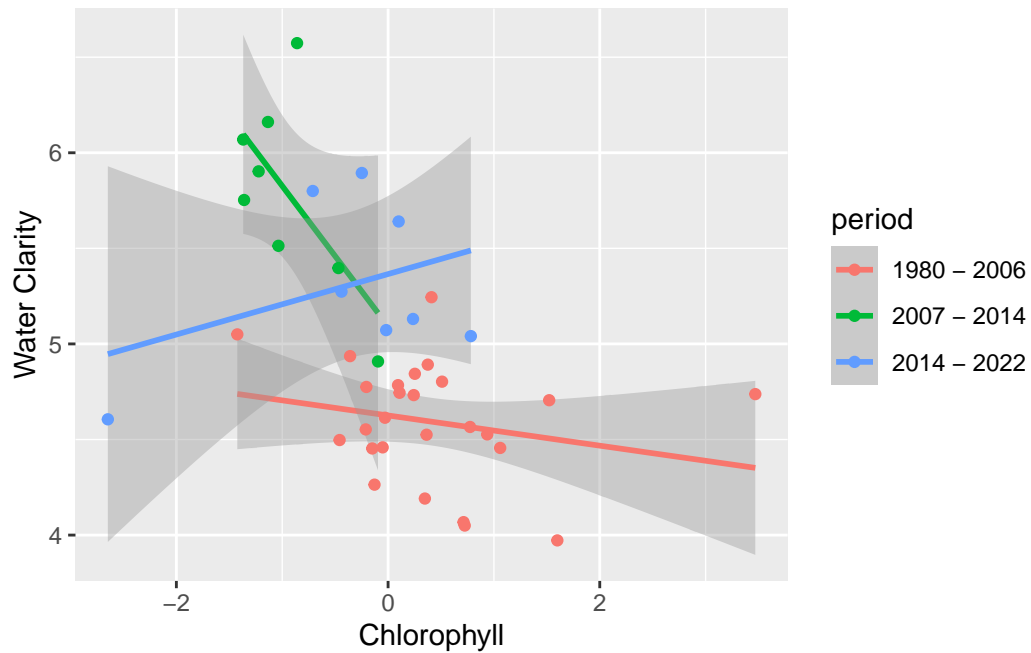
[1] "Zooplankton"



```
`geom_smooth()` using formula = 'y ~ x'
```



```
`geom_smooth()` using formula = 'y ~ x'
```



If we take the Zooplankton-water quality relationship and fit a temporally structured gam and compare it to the linear model, we find similar results. Both predictions also accurately identify 2006 as a breakpoint and a second break point in 2016.

### Linear Model



Optimal (m+1)-segment partition:

Call:

```
breakpoints.formula(formula = y.ts ~ 1)
```

Breakpoints at observation number:

m = 1		26
m = 2		26 36
m = 3	13	26 36
m = 4	7 13	26 36
m = 5	7 13 19	26 36

Corresponding to breakdates:

m = 1		26
m = 2		26 36
m = 3	13	26 36
m = 4	7 13	26 36
m = 5	7 13 19	26 36

Fit:

m	0	1	2	3	4	5
RSS	11.3356	2.3579	0.6534	0.6505	0.6468	0.6457
BIC	71.6581	13.1864	-33.2407	-25.9477	-18.7148	-11.3127

	prediction	year
26	4.580172	2006

	prediction	year
36	5.798336	2016



Optimal (m+1)-segment partition:

Call:

```
breakpoints.formula(formula = y.ts ~ 1)
```

Breakpoints at observation number:

m = 1	26
m = 2	26 36
m = 3	22 28 36
m = 4	12 22 28 36
m = 5	6 12 22 28 36

Corresponding to breakdates:

m = 1	26
m = 2	26 36
m = 3	22 28 36
m = 4	12 22 28 36
m = 5	6 12 22 28 36

Fit:

m	0	1	2	3	4	5
RSS	11.814	3.194	1.882	1.798	1.653	1.651
BIC	73.393	25.936	11.201	16.747	20.693	28.119

	prediction	year
26	5.007736	2006

	prediction	year
36	5.700338	2016