NTL_LTER_TR Case Study

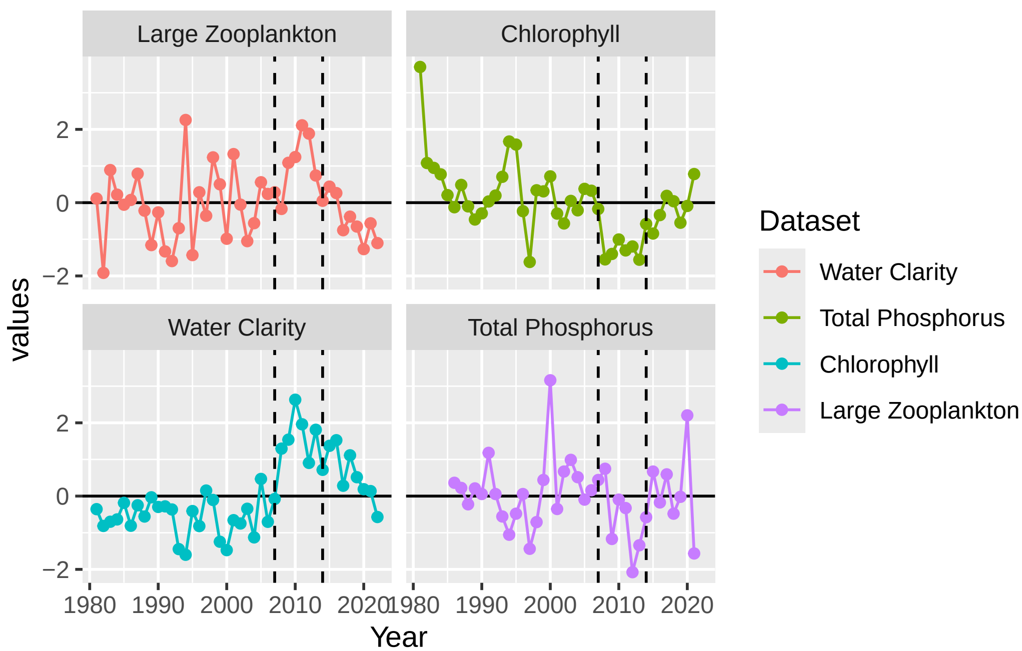
Approach for running LTER-NTL Trout Lake data using temporally structured GAMs and linear regression models with time periods defined a-priori.

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	105.15	105.79	No difference
Chlorophyll	119.34	106.87	Period
Large Zooplankton	122.18	115.84	Period

Covariates	Period	Interaction
Chlorophyll	36.31	33.18
Total Phosphorus	39.34	43.14
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 wach variable.

We find that water clarity, chlorophyll, and large zooplankton abundance are all better explained by a model that includes apriori 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	0.2361234	20.476500	0.0000000
mean_chl	-0.0782362	0.0736806	-1.061829	0.2955856
as.factor(period)2	2.2005743	0.5403339	4.072619	0.0002529
as.factor(period)3	1.7845049	0.7697864	2.318182	0.0264058
mean_chl:as.factor(period)2	-0.6484809	0.2837985	-2.285005	0.0284855
mean_chl:as.factor(period)3	-0.3825131	0.2841483	-1.346174	0.1869010

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"
```

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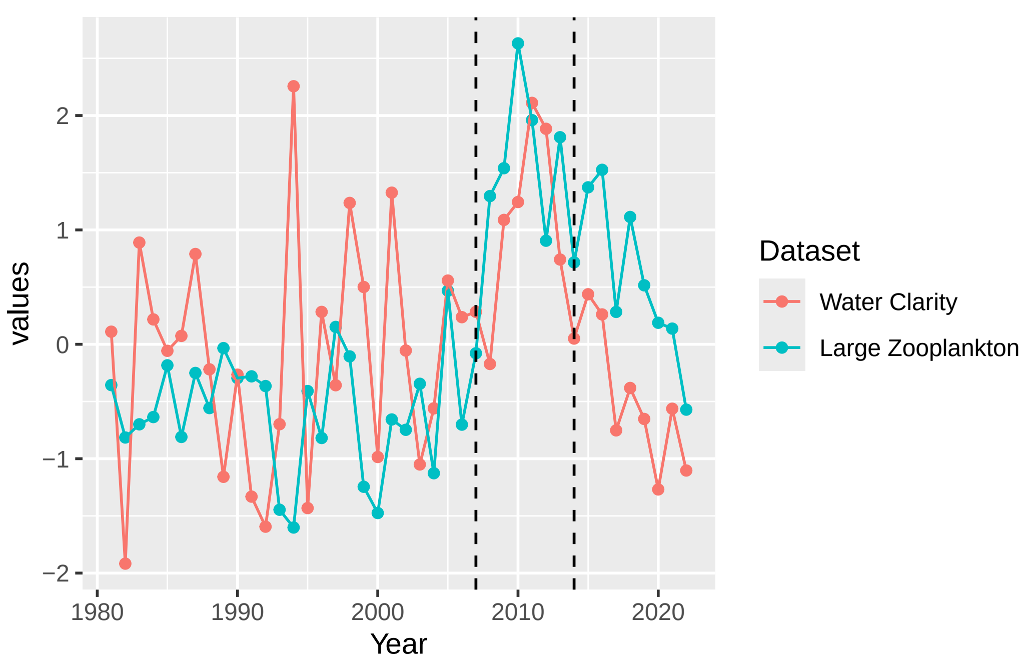
[1] "Zooplankton"
```



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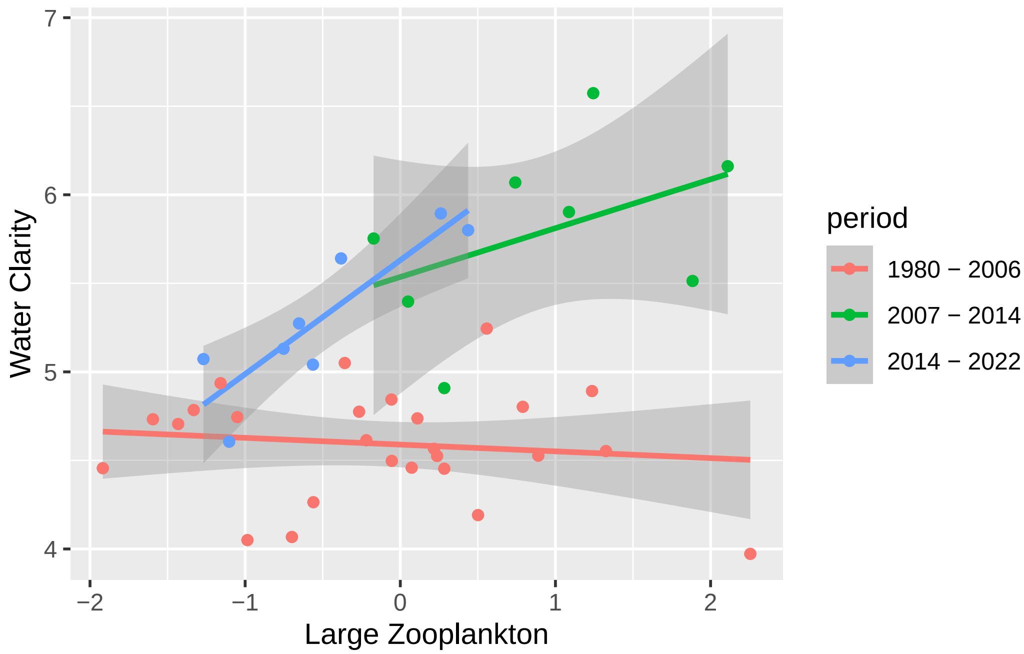
`geom_smooth()` using formula = 'y ~ x'
```

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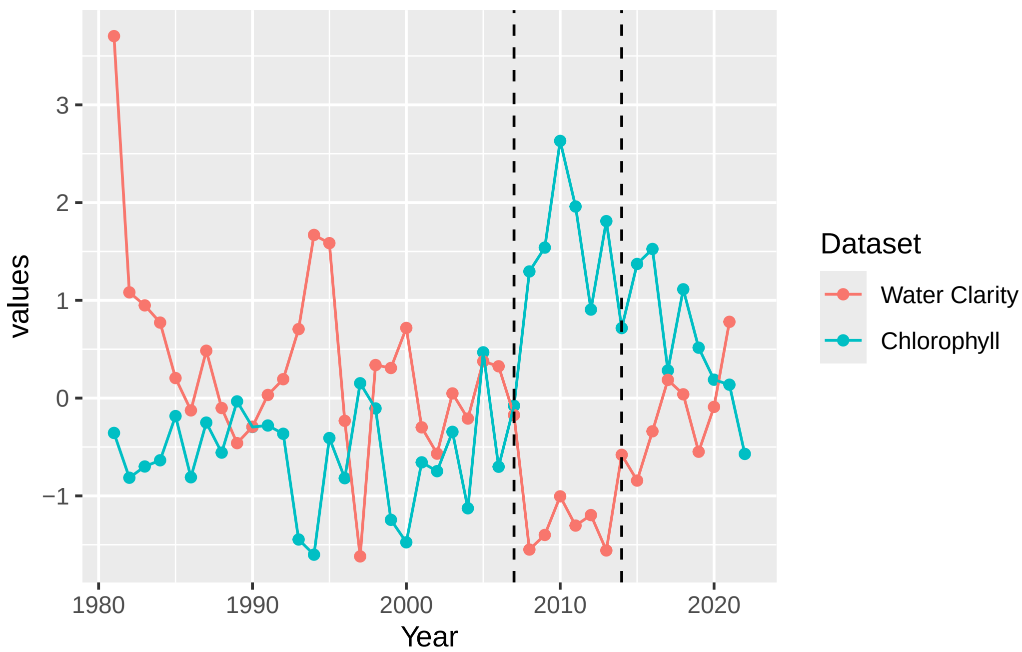
(`geom_point()`).

Warning: Removed 1 row containing missing values or values outside the scale range
(`geom_line()`).
```




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

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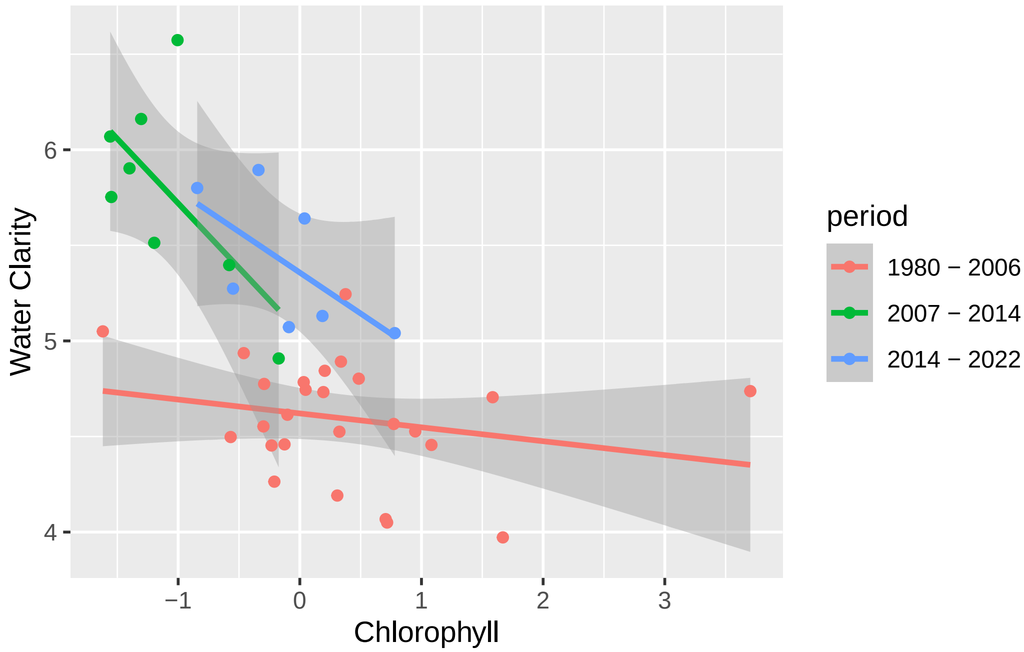
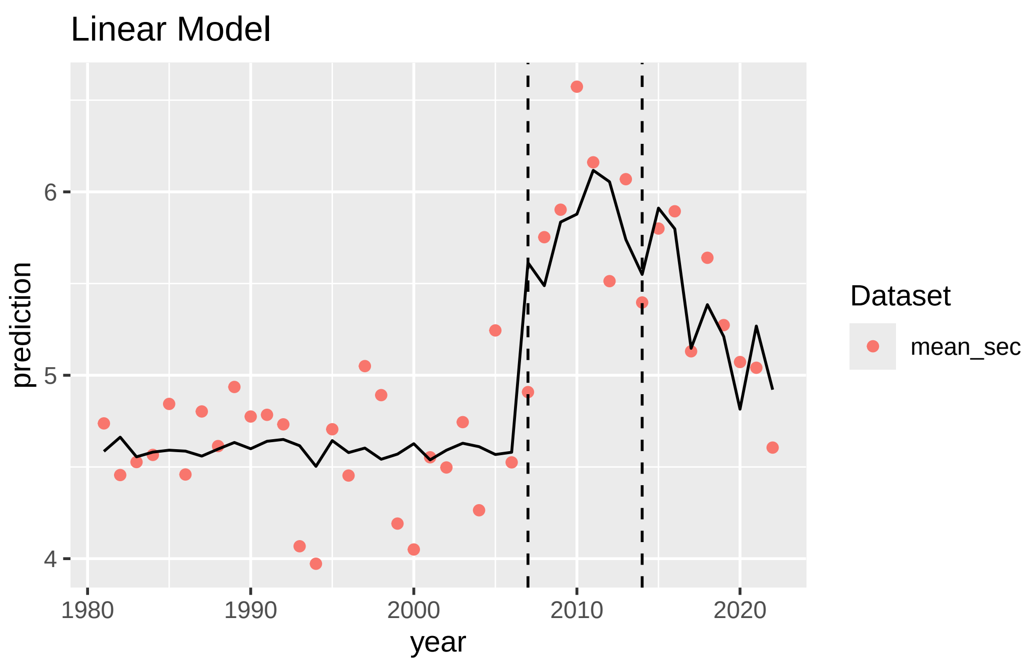
(`stat_smooth()`).

Warning: Removed 1 row containing missing values or values outside the scale range
(`geom_point()`).
```



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 acccurately identify 2006 as a breakpoint and a second break point in 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      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
```