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Moving Window Estimates of Catchability to Detect Non-stationarity in Stock Assessments

or

Why Did We Select 1994/95 as the Timing for Splitting Surveys to Reduce Retrospective Patterns?

by

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Summary

At the GARM III Biological Reference Points meeting, a number of stock assessments exhibited strong retrospective patterns in their base case formulations. A solution to reduce the retrospective patterning was to split the survey time series. This working paper uses an approach recommended by the Retrospective Working Group (presented at the GARM III Methods meeting) to identify the timing of change that leads to a retrospective pattern. Specifically, a moving window analysis was employed to detect non-stationarity in the q estimates. This working paper extends the analyses to consider the strength of the signal that change has occurred.

These analyses used the VPA formulations for four simulated data sets from the GARM III Methods meeting and eleven stock assessments from the GARM III Biological Reference Points meeting. The number of years in the moving window was defined by the user (W). Given a total of N years in the full VPA, there are N-W+1 VPA input files created. From each of these VPA analyses, the index specific estimates of q were compiled and subjected to two types of analyses: 1) a contour surface plot of normalized q (divide each q series by its mean) to visually detect changes and 2) a "Rago Razor" to estimate the best break year using both the q estimates and their associated coefficients of variation.

The simulated data sets confirmed that both approaches could detect and define the approximate time for the sources of non-stationarity leading to retrospective patterns. When applied to the GARM stocks, both approaches found the strongest signals in those stocks exhibiting the strongest retrospective patterns: GOM winter flounder, SNEMA winter flounder, and GB yellowtail flounder. Both approaches also agreed that five stocks showed little to no non-stationarity: CCGOM yellowtail flounder, SNEMA yellowtail flounder, GOM cod, GOM haddock, and GB haddock. The remaining three stocks, GB winter flounder, GB cod, and witch flounder, were intermediate between the strong obvious patterns of the first group and the weaker non-smooth patterns of the second group, consistent with moderate non-stationarity. There was also a strong agreement among stocks using both approaches that if a split was needed, splitting the surveys sometime around 1995 led to the best model.

While identification of a reasonable break year is a necessary step, implementation of a break year in the assessment may not be sufficient to reduce the retrospective pattern to acceptable levels. Moreover, it does not correct the underlying cause of the retrospective pattern. It must be reiterated that the resulting catchability estimates are aliasing the potential simultaneous effects of missing catch, increasing natural mortality and changing catchability. Of these, changes in actual catchability are considered to be the least likely factor.

Introduction

At the GARM III Biological Reference Points meeting (GARM 2008b), a number of stock assessments exhibited strong retrospective patterns in their base case formulations. A solution to reduce the retrospective patterning was to split the survey time series with the assumption that changes in the catchability coefficient for the two periods would alias unknown mechanisms such as missing catch, changes in natural mortality, or spatial effects including closed areas, as opposed to an actual change in survey. This approach was based on the Georges Bank (GB) yellowtail flounder assessment which had a benchmark assessment in 2005 that recommended such a split in the surveys. The GB yellowtail split was set at 1995, and so by analogy, this same split was used for the other GARM species. The question naturally arose, should all the stocks have the same split year or should the same intensive examination of factors that was undertaken for GB yellowtail be done for all the other species as well?

This working paper uses an approach recommended by the Retrospective Working Group (presented at the GARM III Methods meeting, GARM 2008a) to identify the timing of change that leads to a retrospective pattern. Specifically, a moving window analysis was employed to detect non-stationarity in the q estimates. This non-stationarity is an indication that something has changed, but the source cannot be identified from these analyses (see GARM 2008a). This working paper extends the analyses to consider the strength of the signal that change has occurred.

Methods

These analyses used the VPA formulations for four simulated data sets from the GARM III Methods meeting (GARM 2008a) and eleven stock assessments from the GARM III Biological Reference Points meeting (GARM 2008b). The four simulated datasets included a base case, with no misspecification introduced into the data, and three datasets with misspecification introduced into the second half of the time series: 1) reported catches were reduced to 1/3 their actual value; 2) natural mortality was increased from 0.2 to 0.5 in the simulated population but assumed to 0.2 in the VPA; 3) all q_i were tripled. All of the VPAs (simulated and real datasets) treat the survey tuning indices "East Coast" style, meaning that indices at age are entered as independent tuning series. A wrapper program was developed to create subsets of the data included in the VPA to allow the moving window analyses. The number of years in the moving window was defined by the user (W). Each moving window analysis was labeled by the midpoint of the years contained. Given a total of N years in the full VPA, there are N-W+1 VPA input files created. For example, if the full assessment spanned 1973-2006 (34 years), and a moving window size of 9 years was selected, there would be 26 moving windows denoted as 1977, 1978, …, 2002. Each of the moving window VPA input files were run and the wrapper program collected the estimated catchability coefficients and associated asymptotic CVs (based on the hessian, not bootstrapping). If a particular index in a moving window had no positive values or only one positive value (zeros are treated as missing), then this index was not included in the VPA for that moving window. The wrapper program also checked for solutions at the boundary values (i.e., endpoints of the

feasible range) of population estimates in the terminal year plus one. If a solution occurred at a boundary value, then the results from this moving window were not included in the analyses.

Preliminary exploration of different moving window sizes (W) did not appear to produce radically different trends in q estimates. A tradeoff had to be made between smaller window sizes which were able to respond more quickly to change but tended to be noisier versus larger window sizes which were more stable but tended to smooth, making detection of changes more difficult. A general rule of thumb that there had to be at least as many years in the VPA as there were ages used in the formulation was employed to prevent window size from becoming too small.

Once all of the moving window VPAs were run for a particular stock, a surface plot of normalized q estimates was created. These plots divided each moving window q by the mean q for that index. For example, each of the GB yellowtail fall age 1 estimates from the 26 moving windows were divided by the mean of the 26 values. This created a normalized series centered on one such that all the series could be plotted as a surface plot. If this normalization step had not been taken, then differences in magnitude of q estimates due to different catchabilities for each index would have swamped the trends and prevented interpretation of common time changes. These normalized q surface plots were recommended in the Retrospective Working Group (GARM 2008a) as a way to detect the timing of an intervention that leads to retrospective patterns, and also as a diagnostic to delineate year effects from cohort effects. For example, a year effect would manifest itself as a steep parallel shift in the contours, while a cohort effect would be more likely to appear as contours that break off on a diagonal.

A second set of analyses used the moving window q estimates in a "Rago Razor" to determine the best break year. The "Rago Razor" was used in the GARM III Biological Reference Points meeting (GARM 2008b) with stock recruitment data to determine a spawning stock size at which recruitment was expected to be increased when SSB was greater than the break point. In a similar manner, the "Rago Razor" used here examined each year and computed the mean q for all the years prior to the break year, denoted the early period, and the mean q for all the years since (and including) the break year, denoted the recent period. The sum of the mean squared residuals (sum MSR) was defined as

$$sum\ MSR = \sum_i \sum_{y<B} \left(\frac{q_{i,y} - q_{i,e}}{\sigma_{i,y}} \right)^2 + \sum_{y \geq B} \left(\frac{q_{i,y} - q_{i,r}}{\sigma_{i,y}} \right)^2$$

where i is an index
y is the midpoint year of a moving window VPA
B is the break year
$q_{i,y}$ is the catchability estimate for index i in year y
$q_{i,e}$ is the mean q for index i in the early period (years < B)
$q_{i,r}$ is the mean q for index i in the recent period (years ≥ B)
$\sigma_{i,y}$ is the standard deviation of the q estimate for index i in year y .

The break year with the lowest sum MSR was declared the best. The "Rago Razor" was considered to be an objective, but ad hoc approach to partitioning the stock-recruitment function into two groups. The minimum variance approach selected here is similar to a minimum Chi –Square test with a high, but unknown degree of correlation between estimates. The method has some heuristic appeal but inferential aspects of this estimator are unknown and in need of additional research.

In some cases, the estimated CV for a given q was very low (<10%). The very low CVs had a disproportionate impact on the sum MSR calculations. These CV estimates were not considered a reliable estimate of the true uncertainty associated with the values, but instead random chance events due to small sample sizes. Based on preliminary explorations, any CV < 10% was increased to 10% for the calculation of sum MSR. An exception to this approach was that in a few cases the estimated CV was exactly zero, these CV were set to missing and did not enter the sum MSR calculations. A similar calculation of sum MSR was computed without a break, meaning the average q was over all years, for comparative purposes.

Results and Discussion

Normalized q surface plots for each stock are presented in Figure 1. There are two plots for each stock, the top panel groups the indices by survey, the bottom panel groups the indices by age. The simulated data are plotted first, followed by the 11 GARM stocks in alphabetical order. The simulated data with changes in catch, M, or q all show strong patterns in these normalized q surface plots that roughly correspond with the actual timing of the change (1995). In contrast, the simulated base case (which has no misspecification) does not show strong patterning over time, and the magnitude of change in q is much smaller than the other three simulated data cases. This verifies the result found in the Retrospective Working Group report that moving window analyses can detect the timing of an intervention that results in a retrospective pattern in the full stock assessment (GARM 2008a).

Examination of the normalized q surface plots for the VPA stock assessments from the GARM III Biological Reference Points meeting shows some holes in the contour surface that were not seen in the simulated data. The holes have two sources. The more common source is a survey time series that does not extend over the entire time period of the assessment. For example, in the CCGOM yt plots, the MENH surveys did not begin until 2000 (fall) or 2001 (spring). Thus, moving windows that do not include years since 2000 will not have any data for these surveys, resulting in no q estimate. Individual index series which contain a string of zero values can also form smaller holes in the surface plots, although this is much less common. This type of hole causes a problem for interpretation of the normalized q surface plots because of the normalization itself. The short time series will still have a mean of 1.0, meaning that an overall decreasing trend can be obscured by a short time series in recent years which will appear as a high to low series over those years. It is best to focus on series which span the entire range of the assessment when looking for break points, even though the short time series can be quite influential in the stock assessment result.

The other type of hole that can form is when a moving window VPA finds its solution at a boundary condition. The software wrapper that ran the moving window analyses checked for solutions at the boundary conditions and removed those q estimates (which were typically far from any other values). This type of hole appears as a vertical gap for all indices, for example the GB cod 1981-1993 thirteen year moving window VPA resulted in a boundary condition solution and so these q values appear as a vertical gap at 1987.

Notwithstanding the holes, the stock assessment normalized q surface plots still show some patterns. Some stocks appear to have trade-offs between increasing and decreasing trends in different surveys or ages. For example, CCGOM yt has some indices which increase over time (change from red to blue) and others that decrease over time (change from blue to red). Other stocks appear much more consistent in the direction of change. For example, GOM winter flounder shows increased q for all indices over time, with a rather large change in magnitude. Other stocks do not appear to show any patterning over time. For example, GOM cod does not show any strong trends over time. Be sure to take note of the scale bar for each stock, as the colors vary among plots as does the magnitude of change in normalized q values.

The "Rago Razor" results are shown in Figure 2 comparing the sum of mean squared residuals between moving window q estimates and early and recent means for given break years (points) and overall mean with no break (red line). The ratio between the no break line and the best break (meaning the lowest sum MSR) is an indication of how strong an improvement is made by breaking the survey series. These plots are shown for the simulated data first and then arranged by species next. The simulated base case shows only a small improvement in sum MSR by breaking the time series relative to the overall mean. The simulated base case also happens to find a minimum quite close to the midpoint of the time series. This is not unexpected because a break year at the midpoint would be expected to produce the lowest sum MSR on average if the points were all randomly distributed. Since neighboring windows share (W-2) years of data, there is a lot of correlation among the observations. We would expect this correlation to create an even stronger tendency to favor solutions at the midpoint unless there are large outliers in the underlying data at one end of the time series.

In contrast, the three simulated data sets with changes (change catch, increase M, increase q) all show large differences between the two means versus the overall mean and all three cases find 1995 as one of the lowest sum MSR values. The fact that these simulated data do not exactly find 1995 in all three cases demonstrates that even in the best of situations, full time series of indices with strong transition in a single year, the moving window analysis may not identify the exact year of change. This is because the moving window analysis depends on the size of the moving window relative to the length of the time series and the timing and magnitude of the actual change, as well as the distribution of noise among the indices in any given realization. The stock assessment analyses will be additionally impacted by index series which do not span the entire time period.

The stock specific plots of the "Rago Razor" showed clear minimums in most cases. The three stocks with the strongest retrospective patterns, GOM winter flounder, SNEMA winter flounder, and GB yellowtail flounder, had the largest ratios of no break to best break year with well defined minima and smooth patterns. These three stocks also had strong changes in q in the normalized q surface plots. Five stocks exhibited either only a small improvement in sum MSR with the break, non-smooth patterns (due to the influence of index series that did not span the entire time period), or both: CCGOM yellowtail flounder, SNEMA yellowtail flounder, GOM cod, GOM haddock, and GB haddock. The remaining three stocks, GB winter flounder, GB cod, and witch flounder, were intermediate between the strong obvious patterns of the first group and the weaker non-smooth patterns of the second group. These groups are consistent with the stocks which exhibited strong retrospective patterns (the first group), no or minimal retrospective patterns (the second group), and moderate retrospective patterns (the third group). Thus, the ratio of sum MSR from no break to sum MSR with the best break appears to be highly correlated with the presence and strength of the retrospective pattern.

An interesting phenomenon is observed in the plot of the simulated data with a change in catch, where the three earliest break years have a higher sum MSR than the sum MSR from the overall mean. This same phenomenon was observed when these plots were made for the individual indices as well. It is due to the use of the estimated CV when calculating the MSR, but using only the point estimates of q to determine the means in the early and recent periods and overall. The different CVs associated with the different moving windows caused some q estimates to be more influential than others in the sum MSR calculations while the mean calculations applied equal weight to the q point estimates from the moving windows. This could be modified by computing weighted means instead of unweighted means, however, preliminary examination of this modification found that it was not important in terms of detecting the break year nor did it influence the ratio of no break to best sum MSR, and so it was not pursued.

Results of the best break year selection are shown in Figure 3 where the moving window q estimates for each index are plotted with their 95% confidence intervals and the best overall break year and early and recent means are also shown. As before, the simulated data are plotted first followed by the 11 GARM stock assessment results in alphabetical order. Please note that the Figures show the estimated confidence intervals for each q, but very tight CIs (CV < 10%) from the moving window VPA results were replaced by CV=10% in the calculation of the Rago Razor to prevent individual points from being overly influential. For example, GB yt US_fall_6 has two q estimates with much tighter CIs than the other values, which would force the mean in that period to be much closer to the point estimates. These very small q CVs are not thought to be representative of the actual variability in that particular moving window VPA, but rather a statistical artifact due to small sample size and random chance.

The plots of base case simulated data show recent means that are both higher and lower than the early means; however, for the three simulated cases with misspecification, the recent means are only higher than the early means (quite substantially so in some cases). This is expected given the normalized q surface plots, but the strength and consistency of

the increases in the recent period are even more emphasized by the lack of overlap among the confidence intervals in many cases from early and recent periods. The moving window approach also causes transitions to be seen in these plots even though the actual source of change was an abrupt change between 1994 and 1995.

The stock assessment results show more clearly the impact of survey time series which do not span the entire assessment period. For example, CCGOM yt MENH_S_2 has only one q estimate in the early period and thus the MSR is zero for the early period. Other cases have no observations in either the early or recent period, adding nothing to the sum MSR for the best break year. Thus, if there are many indices that do not span the entire assessment period, the estimate of the best break year may be more a reflection of the years of data available in each index rather than a change in an underlying process leading to non-stationarity.

Another feature more clearly seen in Figure 3 stock assessment results than in the normalized q surface plots, is the variability in the q confidence intervals. For example, GB haddock has some indices which appear to have strong trends in the normalized q surface plots (e.g. US_Sp_1), but the large uncertainty associated with some of the estimates makes the confidence intervals overlap for almost the entire time period. This contrasts with cases such as GOM winter NEC_F3_4 which exhibit a strong trend in the q estimates and no overlap of confidence intervals from early and recent years.

The ratios of the no break sum MSR to the best break sum MSR for each stock are presented in Figure 4 and Table 1 arranged in descending order. It is interesting to note the similarity of the results to the F test for significance. The F test statistic for a ratio with 20 degrees of freedom in the numerator (no break) and 19 degrees of freedom in the denominator (best break) is 2.16 at the 95% level of significance and 3.00 at the 99% level of significance. Corresponding values for a 31 year time series (df=30,29) are 1.85 (95%) and 2.41 (99%). However, these F statistics can only be used as general guideposts, not true statistical significance levels, in the moving window results because of the strong correlation among neighboring windows due to sharing (W-2 years) of data. This lack of independence in the q estimates prevents formal statistical testing to define when trends have become “significant.” Nonetheless, the strong correlation between the strength of the sum MSR ratio and the amount of retrospective pattern in the stock assessment makes a strong case that this examination for non-stationarity using moving windows is informative.

The relationship between the best break year and the ratio of no break to best break sum MSR is shown in Figure 5. Note that the simulated data all had the actual change occur in 1995. The stock assessment results appear to follow the simulated data whereby the stocks that did not exhibit strong retrospective patterns have low ratios and years close to the midpoint of their time series. In contrast, the stocks with strong retrospective patterns have higher ratios and break years distributed about 1995. This indicates that there is a basis for selecting 1995 as the break year when splitting survey series to reduce retrospective patterns. The question then arises “how much worse is 1995 than the best break year” because as seen in the simulated data, the best break year may not necessarily

indentify the correct change year. Figure 6 and Table 1 provide the ratio estimates between the no break sum MSR and sum MSR when the break year is set to 1995. The overall pattern of results does not change. The stocks with strong retrospective patterns maintain high ratio values for break year 1995 while the stocks with no retrospective patterns still have positive values. The only stock which exhibited a large change in result was GB winter which had a best ratio of 3.87 (borderline significant) and a 1995 ratio of 1.79 (insignificant). Thus, the moving window analyses demonstrate that selecting 1995 as the break year for all stocks which exhibit a strong retrospective pattern is reasonable.

While identification of a reasonable break year is a necessary step, implementation of a break year in the assessment may not be sufficient to reduce the retrospective pattern to acceptable levels. Moreover, it does not correct the underlying cause of the retrospective pattern. It must be reiterated that the resulting catchability estimates are aliasing the potential simultaneous effects of missing catch, increasing natural mortality and changing catchability. Of these, changes in actual catchability are considered to be the least likely factor. A measure of the plausibility of the change in q can be obtained by expressing the indices in swept area units, such that the derived q's represent gear efficiency measures. Efficiency should range from zero to one. But for species that herd in front of trawls, the q's can exceed one when the footprint area does not include the area swept between the trawl doors and the wings.

References

GARM (Groundfish Assessment Review Meeting). 2008a. Report of the Groundfish Assessment Review Meeting (GARM) Part 2. Assessment Methodology (Models). R. O'Boyle [chair]. Available at http://www.nefsc.noaa.gov/nefsc/saw/

GARM (Groundfish Assessment Review Meeting). 2008b. Report of the Groundfish Assessment Review Meeting (GARM) Part 3. Biological Reference Points. R. O'Boyle [chair]. Available at http://www.nefsc.noaa.gov/nefsc/saw/

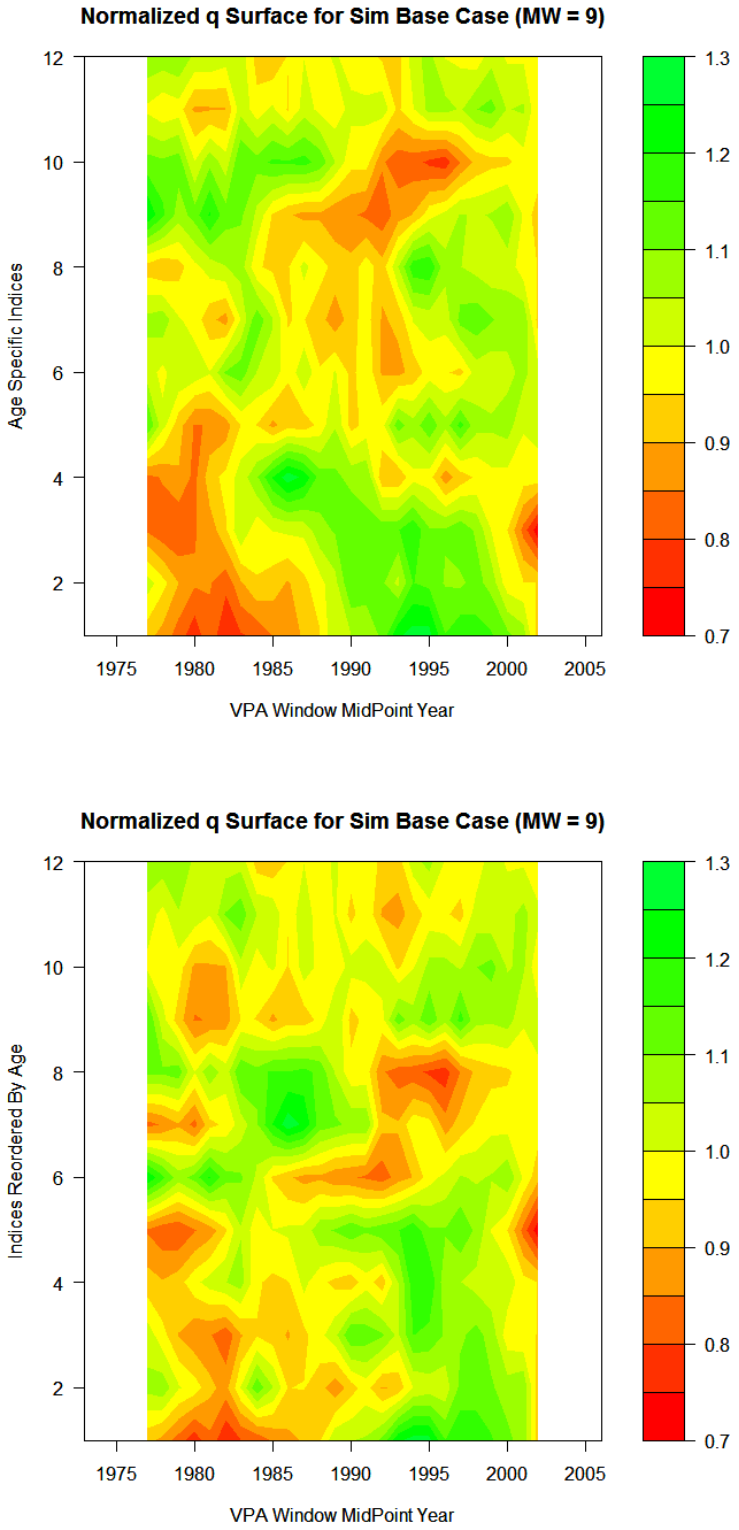
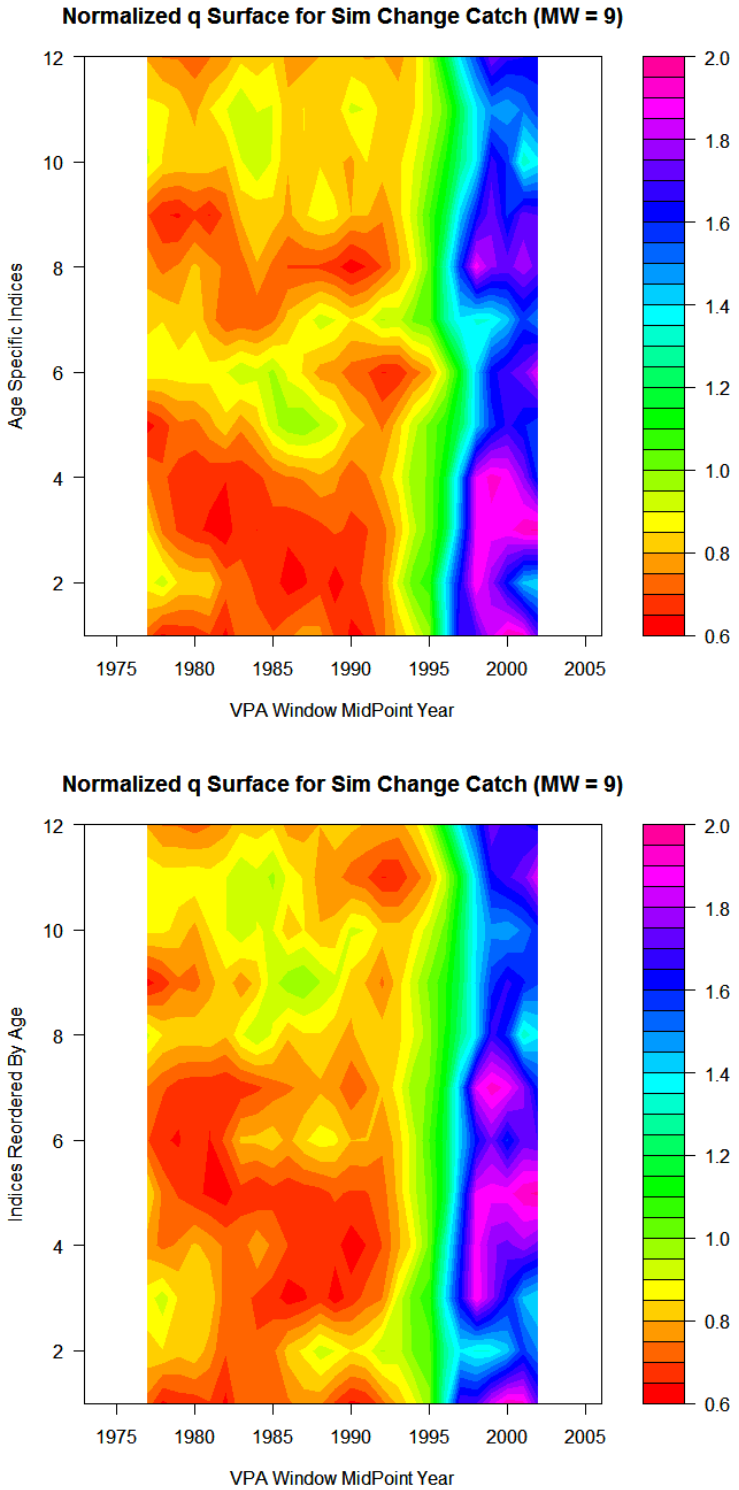


Figure 1. Normalized q surface plots. Top panel grouped by survey, bottom panel grouped by age.



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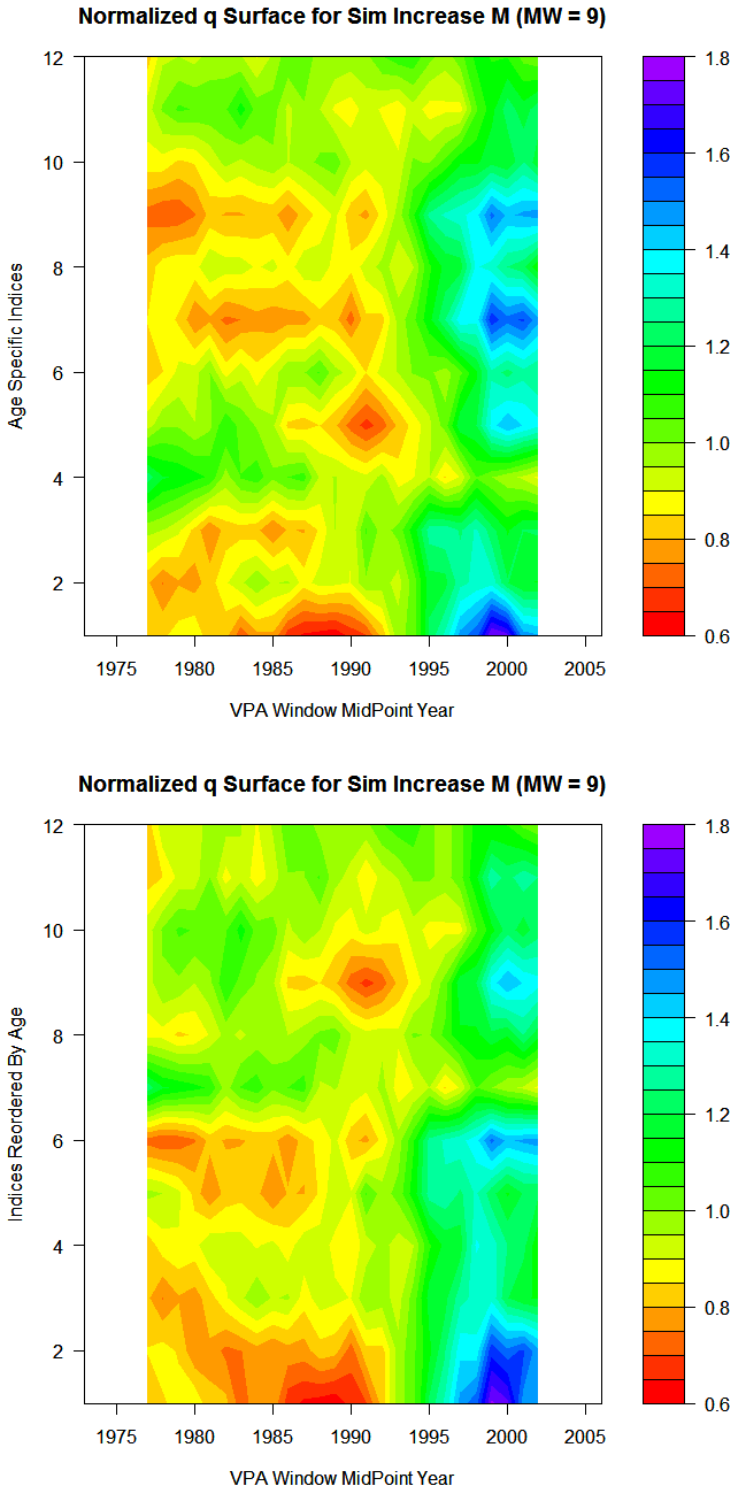

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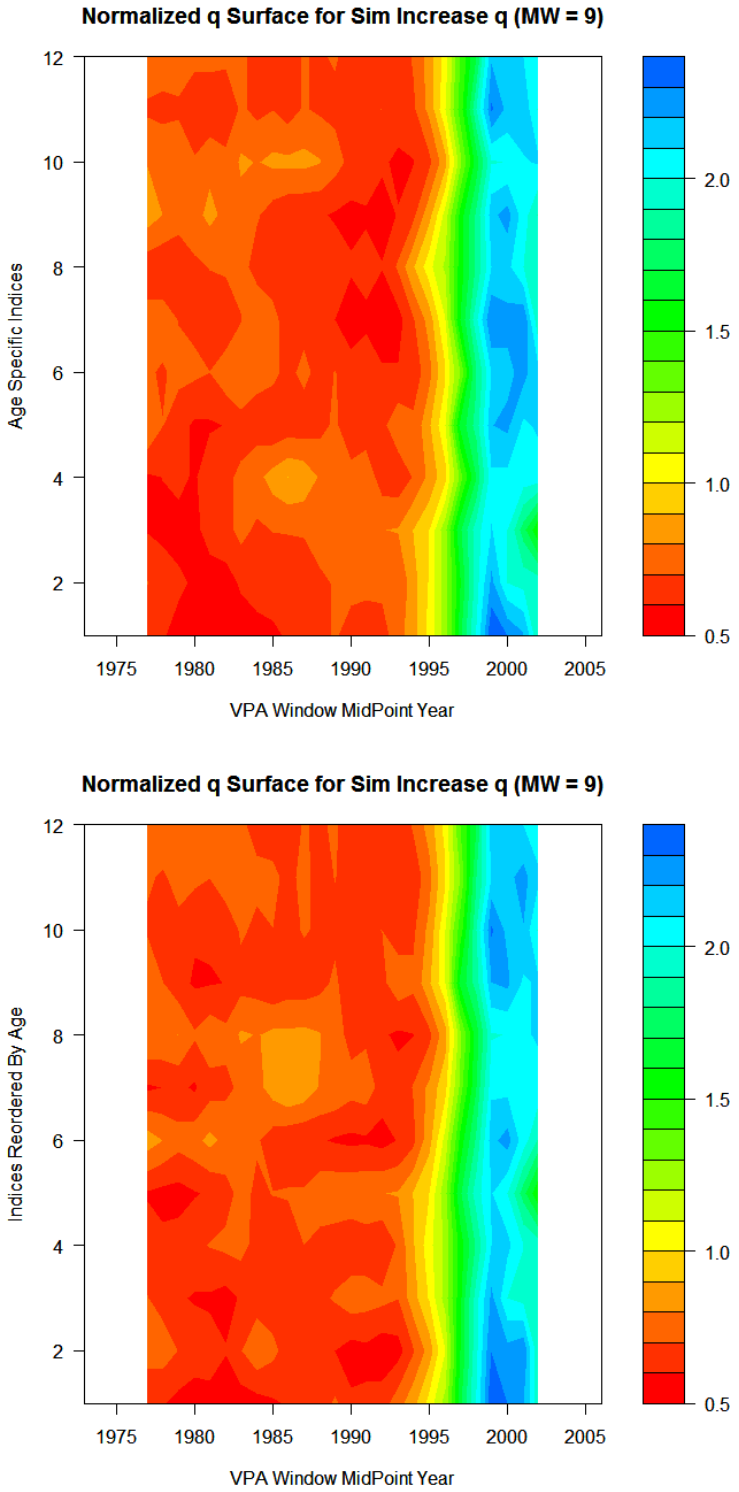

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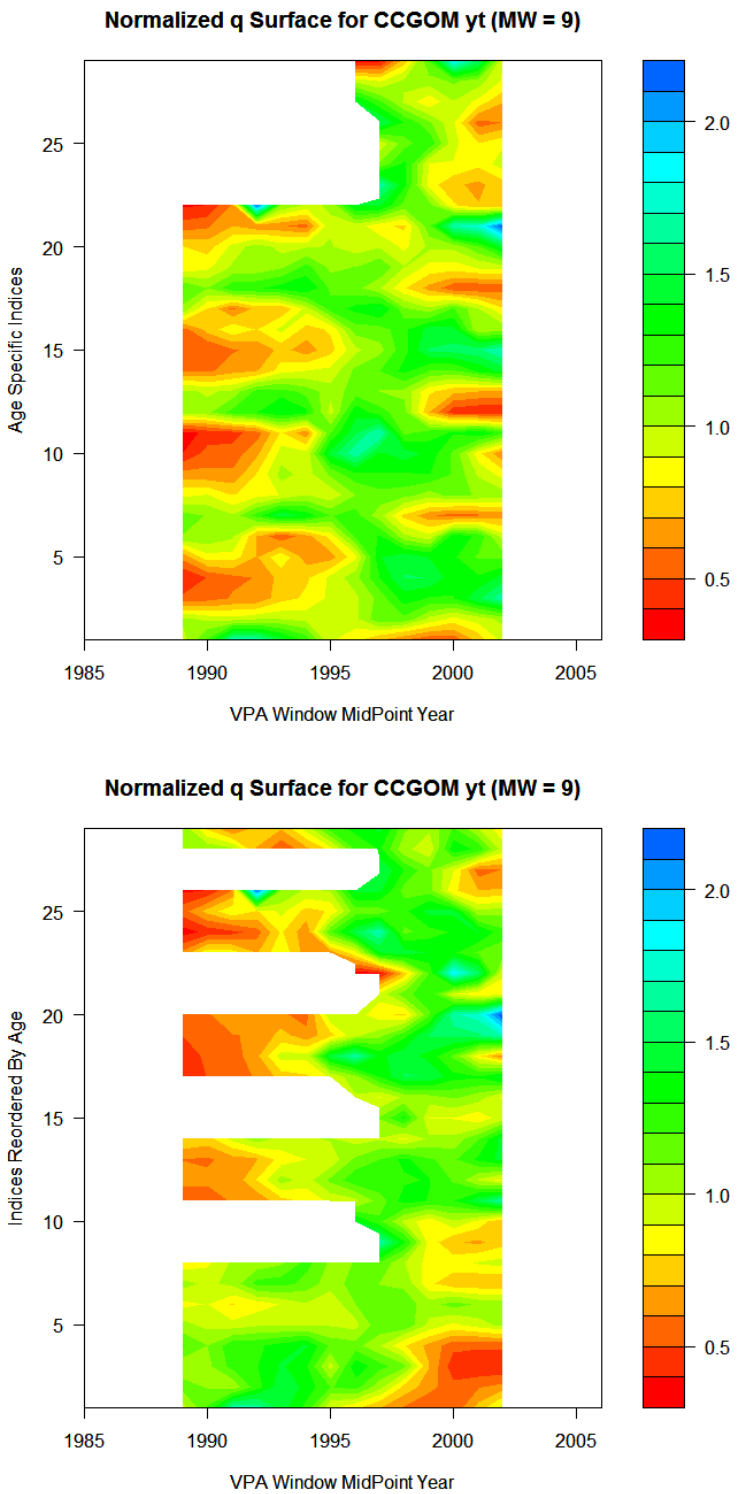

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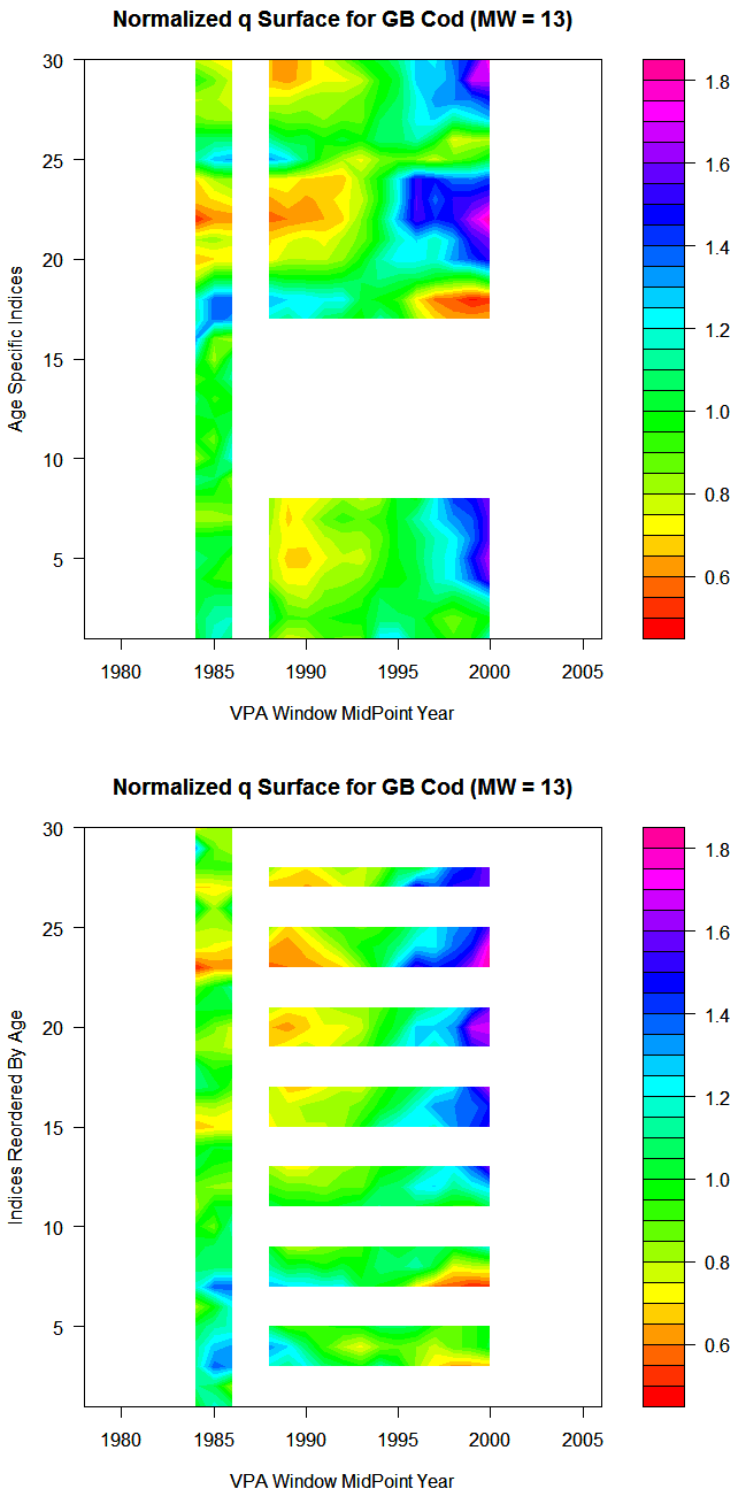

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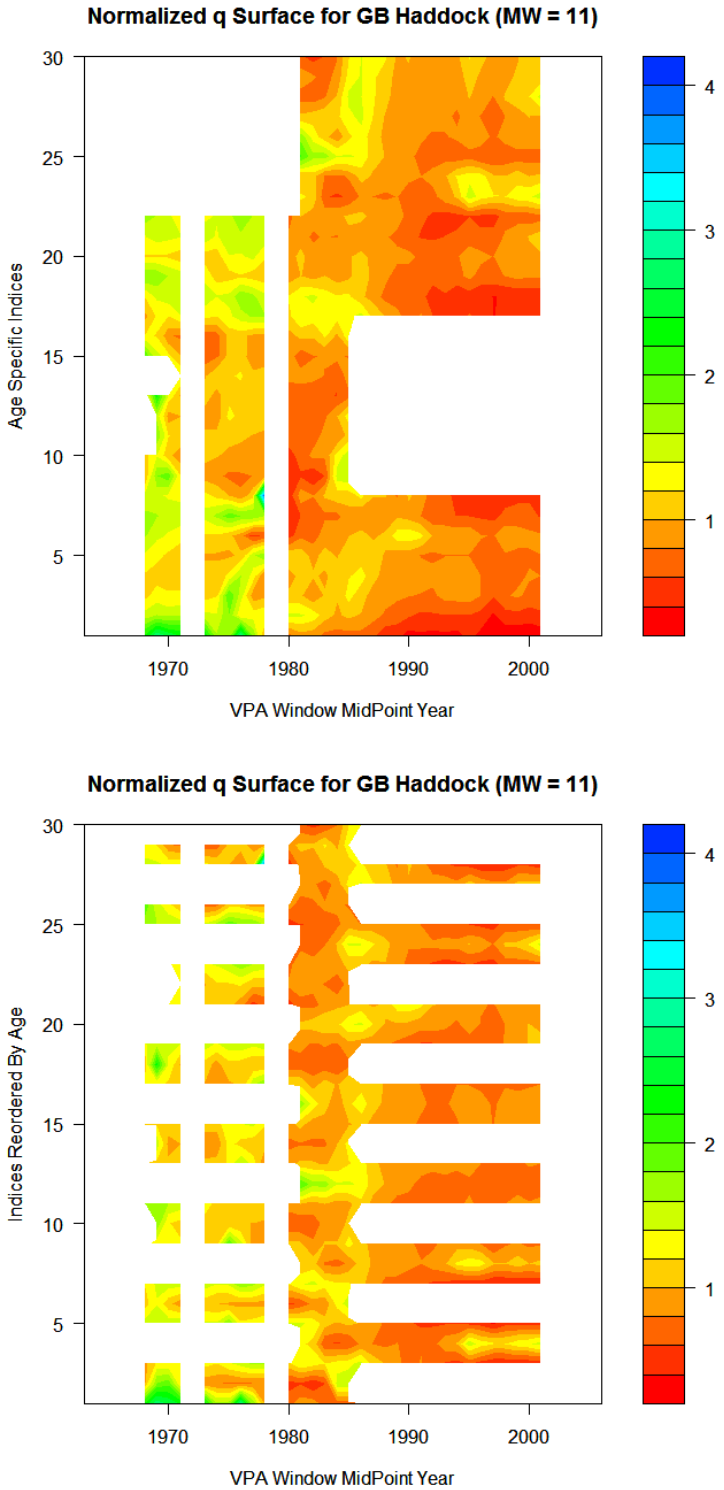

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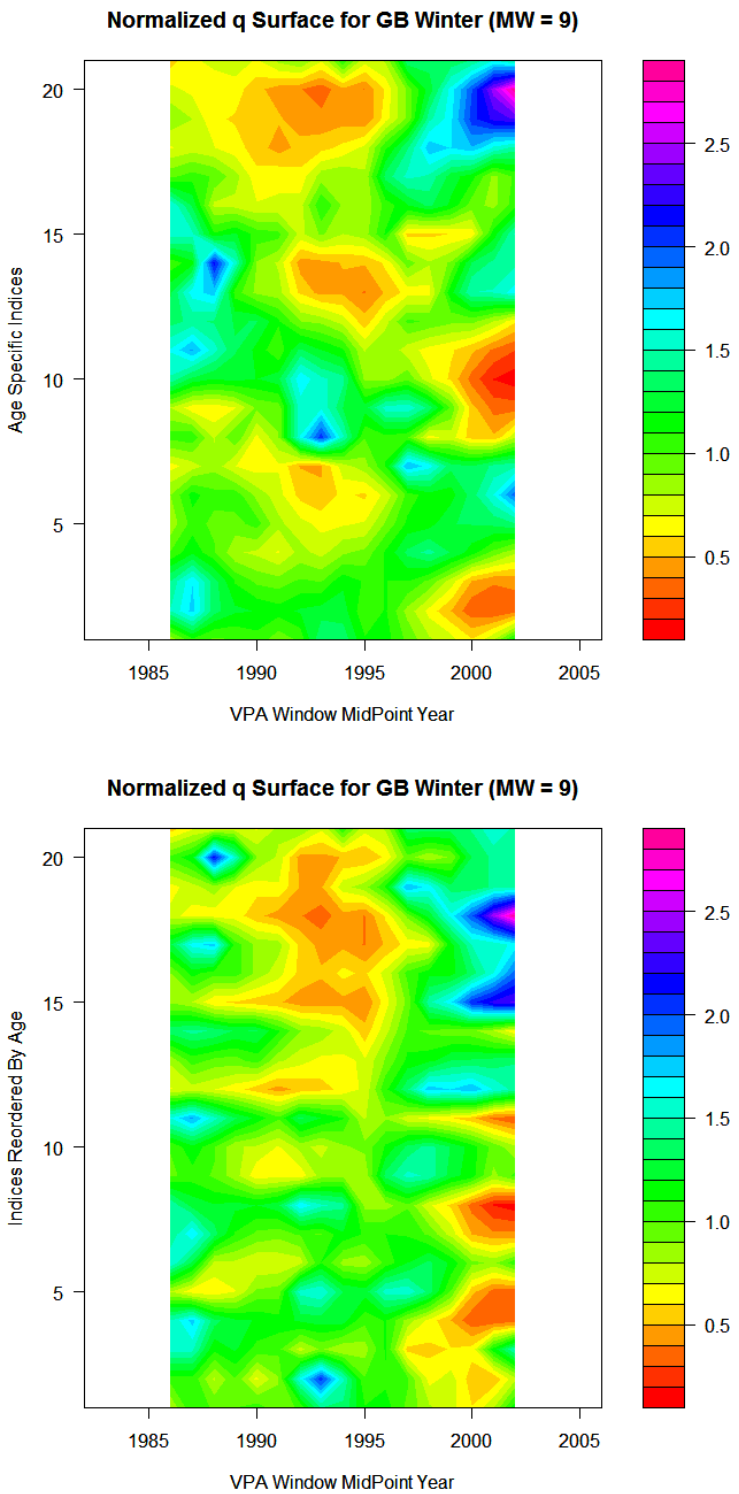

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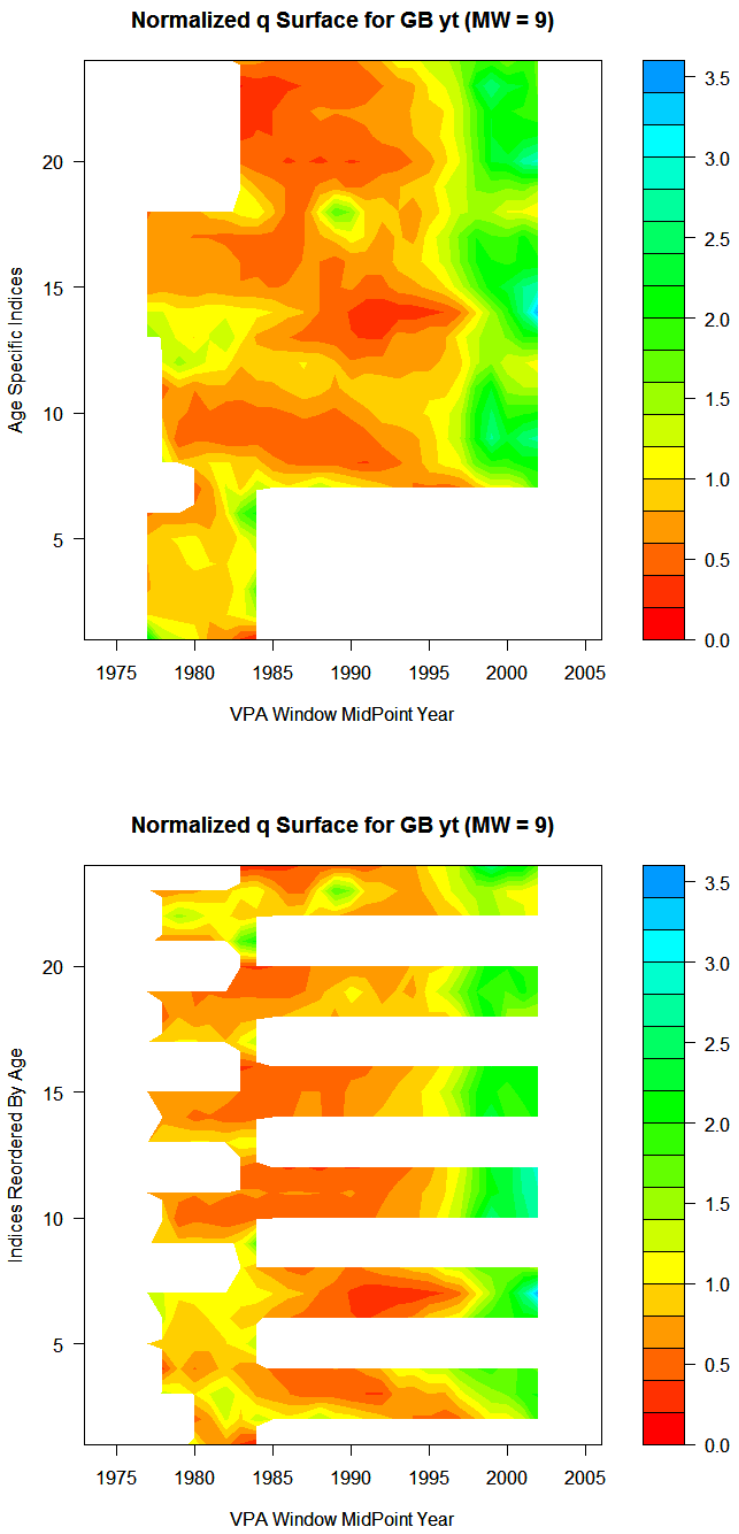

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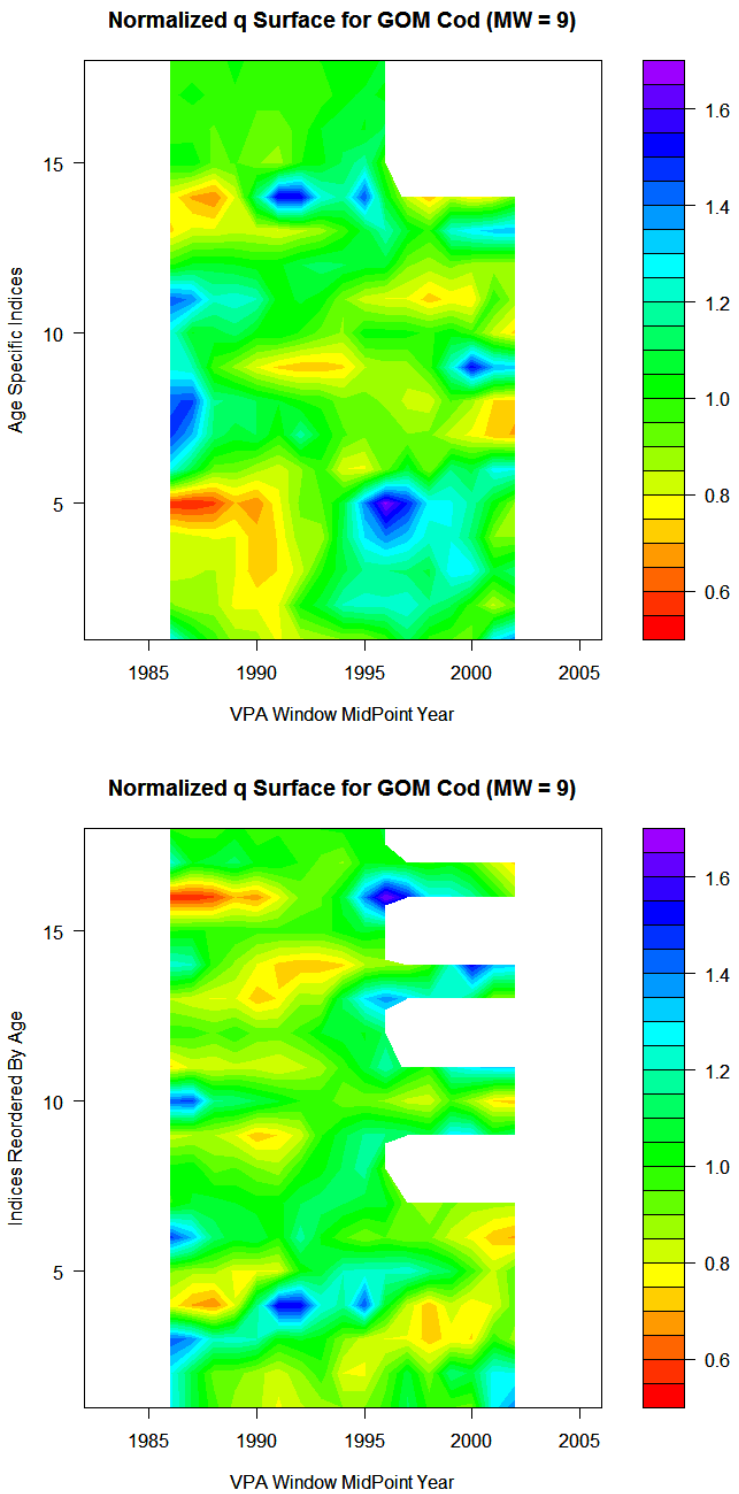

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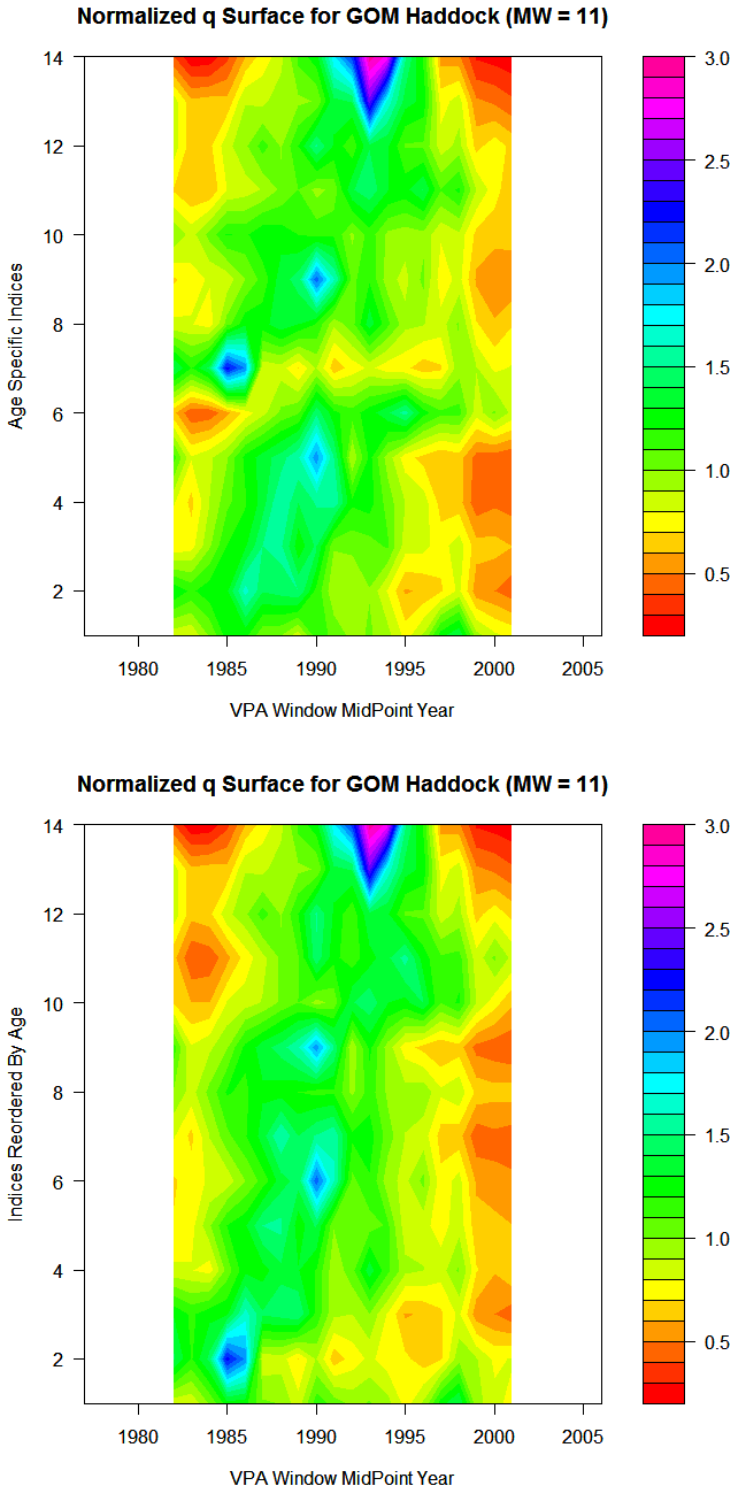

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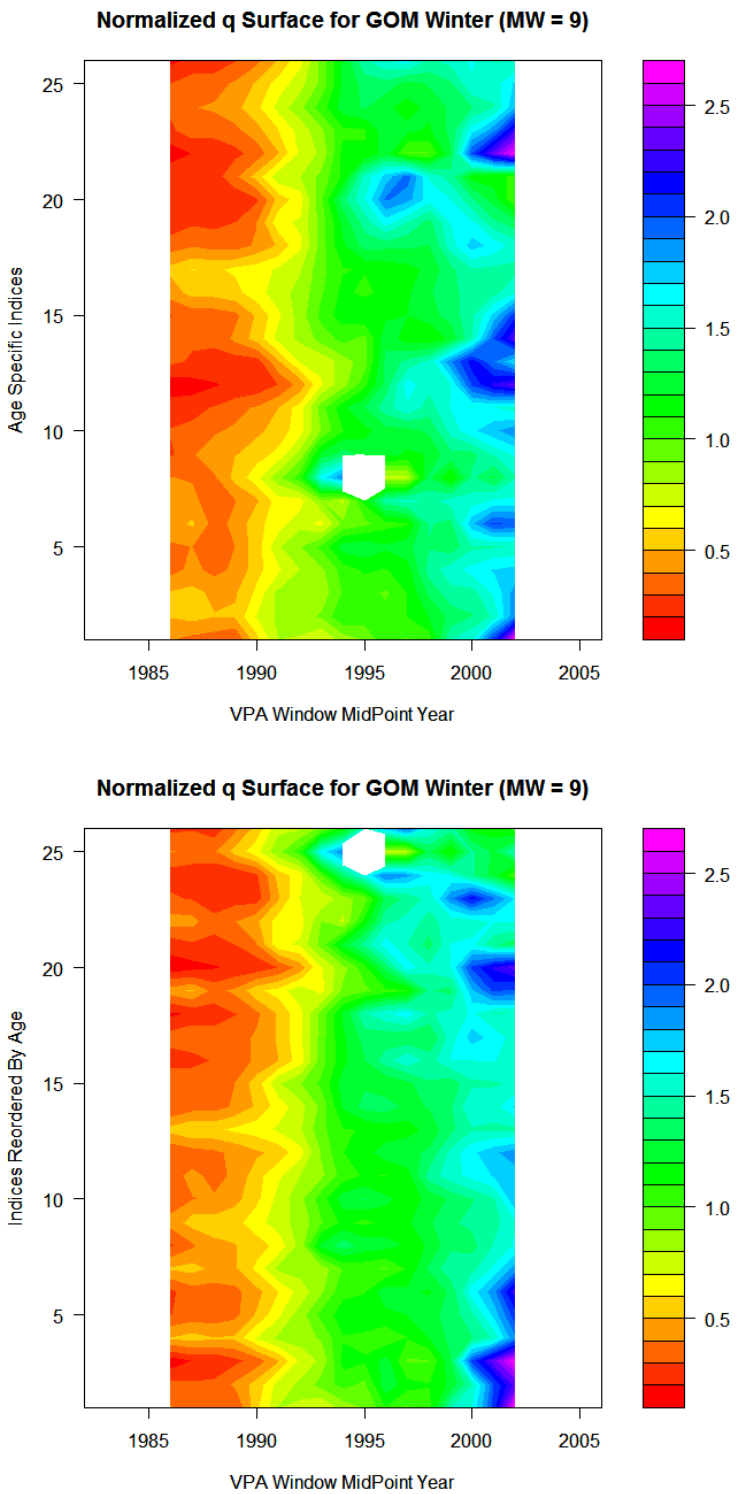

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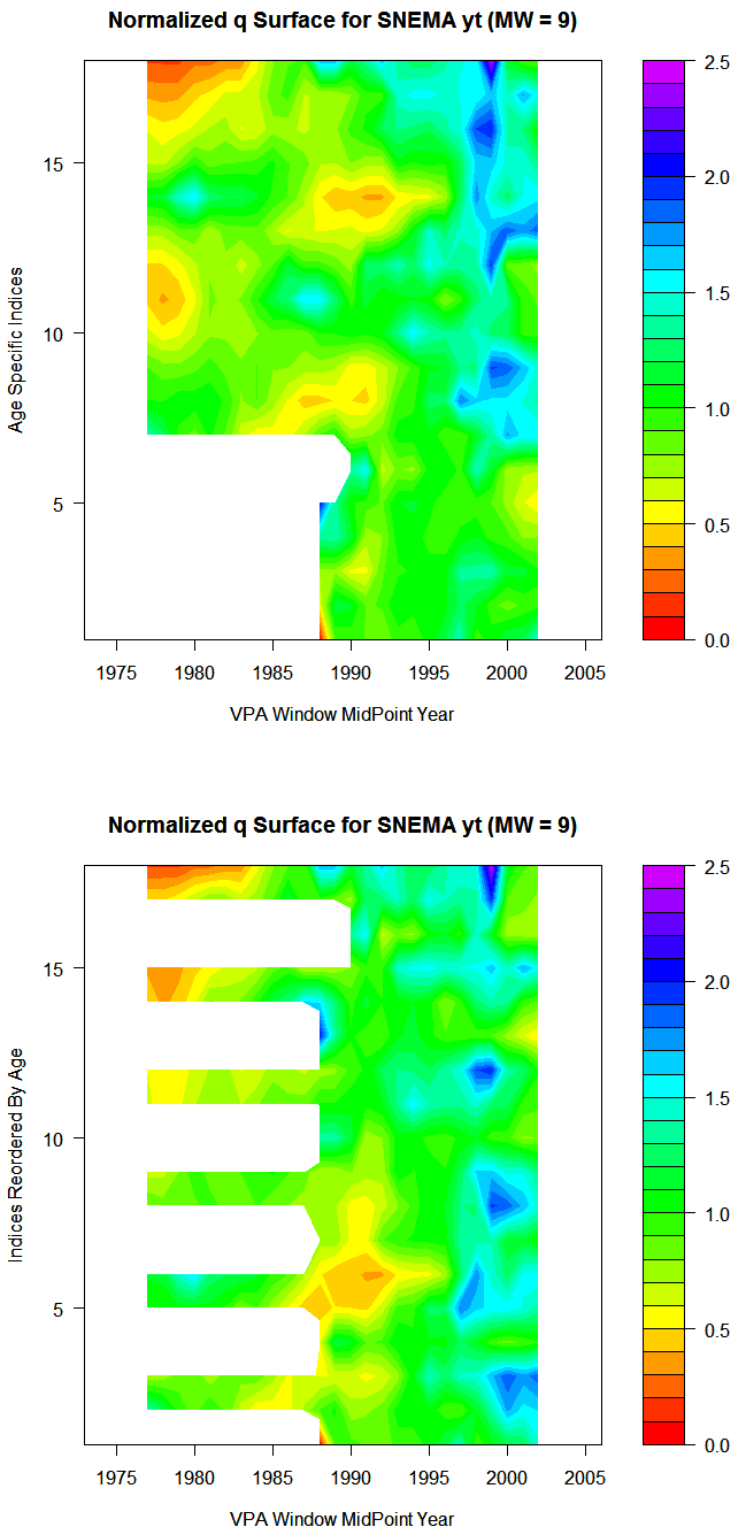

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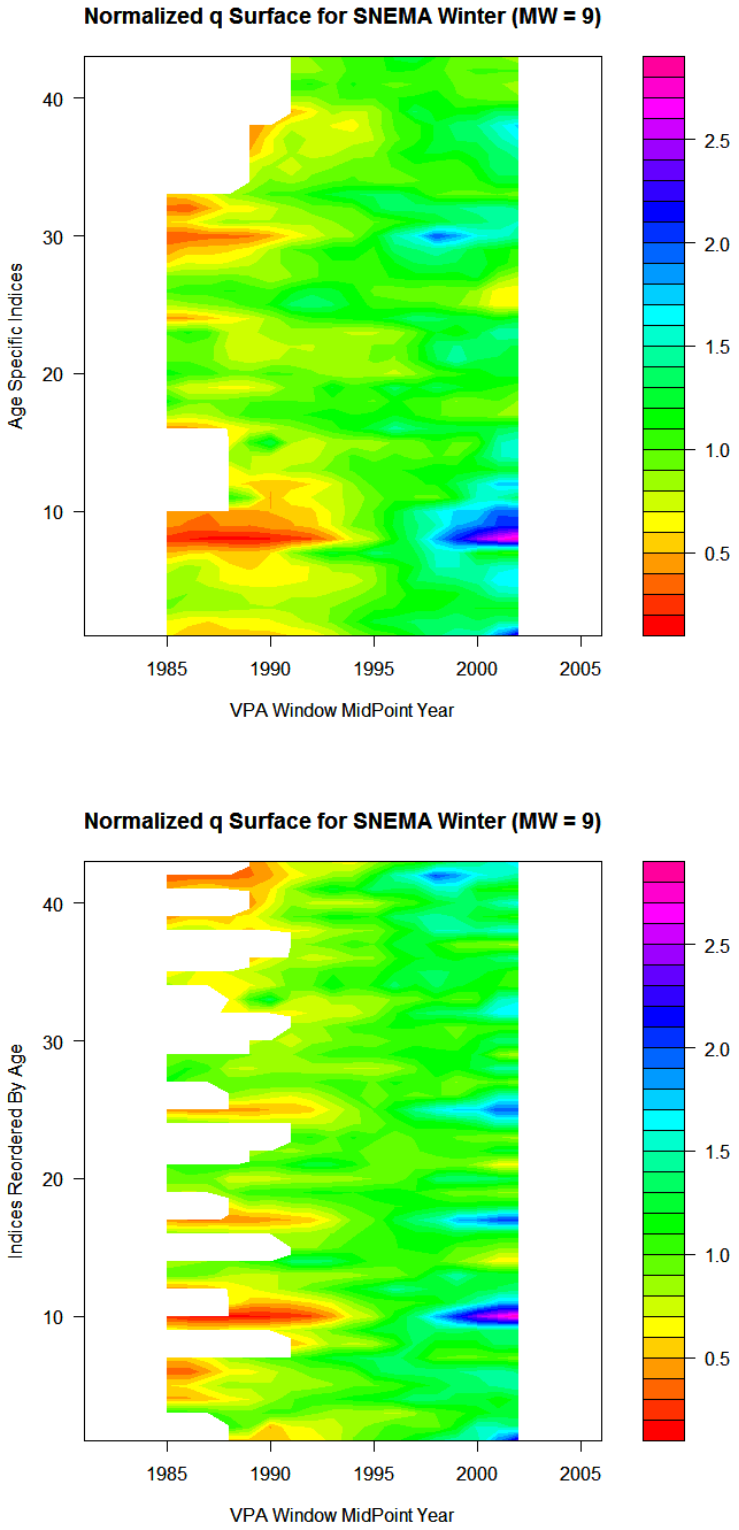

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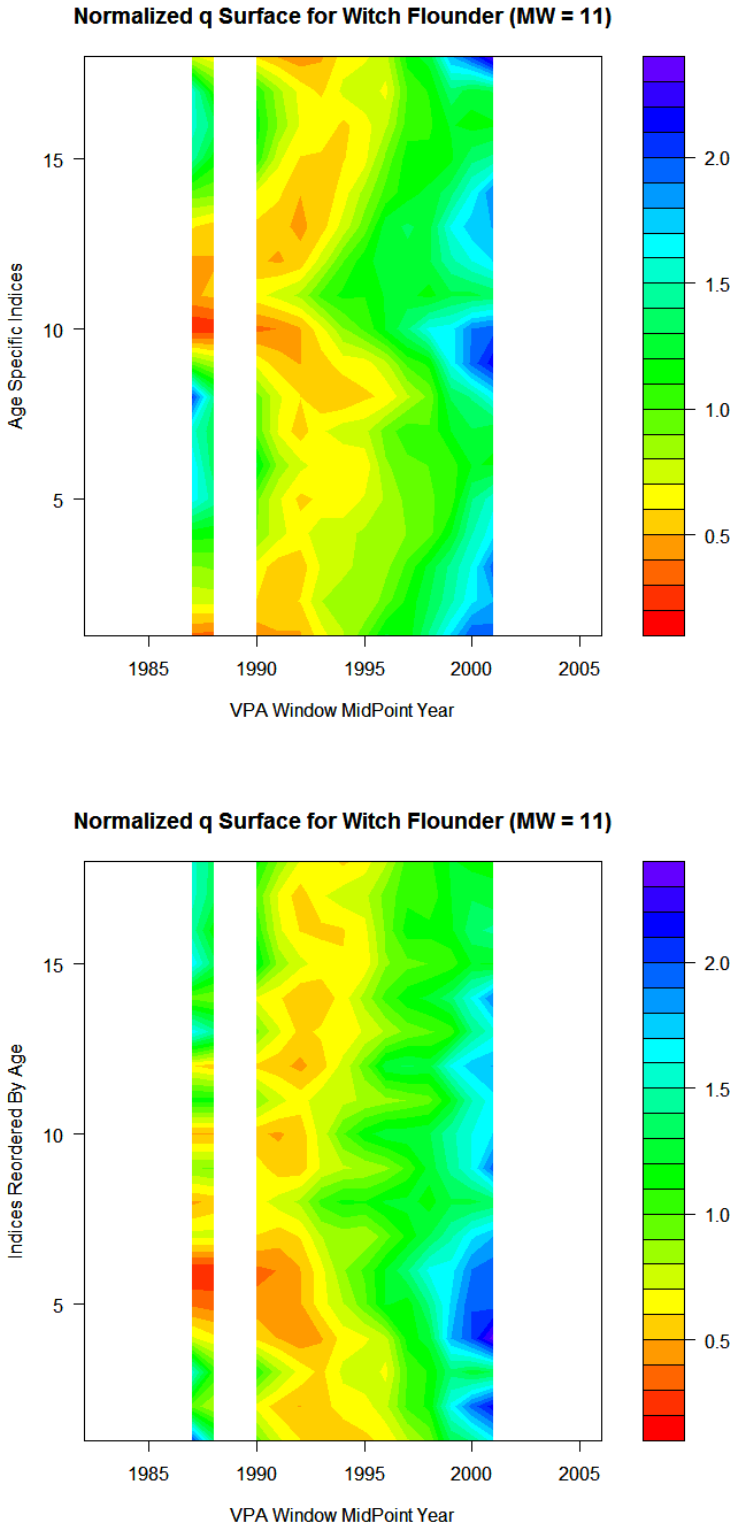

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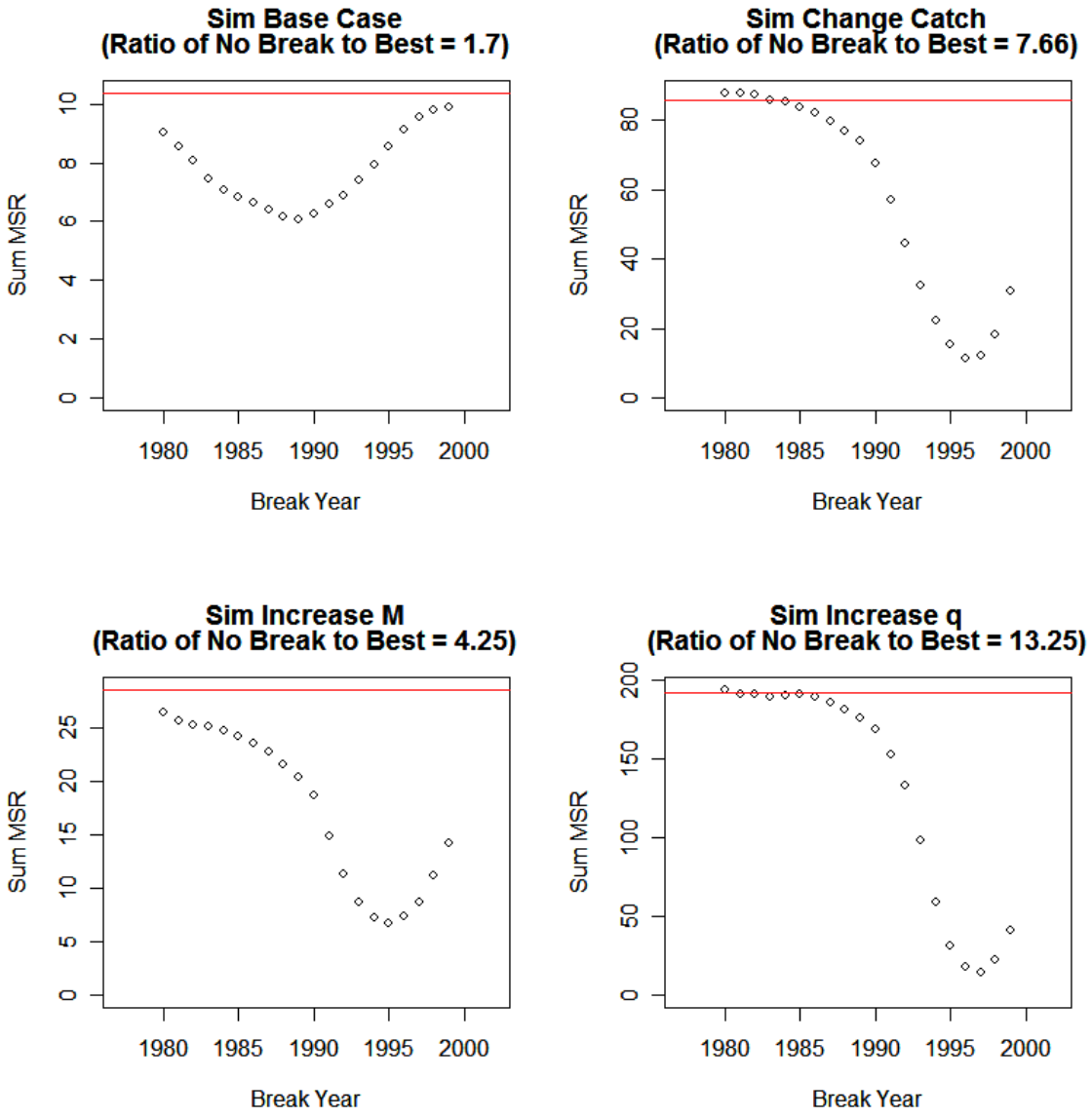
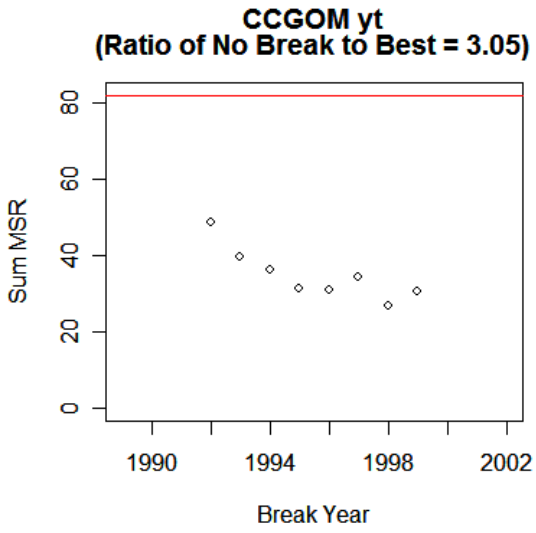
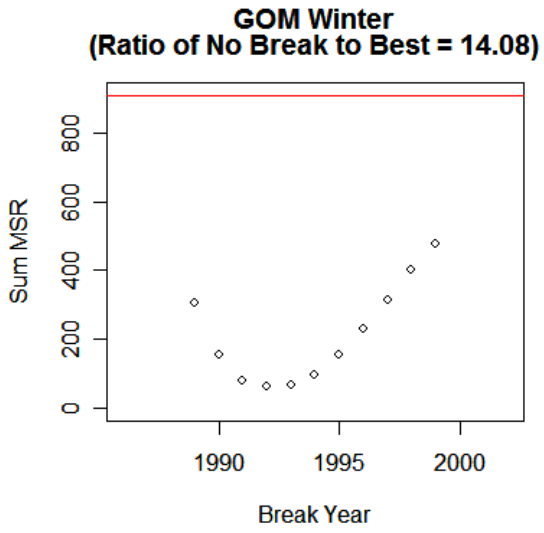
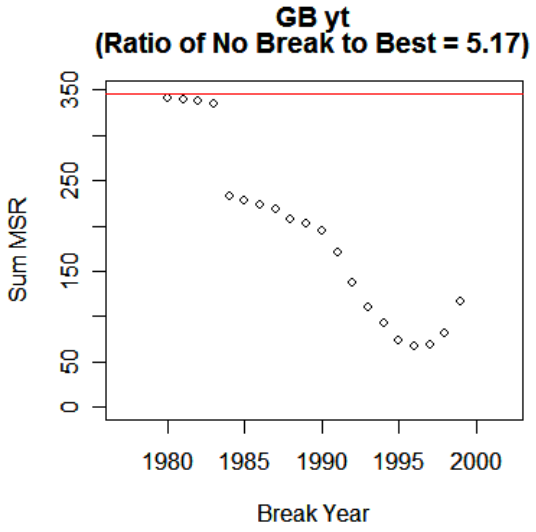
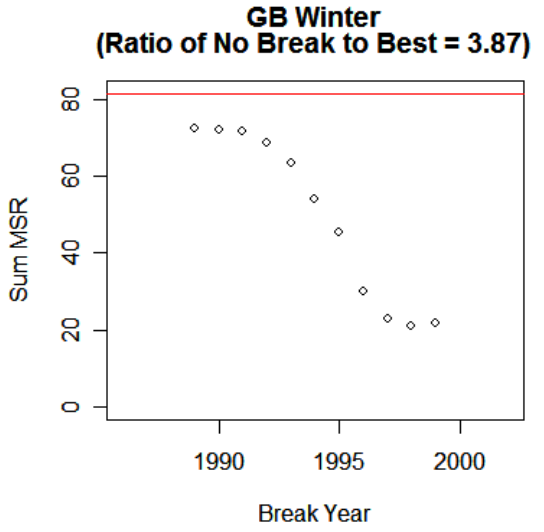


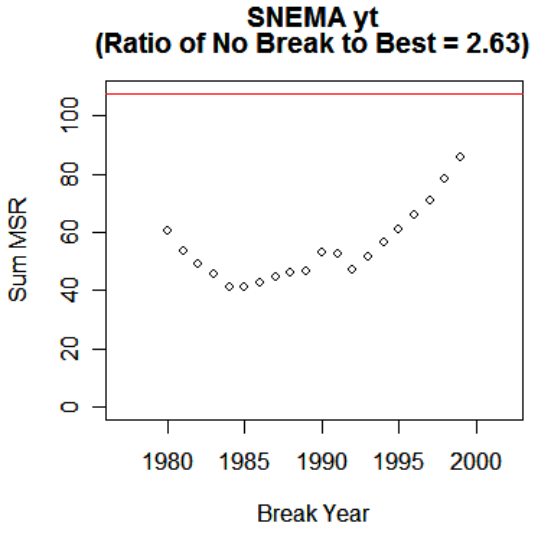
Figure 2. Sum of mean squared residuals between moving window q estimates and early and recent means for given break years (points) and overall mean with no break (red line).

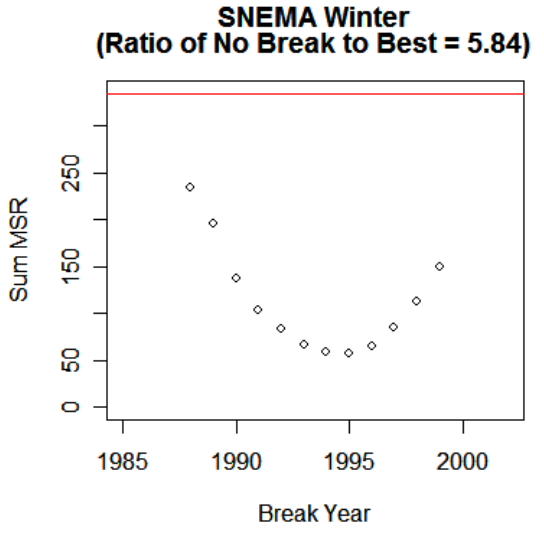

CCGOM yt
(Ratio of No Break to Best = 3.05)
Sum MSR
0
20
40
60
80
1990
1994
1998
2002
Break Year

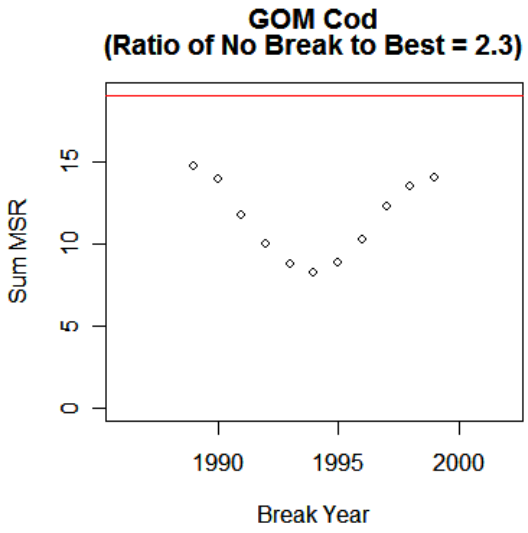

GOM Winter
(Ratio of No Break to Best = 14.08)
Sum MSR
0
200
400
600
800
1990
1995
2000
Break Year

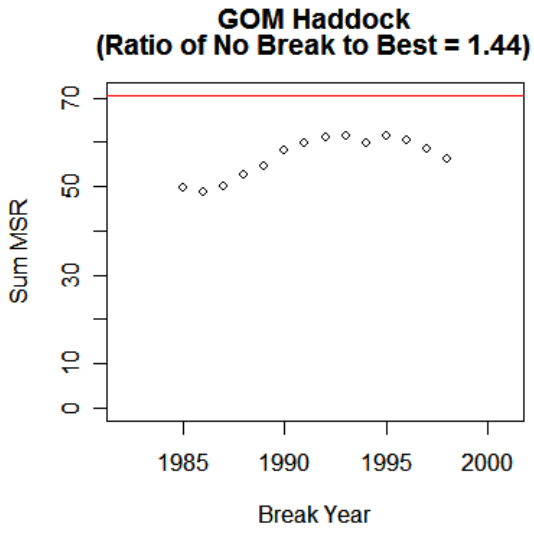

GB yt
(Ratio of No Break to Best = 5.17)
Sum MSR
0
50
150
250
350
1980
1985
1990
1995
2000
Break Year

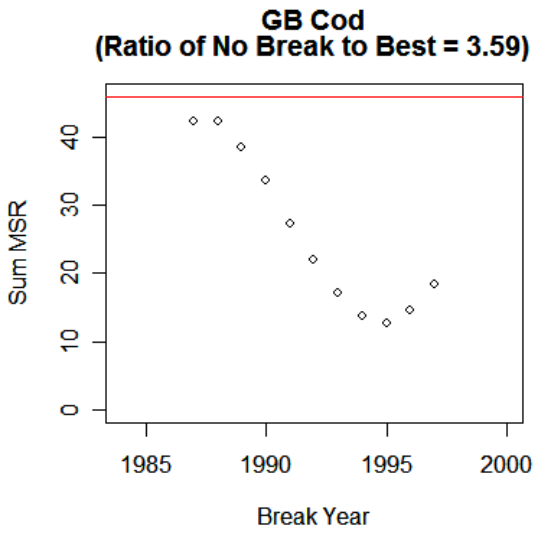

GB Winter
(Ratio of No Break to Best = 3.87)
Sum MSR
0
20
40
60
80
1990
1995
2000
Break Year

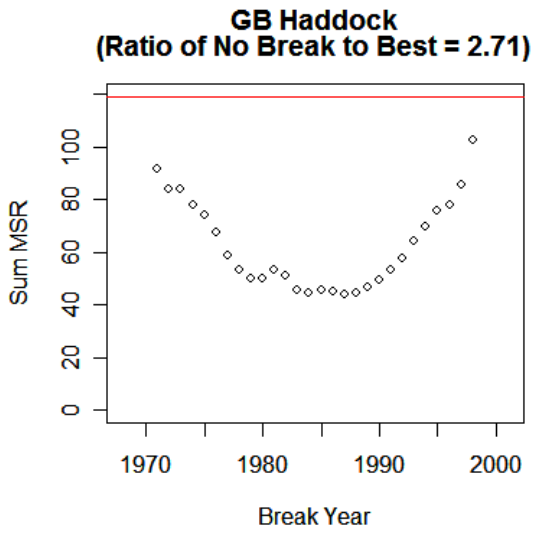

SNEMA yt
(Ratio of No Break to Best = 2.63)
Sum MSR
0
20
40
60
80
100
1980
1985
1990
1995
2000
Break Year

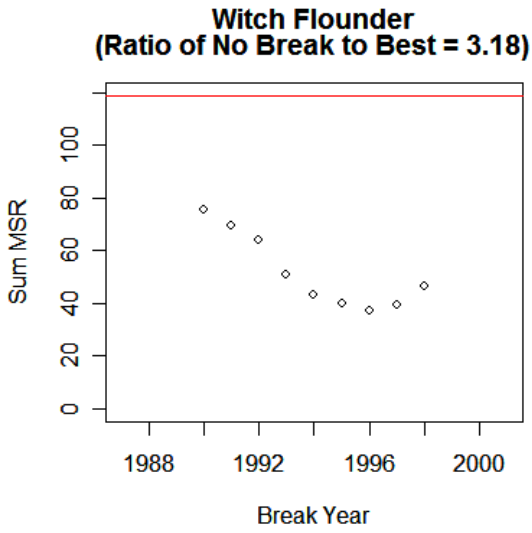

SNEMA Winter
(Ratio of No Break to Best = 5.84)
Sum MSR
0
50
150
250
1985
1990
1995
2000
Break Year


GOM Cod
(Ratio of No Break to Best = 2.3)
Sum MSR
0
5
10
15
1990
1995
2000
Break Year


GOM Haddock
(Ratio of No Break to Best = 1.44)
Sum MSR
0
10
30
50
70
1985
1990
1995
2000
Break Year


GB Cod
(Ratio of No Break to Best = 3.59)
Sum MSR
0
10
20
30
40
1985
1990
1995
2000
Break Year


GB Haddock
(Ratio of No Break to Best = 2.71)
Sum MSR
0
20
40
60
80
100
1970
1980
1990
2000
Break Year


Witch Flounder
(Ratio of No Break to Best = 3.18)
Sum MSR
0
20
40
60
80
100
1988
1992
1996
2000
Break Year

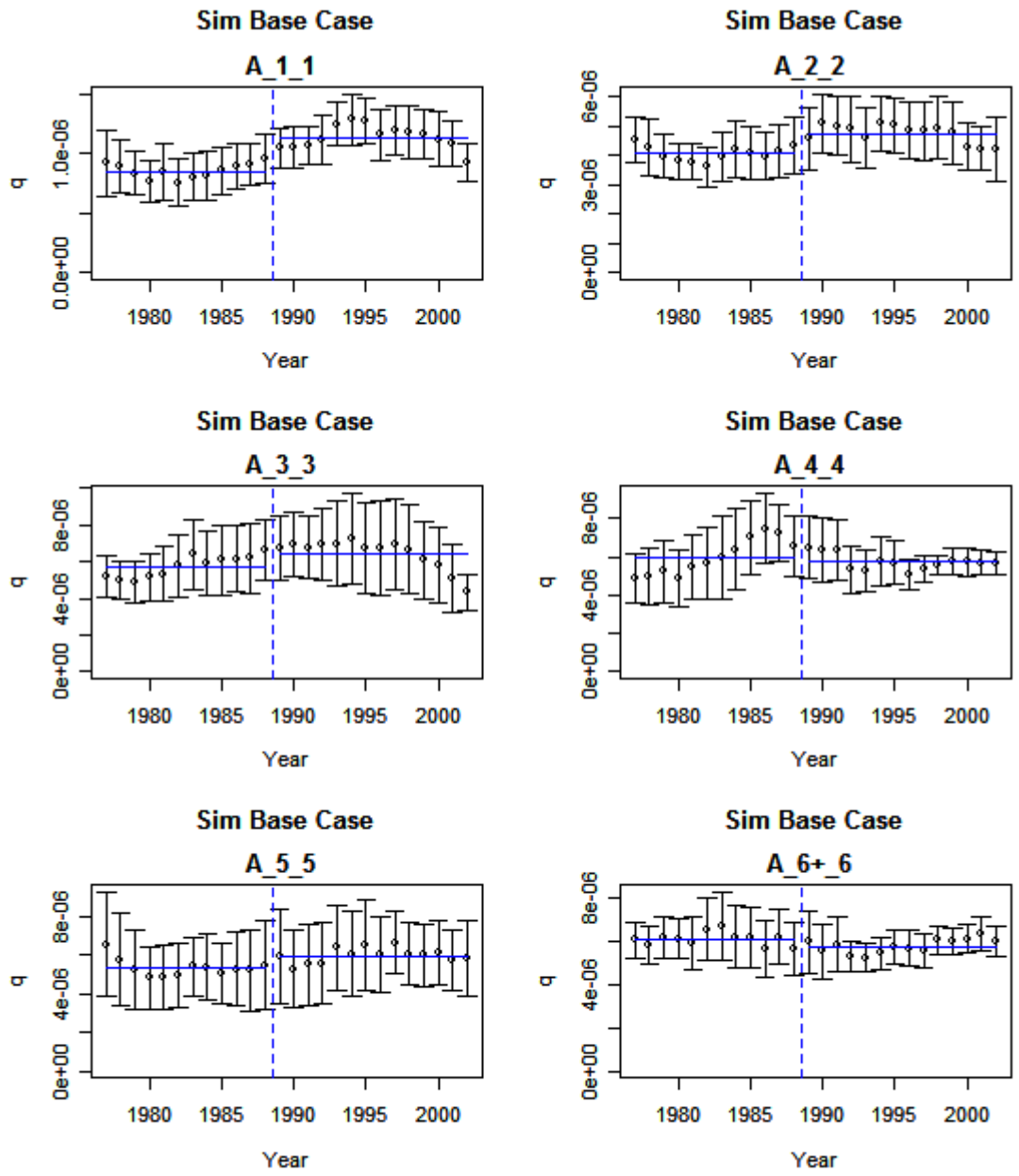


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

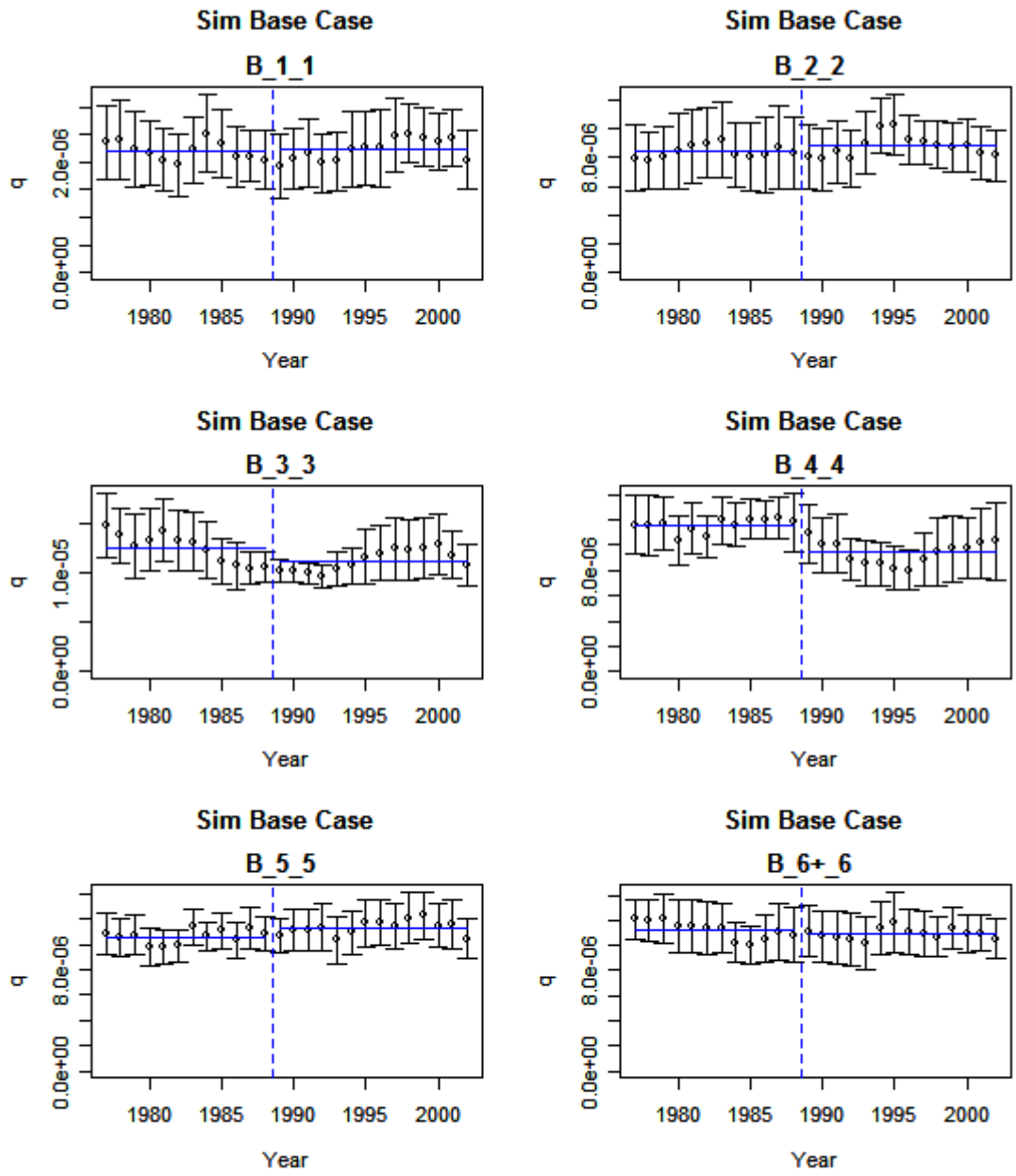


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

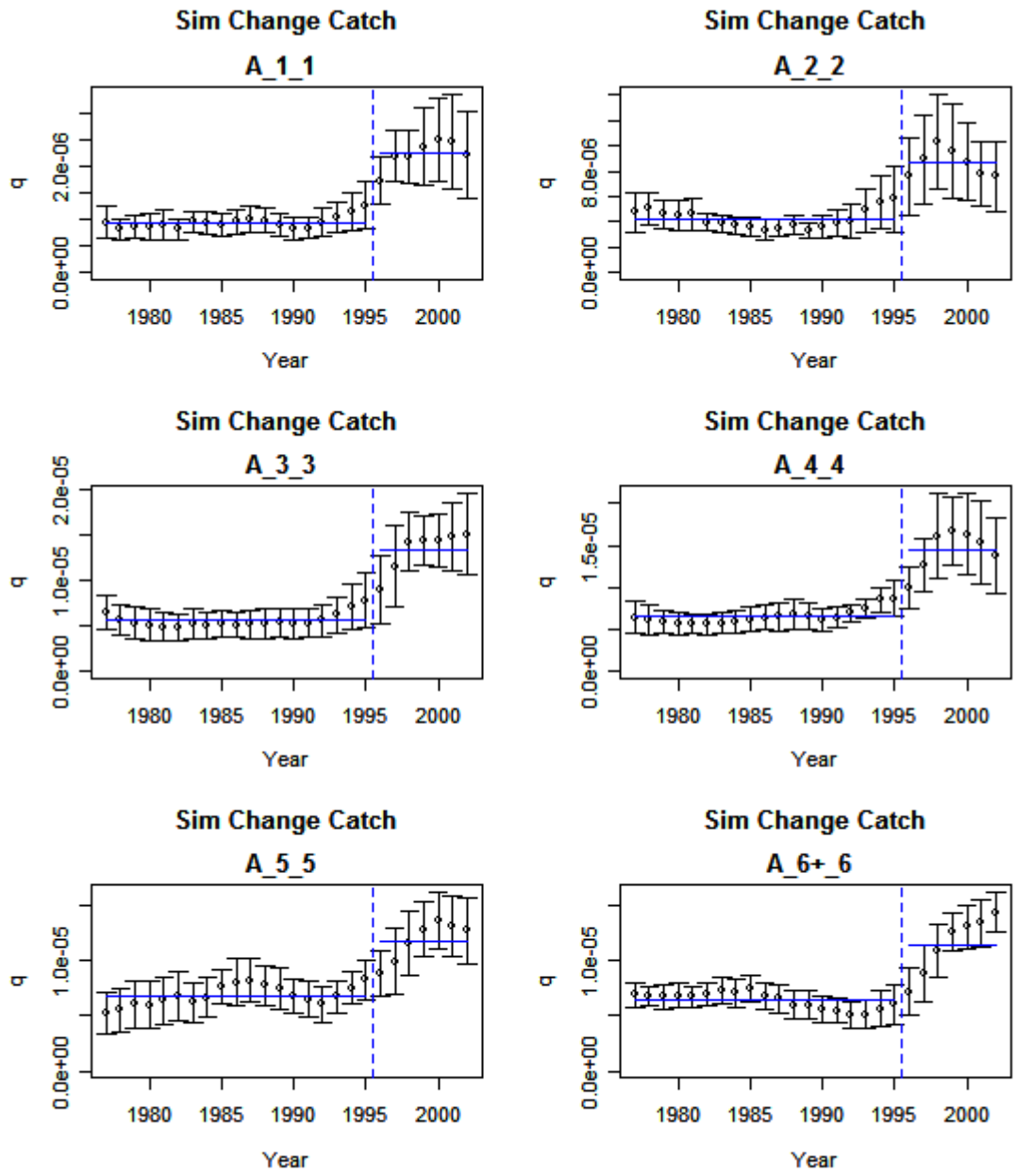


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

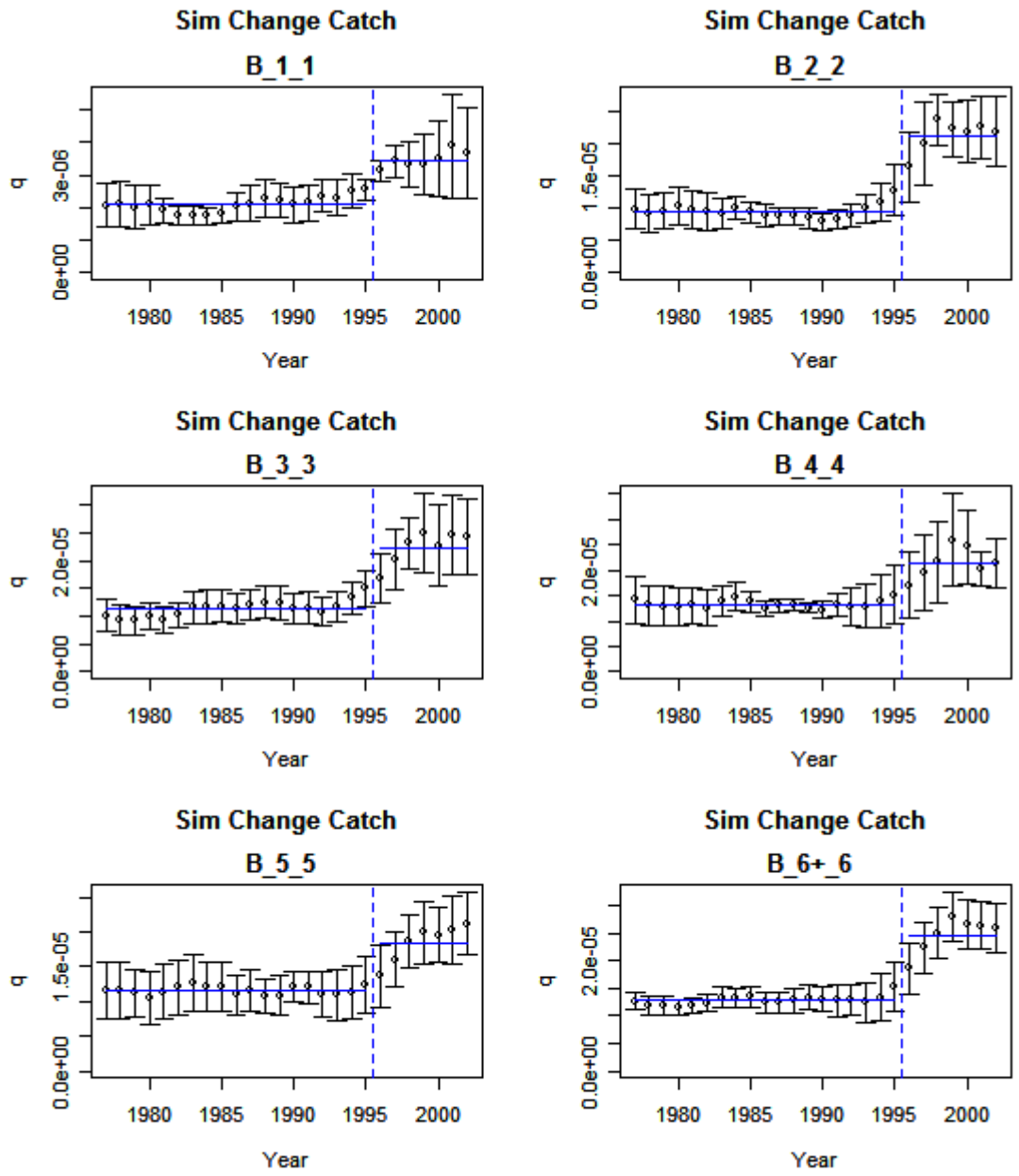


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

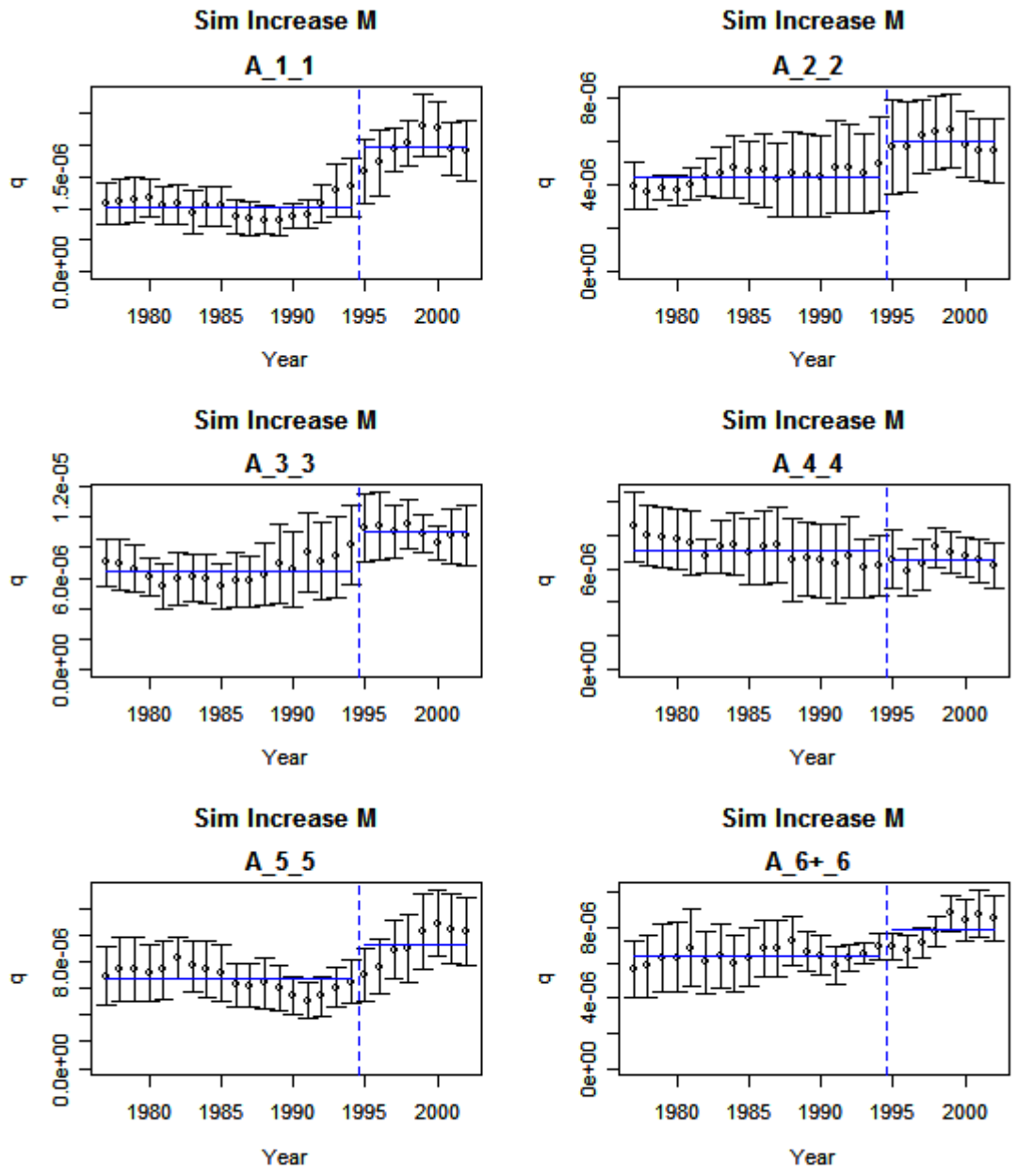


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

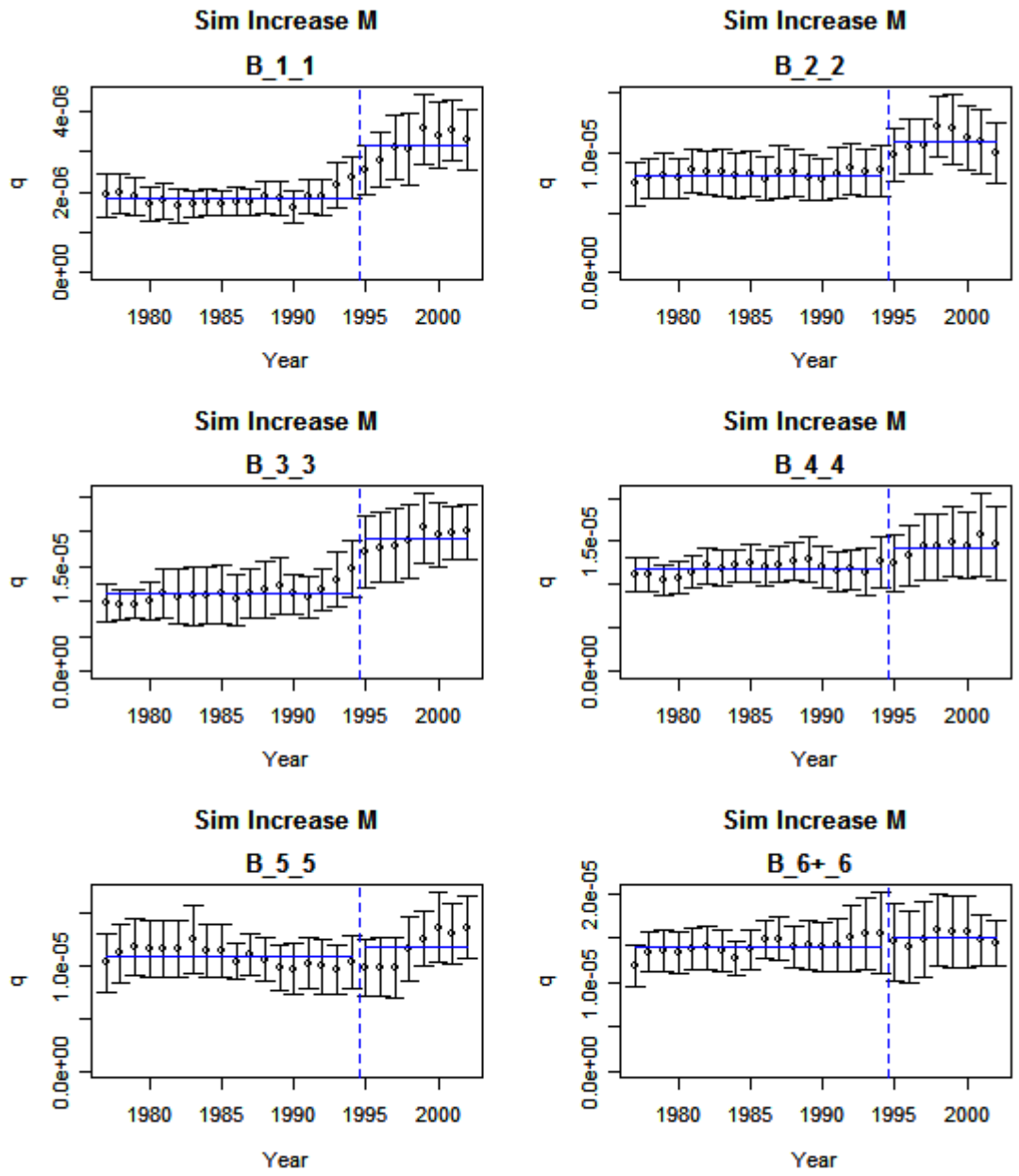


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

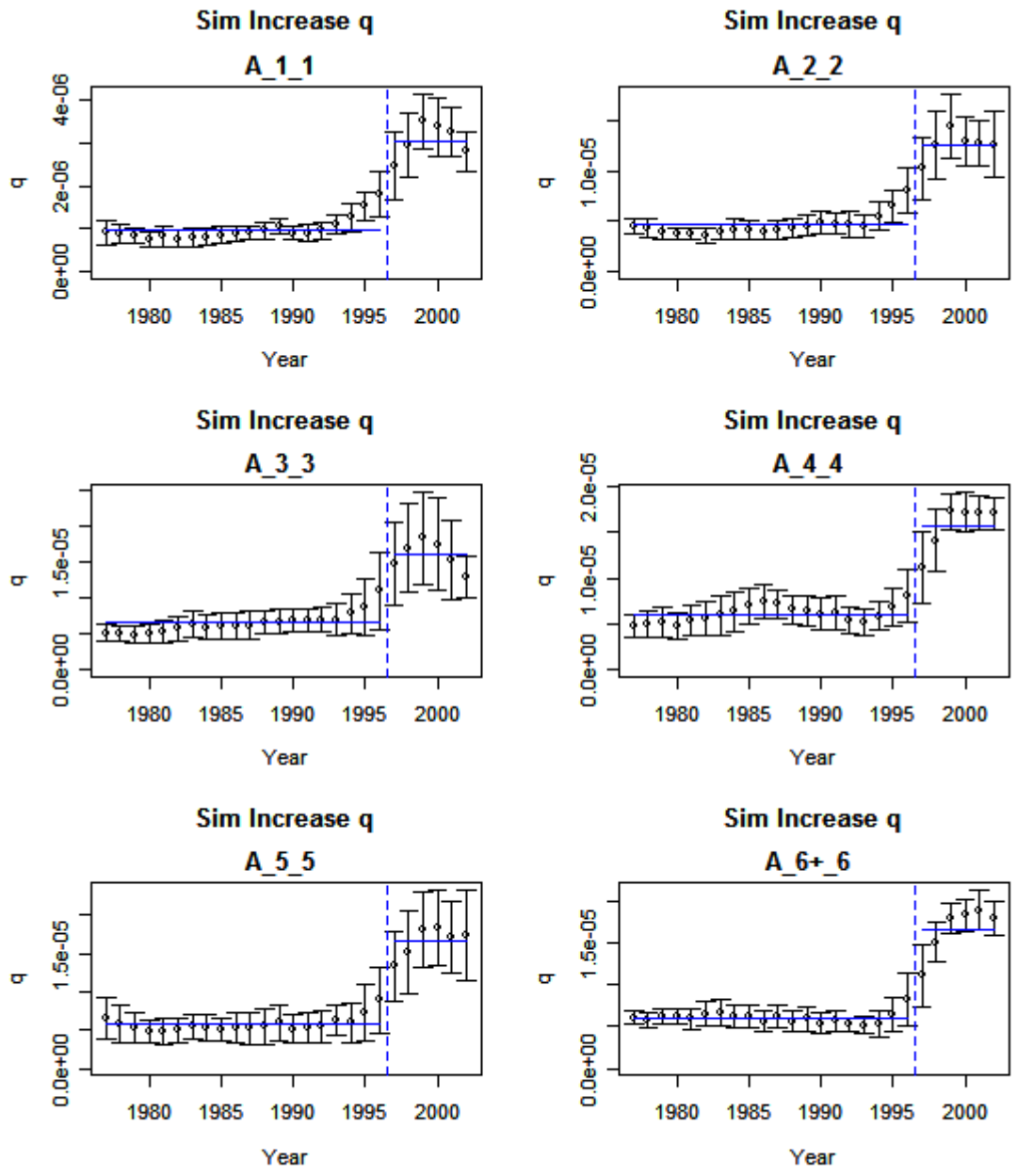


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

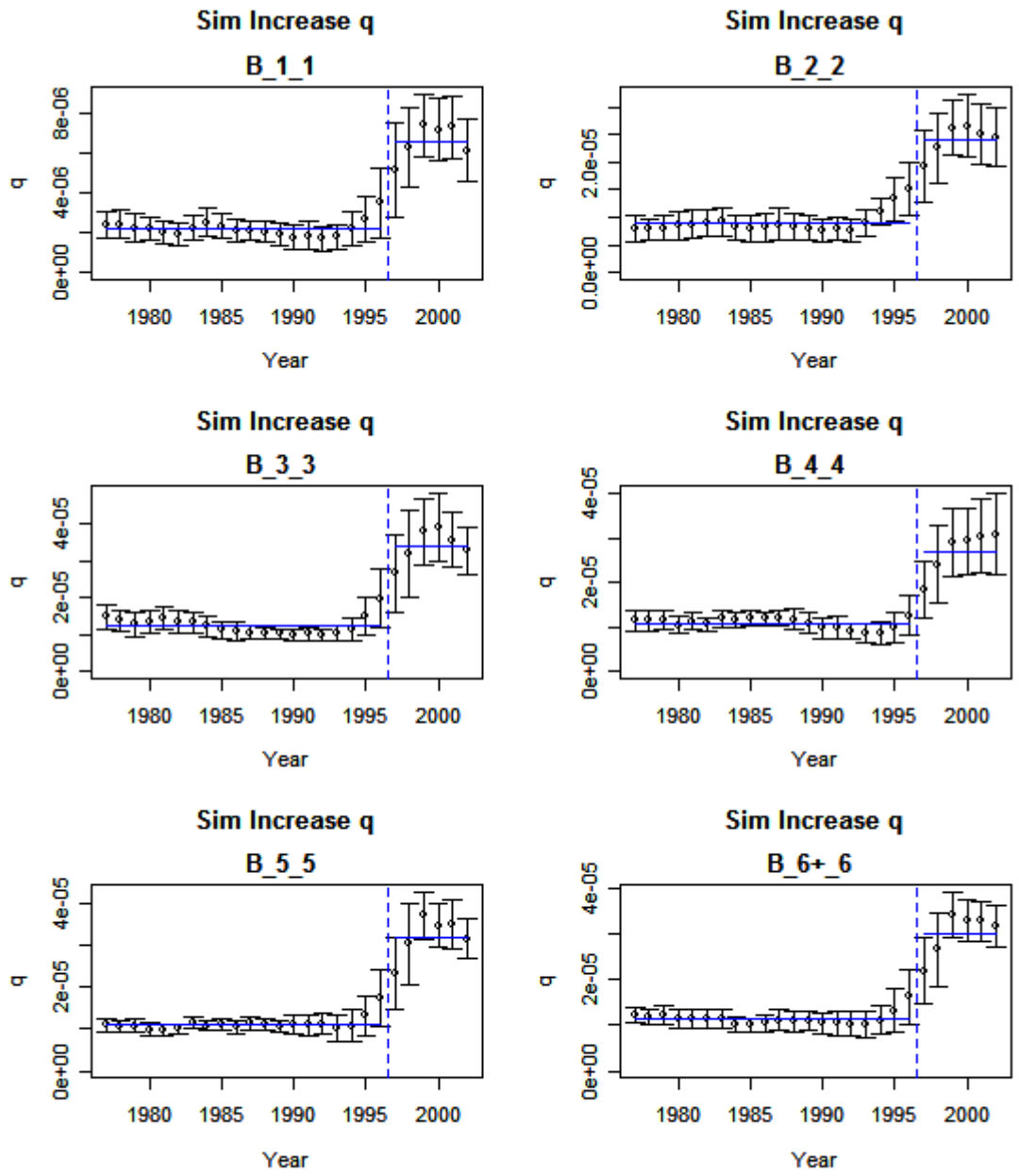


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

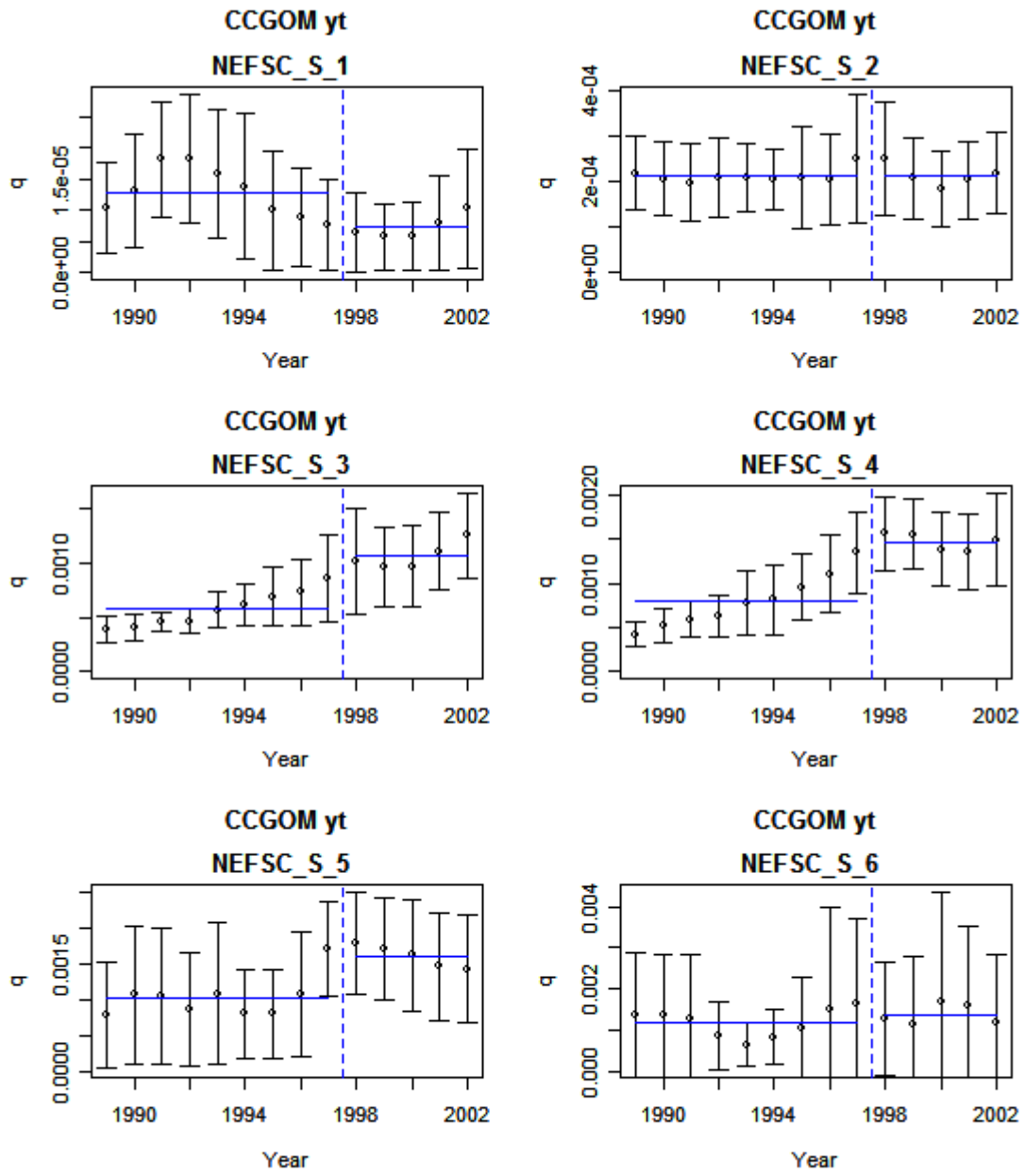


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

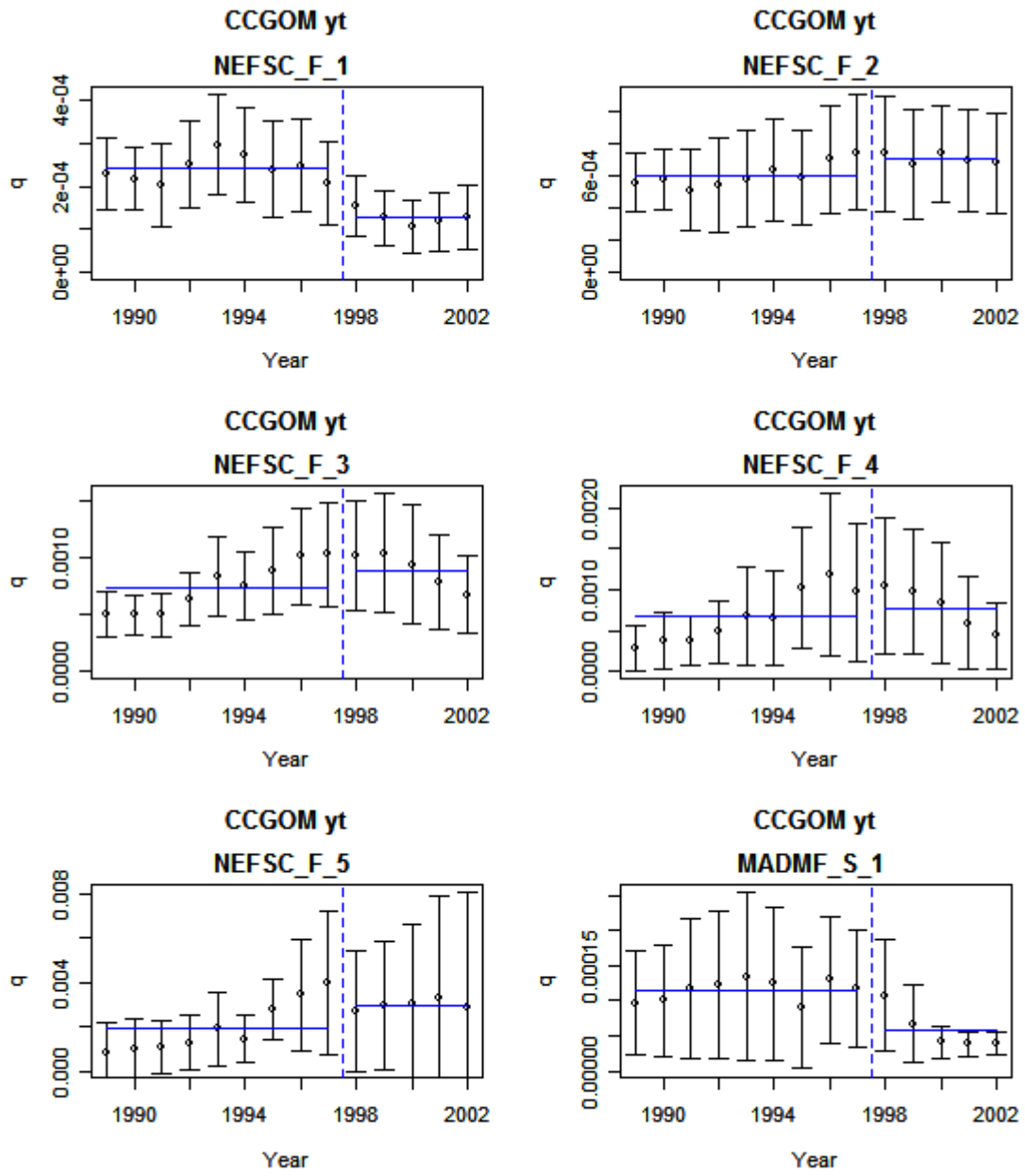


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

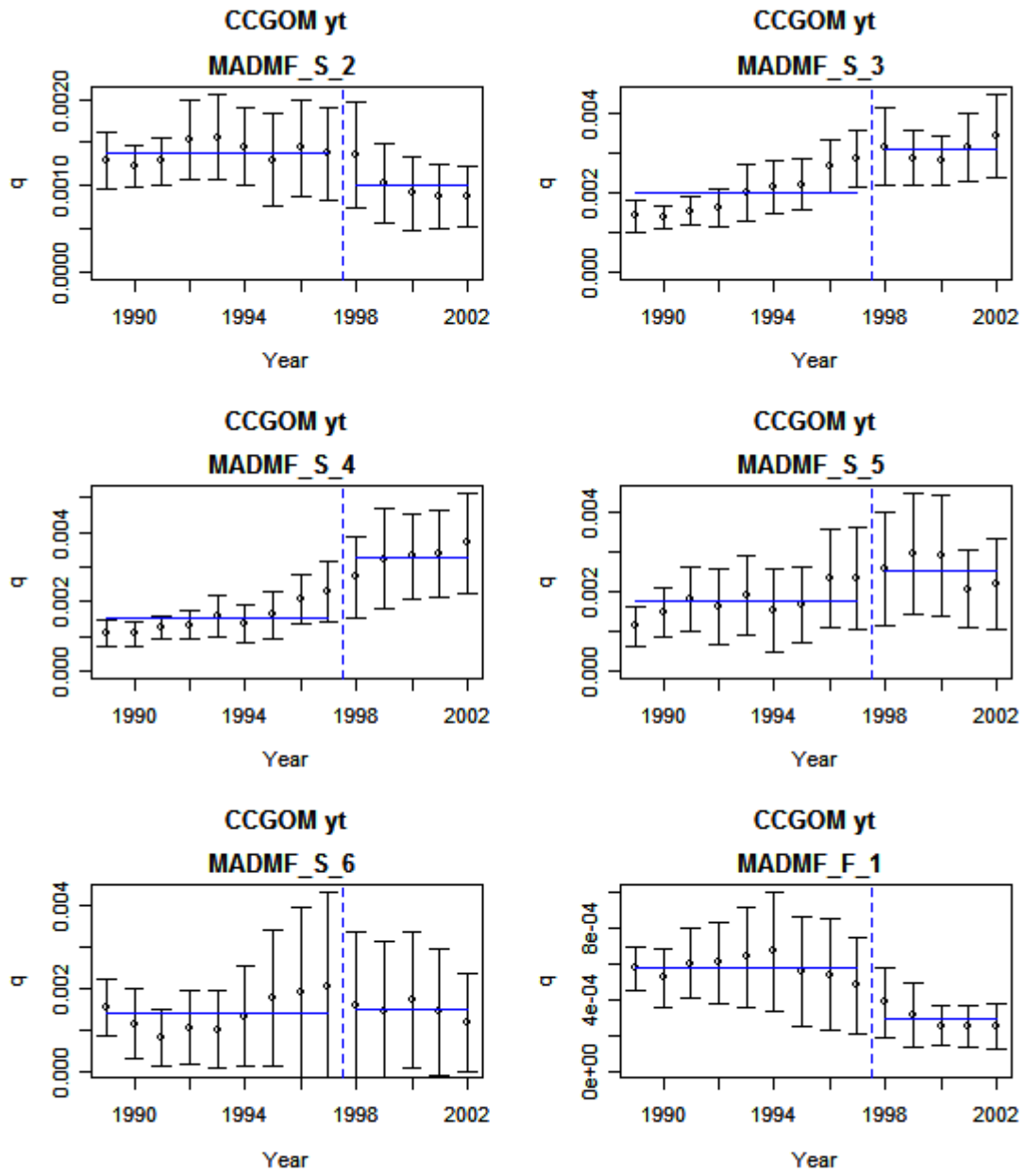


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

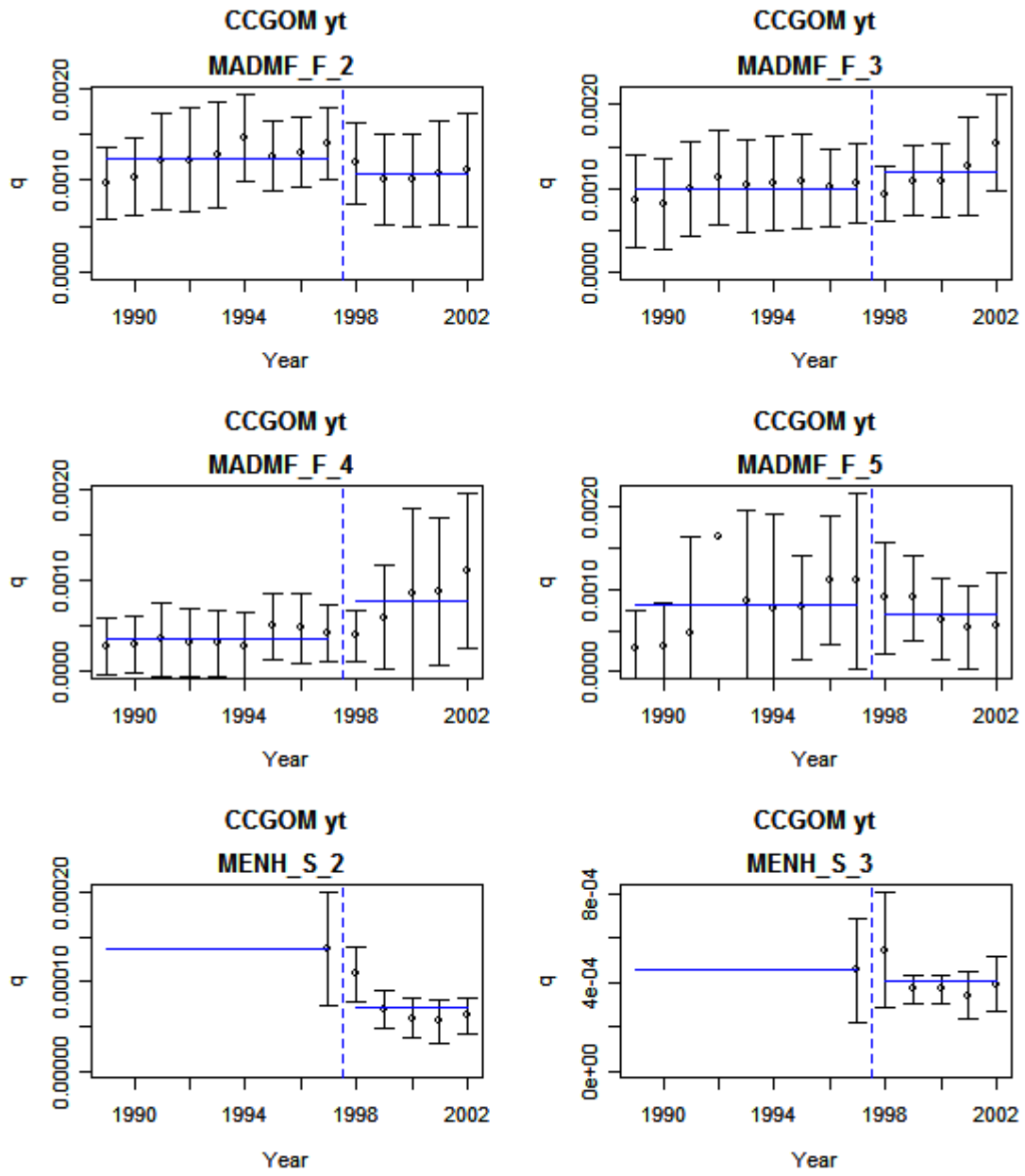


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

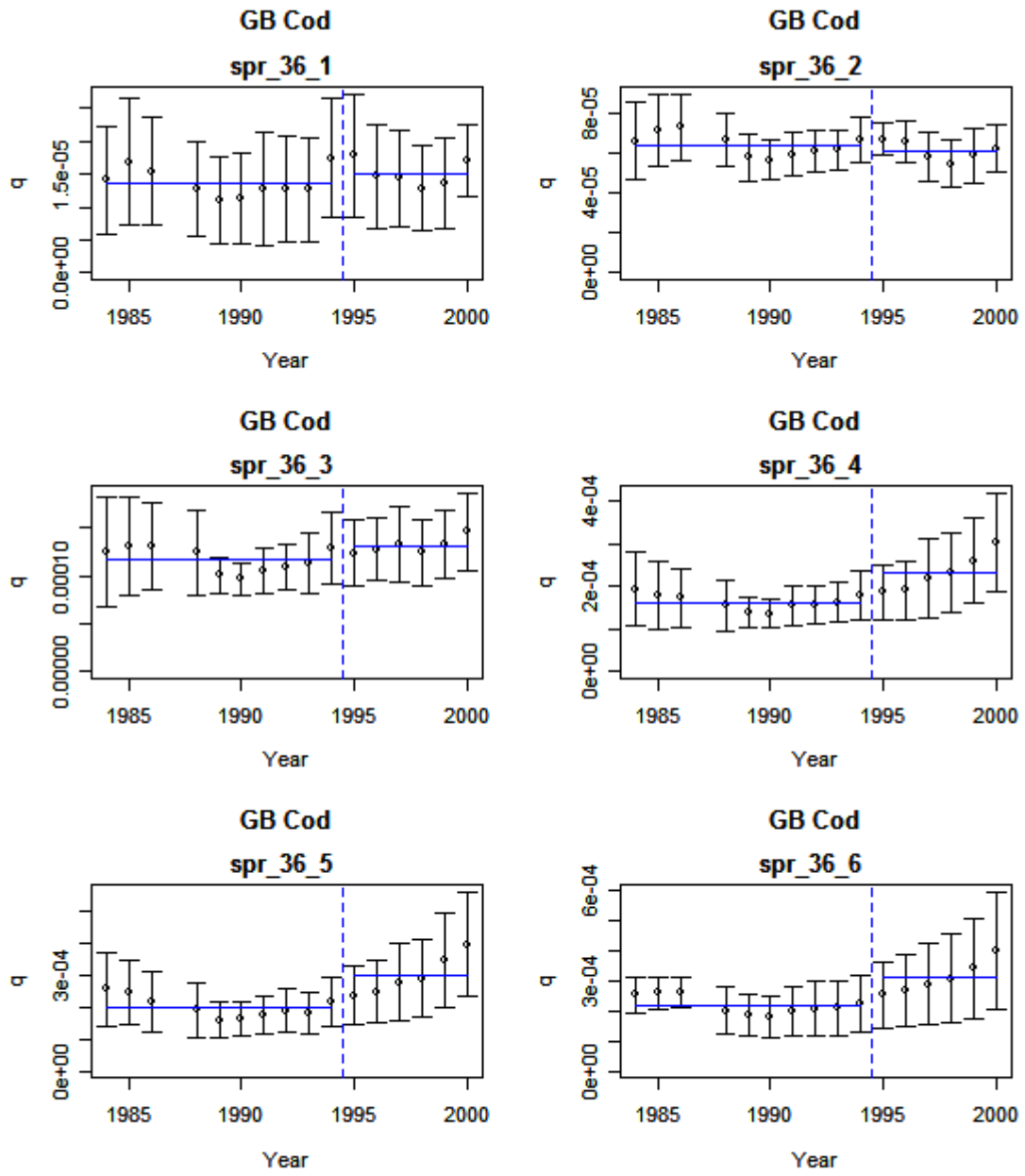


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

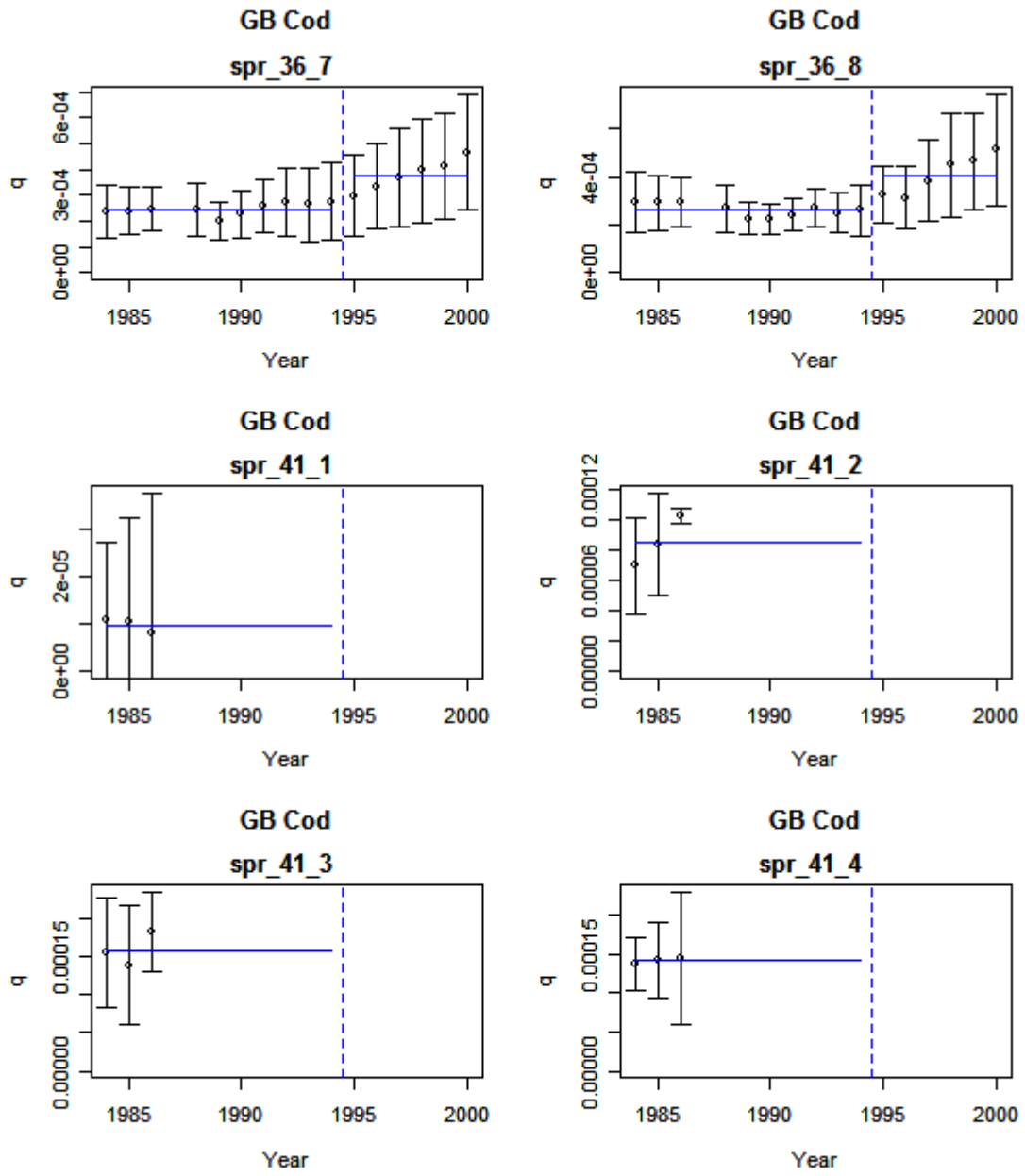


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

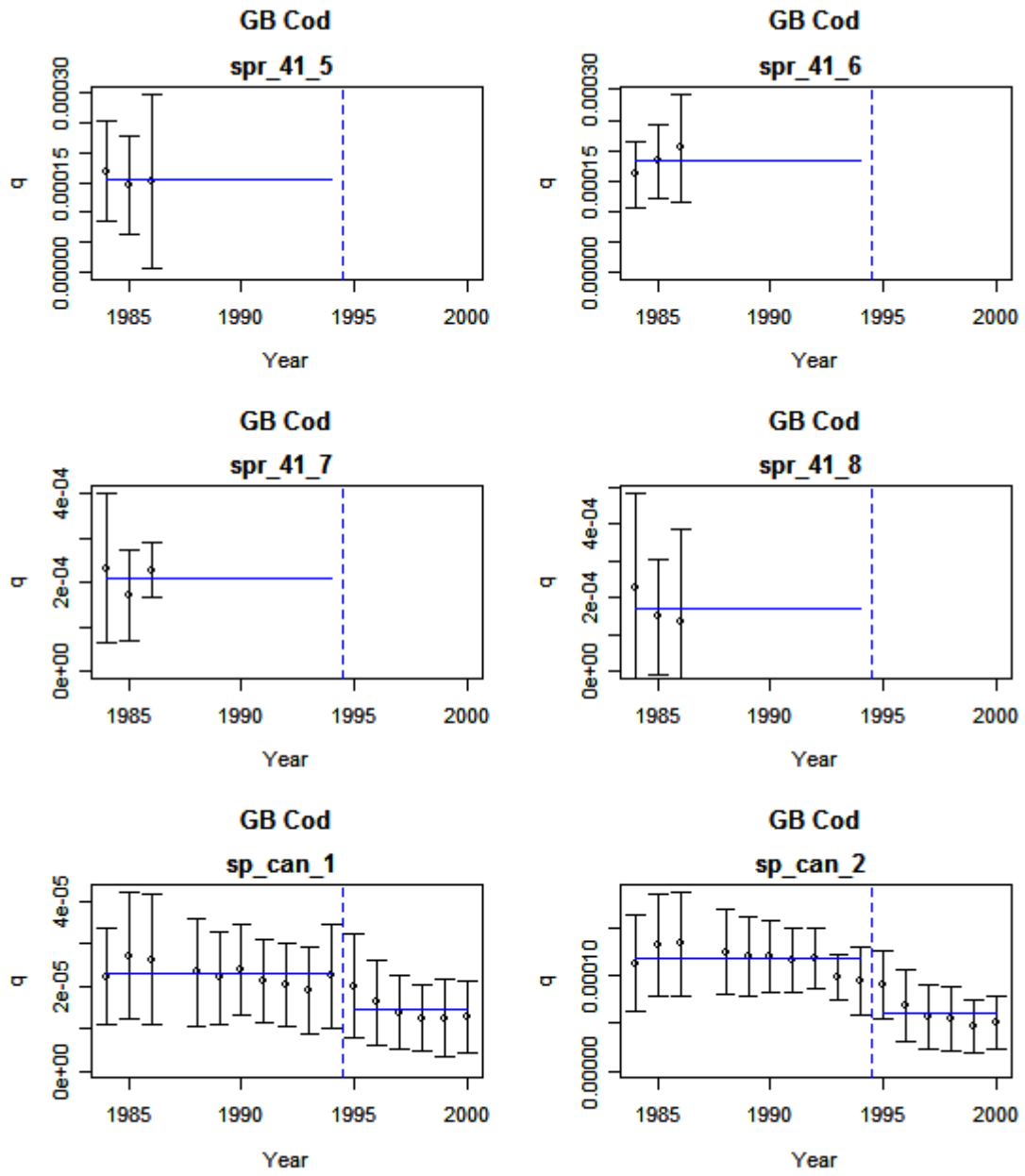


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

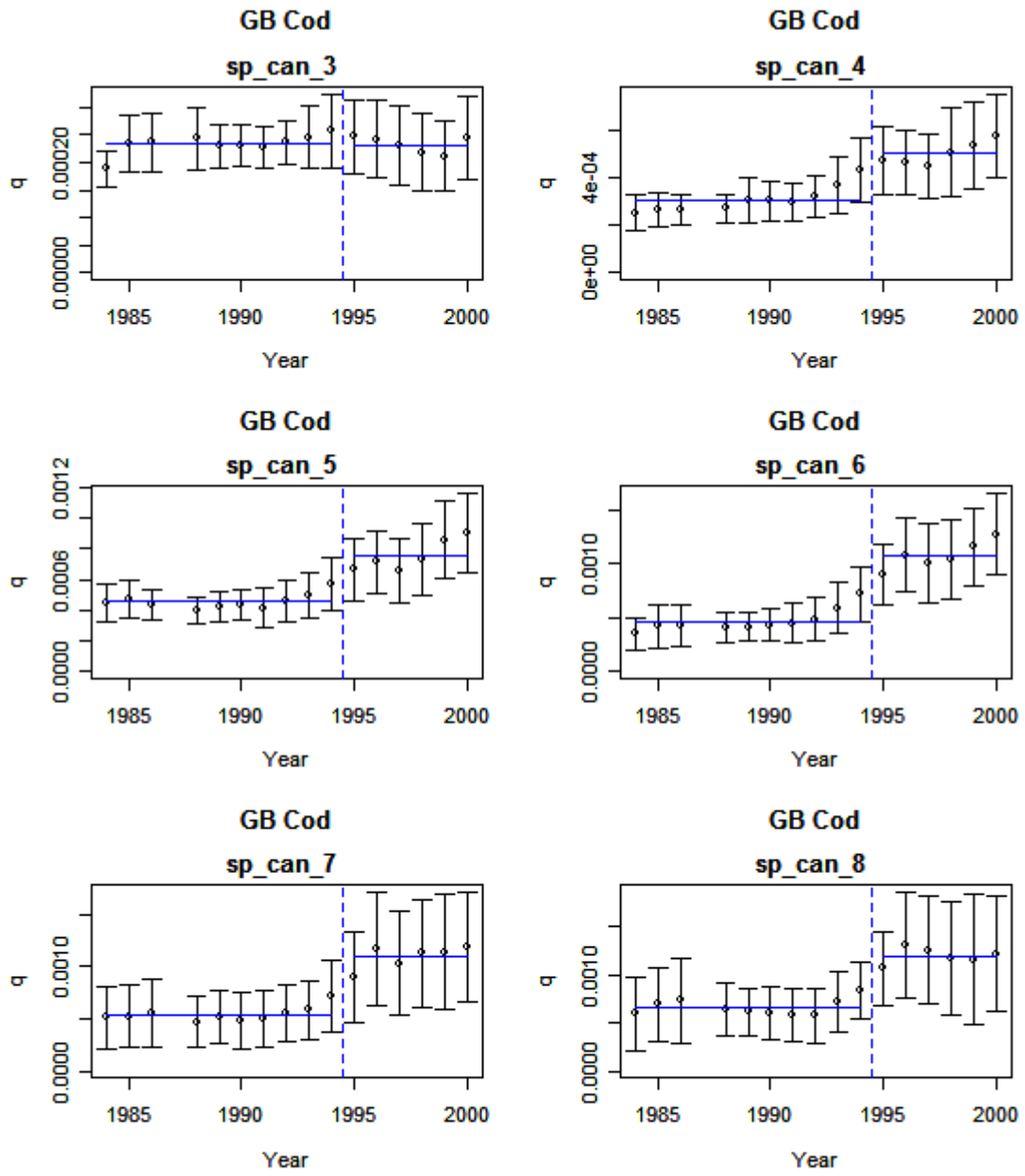


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

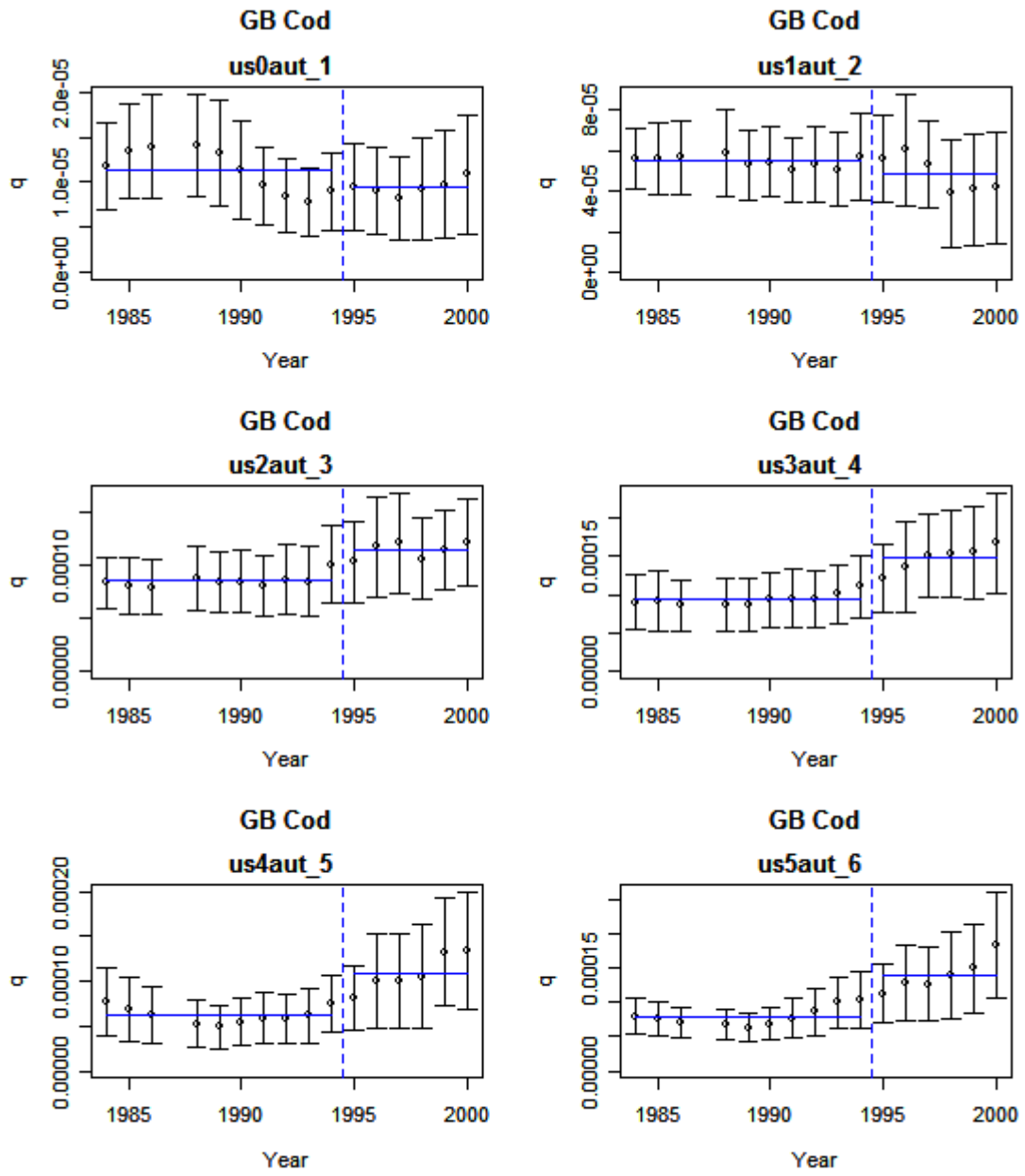


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

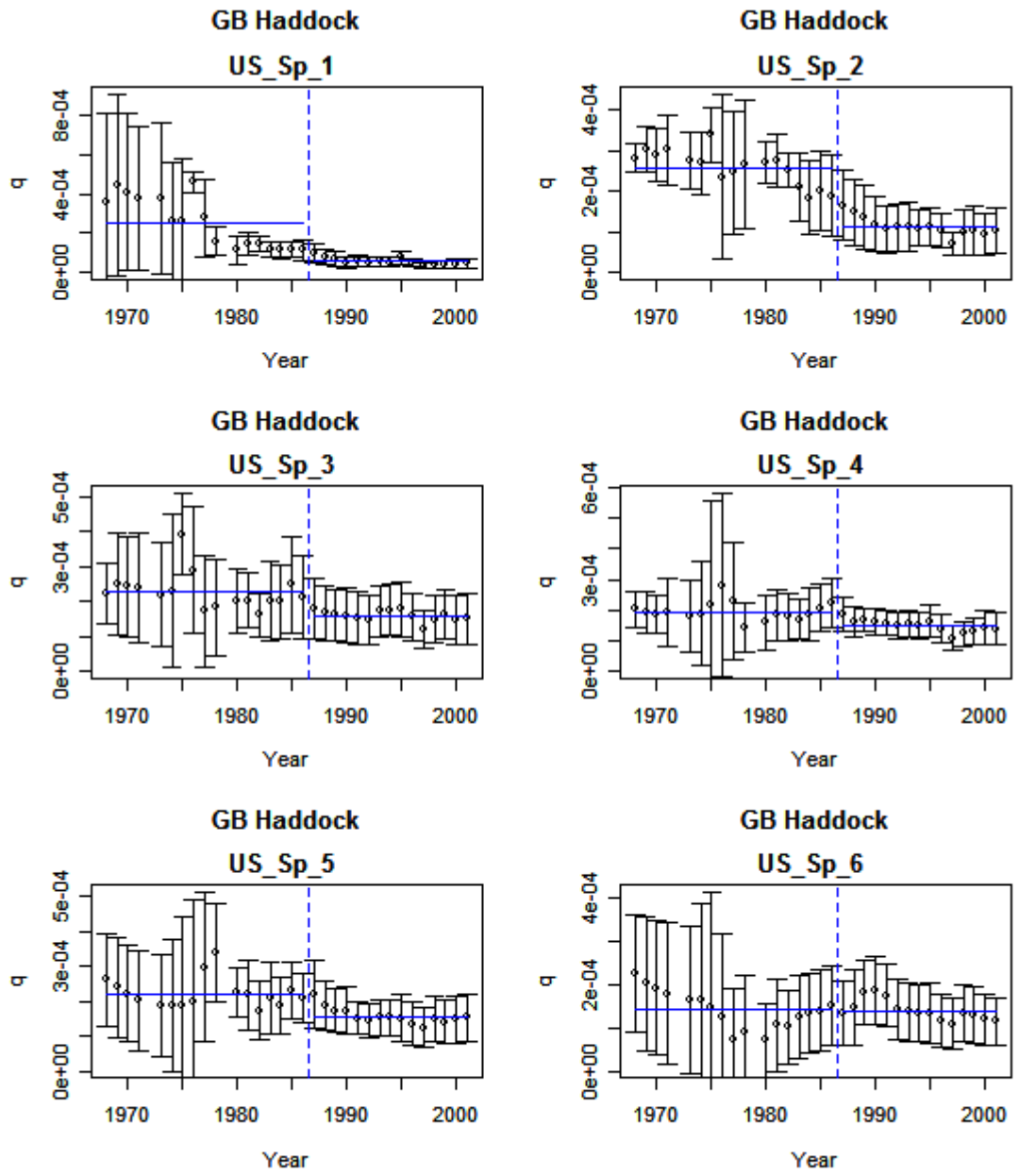


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

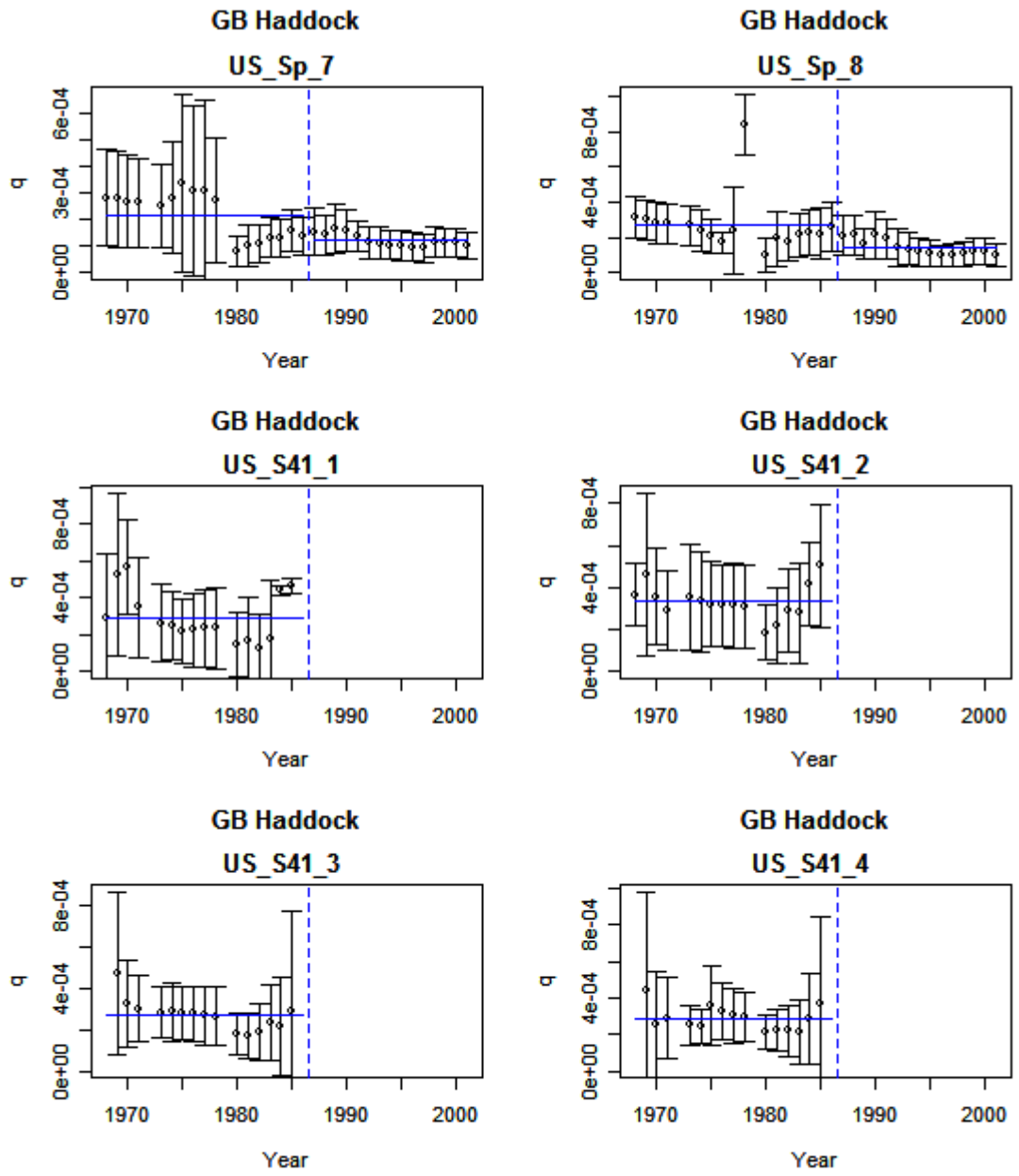


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

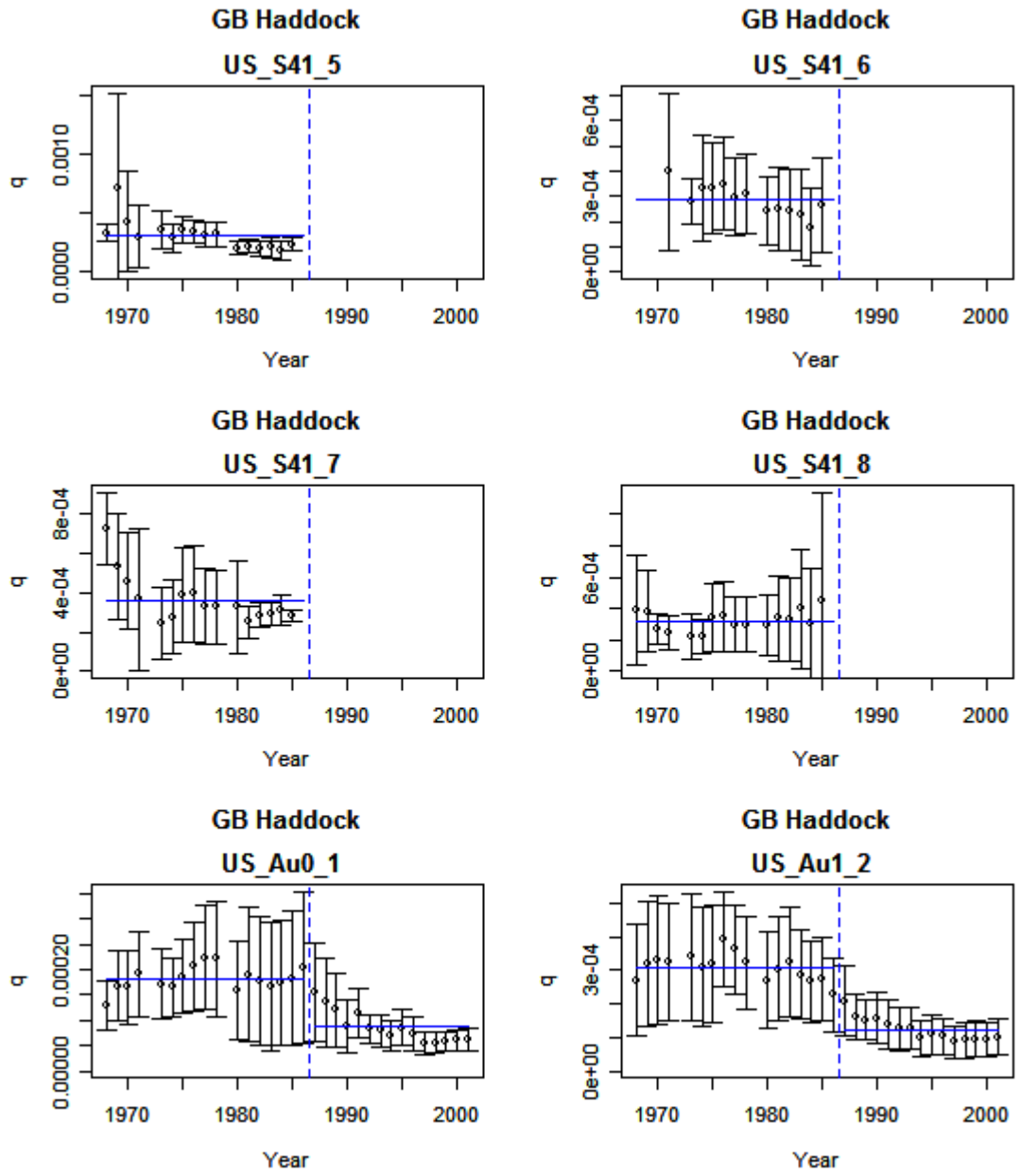


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

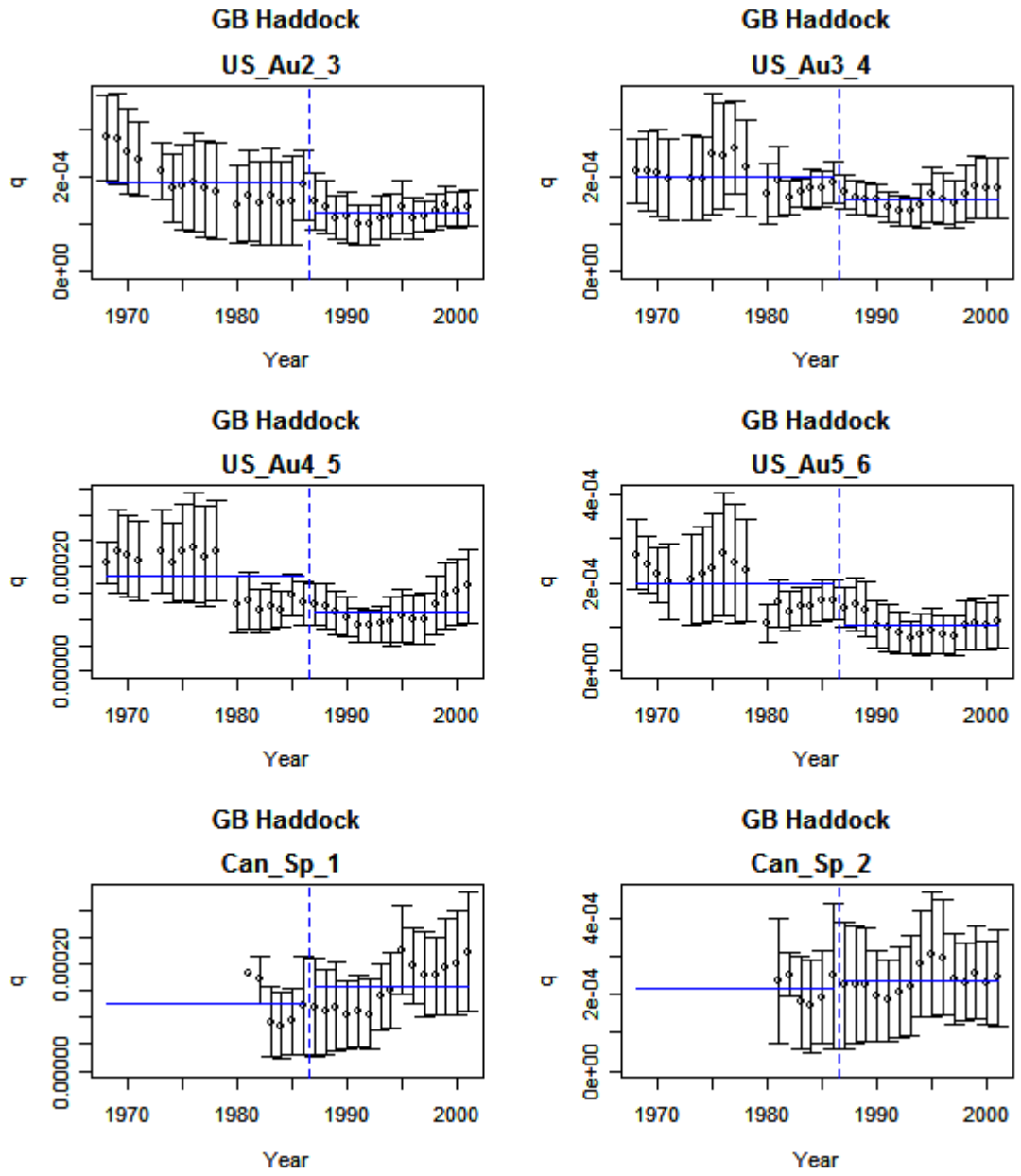


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

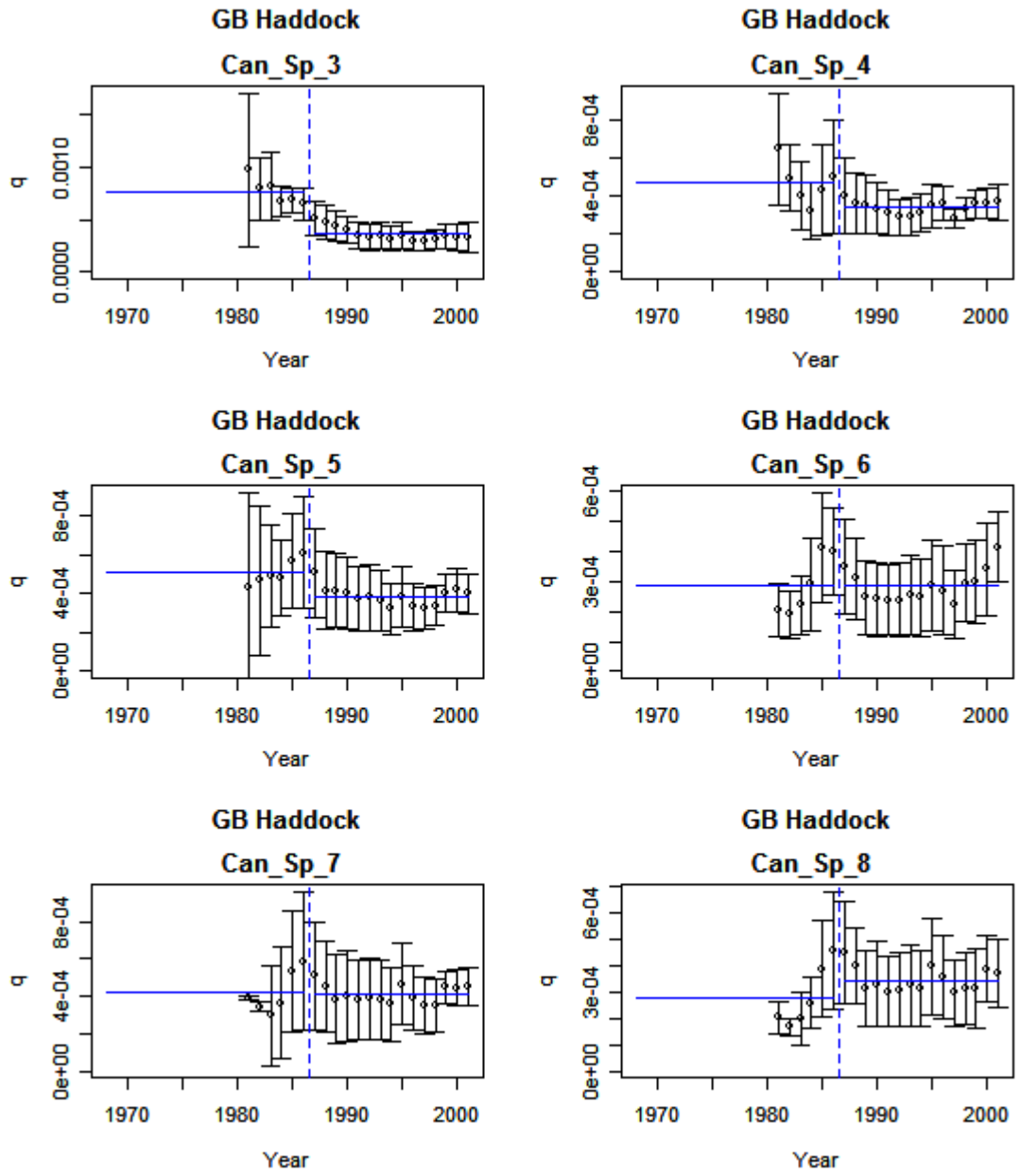


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

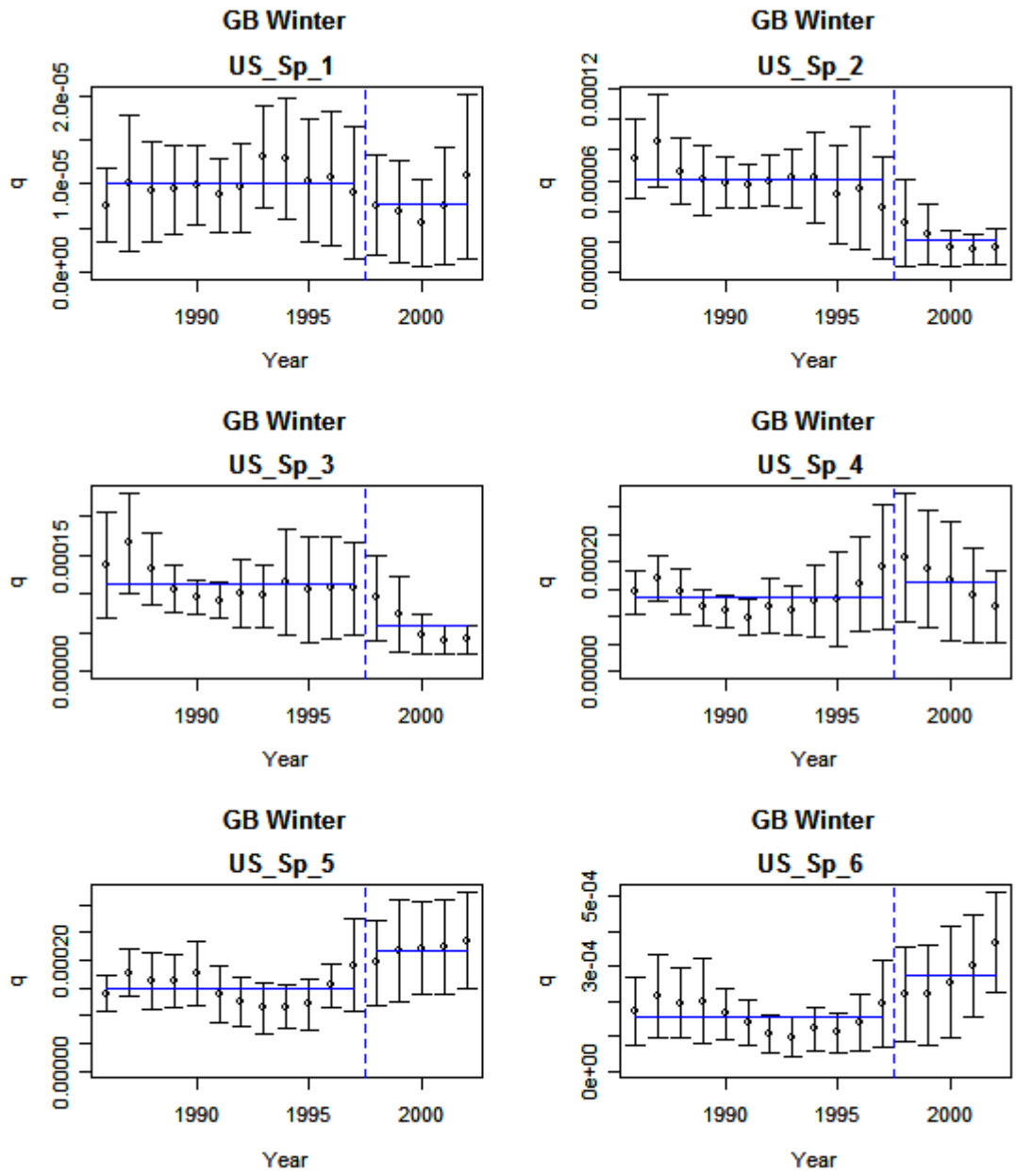


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

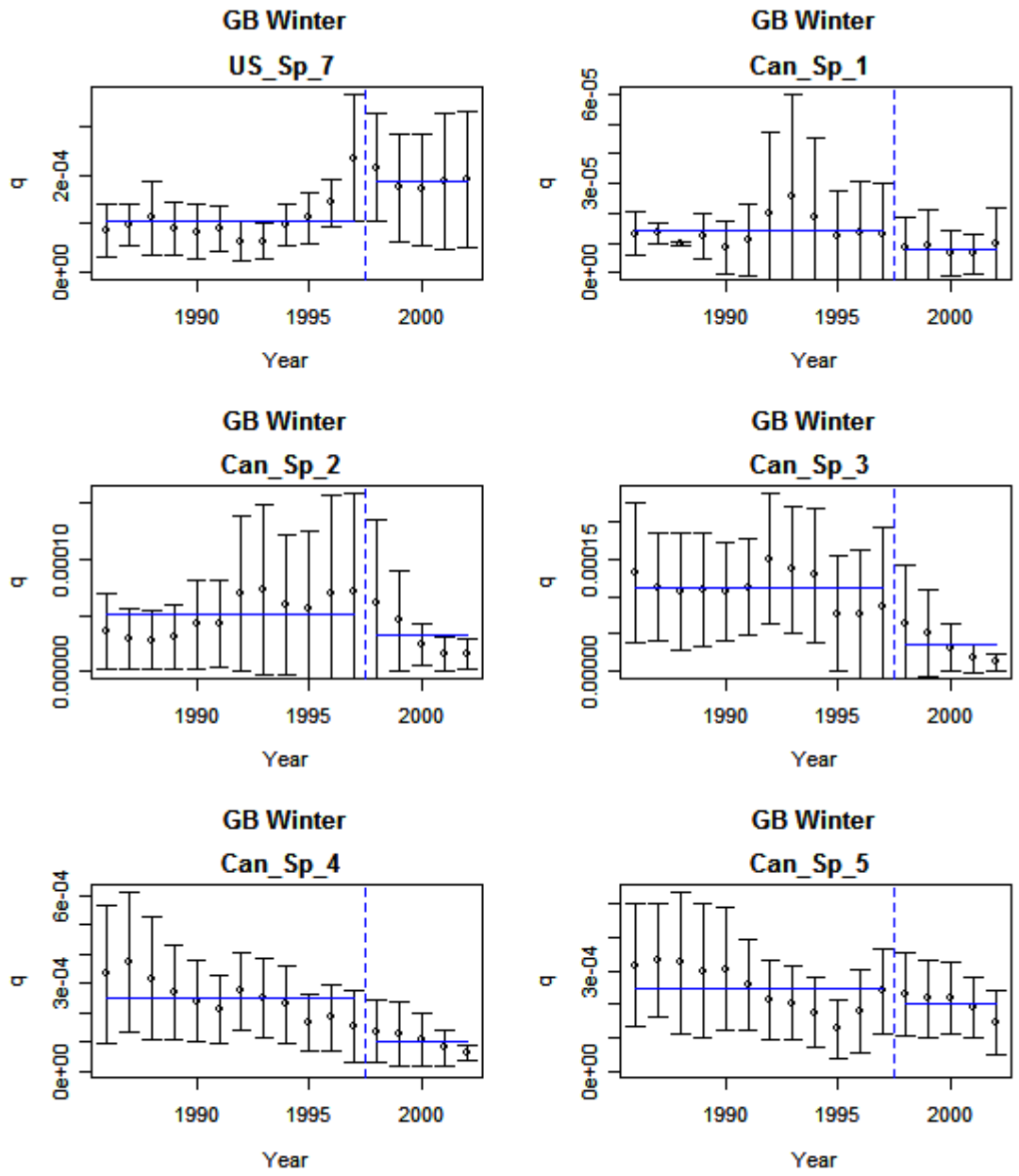


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

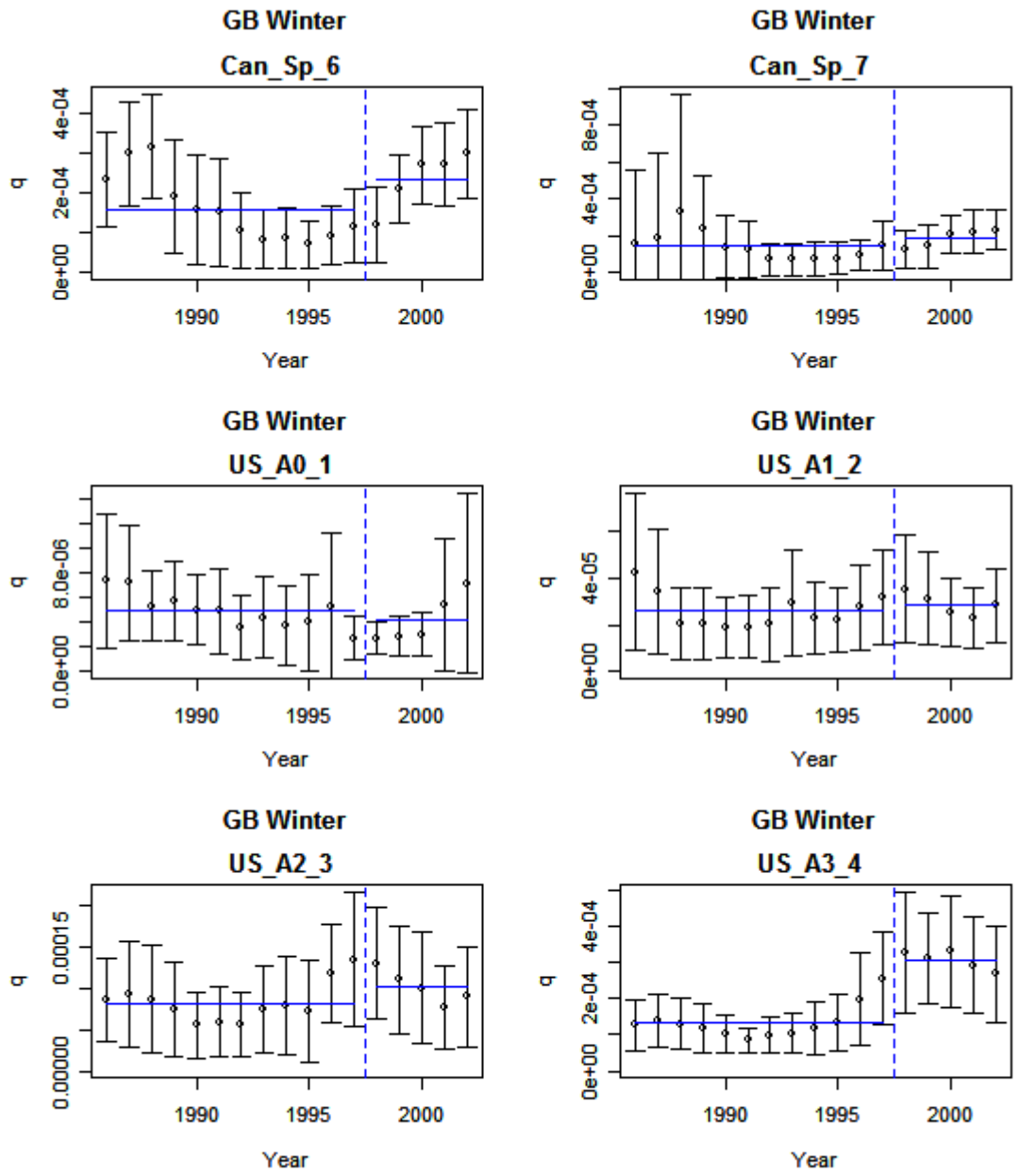


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

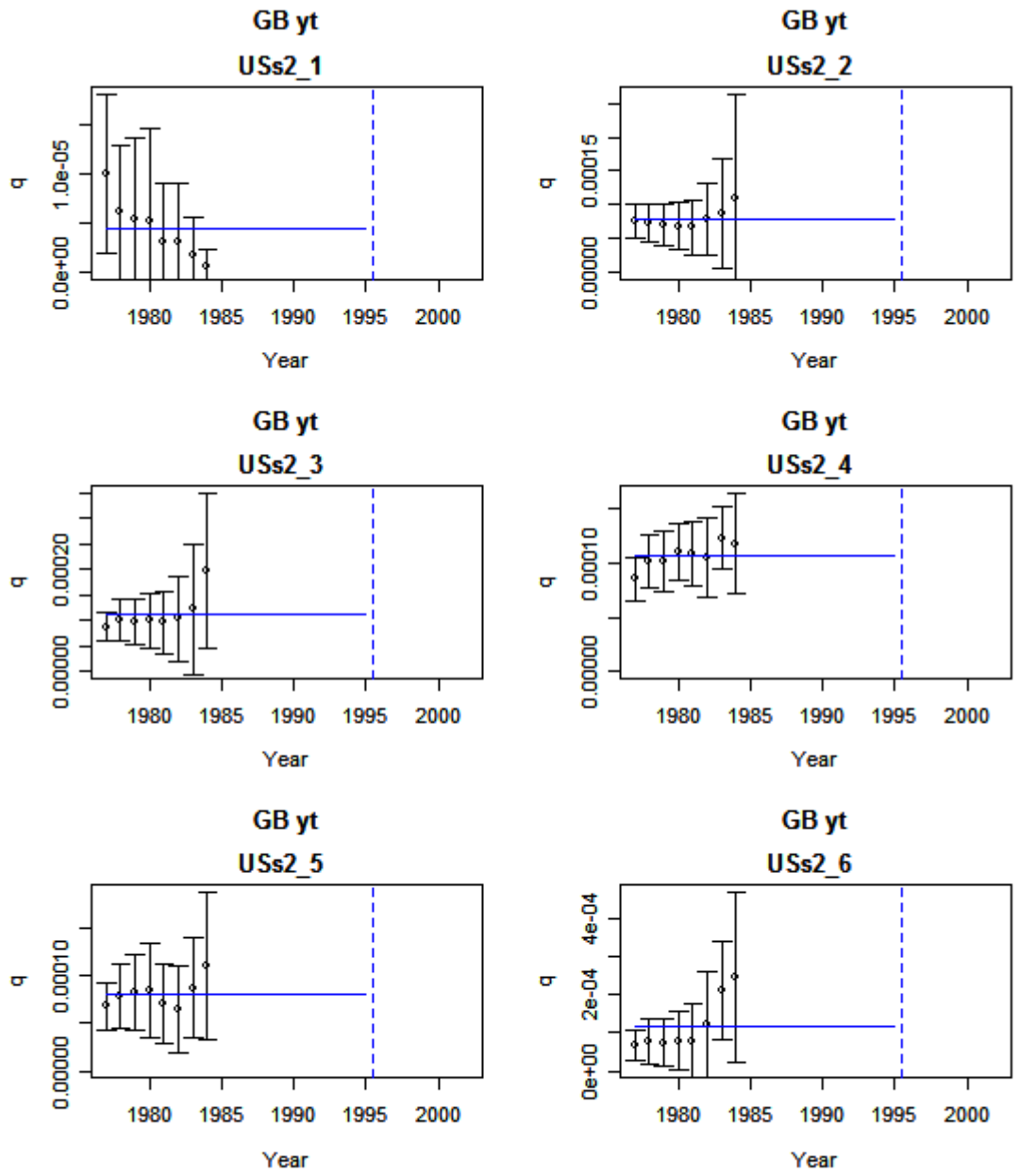


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

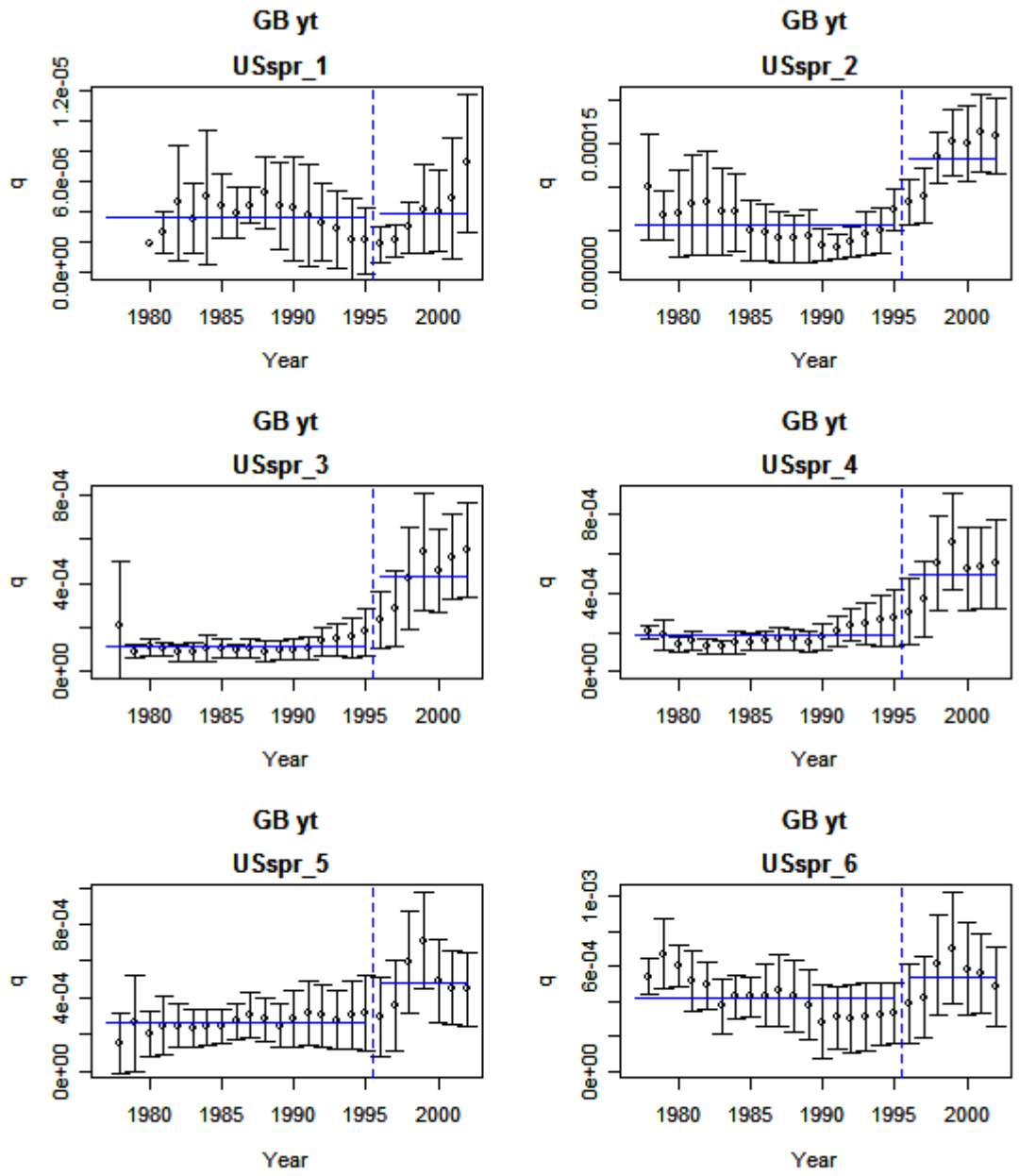


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

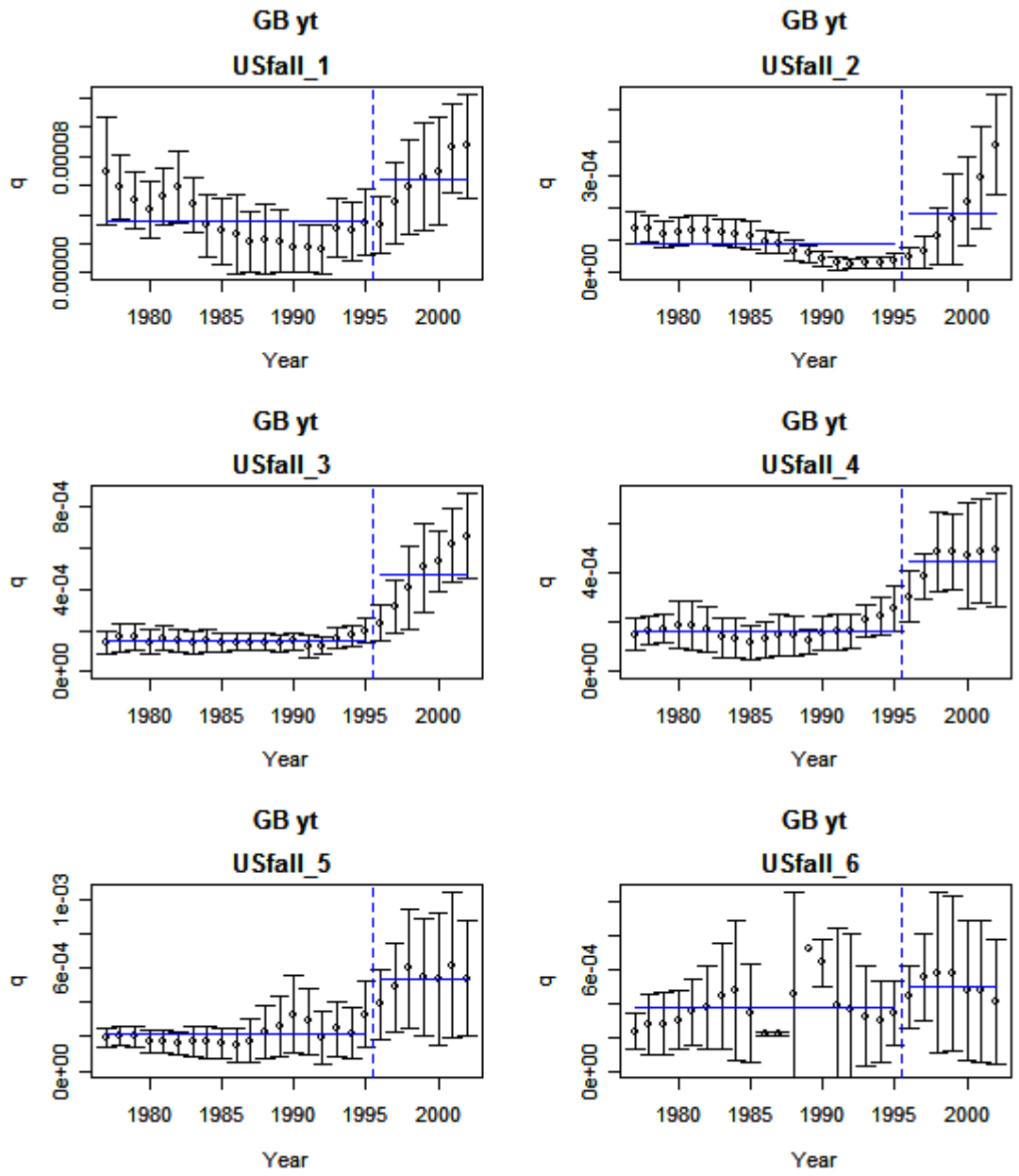


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

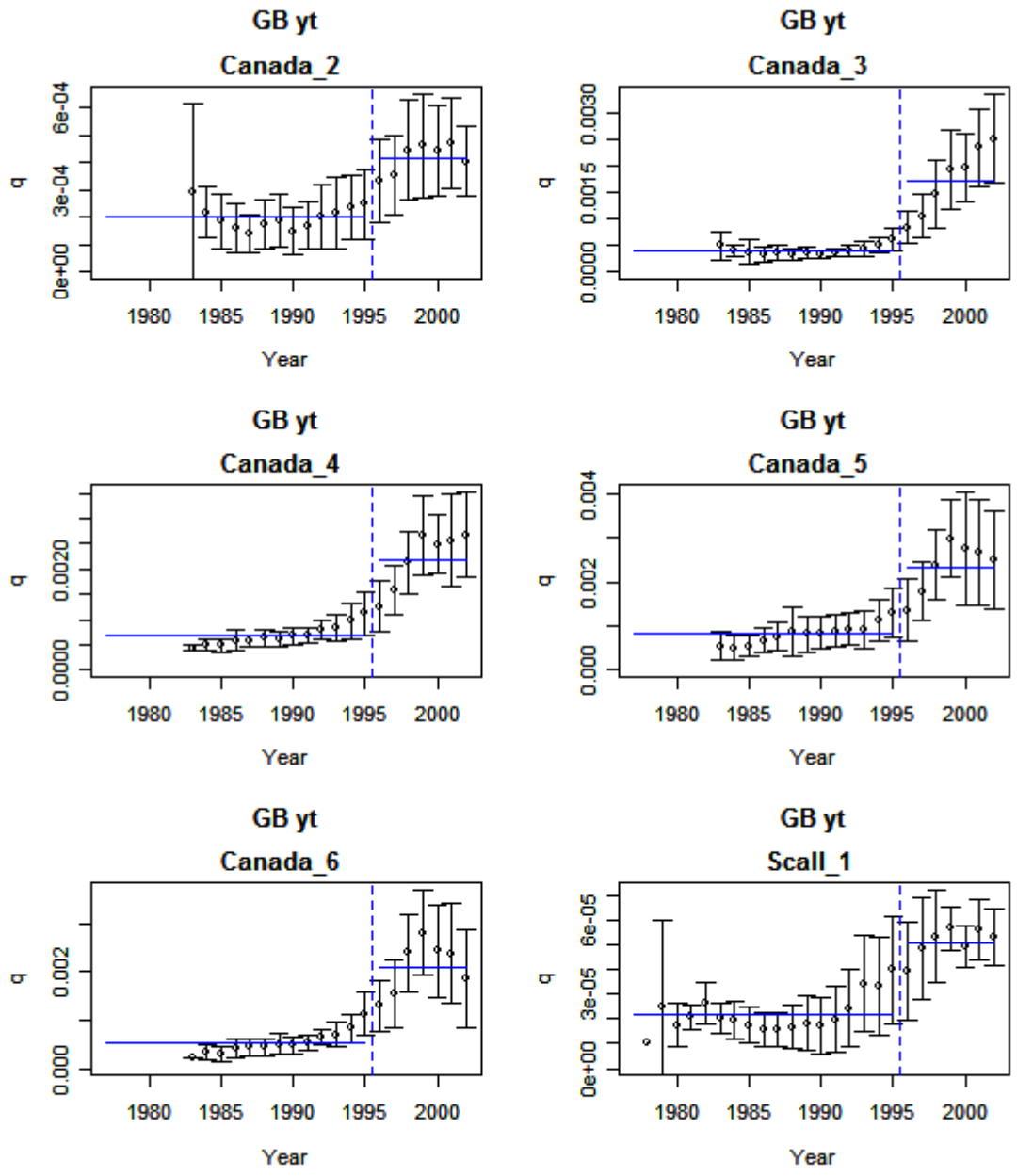


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

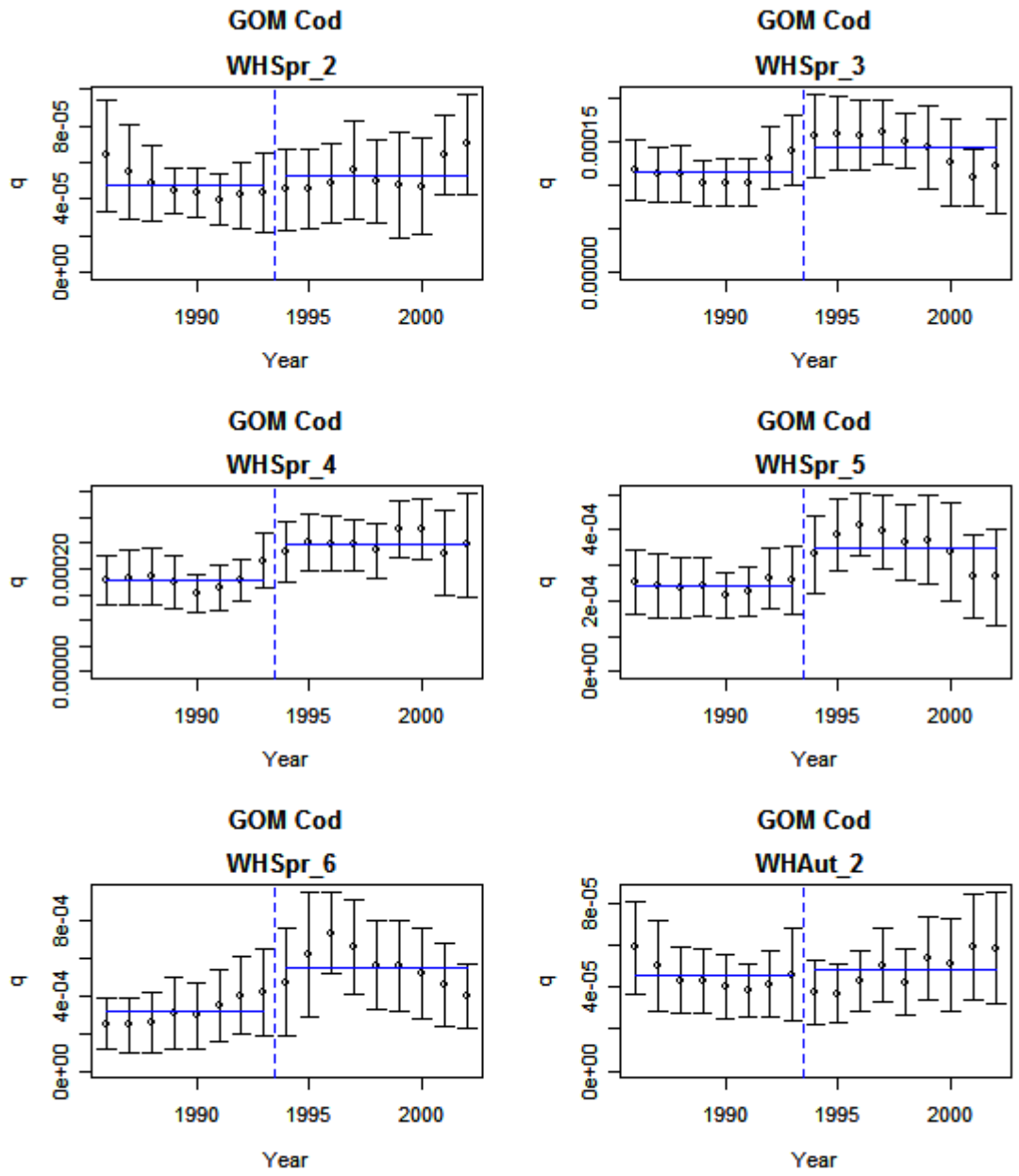


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

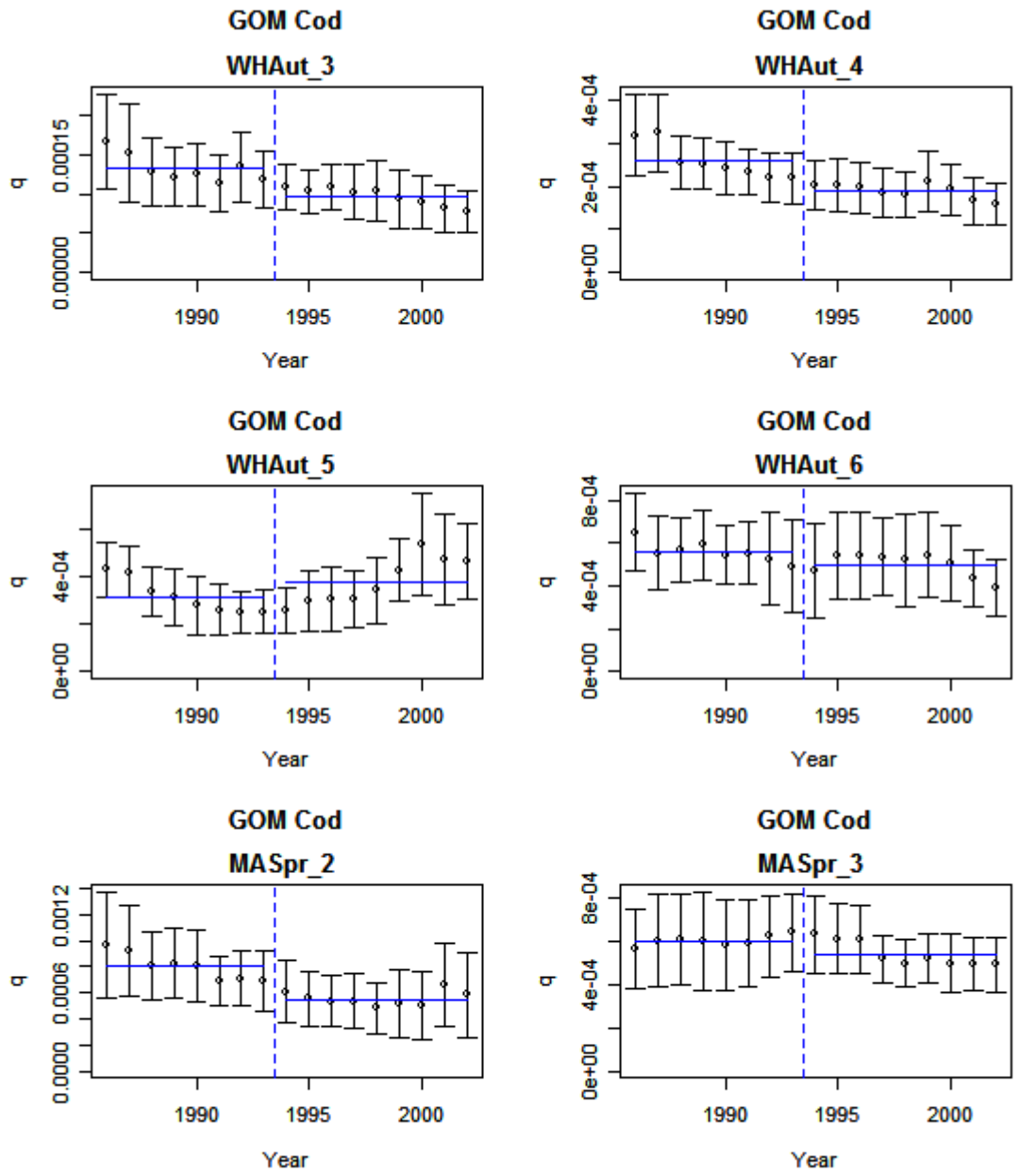


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

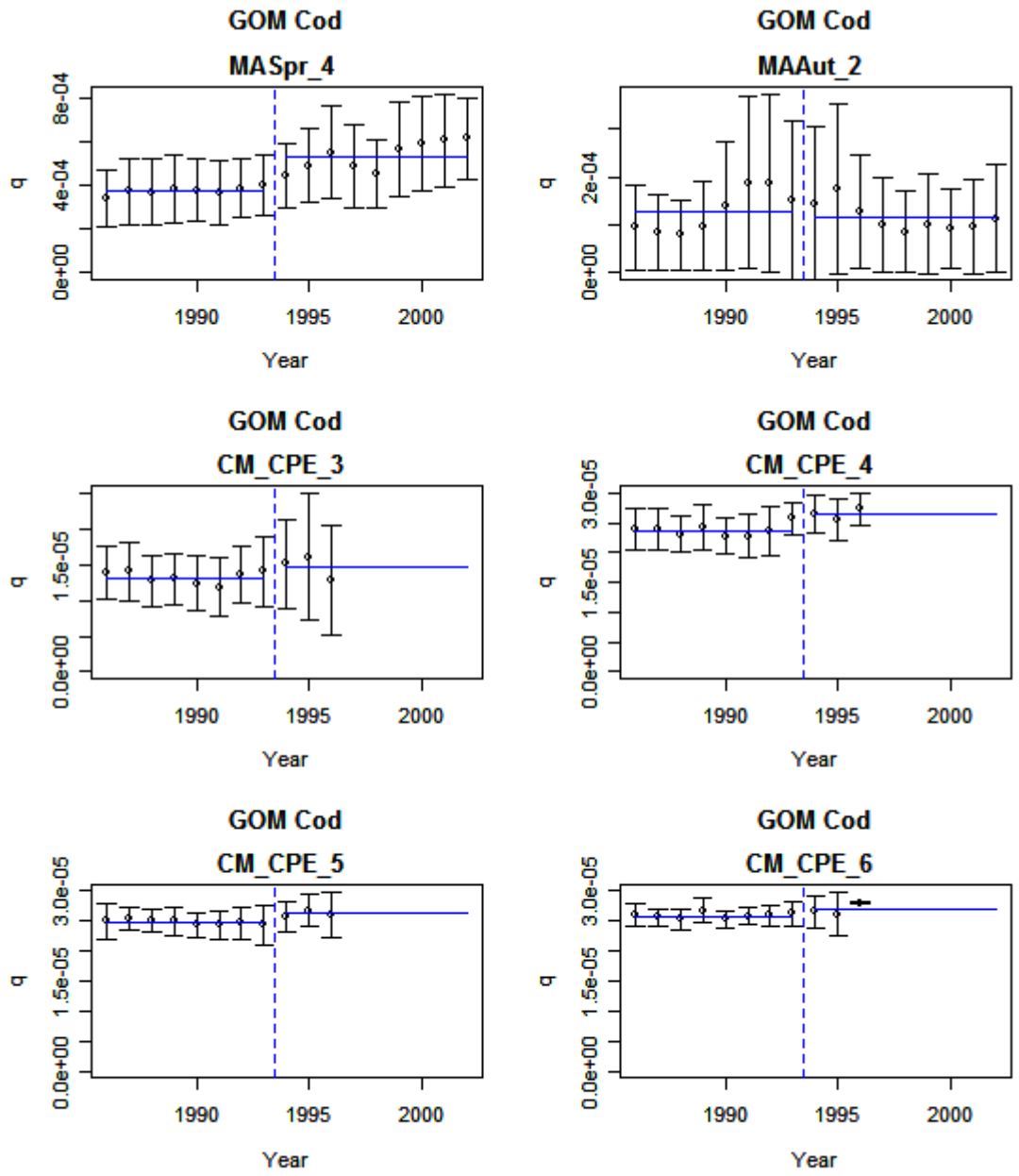


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

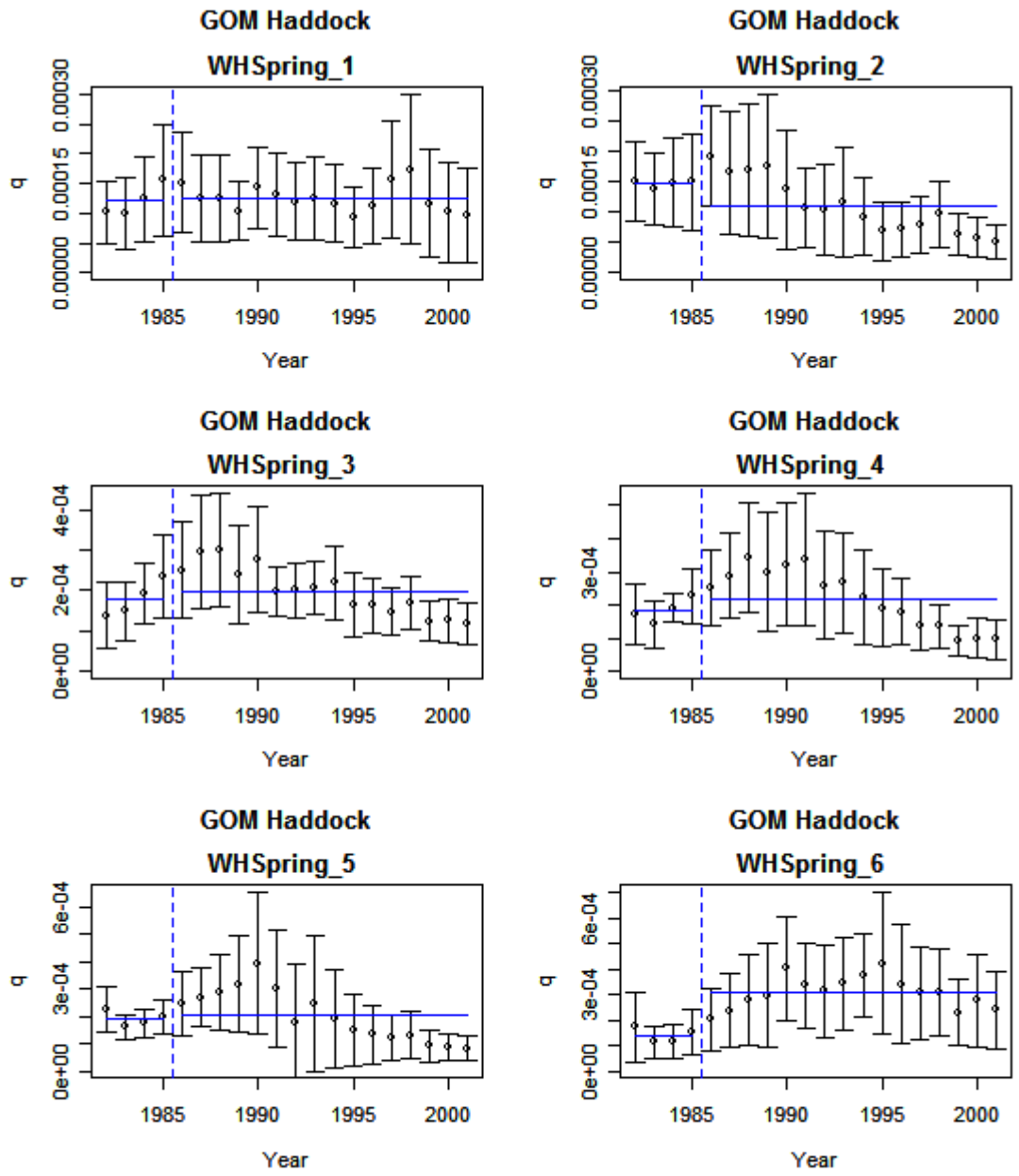


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

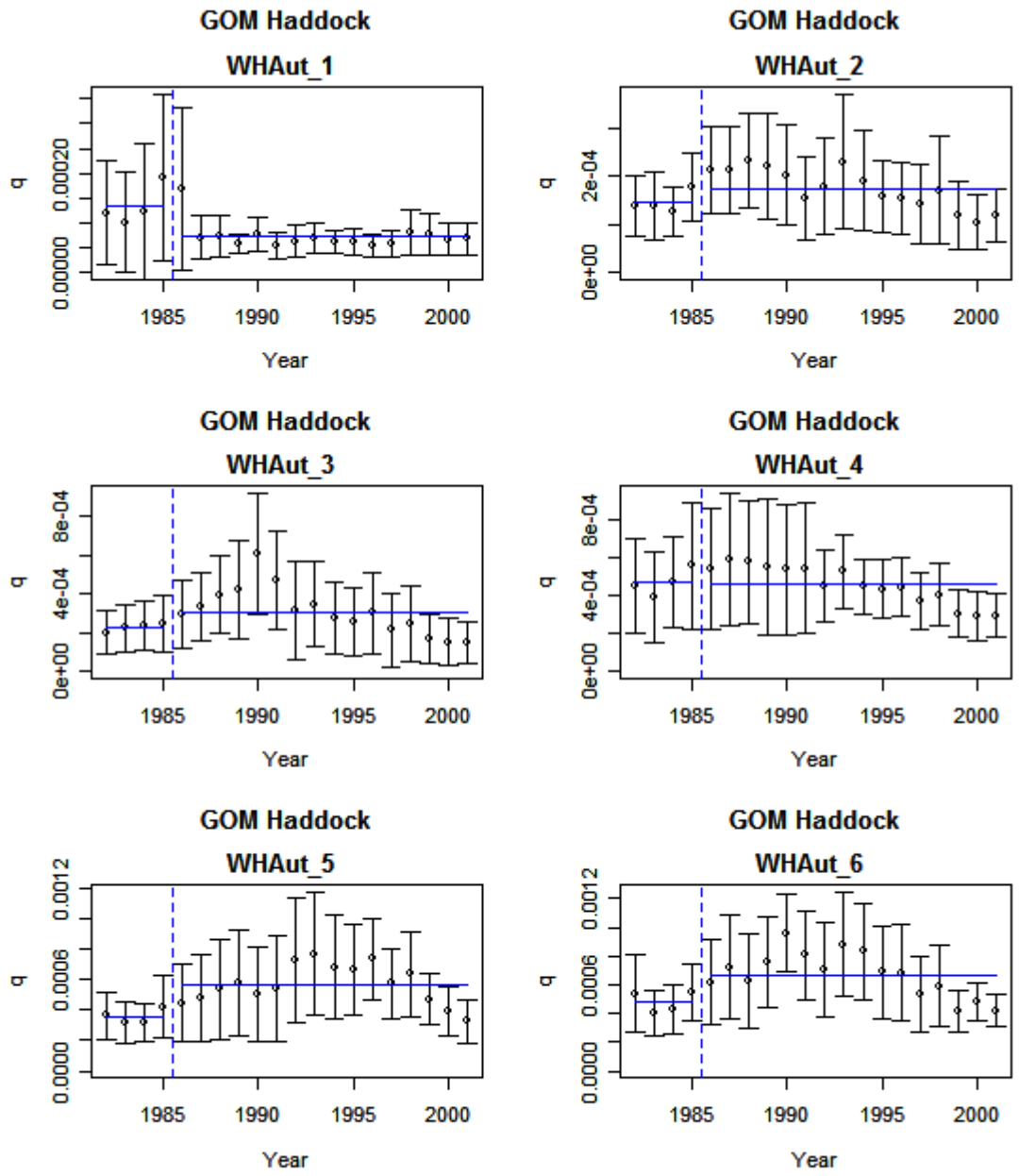


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

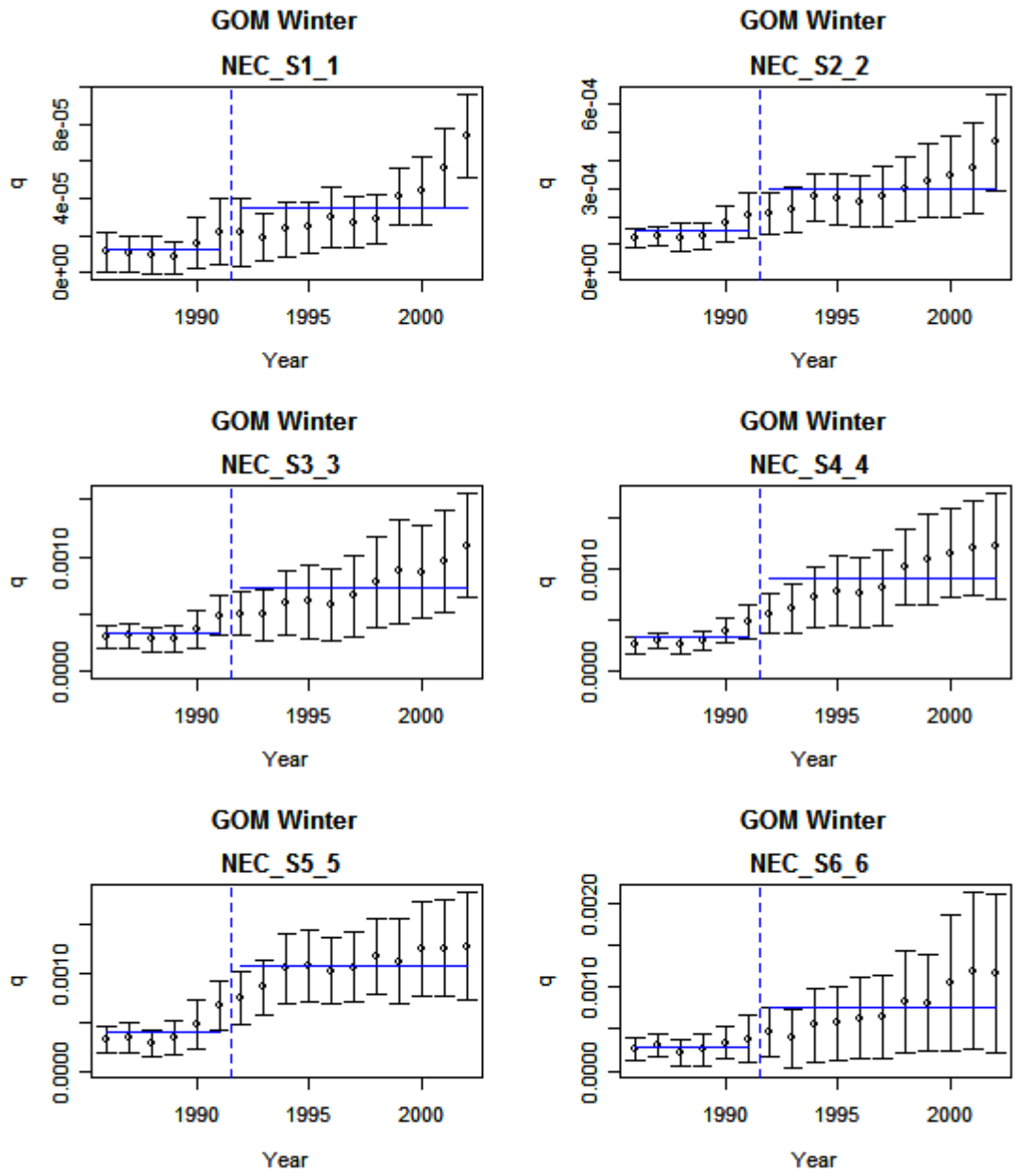


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

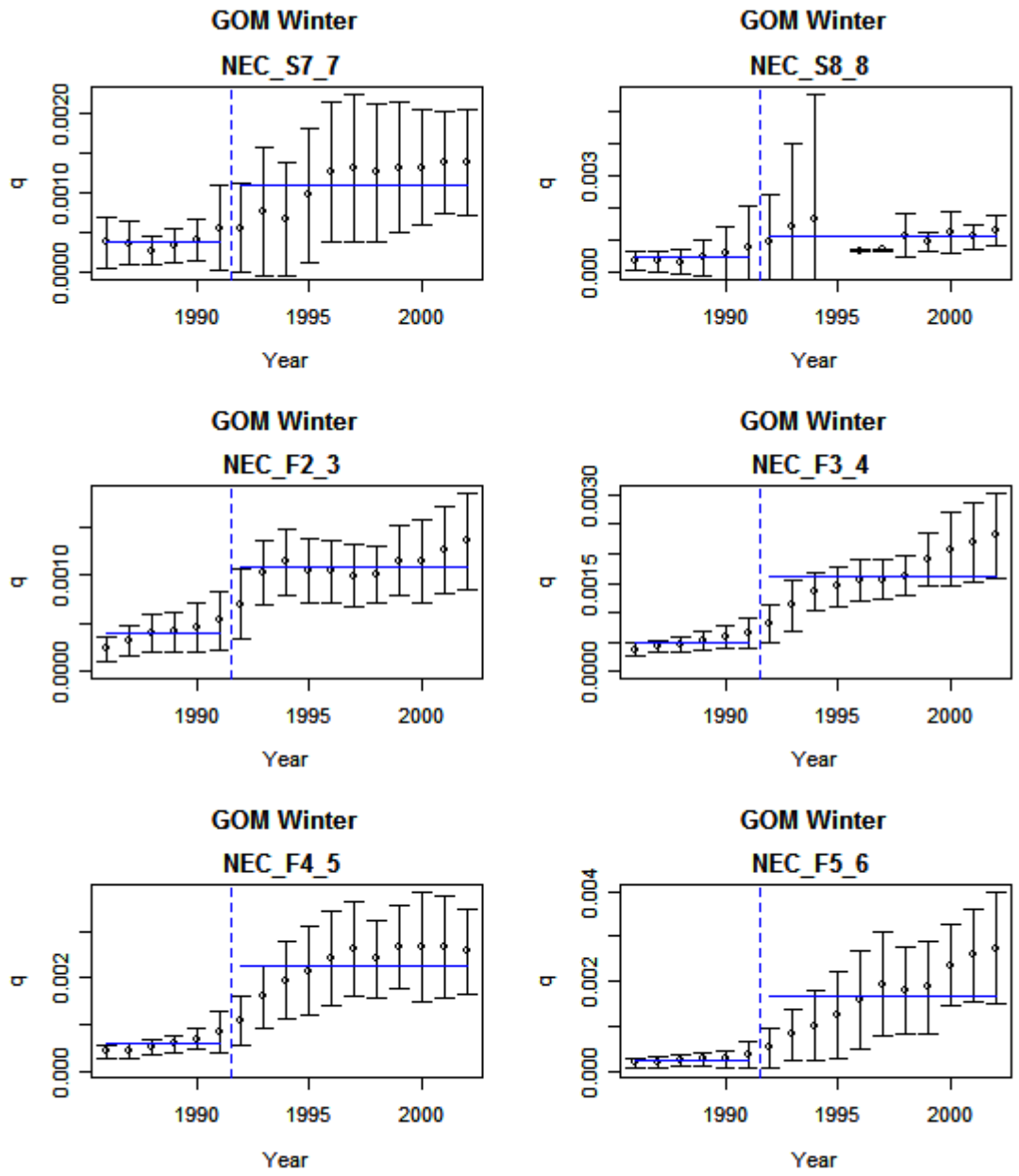


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

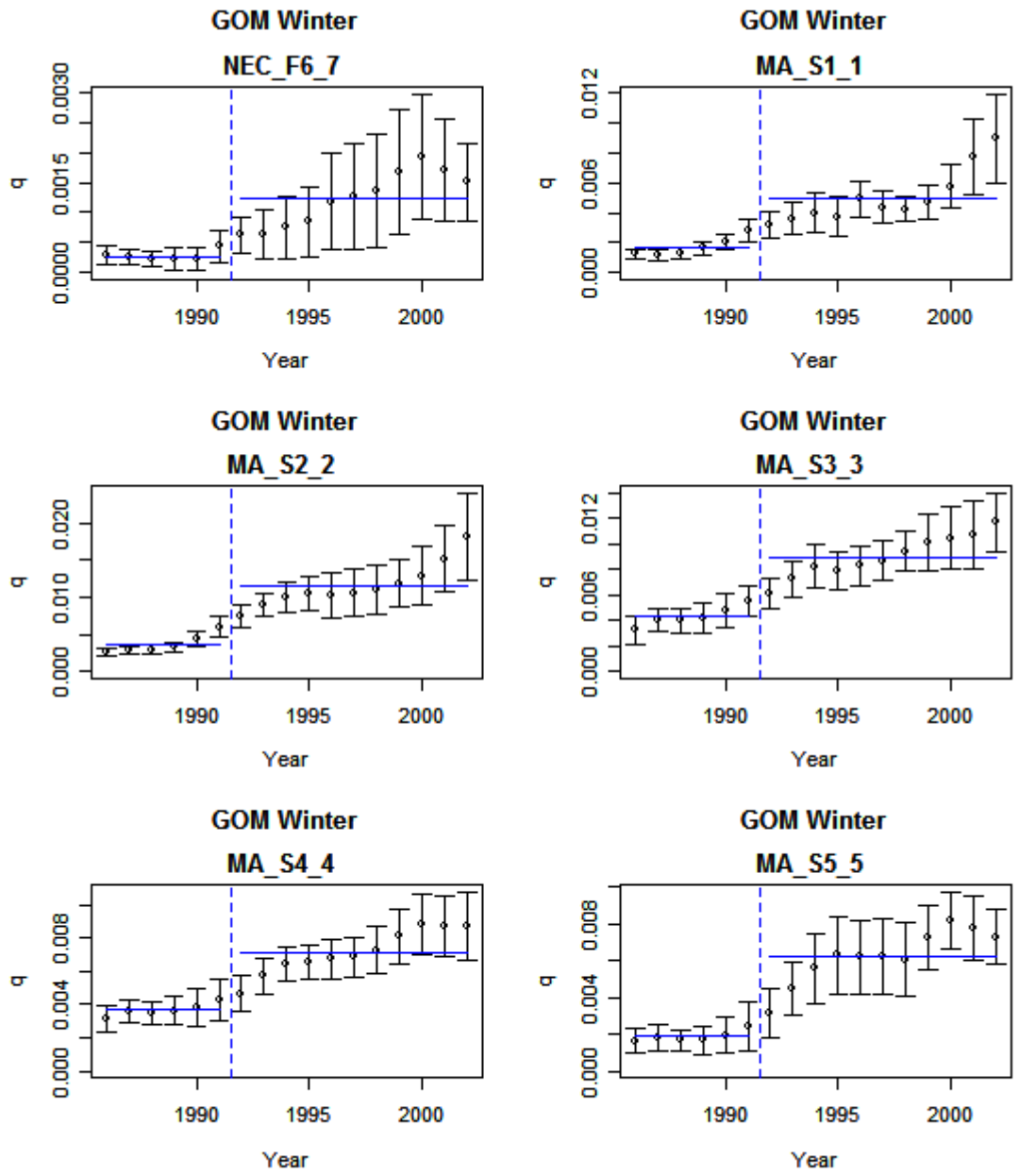
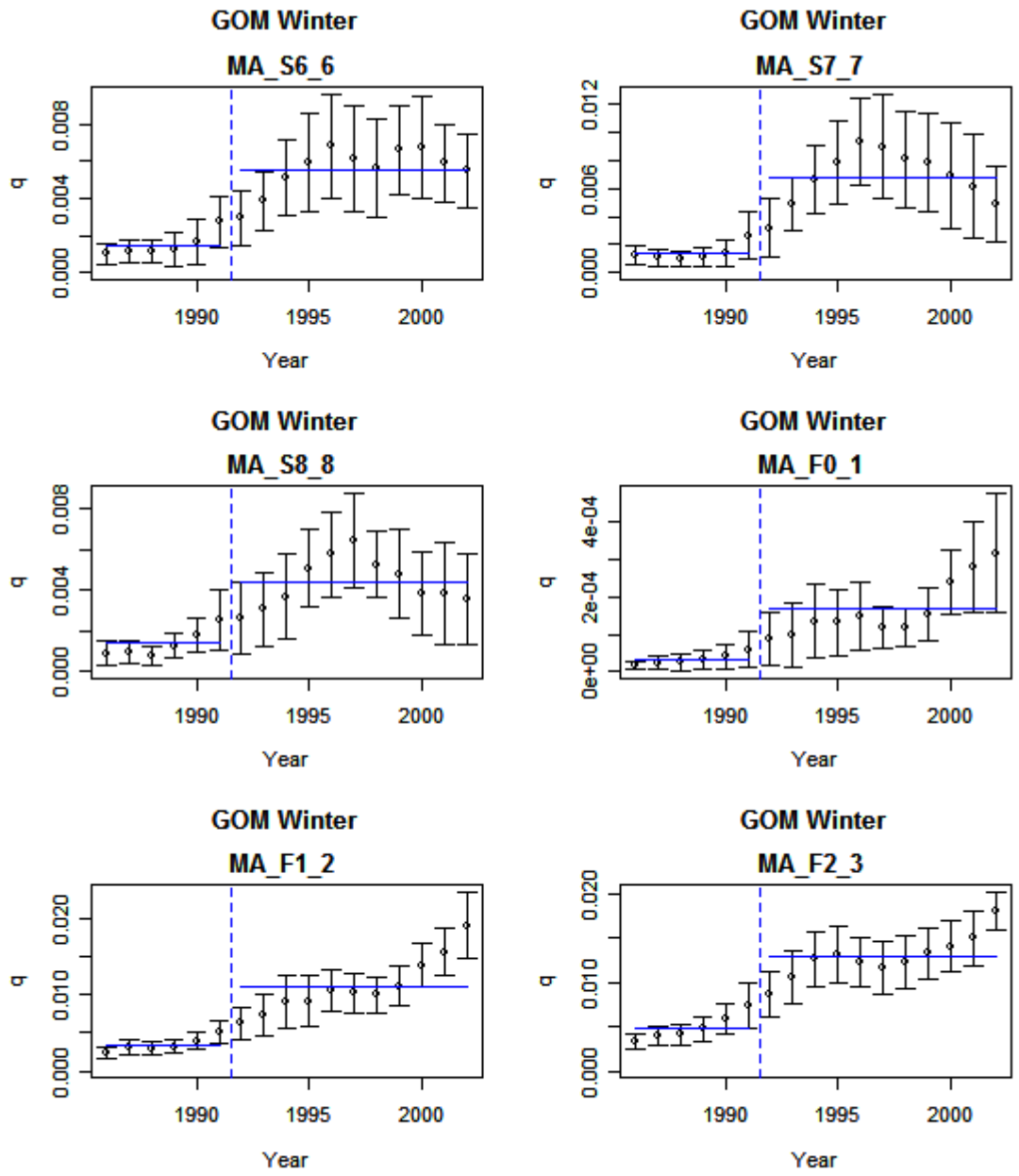


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).



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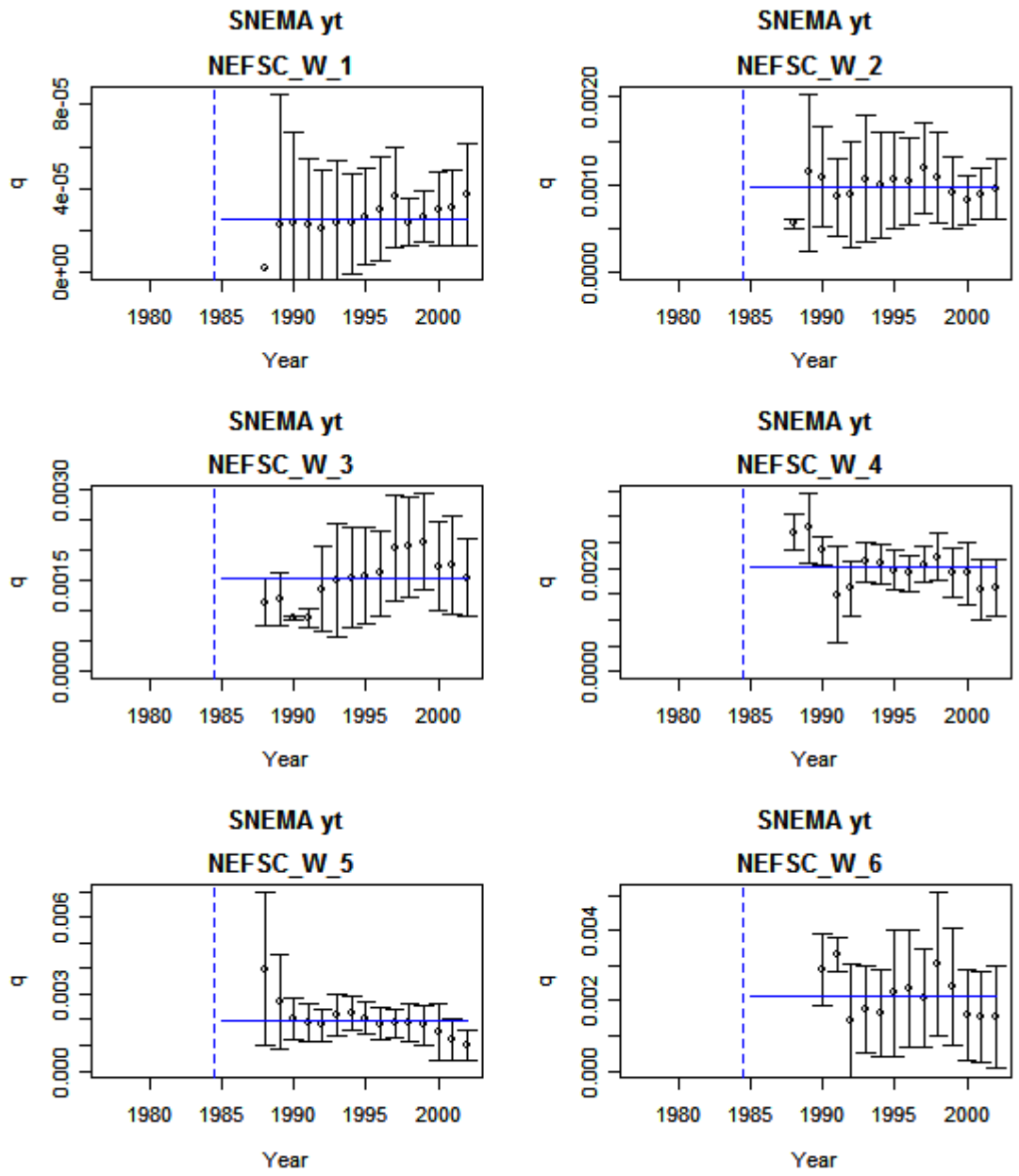


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

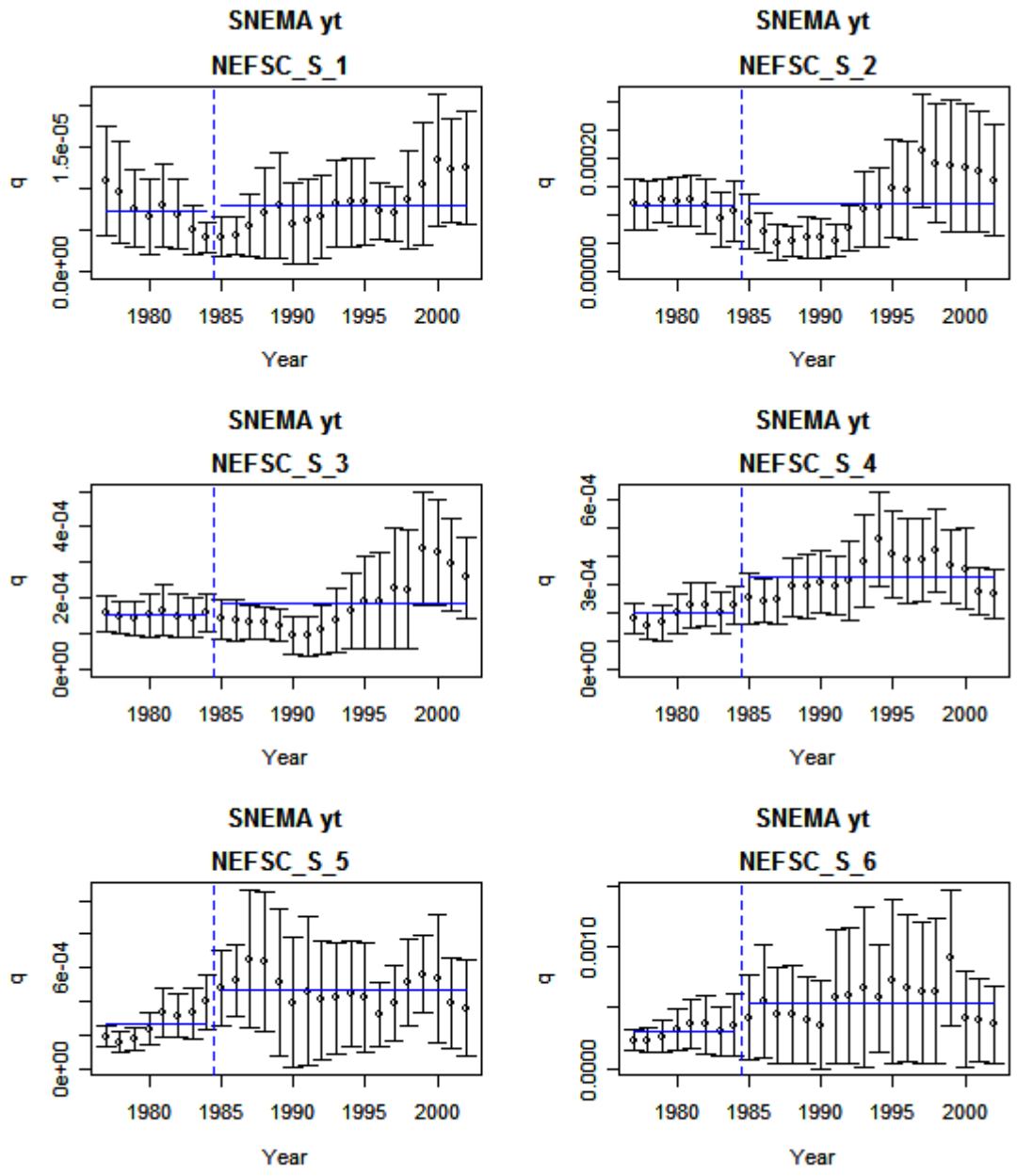


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

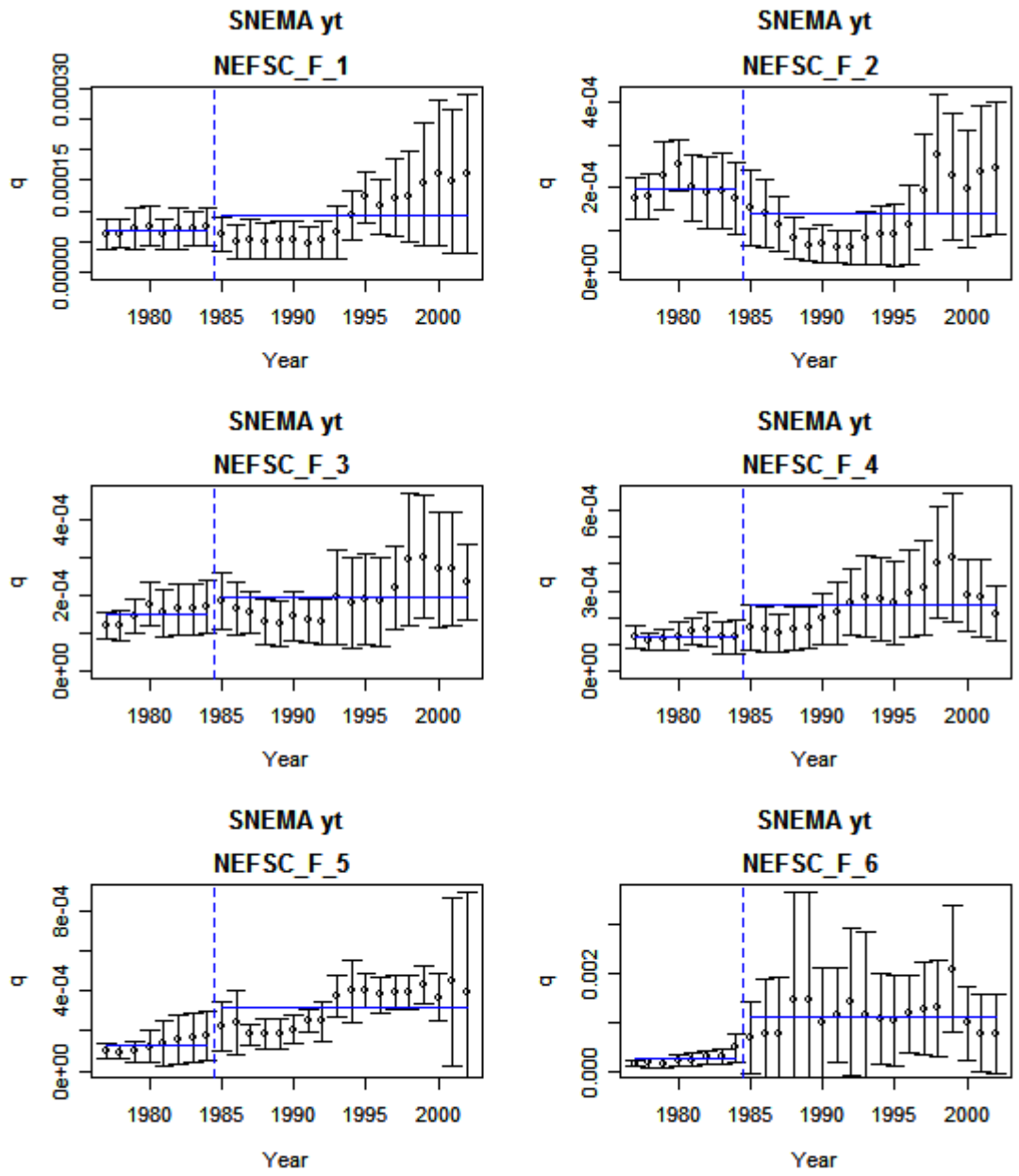


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

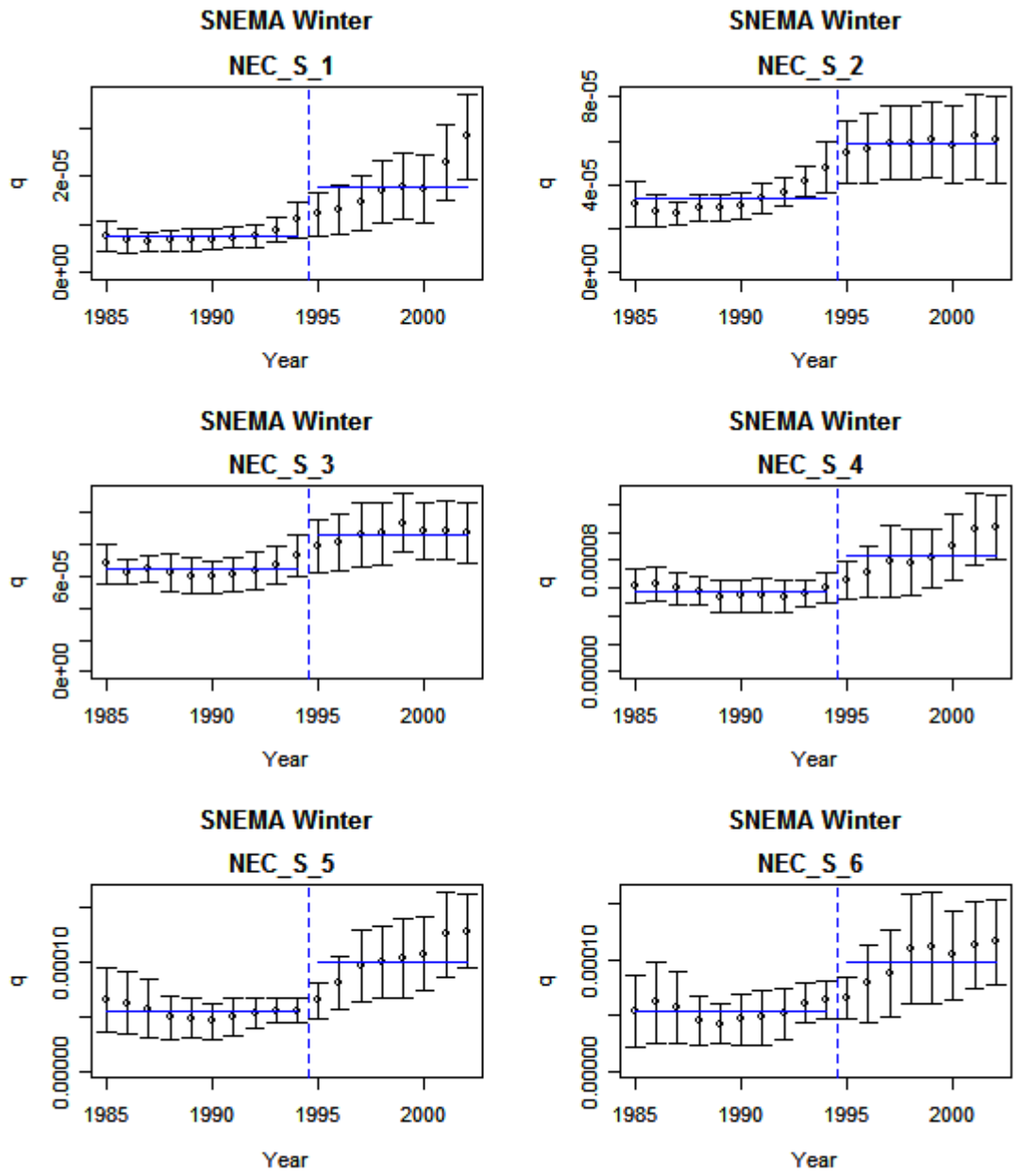


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

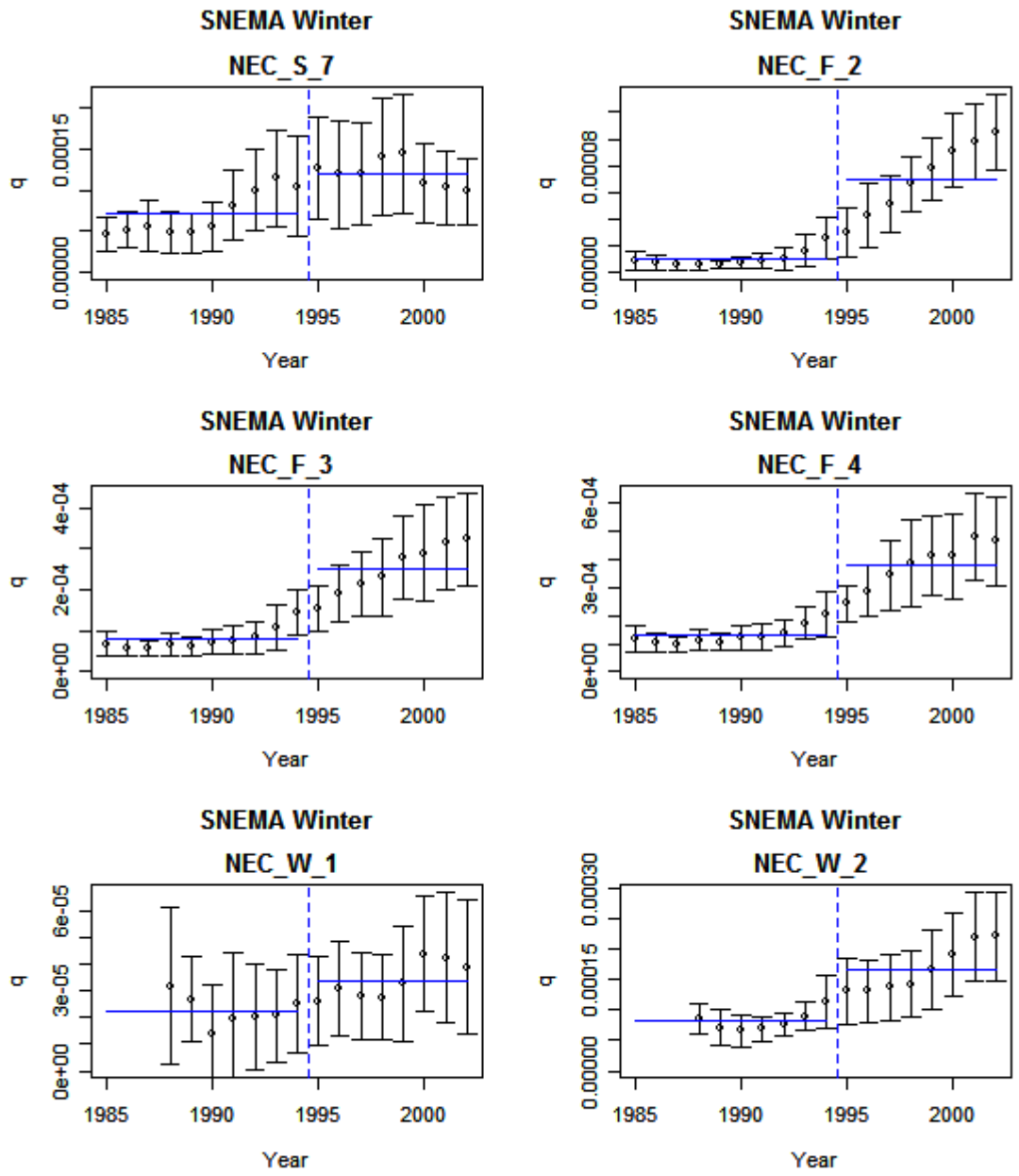


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

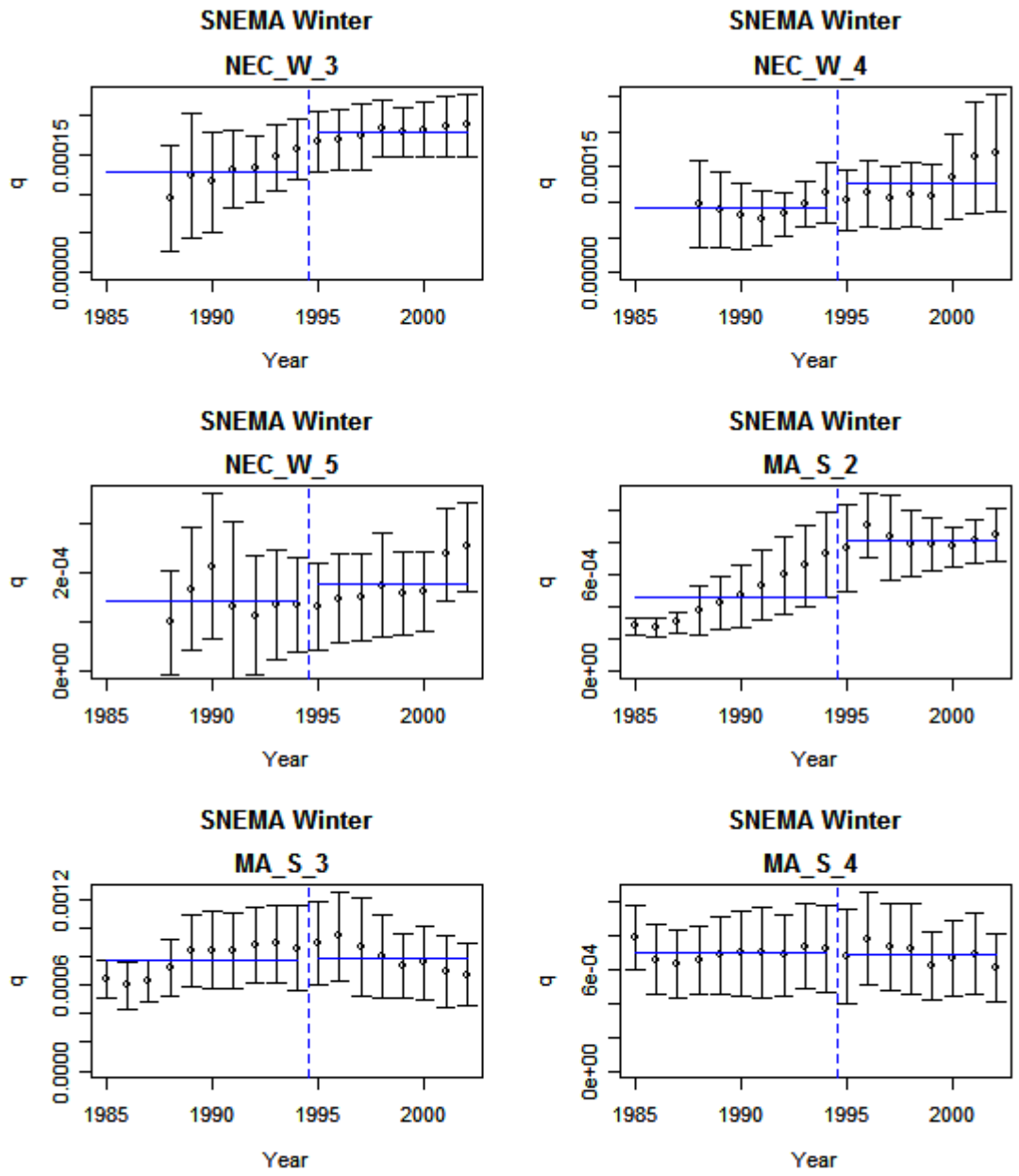


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

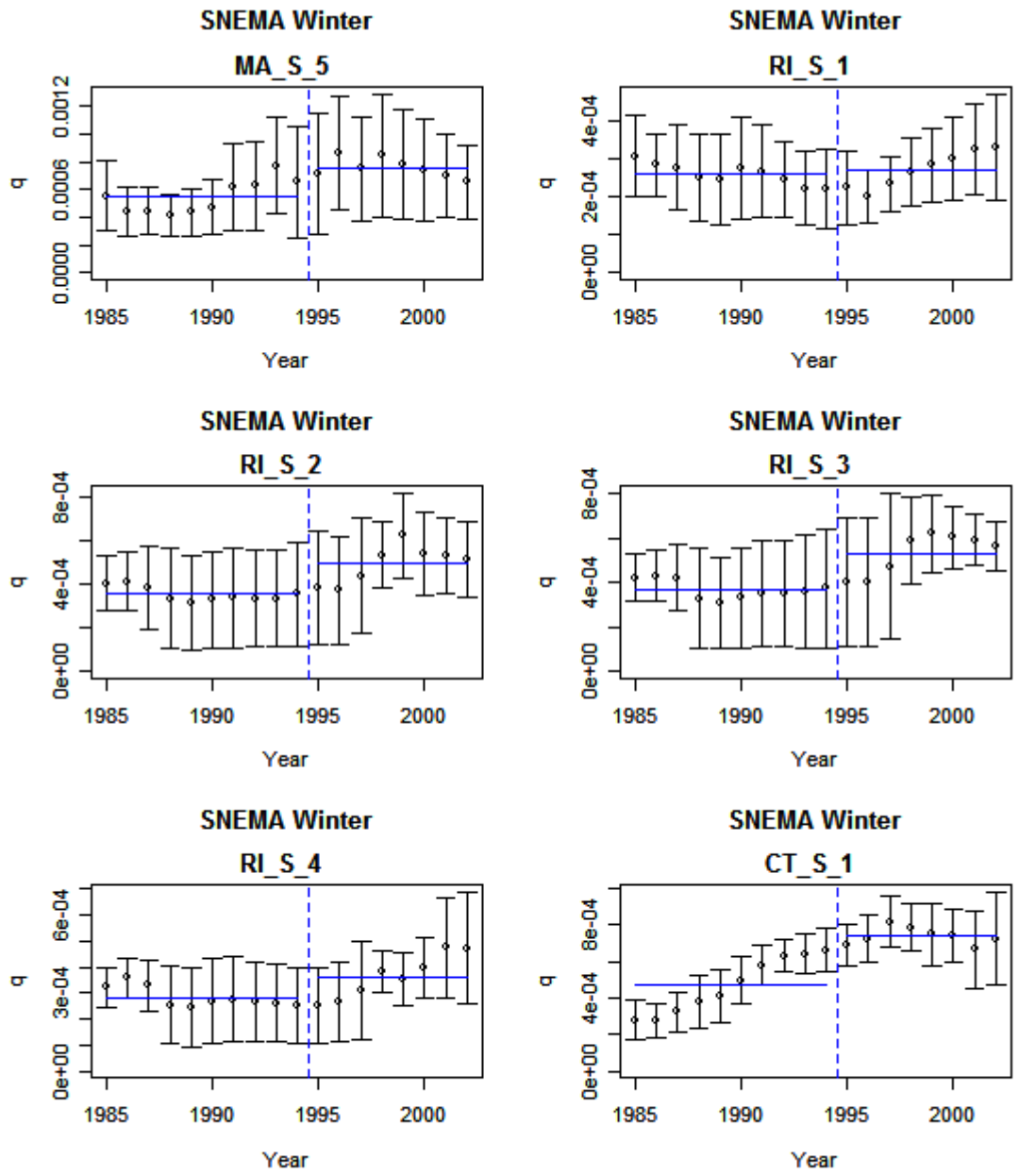


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

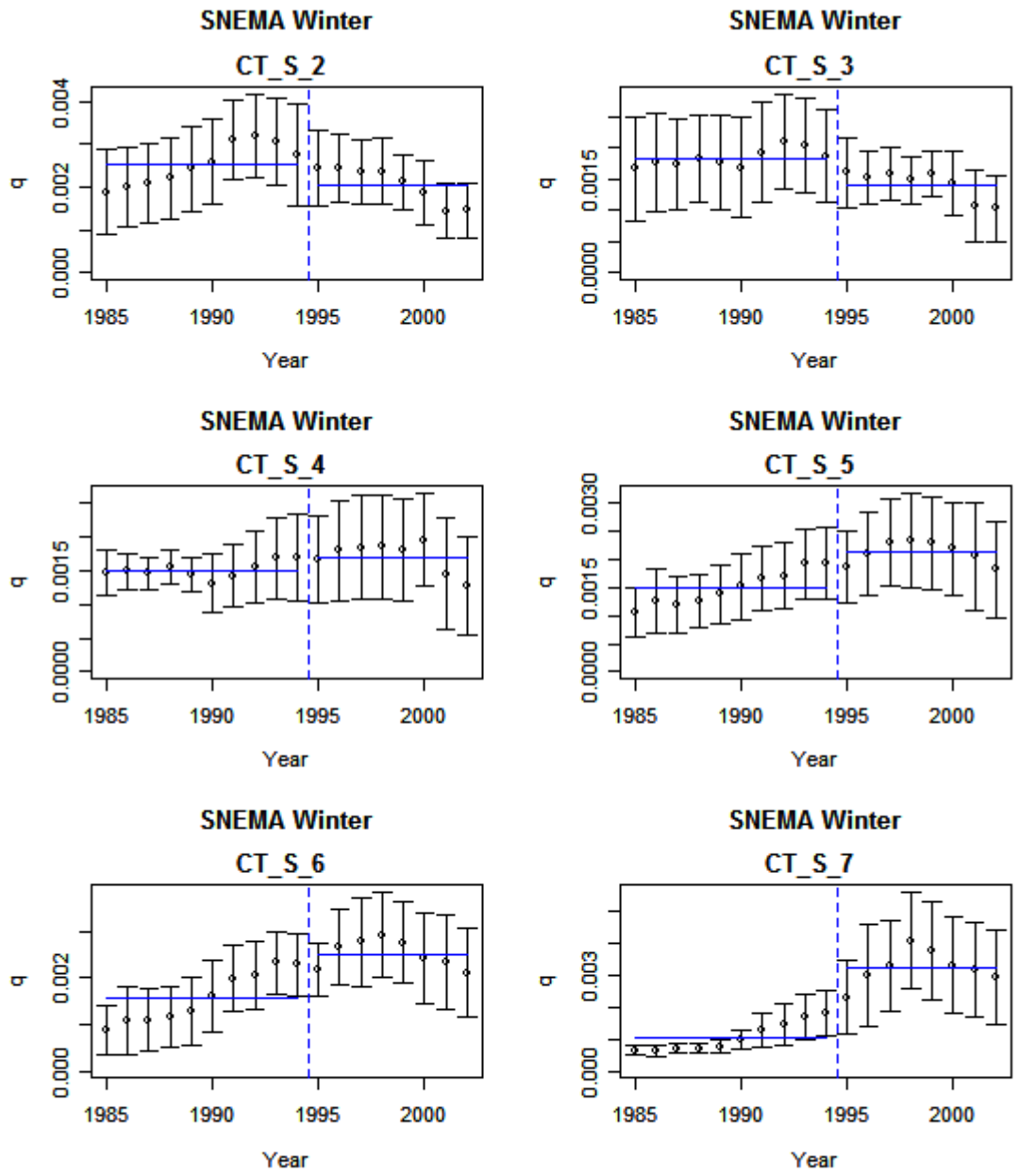


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).

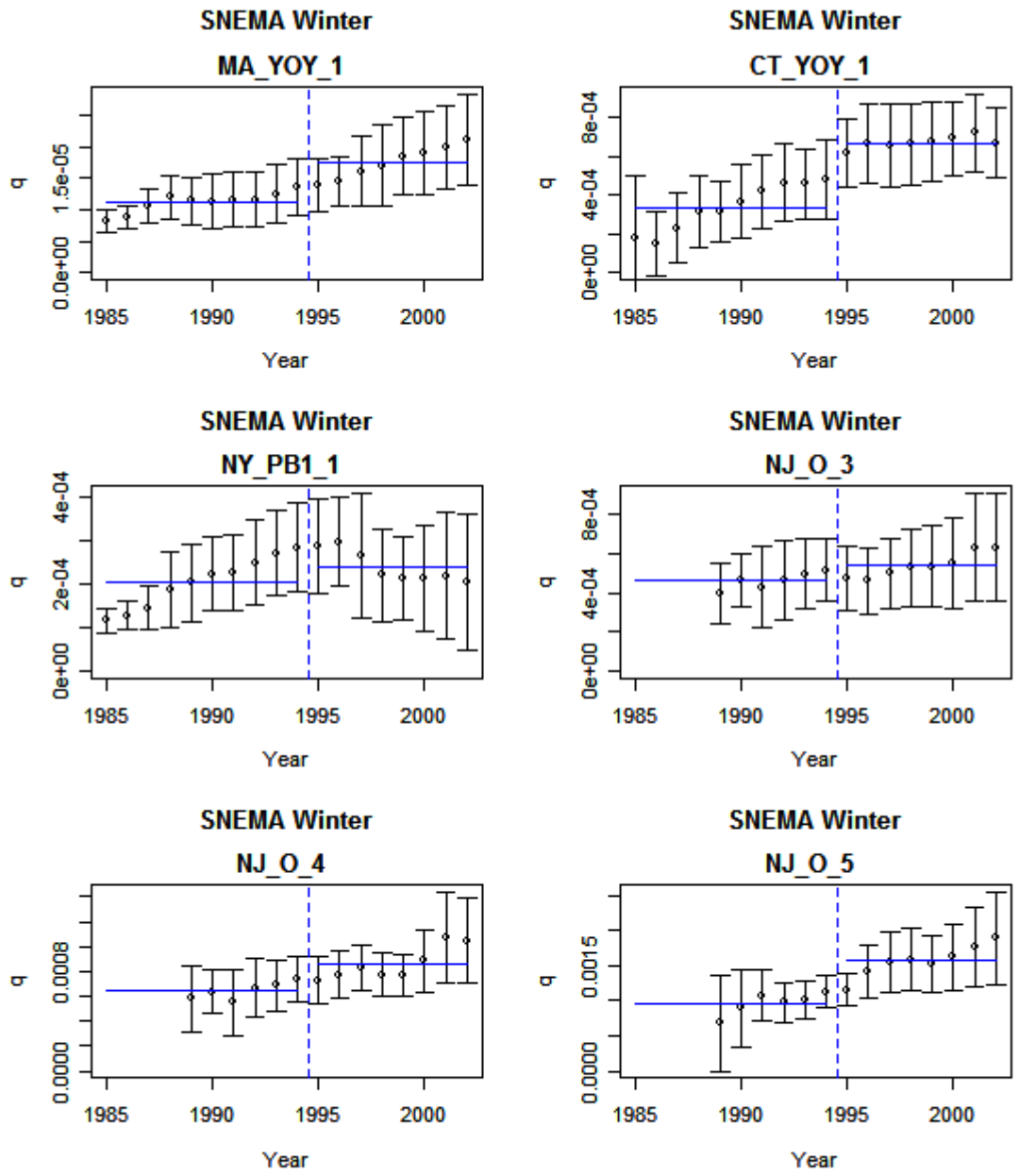
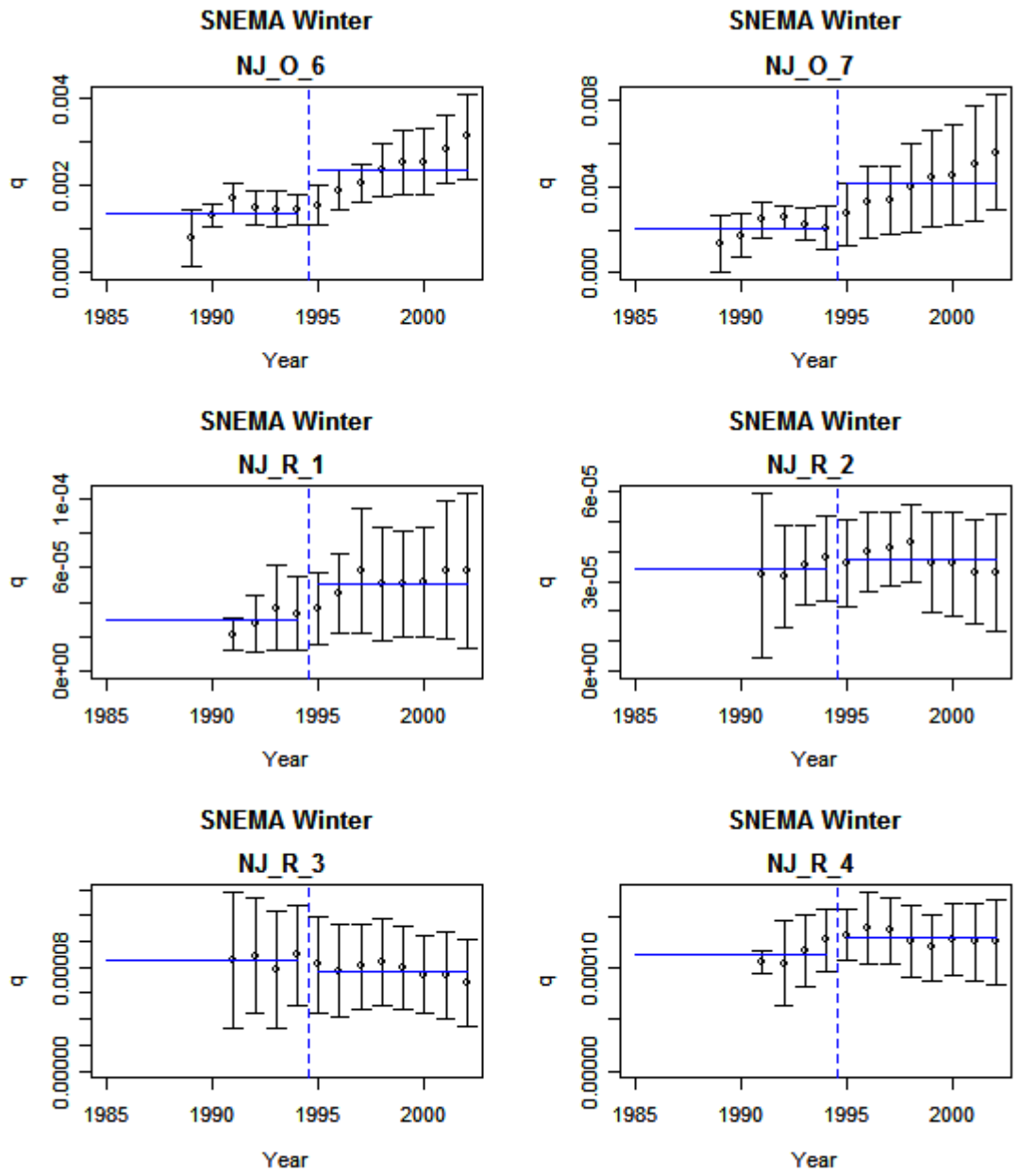


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).



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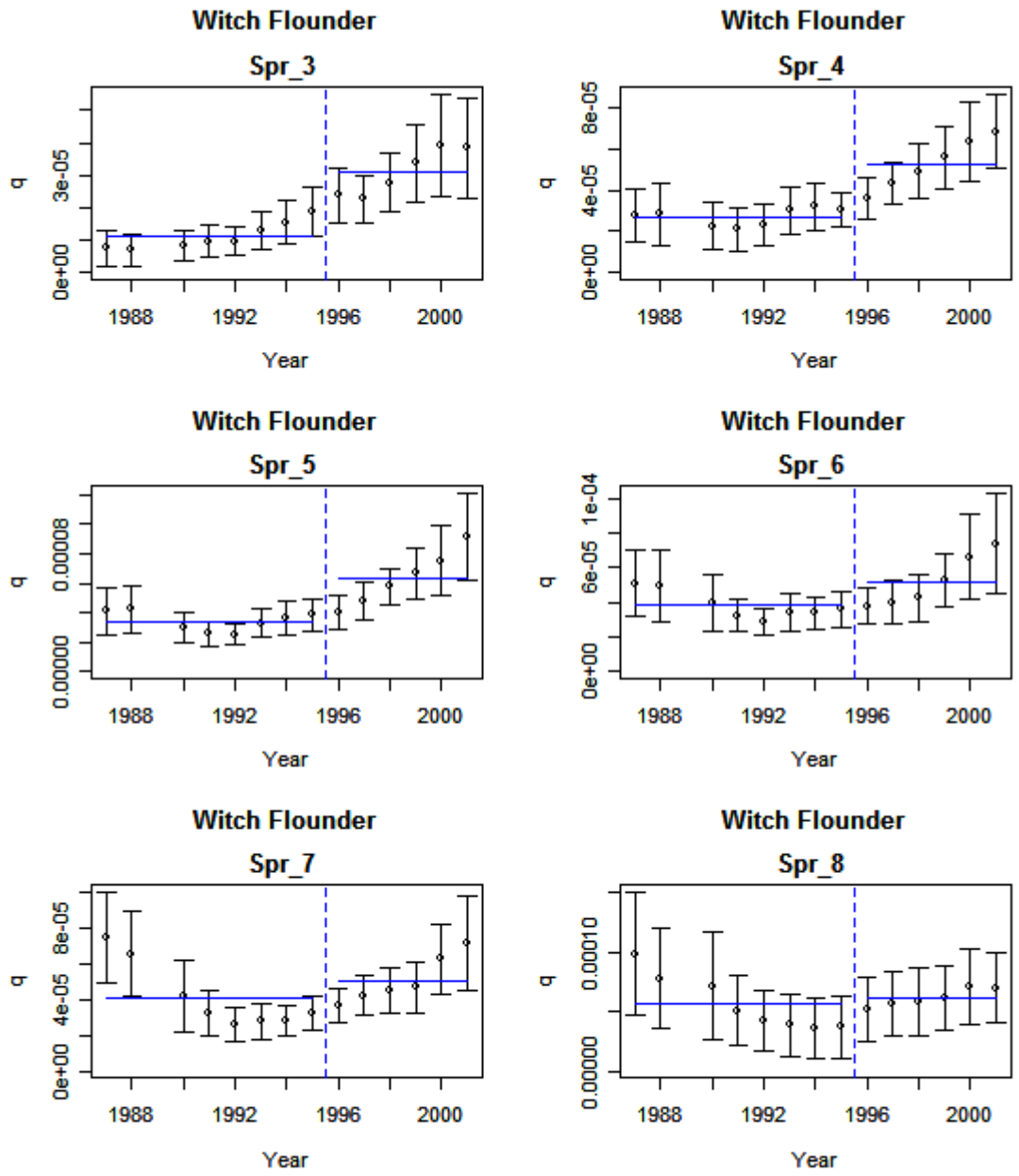

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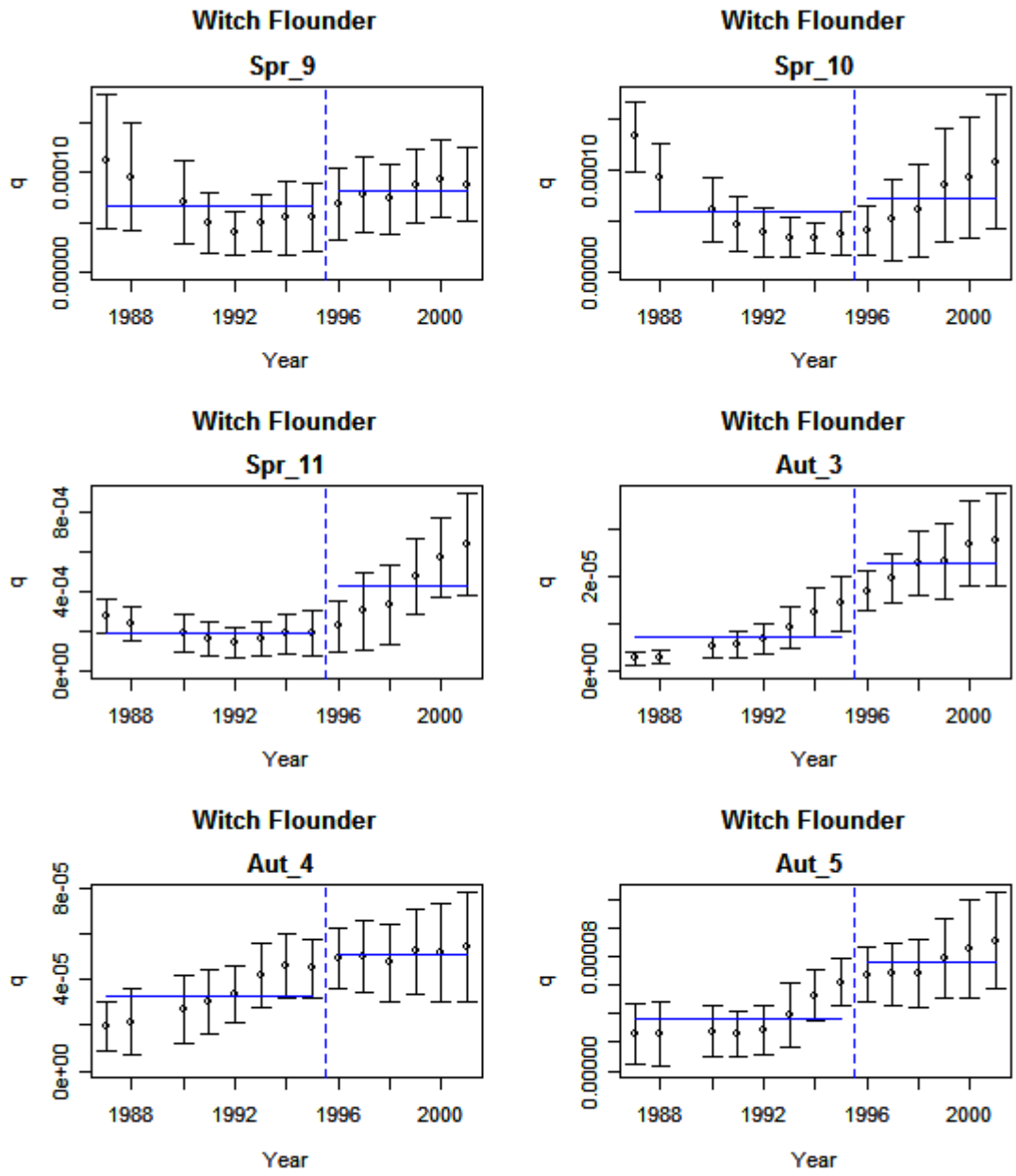
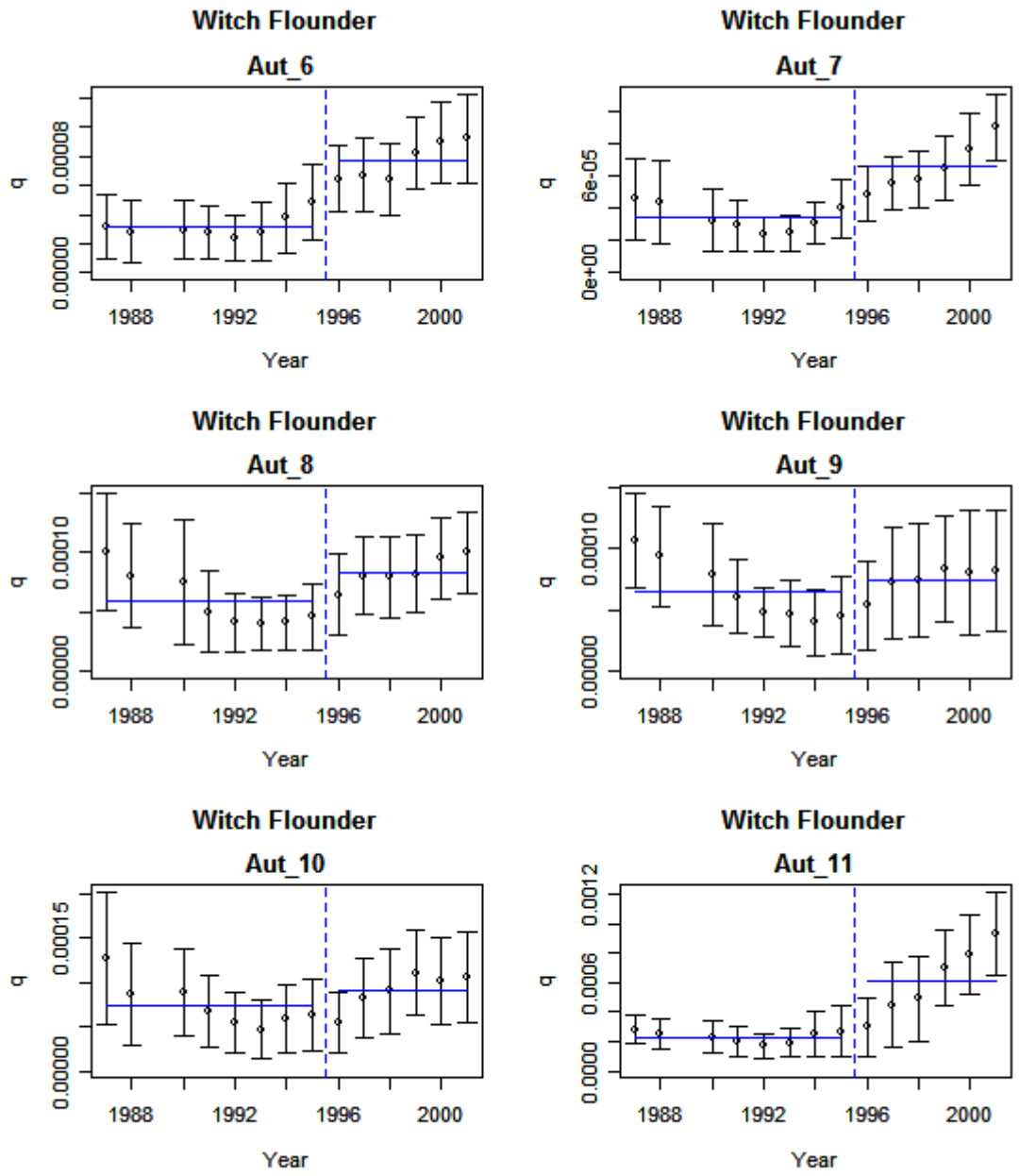


Figure 3. Moving window q estimates with 95% confidence intervals with best break year (vertical dashed blue line) and early and recent mean q values (horizontal solid blue lines).



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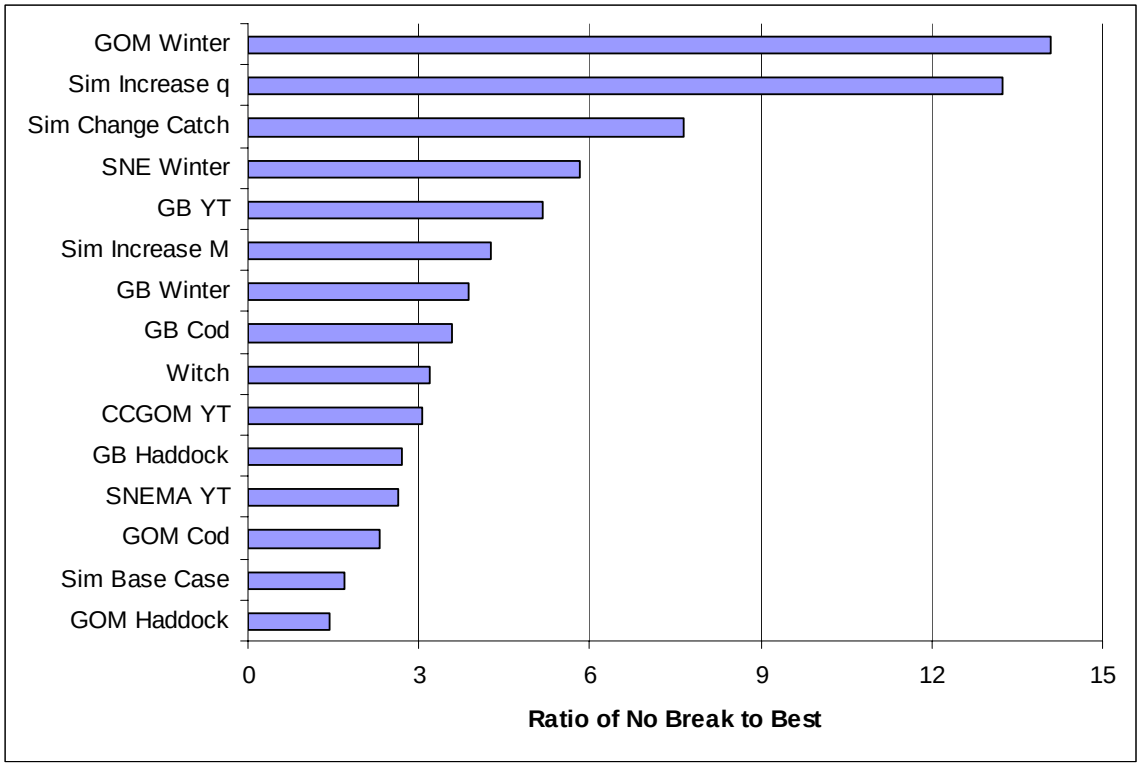

Figure 4. Ratio of no break sum MSR to best break year sum MSR by stock arranged from largest to smallest.

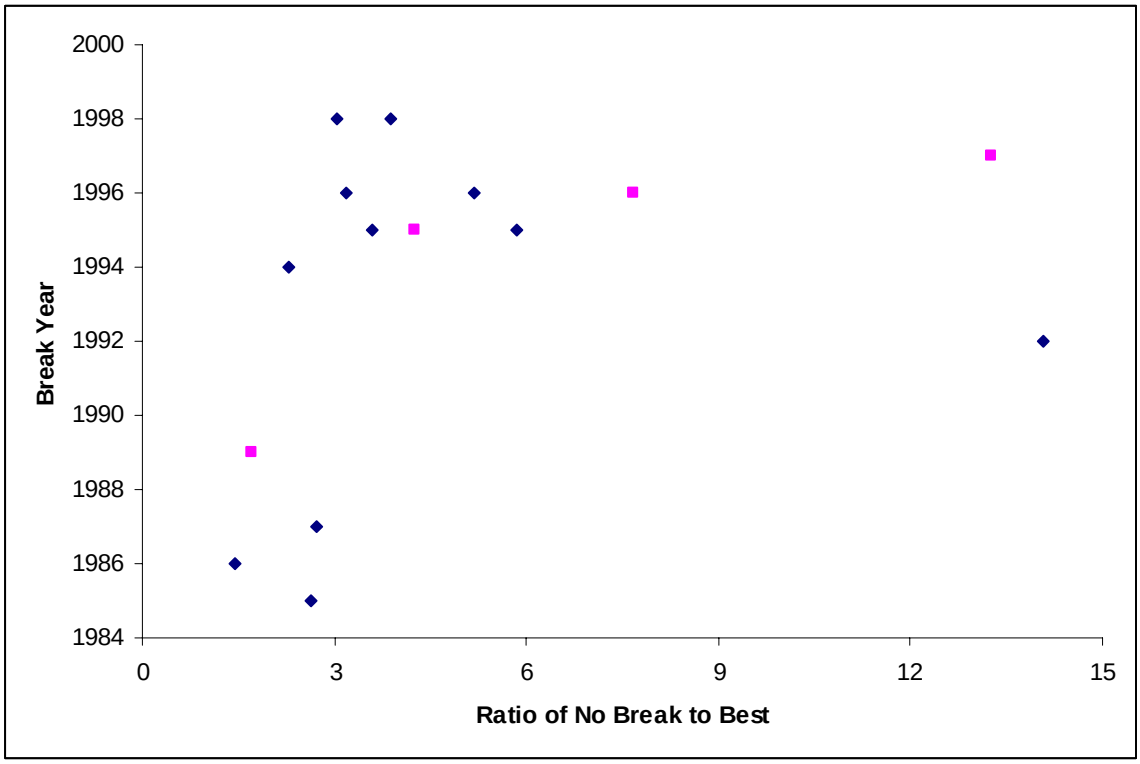

Figure 5. Ratio of no break to best sum MSR plotted against break year. Squares denote simulated data, diamonds denote stock assessment data.

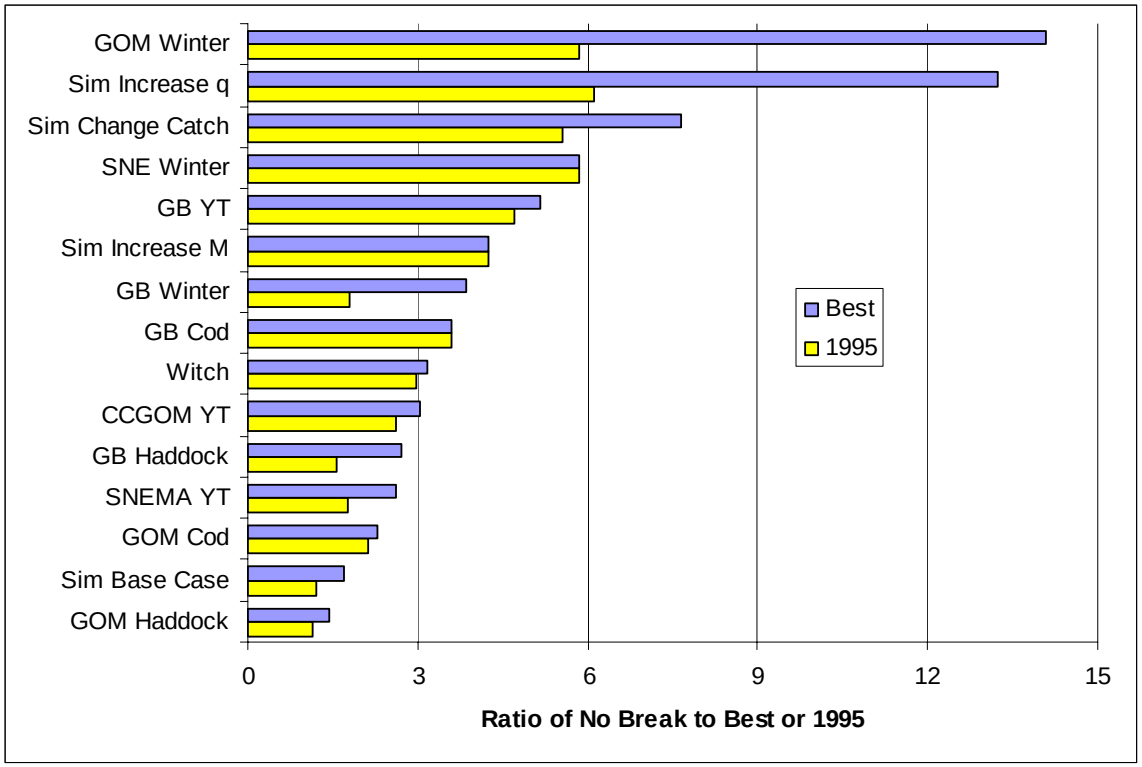

Figure 6. Same as Figure 4, except the ratio of sum MSR from no break and 1995 break year added.

Table 1. Ratio of no break to best sum MSR, best break year, and ratio of no break to 1995 break year sum MSR by stock.

Stock	Ratio of No Break to Best	Break Year	Ratio of No Break to 1995 Break Year
GOM Winter	14.08	1992	5.86
Sim Increase q	13.25	1997	6.11
Sim Change Catch	7.66	1996	5.57
SNE Winter	5.84	1995	5.84
GB YT	5.17	1996	4.71
Sim Increase M	4.25	1995	4.25
GB Winter	3.87	1998	1.79
GB Cod	3.59	1995	3.59
Witch	3.18	1996	2.99
CCGOM YT	3.05	1998	2.61
GB Haddock	2.71	1987	1.57
SNEMA YT	2.63	1985	1.76
GOM Cod	2.30	1994	2.14
Sim Base Case	1.70	1989	1.21
GOM Haddock	1.44	1986	1.15