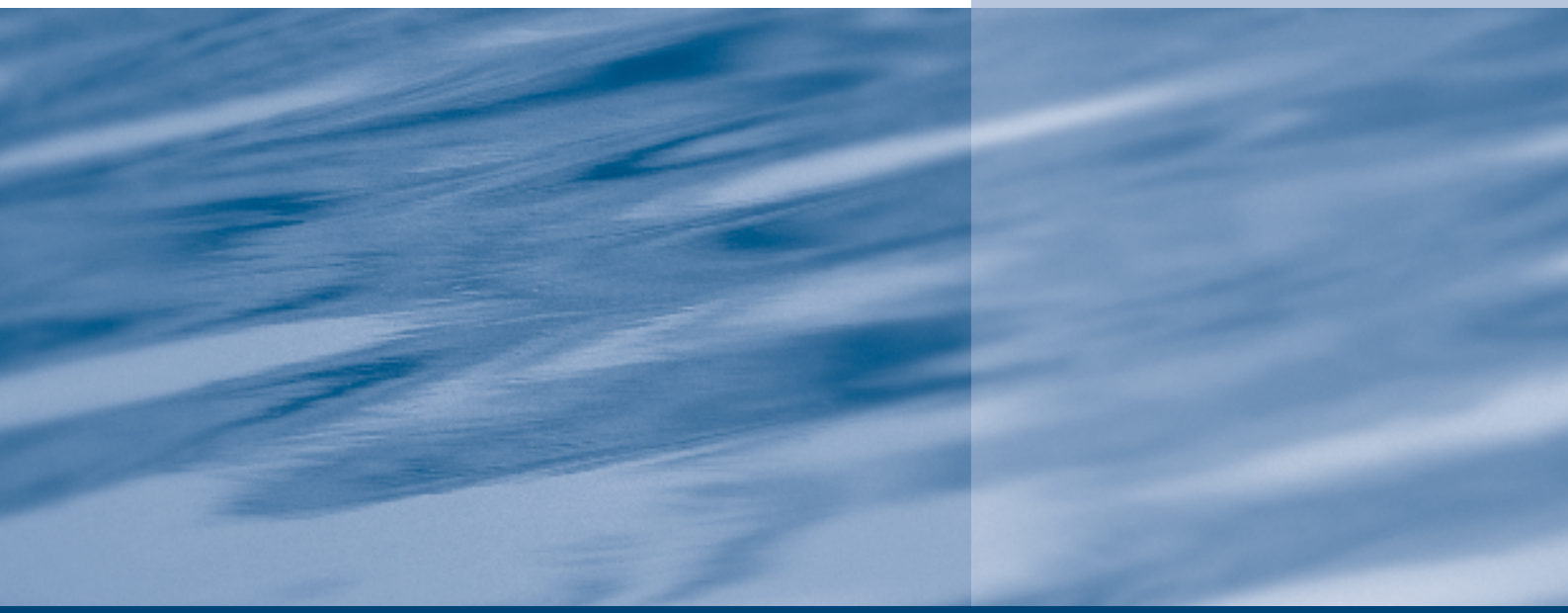

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Producing Generalised LIFE Response Curves

Science Report SC990015/SR

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Executive Summary

The LIFE methodology has demonstrated that it is possible to link changes in benthic invertebrate community structure (as sampled routinely by Environment Agency biologists) with indices of historical river flow at a gauge close to the sample site. This report investigates the response of LIFE observed/expected (O/E) score to preceding gauged flows through a linear modelling framework.

Data were supplied by the Environment Agency in Excel files – key data were extracted from the three main tables and loaded into a relational database. This initially included all available macroinvertebrate sample data up to December 1999 and some data from 2000 and 2001. Later it was agreed to take advantage of the macroinvertebrate data available since 2001, and thus the LIFE score database was extended to the end of 2003. To match this, all flow indices were re-calculated for water years 1989-2002. Additional data derived by the Centre for Ecology and Hydrology (CEH) were added to the database. RIVPACS was run for the majority of the sample sites, either using site characteristic data held already in the CEH Dorset Invertebrate Database, or the site characteristics provided with the data. The RIVPACS outputs were the most probable RIVPACS group and expected LIFE scores, for spring, summer, and autumn samples. The Institute of Hydrology Report 108 low flow quality classification was also added for each gauging station.

Following exploratory data analysis, some sites were excluded from the data-set on the basis that their characteristics (e.g. deep water and silty bed) make their macroinvertebrate community unlikely to respond to flow in the manner for which the LIFE index was designed.

Linear modelling demonstrated that autumn LIFE O/E score does, indeed, vary systematically with flow. Flow variables from the immediately preceding summer are the most important in explaining variation. The relative importance of high and low flow variables can depend on how they are standardised. The simplest models, which explain variation in LIFE score solely on preceding flows, confirm the validity of the LIFE approach, but do not explain a high proportion of overall variation in LIFE score.

Various site-specific factors were used to improve the fit of the model, most notably splitting the sites into categories based on base flow index (BFI), and also on whether there are significant artificial influences in the catchment. These give model R^2 values of between 0.1 (high BFI) to 0.2 (low BFI). Adding the immediately preceding spring sample LIFE O/E as an explanatory variable increases R^2 to 0.4. A ‘site’ factor that encompasses all unexplained variation in mean LIFE O/E increases R^2 to 0.6, an encouraging result that indicates a maximum value for R^2, but still retains a common slope. A simple approach of adding RIVPACS group (two to four categories) as an interaction term (i.e., affecting slope of response) did not add to the model fit.

There is a trend for higher BFI sites to show negative relationships between LIFE O/E and winter Q10 (high flow index). These sites are also more strongly associated with Q95 (low flow index) flows from the previous summer, although this trend is weak, and is dependent on the method of flow standardisation. Both these relationships can be masked easily by inter-site differences. Analysis of the autocorrelation of residuals from the model suggested that the year-to-year correlation of autumn LIFE O/E largely results from the correlation in the explanatory flow variables. Also, there was little evidence for the perceived greater lag of baseflow-dominated catchments, beyond that explainable by the lag in the flows themselves.

In general, low flow duration indices are probably not the most sensitive indicators of LIFE response in baseflow-dominated catchments – alternative indicators that emphasise drought duration could give improved model fits.

There is still, clearly, considerable unexplained site-to-site variation in the LIFE O/E scores, as illustrated by the wide variation in slopes of the individual sites' LIFE O/E versus flow relationship. For the analysis undertaken, the data supported common LIFE versus flow slopes for all sites, although there was evidence of an interaction effect between artificial influences and preceding summer Q10: the more influenced catchments had more depressed LIFE O/E values when summer Q10 was low, but had LIFE O/E scores similar to the less influenced catchments when summer Q10 was high. This was not the case for LIFE versus preceding summer Q95.

Analysis of replicate data taken within a season allowed an average total within-season standard deviation of LIFE score to be calculated – consistent with previous work, this decreases with number of taxa observed. The average total within-season variance was compared with the total mean squares of LIFE score to indicate the maximum potential model R^2 possible, which was in the region of 0.75 – the quoted R^2 values for models should be viewed with this in mind.

Unexplained variation in mean LIFE O/E can, hopefully, be tackled by improvements to RIVPACS, perhaps by incorporating catchment characteristics from digital data-sets. Unexplained variation in the slope of the response of LIFE to flow could be tackled in several ways, including a more sophisticated application of the RIVPACS groupings. In addition, it is likely that adding additional site factors, such as habitat types and/or channel geometry, would improve the methodology. This unexplained variation needs to be addressed for single LIFE O/Es to be a useful tool in determining abstraction and/or flow stress without supporting information. However, the models as they stand would be extremely useful in helping to determine response where only small amounts of data are available.

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Acknowledgements
We owe particular thanks to the late David Balbi for his scrupulous work in identifying suitable data series for this project; without his dedication our analysis would have been extremely limited. In addition, we thank Doug Wilson for his guidance in setting up the project, and the project board (Juliette Hall, Chris Extence, Richard Chadd, and Robert Willows, plus Dan Cadman); all of their advice has been greatly appreciated. Furthermore, we are grateful for advice from Andy Young, Tracey Goodwin, and Bente Clausen. Finally, we thank Alice Hiley (Environment Agency) and Charlie Stratford (CEH Wallingford) for their tireless work in sorting out the data.

1 Introduction

The LIFE methodology (Extence *et al.* 1999) has demonstrated that it is possible to link changes in benthic invertebrate community structure (as sampled routinely by Environment Agency biologists) with indices of historical river flow at a gauge close to the sample site.

These relationships allow a better understanding of the hydroecological processes that operate in rivers of different types. In turn, this understanding should contribute to the cost effective yet environmentally sound management of water resources. As LIFE has used existing national data-sets, there is great potential to develop a standard methodology for ecological flow assessment. In particular, methodologies are required to:

- determine environmental water requirements under CAMS;
- determine flow rates below which unacceptable ecological damage occurs when considering abstraction licensing at the catchment and sub-catchment level.

A range of issues that require further investigation was reported by Balbi and Extence (2000), along with a suggested twin track of further R&D:

- investigate links between LIFE score and RIVPACS;
- production of generalised LIFE response functions.

The R&D project reported herein covers the latter. The overall deliverables will be a statistical model able to predict LIFE scores from time-varying hydrological and steady-state catchment variables. The key criteria for variable selection will be the utility of the variables in water resources management, and an understanding of the conceptual mechanism of how the variation in those variables affects river benthic ecology.

1.1 The usefulness of the LIFE approach

Much previous work on environmental flows concentrated on the use of hydraulic-habitat models, but this approach, which links hydraulic conditions to habitat preferences, requires site-specific hydraulic and biological data. However, existing scoring systems, such as BMWP and ASPT, were designed for water-quality assessment purposes, and so their use in environmental flow assessment is unclear.

There is thus a pressing need for environmental flow tools that:

- are simple and rapid to apply;
- consider macroinvertebrates.

The LIFE index works at species or family level using existing biomonitoring data. Every taxon has a velocity preference score from I to VI, and the standard logarithmic abundance categories are used (A to E). A matrix is then used to give a score of between 1 and 12 for each taxon in the sample. These are added together and the average score per taxon is calculated. Importantly, the index thus produced is expected to be sensitive to both natural and artificial flow changes, and thus allows an extrinsic hypothesis to be tested. This is distinct from other recent work in which several less-specific indices (e.g., species richness, diversity) are compared with a large number of flow variables to identify correlations.

1.2 Previous work

Previous work is summarised in Extence *et al.* 1999. They demonstrated how LIFE scores calculated from historical monitoring data could be linked to historical flow data at nearby gauges (*Figure 1-1*). They tested a series of flow indices, including moving averages of varying lengths, plus other summary statistics (e.g., flow duration, mean, extremes), and picked the best correlations. Some commonalities were noted between river types. LIFE scores at species level produced better relationships than those at family level. Problems with this approach, including different 'optimum' flow variables being selected independently for each site and other statistical issues, especially correlations in flow data caused by overlapping periods of record, led to the formulation of this R&D project.

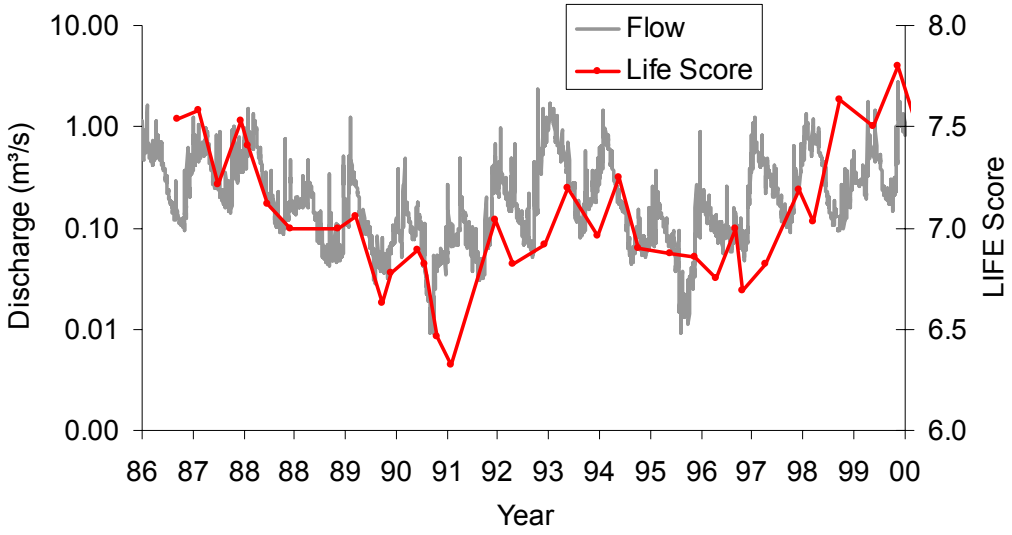

Figure 1-1. Example time series of river flow and LIFE score

This project's aim is to overcome the lack of data at individual sites by creating models based on pooled data. It seems probable that the LIFE score is well-behaved statistically, allowing multiple regression to be used as the primary analysis technique. The decision was also taken to work with family level data to allow the largest choice of paired data-sets. Moving averages were not chosen to index flows for two reasons – firstly, they are not commonly used in water resources and, secondly, there are problems when either the time periods for successive index points overlap in time or different intercorrelated averaging time periods are compared. Instead, simple 6-monthly flow indices were chosen (Q10, Q50, and Q95) for 'summer' (April to September) and 'winter' (October to March) periods. These also fit well with the invertebrate sampling data, the majority of which are collected in autumn or spring.

To prepare for this analysis, a wide-ranging search of Environment Agency data was carried out by David Balbi (Balbi, 2001). The following paragraphs outline the selection criteria applied by David, criteria originally specified in the project specification and subsequently modified slightly.

All sites with at least two samples per year between 1995 and 2000 and good average water quality (Lincoln Quality Index of C or better, based on rich habitat) were accepted and classified as selection class 1 sites. Those Agency Areas that resulted in less than twenty

suitable sample sites in criteria 1 were assessed further using two additional sample selection criteria, until more than twenty sites were identified or criteria were exhausted, as follows:
Class 2. At least one sample per year for nine years (1992 to 2000).
Class 3. At least twenty samples in the past twenty years (1980 to 2000).

The invertebrate sample sites satisfying the required criteria were paired with gauged sites, based on proximity and duration of flow record, using information supplied by Agency Hydrologists. Lists of paired sites were then sent to Agency staff for comment, considering a number of key points. In those areas with a paucity of paired sites, Hydrologists were also asked to suggest gauged flows for unpaired invertebrate sample sites.

2 Database

2.1 Introduction

Data were provided in three main Excel files, flow statistics (indexed by gauging station number, and date), invertebrate samples (indexed by B4W site number and date), and paired sites, linking gauging station number, and invertebrate site number. Within the flow file, separate worksheets provided the fixed characteristics of the gauging stations and the time-varying flow indices. The invertebrate samples file was structured similarly. The paired-sites file contained a master list of paired sites plus individual workbooks for each region, in which more details were provided on the pairs selected and rejected, arranged on an area-by-area basis. Excel files were also provided with the raw flow data and the raw invertebrate taxa data from each sample (*Figure 2-1*).

Key data were extracted from the three main tables and loaded into a relational database. This enables efficient storage of the data without duplication, coding of virtually all categorical data, checking of codes for consistency,[1] and flexible retrieval of data in a variety of tabular formats suitable for statistical analysis.

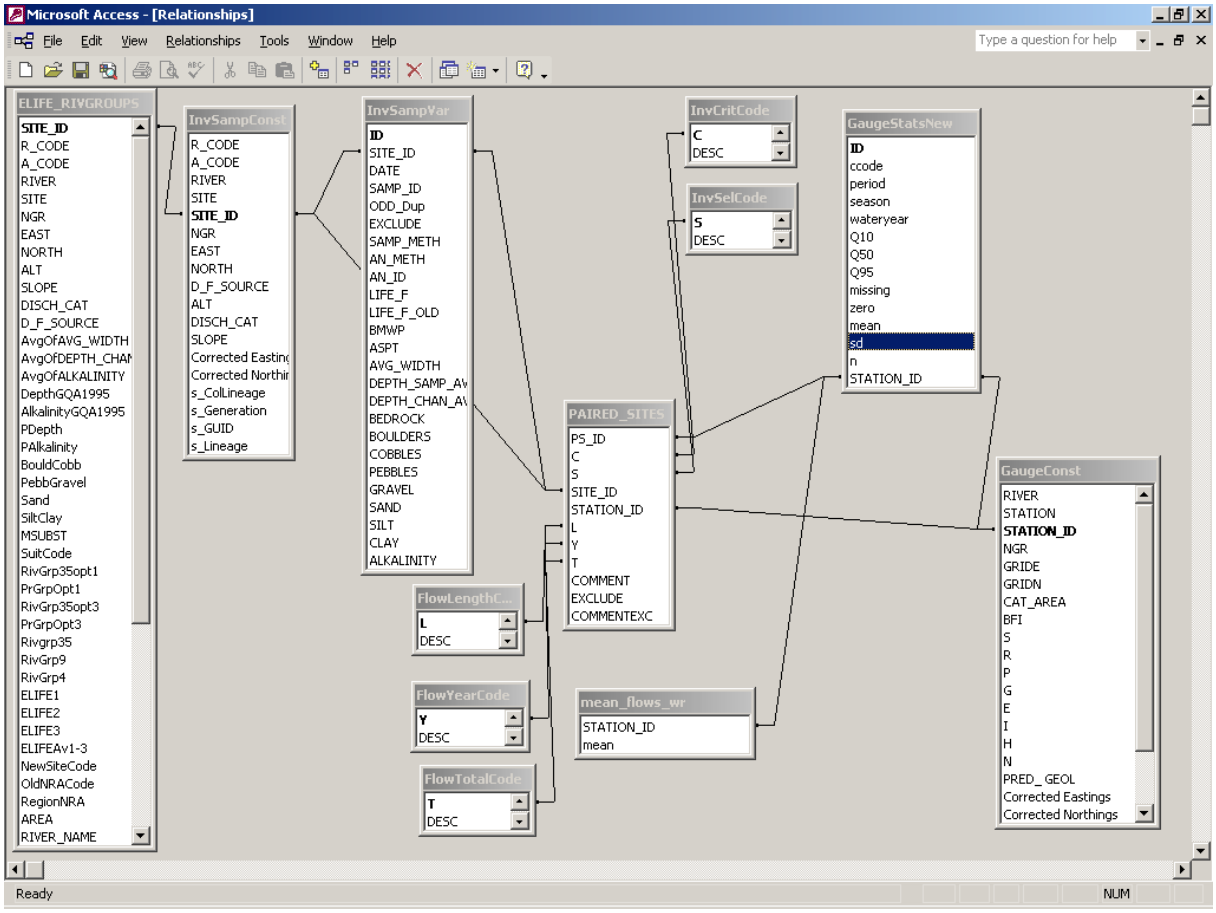

Figure 2-1. Relationships between tables in the LIFE database created for this project

[1]The coding highlighted one error in the paired sites, where invertebrate site 36186 was in the database twice under different names.

The database was initially constructed with all the available macroinvertebrate sample data up to December 1999 and some data from 2000 and 2001. Flow indices were provided for an agreed standard time period from October 1989 to September 1999 (water years 1989-1998). Later in the project, it was agreed that we should take advantage of the macroinvertebrate data available since 2001, particularly as this represented a period of relatively high flows, to compare with the low flows in 1989-1992 and 1996-1997. Thus, the LIFE score database was extended to the end of 2003. To match this, all flow indices were re-calculated for water years 1989-2002. This updating initially highlighted inconsistencies between the LIFE scores previously provided and those provided later from B4W. To maintain consistency, the 2001-2003 data were recalculated using the Environment Agency's LIFE calculator spreadsheet. Overall, this increased the number of years in the standard period from 10 to 14.

2.2 Additional data

Additional data derived by the Centre for Ecology and Hydrology (CEH) were added to the database. RIVPACS was run for the majority of the sample sites, using the site characteristics provided with the data or, where these were incomplete, site characteristic data from the 1995 GQA survey held in the CEH Dorset Invertebrate Database. Where multiple readings for depth, alkalinity, and substrate were available, they were averaged. 16 sites did not have either depth or alkalinity data, so RIVPACS could not be run for these sites. The RIVPACS outputs were the most probable RIVPACS group (4, 9, and 35 categories) and RIVPACS expected LIFE scores for spring, summer, and autumn samples. The four categories were also merged into three (1, 2&3, 4) and two (1-3, 4) categories for comparative analysis. The Institute of Hydrology's low flow quality classification was also added for each gauging station. This consists of two codes, each labelled A to C. The first code is for hydrometric sensitivity to low flows, the second for degree of artificial influences. Only the latter has been used in this project; it is calculated from gauged flow data and the magnitude of licensed upstream abstractions and discharges (*Table 2-1*). There are clearly some limitations with this classification, the grade does not distinguish between net positive and net negative influences, and is based largely on licensed quantities, not actual amounts.

Table 2-1. Institute of Hydrology artificial influences classification

Artificial influences grade	Difference between gauged and natural Q95 ratio (per cent)
A	<20
B	20-50
C	>50

2.3 Functions of the database

The database was used to match flows to LIFE scores via the paired sites table, and to produce tabular files suitable for statistical analysis. Some pre-processing of data was also carried out by the database, including restriction of sample occasions to particular parts of the year, selection of sites with more than a certain number of samples, exclusion of flow records with significant missing values, and calculation of standardised flow statistics.

2.4 Abbreviations and factor codings

IPS, IPW (with a flow variable): immediately preceding summer, winter
YBS: year before summer
z (e.g. IPSQ95z): flow indices normalised as z scores (i.e., by subtracting the mean value of the index for that station and then dividing by the standard deviation (SD) of the index for that station)
dMEAN (e.g. IPSQ95dMEAN): flow indices standardised by dividing by the mean flow for the station
CAT.AREA: catchment area
CURRAI2: current artificial influence class, merging categories A and B together
BFI: base flow index
RIVGRP4,9,35. Most probably RIVPACS group of sample, at the 4, 9, or 35 category level.
SMB: six months before – used in combined spring and autumn analyses
SMBT: six months before that (i.e. 7-12 months before sample) – used in combined spring and autumn analyses

Regression models are shown in Wilkinson and Rogers (1973) notation.
For example LIFE ~ A + B + A:B models LIFE score predicted by two variables, A and B, plus an interaction term which can be considered as A multiplied by B, plus an error term. A and B can be factors (a set number of levels) or continuous variables.

2.5 Data excluded from analysis

Around 5 per cent of the macroinvertebrate data-set was bankside sorted rather than laboratory sorted. This is largely data from Environment Agency North West Region. On advice from the Environment Agency, these data were excluded from most of the subsequent analyses.

For the calculated seasonal flow statistics, a season was excluded if more than 20 days were missing data in the 180 day period. This was a pragmatic decision, rather than based on any objective criteria; the 20 day period was chosen after looking at the impact (in terms of number of matched flow-sample combinations) remaining after varying the period from 0 to 40 days.

3 Exploratory (graphical and tabular) data analysis

The sequence of analysis was as follows:

- Initial exploratory graphical analysis (described in this section).
- Statistical analysis (described in the next section).
- Further, more targeted graphical analysis. This generally used a data-set of autumn LIFE scores (samples taken in September, October, and November) and flow indices from the 6 months preceding the sample. These graphs are also presented in this section.

This led to the discovery of some further anomalies in the matching of flow and LIFE score data. The anomalous sites were removed from the data-sets used in the subsequent analyses.

3.1 Regional distribution of sites

There is some geographical variation in coverage, with around 60 sites available from Anglian, North East, and Southern Regions, and hardly any sites in the South West and Welsh Regions (*Table 3-1*).

Table 3-1. Total number of sites and mean LIFE score by Region

Region	Number of sites	Mean LIFE score
ANG	60	6.62
MID	44	7.08
NE	58	7.15
NW	32	7.63
SO	59	6.77
SW	1	7.48
TH	34	6.78
WEL	2	7.43

3.2 Time series of LIFE scores

Time series of LIFE scores were plotted for each region, and a smoothed regression line over-plotted. These are illustrated in the A4 graphs in Appendix C, in which the horizontal axis illustrates the date (year) since 1990. This highlights:

- there are sites with data points not evenly distributed through the period of record (these generally have most data in the later years of the period);
- individual sites may exhibit broad upward, downward, or neutral trends;
- individual sites show varying degrees of scatter of LIFE scores – some are more variable than others.

For each site, individual time series of autumn LIFE scores (samples taken in September, October, and November), were plotted along with Q10 and Q95 for the immediately preceding summer.

3.3 LIFE scores versus key flow variables and anomalous sites

Scatter plots of LIFE score versus key flow variables were plotted. Following the initial analysis presented below, the plots shown here in the Appendix C are restricted to showing the relationships between autumn LIFE scores (samples taken in September, October, and November), and Q10 and Q95 flows for the immediately preceding summer. Graphs are shown for ranked flow statistics, flow statistics standardised by mean flow, and normalised statistics.

All sites were classified according to whether their autumn LIFE scores showed positive, negative, or no correlation with the LIFE score. All sites and data were then re-examined by CEH and Environment Agency staff, and several were identified as not being suitable for use with the LIFE methodology – these included:

- sites on silty slow-flowing rivers (LIFE is not designed to work on such systems, which will not show shifts in the composition of taxa responding to velocity and siltation);
- sites with intermittent water-quality problems (at such sites, any water-quality issues are likely to affect the LIFE score and confound any flow–LIFE relationship);
- sites with large changes in regime downstream of reservoirs – such sites were demonstrated by Extence *et al.* (1999) to show atypical LIFE responses to flow and are unlikely to fit a generic model.

The excluded sites are summarised in *Table 3-2*. Other data points were excluded as they may have been over-sampled, notably in the late 1980s and early 1990s. Data were not excluded simply because they did not fit a perceived model of response, hence there are a few sites in the data-set where response of LIFE score to flow looks either negative or zero.

Table 3-2. Paired sites excluded from the analysis

Site	Station	Why excluded?
1924	25023	Mismatch, upstream and downstream reservoir
224	27005	Low variability Grimwith Reservoir
50349	28023	Long-term quality problem
49017	28058	CEH excluded as obtaining variable life scores, but zero flows
55425	30001	Buffering of sewage treatment works and quality
55339	30006	Ponded
55539	31001	Regulated flow
55588	31006	Regulated (CEH decision)
55714	31016	Regulated flow
55854	32002	Regulated flow
55598	32003	Quality
56000	33014	Engineered, poor habitat
56439	33015	Quality
56261	33022	Quality
55953	33034	Sluggish lowland
56262	33039	Sluggish, deep
56435	33058	Quality
55932	33063	Sluggish lowland
54641	37024	Sluggish lowland river
36065	39016	Deep and slow
35829	39078	Water quality problems
35830	39078	Possible water quality problems
43417	40008	Sluggish?

Site	Station	Why excluded?
43697	40025	Deep and silty
41930	41001	Silty and deep
42787	41010	Silty and deep
42793	41019	Water quality problems
42205	41024	ds reservoir
46902	54001	Deep and silty

3.4 Scatter plots between different standardised flow variables

Clearly, the magnitudes of non-standardised flow variables (e.g., Q10, Q50) for the same or successive time period are correlated, but it is less clear how correlated their standardised equivalents will be. *Figure 3-1* illustrates that there is a degree of correlation for low flows over successive summers. *Figure 3-2*illustrates the correlations between standardised Q10, Q50, and Q95 in the same summer – it suggests that correlation between Q10 and Q95 is slight.

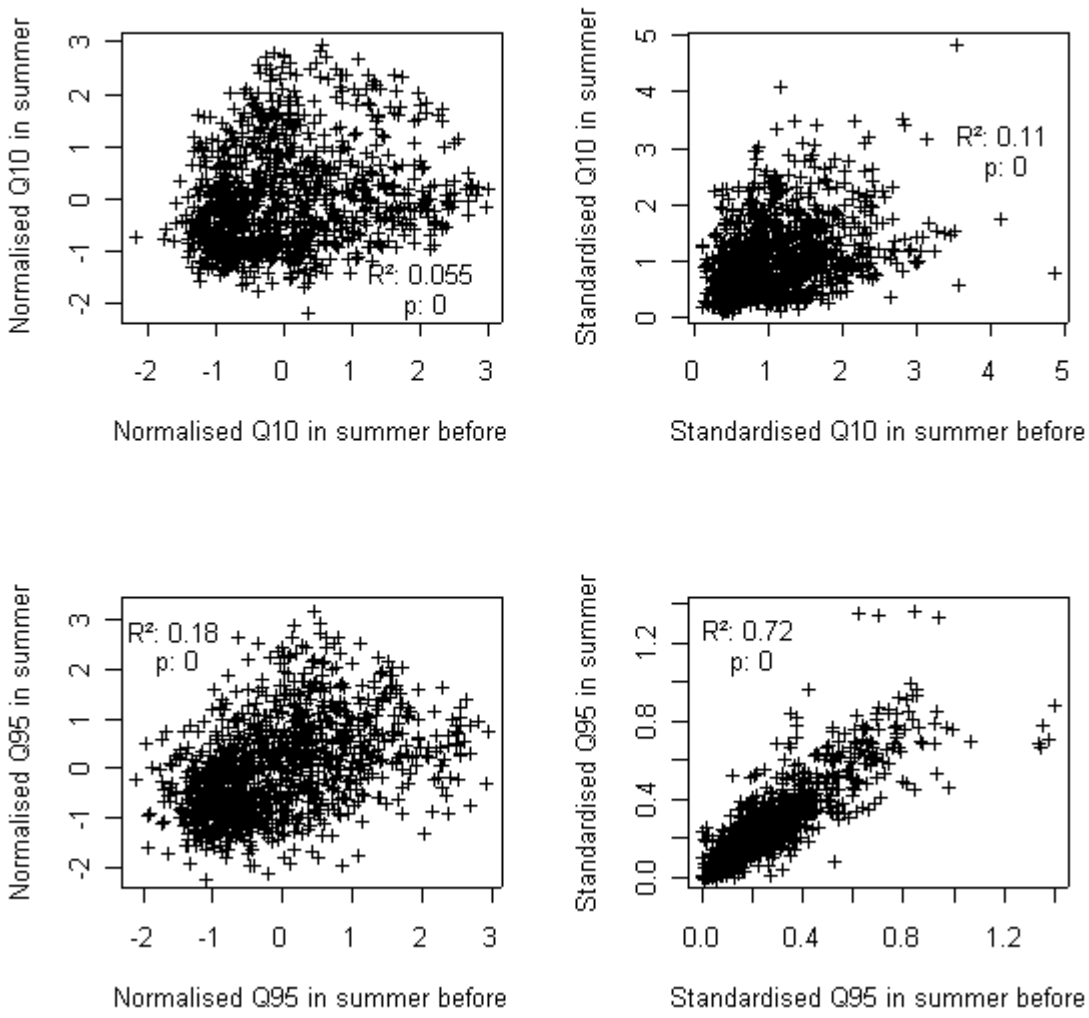

Figure 3-1. Correlation between normalised (left) and standardised (right) and Q10 (upper) and Q95 (lower) for successive years.

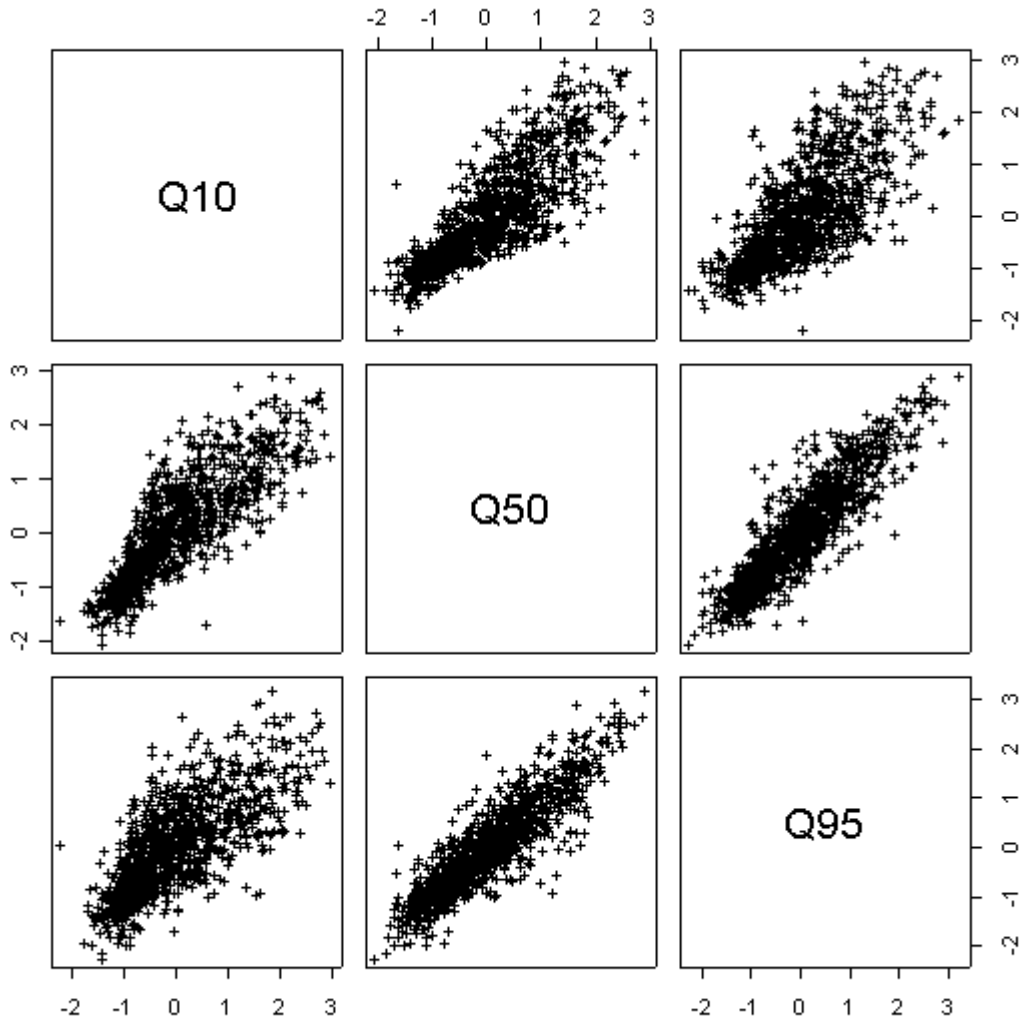

Figure 3-2. Scatter plots between standardised explanatory summer flow variables.

3.5 Temporal correlation of LIFE scores

This particular issue was raised in the specification of work, some temporal autocorrelation is likely between successive samples taken at the same site, which needs to be taken into account in any subsequent statistical analysis. Temporal autocorrelation in LIFE scores is likely to arise from two sources:

- Temporal autocorrelation in the underlying flow data, which influences LIFE scores. As long as the correct flow variables are chosen, this is minimised by simply constructing a good model to predict LIFE from flow.
- Lag in the response of the macroinvertebrate community to any changes in flow. The extent of this effect can be characterised by examining autocorrelation in the residuals of any model that predicts LIFE from flow. Autocorrelation of this type represents variation that cannot be explained using the physical explanatory variables. For regularly spaced time-series data, simple auto-regressive models can be explored. However, in this study, because there are generally missing years in each LIFE time

series, such methods would be very difficult to apply. If such autocorrelation is significant, characterising flow-related ecological stress from a single year of sample data is error-prone.

If autocorrelation is present, hypothesis tests should not be made on the basis that the samples are completely independent, and the statistics associated with the regression coefficients will look artificially high. *Figure 3-3*shows the relationships between spring and the following autumn, autumn and the following spring, autumn and the following autumn and spring and the following spring. The data shown in the spring–autumn and autumn–spring graphs are mostly, but not exclusively, the same because of the incomplete nature of the time series. *Figure 3-4*illustrates the temporal correlation for autumn LIFE observed/expected (O/E) scores for the three base flow index (BFI) categories (low, 0.4; medium, 0.4-0.7; high, >0.7) used in the subsequent analysis.

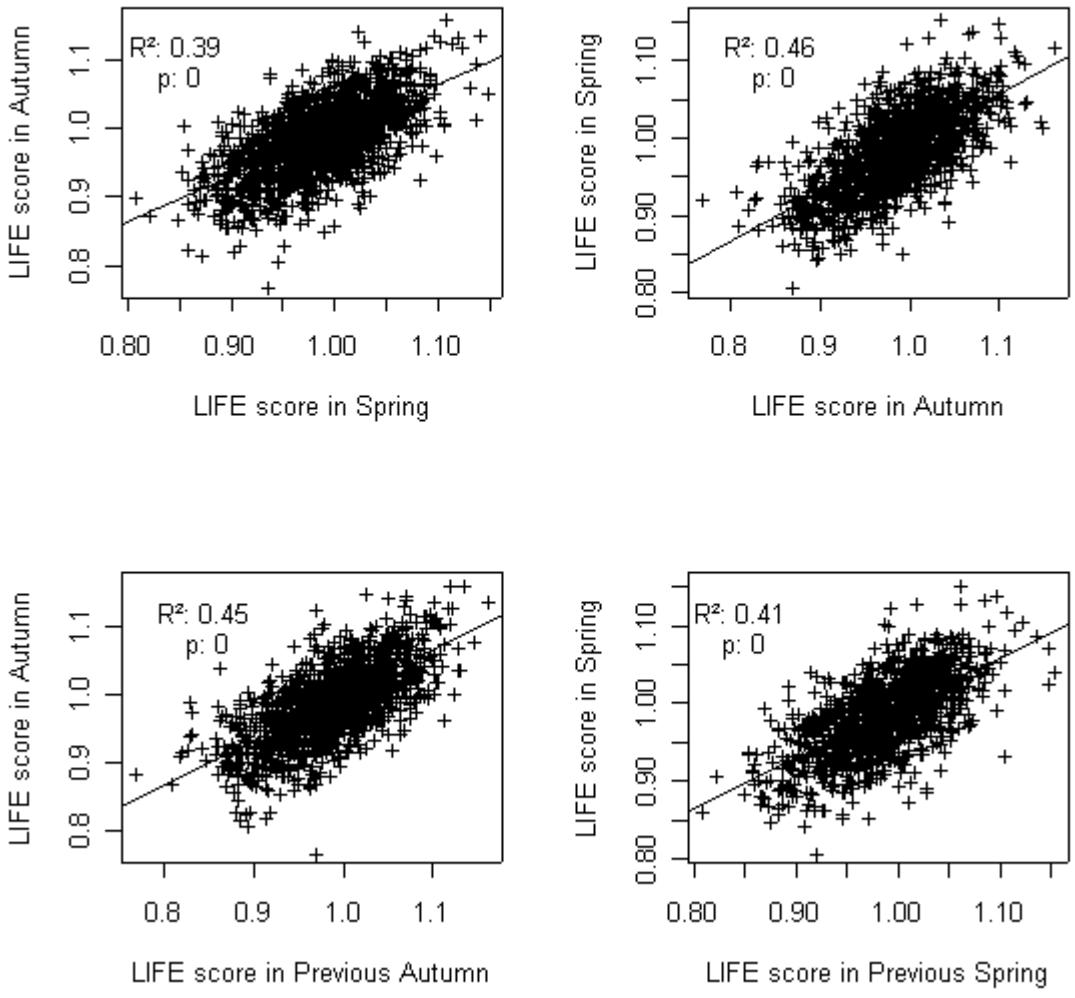

Figure 3-3. Temporal correlation in LIFE O/E scores.

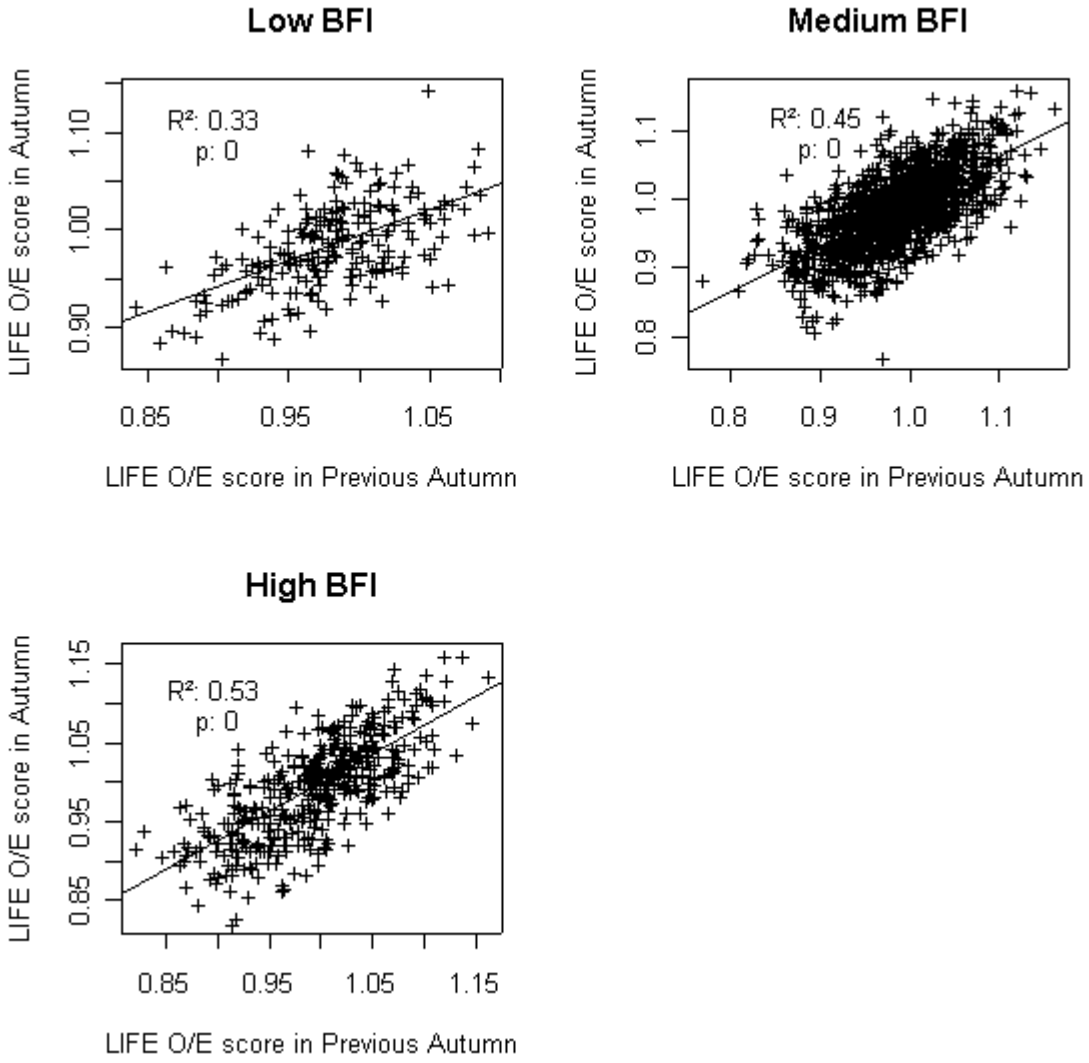

Figure 3-4. Temporal correlation in autumn LIFE O/E scores for three BFI categories (see Section 4.5).

3.6 Subsets of data used in subsequent analysis

Clearly, the overall data-set is fairly large, with approximately 7359 macroinvertebrate samples since 1 January 1989, but it is difficult, if not impossible, to analyse the data together in a linear model. When the data were restricted to samples with matching summer flow statistics, the samples reduce to 4008, and selecting particular seasons (e.g., autumn) reduces this figure further. Hence a number of subsets of data were selected for further analysis as in *Table 3-3*.

Table 3-3. Main subsets of data used in analysis

Subset ref.	Description	Number of records
0	All data, not used for any single analysis	7359
1	Autumn samples with matching flows from the preceding summer. Minimum of five data points over 14 years	1533
2	As subset 1, but including matching spring samples	1222
3	As subset 1, but with matching flows from three preceding seasons (preceding summer, preceding winter, and summer from year before)	1482
4	As subset 3, but including matching spring samples	1182
5	Both autumn and spring samples, matched to flow data 1-6 and 7-12 months before sample	2874

4 Regression analysis

4.1 Introduction

After the initial exploratory analysis, we simplified the first round of investigation of the relationship between LIFE O/E and river flow. It was clear that the significant intra-annual variation in score would be difficult to take into account in a simple regression model. It is plausible that different mechanisms affect macroinvertebrate response to flow at different times of year, and a model that incorporated differing flow indices depending on season would be fairly complex. Furthermore, the requirement of the project was to look for relationships between simple, seasonal (summer, winter) flow indices.

Thus, the first analysis was restricted to autumn LIFE O/E as the response variable. Making this restriction also reduced autocorrelation in the response variable to some extent. It was postulated that low flow stress would be greatest in the autumn period, as autumn samples would integrate the effects of flows and flow events throughout the summer. For each sample, gauged Q10, Q50, and Q95 statistics were extracted from the database and matched for the immediately preceding summer (coded IPS), the immediately preceding winter (coded IPW), and the summer of the year before (coded YBS).

We developed a set of multiple regression models to predict autumn LIFE O/E to standardised flow exceedance variables (Q10, Q50, and Q95) from the years that contained and preceded a sample. The flow variables used represented roughly[2] 0-180 days before the sample (immediately preceding summer), 180-360 days (preceding winter) and 360-480 days (summer of year before).

Model variables were selected and tested using a combination of stepwise backward selection from a larger model, combined with a common sense view of the processes likely to occur. The primary test of the model was the magnitude of the adjusted R^2; this is a model R^2 penalised to favour simpler models over more complex ones. When important variables are mentioned below, they are positively related to LIFE O/E except where stated otherwise.

Non-linearity in the response between LIFE O/E and flow, particularly at lower flows and LIFE values, was tested by inserting quadratic terms into the model. These were not, in general, significant.

4.2 Standardising flow variables

A key issue that had to be addressed at the outset of the analysis was to allow the analysis of LIFE score against flow across many sites. Clearly sites with a greater catchment area and/or greater rainfall have greater mean flows, which is reflected in their greater channel dimensions. However, the postulated mechanism through which LIFE score is linked to flow is largely based on sensitivity to water velocity and siltation, driven by flow variability and

[2]This is not exactly the case as the autumn samples were taken over the period September, October, and November, but this ± 1 month discrepancy should not affect the overall results too much or in any systematic way.

channel dimensions. As no data on channel dimensions are available, flow variables at a site must be standardised to make them comparable. Four approaches were tested.

Divide by long-term mean flow
This is the simplest approach, although outputs are potentially sensitive to the length of the long-term period of record. Rivers with a flashy regime or large difference between magnitude of high and low flows will continue to have a considerably wider range of values than less flashy or baseflow-dominated rivers. Similarly, high-flow indices (such as Q10) naturally have a greater range than low flow indices (such as Q95).

Normalise flow statistics
An alternative to the above, normalisation of a set of statistics converts a set of flow statistics for a site into a common range with a mean of 0 and a SD of 1. The sample mean of the statistics ($\bar{x}$) is subtracted from the statistic (e.g. summer Q95 for 1994), which is divided by the sample SD of the statistics (s):

$$z = \frac{x - \bar{x}}{s}$$

This standardises both the overall magnitude of flow and the variability, but is not such a severe standardisation as is the ranking of flows (see below).

Rank statistics over standard period
Table 4-1 shows an example of summer Q95 ranks. Ranking forces the flow data to a common scale regardless of the range or flashiness of the regime. The majority of sample sites did not have samples taken in every year, but this did not affect the ranking process, which was always carried out on the standard period of the record. Ranking the flow data was used in the initial data analysis, but was not used for the final analysis using the revised data-set updated to 2003.

Table 4-1. Example of ranking flow data for gauging station 347: Wharfe at Flint Mill, Weatherby

Year	Summer Q95 (m^3/s)	Rank
1995	1.797	1
1996	2.015	2
1990	2.120	3
1994	2.128	4
1992	2.131	5
1991	2.250	6
1997	2.598	7
1999	2.820	8
1993	3.137	9
1998	3.790	10

Include long-term mean flow as a term in the analysis
The approach of dividing flow by long-term mean flow is equivalent to predicting flow by the long-term mean with a coefficient of 1 and intercept through the origin. However, standardisation is simply a mechanism for coping with morphological scale effects, which may not scale in such a simple manner. For example, hydraulic geometry theory suggests that upstream and/or downstream changes in water depth, velocity, and width are governed by

flow changes and power laws with exponents that always sum to 1. If velocity is the major mechanism that actually links flow changes to LIFE score changes, one would expect alternative standardisation coefficients and intercepts to reflect actual hydraulic geometry exponents for velocity. With the data available in this project, this can be mimicked by including non-standardised flow and long-term mean flow as separate coefficients in the LIFE score regression model.

4.3 Standardising LIFE scores

Two approaches to standardising the LIFE score response were tested – firstly, LIFE scores were divided by the mean score for each site and, secondly, LIFE scores were divided by the RIVPACS expected LIFE score for the site (LIFE O/E). The former approach gives better regression-line fit than the second, but it is much less useful as a practical modelling tool. Thus most results are presented using the LIFE O/E data as the response.

Standardisation by O/E retains some variation in mean score, because expected LIFE score does not correspond to the mean LIFE score, partly through a RIVPACS model error and partly through inter-site differences in the levels and effects of abstraction and other flow-related stresses. Efforts to explain the residual variation in the O/E model are illustrated below.

4.4 Analysis using autumn data only

Firstly, separate regressions were carried out for each site separately. There were many positive relationships, but for most the slope was not statistically significant. When the data were pooled together with standardised flows, the relationships were highly significant and positive. Stepwise regression with backward selection was used with nine explanatory flow variables (Q10, Q50, and Q95 from the IPS, IPW, and YBS periods). This represents three non-overlapping periods of 0-180, 181-360, and 361-540 days before the samples. Not surprisingly, standardising LIFE score by each site's mean LIFE score gave a better model fit than standardising by RIVPACS expected LIFE score, but most of the results below are for LIFE O/E as this is the more practical indicator.

Both standardised Q10 and Q95 flow variables offered significant predictive power, while Q50 did not. In several cases, Q10 explained more variation in LIFE O/E than did Q95. However, this could, in part, arise because Q10 varies in magnitude more than Q95 does. This is supported by results that show a greater influence of Q95 compared to Q10 when using the normalised statistics rather than standardised (flow/mean flow). Residuals from all regressions are well distributed with no indication of heteroscedasticity (variance increasing with the mean) or non-normality (*Figure 4-1*) – this applies to the regressions in the following sections as well.

When relating LIFE O/E to flow, adding the IH Report 108 artificial influences index significantly improved the model fit, which indicates at a very crude level that regulation by abstractions and discharges depresses the LIFE score. Across all autumn samples, sites linked to category A and B gauges (natural or slightly influenced) gave a mean LIFE O/E of 0.994, while category C (more heavily influenced) gave a mean LIFE O/E score of 0.975. The results of adding this as a two-category factor (CURRAI2: level 1 = A or B, level 2 = C) interaction term are extremely interesting (*Figure 4-2*). There is a common slope for the LIFE–Q95 relationship, regardless of artificial influence. However, for Q10, there is an

interaction (IPSQ10z:CURRAI2) with a considerably increased slope for category C sites (Model 1):

LIFE.Y ~ IPSQ10z + IPSQ95z + CURRA12 + IPSQ10z : CURRAI2 (Model 1)

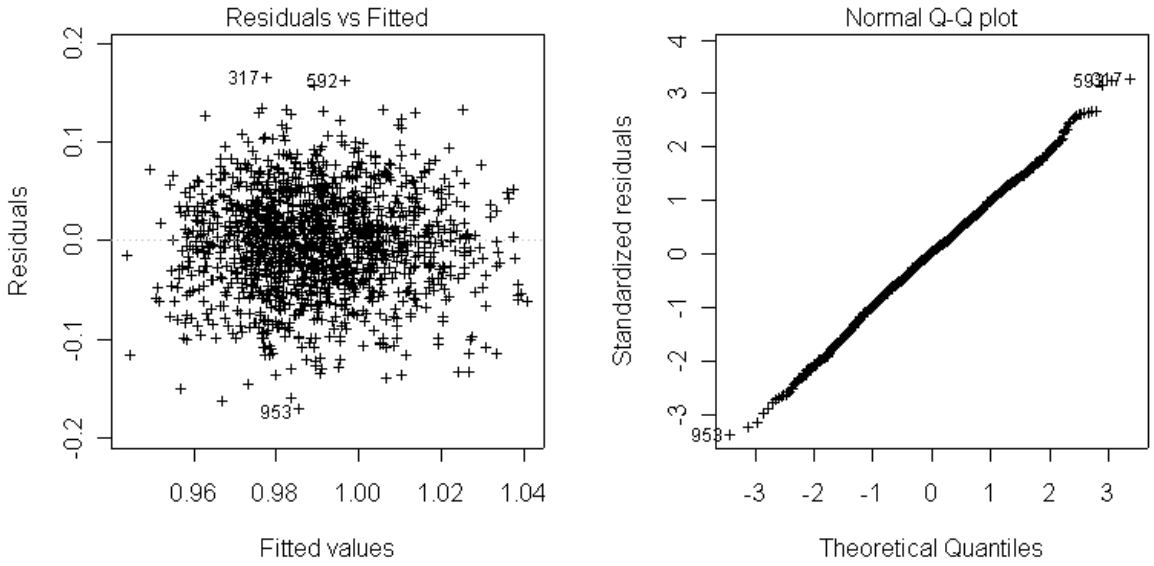

Figure 4-1. Residuals distribution for LIFE ~ IPSQ95 + IPSQ10 + CURRAI2

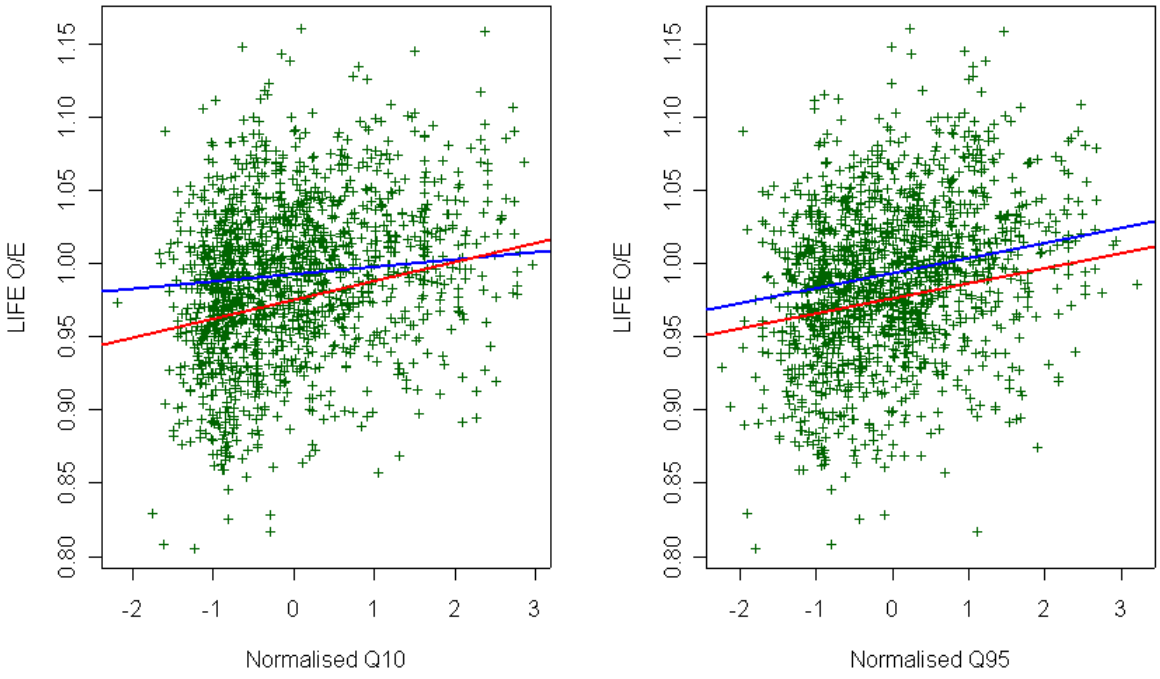

Figure 4-2. Relationship between LIFE O/E and summer Q10, Q95 plus artificial influences index. Blue line indicates category A or B, red line indicates category C.

As would be expected, adding the artificial influences index to any model already standardised by each site's mean LIFE score is not fruitful as all inter-site differences in mean LIFE score have already been eliminated. Since this is an observational study, rather than a designed experiment, it is clearly not possible to demonstrate a causative link; it could easily be some other aspect of the category C catchments that causes depressed LIFE scores. Given that improved representations of abstraction pressure are being developed, this clearly offers a fruitful line for further enquiry.

The effects of BFI and RIVPACS group as predictors are discussed in the following sections.

4.5 Effects of base flow index

The stability or variability of flows at a site might be expected to influence the strength and nature of relationships between the macroinvertebrates (and hence LIFE) and flow variables. Base flow index (BFI) is a simple measure of the stability of a flow regime, derived from the flow data record by separating flow into 'quickflow' and 'baseflow'. It can also be estimated reliably from catchment geology and soil characteristics. An extensive modelling exercise was undertaken to test how variations in BFI might link to LIFE score. This included testing interaction terms between BFI and other explanatory variables and also using generalised additive models (GAMs) and the effect of BFI as a spline function (i.e., a series of smoothly joined polynomial curves), while constraining other predictor variables as linear. The latter models test whether there is any non-linear trend between BFI and LIFE O/E, after the effects of other model variables are taken into account. BFI variation does clearly have an effect, but the pattern is complex. Three patterns have become apparent:

1. There is a better relationship between flows (as defined in this project) and LIFE in low baseflow catchments compared to high baseflow catchments.
2. The GAM model suggested similar responses, whether normalised or standardised flows were used (*Figure 4-3*, Models 2 and 3). The results suggested three BFI categories – BFI < 0.4 (no relationship between BFI and LIFE), 0.4 ≤ BFI ≤ 0.7 (positive relationship), and BFI > 0.7 (no relationship). These classes are termed low, medium, and high BFI below. These categories were used to develop sub-models of LIFE response to flow, described below.
3. Using BFI as an interaction term with flow variables indicated that the rate of decrease of LIFE score with higher winter Q10 value is greater in catchments with a high BFI. There could be any number of reasons for this. For instance, BFI could be correlated with habitat quality, which could indicate a lack of refugia in more engineered lowland rivers. Alternatively, it could represent reduced macrophyte cover following winter high-flow events.

LIFE O/E ~ IPSQ95z + IPSQ10z + IPWQ95z + IPWQ10z + CURRAI2 + s(BFI) Model 2

LIFE O/E ~ IPSQ95dMEAN + IPSQ10dMEAN + IPWQ95dMEAN + IPWQ10dMEAN + CURRAI2 + s(BFI) Model 3

where s(BFI) is a spline curve function of BFI that describes its relationship with LIFE O/E after allowing for the effect of flow variables (*Figure 4-3*).

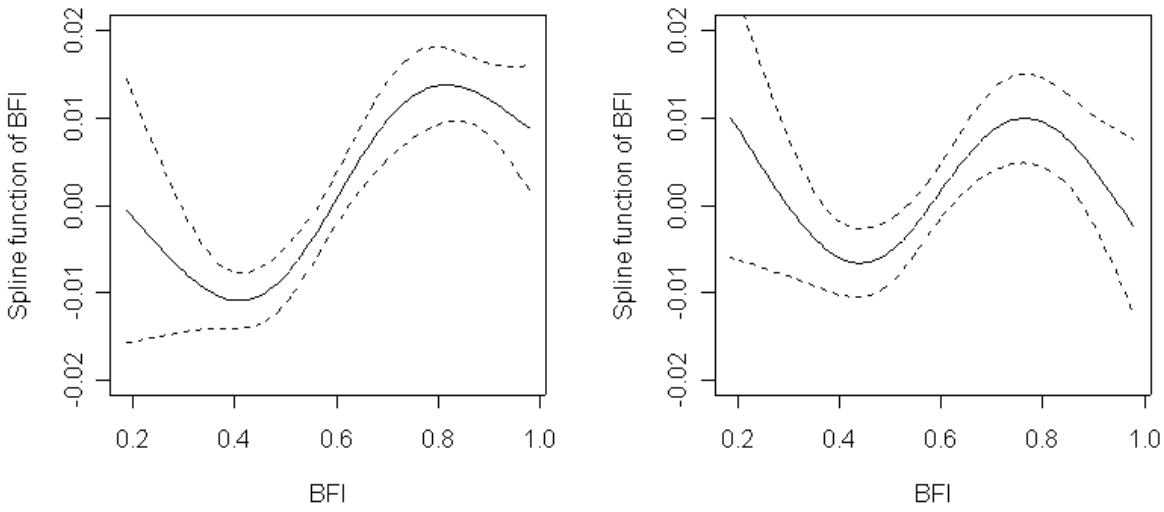

Figure 4-3. Relationship based on splines between BFI and LIFE score when using normalised flows (left-hand graph) and /mean flows (right-hand graph).

Simple univariate regressions between LIFE O/E and immediately preceding normalised Q95 and Q10 are given in *Figure 4-4*.

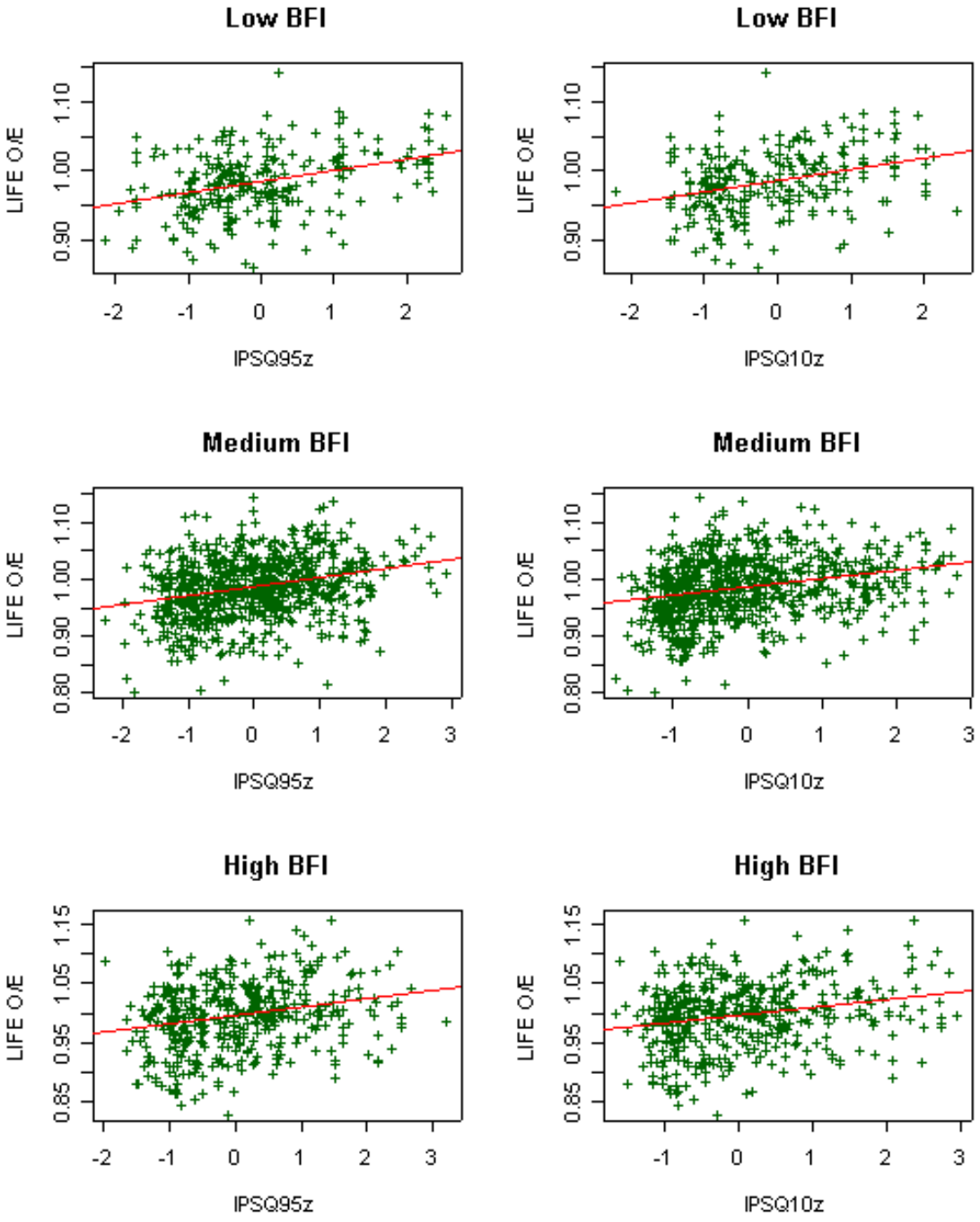

Figure 4-4. Simple univariate relationships between LIFE O/E and Q95 (left) or Q10 (right).

Finally, *Table 4-2* and *Table 4-3* illustrate the magnitude of the univariate regression coefficients for both normalised and standardised flow data. In both cases, there is a trend for the higher BFI sites to have slopes that are less steep, although this trend is enhanced, perhaps not surprisingly, when the flow data are standardised by dividing by mean flow.

Table 4-2. Slopes of univariate response of LIFE O/E to normalised flow for different BFI categories

BFI category	Slope of response for Q95	Slope of response for Q10*
<0.4	1.12	0.69 ns
>0.4 and <0.7	1.01	0.73
>0.7	0.98	0.56 ns

*ns indicates parameter not significant at $p = 0.05$.

Table 4-3. Slopes of univariate response of LIFE O/E to standardised flow for different BFI categories

BFI category	Slope of response for Q95	Slope of response for Q10
<0.4	0.27	0.030
>0.4 and <0.7	0.18	0.024
>0.7	0.05	0.018

4.6 Number of flow variables

Without the incorporation of a 'site' factor (see below), there was no clear consistent pattern between BFI and the strength of the relationship between LIFE and the various preceding flow variables. Following the results of Extence *et al.* (1999), one would expect that higher BFI sites to show stronger relationships with the longer-lagged flow variables (particularly the summer of the year before). In all cases the strongest (as measured by slope) and best fitting (as measured by standard error of slope) relationships were found with flow variables that closely preceded the sample (i.e., summer variables that preceded autumn samples). For the highest BFI sites, there were generally fewer significant variables – using normalised flows, for BFI >0.7, only one flow variable (preceding summer Q95) was significant, whereas for BFI <0.4, summer and winter Q10 and Q95 were all significant. The significant flow variables found are summarised in *Table 4-4*.

Table 4-4. Significant flow variables for models predicting LIFE O/E in three separate BFI categories

Model	BFI class	Adj R^2	CURRAI2	IPSQ95	IPSQ10	IPWQ95	IPWQ10	YBSQ95	YBSQ10
Results using normalised flows									
4	<0.4	0.18	Y	Y	Y	Y	Y		
5	0.4-0.7	0.21	Y	Y	Y				Y
6	>0.7	0.12	Y	Y					
Results using standardised flows									
7	<0.4	0.23	Y	Y	Y	Y			Y
8	0.4-0.7	0.21	Y	Y	Y				Y
9	>0.7	0.13	Y	Y	Y			Y	

NB samples matched to preceding flows only, not spring LIFE scores as well.

4.7 Catchment characteristics, RIVPACS groups, and site

It is simple to add a site factor to represent all unexplained between-site variation in site mean LIFE O/E score. When this is done, regression adjusted R^2s increase dramatically (from 0.1-0.3 to around 0.6). Regression residuals are also well behaved (*Figure 4.5*). For normalised flows, preceding summer Q10 and Q95 are most significant, followed by winter Q95. Previous summer Q95 has a weakly discernible effect (*Table 4-5*).

With three models representing low, medium, and high BFI, the adjusted R^2 is similar, not surprisingly as the BFI effect is included in the effects of' site'. In each case both the

preceding summer Q10 and Q95 are still the major controlling variables (*Table 4-5*). However, for low and medium BFIs, winter Q95 is also significant. For low BFI, winter Q10 is significant (positive relationship), but with high BFI, winter Q10 has a negative relationship with LIFE O/E. For medium and high BFIs, Q95 from the summer before has a weak effect. These results, while not conclusive, provide some evidence for a longer lag in the correlation of low flows with LIFE scores on more permeable catchments. However, across all BFI categories, the majority of the controlling effect is provided by flows in the immediately preceding 6 months. It also highlights the opposite effect of high winter flows on LIFE score on high compared to low baseflow catchments. These effects are subtle and are not seen when the SITE ID factor is omitted, as they are masked by the greater unexplained variability in LIFE O/E.

Table 4-5. Significant flow variables for LIFE O/E models that include a Site ID factor for sites in three separate categories of BFI, and for all sites analysed together

Model	BFI class	Adj R^2	IPSQ95	IPSQ10	IPWQ95	IPWQ10	YBSQ95	YBSQ10
10	All together	0.61	Y	Y	Y		Y[#]	
11	<0.4	0.63	Y	Y	Y	Y		
12	0.4-0.7	0.61	Y	Y	Y		Y[#]	
13	>0.7	0.63	Y	Y		Y*	Y[#]	

*Coefficient negative.
[#]Coefficient included by stepwise regression, but partial p >0.05 (i.e., weak effect).

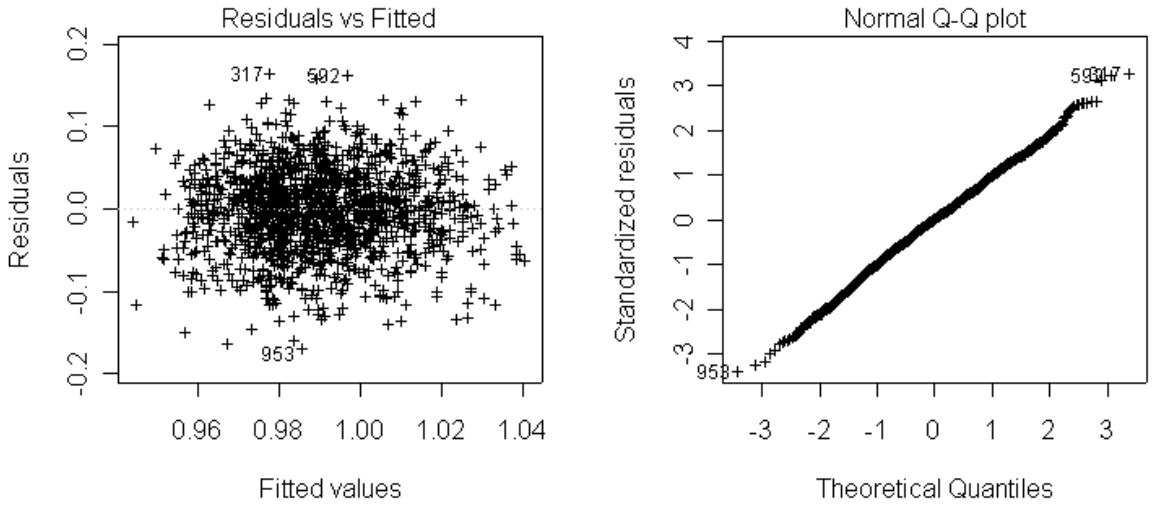

Figure 4-5. Regression diagnostic plots for model with Site ID factor

For flows standardised by mean flow, again for high BFI sites, winter Q10 is again negatively associated with LIFE, but the preceding summer Q95 is not significant. For low BFI sites, the year before summer Q10 replaces winter Q95 in the model. These results may simply show that, overall, high flows have more control on LIFE scores because they vary in magnitude more than low flows do.

A site factor may be added as an interaction term to various flow terms, which is equivalent to separate regression models for each site, with slope and intercept being allowed to vary. These models do have to be kept simple though, to aid interpretation and to not use large

numbers of degrees of freedom. In practice, the site-by-flow interaction is not significant, which indicates that there is no evidence that the different sites have different slopes of response of LIFE score to flow. This could, at least in part, result from the relatively small numbers of data points available to estimate the relationship for each site (between five and 14).

In general, catchment, site characteristics (e.g., catchment area, water width), and RIVPACS group (2, 3, 4 categories) did not add major explanatory power to the LIFE O/E models. In particular, RIVPACS group did not seem to affect the slope of response of LIFE score to flow. One exception was that when RIVPACS group was set to two categories (separating out lowland streams), and used to predict mean-standardised LIFE score (STD_LS).

STD_LS ~ IPSQ10z + IPSQ95z + RivGrp2 (Model 14)

The lowland streams had higher mean-standardised LIFE scores than the non-lowland streams.

The lack of clear relationships with RIVPACS group for the LIFE O/E data could have been because of the over-riding unexplained variation in mean LIFE score. However, it is still difficult to see any relationship when LIFE was standardised by mean site LIFE score. Thus, either a relationship is simply not evident with this data-set, or a relationship is being masked by some atypical sites.

4.8 LIFE score versus ASPT

In the initial phase of analysis (using 1990-1999 data), the prediction of standardised APST score and standardised LIFE score by flow was compared. The ASPT score is calculated in a comparable manner to the LIFE score, but does not take into account observed abundances, and each taxon is weighted by its perceived sensitivity to organic pollution. Before the publication of the LIFE method, ASPT score had been used to index the response of the macroinvertebrate community to flow (Armitage and Petts, 1992; Brown *et al.*, 1991). In the current study data-set, the adjusted R^2 was 0.09 for predicting ASPT using ranked flow data, compared to 0.35 for predicting LIFE. Thus, LIFE score is more closely related to flow variation than is ASPT, as intended.

4.9 Use of spring scores as a predictor of autumn scores

Spring LIFE O/E scores are strongly correlated with autumn LIFE O/E scores. Adding spring LIFE O/E to the model that predicts autumn LIFE O/E gives statistically significant improvements to the fitted models, with adjusted R^2 values of 0.37, 0.43 and 0.47 for the three BFI categories. This suggests greater intra-annual lag in the community response within the higher BFI catchments. *Table 4-6* illustrates the R^2 values for a selection of models that predict LIFE score in the autumn from LIFE score in the spring plus normalised flows.

Table 4-6. Comparison of R^2 values for models with and without OELIFE_SPRING and SITE.ID

Model	Model form	Adjusted R^2
14	LIFE.Y ~ IPSQ10z + IPSQ95z + SITE.ID + OELIFE_SPRING	0.617
15	LIFE.Y ~ IPSQ95z + SITE.ID + OELIFE_SPRING	0.616
16	LIFE.Y ~ IPSQ95z + OELIFE_SPRING	0.423
17	LIFE.Y ~ IPSQ95z + SITE.ID	0.585

4.10 Both spring and autumn samples together

A data matrix was constructed with both spring and autumn LIFE O/E scores as response variables, predicted by flows in the appropriate preceding 6 months and the 6 months before that (i.e., 7-12 months before the sample was taken). A two-level factor SEASON identified whether the data point was spring or autumn, and this was used as an explanatory variable in the model. The flow variables that represented 7-12 months before offered no additional predictive power so were dropped, The adjusted R^2 of this overall model was 0.10. The season factor was significant and indicated that there are, on average, higher LIFE O/E scores in spring than in autumn, *even controlling for the fact that flows are higher in winter than in summer*. In contrast to the previous analysis using 1990-1999 data, the slope of response to flow was no different for spring and autumn samples (i.e., there was no flow–season interaction to the response). A GAM model suggested the same three BFI categories as determined for the autumn data alone, giving adjusted R^2s for low, medium, and high BFIs of 0.13, 0.19, and 0.13, respectively. On average, higher BFI corresponds to higher LIFE O/E.

LIFE.Y ~ SEASON + SMBQ95z + SMBQ10z + CURRAI2 Model 18
LIFE.Y ~ SEASON + SMBQ95z + SMBQ10z + CURRAI2 + s(BFI) Model 19

where s(BFI) is a spline function of BFI effect of order 5.

4.11 Adding mean flow as a term in the model

The addition of mean flow was suggested in the original brief, and was tested by comparing the models that predicted unstandardised LIFE score:

LIFE ~ ELIFE3 + log(IPSQ95dMEAN) + log(IPSQ10dMEAN) Model 20
and

LIFE ~ {ELIFE3 – log(MEANFLOW)} + log(IPSQ95RAW) + log(IPSQ10RAW) Model 21

Adjusted R^2 was 0.55 for the first case, and 0.35 for the second. These R^2 values cannot be compared to the values for the models that predict LIFE O/E – for the simple model LIFE_F ~ ELIFE3, the R^2 is 0.48.

4.12 Autocorrelation in LIFE scores

In Section 3, as the extent to which successive autumn LIFE O/E values are correlated is demonstrated, and this correlation is shown to be greater in higher BFI catchments. As discussed above, there are at least two separate sources of autocorrelation, arising from the controlling flow data and from lag in the community response. To test this, the residuals from

models 4-6 (basic models in the three BFI classes) and model 10 (model with a 'site' factor) were extracted. For models 4-6, the residuals were standardised by their mean value on a site-by-site basis, to remove any spurious correlations caused by differences in LIFE O/E.[3]

Where a sample could be matched with a sample from the following year at the same site, the residual was matched to the residual for the subsequent year. Residuals were then correlated against residuals for the subsequent year. The results are presented in *Table4-7*, along with information on the correlation of LIFE scores.

Table 4-7. Correlation between successive autumn LIFE O/Es and for residuals from models that predict autumn LIFE O/Es from flows

BFI category	Correlation R^2 between successive autumn LIFE O/Es (data matched to flow variables)	Correlation R^2 between successive autumn LIFE O/Es (data not matched to flow variables): larger data-set	Correlation R^2 between successive model residuals, standardised by their site mean values
<0.4	0.26	0.33	0.036
0.4–0.7	0.42	0.41	0.023
>0.7	0.50	0.53	0.013

The correlation R^2 for these analyses were extremely low (less than 0.04). This result is important as it suggests that autocorrelation between successive autumn LIFE O/E values is largely caused by autocorrelation in the flow statistics.

4.13 Data from the North West Region

Bank-sorted data from the North West Region were excluded from the above analysis. However, it was thought useful to test the relationship between LIFE score and discharge in this region. Matching autumn samples to flows the immediately preceding summer gave 72 data points from 13 rivers, whereas matching autumn samples to flows in the preceding 18 months gave 55 data points from the same 13 rivers. Stepwise regression with backwards selection was used to fit a model, and further terms were deleted by hand (*Table 4-8*).

Table 4-8. Models for the North West Region

Model	Model form	Adjusted R^2	Figure
22	LIFE.Y ~ IPSQ10z + IPSQ95z + BFI	0.31	*Figure 4-6*
23	LIFE.Y ~ IPSQ10dMEAN + IPWQ95dMEAN + YBSQ95dMEAN	0.40	*Figure 4-7*

The artificial influences indicator could not be included for the North West Region as there were no class C (highly influenced) gauges.

[3]The same thing could be accomplished by using LIFE/(mean site LIFE score) as the response variable, which again removes inter-site differences in mean LIFE score.

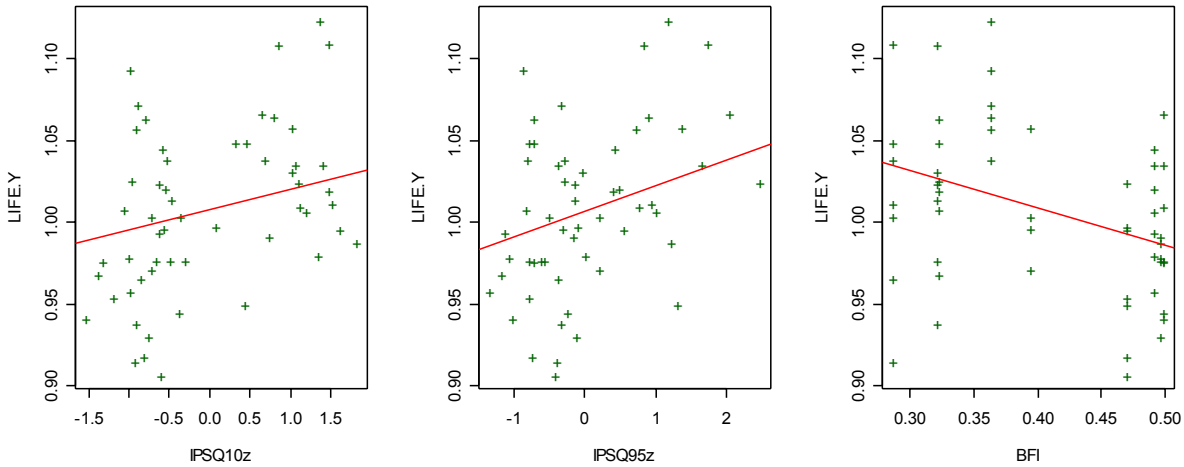

Figure 4-6. Relationships between normalised flows, BFI, and LIFE O/E for North West Region rivers, together with the fitted regression lines (for average values of the other predictor variables).

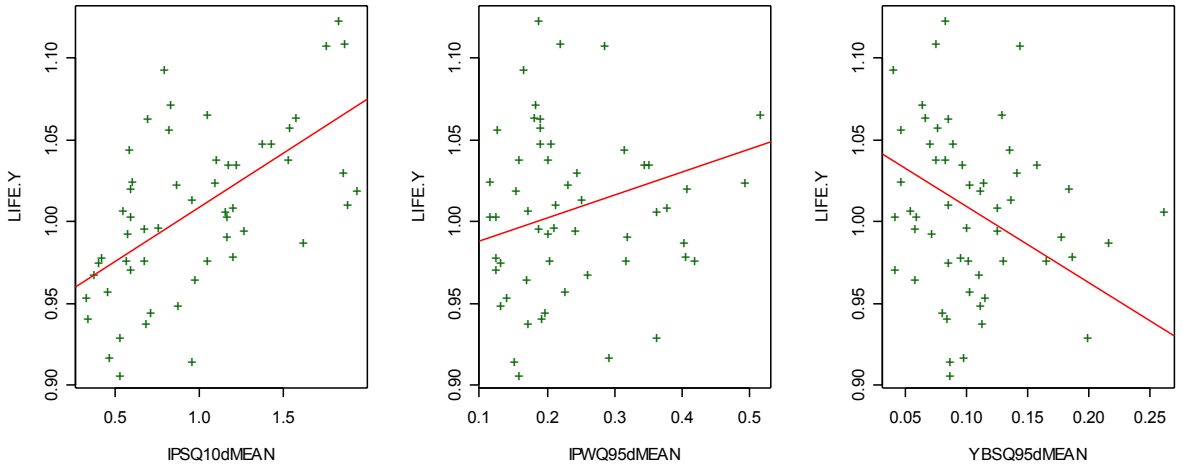

Figure 4-7. Relationships between flow (standardised by mean flow), BFI, and LIFE for North West Region rivers, together with the fitted regression lines (for average values of the other predictor variables).

As a contrast, this exercise was repeated for the North East Region. Using normalised flows, this gave a best model of:

LIFE.Y ~ IPSQ10z + IPSQ95z + BFI + CURRAI2

and an adjusted R^2 of 0.13. Using flows standardised by mean flow the best model was:

LIFE.Y ~ IPSQ10dMEAN + IPWQ95dMEAN + BFI + CURRAI2

and roughly the same goodness of fit with an adjusted R^2 of 0.12.

5 Sampling variation in observed LIFE

5.1 Introduction

Uncertainty in observed LIFE values because of replicate macroinvertebrate sampling variation and within-season variation in observed LIFE influences the precision of any assessments of flow-related stress at river sites based on the O/E ratio of observed (O) to RIVPACS site-specific expected (E) values of LIFE.

Variation in observed LIFE through sampling variation also limits the maximum potential strength of the relationship between observed life and any critical flow parameters.

Therefore, it is important to have an estimate of the variance in LIFE between replicate samples taken on the same day, and of the variance between macroinvertebrate samples taken over the same seasonal period at any one site that are all associated with the same value of the flow statistic (e.g., summer Q10 or Q95).

5.2 Overview of biological assessment methods study results

Furse *et al*. (1995) conducted a detailed investigation of the effect of replicate sampling variation on the observed values of BMWP score, number of BMWP taxa, and ASPT. This designed study was carried out at 16 sites – four RIVPACS major stream types at each of the four NRA 1990 River Quality Survey (RQS) biological quality grades. Both CEH and the Environment Agency refer to these sites as the BAMS (Biological Assessment Methods) sites. At each BAMS site in each of the three RIVPACS seasons –'spring' (March–May), 'Summer' (June–August) and autumn (September–November) – three replicate samples were taken, two by one person and a third by a second person. Clarke *et al.* (2003) summarised the analysis and results. Replicate sampling variation in ASPT was found to be roughly constant; it did not depend on either the physical type or biological quality of the site, but only on whether the ASPT was based on single-season samples or on combined samples from two or three seasons (*Table 5-1*). By working with the square root transformed values of BMWP score and of number of BMWP taxa, their replicate sampling SDs were also found to be roughly constant, depending only on the number of seasons involved (*Table 5-1*).

Table 5-1. Overall estimates of replicate sampling SD for the square root of number of BMWP taxa (√T), the square root of BMWP score (√S), and of ASPT – taken from Clarke *et al.* (2003).

Seasons involved in overall sample	√T	√S	ASPT
1	0.228	0.588	0.249
2	0.164	0.418	0.161
3	0.145	0.361	0.139

As part of the previous R&D study to investigate the relationship between the LIFE index and RIVPACS (*Putting LIFE into RIVPACS*), Clarke *et al.* (2003) used the replicate samples

macroinvertebrate community data at the BAMS sites to investigate the effect of replicate sampling variation on observed LIFE values. They found that replicate sampling variation did not appear to vary systematically between different types of site or between seasons. Sampling variance in LIFE did not appear to increase systematically with the mean of the replicate LIFE values.

However, Clarke *et al.* (2003) did find that the replicate sampling SD of LIFE did decrease with the average number of LIFE-scoring families involved in calculating the replicate values of LIFE for that site-season combination (Spearman rank correlation = –0.54). The highest values of SD (i.e., >0.5) all occur when the replicate values of LIFE are based on an average of less than five families. At the other extreme, when the average number of LIFE-scoring families found in replicate samples is at least 15, the sampling SD is always relatively small (i.e., <0.2).

Based on the BAMS data-set, the relationship between replicated sampling SD of LIFE and the number (N_{LIFE}) of LIFE-scoring families present is best estimated by a linear regression relationship between log SD and N_{LIFE} (*Figure 5-1*), which is statistically significant (r = –0.68; p = 0.001) and given by (standard errors of regression coefficients given in brackets):

$$\log_e \text{SD} = \underset{(0.224)}{-0.528} \underset{(0.0180)}{- 0.1154\, N_{LIFE}} \qquad (5.1a)$$

which can be re-written as:

$$\text{sampling SD} = 0.590(0.8945)^{N_{LIFE}} \qquad \textbf{(5.1)}$$

Equation (5.1) can be used to provide an estimate of the unknown replicate sampling SD for any site using just the observed number of LIFE-scoring families present in a single sample; examples are given in *Table 5-2*. The BAMS study estimate of the overall average replicate sampling variance of LIFE was 0.1064, giving an average replicate sampling SD of 0.326.

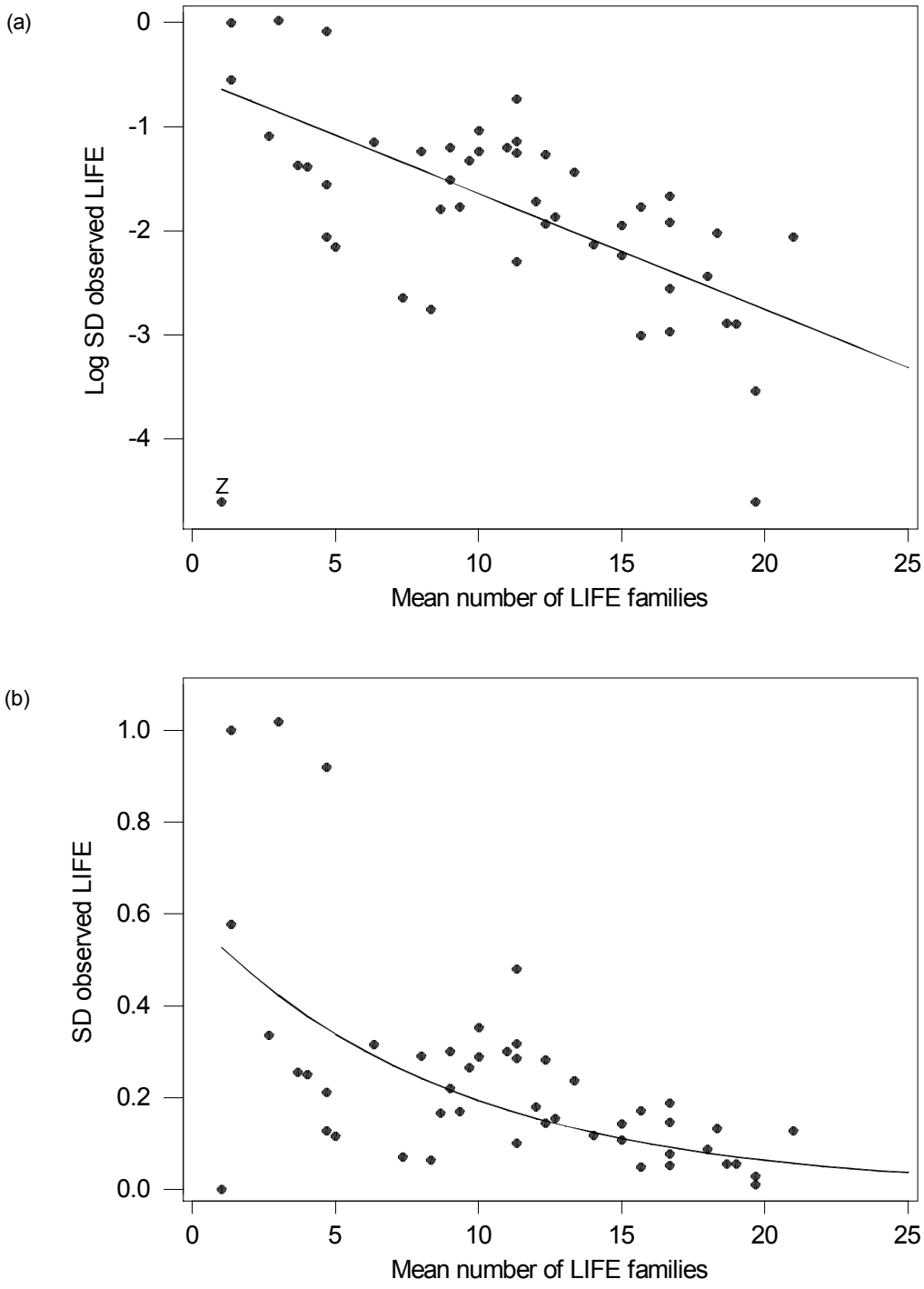

Figure 5-1. Relationship between SD of the three replicate values of LIFE for each season at each BAMS site and the mean number (N_{LIFE}) of LIFE-scoring families present in each replicate. Figures (a) and (b) show SD on logarithmic and untransformed scales, respectively. Fitted lines are based on Equation (5.1).

Table 5-2. BAMS-study estimate, based on Equation (5.1), of replicate sampling SD of observed LIFE for sites where N_{LIFE} LIFE-scoring families are present in a sample.

Number of LIFE-scoring families present (N_{LIFE})	Sampling SD
1	0.528
2	0.472
3	0.422
4	0.378
5	0.338
6	0.302
7	0.270
8	0.241
9	0.216
10	0.193
12	0.155
15	0.111
20	0.063
25	0.036
Average BAMS sampling SD	0.236

Thus, the BAMS study information can be, and has been, used to provide estimates of the susceptibility of biotic indices, such as BMWP score, number of BMWP taxa, ASPT, and LIFE, to variation caused by differences between replicate RIVPACS samples in their macroinvertebrate community composition and abundances. Although variation between replicate samples is likely to be the major source of variation and uncertainty in biotic index values at a site within a RIVPACS season, there is also additional within-season temporal variation in the sampled macroinvertebrate community and hence in the index values. The aim of the current study is to use any available data on sites for which more than one macroinvertebrate sample was taken in the same RIVPACS season, but not necessarily on the same day.

5.3 Data available for analysis of within-season variation

CEH were provided with the observed values of LIFE based on macroinvertebrate family-level composition for a total of 8241 samples over the period 1974-2003. Samples came from a total of 289 sites, with the total number of macroinvertebrate samples per site ranging from nine to 58. *Table 5-3* gives the overall number of samples taken in each month of each year.

Table 5-3. Total number of samples available for each month of each year

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
1974	0	0	0	0	0	0	0	0	0	0	1	0	1
1975	1	0	0	0	1	1	0	0	0	0	0	1	4
1976	1	0	0	0	0	2	0	0	0	0	0	2	5
1977	1	0	0	0	0	1	2	0	0	0	3	0	7
1978	0	0	1	0	1	0	1	2	2	0	1	1	9
1979	3	0	0	0	4	0	1	3	2	0	3	1	17
1980	5	1	1	1	1	6	2	1	3	1	3	3	28
1981	4	1	5	0	2	5	0	1	0	1	3	0	22
1982	3	2	1	4	2	5	0	1	5	4	4	0	31
1983	6	3	5	2	0	2	3	3	6	0	3	3	36
1984	6	3	16	4	3	8	11	8	2	9	12	2	84
1985	8	15	20	16	15	6	18	13	17	14	7	13	162
1986	3	8	3	13	16	24	7	15	17	19	9	9	143
1987	6	17	26	17	13	20	18	20	12	13	22	13	197
1988	6	20	13	10	9	31	6	17	18	16	12	10	168
1989	7	11	23	19	27	46	20	19	32	36	55	27	322
1990	7	11	101	74	42	75	86	61	67	113	65	6	708
1991	2	12	64	84	87	47	107	77	49	99	59	22	709
1992	11	23	37	63	73	73	70	46	51	62	37	38	584
1993	12	14	45	37	65	65	66	47	39	73	80	9	552
1994	0	7	36	29	57	51	33	37	35	52	63	20	420
1995	0	3	82	95	112	0	1	5	78	120	88	0	584
1996	3	0	20	58	132	28	14	24	42	110	54	23	508
1997	3	5	41	62	95	26	39	31	71	107	39	16	535
1998	0	3	51	62	128	3	12	13	57	68	96	4	497
1999	0	5	56	83	75	8	8	24	51	95	82	14	501
2000	0	1	81	51	151	18	17	9	70	91	39	29	557
2001	2	0	1	6	41	6	12	16	46	49	64	7	250
2002	4	1	47	84	64	4	16	11	80	56	43	2	412
2003	0	0	38	36	35	0	2	1	31	30	15	0	188
Total	104	166	814	910	1251	561	572	505	883	1238	962	275	8241

However, in only a very small proportion of cases was more than one sample taken from the same site on the same day (

Table 5-4). In total there were only 12 cases in which two replicate samples were taken on the same day at the same site. For the purpose of this analysis, the small percentage of samples from December, January, or February were ignored and data were grouped into the three RIVPACS seasons recommended for sampling macroinvertebrates, This was done to estimate variance between samples taken at the same site in the same RIVPACS season, but not necessarily on the same day.

In total, there were 138 cases in which two samples were taken from the same site in the same season of one year (*Table 5*). In an additional 12 cases three samples had been taken within one season, one case with four samples – River Derwent at Whatstandwell (SK331543 – site ID 47138) in the summer of 1987 – and one case with five samples – River Ribble at Brockholes Bridge (SD576300 – site ID 64957) in the summer of 1993). Thus, in a total of 152 cases a site was sampled more than once during the same 3 month seasonal period within 1 year, and the cases were spread evenly across the three RIVPACS seasons.

Table 5-4. Number of cases in each RIVPACS season with one or two samples per site per day

	Cases with *s* samples per site per day	
	1	2
Spring (March–May)	2957	9
Summer (June–September)	1638	0
Autumn (August–November)	3077	3
Total	7672	12

Table 5-5. Number of cases in each RIVPACS season with 1, 2, 3, 4, or 5 samples per site per season per year

	Cases with s samples per site per season per year				
	s = 1	s = 2	s = 3	s = 4	s = 5
Spring (Mar-May)	2864	48	5	0	0
Summer (Jun-Sep)	1541	38	4	1	1
Autumn (Aug-Nov)	2970	52	3	0	0
Total	7375	138	12	1	1

Obviously, one reason why more than one sample per season was taken on occasion at some sites could have been because local biologists were investigating a known or suspected change in water quality or environmental stress. Thus, these multi-sample cases might give an overestimate of the 'natural' within-season temporal variability in LIFE. However, this is the best information available. As random examples, the variation among the four samples taken in summer 1987 at the Whatstandwell site (*Figure 5-2*) is much less than the long-term variability at the site, whereas the range of 1.02 in LIFE values among the five samples taken in summer 1993 at the Brockholes Bridge site (*Figure 5-3*) is relatively large. Three samples were also taken from the latter site during autumn 1993, which suggests a concern about the biological quality at the site.

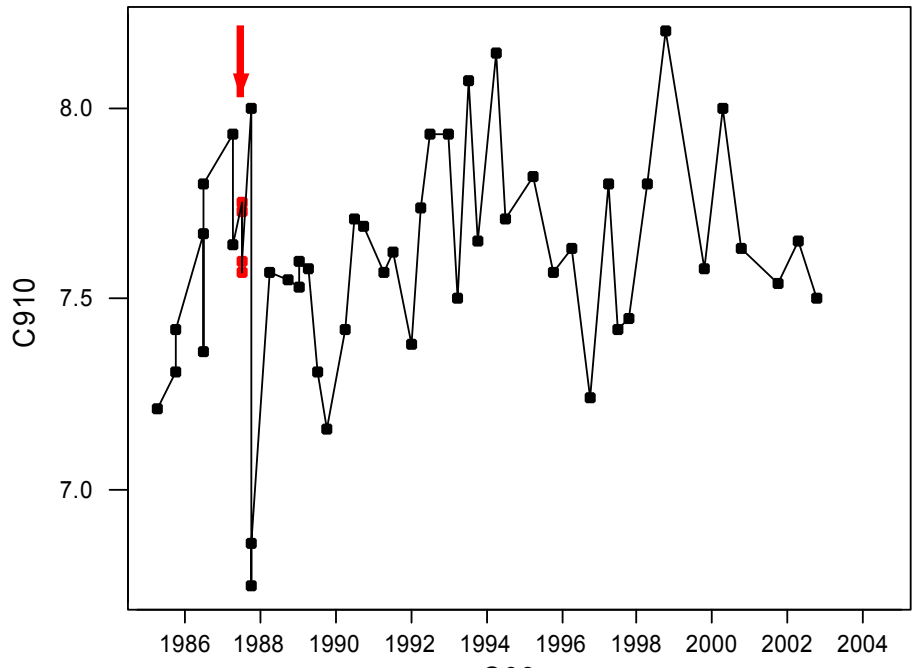

Figure 5-2. Plot of LIFE for samples taken from the River Derwent at Whatstandwell (SK331543 – site ID 47138) over the period 1985-2002; the arrow highlights summer 1987 when four samples were taken during one season.

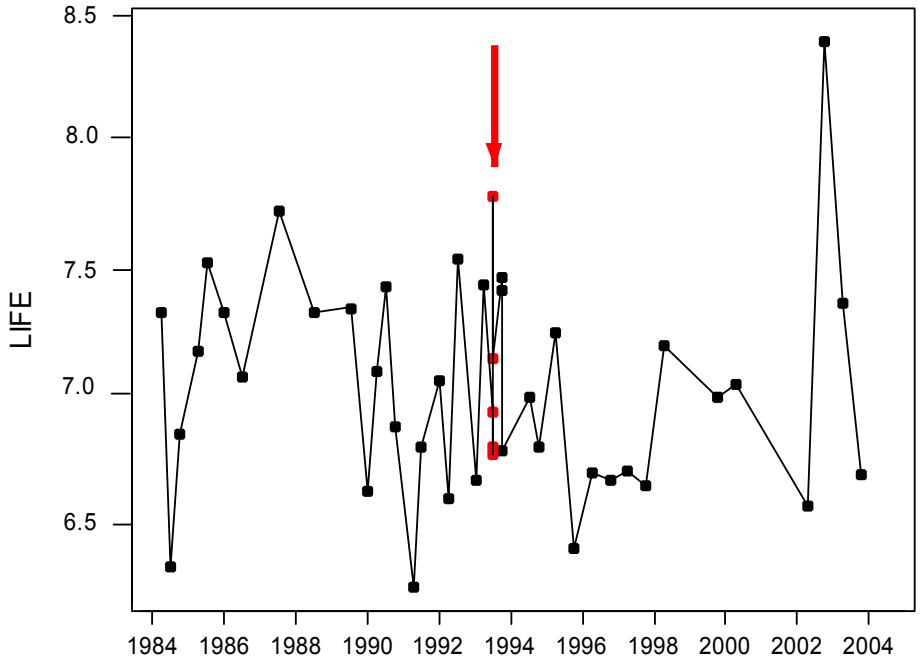

Figure 5-3. Plot of LIFE for samples taken from the River Ribble at BrockHoles Bridge (SD576300 – site ID 64957) over the period 1984-2003; the arrow highlights summer 1993 when five samples were taken during one season.

5.4 Statistical estimation of variability

The variance in LIFE caused by replicate sample variation is estimated from the 12 cases in which two replicate samples were taken on the same day (akin to the BAMS replicate study). This is not sufficient information to derive accurate estimates of the inter-replicate (same-day) variance, but it is the best available within this study. Variance in index values between samples taken from the same site in the same season, but on different days, include the variance (σ_R^2) that arises from inherent variation between replicate macroinvertebrate samples, but also an additional variance component (σ_S^2) from short-term (i.e., within-season) temporal variability.

The two variance components, σ_R^2 and σ_S^2, were appropriately estimated using an unbalanced nested general analysis of variance that eliminated all differences between site–year–season combinations. The analysis was performed using model procedure GLM in the Minitab statistics software package (Minitab Release 13.1). The total within-season variance in observed LIFE is then estimated by $\sigma_T^2 = \sigma_R^2 + \sigma_S^2$. Expressing each variance component as a percentage of this total also gives an impression of their relative magnitude and contribution to uncertainty in site assessments.

As there were so few true replicate samples, the estimates of both variance components are unlikely to be precise, as is the estimate of the relative size and importance. Therefore, an alternative, simpler estimate, σ_A^2, of the total within-season variance in LIFE was obtained using a one-way ANOVA in which each site–year–season combination was treated as a different group and σ_A^2 is the weighted-average within-group variance obtained from the ANOVA model error mean square. The two estimates, σ_A^2 and σ_T^2, of total within-season variability are usually similar, although in theory σ_T^2 should be the better estimator as it correctly separates replicate within-day variance from the between-day variance.

Table 5-6 estimates the variances components for variation in observed LIFE. The estimate of the average replicate SD based on the 12 cases with two samples taken on the same day is only 0.147, which is considerable less than the equivalent BAMS study estimate of 0.326. However, the number of LIFE-scoring taxa per sample in the BAMS study was less (median = 11, range 1-25) than that for the replicate samples in the current study (median = 18, range 3-36). It has already been shown that the sampling SD of LIFE decreases with the number of LIFE-scoring taxa present (*Table 5.2*, *Figure 5.1*). This may be sufficient to explain the discrepancy in the two estimates of average replicate SD.

The overall estimates of within-season sampling SDs are 0.270 or 0.277 (*Table 5-6*). These are only moderately less than the overall average replicate sampling SDs from the BAMS study (*Table 5-2*), which suggests that they are realistic estimates of the typical variation (i.e., SD) that can occur in observed LIFE values by chance within any one season at a single site.

Table 5-6. Estimates of the components of within-season variability in observed LIFE.

Source of variation	d.f.	Symbol	Variance estimate	Per cent variance	SD = $\sqrt{\sigma^2}$
Between same-day replicates	12	σ_R^2	0.0215	28%	0.147
Within-season temporal	157	σ_S^2	0.0553	72%	
Total within-season variance		$\sigma_T^2 = \sigma_R^2 + \sigma_S^2$	0.0768	100%	0.277
Simple average within-season variance	169	σ_A^2	0.0728		0.270

In the current data-set, the within-season sampling SD was also found to decrease with the average number (N_{LIFE}) of LIFE-scoring families present per sample. The relationship was best estimated by a linear regression relationship between log SD and N_{LIFE} (*Figure 5*), which is statistically significant (r = –0.33; p = 0.001) and given by (standard errors of regression coefficients given underneath in brackets):

$$\log_e \text{SD} = -0.990 - 0.0581\ N_{LIFE} \qquad (5.2a)$$
$$\qquad\qquad (0.263) \quad (0.0137)$$

which can be re-written as:

$$\text{sampling SD} = 0.372(0.9436)^{N_{LIFE}} \qquad (5.2b)$$

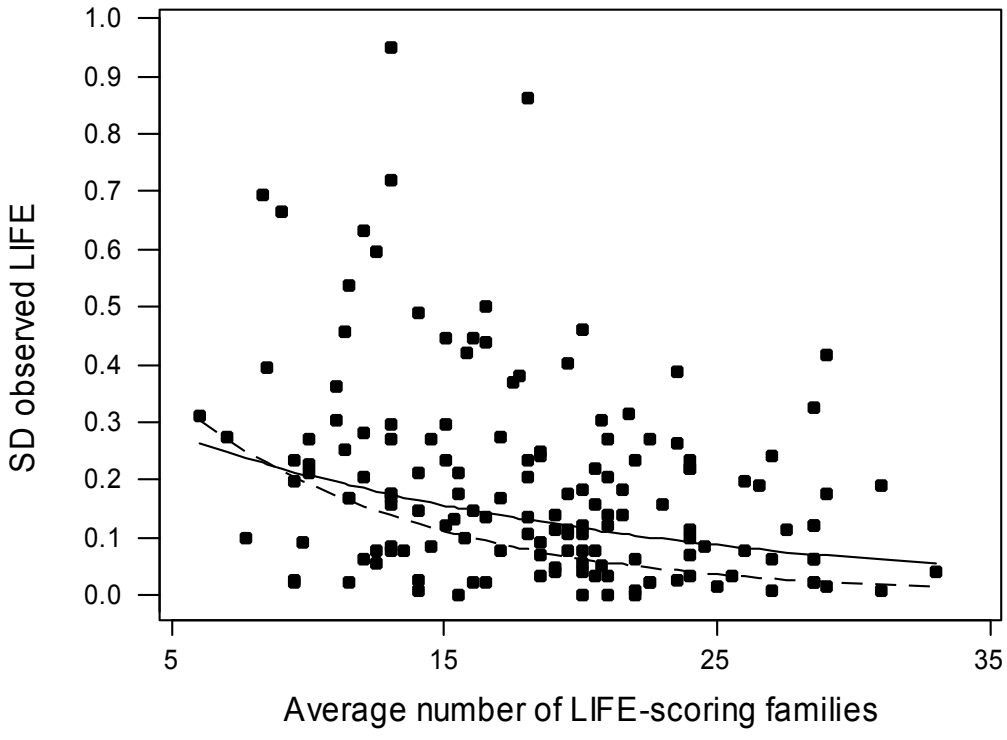

Figure 5-4. Relationship between SD of observed LIFE within a season at a site and the average number of LIFE-scoring families present in each sample. Solid line denotes the fitted regression relationship of Equation (5.2), while the dashed line gives the equivalent regression relationship from the BAMS study sites for the replicate sampling SD.

In *Figure 5-4*, the equivalent relationship between replicate sampling SD and N_{LIFE}, given by Equation (5.1) is superimposed for comparison. The two estimated relationships are generally consistent in that the within-season sampling SD, estimated from this study, is higher than the purely replicate (within day) sampling SD estimated from the BAMS study. The two relationships are compared in *Table 5-7*, which can be used to derive estimates of uncertainty in observed values of LIFE for other studies.

Table 5-7 Estimates of sampling SD of observed LIFE in relation to average number of LIFE-scoring families present in a sample; replicate sampling SD estimates based on Equation (5.1) from the BAMS study; within-season sampling SD based on Equation (5.2) from this study; estimates in brackets are extrapolations beyond the available data range

Number of LIFE-scoring families present (N_{LIFE})	Replicate sampling SD (from BAMS)	Within-season sampling SD (this study)
1	0.528	(0.351)
2	0.472	(0.331)
3	0.422	(0.312)
4	0.378	(0.295)
5	0.338	0.278
6	0.302	0.262
7	0.270	0.247
8	0.241	0.233
9	0.216	0.220
10	0.193	0.208
12	0.155	0.185
15	0.111	0.155
20	0.063	0.116
25	0.036	0.087
30	(0.021)	0.065
35	(0.012)	0.049

In summary, replicate sampling and within-season variability in LIFE score decreases with the number of taxa present in the samples. Thus, in poorer quality or highly impacted sites with fewer taxa present, LIFE O/E is expected to be lower, but also more prone to sampling variability. Hence LIFE O/E estimations are less precise than those for high-quality unstressed sites.

The figures for simple, average within-season sampling variance was compared with the overall variation in LIFE score from the data-set as a whole, measured as total mean squares. This represents a rough calculation of within-season sampling variance as a proportion of the total variance of LIFE scores. It gives (in units of variance, i.e., LIFE O/E squared) both an estimated lower limit to the total sum of squares of the data, and an estimated maximum possible R^2 for any regression model (*Table 5-8*).

Table 5-8. Comparison of simple average within-season variance and total variance in LIFE (family)

A. Simple average within-season variance	0.0728
B. Mean sum of squares of LIFE (family) in data-set	0.2637
Ratio A/B	0.27 or 27 per cent
Maximum model R^2 :1 – (A/B)	0.72 or 72 per cent

This analysis does not include uncertainties in expected LIFE. Also, it does not include the variation in sampling variance with number of LIFE-scoring families, and the sampling variance is based on limited data. However, it does give a very rough indication of the maximum possible R^2 of a model that predicts LIFE (family) of around 0.75.

6 Conclusions

Although over 8000 macroinvertebrate samples are available for analysis in the database, only a much smaller subset could be analysed together. Linear modelling has demonstrated that autumn LIFE O/E does, indeed, vary systematically with flow. Flow variables from the immediately preceding summer are the most important in explaining variation. The relative importance of high and low flow variables can depend on how they are standardised. The simplest models, which explain variation in LIFE O/E solely on preceding flows, confirm the validity of the LIFE approach, but they do not explain a high proportion of overall variation in LIFE O/E.

Factors that improve the fit of the basic LIFE flow model are

- whether there are significant artificial influences in the catchment;
- base flow index –(BFI),by dividing the data into several sub-models based on classes of BFI;
- immediately preceding spring sample LIFE O/E;
- a 'site' factor to encompass all unexplained variation in mean LIFE O/E.

There is a trend for higher BFI sites to show negative relationships between LIFE O/E and winter Q10, for which there are several logical reasons. These sites are also more strongly associated with Q95 flows from the previous summer, although this trend is weak. Both these relationships can easily be masked by inter-site differences. Overall, we saw little evidence of the increased response time of baseflow-dominated catchments noted by Extence *et. al.* 1999. The relationship with BFI is clearly important, but it is complex and needs further investigation. Predicting LIFE O/E from flow and artificial influences for the different BFI categories shows relatively low, but highly significant, R^2 values; lower BFI catchments show stronger relationships (R^2 of 0.23 versus 0.13).

The tendency for higher BFI catchments to show lower model R^2 values could indicate that the basic flow variables chosen (summer, winter Q10, Q95) are not appropriate for such catchments. This is supported by the observation that in a groundwater-dominated river, Q95 may not vary that much, even under drought conditions. It is probably more appropriate to choose alternative indices for these catchments, such as durations under threshold.

Although RIVPACS is a good predictor of the expected LIFE score at unstressed reference sites (Clarke *et al.* 2003), there is still clearly a considerable unexplained site-to-site variation in the LIFE O/E for our study sites subject to varying degrees of stress. Part of this inter-site variation in LIFE O/E can be explained by adding BFI to the models. This is illustrated by the wide variation in slopes of the individual site's LIFE O/E versus flow relationship. It was disappointing that the RIVPACS biological site group could not be related to slope of response – further in-depth analysis could be undertaken here. For the analysis undertaken, the data supported common LIFE versus flow slopes for all sites, although there was evidence of an interaction effect between artificial influences and preceding summer Q10 – the more artificially-influenced catchments had more depressed LIFE O/E values when summer Q10 was low, but had LIFE O/Es similar to those of the less artificially-influenced catchments when summer Q10 was high.

Incorporating either previous spring LIFE O/E or a site factor improves model R^2 to around 0.4 and 0.6, respectively. This confirms both the strong variation of LIFE score with flow

across sites and the unexplained site-to-site variation in mean LIFE O/E score. The R^2 of 0.6 represents the upper limit of what can be achieved with the current flow variables and linear modelling. The unexplained variation in mean LIFE O/E score is hindering attempts to discern patterns of differing slope of response of LIFE O/E to flow. The 'site"' factor could, indeed, represent, at least in part, site factors such as channel geometry and habitat diversity not currently included in the models presented.

Autocorrelation in LIFE O/E scores has been handled in part by restricting the majority of the analysis to autumn LIFE O/E data. However, autocorrelation of autumn–autumn scores is still important, especially in high BFI catchments, which have more strongly correlated flows. An analysis of the autocorrelation of model residuals suggests that the obvious autocorrelation in autumn LIFE O/E can be explained largely by autocorrelation in the driving flow variables.

Analysis of replicate data taken within a season has allowed calculation of an average total within-season SD of LIFE score. Consistent with previous work, this decreases with number of taxa observed. This has important implications for the detection of low flow stress. Not only will uncertainty increase because data points will be towards the lower end of the regression relationship, but also it is likely to increase because fewer taxa will be observed. A simple comparison of the average total within-season variance with total mean squares of the LIFE response variable suggests an upper limit of R^2 of around 0.75. The model R^2 values quoted in this report should be compared with this figure.

Unexplained variation in mean LIFE O/E can, hopefully, be tackled by improvements to RIVPACS, perhaps by incorporating catchment characteristics from digital data-sets, plus further work on flow standardisation. Unexplained variation in the slope of the response of LIFE to flow could be tackled in several ways, including a more sophisticated application of the RIVPACS groupings and incorporation of additional site and/or habitat data. This unexplained variation needs to be addressed for single LIFE O/Es to be a useful tool in determining abstraction and/or flow stress without supporting information. However, the models as they stand would be extremely useful to assist in determining the response when only small amounts of data are available.

7 Recommendations

The recommendations are given in a very rough order or priority.

1. A priority is to link this work with current and planned Environment Agency practice for using LIFE in river flow management. This could be achieved by:

- A presentation of the results of the current work by CEH staff to Environment Agency water resources and ecology staff who work on applying LIFE in various contexts, such as the Water Framework Directive (WFD) and CAMS.
- A case study that applies the models from this study, along with Environment Agency water resources tools, to a catchment with good hydrological and macroinvertebrate data. Two options are:
    - application to the Kennet catchment by CEH is ongoing as part of the EU Harmoni-Rib project;
    - application to a catchment in the Northern Area of the Anglian Region.

2. Given the success of incorporating an extremely simple measure of abstraction pressure, it would be productive to expand the data-set using improved, quantitative information on hydrological pressures. The derivation of these data is already being undertaken by CEH for the Environment Agency as part of WFD work. Closer linkage of LIFE with Low Flows 2000 would allow a much more comprehensive data analysis, as it would remove the requirements to chose only sites close to gauging stations. This could be given a trial in a pilot catchment, as mentioned above.

3. The unexplained variation in mean LIFE O/E needs to be improved, as this is currently masking potential differences in slope of response across sites. Improvement of the expected LIFE scores could be made by incorporating digitally-derived catchment characteristics, such as BFI from HOST (hydrology of soil types) into RIVPACS.

4. While there is still some unexplained variation in mean LIFE O/E, more sophisticated modelling of the slope of response of LIFE to flow is also required. Evidence for non-linear effects at the extremes of LIFE O/E and flow (e.g., low flows) is still unclear. If it does exist, this relationship is still masked by the large site-to-site differences. Simple visual examination of some of the plots of LIFE O/E versus flow suggests some kind of non-linearity. Site and/or habitat characteristics could explain the differing slopes of response of LIFE O/E to flow. The addition of improved site characteristics, such as basic channel geometry and habitat quality, should be attempted for sites with good time series of family- or species-level LIFE scores. Pilot testing of improved site characteristics could be undertaken in tandem with the Environment Agency–CEH RAPHSA project, and also with any other pilot study.

5. Further understanding of the differences in response of the communities across the BFI continuum is certainly possible with the current LIFE data-set, but would require more specific flow indices. A systematic evaluation of a wider suite of flow indices, and of correlations between the different indices within a year and between years for the same indices, would be useful. A list of potential indices is given in Appendix B.

6. Improved modelling of the autocorrelation in LIFE score and its dependence on autocorrelated flow data.

7. An updated comparison of the effectiveness of family-level versus species-level LIFE response (as undertaken by Extence *et al.* 1999), using the methods in this report and updated data.

8. Further investigation of the various sources of uncertainty that affect the LIFE score is important, given the evidence presented here of the high contribution of within-season sampling uncertainty to total variation in LIFE score. It would be useful to be able to partition the causes of the obvious tighter relationships observed for species-level data into the greater taxonomic characterisation of the community versus the tighter flow preferences of species-level data over family-level data.

9. It would be useful to test the validity of the approach adopted for this study in other countries. Environment Agency funding would clearly not be actively sought for such a study, but Environment Agency collaboration and advice would be useful.

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Appendix A: Further details of individual models

(Section 4.5 Effects of base flow index) – three BFI categories

```
(Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1 )
```

A1 - Most parsimonious models (flows standardised by z scores)

```
Call:
lm(formula = LIFE.Y ~ IPSQ95z + IPSQ10z + IPWQ95z + IPWQ10z +
    CURRAI2 + BFI, subset = BFI < 0.4)

Residuals:
      Min        1Q    Median        3Q       Max
-0.105087 -0.024782  0.001439  0.023798  0.151073

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.948243   0.021568  43.966   <2e-16 ***
IPSQ95z      0.009768   0.004081   2.394   0.0174 *
IPSQ10z      0.006662   0.004442   1.500   0.1350
IPWQ95z      0.005915   0.003616   1.636   0.1032
IPWQ10z      0.005200   0.003393   1.533   0.1267
CURRAI22INF -0.013168   0.006004  -2.193   0.0292 *
BFI          0.127454   0.063402   2.010   0.0455 *
---

Residual standard error: 0.04172 on 244 degrees of freedom
Multiple R-Squared: 0.2004,     Adjusted R-squared: 0.1807
F-statistic: 10.19 on 6 and 244 DF,  p-value: 4.638e-10


Call:
lm(formula = LIFE.Y ~ IPSQ95z + IPSQ10z + YBSQ10z + CURRAI2 +
    BFI, subset = BFI > 0.4 & BFI < 0.7)

Residuals:
      Min        1Q    Median        3Q       Max
-0.163155 -0.031360  0.001752  0.031698  0.151941

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.880934   0.011288  78.042  < 2e-16 ***
IPSQ95z      0.009317   0.002833   3.288  0.00105 **
IPSQ10z      0.007575   0.002648   2.860  0.00435 **
YBSQ10z      0.003145   0.001883   1.670  0.09526 .
CURRAI22INF -0.016676   0.004109  -4.058 5.45e-05 ***
BFI          0.205649   0.020619   9.974  < 2e-16 ***
---

Residual standard error: 0.04732 on 760 degrees of freedom
Multiple R-Squared: 0.2128,     Adjusted R-squared: 0.2076
F-statistic: 41.08 on 5 and 760 DF,  p-value: < 2.2e-16


Call:
lm(formula = LIFE.Y ~ IPSQ95z + CURRAI2 + BFI, subset = BFI >
    0.7)

Residuals:
      Min        1Q    Median        3Q       Max
-0.150008 -0.031523  0.002617  0.034949  0.146090
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.878064   0.025584  34.321  < 2e-16 ***
IPSQ95z      0.014174   0.002617   5.415 1.01e-07 ***
CURRAI22INF -0.021599   0.006978  -3.095  0.00209 **
BFI          0.138769   0.029085   4.771 2.50e-06 ***
---

Residual standard error: 0.05326 on 440 degrees of freedom
Multiple R-Squared: 0.1264,     Adjusted R-squared: 0.1204
F-statistic: 21.21 on 3 and 440 DF,  p-value: 7.5e-13
```

A2 - Most parsimonious models (flows standardised by dividing by mean)

```
Call:
lm(formula = LIFE.Y ~ IPSQ95dMEAN + IPSQ10dMEAN + IPWQ95dMEAN +
    YBSQ10dMEAN + CURRAI2 + BFI, subset = BFI < 0.4)

Residuals:
      Min        1Q    Median        3Q       Max
-0.115669 -0.026833  0.001542  0.028059  0.148604

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.932653   0.020922  44.578  < 2e-16 ***
IPSQ95dMEAN  0.125607   0.060332   2.082  0.03839 *
IPSQ10dMEAN  0.021493   0.005013   4.287 2.61e-05 ***
IPWQ95dMEAN  0.042605   0.030856   1.381  0.16861
YBSQ10dMEAN  0.008698   0.005718   1.521  0.12953
CURRAI22INF -0.015873   0.005922  -2.680  0.00786 **
BFI          0.016552   0.064515   0.257  0.79773
---

Residual standard error: 0.04039 on 244 degrees of freedom
Multiple R-Squared: 0.2506,     Adjusted R-squared: 0.2321
F-statistic:  13.6 on 6 and 244 DF,  p-value: 2.618e-13


Call:
lm(formula = LIFE.Y ~ IPSQ95dMEAN + IPSQ10dMEAN + YBSQ10dMEAN +
    CURRAI2 + BFI, subset = BFI > 0.4 & BFI < 0.7)

Residuals:
      Min        1Q    Median        3Q       Max
-0.160194 -0.031315  0.002343  0.031361  0.156594

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.862720   0.012263  70.350  < 2e-16 ***
IPSQ95dMEAN  0.064975   0.024715   2.629  0.00874 **
IPSQ10dMEAN  0.017699   0.003422   5.173 2.95e-07 ***
YBSQ10dMEAN  0.007698   0.003121   2.466  0.01388 *
CURRAI22INF -0.021735   0.004232  -5.136 3.56e-07 ***
BFI          0.168301   0.023253   7.238 1.12e-12 ***
---

Residual standard error: 0.04729 on 760 degrees of freedom
Multiple R-Squared: 0.2137,     Adjusted R-squared: 0.2085
F-statistic:  41.3 on 5 and 760 DF,  p-value: < 2.2e-16


Call:
lm(formula = LIFE.Y ~ IPSQ10dMEAN + IPWQ95dMEAN + YBSQ95dMEAN +
    CURRAI2 + BFI, subset = BFI > 0.7)

Residuals:
      Min        1Q    Median        3Q       Max
```

```
-0.154802 -0.032258  0.002083  0.035257  0.147137

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.832305   0.028161  29.555  < 2e-16 ***
IPSQ10dMEAN  0.009821   0.004352   2.257  0.02452 *
IPWQ95dMEAN  0.074892   0.018386   4.073 5.50e-05 ***
YBSQ95dMEAN -0.065113   0.020098  -3.240  0.00129 **
CURRAI22INF -0.021012   0.007019  -2.994  0.00291 **
BFI          0.167893   0.033685   4.984 8.98e-07 ***
---

Residual standard error: 0.05285 on 438 degrees of freedom
Multiple R-Squared: 0.1434,     Adjusted R-squared: 0.1337
F-statistic: 14.67 on 5 and 438 DF,  p-value: 2.614e-13
```

A3 - BFI categories: reduced models with catchment area

```
Call:
lm(formula = LIFE.Y ~ IPSQ95z + IPSQ10z + CAT_AREA, subset = BFI <
    0.4)

Residuals:
      Min        1Q    Median        3Q       Max
-0.114031 -0.027002  0.000996  0.023958  0.116785

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 9.784e-01  3.623e-03 270.012  < 2e-16 ***
IPSQ95z     1.038e-02  4.109e-03   2.527  0.01213 *
IPSQ10z     7.950e-03  4.509e-03   1.763  0.07909 .
CAT_AREA    2.180e-05  6.837e-06   3.189  0.00161 **
---

Residual standard error: 0.04235 on 247 degrees of freedom
Multiple R-Squared: 0.1661,     Adjusted R-squared: 0.156
F-statistic:  16.4 on 3 and 247 DF,  p-value: 9.416e-10

> summary(zzlm2)

Call:
lm(formula = LIFE.Y ~ IPSQ95z + IPSQ10z + CAT_AREA, subset = BFI >
    0.4 & BFI < 0.6)

Residuals:
      Min        1Q    Median        3Q       Max
-0.162841 -0.029847  0.002144  0.031141  0.180721

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.802e-01  2.398e-03 408.684  < 2e-16 ***
IPSQ95z      8.827e-03  3.154e-03   2.799  0.00531 **
IPSQ10z      9.229e-03  3.088e-03   2.989  0.00293 **
CAT_AREA    -5.369e-06  2.338e-06  -2.297  0.02200 *
---

Residual standard error: 0.04846 on 562 degrees of freedom
Multiple R-Squared: 0.1107,     Adjusted R-squared: 0.106
F-statistic: 23.32 on 3 and 562 DF,  p-value: 3.062e-14

> summary(zzlm3)

Call:
lm(formula = LIFE.Y ~ IPSQ95z + IPSQ10z + CAT_AREA, subset = BFI >
    0.6)
```

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.171530 -0.031681  0.002146  0.035911  0.155917

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.002e+00  2.212e-03 452.879  < 2e-16 ***
IPSQ95z     1.201e-02  3.602e-03   3.334 0.000905 ***
IPSQ10z     3.527e-03  3.440e-03   1.025 0.305537
CAT_AREA    2.241e-06  2.516e-06   0.891 0.373411
---

Residual standard error: 0.05275 on 652 degrees of freedom
Multiple R-Squared: 0.0696,     Adjusted R-squared: 0.06532
F-statistic: 16.26 on 3 and 652 DF,  p-value: 3.353e-10
```

A4 - Best models for North West Region bankside sorted data

```
Call:
lm(formula = LIFE.Y ~ IPSQ10z + IPSQ95z + BFI)

Residuals:
      Min        1Q    Median        3Q       Max
-0.102407 -0.025569  0.004777  0.024130  0.102062

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.102364   0.028211  39.076  < 2e-16 ***
IPSQ10z      0.012707   0.008087   1.571  0.12230
IPSQ95z      0.015771   0.008916   1.769  0.08289 .
BFI         -0.233956   0.068158  -3.433  0.00119 **
---

Residual standard error: 0.04159 on 51 degrees of freedom
Multiple R-Squared: 0.3542,     Adjusted R-squared: 0.3162
F-statistic: 9.323 on 3 and 51 DF,  p-value: 5.114e-05

Call:
lm(formula = LIFE.Y ~ IPSQ10dMEAN + IPWQ95dMEAN + YBSQ95dMEAN)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0878954 -0.0241254 -0.0003187  0.0226530  0.0781071

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.95851    0.01715  55.893  < 2e-16 ***
IPSQ10dMEAN  0.06646    0.01173   5.664 6.85e-07 ***
IPWQ95dMEAN  0.14139    0.07148   1.978  0.05334 .
YBSQ95dMEAN -0.46949    0.15400  -3.049  0.00364 **
---

Residual standard error: 0.03897 on 51 degrees of freedom
Multiple R-Squared: 0.4331,     Adjusted R-squared: 0.3998
F-statistic: 12.99 on 3 and 51 DF,  p-value: 2.018e-06
```

A5 - Effects of adding mean flow term to model

```
Call:
lm(formula = I(LIFE_F - ELIFE3) ~ log(IPSQ95RAW) + log(IPSQ10RAW) +
    log(MEANFLOW) + CURRAI2 + BFI, subset = BFI > 0.4)

Residuals:
     Min       1Q   Median       3Q      Max
```

```
-1.14101 -0.21397  0.01692  0.23090  1.17921

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    -0.29375    0.06419  -4.576 5.22e-06 ***
log(IPSQ95RAW)  0.07756    0.02280   3.402  0.00069 ***
log(IPSQ10RAW)  0.15340    0.02131   7.199 1.06e-12 ***
log(MEANFLOW)  -0.21624    0.02330  -9.282  < 2e-16 ***
CURRAI22INF    -0.10695    0.02459  -4.350 1.48e-05 ***
BFI             0.39857    0.06569   6.067 1.73e-09 ***
---

Residual standard error: 0.3482 on 1219 degrees of freedom
Multiple R-Squared: 0.1545,     Adjusted R-squared: 0.1511
F-statistic: 44.56 on 5 and 1219 DF,  p-value: < 2.2e-16


Call:
lm(formula = LIFE.Y ~ IPSQ95dMEAN + IPSQ10dMEAN + CURRAI2 + BFI,
    subset = BFI > 0.4)

Residuals:
      Min        1Q    Median        3Q       Max
-0.163018 -0.032092  0.002268  0.033589  0.167515

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.945387   0.006720 140.688  < 2e-16 ***
IPSQ95dMEAN  0.011860   0.011398   1.041 0.298293
IPSQ10dMEAN  0.018677   0.002705   6.905 8.06e-12 ***
CURRAI22INF -0.017464   0.003620  -4.825 1.58e-06 ***
BFI          0.037966   0.011195   3.391 0.000718 ***
---

Residual standard error: 0.05127 on 1220 degrees of freedom
Multiple R-Squared: 0.114,      Adjusted R-squared: 0.1111
F-statistic: 39.24 on 4 and 1220 DF,  p-value: < 2.2e-16
```

Appendix B: Potential additional flow indices

Several authors have published descriptions of flow indices of potential use for ecological studies, two of the most well-known being Richter *et al.* (1996) and Clausen and Biggs (2000). Authors have also looked into the intercorrelation between the indices (Olden and Poff, 2004), and their relationships with river ecology (Clausen and Biggs, 1997; Riis and Biggs, 2003).

A list of potential flow indices is:

General variability:

SK	Skewness defined as MF/Q50
CV	Coefficient of variation of all daily flows
CON	Constancy (Colwel, 1974)

Seasonal variability:

	Coefficient of variation of mean monthly flow in:
JANCV	January
FEBCV	February
MARCV	March
APRCV	April
MAYCV	May
JUNCV	June
JULCV	July
AUGCV	August
SEPCV	September
OCTCV	October
NOVCV	November
DECCV	December

High flow:

Q1	The 1st percentile from the flow duration curve/Q50
Q10	The 10th percentile from the flow duration curve/Q50
Q25	The 25th percentile from the flow duration curve/Q50
MAMAX	Mean annual 1-day maximum/Q50
MAMAX7	Mean annual 7-day maximum/Q50
MAMAX30	Mean annual 30-day maximum/Q50
MAX50	Median of the annual maxima/Q50
	Mean peak flow divided by Q50 for events higher than:
PEA1	1 times Q50
PEA3	3 times Q50
PEA7	7 times Q50
PEA25	the 25th percentile

Low flow:

BFI	Baseflow index (Gustard *et al*., 1992; Institute of Hydrology 1980)
Q75	The 75th percentile from the flow duration curve/Q50
Q90	The 90th percentile from the flow duration curve/Q50
MAMIN	Mean annual 1-day minimum/Q50
MAMIN7	Mean annual 7-day minimum/Q50

MAMIN30 Mean annual 30-day minimum/Q50
MIN50 Median of the annual minima/Q50

Change of flow:
NODAYRISES Average ratio of days with increasing flow
Median of difference between natural logarithm of flows (in $m^3 s^{-1}$):
KPOS between two consecutive days with increasing flow
KNEG between two consecutive days with decreasing flow

Appendix C: Supplemental graphs

F

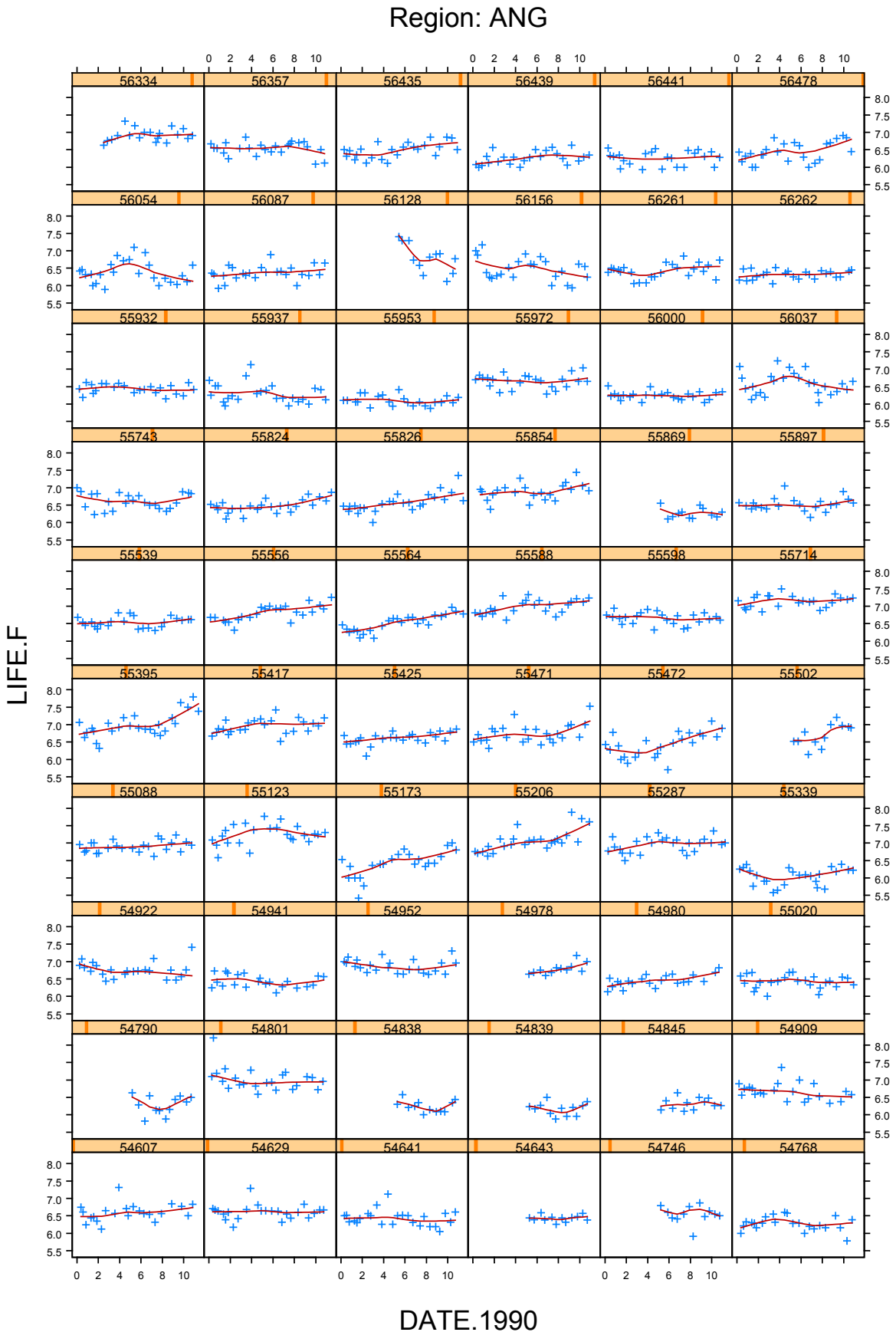


Figure C-1. Time series of LIFE scores: sites in the Anglian Region.

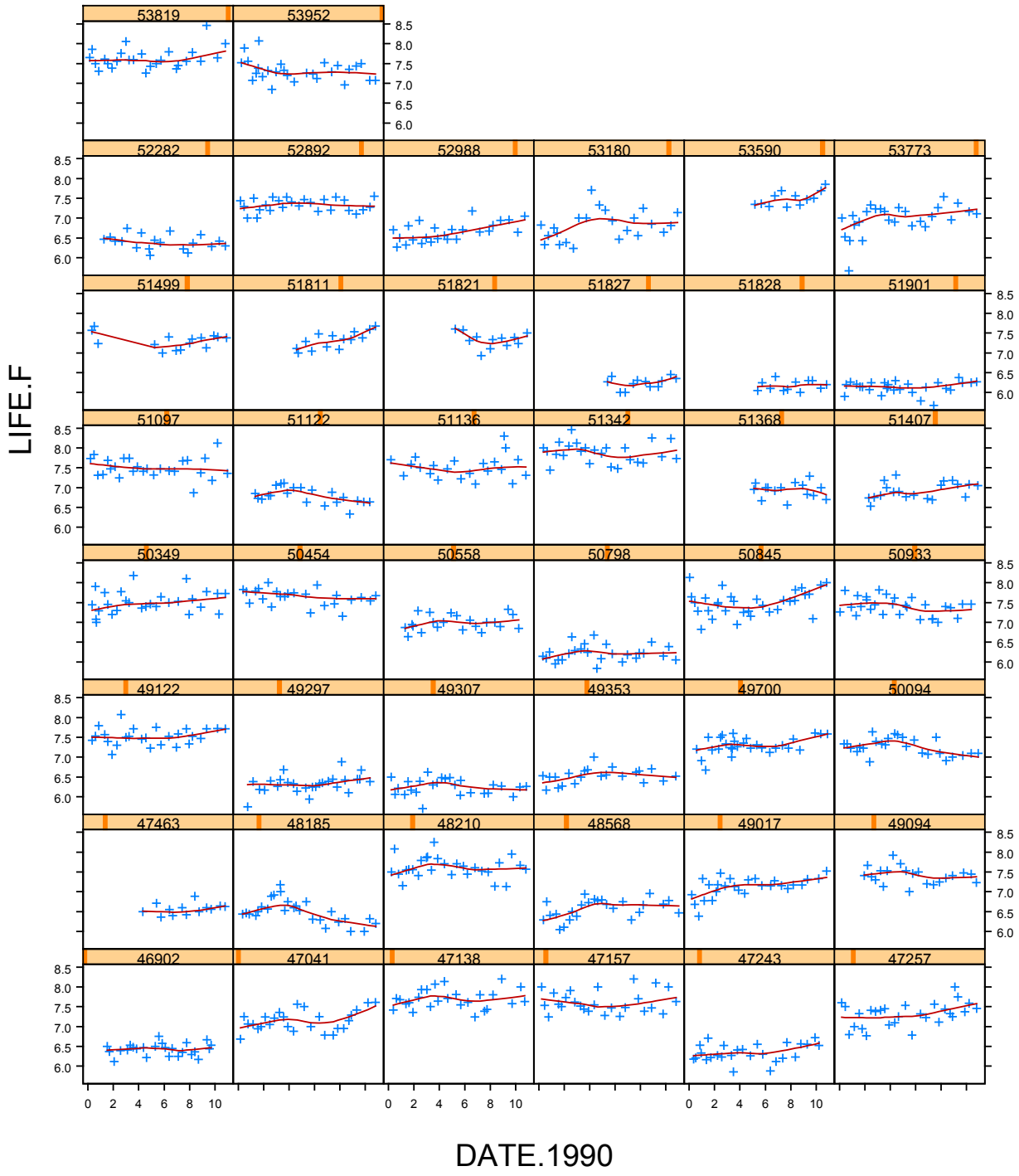


Figure C-2. Time series of LIFE scores: sites in the Midland Region.

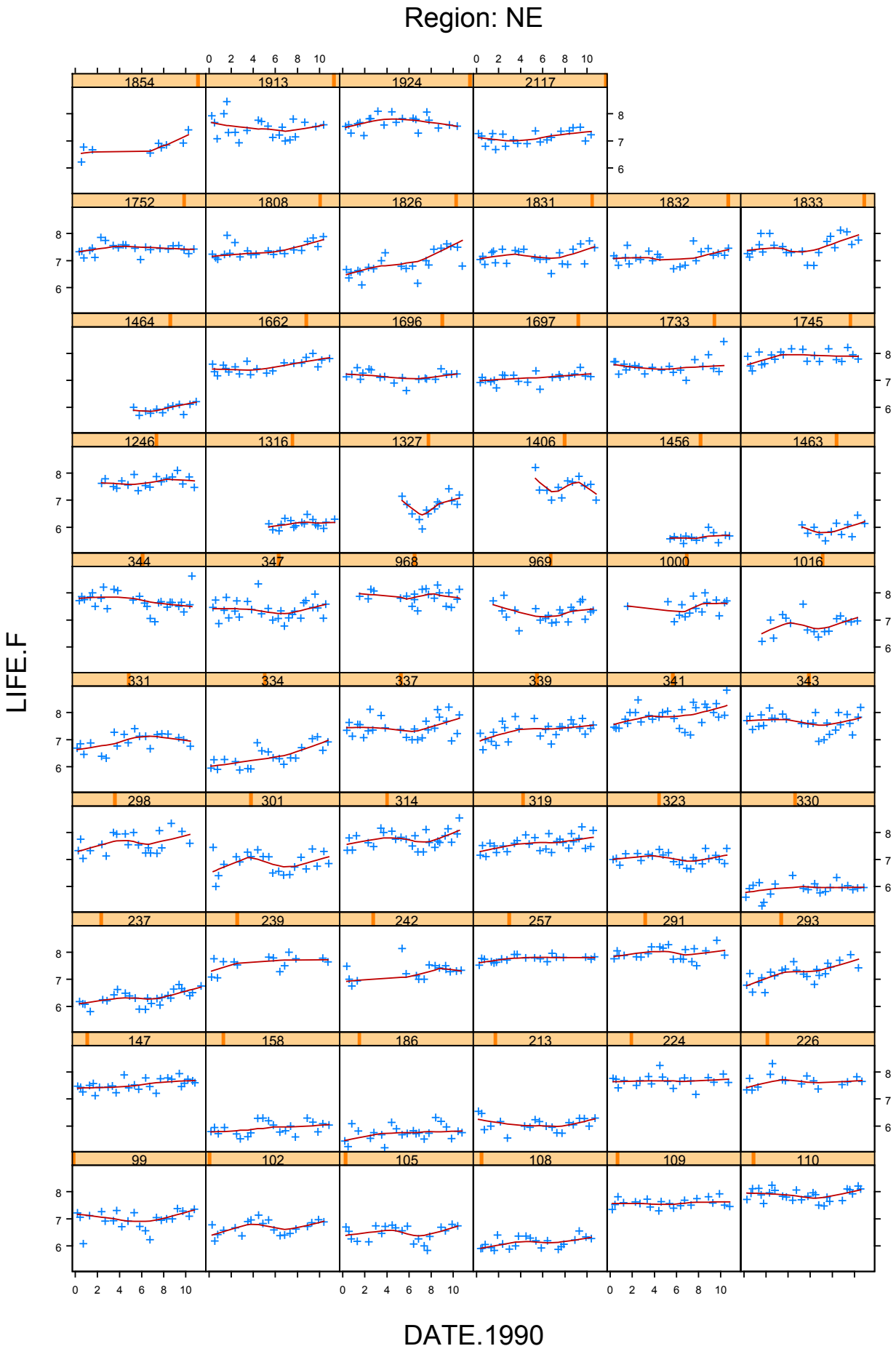


Figure C-3. Time series of LIFE scores: sites in the North East Region.

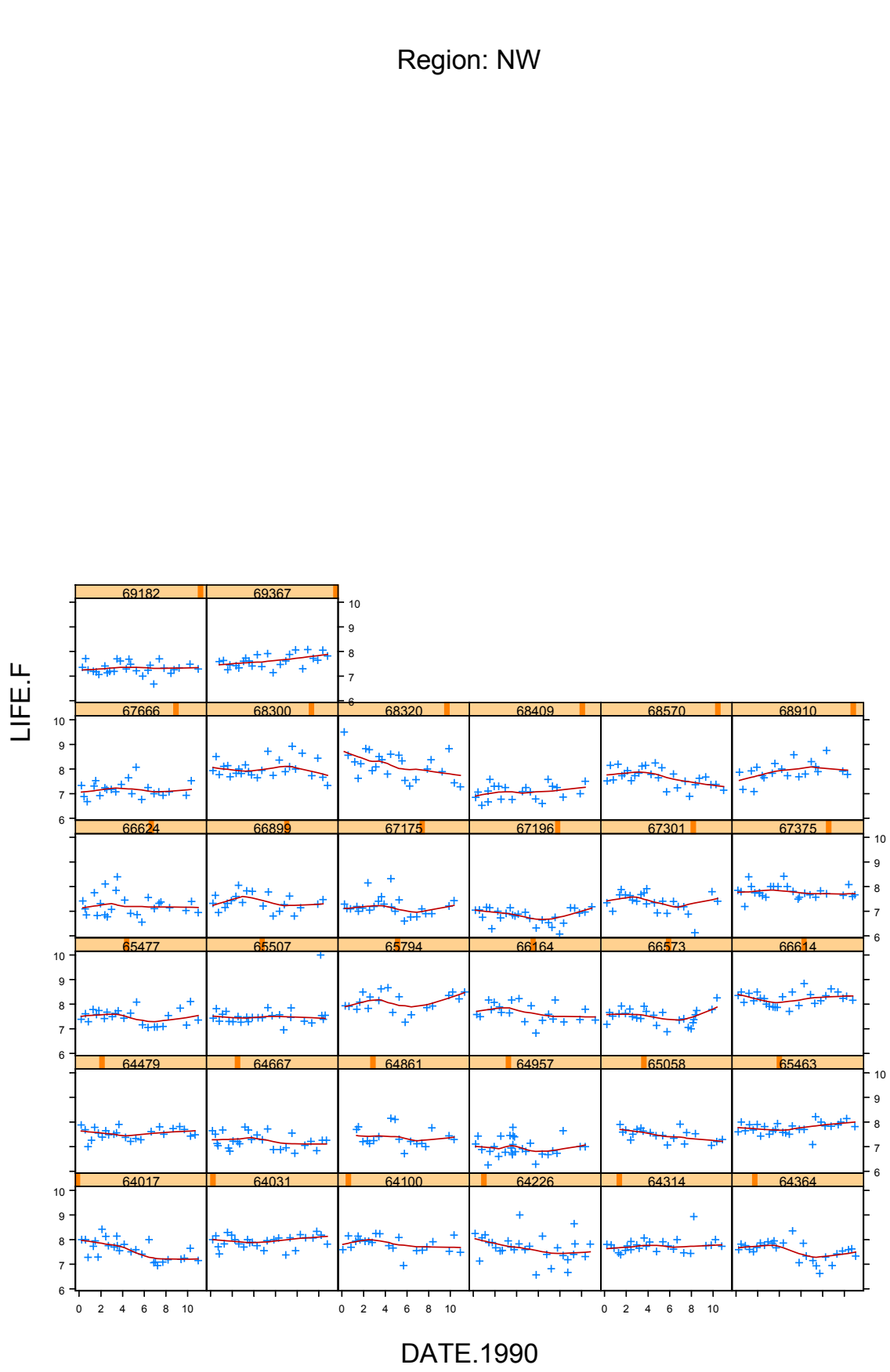


Figure C-4. Time series of LIFE scores: sites in the North West Region.

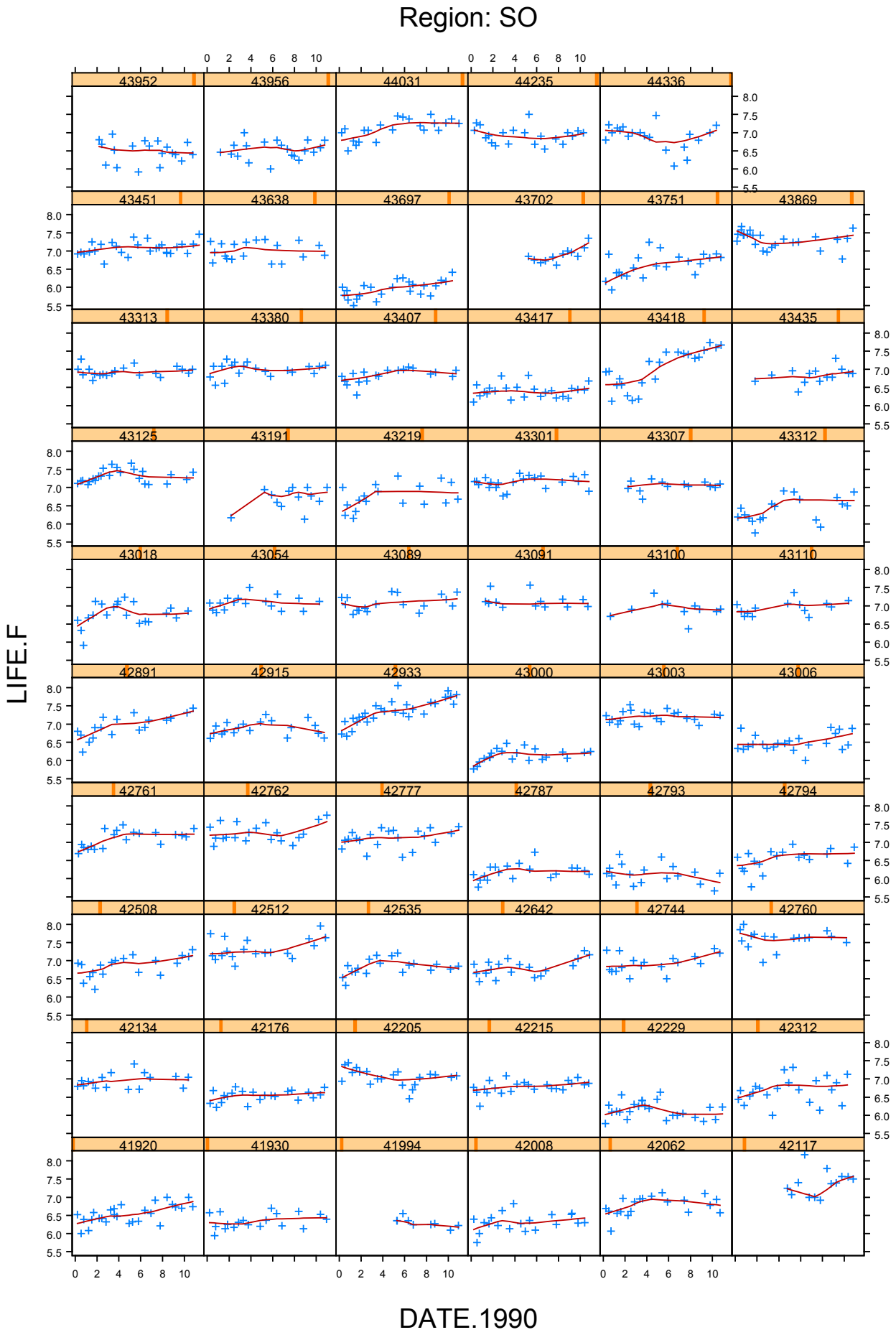


Figure C-5. Time series of LIFE scores: sites in the Southern Region.

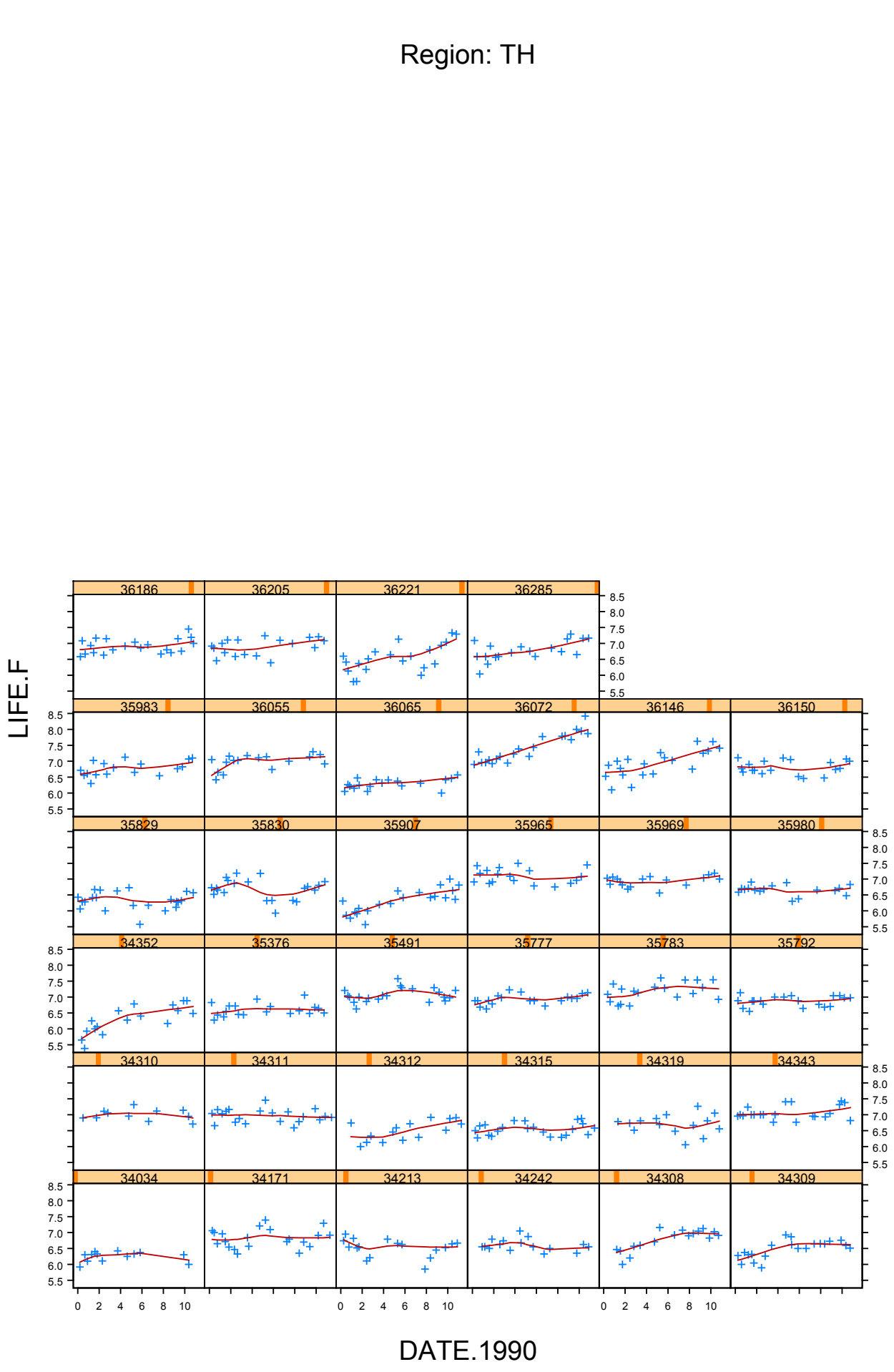


Figure C-6. Time series of LIFE scores: sites in the Thames Region.

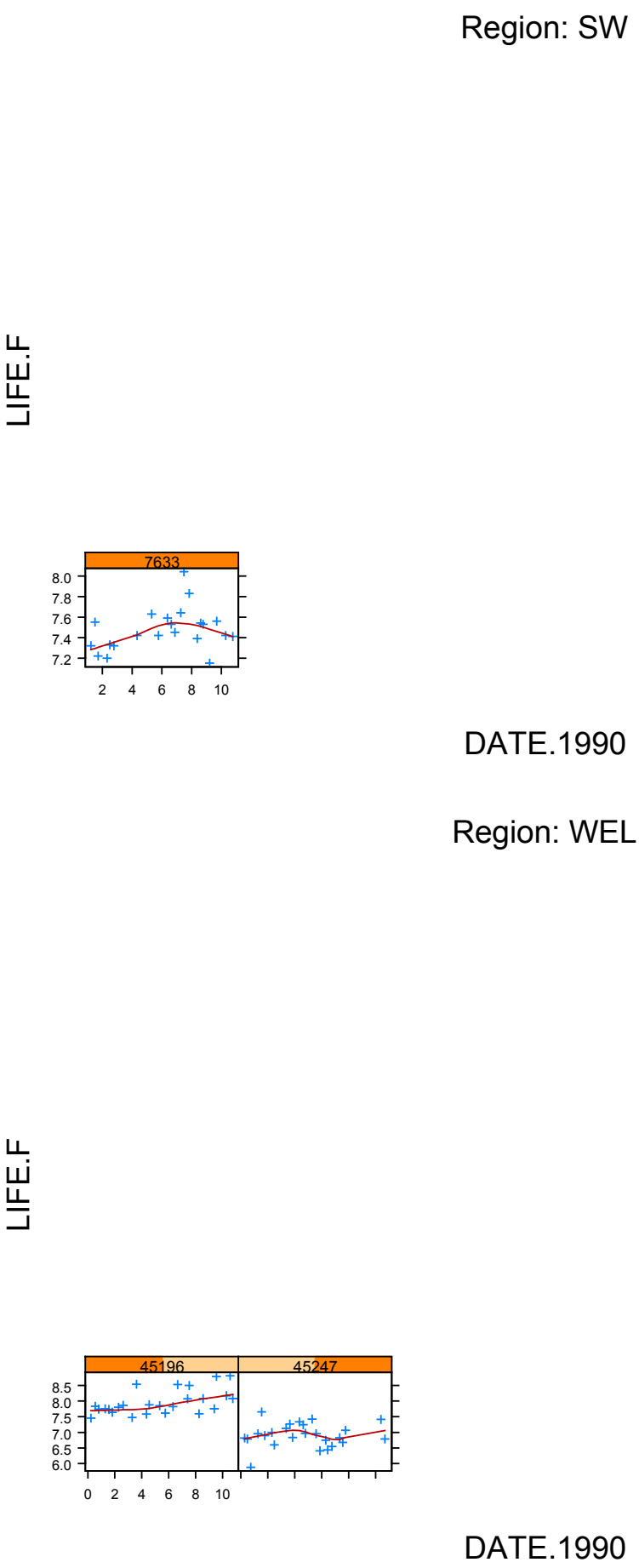


Figure C-7. Time series of LIFE scores: sites in the Welsh and South West Regions

Figure C-8. Individual regression lines for each site for autumn LIFE O/E versus normalised Q95 and Q10 from immediately preceding summer

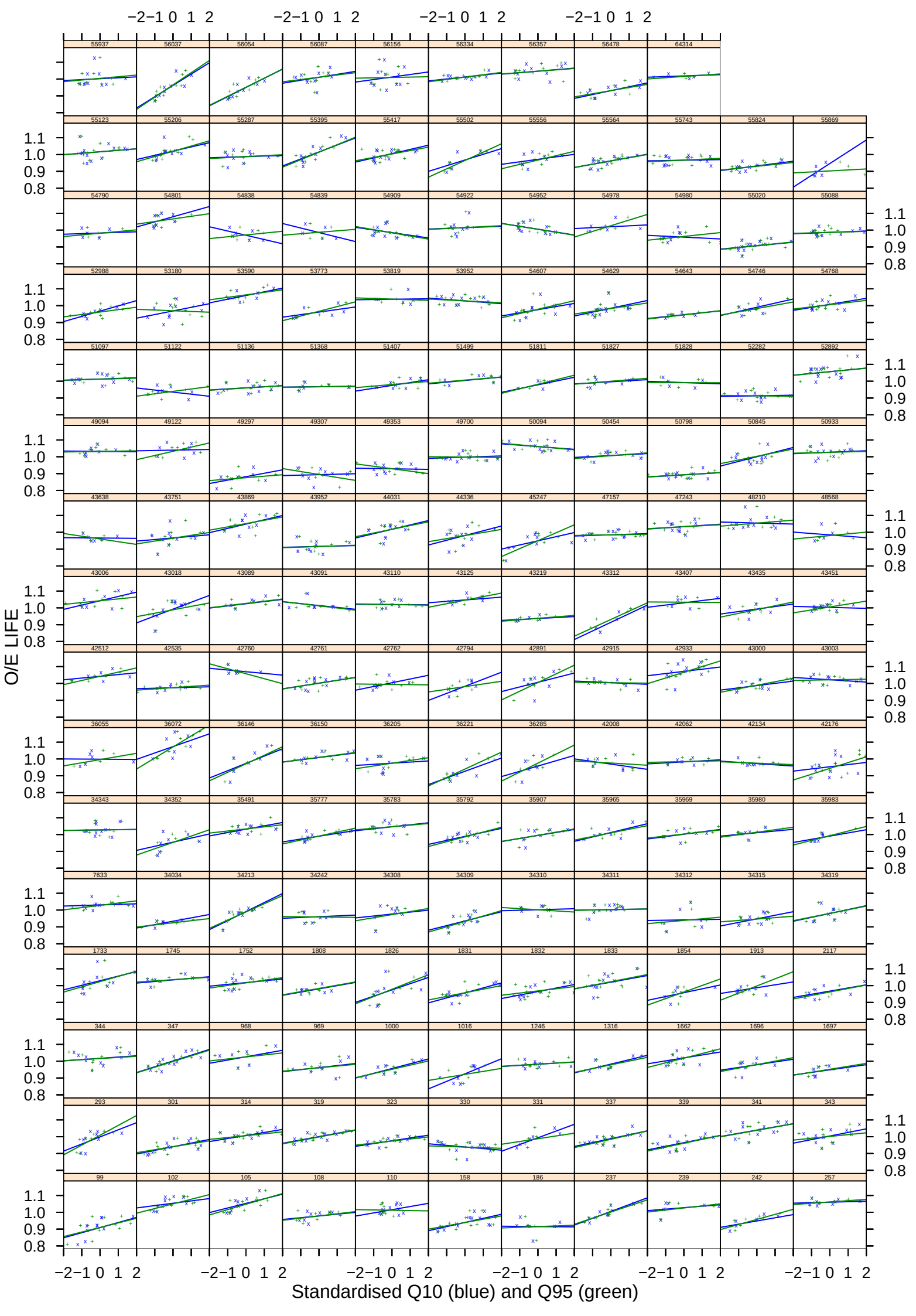
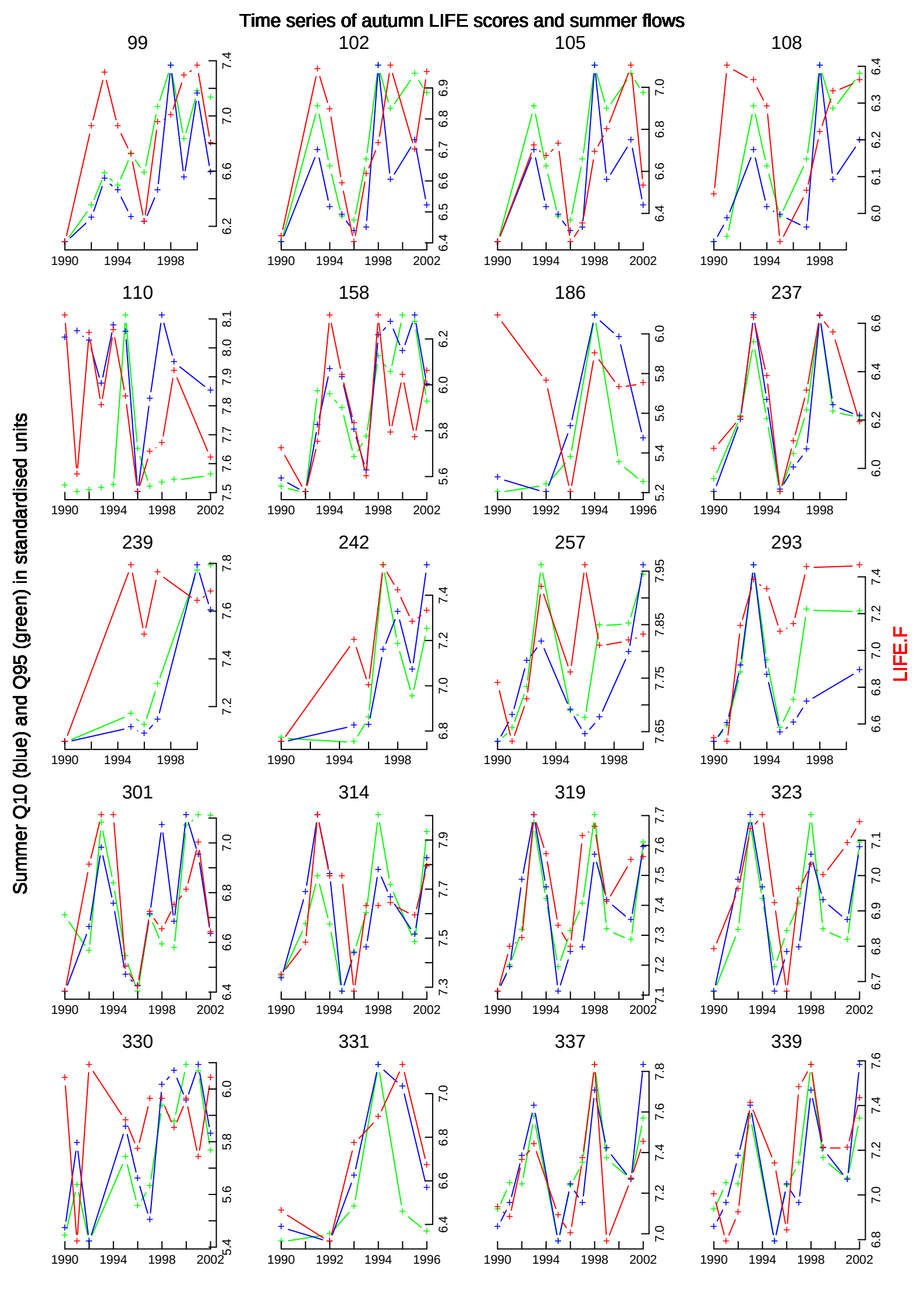
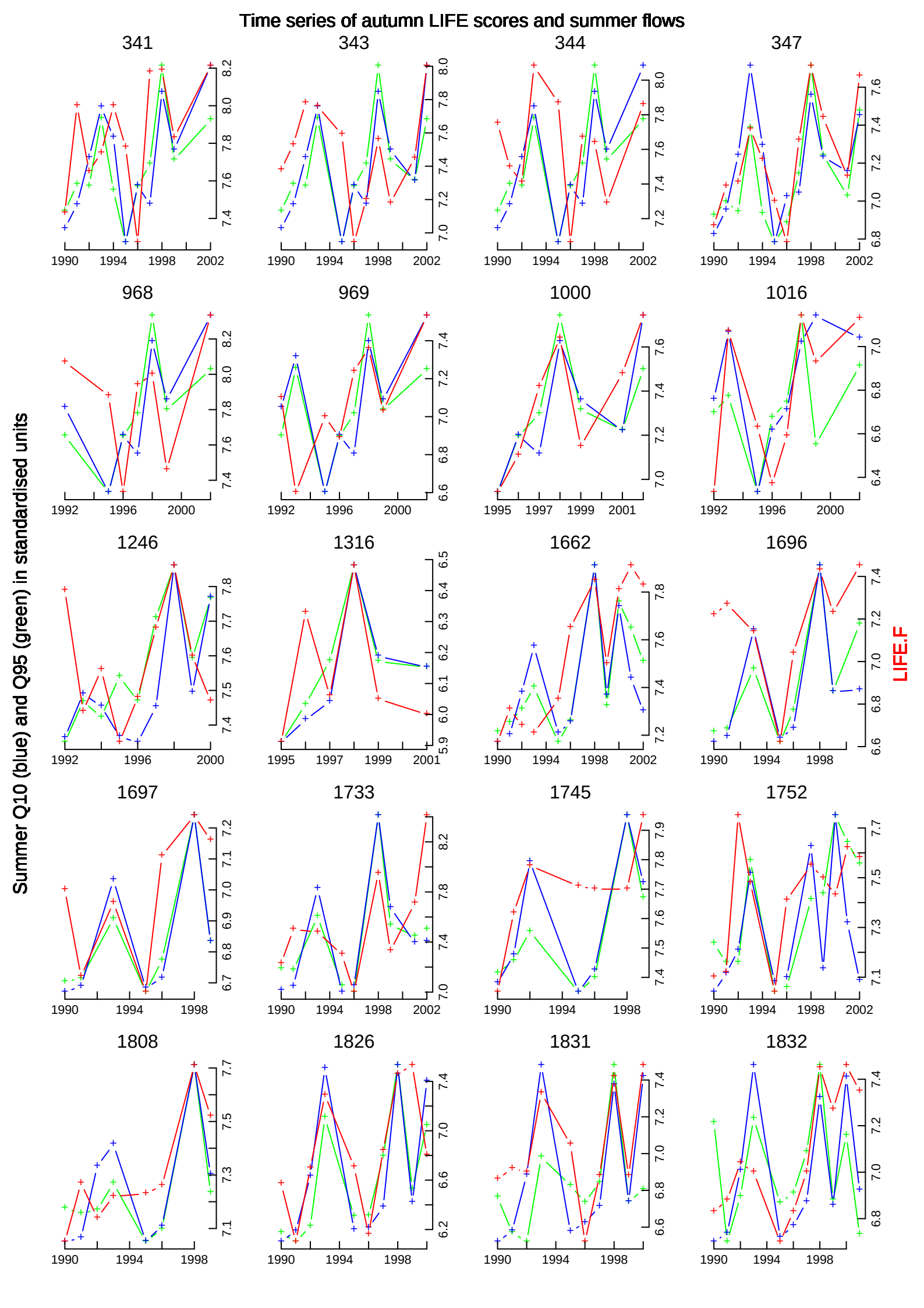
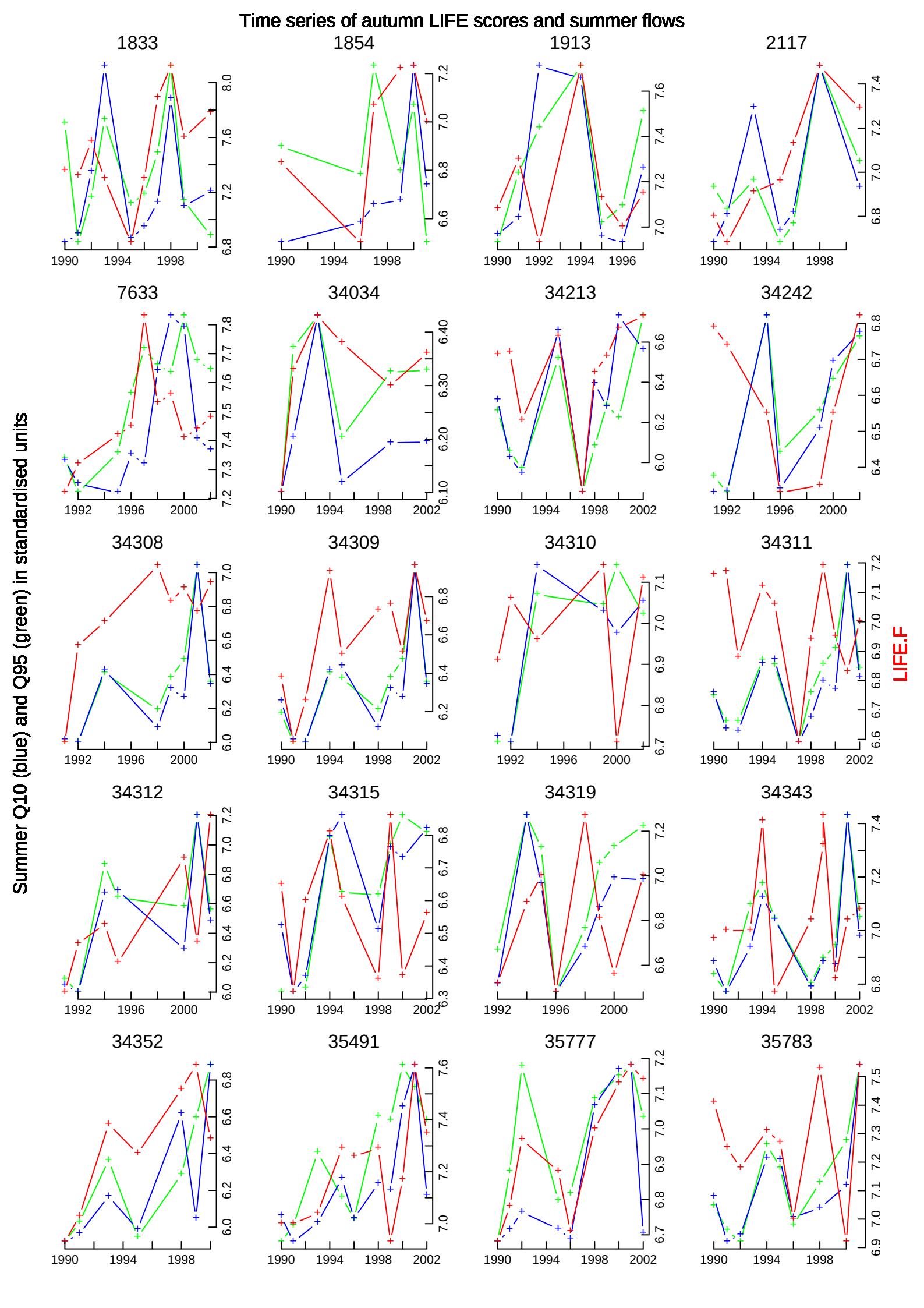
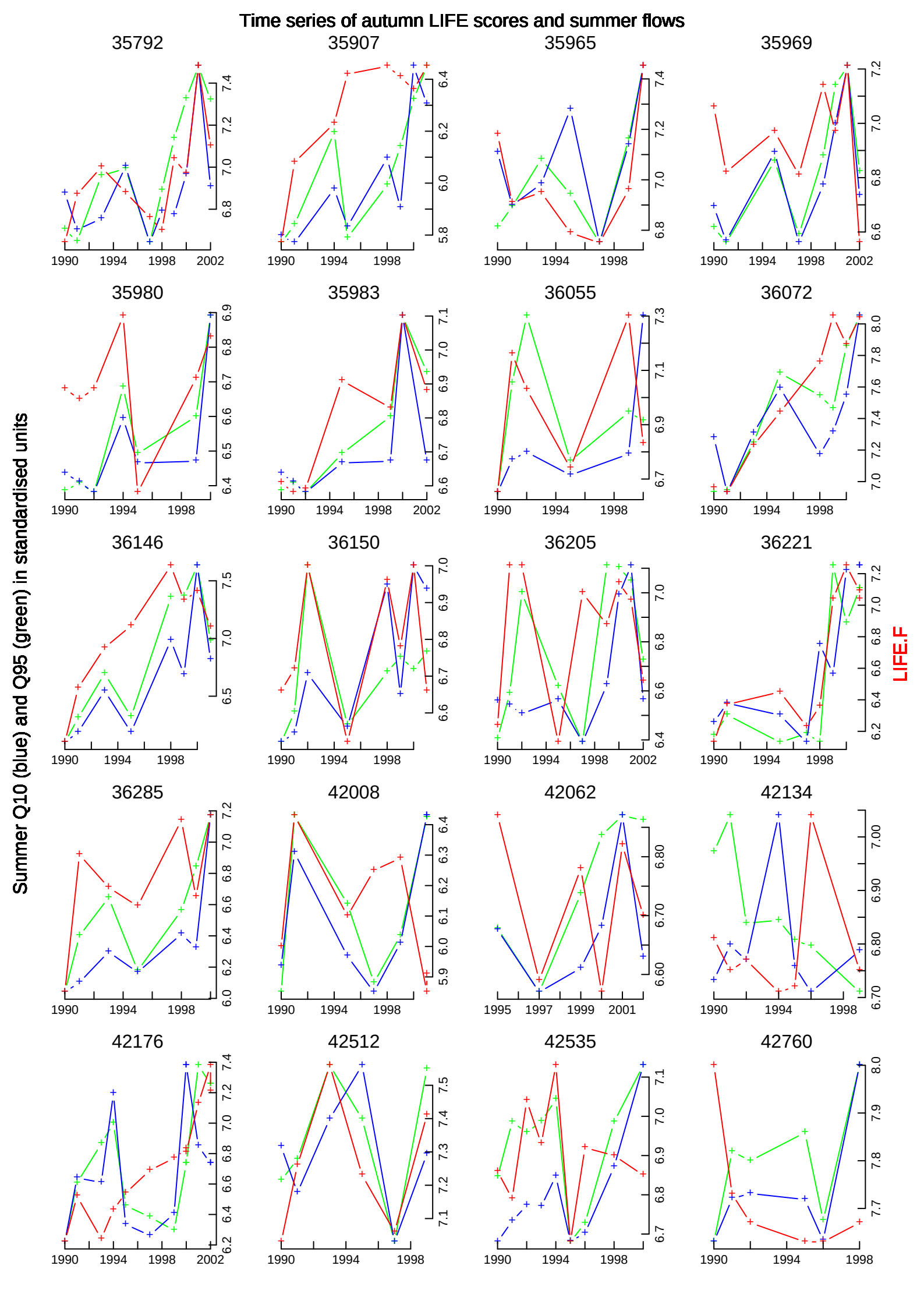

O/E LIFE
Standardised Q10 (blue) and Q95 (green)
55937 56037 56054 56087 56156 56334 56357 56478 64314
55123 55206 55287 55395 55417 55502 55556 55564 55743 55824 55869
54790 54801 54838 54839 54909 54922 54952 54978 54980 55020 55088
52988 53180 53590 53773 53819 53952 54607 54629 54643 54746 54768
51097 51122 51136 51368 51407 51499 51811 51827 51828 52282 52892
49094 49122 49297 49307 49353 49700 50094 50454 50798 50845 50933
43638 43751 43869 43952 44031 44336 45247 47157 47243 48210 48568
43006 43018 43089 43091 43110 43125 43219 43312 43407 43435 43451
42512 42535 42760 42761 42762 42794 42891 42915 42933 43000 43003
36055 36072 36146 36150 36205 36221 36285 42008 42062 42134 42176
34343 34352 35491 35777 35783 35792 35907 35965 35969 35980 35983
7633 34034 34213 34242 34308 34309 34310 34311 34312 34315 34319
1733 1745 1752 1808 1826 1831 1832 1833 1854 1913 2117
344 347 968 969 1000 1016 1246 1316 1662 1696 1697
293 301 314 319 323 330 331 337 339 341 343
99 102 105 108 110 158 186 237 239 242 257
0.8 0.9 1.0 1.1
−2 −1 0 1 2

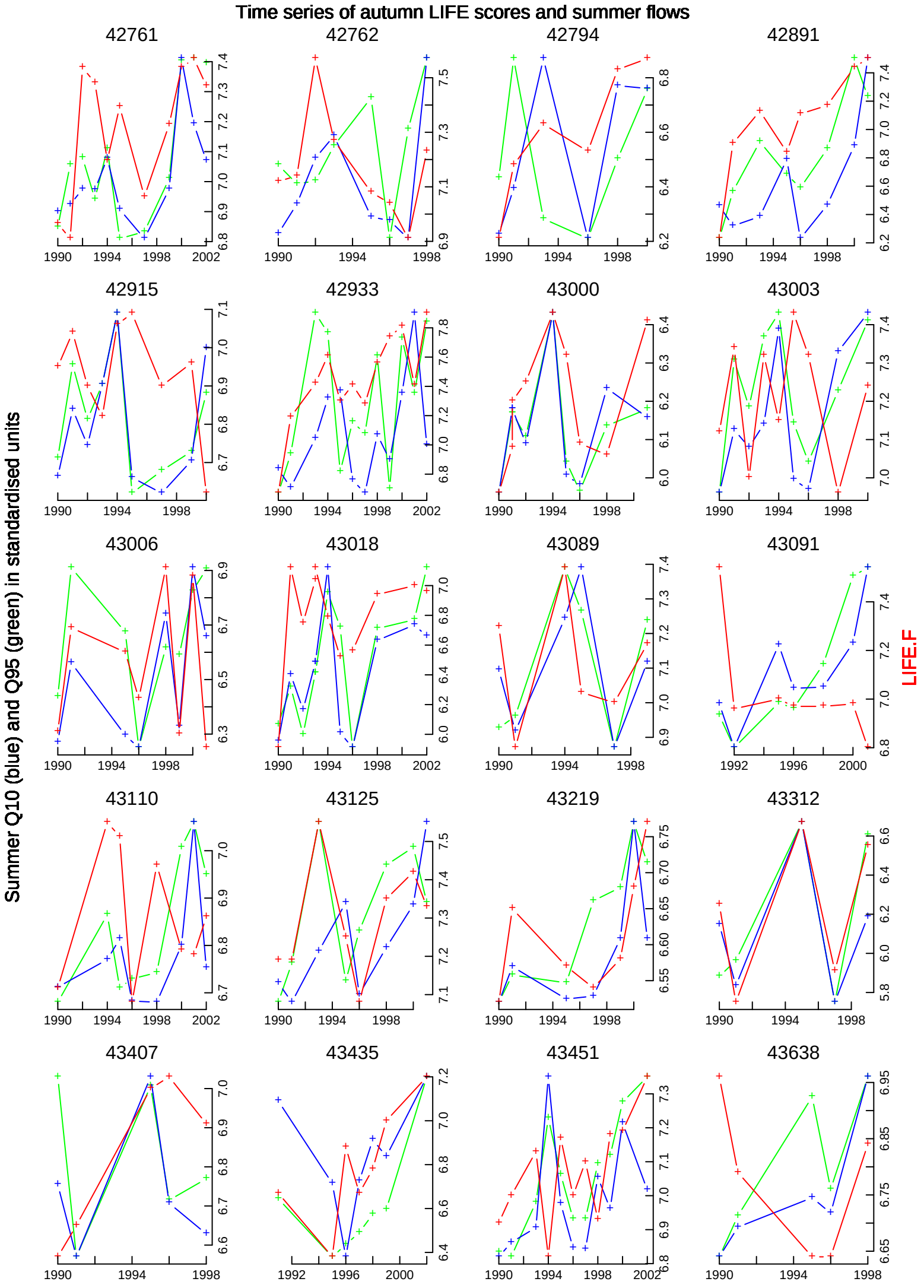
Figure C-9. Individual time series for each site for autumn LIFE O/E and normalised Q95 and Q10 from immediately preceding summer

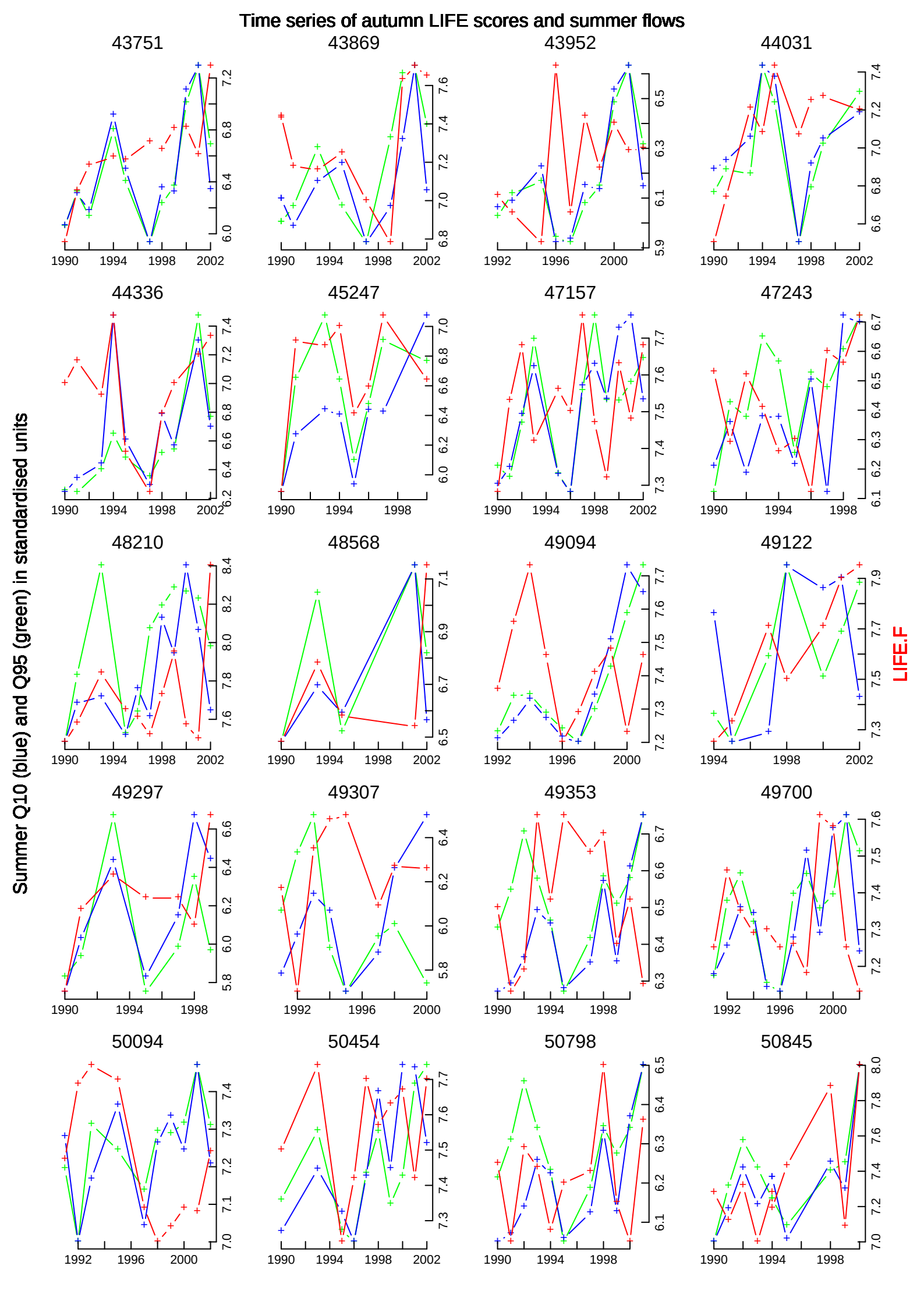

Time series of autumn LIFE scores and summer flows
99
102
105
108
110
158
186
237
239
242
257
293
301
314
319
323
330
331
337
339
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F

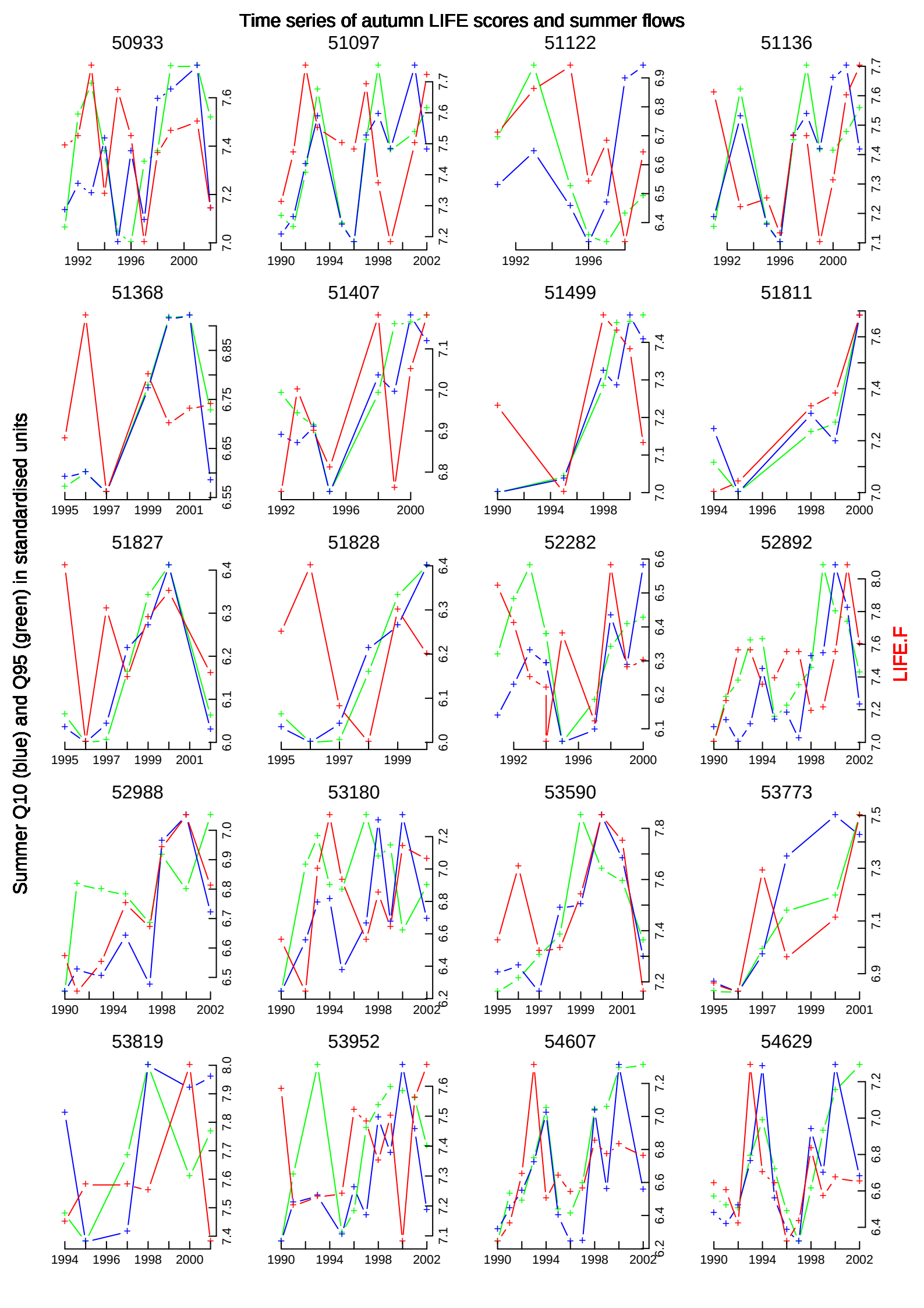

Time series of autumn LIFE scores and summer flows
341
343
344
347
968
969
1000
1016
1246
1316
1662
1696
1697
1733
1745
1752
1808
1826
1831
1832
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F

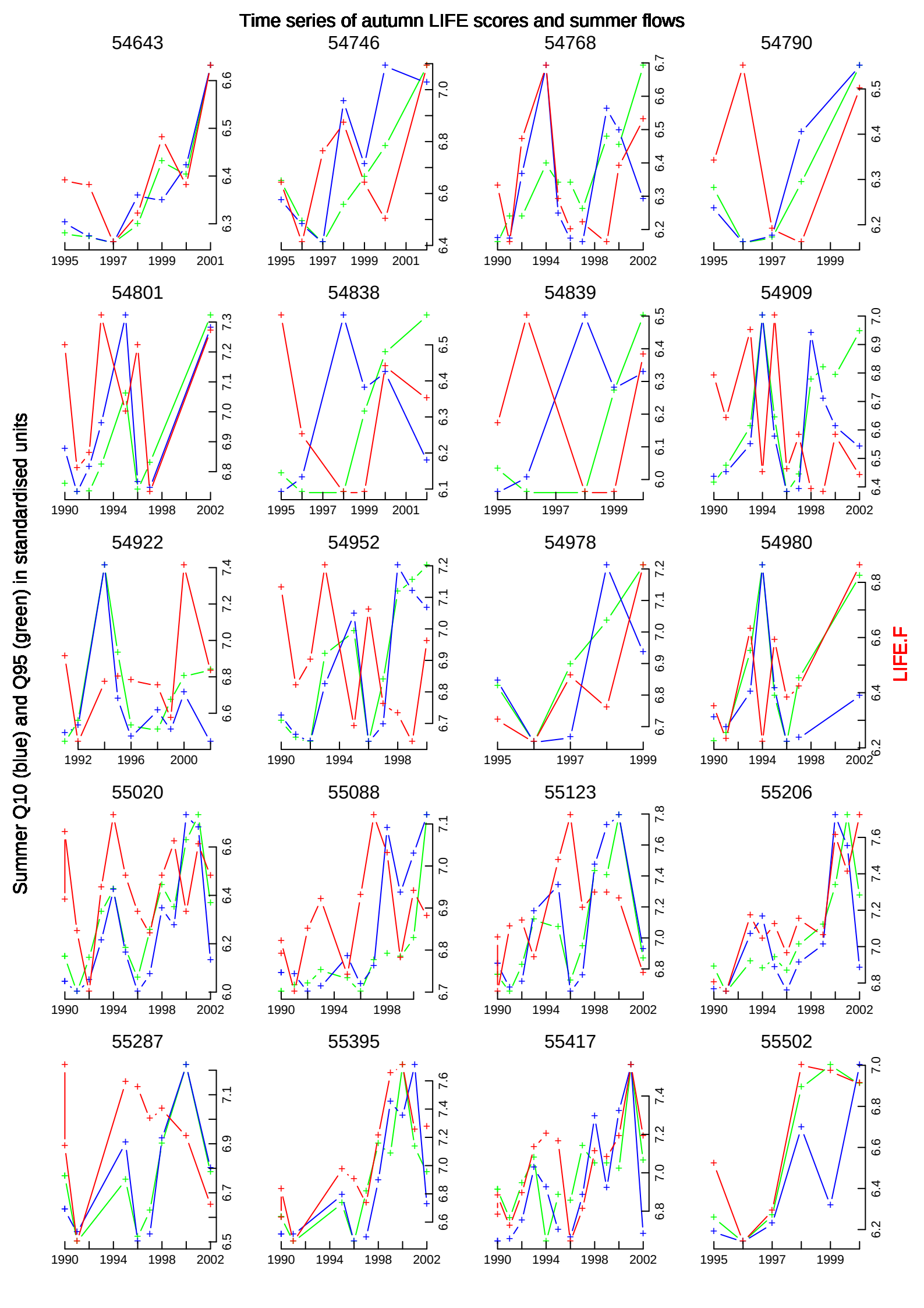

Time series of autumn LIFE scores and summer flows
1833
1854
1913
2117
7633
34034
34213
34242
34308
34309
34310
34311
34312
34315
34319
34343
34352
35491
35777
35783
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F

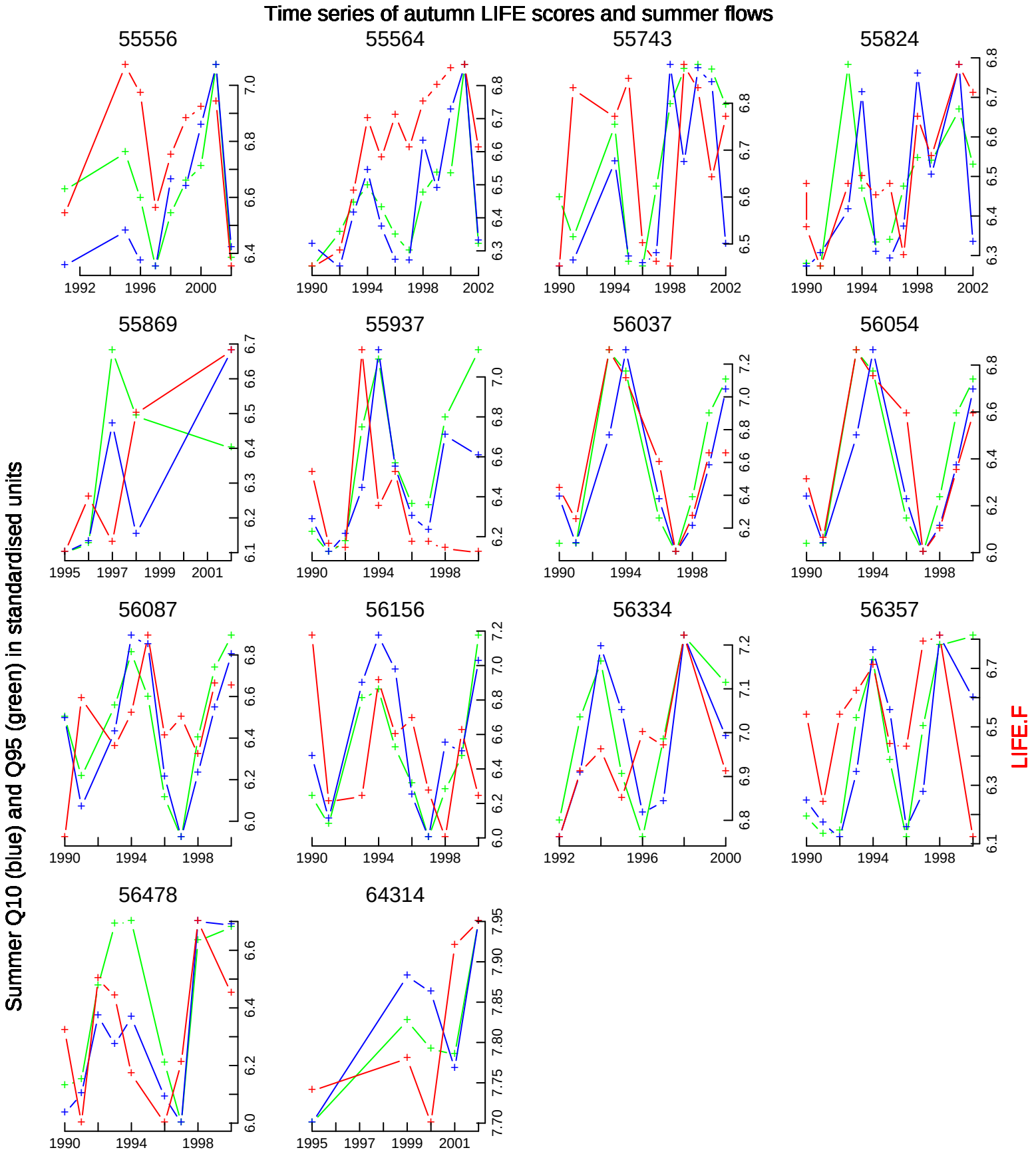

Time series of autumn LIFE scores and summer flows
35792
35907
35965
35969
35980
35983
36055
36072
36146
36150
36205
36221
36285
42008
42062
42134
42176
42512
42535
42760
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F


Time series of autumn LIFE scores and summer flows
42761
42762
42794
42891
42915
42933
43000
43003
43006
43018
43089
43091
43110
43125
43219
43312
43407
43435
43451
43638
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F


Time series of autumn LIFE scores and summer flows
43751
43869
43952
44031
44336
45247
47157
47243
48210
48568
49094
49122
49297
49307
49353
49700
50094
50454
50798
50845
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F


Time series of autumn LIFE scores and summer flows
50933
51097
51122
51136
51368
51407
51499
51811
51827
51828
52282
52892
52988
53180
53590
53773
53819
53952
54607
54629
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F


Time series of autumn LIFE scores and summer flows
54643
54746
54768
54790
54801
54838
54839
54909
54922
54952
54978
54980
55020
55088
55123
55206
55287
55395
55417
55502
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F


Time series of autumn LIFE scores and summer flows
55556
55564
55743
55824
55869
55937
56037
56054
56087
56156
56334
56357
56478
64314
Summer Q10 (blue) and Q95 (green) in standardised units
LIFE.F

We welcome views from our users, stakeholders and the public, including comments about the content and presentation of this report. If you are happy with our service, please tell us about it. It helps us to identify good practice and rewards our staff. If you are unhappy with our service, please let us know how we can improve it.