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THE RELATIONSHIP OF HERRING SCHOOL SIZE TO SEABED STRUCTURE AND LOCAL SCHOOL ABUNDANCE IN THE NW NORTH SEA

D.G. Reid

FRS Marine Laboratory, PO Box 101, Victoria Road,
Aberdeen, AB11 9DB, Scotland, UK

ABSTRACT

It is common knowledge among fishermen that demersal fish tend to aggregate on or over seabeds with a specific characteristic. While the explanation for this relationship may be obvious in the case of demersal fish, it is less clear that the same should be true for pelagic fish. However, considerable anecdotal evidence exists suggesting that herring in the NW North Sea show a preference for aggregating in areas where there is a rapid change in water depth and where the seabed is rougher and harder.

This relationship was examined using a school database developed in the EU funded CLUSTER project. The database includes all herring schools extracted from acoustic surveys carried out in July from 1993 to 1997. Each school entry in the database includes a range of individual descriptors such as; length, height, area, energy (S,) and density. Each school is also assigned to an individual one nmi EDSU. A database for the EDSU has also been compiled which includes; depth CV, a slope classification and a substrate classification. By cross relating these two databases it has been possible to assign schools to EDSU and hence to seabed characteristics. A simple non-parametric analysis of these data is presented showing that herring schools tended to be larger and denser over complex sea beds. Herring schools were also shown to be larger when found further from their nearest neighbour. The relevance of these findings to acoustic survey design and analysis and to understanding the implication of commercial fishing activity are discussed.

INTRODUCTION

Acoustic surveys are generally used in fisheries science for stock assessment purposes, mostly for pelagic species but also for some demersal stocks (MacLennan and Simmonds, 1992). However, such surveys also produce highly resolved data which can be analysed to

give information which is useful for in a wide variety of ways Reid (2000). One of the approaches which has attracted considerable interest in recent years is the use of image processing methodologies to extract detailed information on the schooling and clustering behaviour of commercially important pelagic fish species (Reid and Simmonds, 1992; Swartzman, 1997; Petitgas et al., 1996 and 1999; Freon et al., 1992 and 1996; Soria et al., 1998).

This type of approach was used in the context of a collaborative EU project on the aggregation patterns of commercial pelagic fish (CLUSTER) involving Scotland, France, Spain and Greece (Petitgas et al., 1999; Reid et al., 2000). The outcome from the image processing analysis was a series of databases of fish schools seen on the echogram along with a wide range of descriptors of the schools themselves (shape, structure, energy, position, etc) and also extensive descriptors of the school surroundings (depth, water depth, seabed, hydrography, etc) (Reid et al., 2000). These databases could then be analysed to determine important patterns and links between the school descriptors themselves and the wide range of external variables.

Much of these analyses concentrated on the use of complex modelling and visualisation techniques such as Generalised Additive Models – GAM (Hastie and Tibshirani, 1990; Swartzman, 1997), Neural Networks (Bishop, 1996; Haralabous and Georgakarakos, 1996) or Spatial Point Processes (Ripley, 1988; Petitgas and Levenez, 1996). However, I felt that there was also a need for a simple and intuitive analysis approach that allowed the visualisation of simple bi-variate relationships in an easily interpretable manner.

The present paper presents such an approach based on the use of classes for the main school descriptors and a **stepwise** approach to the selection of valid relationships. The approach is descriptive rather than inferential, but can provide useful insights into the relationships under study.

MATERIALS AND METHODS

Schools Database

The school database used in this analysis was derived from acoustic surveys for herring carried out as part of the ICES coordinated herring acoustic surveys of the North Sea and adjacent waters (1993-1997). Acoustic data were collected using a **SIMRAD** EK500 system at 38 KHz. The data were logged on a computer running the **BI500** echo integrator software. The digital echograms were then analysed to extract the herring schools using Image Processing software designed at FRS-MLA on an **ImagePro** platform. The image processing steps followed the procedures described in Reid and Simmonds, 1992. The structure of the school database and the extracted descriptors were described in Reid et al. (2000). The end product from these analyses was a database containing all identifiable herring schools from each survey. The database included a wide range of descriptors of the schools themselves (shape, structure, energy, position, etc) and also extensive descriptors of the school surroundings (depth, water depth, seabed, hydrography, etc).

Analysis

This database and others collected under the auspices of the CLUSTER project have been subjected to a wide range of complex analysis methodology. These concentrated mainly on

multivariate approaches using techniques such as Generalised Additive Models or Neural Nets. While these are undoubtedly invaluable tools, particularly in the presence of interactions, they can also be difficult to interpret in simple biological terms. The intention in this paper was to use a deliberately simple and non-parametric approach to the analysis through which basic bi-variate relationships could be discerned.

Initial bi-variate scatter plots provided little-or no information. An example for school area against depth CV is given in Figure 1a. So the first step in the analysis was to sort the pooled data set for all years for four key school descriptors (Length, Area, Energy (S_A) and Density) into 10 classes based on the 10 percentile divisions. The database was then queried to provide the mean value for all these external parameters for each class from the pooled data for all years. These were then again plotted as xy scatter plots. An example of this treatment, using the same data as in Figure 1a is presented in Figure 1 b. The resultant pairings were then sifted to select only those which showed clear trends. The data were then re-analysed to give the same means by 10 percentile classes but for each year individually. An example of this for the same data again is presented using three point moving average to smooth the traces in Figure 1c. The resultant plots were again sifted to remove all pairings where the years showed different patterns or were different from the pattern in the pooled data plots. Pairing were considered as valid for the sift when four or more years showed patterns similar to each other and that seen in the pooled data. Patterns were generally expected to be linear trends, however other patterns, eg dome distributions or exponential patterns were also acceptable.

The outcome from this process was that relatively few bi-variate pairings survived the sifting. Table 1 shows the selected pairings. The shaded cells represent those pairings, which were passed through the sifting process. In these cases all or four out of five years showed similar patterns to each other AND to that of the pooled data. The pairings represented by the unshaded cells were for cases where one or more of the other school descriptors did show a relationship with one of the other external parameters which was similar in concept, eg nearest neighbour distance and the number of schools per EDSU. These have been included to allow a fuller survey of the relationships between school descriptors and key external variables.

RESULTS

Following the sifting process described in the Materials and Methods, two main categories of external parameter appeared important in relation to the school morphometry. These can be broadly described as seabed structure (Depth CV and Bottom roughness) and local school abundance (Nearest neighbour distance, herring schools per nmi and herring schools in cluster). Position in the water column was also shown as important, although this could be considered as an **artefact** (see below). In some of the cases presented below, relationships were apparent between an external factor and some school descriptors but not others. Plots for these pairing have also been included to allow an overall survey of the relationships of seabed structure and local school abundance to school descriptors.

Seabed Structure

Three descriptors of seabed structure were included in the database. These were; DCV • the CV of all the depths recorded across a one nmi EDSU; BR • Bottom roughness, a four category characteristic (flat, undulating, bumpy to spiky), (Reid *et al.*, 2000); and SL • slope, a three category classifier for the slope of the seabed (flat, medium and steep), (Reid *et al.*, 2000).

Depth CV • DCV

DCV is an expression of the **changability** in depth across a single one nautical mile EDSU. For four out of the five years studied, there was a distinct trend discernable in the lengths, areas and energies of the schools (Figs 2a, b, c). Greater DCV tended to be associated with schools of greater area and length. 1996 showed a different pattern with no obvious trend in school size with DCV. The picture for school S_a (Fig. 2c) was slightly different. The 20% of schools with the greatest energy were associated with distinctly higher DCV values than the remainder. This was also true in 1996. School density (Fig. 2d) showed no relationship to DCV.

Bottom Roughness • BR

BR is a subjective **categorisation** of the topography of the seabed. All four school descriptors showed weak but distinct trends in relation to BR (Figs 3a, b, c, d). The more topographically diverse EDSUs were associated with larger schools with higher energies and greater densities.

No relationship was seen with slope of the seabed

Local School Abundance

Three different descriptors were used to **characterise** a school in relation to the schools in it's immediate locality. These were: (NN • Nearest neighbour distance, HE • herring schools per one nmi EDSU and HC – the number of herring schools in the same cluster). The relationships were more complex but some general trends were apparent.

Nearest neighbour distance • NN

There was a general **tendancy** for all school descriptors to rise with increased NN distance, and in many cases this was particularly marked for the largest 20% of schools (Figs 4a, b, c, d). This was most apparent for school energies and densities (Figs 4c, d). In 1994, 95 and 97 school lengths and areas (Figs 3a, b) increased with NN distance, however in 1993 both descriptors tended to diminish as NN distance increased. In 1996, school area did show an increase with NN distance, but the signal was noisy. School length in 1996 actually decreased with NN distance in the lower length classes, but then showed **a** sharp increase in the top two classes.

Herring schools per EDSU • HE

The picture from the analysis in relation to the number of schools in the EDSU was even more complex (Figs 5a, b, c, d). In general, increase in the number of schools per EDSU was related to longer schools (all years except 1995), less dense schools (all years) and possibly lower school energies (1995, 96 and 97) (Figs 5a, c, d). In 1993 school area went up with HE (Fig. 5b), it showed no trend in 1994, 96 and 97, and went down in 1995.

Herring schools per cluster • HC

An equally complex but different picture could be seen for the relationships to the number of schools in the cluster (Figs 6a, b, c, d). School energies (except 1993) and densities (Figs 6c, d) both showed a reduction with HC. No general pattern for length or area was apparent (Figs 6a, b).

Position in the Water Column - WCP

Position in the water column is presented as a proportion, between the depth of the mid-point Of the school and the total water depth at the school location. There was clear evidence of trends in all school descriptors in relation to their position in the water column (Figs 7a, b, c, d). Schools tended to be shorter and have reduced areas and energies when closer to the seabed. This may be an artifact Schools are 3D objects and their height, length and area all tend to be correlated. So schools found closer to the seabed might be expected to be restricted in height, and hence length and area. However, it is interesting that the density of the schools tends to increase the closer they are to the seabed (Fig. 7d). This is unlikely to be an artifact.

The matrix of all the pairings which, passed through the sifting process, plus the other related parings which failed to pass, are presented in Table 1.

Descriptor	Length class	Area class	SA class	Density class
DCV	All years (+ve)	All years (+ve)	All years (+ve)	No relationship
BR	All years (+ve)	All years (+ve)	All years (+ve)	All years (+ve)
WCP.	All years (+ve)	All years (+ve)	All years (+ve)	All years (-ve)
NN	94, 95, 97 (+ve) 93, 96 (-ve)	94, 95, 96, 97 (+ve) 93 (-ve)	All years (+ve)	All years (+ve)
HE	All years except 95 (+ve)	No relationship	93, 94 (+ve) 95, 96, 97 (-ve)	All years (-ve)
HC	No relationship	No relationship	All years except 93 (-ve)	All years (-ve)

DISCUSSION

The aim of the present analysis was two-fold. The first aim was to determine if there was a simple way of visualising bi-variate relationships between herring school structures derived from acoustic data and a variety of key external parameters, and doing so in a convincing manner. The second aim was to find out what those relationships were and therefore identifying those key external parameters.

The analysis methodology adopted was simple and largely intuitive. The process of sorting data into classes is common to a wide range of non-parametric statistical analyses Siegel (1956). The second element of the analysis was the search for trends in the pooled data, which were then also matched when the data were split into years. While this was essentially a subjective approach the two stage nature of the sifting process should have ensured that the final selected pairing were robust to spurious relationships.

The parings, which came through the sifting process as important also suggest that this simple mode of analysis may have worked reasonably well. Two types of external variable showed up as important, seabed structure and local school abundance.

A link between herring distribution, a pelagic fish, and the topography Of the seabed may at first seem counter-intuitive. However, as the plots of water column position show, herring

schools are mostly found in the deepest 10% of the water column. Herring distribution has been shown to be related to both seabed substrate and (Maravelias, 1999; Maravelias *et al.*, 2000). Reports from commercial vessels and other anecdotal sources suggest that herring are often found associated with high relief in the seabed. Additionally, herring is a substrate spawner, and in this part of the North Sea spawns in autumn in high energy areas often characterised by gravel (Parrish and Saville, 1965; Blaxter, 1990). The acoustic survey in this area is designed to survey pre-spawning aggregations of herring, and it has been suggested that herring may aggregate close to their spawning areas in advance of actual spawning (Haegele and Schweigert, 1985). Taken together, all these sources would suggest that a link between the structure of the seabed and herring aggregations is not unlikely. The present study suggests that herring schools tend to be larger, have higher energy and are denser in areas where the seabed is more variable.

The second type of external variable, which showed a relationship with school structure, was a group of local school abundance parameters; nearest neighbour distance and number of herring schools in the same EDSU or cluster. Three school descriptors (Area, S_A and density) showed a pattern of increase with nearest neighbour distance. So as the schools were found further apart they tended to be bigger and have more fish in them. In three years they also tended to be longer, but this was reversed in the other two years. The other two parameters HE and HC represented the reciprocal of nearest neighbour distance, in that, more schools in an EDSU or cluster would be expected a priori to correlate with schools closer together. In general this expectation is borne out. Distinct trends were only apparent for density, where for both external variable (HE and HC) there was a decrease in density with more schools. The school energy also showed a pattern of decrease in relation to the number of schools in the cluster, which was also shown for three out of five years in relation to schools per EDSU. The results for length were quite different, with four out of five years showing an increase with the number of herring schools in the EDSU. Interestingly, length was the only one of the school descriptors, which did not show a relationship to the nearest neighbour distance.

A tendency for pelagic fish schools to be bigger when more isolated has been reported elsewhere. Petitgas *et al.* (1999) reported similar behaviour in a number of pelagic species. Soria *et al.* (1998) suggested that this phenomenon may be the result of point observations of a dynamic process of school formation and break up. They suggested that a particular group of fish may be found aggregated in a single, large school or in a number of smaller schools and that they might cycle from one state to the other. A survey ship could therefore see them in either state by chance, and would either see many, small, closely adjacent schools, or one large, isolated schools. Alternatively, it may be that the fish behaviour is different in different situations. In this study, the strongest signal was for isolated schools to be densely packed. One could speculate that fish in a single isolated school may respond to a perceived increase in vulnerability to predators by packing more closely.

As mentioned above, the tendency for schools to be smaller the closer they are found to the seabed may be an artifact. Schools, which are close to the seabed will necessarily be constrained in maximum dimensions, and the correlation reported here may be a result of this. However, while this may be the case, it remains interesting that this occurs. It suggests that as fish aggregate into larger schools, they tend to rise off the bottom. It would be theoretically possible for the schools to extend horizontally when they get bigger. This would result in the type of layer structures seen in many acoustic surveys. This has implications, particularly in relation to commercial fishing practice. Large schools, which tend to be found higher in the water column, would also be expected to be more easy to detect using fishing sonars. Furthermore, they would be more attractive as targets for purse

seine operators. Conversely, if the large schools extended horizontally, they would be less likely to be detected on sonars, but probably more vulnerable to trawl operations. The link between seabed topography and school size confirms previous anecdotal observations. It opens up the possibility of using seabed data as an external conditioning variable to improve the accuracy of acoustic survey estimates. It also has the potential for being used as a stratification parameter. It may be desirable to sample more intensively in those areas characterised by variable seabed topography.

The link between local school abundance and size (particularly the nearest neighbour relationship) suggests that isolated schools tend to be larger than those found close together. Trawling operations are less likely to be successful on single isolated schools than on groups of many schools. These schools also contribute significantly to the calculated stock biomass, the few large schools seen on this survey can account for up to half of the total biomass. It is therefore, important for survey operatives to continue to make every effort to sample from such schools, as well as from the aggregations of many smaller schools.

In conclusion, this study has demonstrated a simple **stepwise** visualisation process for isolating and confirming pair-wise links between herring school descriptors and a variety of external parameters. The most important external variables were seabed topography and local herring school abundance.

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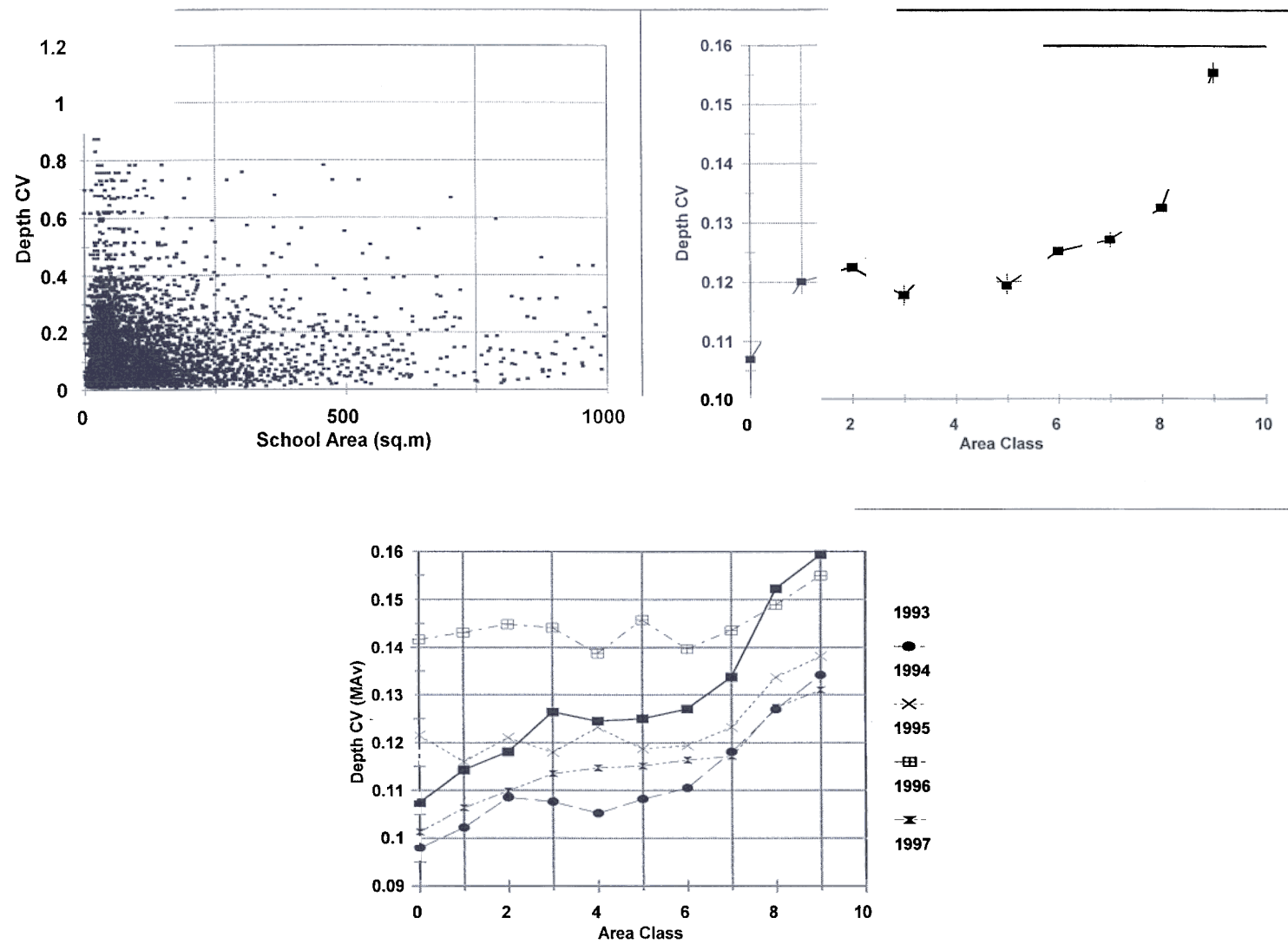


Figure 1 Example data set at different stages of the analysis. a. Top left. Scatter plot of raw data. b. Top right. Mean Depth CV by Area Class for all years pooled. Bottom. c. Mean Depth CV (Moving average) by Area Class for all years separately.

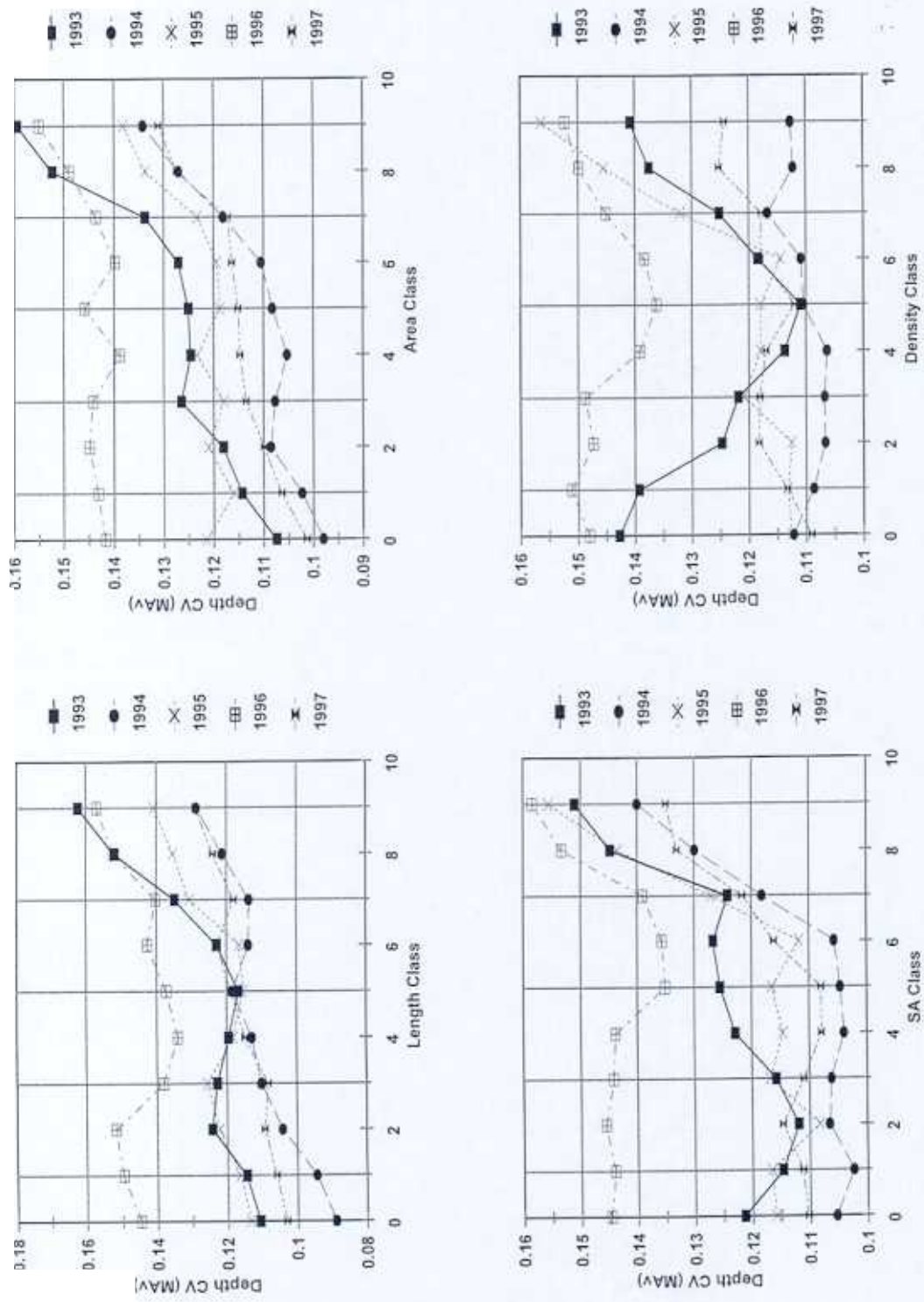


Figure 2. Mean Depth CV for each year separately against classified school descriptors a. Top left – School length. c. Top right – School area. b. Bottom left – School energy (S_a) and d. Bottom right – School density

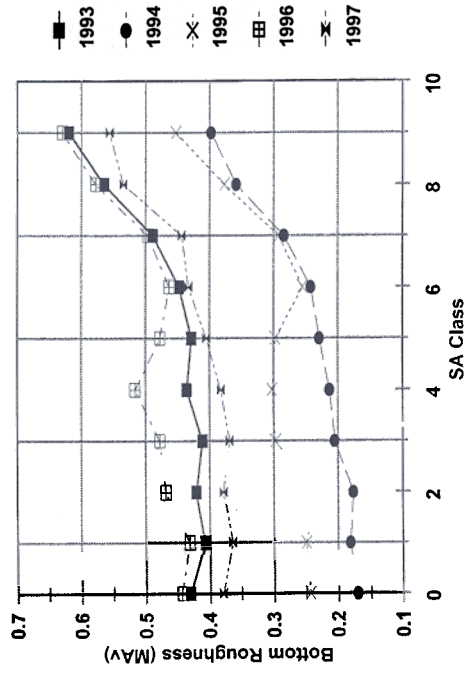
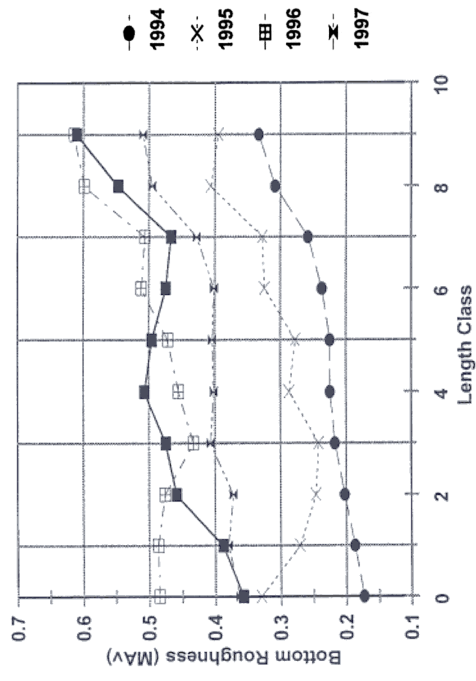
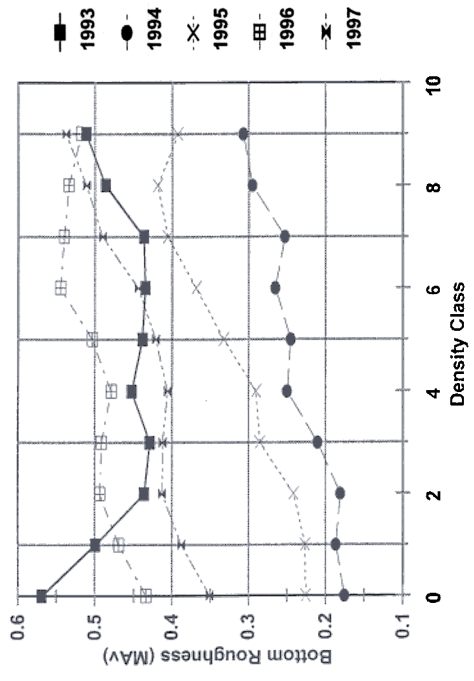
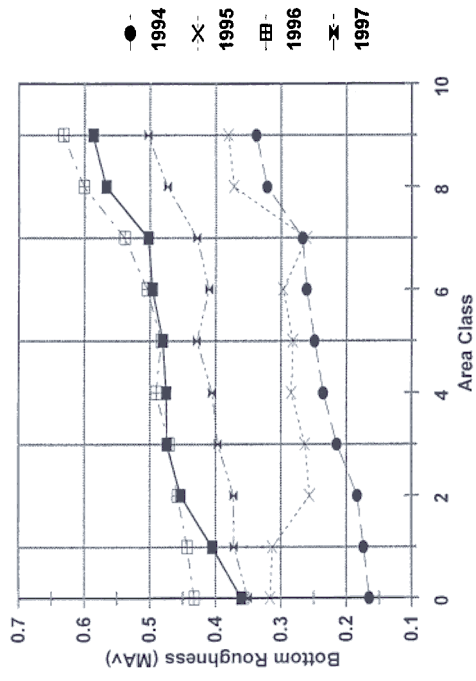


Figure 3. Mean Bottom roughness for each year separately against classified school descriptors a. Top left School length. c. Top right – School area. c. Bottom left – School energy (S_a) and d. Bottom right – School density

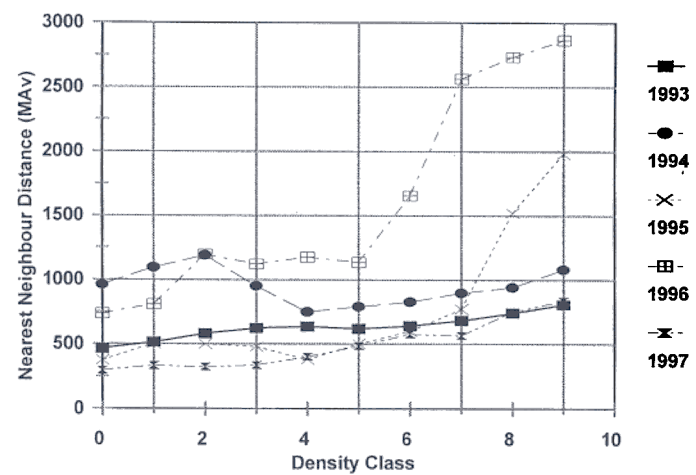
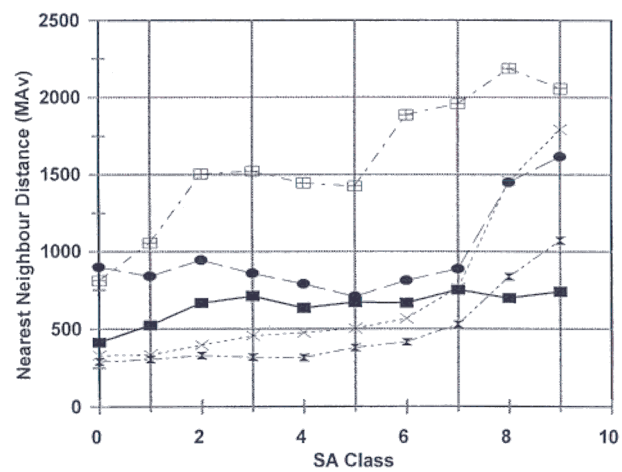
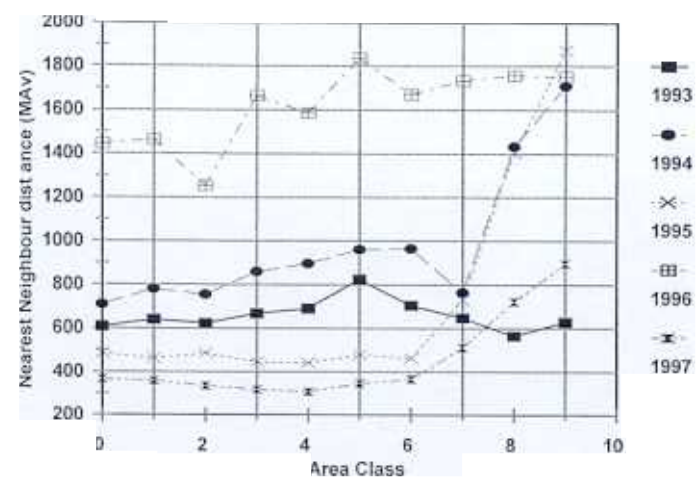
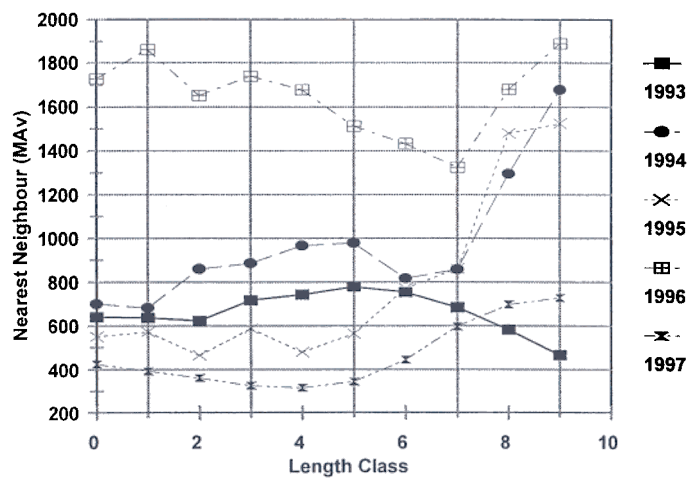


Figure 4. Mean Nearest neighbour distance for each year separately against classified school descriptors a. Top left – School length. c. Top right – School area. c. Bottom left – School energy (S_a) and d. Bottom right – School density

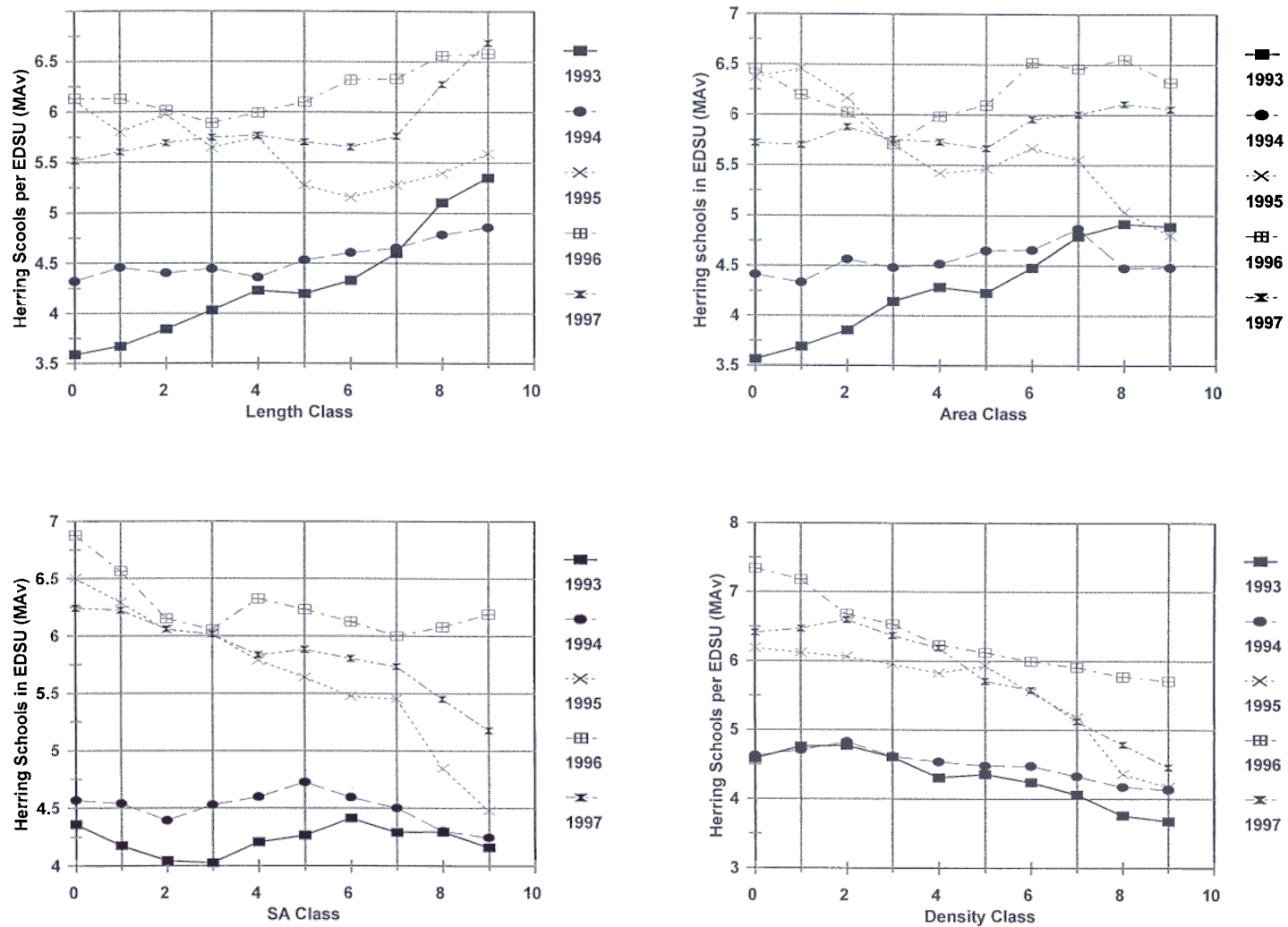


Figure 5. Mean number of herring schools per EDSU for each year separately against classified school descriptors a. Top left – School length. c. Top right – School area. c. Bottom left – School energy (S_a) and d. Bottom right – School density

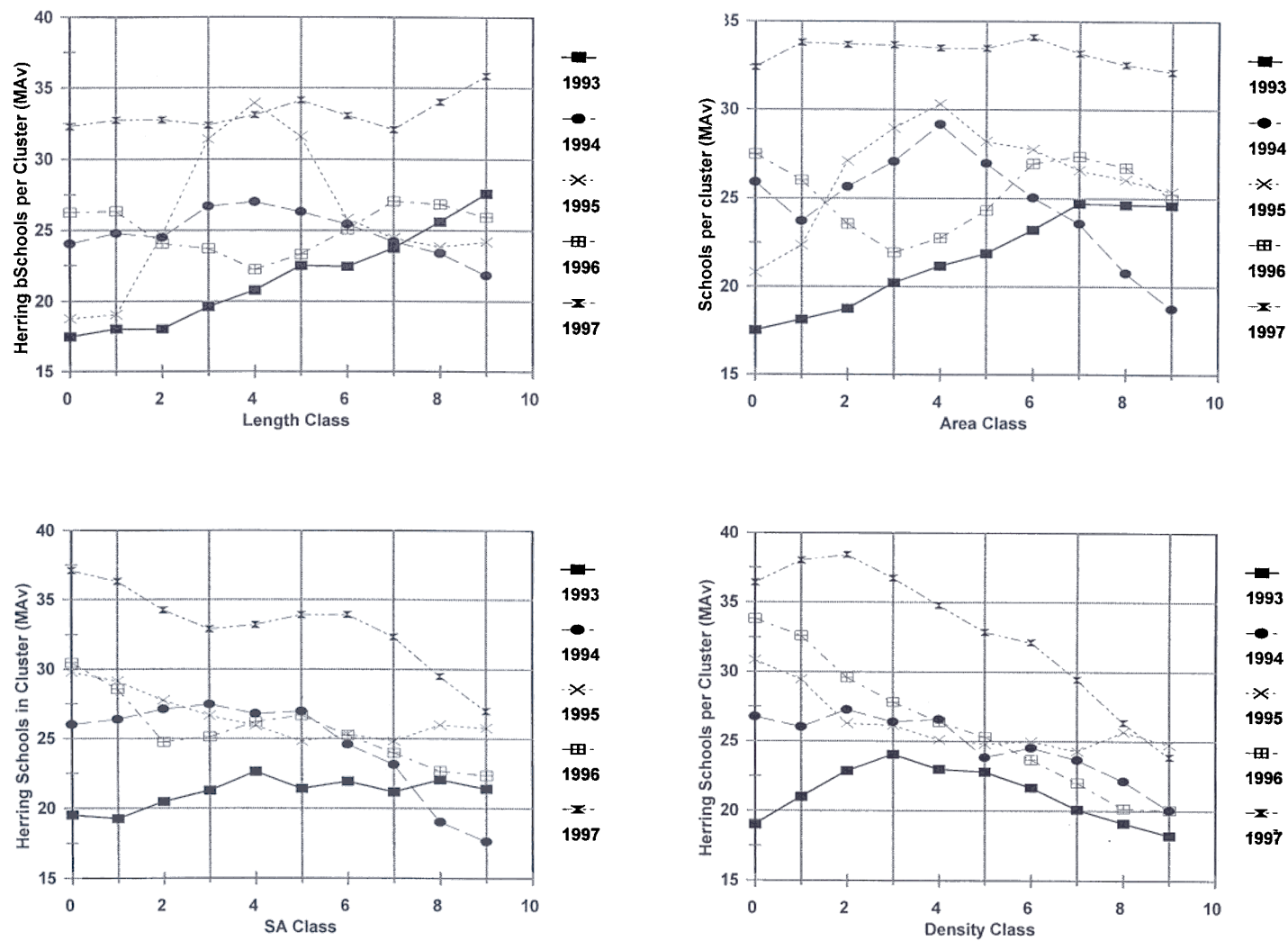


Figure 6. Mean herring schools per cluster for each year separately against classified school descriptors a. Top left – School length. c. Top right – School area. c. Bottom left – School energy (S_a) and d. Bottom right – School density

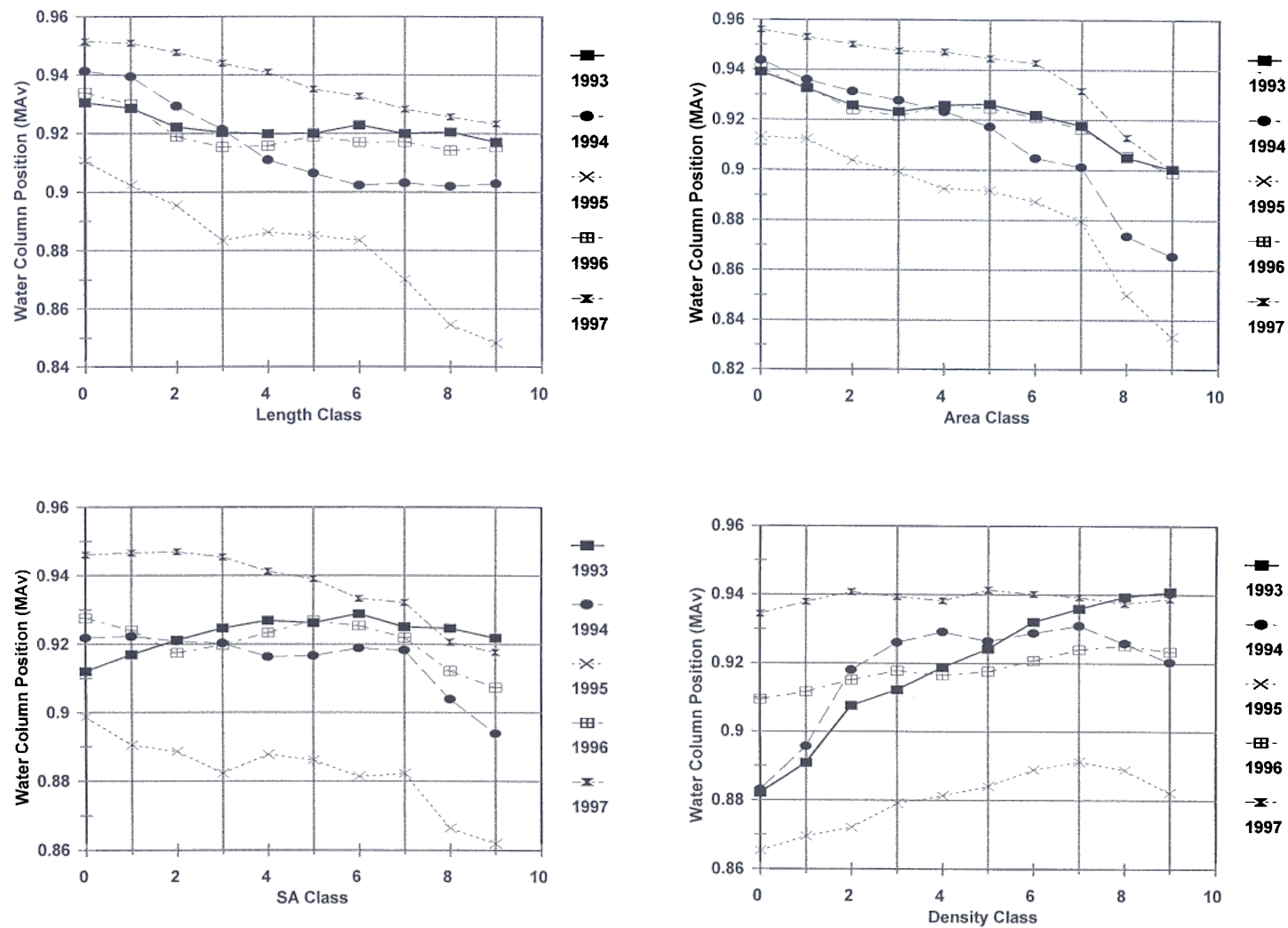


Figure 7. Mean Water Column Position for each year separately against classified school descriptors a. Top left – School length. c. Top right – School area. c. Bottom left – School energy (S_a) and d. Bottom right – School density.