Contribution to D12 (AUTH, APRA-SMR, FIC and UEA)

Downscaling of extreme indices in Greece

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AUTH

Introduction

AUTH has developed three statistical downscaling models in order to identify the relationship between large-scale circulation and extreme temperatures / precipitation. ARPA-SMR used two models in order to downscale extreme events. A downscaling method has been applied by UEA that models seasonal indices of extreme rainfall at UK stations using large-scale circulation. Finally, FIC has developed a method using low-resolution atmospheric fields in order to estimate high-resolution surface for temperature and precipitation.

Data

Predictors and Predictands

Different downscaling models with different predictors estimate the same predictands in order to evaluate the most efficient model for the Greek area. The predictands are the seasonal "core" extreme indices (Table 1). The majority of the predictors were selected from the NCEP reanalysis data (Table 2). The calibration period for all models is 1958-1978 & 1994-2000 and the validation period is 1979-1993. The skill measures of the models are Spearman correlation and Biases.

Table 1. The "core" extreme indices of Predictands

Precipitation related Indices	
Designation	*Description*
Pq90	90^{th} percentile of rainday amounts (mm/day)
Pxcdd	Max no. consecutive dry days
Px5d	Greatest 5-day total rainfall
Pint	Simple Daily Intensity (rain per rainday)
Pf90	No of events >long term 90^{th} percentile
Pn90	% of total rainfall from events>long term P90
Temperature related indices	
Designation	*Description*
Txav	Mean Maximum Temperature
Tx90	Tmax 90^{th} percentile
Tnav	Mean Minimum Temperature
Tn10	Tmin 10^{th} percentile
Tnfd	Number of frost days (Tmin <0^{o} C)
Txhw90	Heat wave duration

Table 2.Predictors of the different methods

Greece

Methods	Multiple Regression Analysis	Canonical Correlation Analysis (CCA)	Artificial Neural Network (ANN)
Precipitation Indices	-Circulation types 500hPa	-Geopotential heights at 500hPa -Anomalies at 500hPa	-Geopotential heights at 500hPa -Anomalies at 500hPa
Temperature Indices	-Circulation types Thickness 1000-500hPa	-Thickness fields 1000-500hPa -Anomalies 1000-500hPa	Thickness fields 1000-500hPa -Anomalies 1000-500hPa
Window	20°W-50°E and 20°N-65°N	0°-32.5°E and 30°N-55°N	0°-32.5°E and 30°N-55°N

Italy

Methods	Multiple Linear Regression Analysis	Canonical Correlation Analysis (CCA)
Precipitation Indices Temperature Indices	The 4 PCs that derived from -Mean Sea Level Pressure (MSLP) -Geopotential height at 500hPa (Z500) -Temperature at 850hpa (T850)	The 1st EOFs of predictands and predictors that explain 97.5% from the total variance *Predictors*: the same as MLR *Predictands*: the seasonal core extreme indices
Window	30°W-30°E and 30°N-60°N	30°W-30°E and 30°N-60°N

UK

Methods	Canonical Correlation Analysis (CCA)
Precipitation Indices Temperature Indices	-Mean Sea Level Pressure (MSLP) -Specific Humidity at 700hPa (SH700) -Relative humidity at 700hPa (RH700) -Temperature at 700hPa (T700)
Window	60°W-60°E and 20°N-80°N

Spain

Methods	FIC Method
	-Thickness fields 1000-500hPa -Sinusoid function of the day of the year with maximum in June 22nd, to consider the clear sky radiation influence on the warming/cooling of the surface air (seasonal factor) and -Weighted average of the surface grid-point mean daily temperatures of the ten previous days, to account for the soil thermal inertia influence (soil memory factor).
	2.5°E-45°E and 30°N-55°N

Methods

The different methods used are:

A) Greece

A1) Multiple Regression Analysis using the circulation types approach

According to the results of D10, the classification of the circulation types for the 500hPa has proven to be the most appropriate of the construction of the Multiple Regression Model for the precipitation indices. On the other hand, the classification of the circulation types for the thickness (1000 – 500hPa) has proven to be the most appropriate for the construction of the model, in order to simulate the temperature indices. For every index, season and station, a different model has been constructed, according to the relationship of the circulation types, the precipitation indices and the temperature indices. The selection of the most efficient model has been done by combining the correlation coefficient values of the observed with the simulated as well as the RMSE values (Maheras et al., 2000; Maheras and Anagnostopoulou, 2003; Maheras et al., 2004).

A2) Canonical Correlation Analysis (CCA)

This method isolates linear combinations of multiple predictor variables and linear combinations of multiple predictand variables that have maximum correlation coefficients. This approach assumes that the relationship between predictor and predictand will remain stable in the future climate, an assumption based on physical interpretability of the relationship found and in the ability of the statistical model to reconstruct local climate anomalies form the large scale observation in an independent historical period (Barnett and Preisendorfer 1987; Von Storch and Zwiers 1999).

For the simulation of the precipitation indices, SLP and 500hPa geopotential values have been used, while for the simulation of the temperature indices the thickness (1000-500hPa) values have been used.

A3) Artificial Neural Network (ANN)

Artificial Neural Network models have a structure based on human neural system. Acting as black box models permit the estimation of a number of parameters from predictor parameters, the two groups been connected by non-linear relations. These models have three layers (input – hidden – output) or a more complex structure. The main advantage of ANNs is that no initial transfer function is needed to be chosen and the system is self-training (Trigo and Palutikof, 1999).

As for the previous models, for the construction of the model for the simulation of the precipitation indices, SLP and 500hPa geopotential values have been used, while for the simulation of the temperature indices the thickness (1000-500hPa) values have been used.

B) Italy

The downscaling models developed by ARPA-SMR in order to downscale extreme events from Greece are based on two methods:

1. the multiple linear regression based on the principal components of the data sets used in the analysis (MLR);
2. the multivariate regression based on canonical correlation analysis (CCA)

Both methods are based on a multiple linear regression with predictors derived from NCEP reanalysis: geopotential height at 500mb (Z500), mean sea level pressure (MSLP), temperature at 850mb (T850) and specific humidity at the levels: 1000mb, 950mb, 850mb, 750mb, while the predictands are the seasonal “core” extreme indices (7 indices for precipitation and 6 indices for temperature).

The predictors used in the MLR method are the first 4 PCs of the above fields. The downscaling based on CCA analysis has been performed using like input data the first EOFs of predictands and predictors that explain 97.5% from the total variance, while the CCA pairs used in the downscaling model has been selected such as the correlation between them to be statistically significant.

The model has been calibrated on the period 1958-1978+1994-2000 and validated on the period 1979-1994.

The skill of the statistical models evaluated by the BIAS, RMSE and Spearman rank-correlation coefficient has been revealed that the seasons with best performances is winter followed by autumn. High performances have been obtained for mean fields (mean daily precipitation, mean maximum and minimum temperature) and some extreme of precipitation and temperature (number of consecutive dry days, 90th percentile of maximum temperature, 10th percentile of winter minimum temperature, number of winter frost days). The comparison between two statistical downscaling methods reveals that the skill of the CCA is in generally better than those provided by the MLR methods.

C) United Kingdom

A downscaling method is being developed to the applied to the entire European regional dataset which models the STARDEX indices of rainfall extremes using large scale patterns of circulation. Rather than modelling the daily rainfall itself, then calculating the indices, this method will use seasonal measures of large-scale circulation variability to model the seasonal indices of extremes directly. The predictands will be the six core STARDEX indices of rainfall extremes calculated seasonally. Predictors will be selected from circulation variables, calculated over the entire European and East Atlantic region. From our work preparing D10, the best predictor seems to be sea level pressure but other variables will be considered including temperature, geopotential height and relative humidity at three atmospheric levels as well as sea surface temperature. The model uses canonical correlation analysis. Two methods to select predictors will be tested: using just the variable with the best correlation with the indices (MSLP); and a cross-validation of all possible predictor combinations.

D) Spain – FIC

D1) Description of the method.

The method estimates high-resolution surface meteorological fields for a day "X", in two steps: in the first step, the "n" most similar days to the "X" day, attending to their low-resolution atmospheric fields, are selected from a reference dataset. In the second one, high-resolution surface information is estimated in a different way for precipitation and temperature. Rainfall estimations for a point are done by means of a simple average of the observed precipitation amounts in the "n" analogous days, in that point. Temperature is obtained applying a further multiple linear regression analysis that searches for relationships (in the "n" day's population) between some atmospheric variables (predictors) and the surface temperature (predictand).

The first step selection of the "n" days is an analogical technique. Precipitation is known to present strong non-linear relationships with its potential predictor variables, what makes analogical techniques, that, do not assume any hypothesis about predictor/predictand relationships, specially indicated for its diagnosis. The method's level of performance depends upon the extension and quality of the atmospheric and surface reference datasets and, very remarkably, upon the similarity measure used to determine similarity among days. In this sense, the similarity measure must contain diagnostic capability regarding high-resolution precipitation fields (low-resolution atmospheric fields considered similar by the measure must be associated with similar high-resolution precipitation fields).

Regarding temperature, the two steps procedure is necessary to consider the non-linear influence of cloudiness over the surface temperatures. Precipitation is strongly related to cloudiness, so the previous selection of very similar days regarding precipitation, is implicitly guarantying also very similar cloudiness conditions for the selected days, what makes the further diagnosis by multiple linear regression very accurate. In this regard, Lorenz, suggested that if linear analyses were applied to analogous synoptic situations, the non-linear character of the atmosphere would be more tractable.

- **First step: the analogical technique**

As pointed earlier, in the first step, the "n" most similar days to the "X" day, attending to their low-resolution atmospheric fields, are selected from a reference dataset. The similarity measure must contain diagnostic capability regarding high-resolution precipitation fields. In this sense, the similarity measure must assess the likeness of as many as possible precipitation forcings associated to the low resolution atmospheric configurations of the days being compared.

In an initial selecting procedure, the mean daily geostrophic flux fields at 1000 and 500hPa were found to offer the best performance, among the many different predictor sets tested.

The similarity measure between two days must be a scalar magnitude (to allow ordering), that summarises the resemblance of this two days with regard to their mean geostrophic 1000 and 500 hPa wind fields.

The good performance of Euclidean distances is backed up by analogue technique literature.

The similarity between two days is calculated determining (and standardising) independently those days likeness regarding each of the final four predictor fields "p":

1000 hPa wind speed field, 1000 hPa wind direction field, 500 hPa wind speed field and 500 hPa wind direction field.

The likeness of days "i" and "j" regarding each predictor field "p" (for example, 1000hPa geostrophic wind speed), is calculated as an euclidean distance with:

$$D_{spd1000}(i,j) = \sqrt{\frac{\sum_{k=1}^{N}\left(Spd1000_{ik} - Spd1000_{jk}\right)^2 \cdot P_k}{\sum_{k=1}^{N} P_k}} \quad , (*)$$

where $Spd1000_{ik}$ is the value of the 1000 hPa geostrophic wind speed of the day "i", at the grid point "k" of the grid used to represent atmospheric fields; P_k is the weighting coefficient of the "k" grid point . P_k coefficients are necessary to consider the greater influence on Iberian precipitation of the wind features closer to the Peninsula. P_k coefficients can be different for 1000 and 500 hPa predictors. "N" is the number of the atmospheric grid points, that is determined by the spatial domain and the resolution of the referred grid.

Once $D_{spd1000}(i,j)$ has been calculated, it has to be standardised. The standardisation is done by means of substituting $D_{spd1000}(i,j)$ by $cent_{spd1000}$, that is the closest centil of the reference population of Euclidean distances among predictor fields *"spd1000"*, to the $D_{spd1000}(i,j)$ value. The centil values are previously determined, obiously independently for each "p" predictor field, over a reference population of more than 3.000.000 values of D_p, calculated applying the previous formulae, with the same P_k values, to randomly selected days (i.e., days multiple of 3). If the closest value to $D_{spd1000}(i,j)$ is $cent_{spd1000}$ = c, that means that about the c% of the 3.000.000 $D_{spd1000}$ values are lower than $D_{spd1000}(i,j)$.The use of centil instead of the original distance allows to consider adimensional and initially equally weighted variables, in the measure.

After the four $D_p(i,j)$ independent calculation and standardisation (determination of the closest four $cent_p$), the final similarity measure between days "i" and "j" is:

$$sim(i,j) = w_{spd1000}cent_{spd1000} + w_{dir1000}cent_{dir1000} + w_{spd500}cent_{spd500} + w_{dir500}cent_{dir500} \, ,$$

where w_p is the weighting coefficient of the predictor field "p". The w_p combination finally selected is: $w_{spd1000}$ = 0,25; $w_{dir1000}$ = 0,25; w_{spd500} = 0,25; w_{dir500} = 0,25;

- **Second step: the multiple linear regression analysis.**

The estimation procedure for temperatures requires, after the selection of the "n" analogous days described above, a further diagnosis by multiple linear regression. Although predictor/predictand relationships determined in this second step are linear, an important part of the non-linear links of free atmosphere variables with surface temperatures is considered with the previous (analogical) stratification. Linear regression performs pretty well to estimate surface maximum and minimum temperatures, due to the near-normal statistical distribution of those variables. It is necessary to remember that, when using linear regression, the predictand quantity is bound to have essentially the same statistical distribution as the predictor/s variable/s. In this regard, potential predictors should present close-to-normal distributions.

The multiple linear regression employs a forward and backward stepwise selection of predictors. The potential predictors are three:

1. mean daily 1000/500 hPa thickness above the surface grid-point, to include the strong relationship between lower troposphere and surface temperatures (meteorological factor),
2. a sinusoid function of the day of the year with maximum in June 22nd, to consider the clear sky radiation influence on the warming/cooling of the surface air (seasonal factor),
3. and a weighted average of the surface grid-point mean daily temperatures of the ten previous days, to account for the soil thermal inertia influence (soil memory factor). Weighting coefficients decrease linearly from a value of 10 for the D-1 day to a value of 1 for the D-10 day.

The non-linear influence of other important meteorological factors, like cloudiness, precipitation and low troposphere wind speed, is considered through the previous analogical stratification. In fact, the regression is performed over a population of "n" days that present very similar precipitation conditions, and subsequently, very similar cloudiness conditions. As the analogical selection searches for days with similar 1000 and 500 hPa geostrophic wind fields to the problem day, low troposphere wind speed fields of the "n" days also tend to be very like.

Results

A) Precipitation indices

From the analysis of the results for the two regions (Western and Eastern Greece), derives that all methods provide relatively similar results for each season and for each index. The results in wintertime are better than all the other seasons while the lowest correlation coefficients are found in the case of autumn. In should be mentioned that the indices concerning the mean precipitation (Pav) and the dry days (Pxcdd) are the ones with the highest correlation coefficients during all seasons. On the other hand although the biases in the case of the Pav are the lowest, the biases of the Pxcdd are quite high. Generally, it can be mentioned that the results for Western Greece are more satisfying than the results in the Eastern region with the exception of the spring results (figures 1-4).

From the comparison of the common methods of CCA it is noticed that although the methods are the same the selection of the predictors and the NCEP data window is decisive and differentiates the results (figures 5-6). For example, in some cases two of the three methods present satisfying correlation coefficients for the precipitation indices, while the correlation coefficients of the third method are either very low of even negative. On the other hand, the two models of MLR_It and the one of the MLR_AUTH don’t present similar results (figures 7-8) due to the fact that the predictors in the MLR_AUTH are the circulation types, which result to a complete different technical approach.

B) Temperature indices

Concerning the temperature indices for western and eastern Greece, it is obvious that the correlation coefficients from the application of all methods are much higher than the ones in the case of precipitation. During winter and spring, these correlation coefficients reach the value of 0.9 in some of the temperature indices. On the contrary, only in the case of autumn, for some indices, the correlation coefficients are found negative (figures 9-10). It is remarkable that the FIC method provides better results, with high correlation coefficients values, comparing to the other methods especially in eastern Greece. The efficiency of the methods in simulating the temperature indices is clear also for the analysis of the biases figures, which in most of the cases are very small (figures 11-12).
Comparing the common methods for the temperature indices it could be noticed that their behaviour during winter is similar. On the contrary, the MLR-Z500 presents negative correlation coefficients in the case of summer and autumn (figures 13-14). Figures 15 and 16 indicate that the three common CCA methods appear to have small biases for the majority of the temperature indices, while the MLR_AUTH for the second group of common methods presents slightly higher biases from the other two methods.

COCLUSIONS

The temperature indices present more satisfactory results with high correlation coefficients and low values for Biases. On the other hand the results for the precipitation indices are not so good. For all the indices the results for the western part of the study region are better than in the eastern part, except for the case of FIC temperature results which are better in eastern Greece.

The methods used give quite satisfactory results, but it is difficult to choose the most efficient model as their results vary from season to season and from station to station. Generally, it could be concluded that the most prevailing factors in the efficiency of a method in simulating temperature and precipitation indices are, the appropriate selection of the predictors and the size and the position of the grid data window.

More specifically, from the three methods used by the AUTH partner, the most efficient one is the Neural Net method, giving the highest correlation coefficients, mostly in the case of the precipitation indices. This could be due to the different way that this method is functioning. On the contrary, from the analysis of the biases the MLR method using the circulation type approach gives the most satisfying results – the lowest biases.

Concerning the evaluation of the common methods (CCA) from the three partners it can be noticed that for the temperature indices the correlation coefficients are high and almost similar for all the methods. The differences in the results for the precipitation indices and the fact that the highest coefficients are found for the methods used by the AUTH partner, could be attributed to the different predictors and window that have be used.

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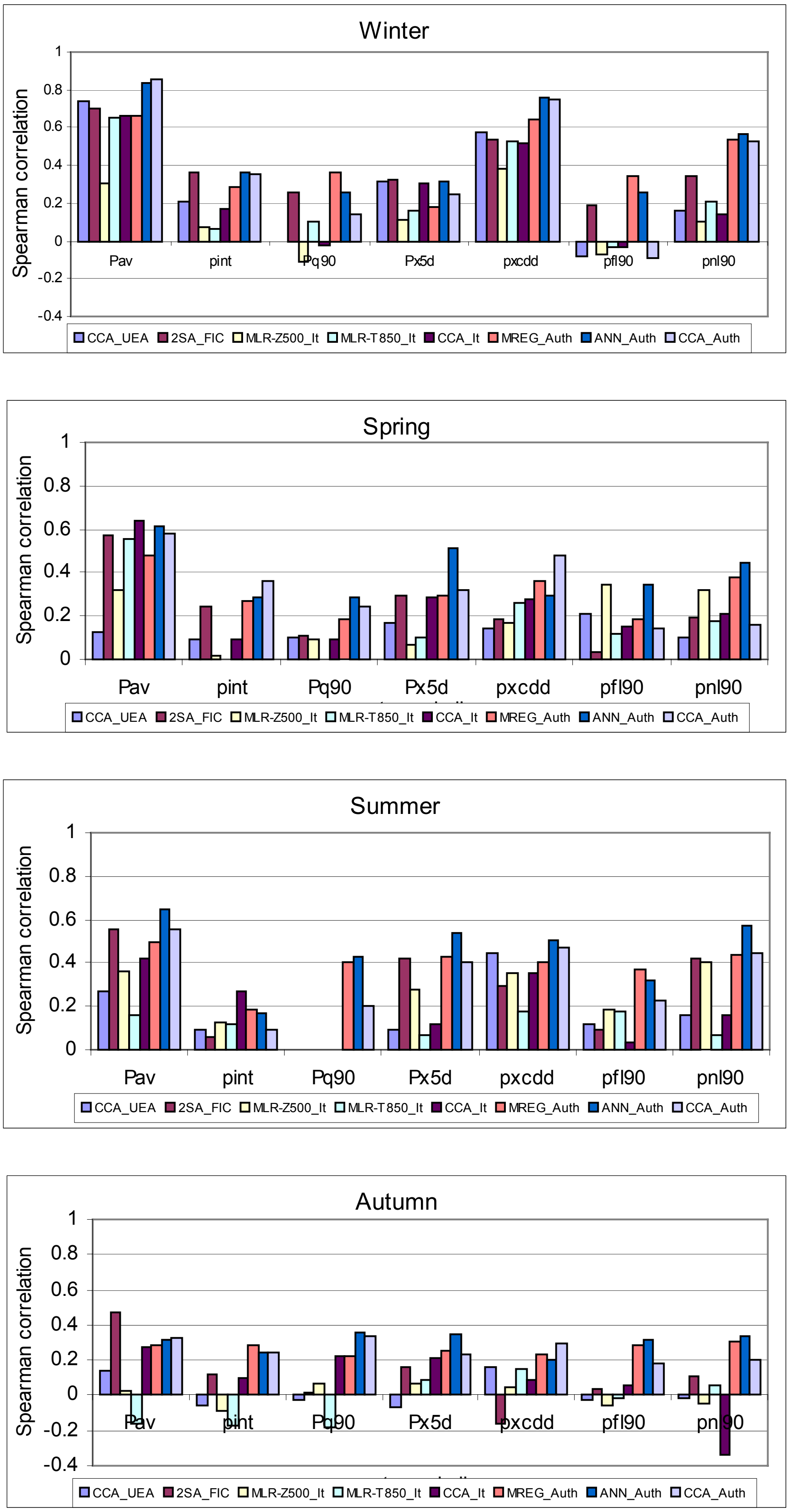

Figure 1. Spearman correlation for precipitation indices, average over the four stations from western Greece for the different downscaling methods.

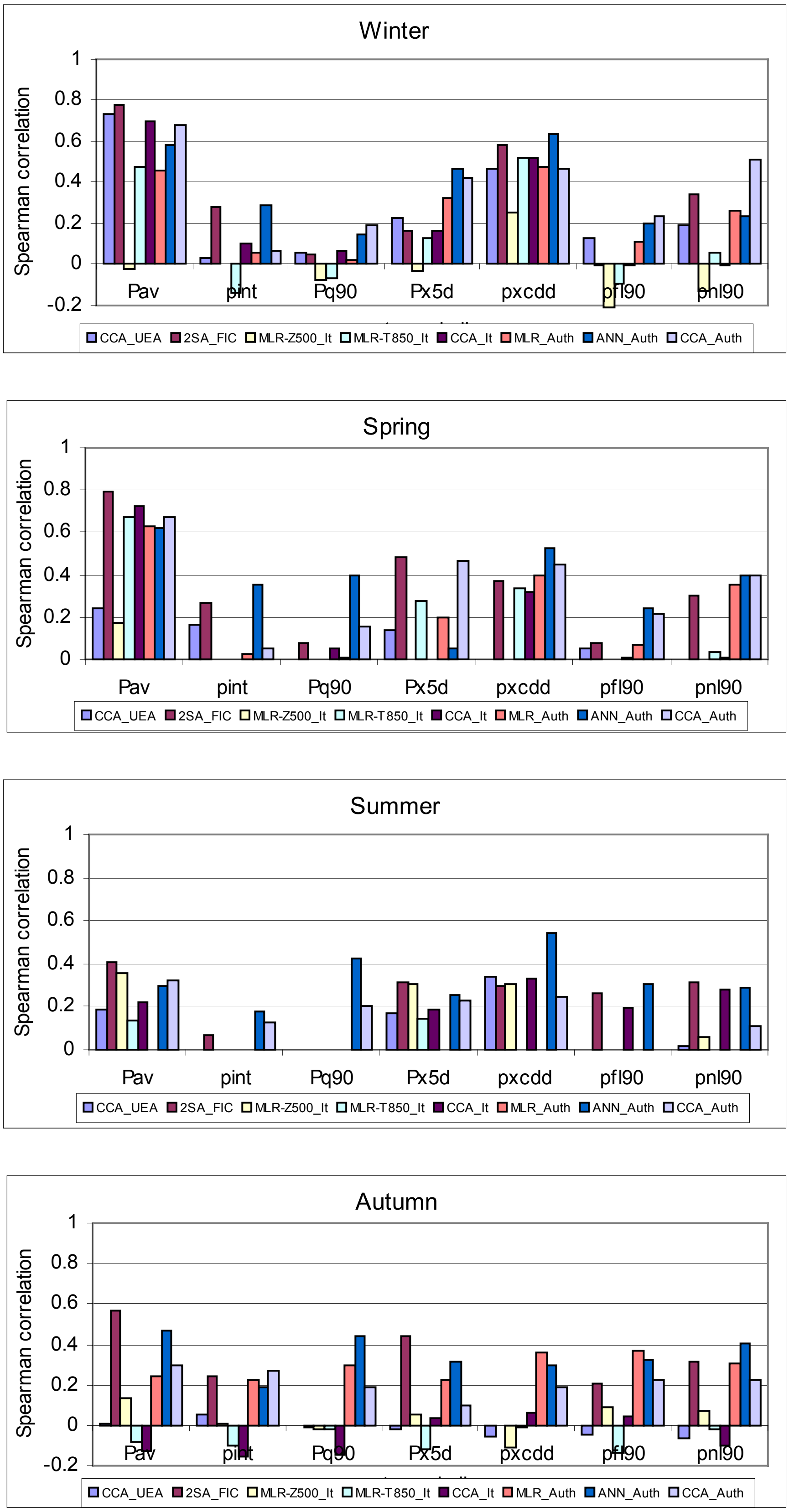

Figure 2. Spearman correlation for precipitation indices, average over the four stations from eastern Greece for the different downscaling methods.

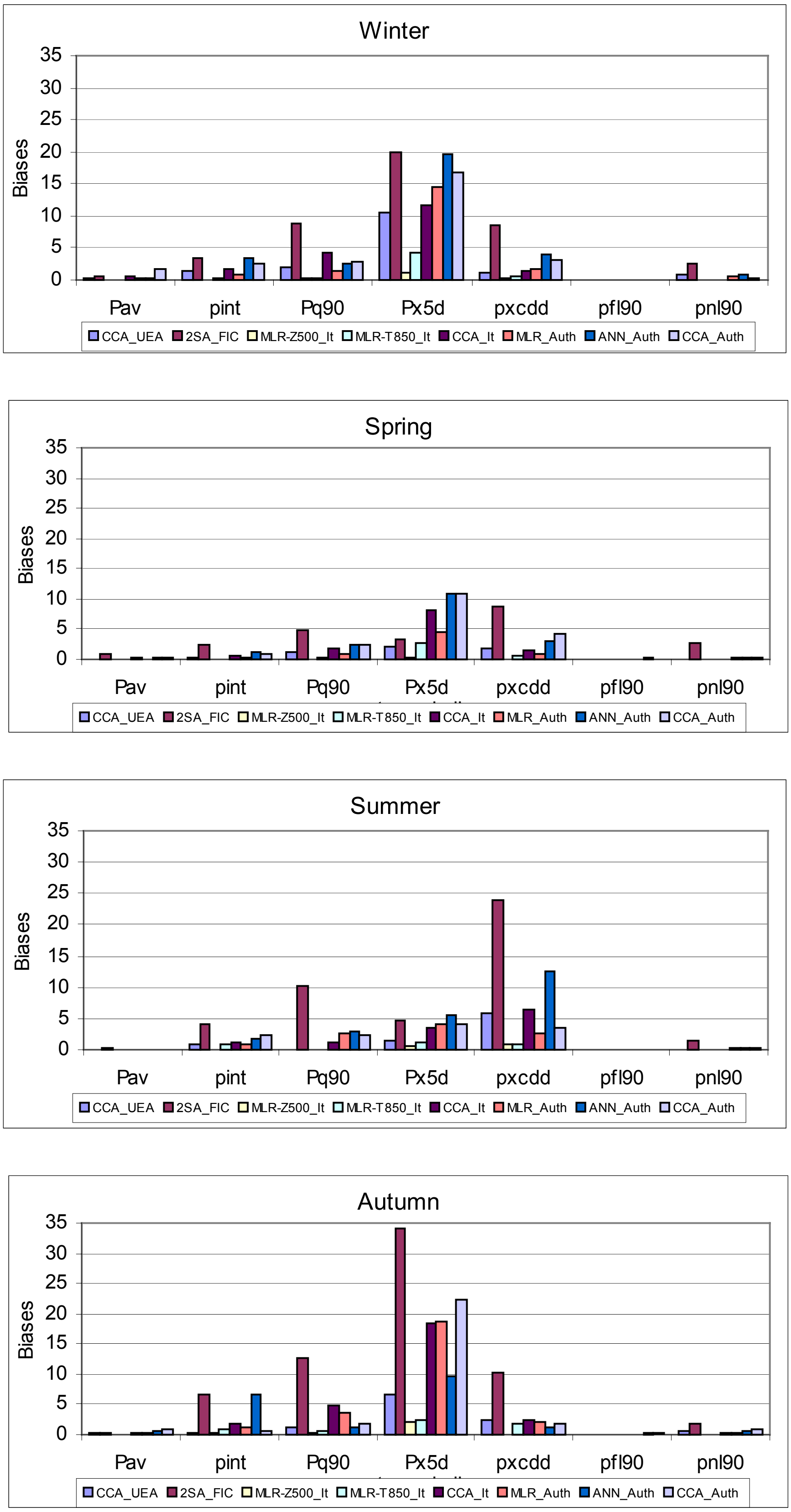

Figure 3. Biases for precipitation indices, average over the four stations from western Greece for the different downscaling methods.

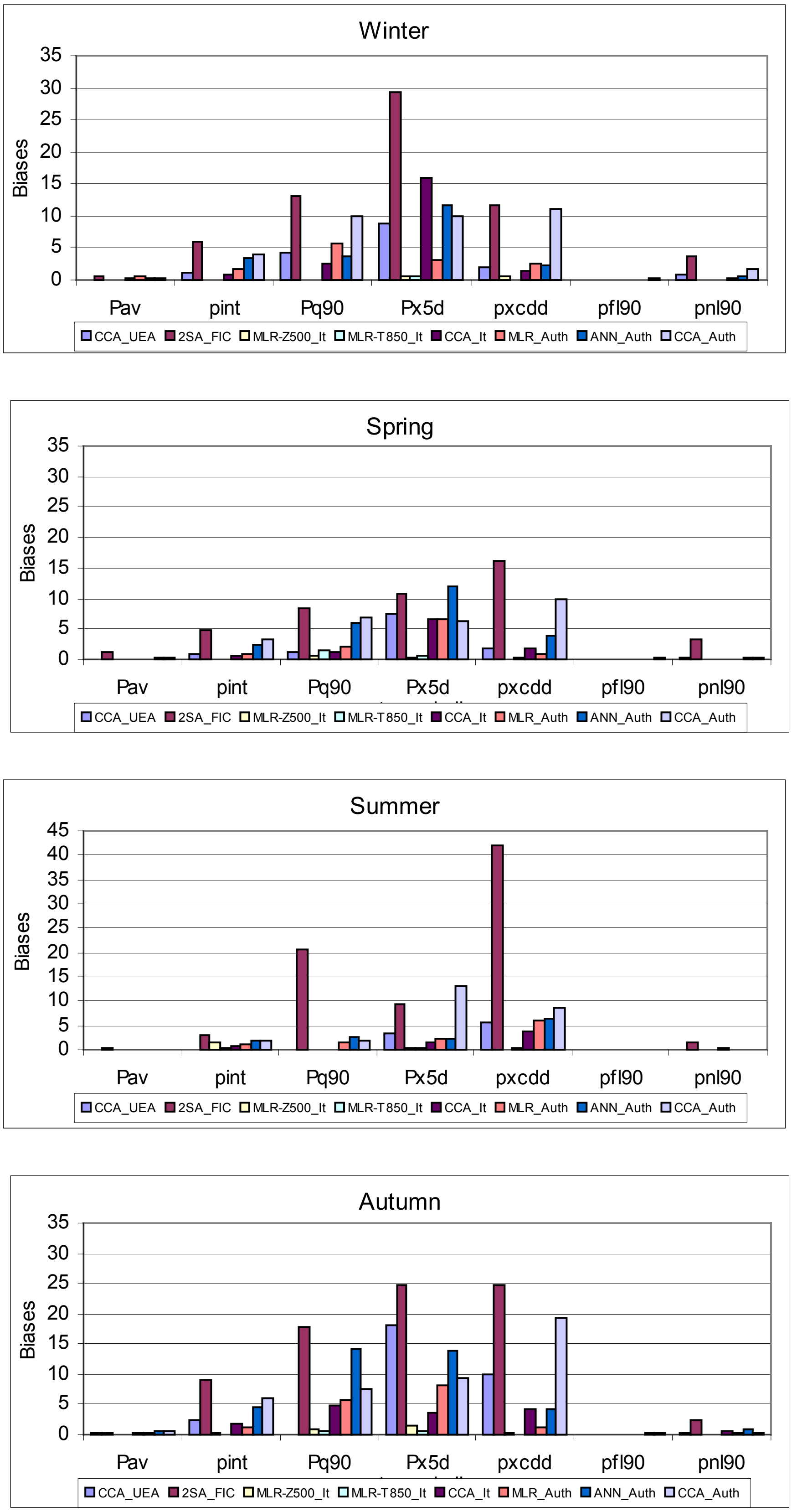

Figure 4. Biases for precipitation indices, average over the four stations from eastern Greece for the different downscaling methods.

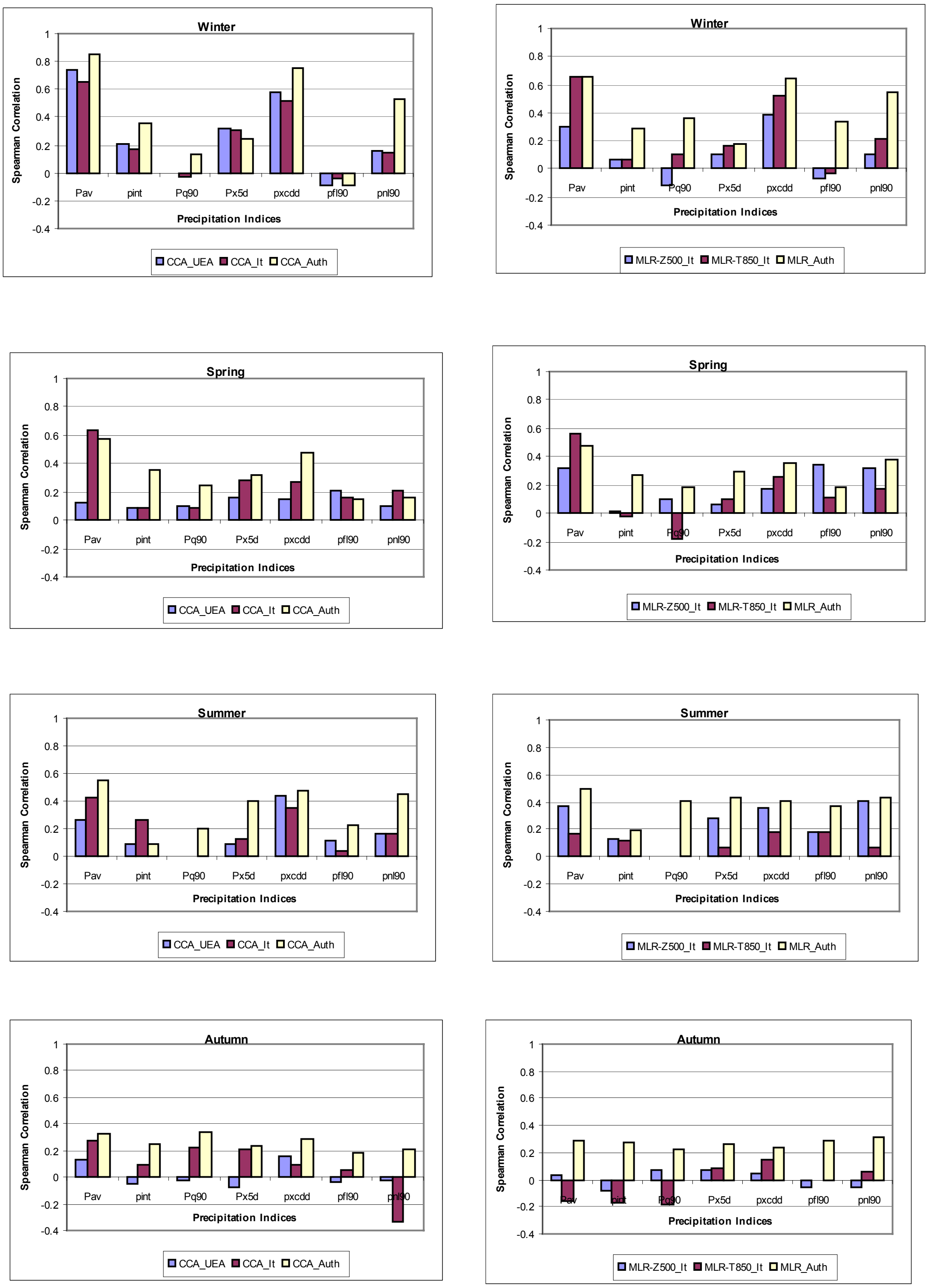

Figure 5. Spearman correlation for precipitation indices, average over the four stations from western Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

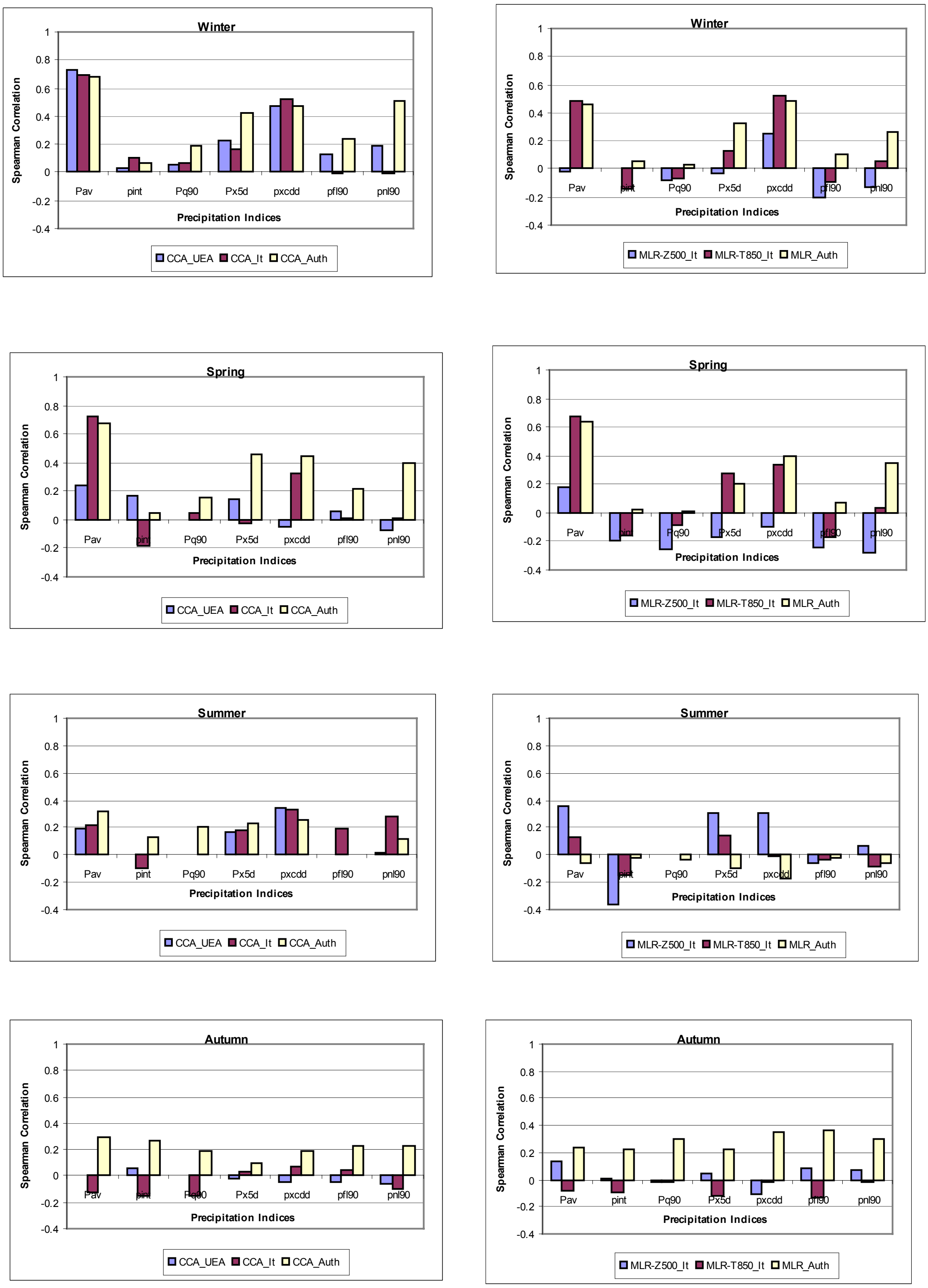

Figure 6. Spearman correlation for precipitation indices, average over the four stations from eastern Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

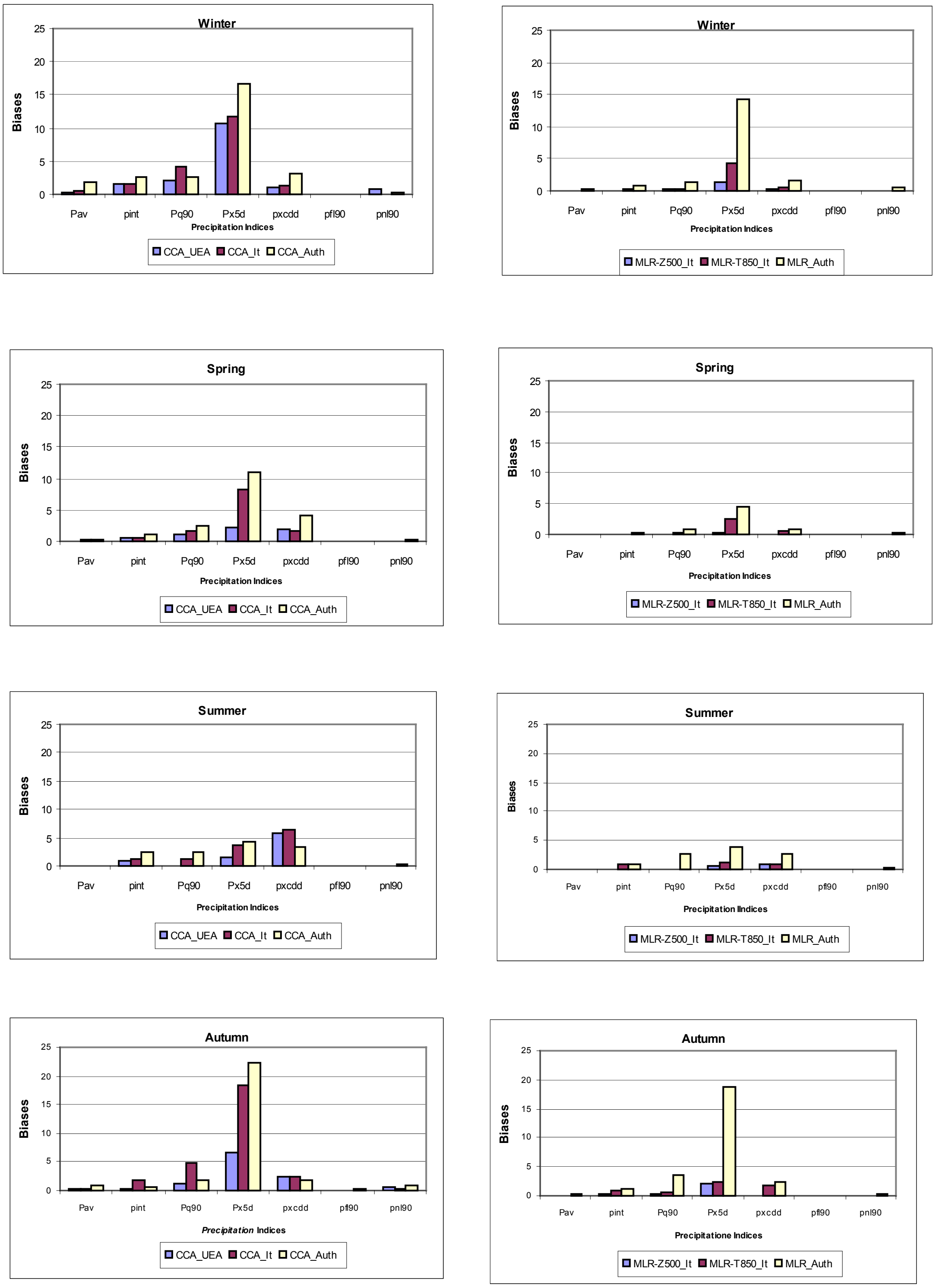

Figure 7. Biases for precipitation indices, average over the four stations from western Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

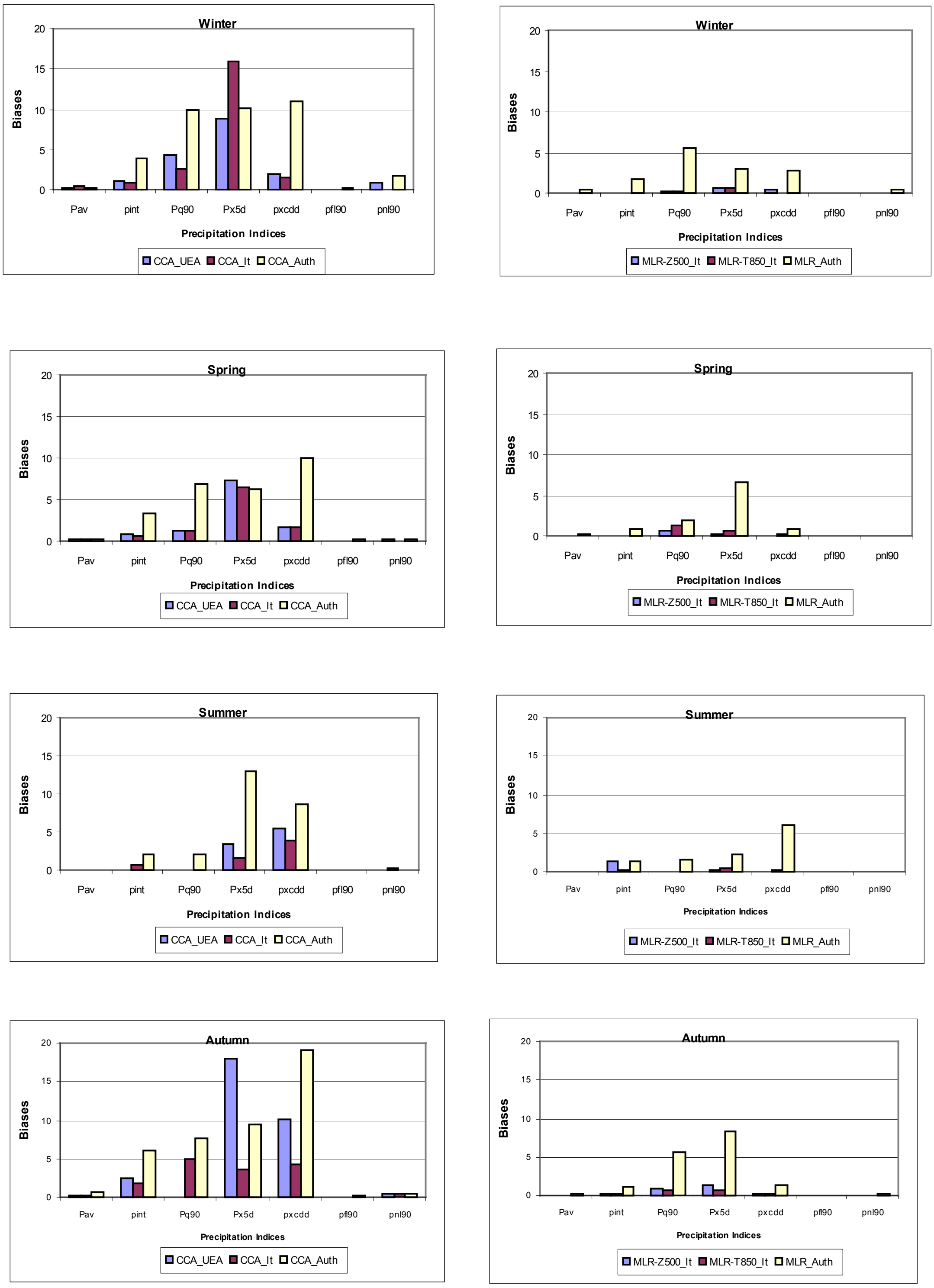

Figure 8. Biases for precipitation indices, average over the four stations from eastern Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

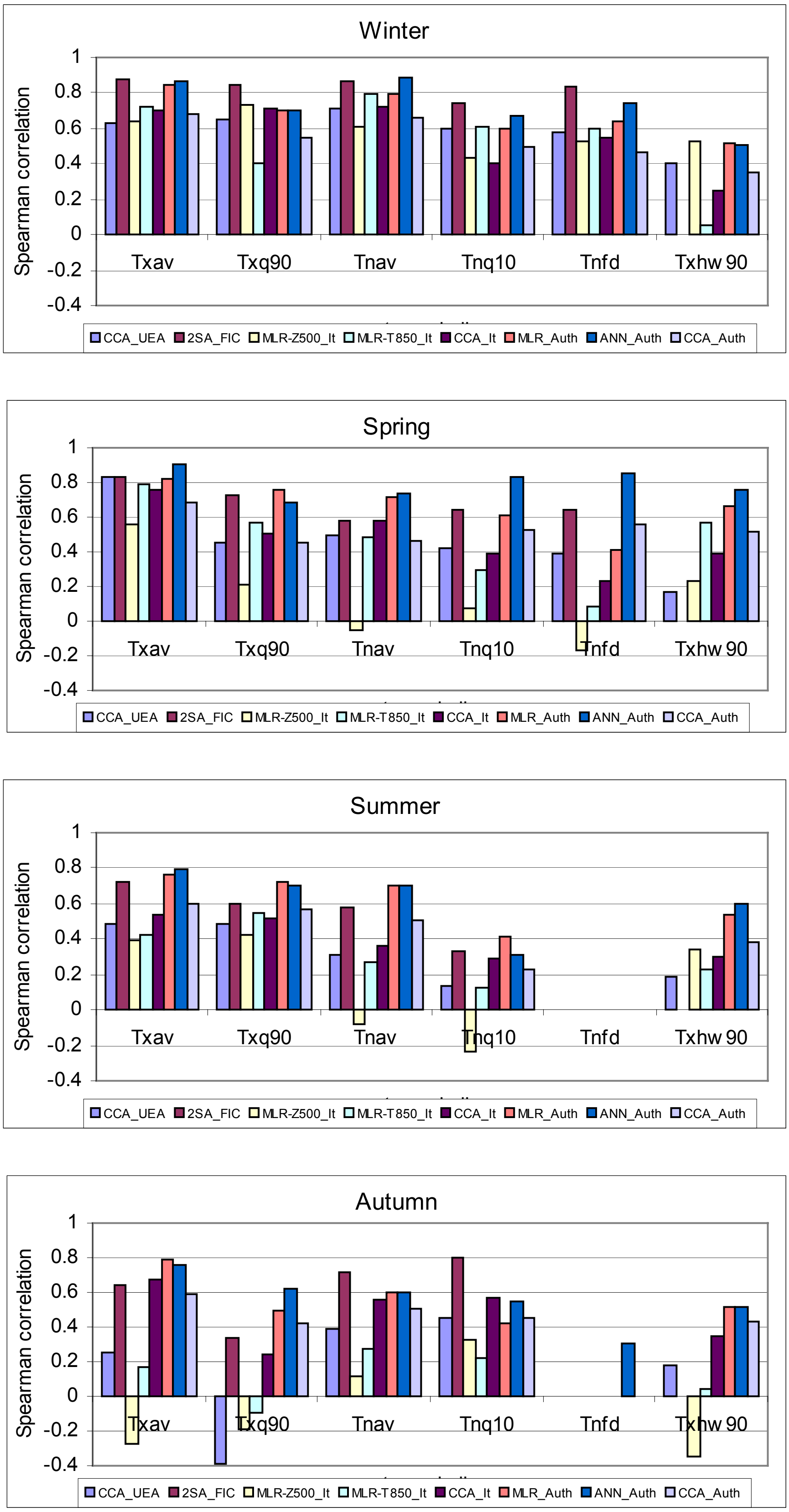

Figure 9. Spearman correlation for temperature indices, average over the four stations from western Greece for the different downscaling methods.

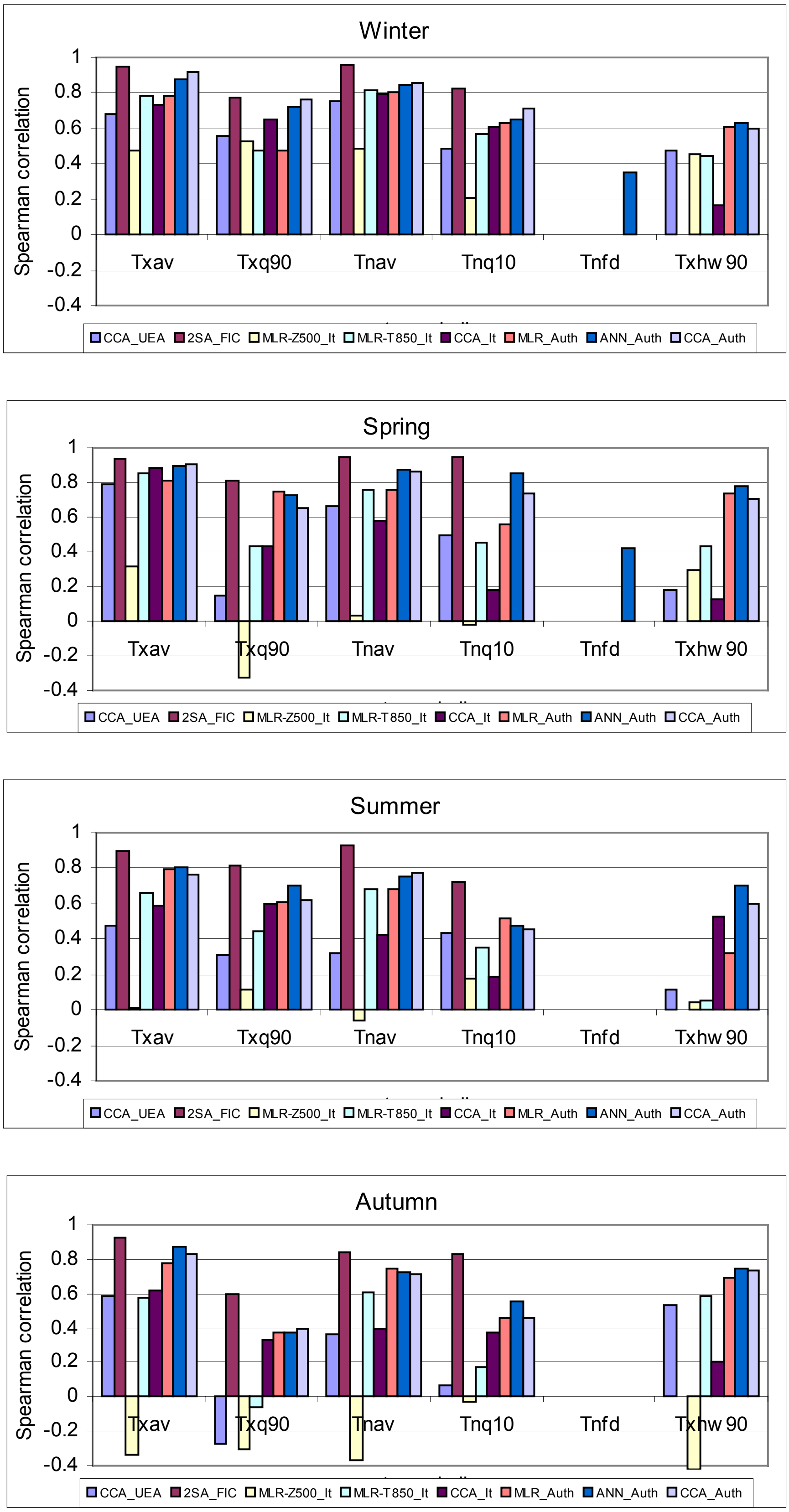

Figure 10. Spearman correlation for temperature indices, average over the four stations from eastern Greece for the different downscaling methods.

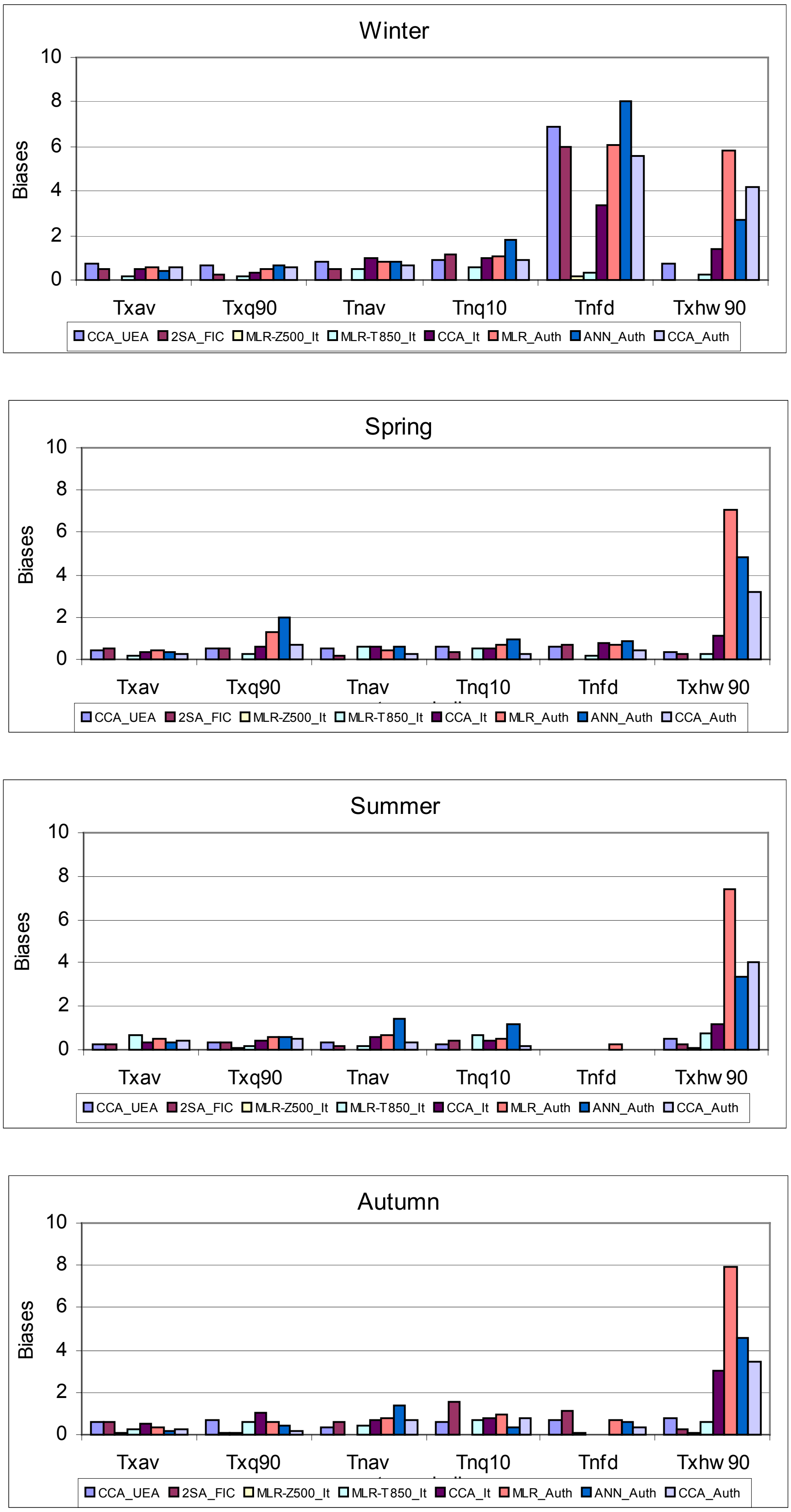

Figure 11. Biases for temperature indices, average over the four stations from western Greece for the different downscaling methods.

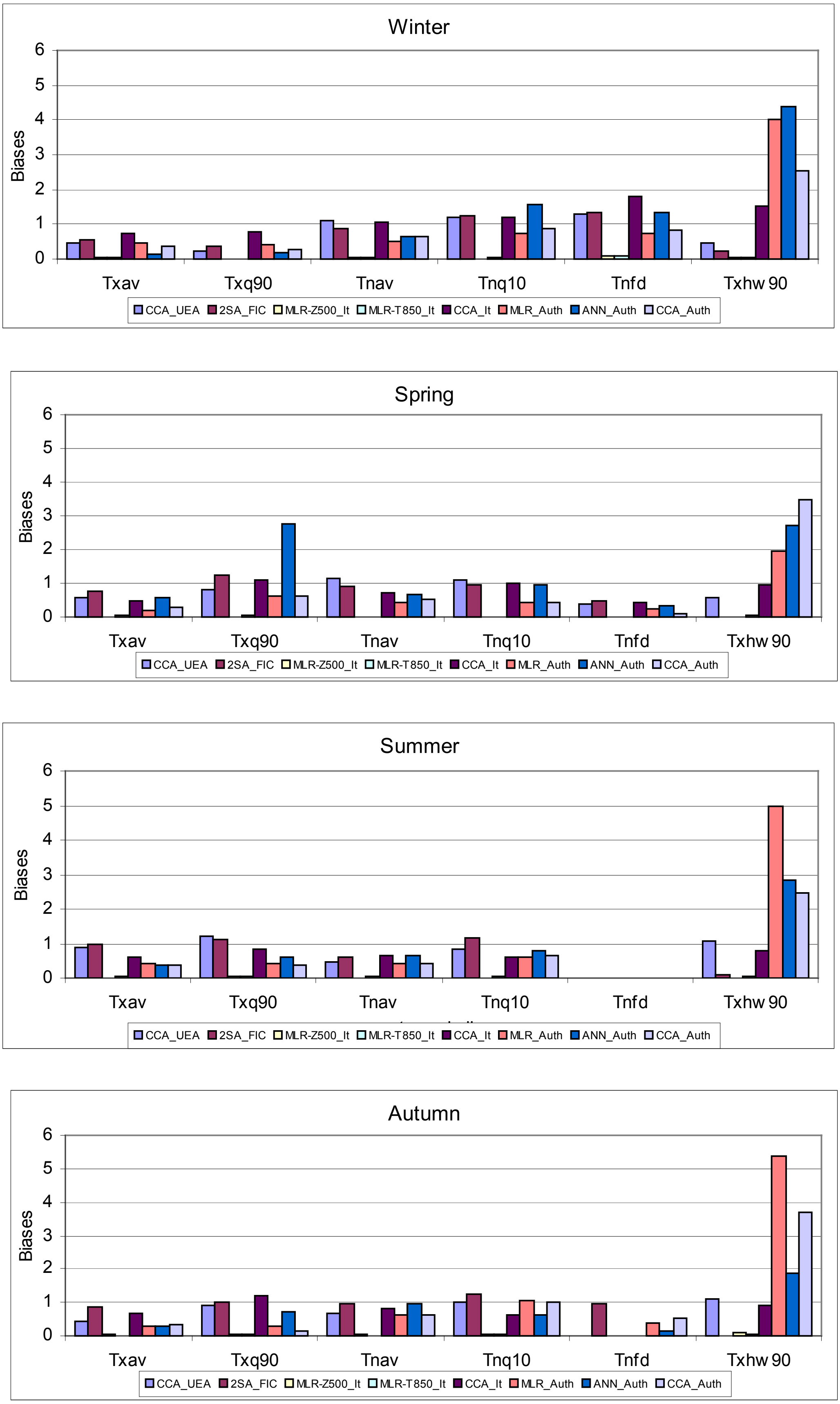

Figure 12. Biases for temperature indices, average over the four stations from eastern Greece for the different downscaling methods.

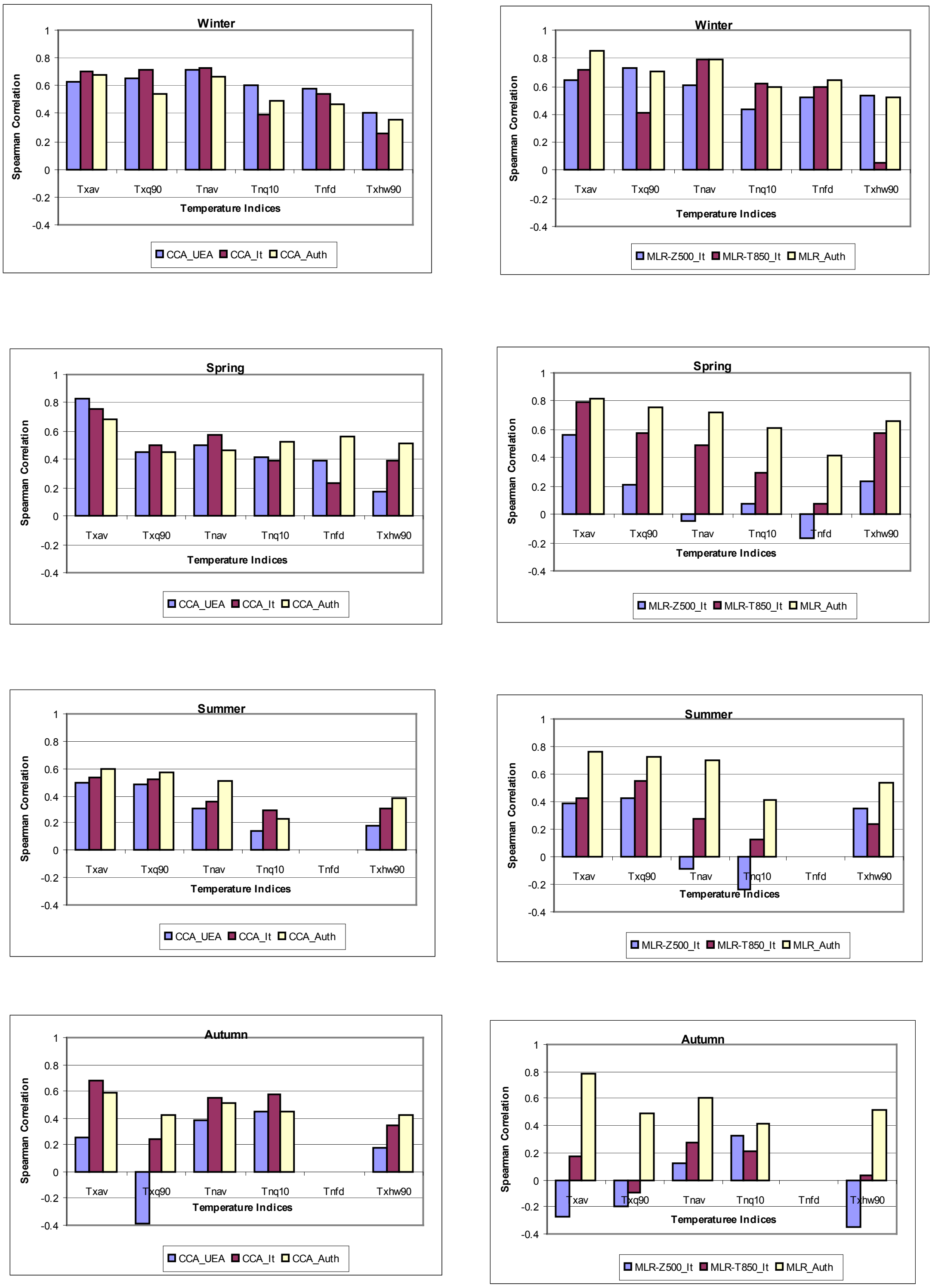

Figure 13. Spearman correlation for temperature indices, average over the four stations from western Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

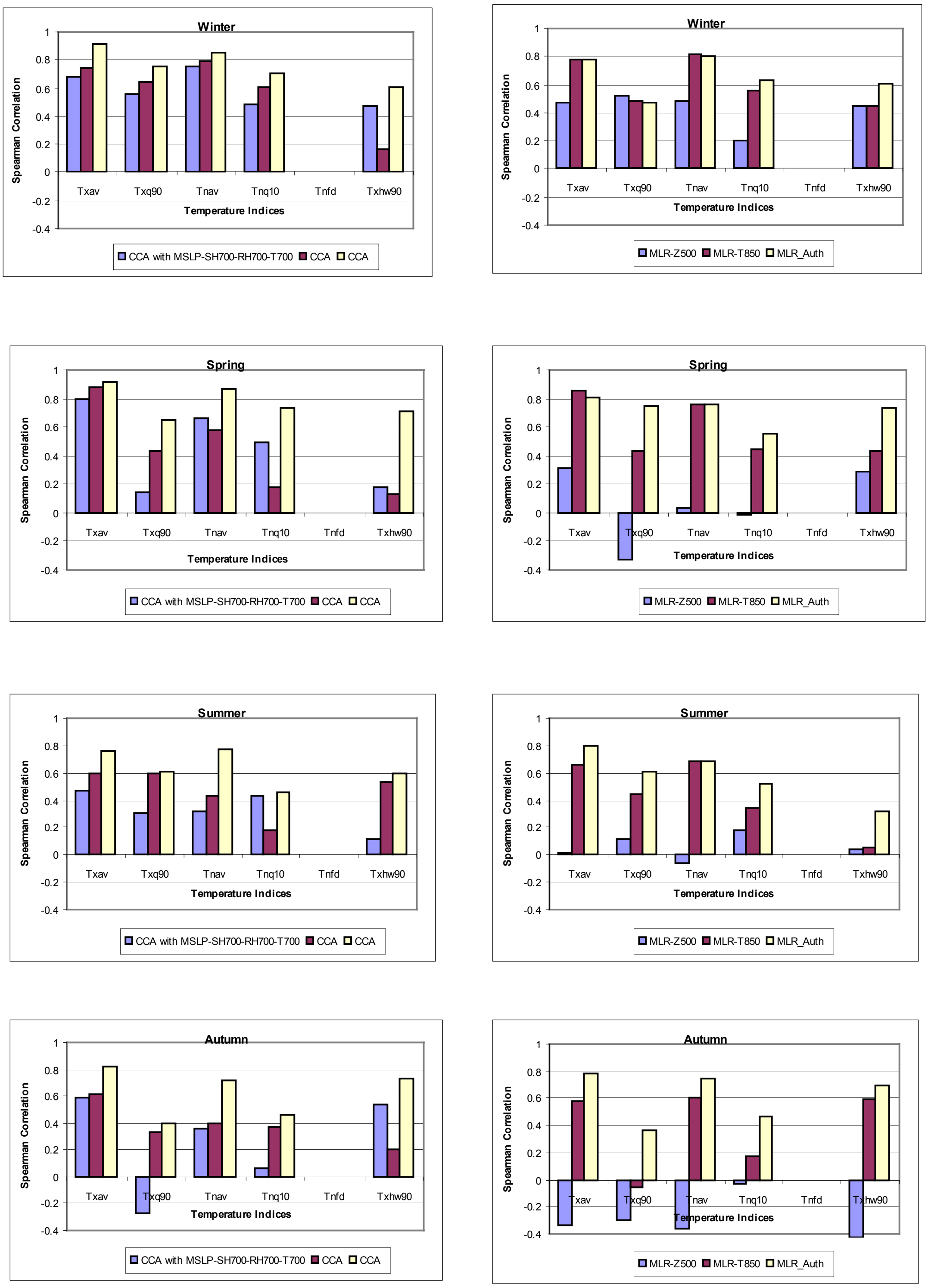

Figure 14. Spearman correlation for temperature indices, average over the four stations from eastern Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

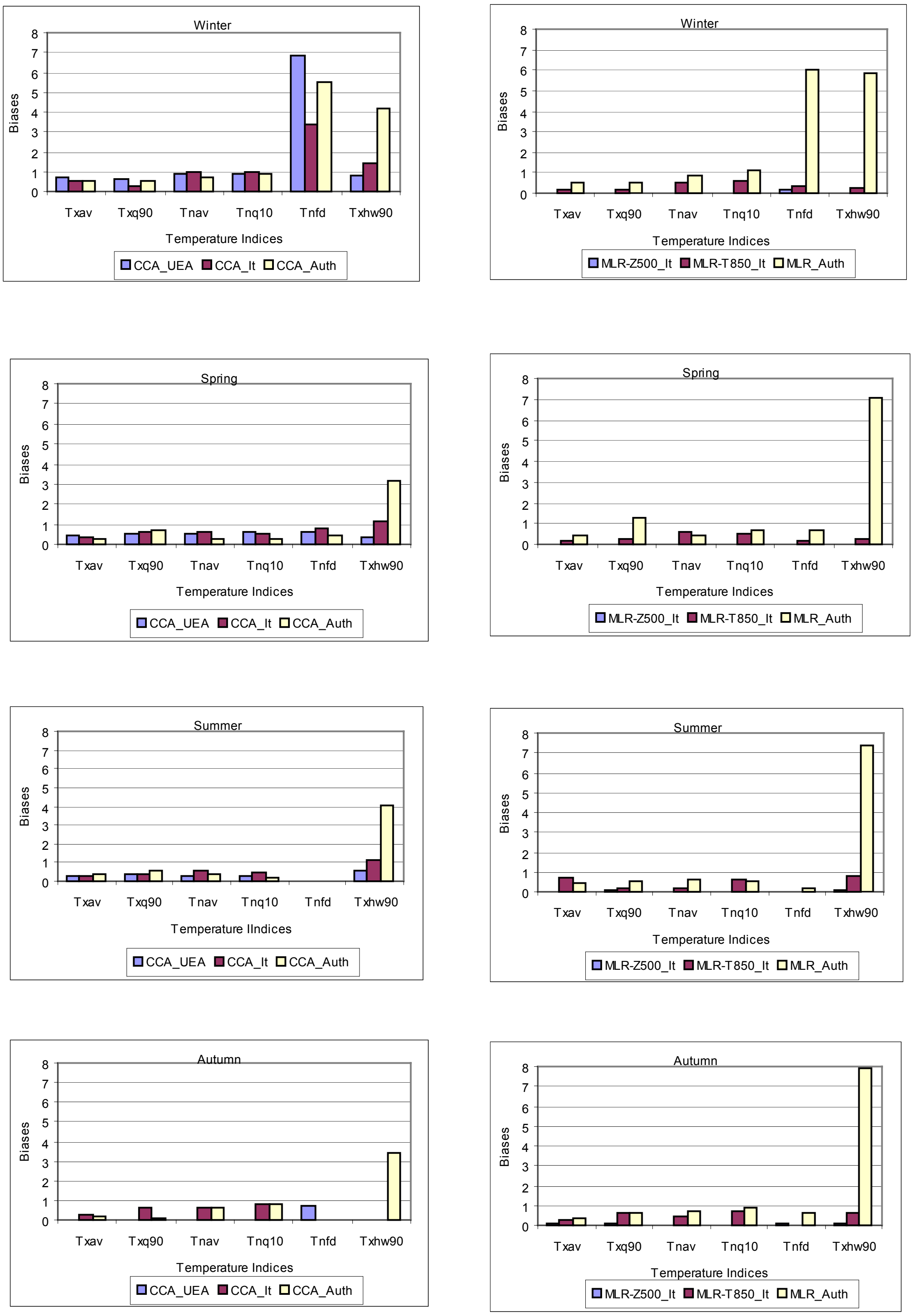

Figure 15. Biases for temperature indices, average over the four stations from western Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).

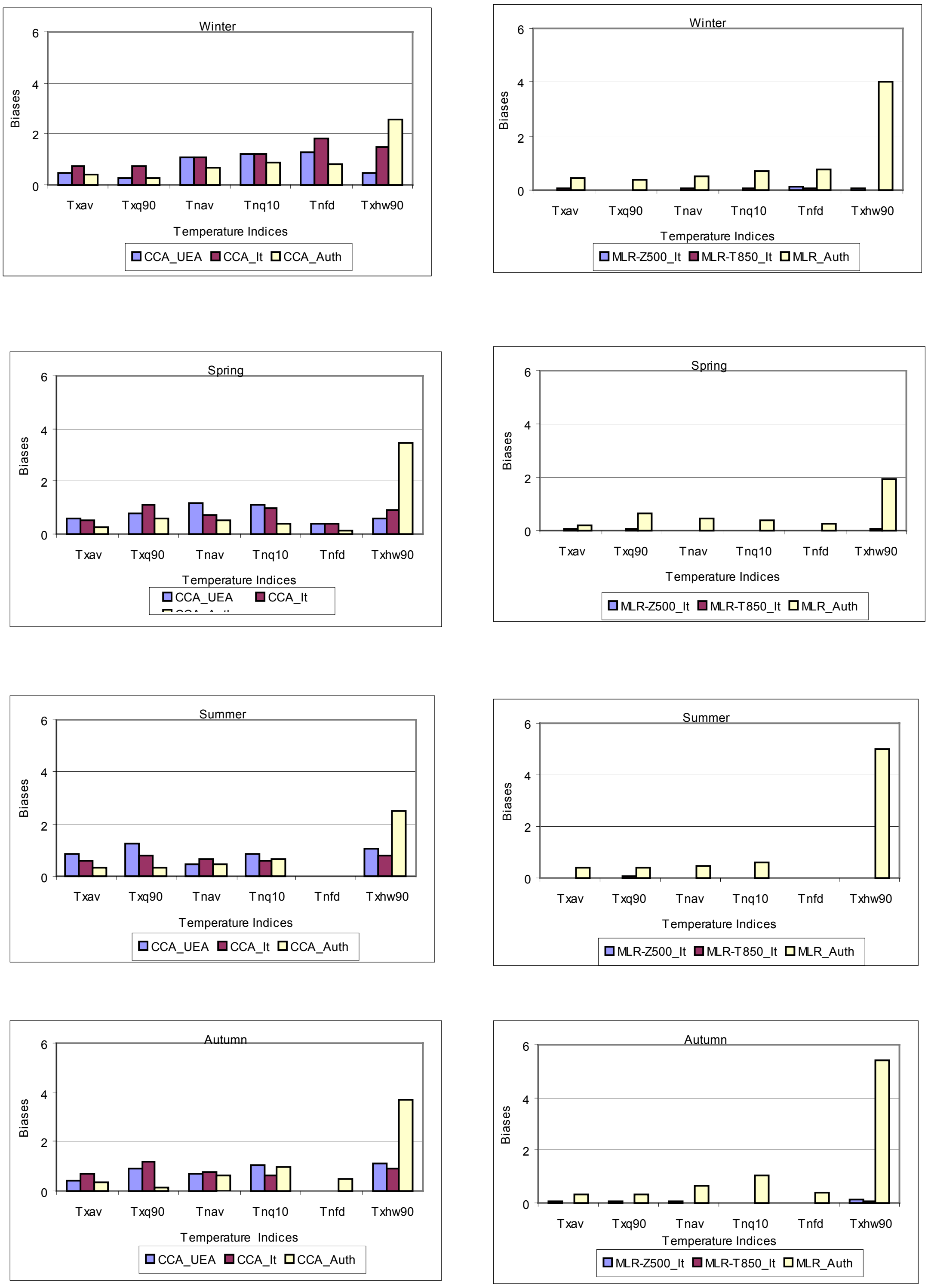

Figure 16. Biases for temperature indices, average over the four stations from eastern Greece of the two groups of the common downscaling methods (Canonical Correlation Analysis_CCA and Multiple Linear Regression_MLR).