ON THE STATISTICAL SIGNIFICANCE OF THE SEALEVEL PRESSURE CLIMATIC SIGNAL SIMULATED BY GENERAL CIRCULATION MODELS FOR THE 21ST CENTURY OVER EUROPE

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In the present paper a rigorous procedure is applied for estimating the statistical significance of the climatic signal in sea level pressure field (SLP) in the 21st century in comparison with the 20th century. The investigation arose from the need to determine the areas with statistically significant climatic signal in the SLP field. Selected predictors of SLP field together with other predictors such as precipitation help to estimate hydrological changes occurring in the Danube basin in the 21st century, especially for spring time. In the first part, the performance of four atmosphere-ocean general circulation models (CNRM, ECHAM5-MPI, EGMAM and IPSL) to simulate daily sea level pressure data from European Reanalysis (ERA-40) during spring over region (30°-65°N; 0°-40°E) is analysed by spatial correlation. We are interested in pressure changes in this area, because in this region there are predictors under different indices for the behavior of hydrological variables for the Danube basin. A 42-year period (1958–1999) from ERA-40 was chosen for testing. After applying a bias correction, the climatic signal for two periods of 42 years within the 21st century (2009–2050 and 2051–2092) was estimated. The scenario A1B, *stream 1*, used in the researches made in the ENSEMBLES project was considered. The climatic signal was estimated first by means of the *t test*. Because *t test's* application has given nonconcludent results, a *Z test* was applied too. Variances used to calculate the *Z test* were estimated using the parameters of an autoregressive model (AR). The parameters of an AR model, by means of the daily sea level pressure was fitted, were estimated on the basis of the concept of the maximum entropy. The advantages of using the *Z test* in comparison with the *t test* are described in detail. For each of the two periods during the 21st century, the areas where the climate signal is statistically significant were determined. The most extended zones with significant climatic signal are found in case of two models, CNRM and ECHAM5-MPI.

Key words: atmospheric circulation, signal-to-noise ratio, climate models, bias correction, Z test.

1. INTRODUCTION

It is well known that Atmosphere-Ocean General Circulation Models (AOGCMs) are recommended in hydrological impact studies as they take into account the interaction between the ocean and the atmospheric circulation at large scale. The disadvantage of their use is the coarse spatial resolution of the output of these models. This is the reason why downscaling procedures are necessary for obtaining local scale information.

It is very important to determine the areas where the used climatic change model gives significant information concerning the change of the hydro-meteorological variable of interest in a certain study.

There are many investigations regarding the detection of the climatic signal, more or less sophisticated, depending on the intended purpose. Among the investigations we mention the estimation of the signal-to-noise ratio (Hayashi, 1982), or the optimal fingerprint method proposed by Hasselmann (1979) and developed in several papers among which Santer *et al.* (1994) and Hegel *et al.* (1996). In Cubasch *et al.* (2001), the notion of "*signal versus noise*" is discussed, where the signal represents the deterministic part of a climatic change and the noise, the random part related to the natural variability. The signal-to-noise ratio compares the strength of the climate change signal to this variability noise. Cubasch *et al.* (2001) also show that the signal in the temperature field is about four times bigger than in the precipitation field. Trenberth (1984) defines the signal-to-noise ratio according to the cross correlation coefficients of the variables emphasizing the North Atlantic Oscillation (NAO) index.

In Ghil *et al.* (2011) several methods for estimating the signal in the climatic time series are reviewed, including spectral analysis and several applications are presented, such as the El Niño-Southern Oscillation (ENSO) phenomenon which is considered the most prominent signal of seasonal-to-interannual climate variability.

Yang *et al.* (2010) present the advantages and disadvantages of using the general circulation models (GCMs) as compared to the regional climate models (RCMs), concluding that a statistical robust downscaling procedure is preferable to using the dynamic downscaling by RCMs. The authors apply a statistical downscaling procedure to estimate the precipitation over the Rhine River using predictors from a general circulation model. Generally, the choice of the predictors is done according to the season and the considered region (Huth, 1996, 1999).

Mareş *et al.* (2008) revealed the need for a rigorous determination of the changes expected in the 21st century in the field of pressure, because the sea level pressure (SLP) as expressed by means of atmospheric indices is an important predictor for both precipitation and the Danube river flow. Mareş *et al.* (2002) found that the North Atlantic Oscillation index during winter influences the moisture state during summer over the Danube basin, quantified by Palmer Drought Severity Index (PDSI) of Briffa *et al.* (1994). Rimbu *et al.* (2002) showed that there is an out-of-phase relationship between the time series of the Danube river discharge anomalies and the NAO index. Bierkens and van Beek (2009) evaluated the predictive skill of the discharges in summer and winter seasons in Europe, focusing on the rivers Danube and Volga, which are the largest rivers in Europe and pass through various climate zones. Together with other predictors, the authors consider the NAO index a good candidate for seasonal prediction of discharge. In Mareş *et al.* (2009a), the NAO index and the first ten principal components (PCs) of the decomposition in Multivariate Empirical Orthogonal Functions (MEOF) of three atmospheric fields (sea level pressure, 500 hPa, and 500–1000 hPa thickness) over the Atlantic-European region (ERA-40) have been introduced as covariates in the modeling of extreme events in the Lower Danube basin discharge. The most significant results are obtained by incorporating the first 10 PCs of MEOF in location parameter of Generalized Extreme Value (GEV) distribution with a month before the month of the discharge level. As shown in Maraun *et al.* (2010) too, where the behavior of a climatic variable is estimated by the statistical downscaling method, it is important, in the first place, to assess the global or regional climatic models performance to reproduce the variable that is called predictor for the region of interest.

Therefore, four AOGCMs, namely ECHAM5-MPI, CNRM, EGMAM and IPSL were considered.

The paper is organized as follows: in Section 2 data and methodology are presented, Section 3 comprises the analysis of the pressure field at sea level. The testing of the models performance to reproduce the SLP from ERA-40 during spring, for the reference period (1958–1999), using spatial correlations, is presented in paragraph 3.1 and the SLP bias correction procedure concerning the reference period and the obtained results are presented in paragraph 3.2. In Section 4 the areas where a statistical significant climatic signal in SLP field existed for two intervals in the 21st century are presented. The conclusions are given in Section 5.

2. DATA AND METHODOLOGY

The present study combines a procedure of model bias with a rigorous method to estimate the statistical significance of a climate signal in the 21st century in several AOGCMs without aiming to investigate causes of this signal.

First of all, before applying the bias procedure, we compared the simulated pressure by the four AOGCMs with the ERA-40 data by spatial correlation analysis. ERA-40 is a re-analysis of meteorological observations from September 1957 to August 2002 produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) in collaboration with many institutions (Uppala *et al.*, 2005).

After the bias correction of the data simulated for the considered sector (30°–65°N; 0°–40°E), an analysis of the climatic signal was done. As the *t test* could not be applied, because of data structure, we used the *Z test*. The *Z test* is more powerful and more rigorous than the *t test*, with the advantage of using a larger number of data for assessing the climatic signal. Before applying the *Z test,* a modeling as autoregressive processes was done both for the ERA-40 values of the pressure and for those simulated by the four models for *A1B* emission scenario, for two periods representative for the first and the second half of the 21st century. The AR model parameters were estimated by means of the maximum entropy method.

Our procedure generally follows the method described by Katz (1982). That author has applied this test to estimate the climatic signal in simulated daily field temperatures in winter and summer from the North American continental area and showed the performance of this procedure compared with others that highlight the climate signal. The region of interest in the present investigation is the European area (30°–65°N; 0°–40°E). This region was found in Mareş *et al.* (2008, 2011) optimal for precipitation evaluation in Danube Middle and Lower basin with pressure predictors under MEOF components or atmospheric indices, in comparison with a more extended region. Also, the highest discharges for the lower Danube basin were registered in the spring months (March, April, May – MAM).

The four models, CNRM, ECHAM5-MPI, EGMAM and IPSL, post-processed in this study, are atmosphere-ocean coupled models. The scenario *A1B*, *stream 1* used in the researches made in ENSEMBLES project (Van der Linden and Mitchell, 2009) was considered. *A1B* is a moderate emissions scenario in which atmospheric greenhouse gas concentrations reach about 850 ppm CO_2-equivalent by 2100 (IPCC 2007).

Because the models have different spatial and temporal resolutions (calendar month or month with 30 day each), for homogeneity, the SLP field over the European region considered was interpolated at a common regular grid with a resolution of 2.5° longitude x 2.5° latitude and all month for all models were considered to have 30 days. The resolution of 2.5° x 2.5° was chosen in order to be compatible with the pressure field in ERA-40. As it is mentioned in Chapman and Walsh (2007), Re-Analysis (ERA-40) directly assimilates observed air temperature and SLP observations into the reanalysis product. The ERA-40 is one of the most consistent and accurate gridded representations of these variables available, and therefore, is a logical choice for observational analyses against which we validate the model biases SLP.

As reference for the 20th century, a period of 42 years, 1958-1999, was chosen. We test the performance of the four global models with the help of the spatial correlation coefficient between SLP from ERA-40 and from control experiments for the period 1958–1999, as well as with the calculation of the root-mean-square error (RMSE) and of the explained spatial variance. In the analysis, the multiannual mean field is considered for the spring season on the mentioned sector.

3. ANALYSIS OF THE PRESSURE FIELD AT SEA LEVEL IN THE 20th CENTURY (1958–1999)

3.1. TESTING THE MODEL PERFORMANCE TO REPRODUCE ERA-40

In order to find the significance level of the correlation coefficient, we have to take into account the fact that the SLP values present a serial correlation. In this case, we have to estimate the equivalent sample size (ESS). There are several methods to find the statistical significance of correlations among the series pairs presenting serial correlations. A part of these methods are presented in Thiebaux and Zwiers (1984), Zwiers and Storch (1995), Ebisuzaki (1997). Beersma and Buishand (1999) apply a jackknife method by which a statistics of interest is recalculated repeatedly after omitting a part of the original data.

Also the correlated time series must have a Gaussian distribution. Even if the daily pressure values during spring deviate from the Gaussian distribution, we have very large data series and, according to the central limit theory (Panofsky and Brier, 1965), the distribution of these variables tend to be a normal one. As the SLP values have a great persistence, they may be modeled by an autoregressive model of first order – AR (1). In this case, we follow the procedure described by Zwiers and Storch (1995) for the ESS estimation. Thus, a pooled estimated value of the lag-1 correlation coefficient between two time series is:

$$r_1 = \frac{\sum_{k=2}^{m}(x_k-\bar{x})(x_{k-1}-\bar{x})+\sum_{k=2}^{n}(y_k-\bar{y})(y_{k-1}-\bar{y})}{\sum_{k=1}^{m}(x_k-\bar{x})^2+\sum_{k=1}^{n}(y_k-\bar{y})^2} \tag{1}$$

where n and m represent the length of the two analyzed series.

For n large, the ESS, denoted now as n_e, is estimated as follows:

$$n_e = \frac{n\,(1-r_1)}{1+r_1} \tag{2}$$

We apply (1) and (2) in order to find the ESS corresponding to the values $n = m = 255$, defining the total number of points of the spring mean multiannual field SLP. In Table 1, the r_1 values, spatial correlation coefficients R between the simulated series for each of the four GCMs and SLP from ERA-40, and n_e values are presented. Here, n_e is the effective number that we have to take into consideration for the sample length (instead of 255), for testing the statistical significance. The spatial correlations coefficients (R) are obtained between the pressure of the ERA-40 data and of the pressure values simulated by each of the 4 models, for the averages over the period 1958–1999. The significance levels correspond to the degree of freedom n_e-2. We note that the effective number n_e is significantly lower than the initial data volume n and this diminution depends on the persistence degree of each pair of correlated series.

The root-mean-square errors (RMSE) were calculated in accordance with the relation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(P_k^s - P_k^{Re})^2} \tag{3}$$

where:

P^s_k and P^{Re}_k represent the simulated pressure and respectively pressure from the ERA-40 reanalysis for the reference period 1958–1999 in the 255 points of the mentioned European sector. While the correlation coefficient is immune to magnitude errors, RMSE is a measure sensitive to magnitude errors.

Table 1

Capacity of models to simulate the mean pressure at sea level during spring, tested by means of the spatial correlation analysis

Model	R	r_1	n_e	Significant level	RMSE	E
CNRM	0.471	0.838	22	~98%	1.816	0.059
ECHAM5-MPI	0.664	0.774	32	>99%	1.107	0.339
EGMAM	0.528	0.881	16	95-98%	1.870	-0.473
IPSL	0.314	0.910	12	<90%	2.857	-3.375

Another measure of the models ability to reproduce the ERA-40 is the explained spatial variance E. If we note with $\boldsymbol{D}$ the difference between the simulated and ERA-40 long term mean pressure and with $\boldsymbol{\sigma^2_D}$ the spatial variance of $\boldsymbol{D}$ and with $\boldsymbol{\sigma_{Re}^2}$ the explaining spatial variance of the ERA-40 field, then, according to van Ulden and van Oldenborgh (2006), E has the following expression:

$$\boldsymbol{E=1-\sigma_D^2/\sigma_{Re}^2} \tag{4}$$

As van Ulden and van Oldenborgh (2006) show, E represents a better measurement than the correlation coefficient because it tests the pressure amplitude variations. In fact, both RMSE and E give the same indications, fact also proved by their values in Table 1. Analyzing these measures, one may note that the smaller RMSE value is given by the ECHAM5-MPI model; E positive value nearest to 1 is also given by ECHAM5-MPI. At the same time, the highest statistical significance level is observed for the ECHAM5-MPI model, a fact that makes us conclude that this model is capable to best reproduce the mean pressure.

The CNRM model, even if it has the correlation coefficient smaller than EGMAM, taking into account the RMSE values, of E and of the significance levels, may be considered on the second place from the point of view of the performance of reproducing the mean pressure. Therefore, the ranking of the models by the ability to reproduce the mean pressure during spring, in the sector 30°–65°N; 0°–40°E, having in view all the values from Table 1, is: ECHAM5-MPI, CNRM, EGMAM and IPSL. Dobler *et al.* (2011) shows that the ECHAM5-MPI is one of the most powerful general circulation models and show why it is selected in the process of downscaling in the Danube and Brahmaputra basins. Similar results were also obtained by Kjellstrom *et al.* (2011) who estimated the explicative variance for determining the SLP performance with a regional climate model. This model belongs to Rossby Center from Sweden and there were analysed the results for Europe obtained of an ensemble of 16 simulations for 1961–2100. The regional climate model uses the boundary conditions of 7 general circulation models. Three of the general circulation models used by Kjellstrom *et al.* (2011), namely CNRM, ECHAM5-MPI (run3) and IPSL are found in the present investigation. They found that the regional climate model with the forcing CNRM has a better performance to simulate pressure at sea level in spring for the reference period 1961-1990, as compared to the ECHAM5-MPI or IPSL forcing. Some differences between the results obtained in the present study and those of Kjellstrom *et al.* (2011) have several causes, mainly because of the used simulation models (RCMs and, respectively, GCMs) and of the different reference periods.

3.2. BIAS CORRECTION OF PRESSURE

Because every climatic model has certain peculiarities concerning the climate variability simulation, a bias analysis is necessary. There are several methods of correction of the models according to the goal had in view. Of the most recent procedures of application of the corrections, we mention those described in Buishand and Lenderink (2004), Salathe (2004), Lenderink *et al.* (2007), Hagemann *et al.* (2009), Van der Linden and Mitchell (2009), Terink *et al.* (2010), Hamlet *et al.* (2010), Piani *et al.* (2010). Lenderink *et al.* (2007) apply two different bias methods of the models to simulate Rhine discharges in the future climate. One of them, known as *delta approach*, uses differences between future climate conditions and simulated current added to observation time series of climate variables. We apply the so called *direct method*, namely the scenarios are corrected according to the control simulations bias. As in this study we are interested in changes produced in the daily pressure values, we apply a method having in view the multiannual daily averages.

The bias for the simulated pressure values by each of the four models was calculated as follows:

$$B_{km}(j) = \frac{1}{N}\sum_{i}^{N} P_{km}^{c}(i,j) - \frac{1}{N}\sum_{i}^{N} P_{k}^{\mathrm{Re}}(i,j) \quad (5)$$

where, $k = 1,..., 255$ grid point, $m = 1,...,4$ models; N = number of years; $j = 1,...,90$ the number of days of the spring months (March, April, May); P^{c}_{km} and P^{Re}_{k} simulated and respectively ERA-40 pressure values for the control period.

The simulated pressure values for the control period (20th century) are corrected as follows:

$$P_{km}^{ccor}(i,j) = P_{km}^{c}(i,j) - B_{km}(j) \quad (6)$$

With the help of the bias from equation (5), the scenarios are also corrected:

$$P_{km}^{scor}(i,j) = P_{km}^{s}(i,j) - B_{km}(j) \quad (7)$$

We present an example of the bias, for the point (47.5°N; 20°E) in Fig. 1. This point is not selected at random, it was found as a significant point in the correlative analysis between SLP and the Danube discharge at Orşova, in the SW of Romania (Huebener *et al.*, 2007; Mareş *et al.*, 2009b). Figure 1 shows that all the models have a different time depending bias in the region of interest for the discharges in the lower Danube basin. All models have in common the fact that in March and the beginning of April they present a scattered *bias* with positive values for EGMAM and IPSL and general negative for CNRM and ECHAM5-MPI. One can note that in the first half of the spring season model biases are larger, in absolute value exceeding 4 hPa. For the point considered as example in Fig. 1, the smallest biases are in the case of CNRM model.

In Fig. 2 the averages over 90 days of the bias corrections for each of the grid points in the region considered in this study are shown. Spatial distribution of these biases are different, depending on the model. The smallest errors in absolute values are found around latitudes 45–50°N. Generally over the analyzed European region, ECHAM5-MPI model presents the lowest values of biases. Our results are in agreement with the Chapman and Walsh (2007) findings for the European region selected in the present study. Demuzere *et al.* (2009) show that ECHAM5-MPI model is capable of reproducing circulation pattern (Lamb weather type), above Western and Central Europe in the season from October to April in the period 1961–2000. Lorenzo *et al.* (2011) investigated the changes in the frequency of the different circulation types computed for the northwest Iberian Peninsula in the 21st century, by means of three different models used in the IPCC 4th assessment report. The above authors calculated for each grid point, the seasonal mean bias as the difference between the mean seasonal SLP values obtained from the CGCMs and those obtained from the NCEP/NCAR data. They found that the ECHAM5 model produces patterns of SLP that are the closest to the reanalysis data. Therefore, the ECHAM5 model can yield realistic SLP fields, resulting for both reanalyses ERA-40 and NCEP/NCAR data.

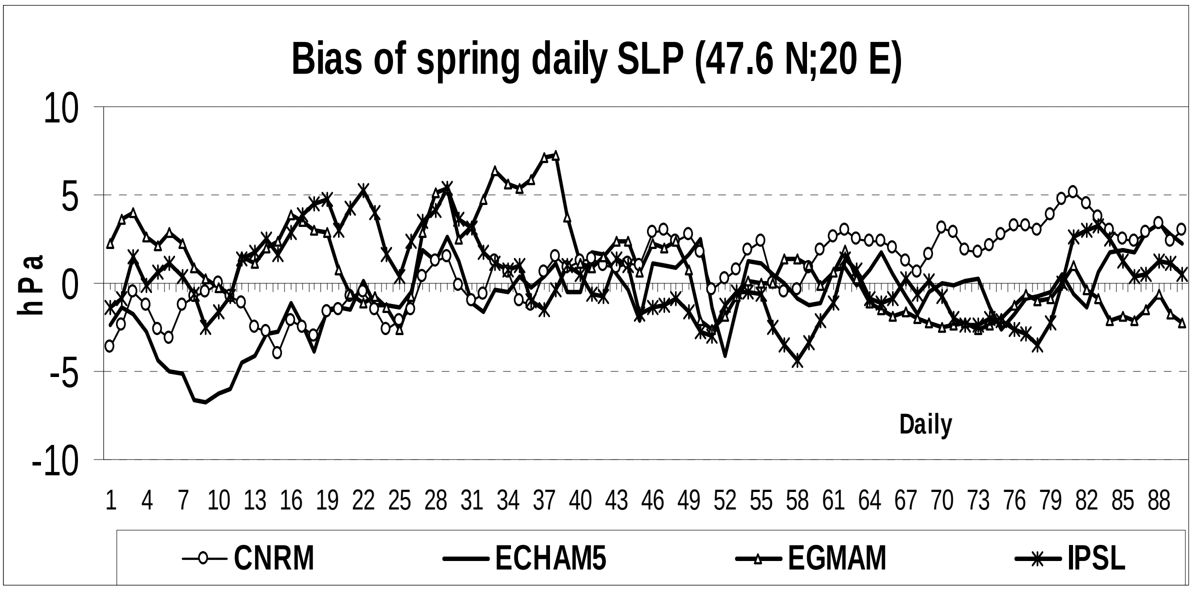
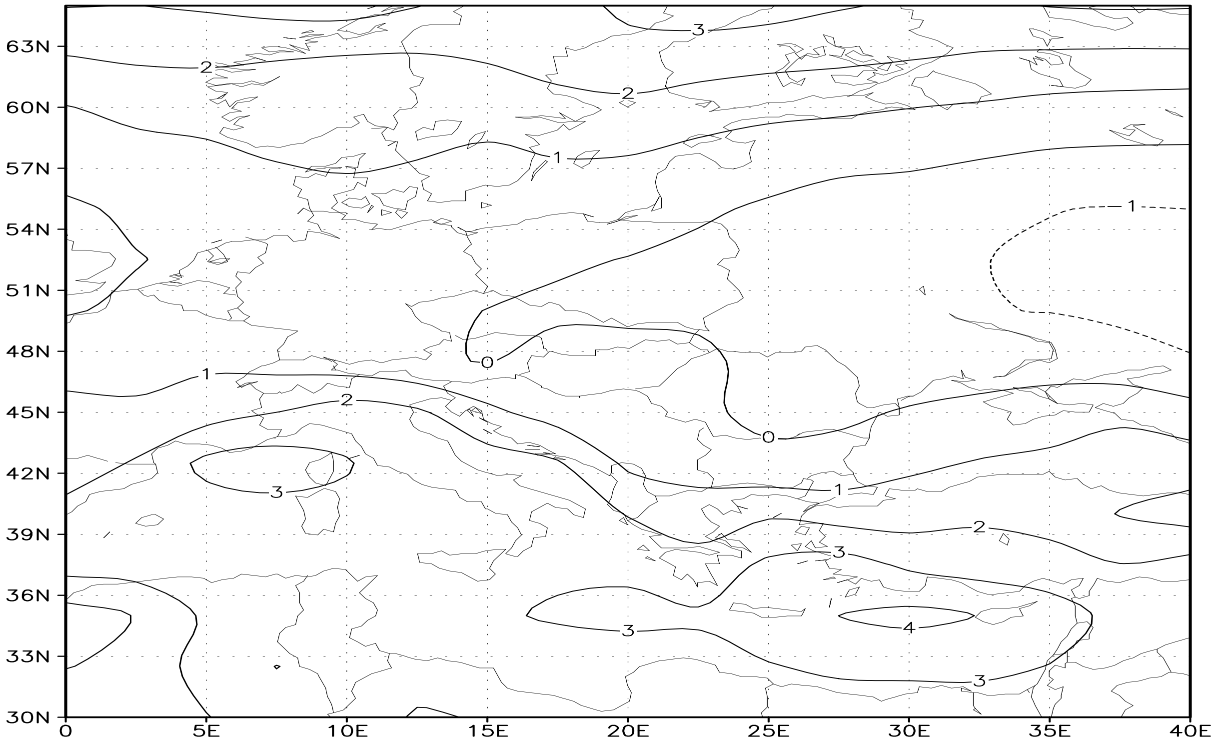


Fig. 1 – The model bias for the daily sea level pressure during spring time, calculated as the difference between the mean of the daily multiannual of the control experiments and ERA-40 (1958–1999).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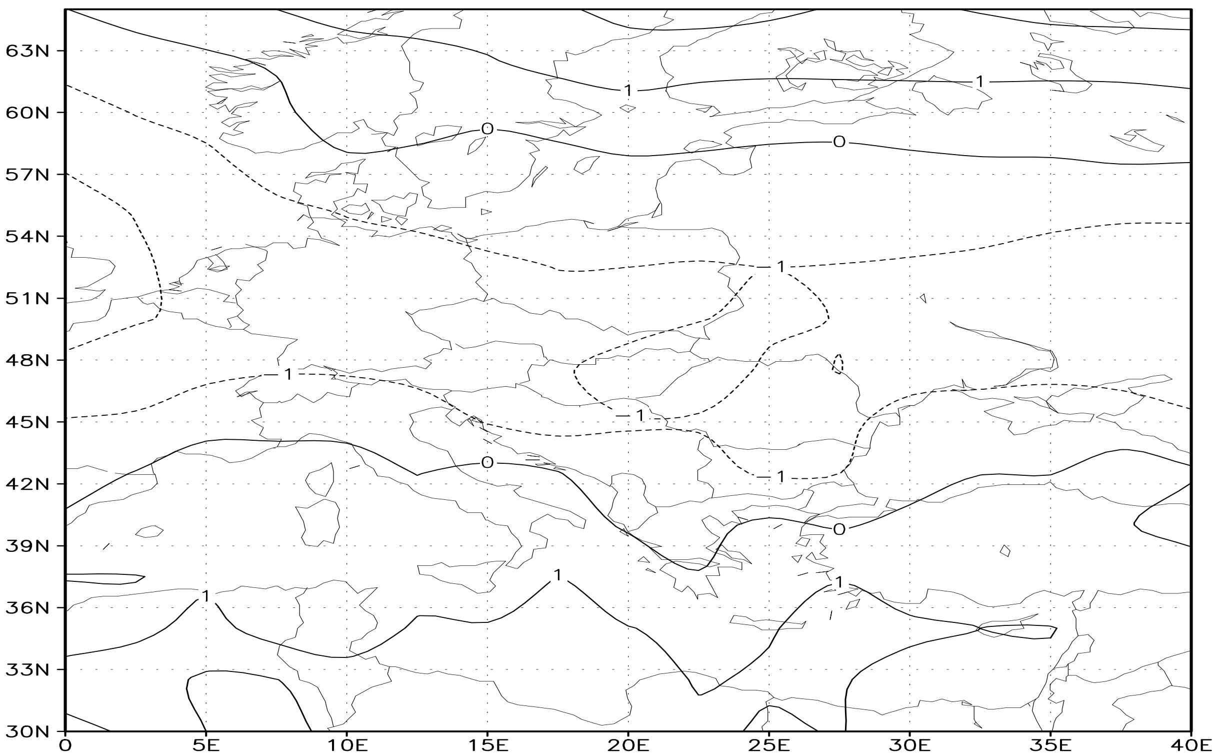
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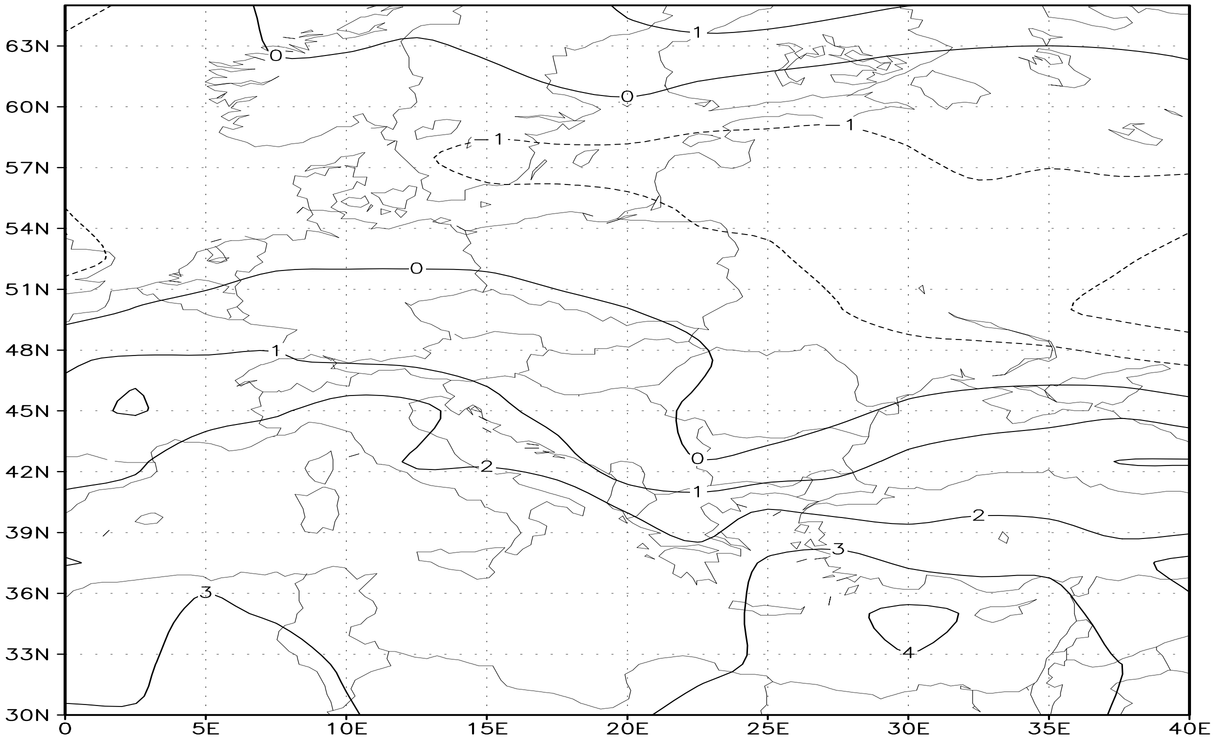

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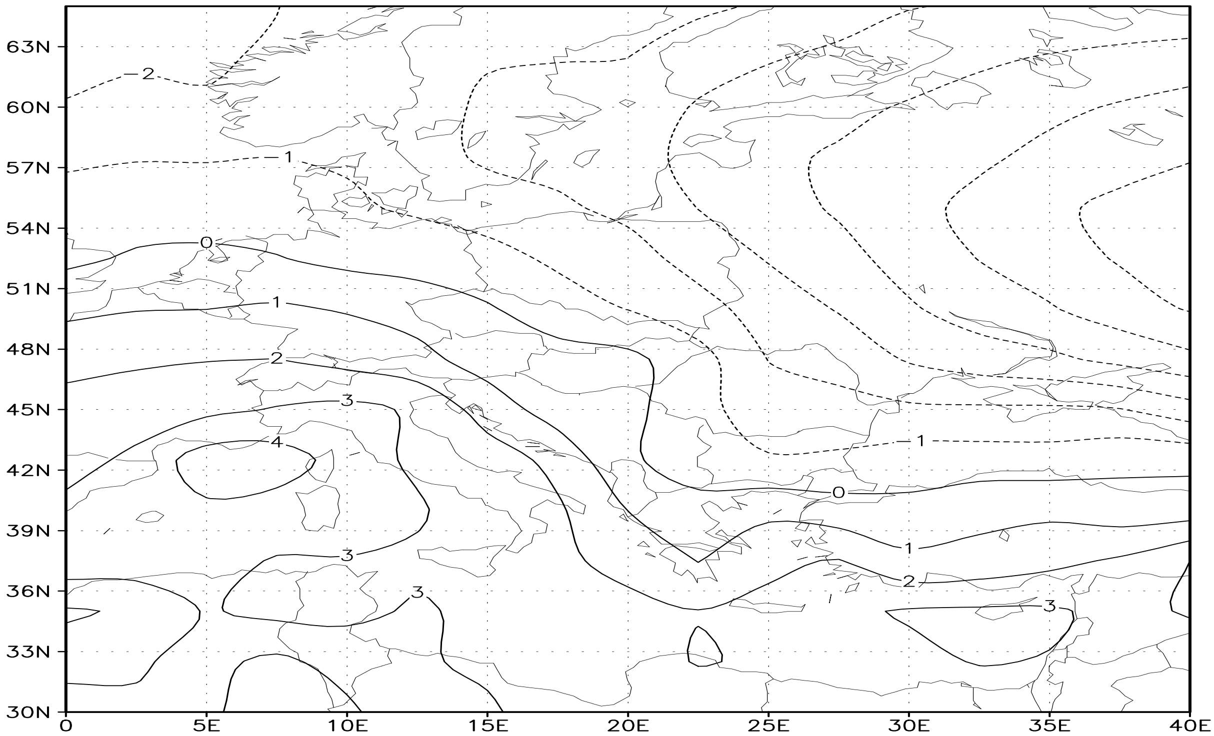

d)

Fig. 2 – The spring average of the model biases: a) CNRM, b) ECHAM5_MPI, c) EGMAM, d) IPSL.

4. ANALYSIS OF THE CLIMATE SIGNAL IN THE DAILY SPRING PRESSURE FIELD IN THE 21st CENTURY AS COMPARED TO THE 20th CENTURY

The goal of this analysis is to test if the difference among the simulated pressure values during spring by the four models in the two intervals of the 21st century and the reference period of the ERA-40 is statistically significant. As mentioned above, for the 20th century, both ERA-40 and simulations are considered for 42 years (1958–1999). For the 21st century, we considered two periods of 42 years each, namely 2009–2050 and 2051–2092. Among the non-parameter tests, the *t test* has been used more frequently in testing statistical significance of climate changes. However, for this test application several conditions have to be fulfilled, among which the time independence of the climate variables, a condition hardly accomplished by the hydro-meteorological variables with serial correlations. This is the reason why many investigations tried to apply different procedures to accomplish the conditions imposed by the *t test*. A review of these procedures is found in Ebisuzaki (1997) and Wilks (1997). One of the procedures is the application of a modified *t test*, using in the place of the sample length an equivalent length (details about ESS were given in paragraph 3.1) by scaling the variances of *t test* calculation with this ESS. This scaling procedure is often named *variance inflation factor* (Wilks, 1997). According to Zwiers and Storch (1995), to test the hypothesis $H_0: \mu_y = \mu_x$ using the samples of size m and n for $\boldsymbol{y}$ and respectively $\boldsymbol{x}$, we calculate:

$$t = \frac{\bar{y} - \bar{x}}{s[1/(m_e)^{1/2} + 1/(n_e)^{1/2}]} \qquad (8)$$

where:

$\bar{y}$ and $\bar{x}$ are the sample means and s^2 is the pooled sample variance.

$$s^2 = \left[\sum_{i=1}^{m} (x_i - \bar{x})^2 + \sum_{i=1}^{n} (y_i - \bar{y})^2 \right] \Bigg/ (m+n-2) \qquad (9)$$

For example, *ESS* for series $\boldsymbol{x}$ is estimated by:

$$n_e = \frac{n}{\left[1 + 2\sum_{\tau=1}^{n-1} \left(1 - \frac{\tau}{n}\right) \rho_{xx}(\tau) \right]} \qquad (10)$$

$\rho_{xx}(\tau)$ is the correlation between the variable x at the t moment and the variable x at the $t+\tau$ moment:

$$\rho_{xx}(\tau) = \frac{1}{n-\tau} \sum_{i=1}^{N-\tau} (x_i - \bar{x})(x_{i+\tau} - \bar{x}) / s_x^2 \qquad (11)$$

where s_x^2 is the variance of sample x.

To apply the test described by (8), the compared variables must be normally distributed, they must not present a serial correlation and the series have to be independent. Theoretically, the standard deviations must be equal to obtain a correct result of the *t test*. In applications, this condition is considered to be correct if standard deviations of the two series does not differ much (Laurmann and Gates, 1977). In the case of our analysis, standard deviations corresponding to the data from the ERA-40 and to simulated data differ slightly. We must verify the hypothesis that the time series pairs (averages spring SLP ERA-40 and corresponding simulated averages) used for the *t test* are independent. The correlation coefficients for 42 years between the seasonal averages of the ERA-40 and respectively of the simulated data are statistically insignificant. For 40 degrees of freedom, the critical threshold for a significance level of 90% is of 0.257, and for a significance level of 95% is of 0.304. In our case, for almost all of the 255 points, the statistical significance is lower than 90%, in many cases being close to zero. Consequently, the hypothesis that the series to which the *t test* is applied must be independent may be practically accepted. To solve the problem of the serial correlations of each series we must calculate n_e both for the ERA-40 values and for each of the simulations for SLP given by the four models. In all cases, the effective length n_e was much bigger than n initial (42 years). This may be explained by the fact that serial correlations are negative at neighbor lags. So, the calculation of *ESS* for the data processed in this paper, that is the pressure mean values in spring, did not lead to the conclusion that the results of applying the *t test* would be trustworthy.

Next, we adjusted by auto-regressive models the pressure spring daily time series of MAM and applied a *Z test* according to the procedure described by Katz (1982, 1992). As Zhao *et al.* (2001) show, this procedure has two main advantages as to the *t test*. First, it is based on a greater number of processed values because the daily values are used instead of the monthly or season ones, avoiding limited size sampling. The second advantage of the *Z test* is that it is not required that time series variances of the control and experiments be equal, or that the series be independent.

An important problem which appears in AR modeling is the determination of the optimum order by which the respective time series is adjusted. There are several estimation procedures of this order, those better known being the Bayesian Information Criterion (BIC), introduced by Schwarz (1978), and the Akaike Information Criterion (AIC) – Akaike (1974). In Mareş and Mareş (2003), seven criteria including *BIC* and *AIC,* were tested, to determine their performances on simulated data with an AR model of order *2* and *4*. Of 100 achievements, the most performing criterion for determining order 2 or 4 for both small samples (up to 50) and bigger samples of 100 was *BIC*. Having in view our former results, as well as those described by Katz (1982), in the determination of the *AR* model order in the present study, we applied *BIC*. We considered that each spring season of each year represents an achievement of an ensemble of 42 achievements (years), each with a length of 90 days.

The steps followed in this paper to detect the changes in the pressure field during spring were the following. First, each time series with a length of 90 (months MAM) was modeled by an AR model of order 1 to 10. The AR model parameters were estimated on the basis of the maximum entropy concept (Burg, 1975, 1978; Ulrych and Bishop, 1975). The model order was determined by the *BIC* procedure for each of the 42 years. The percentages of the occurrence of one of AR orders from 1 to 7, calculated for all the years and all the points, are presented in Table 2. In this table, ERA-40 represents SLP from the control period (1958–1999), and for each climate model, the index *1* or *2* represents the first interval of the 21st century (2009–2050) and, respectively, the second interval (2051–2092). The biggest percentage for ERA-40 correspond to an AR of first order, and for simulated values order *2* or *3*, depending of the model, were obtained.

Table 2

The frequency (%) of an autoregressive process selection calculated for the 255 points defining SLP during spring season*

Ord	ERA-40	CNRM_1	CNRM_2	ECHAM5_1	ECHAM5_2	EGMAM_1	EGMAM_2	IPSL_1	IPSL_2
1	51.6	3.1	1.9	11.9	14.1	14.3	11.1	5.7	4.7
2	38.9	37.7	36.3	64.2	54.1	48.1	53.8	44.8	42.7
3	8.6	50.2	50.9	20.4	28.5	30.7	29.2	38.8	42.9
4	0.8	6.6	9.2	2.8	2.7	5.7	5.3	9.7	8.1
5	0.2	1.6	0.9	0.6	0.5	0.8	0.3	0.8	1.1
6	0.0	0.6	0.7	0.1	0.2	0.3	0.2	0.1	0.5
7	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0

* The determination of a single order corresponding to a point was done according to the maximum percentage obtained for the 42 years.

In the second step, a single order *p* for each point according to the maximum achieved percentage is selected. Then, for each point, the achievements (pressure from ERA-40 and from models) are fit with an *AR* of a previously determined order, varying between *1* and *3*. The percentages resulted from *AR* orders selection for the 255 points are presented in Table 3. From this table, one may see that in 71.4 % of the points the ERA-40 SLP is fit with an *AR* of order 1, while for simulated *SLP* is necessary an *AR* model of order *2* and *3*.

Between the two periods in the 21st century there are no remarkable differences in any one of the models. On the whole, SLP simulated time series for the 21st century are fitted in the most of points with an AR of order 2 in ECHAM5-MPI and EGMAM, with a model of order 3 in CNRM and with AR models both of order 2 and 3 for SLP simulated by IPSL.

Table 3

Selection of the order of an auto-regressive process with BIC, for the spring season daily pressure

Ord	ERA-40	CNRM_1	CNRM_2	ECHAM5-MPI_1	ECHAM5-MPI_2	EGMAM_1	EGMAM_2	IPSL_1	IPSL_2
1	71.4	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0
2	28.6	33.7	25.5	96.1	83.5	75.7	83.1	60-.4	52.9
3	0.0	66.3	74.5	3.9	16.5	23.9	16.9	39.6	47.1

The figures represent the selection frequencies (%) calculated for the 42 years and for all the points (255).

For each point, we calculate the coefficients $\phi_p(p)$ for an AR of order *p* and an estimator $\sigma^2(p)$ of the white noise variance. $\sigma^2(p)$ is an unbiased estimator (Katz, 1982; Ulrych and Bishop, 1975) of the white noise variance for a process *AR(p)*, as a function of the sample length, the model order and the variance corresponding to the process AR(p):

$$\sigma^2(p) = \frac{n}{n-p-1}\hat{\sigma}^2(p) \qquad (12)$$

The recurrence relation for the white noise variance estimation $\hat{\sigma}^2(p)$ is given by:

$$\hat{\sigma}^2(p) = \{1-[\phi_p(p)]^2\}\hat{\sigma}^2(p-1) \quad \text{p = 1, 2,.., M} \qquad (13)$$

Where *M* is the *AR* model order.

Then, the mean of the ensemble of the coefficients *AR (p)* and of the corresponding variances (Chervin, 1980) for each point is determined. The approximate variance of time averages of an *AR (p)* process (according to Katz, 1982) when the sample size *N* is large (*N* in our case is 42 × 90 = 3780) is given by:

$$V_p^2 = \frac{\sigma^2(p)}{[\sum_{k=1}^{p} \varphi_k(p)]^2} \qquad (14)$$

Let's consider the time average and the variance of the simulated values $\overline{X}_s$, $V_{p_s}^2(s)$ and respectively $\overline{X}_{\mathrm{Re}}, V_{p_{\mathrm{Re}}}^2(\mathrm{Re})$ of the ERA-40 values, for a pressure defined in a grid point, under the null hypothesis ($\overline{X}_s - \overline{X}_{\mathrm{Re}} = 0$).

In case *N* is very big, the distribution:

$$Z = \frac{|\overline{X}_s - \overline{X}_{\mathrm{Re}}|}{\sqrt{N^{-1}[V_{p_s}^2(s) + V_{p_{\mathrm{Re}}}^2(\mathrm{Re})]}} \qquad (15)$$

converges to a standard Gaussian distribution.

In eq. (15), we considered the module of the means difference because we are not interested in the difference sign but in its statistical significance. Accordingly, the *Z test* values will be all positive. In Fig. 3 (a-h) the *Z test* geographical distribution for testing the changes in the pressure field during spring for the 21st century (A1B scenario) in comparison with the ERA-40 (1958–1999) is presented. According to *Z test* results, there are small areas where the 21st century changes in the pressure field are not significant. Comparing the models, the *Z test* shows that areas with significant statistical climate signal are similar for CNRM and ECHAM5-MPI. These models contour the most intense nucleus with great statistical significance in the West of the Mediterranean Sea. For EGMAM the intensity of the climate signal is situated in the North-East of Europe. Even though less intense as in the case of CNRM and ECHAM5-MPI models, the climate signal intensity for IPSL model is seen also in the South-West of the Mediterranean Sea.

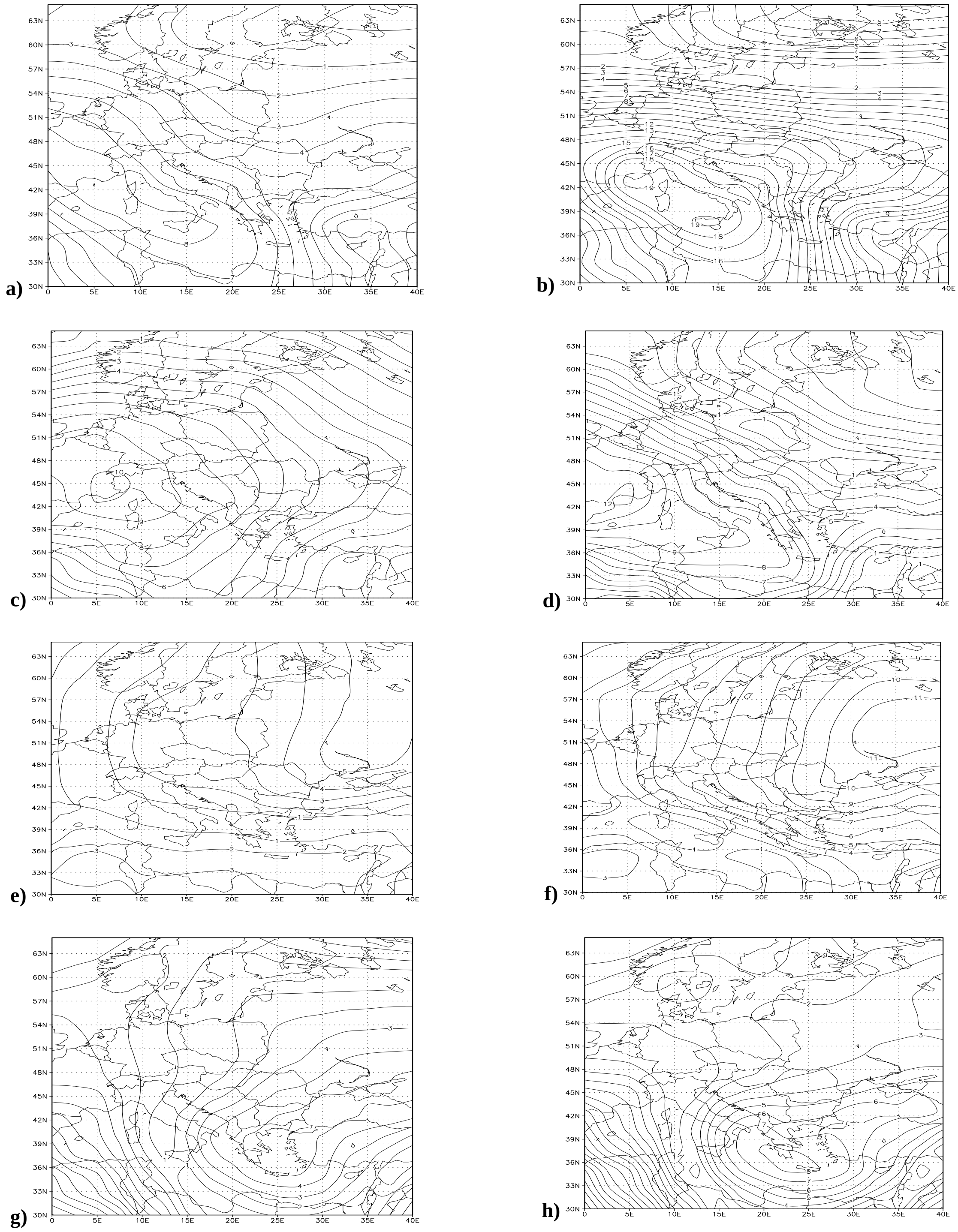

Fig. 3 – Geographic distribution of Z test for testing the pressure field changes during spring for the 21st century (A1B scenario) in comparison with the ERA-40 (1958–1999) for four climate models: a-b) CNRM; c-d) ECHAM5-MPI; e-f) EGMAM; g-h) IPSL. The left graphics represent the interval 2009–2050, and the right ones, 2051–2092. Z distribution values were normalized by the critical value $z^* = 1.96$ corresponding to the 5% significance level (which corresponds to a 2.5% level for a one side test). In the areas where Z values are greater than 1 hPa, the climate changes in the pressure field for the 21st century are statistically significant.

The confidence interval for the mean changes is estimated as follows:

$$\overline{X}_s - \overline{X}_{\mathrm{Re}} \pm z_{\alpha/2}\sqrt{N^{-1}[V^2_{p_s}(s)+V^2_{p_{\mathrm{Re}}}(\mathrm{Re})]} \quad (16)$$

where $z_{\alpha/2}$ satisfies:

$$\Pr\{Z > z_{\alpha/2}\} = \alpha/2 \quad (17)$$

If we choose a confidence interval of 95% using a Gaussian approximation with α = 0.05 then $z_{\alpha/2}$ =1.96. As Katz (1982) showed, while the null hypothesis test shows if a climate change took place or not, the confidence intervals give us information referring to the climate change dimension.

In Table 4 we present the confidence interval calculated according to formula (16), only for *Z test* values corresponding to SLP defined in the point of interest for the Danube basin (47.5° N, 20° E). One can observe that for this point, with the exception of EGMAM model which for both periods of the 21st century shows a slight pressure decrease, the other three models show a pressure growth at sea level. This is in accordance with Cubasch *et al.* (2001), who underlines that the most consistent characteristic of the pressure differences at sea level, obtained from mean ensemble, is of decrease for high latitude and of increase for mid latitudes. Although in Cubasch *et al.* (2001) the results for scenarios *A2* and *B2* are presented, they are similar to those obtained in this study, where scenario *A1B* was used.

Table 4

Confidence intervals (95%) of the differences between the 21st century simulated and ERA-40 mean values pressure during spring in point 47.5° N, 20° E (unities: hPa)

CNRM_1	CNRM_2	ECHAM5-MPI_1	ECHAM5-MPI_2	EGMAM_1	EGMAM_2	IPSL_1	IPSL_2
0.49 ± 0.12	**1.50** ± 0.12	**0.98** ± 0.13	**0.48** ± 0.14	**-0.36** ± 0.13	**-0.98** ± 0.13	**0.18** ± 0.14	**0.29** ± 0.14

The pressure changes at sea level over Europe differ not only according to the scenario, but also according to the analyzed period of the year, as well as to the used model characteristics. Meehl *et al.* (2006) analyzed the changes obtained for several climate variables for different scenario [using Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) *A2, A1B* and *B1*]. As concerns the magnitude of the annual mean SLP change, in A1B scenario, from 1980–1999 to 2080–2099, this was for the Center and East Europe of about 0.8 hPa. The results were obtained with multimember ensemble simulations using the Community Climate System Model version 3 (CCSM3). In Beniston *et al.* (2007), the *SLP* changes dimension during winter simulated with regional climate models in the South of Europe was between *-1* and *1* hPa, and the most significant changes were found in the North-West of Europe. The differences concern the time intervals 2071-2100 and 1961-1990, using scenario *A2*.

5. CONCLUSIONS

The investigations carried in the present study, referring to spring SLP over the European region (30°–65°N; 0°–40°E), aimed at:

– The elimination of an important part of the uncertainty by bias correction of the pressure at sea level, simulated by four GCMs (CNRM, ECHAM5-MPI, EGMAM and IPSL);

– Deriving the climatic signal in the sea level pressure field over the chosen region in Europe during the spring season (MAM), in the *A1B* emission scenario, in two periods within the 21st century (2009–2050 and, respectively 2051–2092), based on ERA-40 data from the period 1958–1999;

– Determination of the areas with a statistical significant climate signal in SLP in the considered European region.

The spatial distribution of the bias correction during spring season is different, depending on the model. The smallest errors in absolute values of the averages over 90 days are found around latitudes 45–50° N.

The *Z test* values have put in evidence the SLP climate signal simulated by the four models for *A1B* emission scenario for the two 21st century intervals (2009–2050 and, respectively 2051–2092), related to the ERA-40 from the period 1958–1999. The statistical significance of the climatic signal differs depending on the model, and of the two intervals. The most extended zones in Europe with a significant climatic signal are found in case of two models, CNRM and ECHAM5-MPI.

Increasing of the performance of the Z test application is facilitated by the fact that the procedure is based on parametric time series modeling involving the fitting of low-order AR processes. The maximum entropy method was used to estimate the AR parameters. Optimal orders of AR models, estimated by means of BIC, led to the conclusion that real processes are more persistent (AR order of 1) while those simulated by the four GCMs are less persistent (AR model order is 2 or 3). Therefore, the *Z test* for detection of a climatic signal is to be preferred to the classic *t test*, and is recommended for use as a powerful tool, provided that the respectively time series be fit by an AR model.

The results of the present study have a strong implication in investigations in which the pressure is used as predictor for hydro-meteorological variables, especially for precipitation, for which the changes during the spring season are very important in the hydrological regime. As well, this study will be of interest not only for our further studies but also for the investigations that need the selection of the SLP predictors from the analyzed region in order to estimate changes in hydro-meteorological variables in the 21st century.

The analysis presented in this paper will be extended to SLP from other seasons and for other climatic variables at the different isobaric levels simulated by GCMs / RCMs. It is also necessary to extend this investigation to a wider region of Europe, in order to estimate the changes in the NAO index in the 21st century.

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