EVALUATION OF GFDL GCM CLIMATE VARIABILITY USING EOFS OF ZONAL AVERAGE TEMPERATURE DATA

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Abstract: In this study the GFDL GCM generated (controlled run) zonal average temperature data are evaluated by comparing their EOFs with those from observed data. Even though the correlation matrices of observed and simulated data are shown significantly different (Polyak and North, 1997b), the EOFs derived are found very similar with very high pattern correlations. This means almost all the information (second-order statistics) derived from the observed data can be reproduced by the EOFs derived from the GFDL GCM simulates. Also, the EOFs from GFDL GCM were found to have more flexible structures than those from the observed. Thus, we may conclude that the GFDL GCM can simulate the Earth's energy balance system reasonably. However, more in detail research should be focused on the effect from various forcings on climate variability, as, in some cases, the effect of external forcings could shadow the system characteristics and mislead the simulation results.

1. INTRODUCTION

The papers by Polyak and North (1997a, b) have motivated author to become interested in the validation problem of GCM simulations. Regardless of admitting that GCMs are far from perfect to simulate the climate variability both in time and space, these are, author believes, still the most powerful and useful tools in the climate research. Especially for the temperature field, which has a long correlation length both in time and space, a rather simple climate model like the energy-balance model (North and Cahalan, 1981) has proven to simulate a realistic temperature field successfully. Therefore, GCMs, which has more complex structure considering every possible aspects of energy and water balance, should give a better simulation provided a proper parameterization is conditioned.

GCM validation problems can be found in many studies (Katz, 1992; Oort, 1983; Santar and Wigley, 1990), where they generally compared the means and standard deviations of different atmospheric characteristics derived from the observed and simulated data. Recently, Polyak (1996), Polyak and North (1997a, b) evaluated the spatial and temporal climate variability of the fluctuations of the surface air temperature field. The surface air temperature is believed to have the best accuracy compared with the other variables GCMs provide. The analysis by Polyak (1996), Polyak and North (1997a, b) were done for the zonal average temperature (9° latitude bands for northern hemisphere), and compared the monthly variation of standard deviations and correlation matrices using the *F*-statistics (Devore, 1991) and *N*-statistics (Rao, 1973). Unfortunately, they reported quite disappointing mismatch between observed and simulated data.

The reasons for their disappointing result may be explained in many ways. However, the most probable one is that the GCM did not consider various external forcings to the climate system. The only forcing considered in the GCM is the concentration of CO_2 gas. Other important forcings such as solar cycle, volcanic aerosol or anthropogenic aerosols were not generally considered. Thus the system output, even though both systems are similar inside, can be very different due to different external forcings. Also the other reasons we may refer are improper parameterization, imperfect modeling for some aspects of meteorology such as the cloud cover, improper consideration of several feedback mechanisms, and so on.

However, regardless of all the reasons, author believes that the temperature field can be modeled properly, which, at least, should be quite realistic in the aspect of its first- and second-order statistics. Thus, the sole object of this research also lies on the validation of the second-order statistics of the same zonal averaged temperature field used by Polyak and North (1997a, b).

One idea we can choose to accomplish the research object might be to remove all the effects of different forcings and compare the system characteristics just the same way as in Polyak and North (1997a). However, even we assume that it is possible to remove the effects of various forcings, it could be a huge job. Also, even though it is worth while to do, only a few are in the position of handling any GCM to take this kind of whole procedure. Thus, author decides to follow a rather simple procedure to check if GCMs have the same or similar system to the earth's. In that sense, the EOF (Empirical Orthogonal Function) analysis is quite promising.

The EOFs is similar to normal modes in mechanical system. We also have similar terms such as principal components in Statistics and eigenvectors in Mathematics. EOF is a common terminology in Atmospheric Sciences. Basically EOFs represent the system characteristics and can reproduce the system output as a linear combination of them. North (1984) also showed that in many systems the EOFs are identical to the normal modes. The diffusion system, the wave propagation, and the forced motion are those among good examples.

One important fact we have to make sure to do the EOF analysis for this research object is that an external forcing will not change the system itself. It is rather easy to imagine that for the case of a mechanical system. For example, a wave propagation system on a rod will have the same normal modes regardless of any kind of forcings (Kaplan, 1991). In fact, this was already observed by Preisendorfer (1979). Preisnedorfer et al. (1981) also provided the general criteria for the EOF-normal mode symmetry to occur. Also, North (1984) showed that in many systems the EOFs are not frequency dependent. He also showed that the symmetry in the mechanical operator and the same symmetry in the forcing cause the EOF-normal mode coincidence although the forcing is not "white".

As it is generally accepted, the temperature field on earth is a kind of diffusion system. Thus, the EOF-normal model symmetry holds such as in the model by North and Kahalan (1981), and we can say the EOFs derived from observed data could be treated as a characteristic feature of the earth system. This characteristic (the shape of EOFs) will not be changed due to any kind of external forcings. Only the eigenvalues will be differently weighted depending on the characteristics of forcings.

Thus, based on the facts mentioned above, we may evaluate the GCM simulates. It can simply be done by deriving and comparing the EOFs for the observed and simulated data. Also by deriving the EOFs which satisfy both the two different systems and by comparing them, we may be able to distinguish a system which has been more affected by the forcings with various characteristics.

In this study, we will evaluate the GFDL GCM generated (controlled) zonal average temperature data (Polyak and North, 1997a, b). Basically the correlation matrices of observed and simulated data along with other summary statistics are borrowed from their results. So, this paper will spare a small portion for the data description.

Summarizing the contents of the paper is as follows. First, the next section is spared for the background of EOF analysis and normal mode for a mechanical system to get insights on the physical meaning of the EOFs. We will also consider a forced system with forcings both white and colored to show that the EOF will remain invariant regardless of the forcings. The following section will be covered with the summary statistics of both observed and simulated data, and the comparison results of EOFs derived in two different ways will cover the last section.

2. EOF AND NORMAL MODES IN THE CASE OF CONTINUUM LINEAR SYSTEM

North (1984) showed that in a large class of linear stochastic models the EOFs (from the data field generated by a model in the class) at individual Fourier frequencies coincide with the orthogonal mechanical modes of the system provided they exist. The class of models contains the wave equation, the diffusion equation, and also the simple model by North and Cahalan (1981), which are all the Hermitian mechanical systems forced according to the following governing equation

$$\mathrm{H}\left(\frac{\partial}{\partial t}, \nabla, \mathrm{r}\right)\Psi(\mathrm{r},t) = f(\mathrm{r},t) \tag{1}$$

along with homogeneous boundary conditions (either $\Psi(\mathrm{r},t)$ or its derivative vanishes on the boundary). Also, $f(\mathrm{r},t)$ is a stochastic field stationary in time and "white" in space, i.e.,

$$\langle f(\mathrm{r},t) f(\mathrm{r}',t')\rangle = \sigma^2(|t-t'|)\delta(\mathrm{r}-\mathrm{r}') \tag{2}$$

where $\delta(\mathrm{r}-\mathrm{r}')$ is a Direc delta function and $\sigma^2(|t-t'|)$ is some given autocovariance function. North explains it as a forcing of randomly located point source with its strength modulated by a stationary process.

The eigenvalues of an operator H are the solutions ϕ_α, α=1, 2,..., of

$$\mathrm{H}\phi_\alpha = \lambda_\alpha \phi_\alpha \tag{3}$$

where the numbers λ_α are the eigenvalues. The eigenvalues of a Hermitian operator are real. The eigenvectors of a normal operator are orthogonal and can be normalized such that

$$(\phi_\alpha, \phi_\beta) = \delta_{\alpha\beta} = \int \phi_\alpha^*(\mathrm{r})\phi_\beta(\mathrm{r})d\mathrm{r} \tag{4}$$

where ϕ_α and ϕ_β correspond to distinctly different eigenvalues λ_α and λ_β. Usually it is possible to show that for well-behaved operators acting upon a bounded domain, the eigenvectors from a complete basis set, which may be expressed

$$\sum_\alpha \phi_\alpha(\mathrm{r})\phi^*_\alpha(\mathrm{r'}) = \delta(\mathrm{r}-\mathrm{r'}) \quad (5)$$

When this holds, any function in the space can be written in the infinite series representation

$$\phi(\mathrm{r}) = \sum_\alpha \varphi_\alpha \phi_\alpha(\mathrm{r}) \quad (6)$$

A normal operator can be decomposed into an expansion of its eigenvectors and eigenvalues

$$\mathrm{H}(\mathrm{r},\mathrm{r'}) = \sum_\alpha \lambda_\alpha \phi_\alpha(\mathrm{r})\phi_\alpha(\mathrm{r'}) \quad (7)$$

Two operators (let say A and B) can have simultaneously the same eigenvectors if, and only if, they commute (that is, if AB=BA). The inverse of an operator A, denoted A^{-1}, ordinarily exist if A has no vanishing eigenvalues. For a product $(AB)^{-1} = B^{-1}A^{-1}$. An operator commutes with itself and any power of itself including its inverse. Conditioned this, Hermitian mechanical systems forced according to (1), (2) have their EOFs coincide with the normal mechanical modes, defined as the eigenfunctions of H.

3. SUMMARY STATISTICS OF GFDL GCM TEMPERATURE SIMULATES

3.1 Data Description

The temperature fields from the simulations by the GFDL coupled ocean-atmosphere GCM is used in the study. Physical analysis of the results of the experiment is provided by Manabe et al. (1991, 1992).

Two kinds of simulated monthly fields of the surface air temperature are available: a control run with CO_2 fixed and a transient run with CO_2 initialized at the 1958 amount and increased by 1% each year thereafter. Both runs are 100 years long with monthly resolution. The spatial grid is 48x40 boxes on the so-called Gaussian grid coordinates. There are 48 boxes around 360° of longitude, hence 7.5° per box. There are 40 boxes along 180° of latitude, hence 4.5° per box. Also the source of the observed data is the United Kingdom's monthly surface observations for 1891-1990 (Jones at al., 1986).

The samples of northern hemisphere surface air temperature studied here (also in Polyak and North, 1997a, b) were obtained by spatially averaging data within different 9° latitude bands. Therefore simulations given for 4.5° width latitude grid were additionally averaged for each pair of the adjacent latitude zones and along all the longitude points. As a result, 10 time series were obtained for each 10 latitudinal bands of 9° width of the northern hemisphere. Analogous averaging was done for the observed data (Polyak and North, 1997).

As the purpose of the study is to validate the simulated surface air temperature variability, we will limit our analysis to the control run. As Polyak and North (1997) said, the air temperature anomalies (seasonal cycle removed) from the control run does not have a deterministic component. However, the transient run anomalies have shown a significant trend.

3.2 Correlation Matrices Comparison

Using the zonal average temperature anomalies for both observed and simulated data the correlation matrices were derived for both lag-0 (the spatial correlation field) and lag-1 month (Table 1). For the correlation matrix for lag-0 of

Table 1. Correlation matrices of observed data (top, lag-0 and bottom, lag-1 cases)

	85.5	76.5	67.5	58.5	49.5	40.5	31.5	22.5	13.5	4.5
85.5	1.00	0.74	0.40	0.14	-0.03	-0.09	-0.08	-0.05	0.00	-0.06
76.5	0.74	1.00	0.80	0.35	0.04	-0.05	-0.04	0.03	0.04	-0.05
67.5	0.40	0.80	1.00	0.69	0.25	0.02	0.00	0.05	0.02	-0.09
58.5	0.14	0.35	0.69	1.00	0.75	0.32	0.16	0.08	0.01	-0.04
49.5	-0.03	0.04	0.25	0.75	1.00	0.76	0.45	0.07	-0.01	0.00
40.5	-0.09	-0.05	0.02	0.32	0.76	1.00	0.78	0.10	-0.05	-0.05
31.5	-0.08	-0.04	0.00	0.16	0.45	0.78	1.00	0.50	0.19	0.08
22.5	-0.05	0.03	0.05	0.08	0.07	0.10	0.50	1.00	0.85	0.64
13.5	0.00	0.04	0.02	0.01	-0.01	-0.05	0.19	0.85	1.00	0.87
4.5	-0.06	-0.05	-0.09	-0.04	0.00	-0.05	0.08	0.64	0.87	1.00

	85.5	76.5	67.5	58.5	49.5	40.5	31.5	22.5	13.5	4.5
85.5	0.15	0.16	0.11	0.10	0.05	0.01	0.03	-0.02	-0.02	-0.07
76.5	0.15	0.26	0.23	0.18	0.11	0.08	0.13	0.06	0.00	-0.06
67.5	0.11	0.22	0.28	0.28	0.17	0.10	0.17	0.11	0.02	-0.06
58.5	0.11	0.21	0.34	0.45	0.30	0.12	0.16	0.12	0.05	0.02
49.5	0.10	0.17	0.29	0.49	0.47	0.29	0.21	0.07	0.04	0.04
40.5	0.04	0.10	0.19	0.36	0.44	0.41	0.32	0.04	-0.02	-0.03
31.5	0.03	0.09	0.14	0.28	0.34	0.37	0.49	0.34	0.21	0.11
22.5	0.01	0.06	0.06	0.11	0.10	0.09	0.37	0.79	0.77	0.65
13.5	-0.03	0.00	-0.02	-0.01	0.02	0.00	0.20	0.75	0.89	0.85
4.5	-0.06	-0.06	-0.12	-0.06	0.01	-0.03	0.07	0.58	0.79	0.93

Table 2. Correlation Matrices of Simulated data (top, lag-0 and bottom, lag-1 cases)Data

	85.5	76.5	67.5	58.5	49.5	40.5	31.5	22.5	13.5	4.5
85.5	1.00	0.47	-0.02	-0.05	-0.16	-0.02	0.00	-0.06	0.05	-0.07
76.5	0.47	1.00	0.58	0.00	-0.11	-0.13	-0.05	0.04	0.01	0.01
67.5	-0.02	0.58	1.00	0.57	0.02	-0.14	-0.12	-0.02	0.04	0.02
58.5	-0.05	0.00	0.57	1.00	0.57	0.04	-0.09	-0.04	-0.01	0.03
49.5	-0.16	-0.11	0.02	0.57	1.00	0.56	0.13	0.12	0.01	0.13
40.5	-0.02	-0.13	-0.14	0.04	0.56	1.00	0.62	0.17	0.12	0.17
31.5	0.00	-0.05	-0.12	-0.09	0.13	0.62	1.00	0.57	0.15	0.26
22.5	-0.06	0.04	-0.02	-0.04	0.12	0.17	0.57	1.00	0.63	0.29
13.5	0.05	0.01	0.04	-0.01	0.01	0.12	0.15	0.63	1.00	0.56
4.5	-0.07	0.01	0.02	0.03	0.13	0.17	0.26	0.29	0.56	1.00

	85.5	76.5	67.5	58.5	49.5	40.5	31.5	22.5	13.5	4.5
85.5	0.05	0.08	0.05	0.05	0.06	0.05	0.05	0.04	0.02	0.00
76.5	0.05	0.17	0.15	0.09	0.10	0.07	0.07	0.07	0.06	0.06
67.5	0.07	0.20	0.23	0.17	0.13	0.09	0.05	0.03	0.04	0.07
58.5	0.04	0.13	0.19	0.26	0.23	0.11	0.04	0.03	0.01	0.05
49.5	0.01	0.03	0.11	0.26	0.35	0.25	0.12	0.08	0.05	0.09
40.5	0.00	-0.02	0.03	0.13	0.31	0.43	0.31	0.17	0.15	0.18
31.5	-0.04	-0.02	0.03	0.07	0.19	0.36	0.43	0.30	0.19	0.24
22.5	-0.02	0.01	0.01	0.06	0.15	0.18	0.30	0.40	0.29	0.25
13.5	0.00	0.01	0.01	0.02	0.07	0.10	0.15	0.30	0.39	0.35
4.5	-0.03	-0.01	0.05	0.06	0.09	0.14	0.16	0.20	0.34	0.56

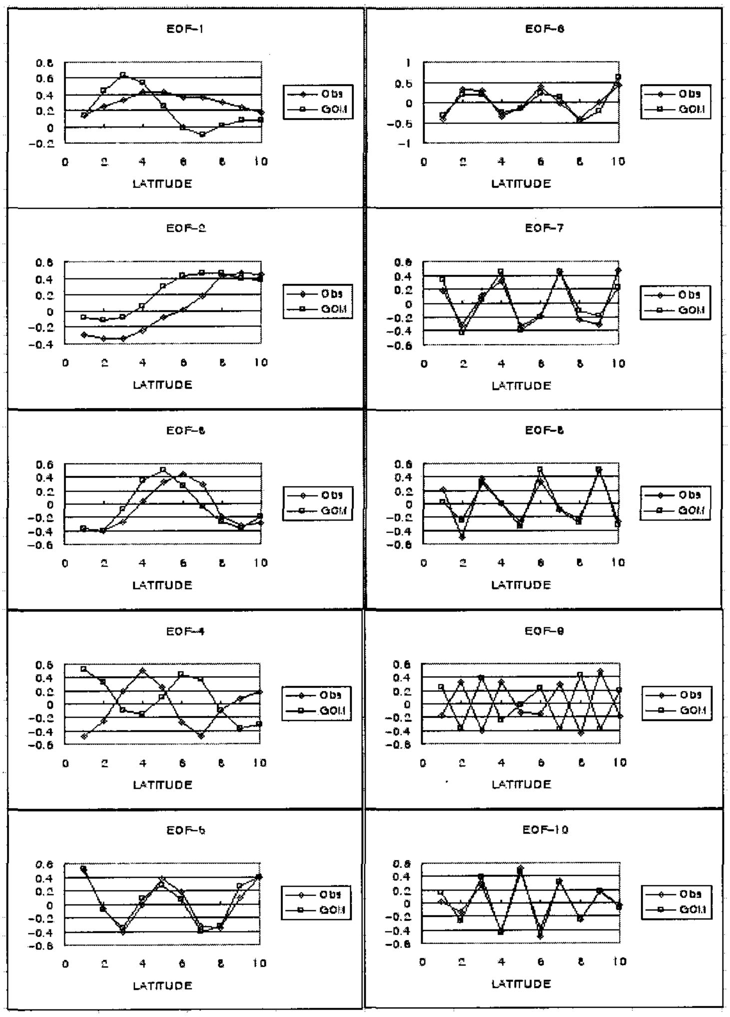

Figure 1. Comparison of EOFs derived from spatial (lag-0) correlation matrices

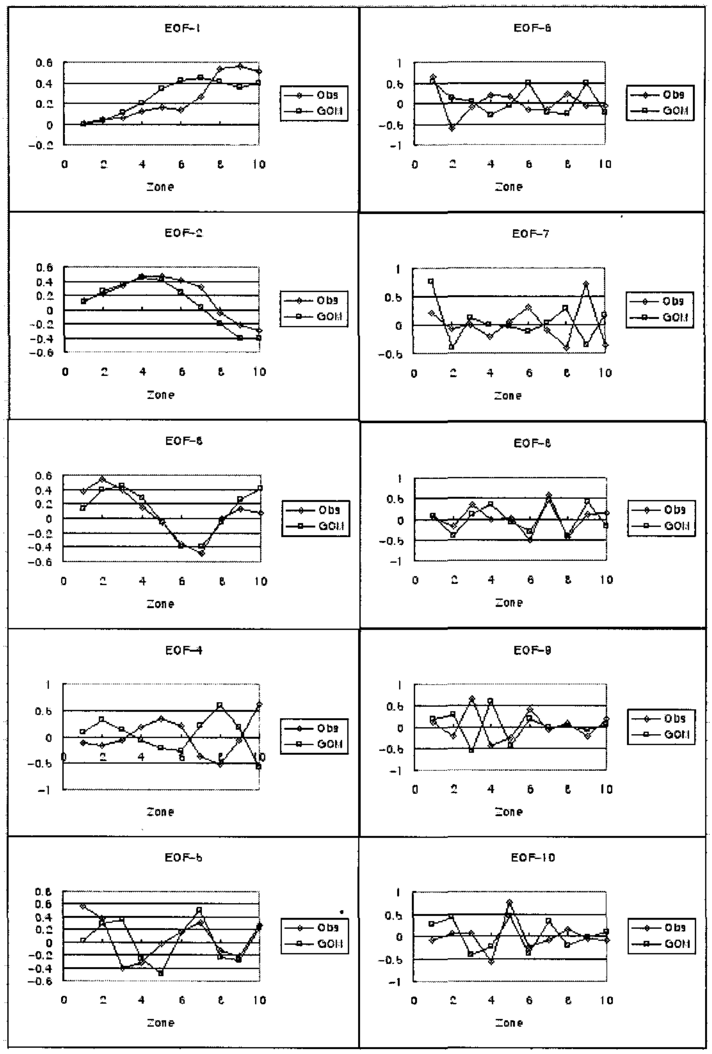

Figure 2. Comparison of EOFs derived from lag-1 correlation matrice

such that

$$C = VLV' \quad (8)$$

The columns of V, denoted by V_i, for i=1, 2,..., 10, are called the eigenvectors of C and the corresponding diagonal elements of L, denoted by λ_i, are called the eigenvalues. For each *i*, the relation $AV_i = \lambda_i V_i$ holds.

Also we can estimate the common eigenvectors (EOFs) by applying the maximum likelihood or least square estimates. For this the genvectors might be difficult to be obtained from a short record of observation (Kim and North, 1993). However in our case, as we have enough data set, we may be able to assume that the EOFs derived are quite accurate (especially the lag-0 case).

From Figure 1, we can also easily find that the EOFs for both observed and GCM simulations are very similar. Basically, 6 out of 10 EOFs are almost identical, another two is exactly the reversed (so we can match them simply

Table 3. Eigenvalues (Cumulative variance) for each EOF

Mode	Observed	GCM	Observed	GCM
	Lag-0		Lag-1	
1	3.02 (30.2)	2.58 (25.8)	2.41 (47.0)	1.51 (46.3)
2	2.69 (57.1)	1.93 (45.1)	1.85 (80.6)	0.71 (68.0)
3	2.24 (79.5)	1.78 (62.9)	0.41 (88.9)	0.53 (84.4)
4	0.97 (89.2)	1.28 (75.7)	0.34 (95.8)	0.28 (91.3)
5	0.56 (94.8)	0.85 (84.2)	0.11 (98.1)	0.17 (96.7)
6	0.29 (97.7)	0.68 (91.0)	0.05 (99.2)	0.08 (99.1)
7	0.11 (98.8)	0.46 (95.6)	0.04 (100.0)	0.02 (99.7)
8	0.07 (99.5)	0.37 (99.3)	-	0.01 (100.0)
9	0.03 (99.8)	0.06 (99.8)	-	-
10	0.02 (100.0)	0.02 (100.0)	-	-

Table 4. Pattern correlation between the observed and simulated EOFs.

Mode	Lag-0	Lag-1
1	0.672	0.881
2	0.678	0.906
3	0.838	0.878
4	0.784	0.946
5	0.961	0.406
6	0.915	0.066
7	0.926	0.284
8	0.928	0.737
9	0.971	0.462
10	0.966	0.463

by use of negative weightings), and the last two, which has the biggest eigenvalues are more or less similar. In case of combining the first and second eigenvalue and comparing it with the others' first or second EOF, we may see a much better match (this opens the possibility that the EOFs could have been intermingled). How these two sets of EOF match can be evaluated using the pattern correlation. The pattern correlation, R_{pat}, is defined by

$$R_{pat} = \left| \sum_i \phi_i^{GCM} \phi_i^{Obs} \right| \tag{9}$$

where ϕ_i^{GCM} and ϕ_i^{Obs} are components of each eigenvectors of simulated and observed data. Summarizing the pattern correlation is as in Table 4.

As you can be seen in Table 4 the pattern correlations between two sets of EOFs is very high, especially in the high modes for lag-0 case and low models for lag-1 case. For the case of lag-0 (spatial correlation) about 50% of total variability is explained by the first two EOFs. Thus major difference between two correlation matrices is come from the differences between these EOFs. However, as the pattern correlations between these first two EOFs are almost 0.7, the difference of the two system we consider may not be significant. If considering all the EOFs, the average pattern correlation is about 0.9 and we may say that these two systems have similar characteristics.

The lag-1 case is more appealing. As the first four EOFs explain more that 95% of total variability, we may more concentrate on the first four EOF. In that case, the average pattern correlation is also more than 0.9, which must be a quite satisfactory result to make sure the resemblance of the two systems. Only the high mode EOFs show somewhat low pattern correlations, which may be mainly due to the matrix singularity and somewhat skewed estimation of EOFs.

It is also interesting that the common EOFs derived are almost identical to those of GCMs. This means that the GCM has more flexible structure and, thus, can mimic the observed better than the case vise versa. Also we can conjecture that the GCMs are less or simply forced than the observed. It is well known that GCMs just mimic the earth system and the simulations used in this research are the one with simplified forcings. The common EOFs for lag-1 case could not be derived because of the same reason mentioned above.

4. CONCLUSION

In this study the GFDL GCM generated (controlled run) zonal average temperature data are evaluated by comparing its EOFs and those from observed data. Even though the correlation matrices of observed and simulated data are shown significantly different (Polyak and North, 1997b), the EOF derived are found very similar (with high pattern correlations). Considering that the output statistics of a system, especially the second-order one, can be totally different depending on the input statistics, a simple comparison of output statistics for the evaluation of a system may mislead the idea on the system itself. They should be given the quantitative consideration of external forcings. The same is also be applied to the GCM evaluation of its capability to reproduce the realistic climate features.

In many kinds of mechanical system such as the wave propagation or diffusion system, as the EOFs, which decide the system characteristics as a linear combination of them along with proper weightings (so-called eigenvalues), is invariant for a external forcings, only the weightings (eigenvalues) will be changed in an ideal case. In our study, we analyzed the correlation matrices both zonal averaged temperature time series of observed and simulated by the GFDL GCM. Basically, we showed that the EOFs for both system are very similar with high pattern correlations so that one can be reproduced by another. Thus, we believe the results by Polyak and North (1997b) is somewhat misleading the capability of GFDL GCM. Also the EOFs from GFDL GCM was found to have more flexible structures than those from the observed.

Based on these findings in our research, we conclude that the GFDL GCM can simulate the earth's energy balance system quite well. However, more in detail research should be given to the effect from various forcings on climate variability, as, in some cases, the effect of external forcings could shadow the system characteristics and mislead the simulation results. Also, how the external forcings are reacted to each EOF to change the variability of a given field is another interesting topic to consider.

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