EMPIRICAL ORTHOGONAL FUNCTION ANALYSIS OF SEA SURFACE TEMPERATURE PATTERNS IN THE LEVANTINE BASIN

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ABSTRACT

Empirical orthogonal function (EOF) analysis of a three years advanced very high resolution radiometer (AVHRR) sea surface temperature (SST) data set from the Levantine Basin are used to determine the dominant patterns of sea surface temperature (SST) variance. Monthly averaged AVHRR data, from January 1998 to December 2000, were used in the study. Processed SST data were retrieved from the German Remote Sensing Center. EOF analysis was used to decompose the time series into its component parts. Empirical decomposition implies the analysis of anomalies of a certain parameter with respect to a certain mean value (temporal or spatial). The analysis of a decomposition of the spatial variance and the temporal variance modes is done in order to identify features in AVHRR data such as fronts, eddies, and annual temperature cycles for the Levantine Basin. The analysis of the spatial anomalies reveals that the first mode accounts for 67.12% of the total variance. It reveals the main features of SST in the LB, and it shows a persistent front aligned northwest southeast which separates the colder surface water to the west from the warmer water to the east. The amplitudes time series show a seasonal modulation, peaking in early summer. The second gradient mode (contributing by 14.50%) shows the presence of gyres in the study area. The analysis of temperal anomalies shows a predominance of the first mode (98% variance), and represents the basin-wide seasonal warming and cooling. This mode peaks in summer and lags by 30 days the first-mode time series revealed by the spatial variance analysis. The first covariance mode has a weak spatial variation in the eigenvectors, while the second and the third modes show more spatial variation. The second and third covariance modes (covariance) carry extremely low energies (0.82% and 0.30% respectively) and therefore they do not contain statistically significant information on the frontal and eddy patterns evident in the AVHRR and in situ data. Higher modes are interpreted as the results of spring heating and fall cooling of shallow river and waters ahead of offshore waters.

Keywords: Mediterranean Levantine Basin, sea surface temperature, empirical decomposition

INTRODUCTION

The eastern half of the eastern Mediterranean is called the Levantine Basin (LB). The LB has experienced major changes in its circulation. The circulation of the LB and its variabilities consists of three predominant and interacting scales: basin scale, subbasin scale, and mesoscale. A meandering jet or thermal front starting southwest of Crete and called the mid-Mediterranean jet (Robinson *et al*., 1991) can be traced as far as Cyprus, but with declining intensity east of Crete. This jet separates cyclones to the north from anticyclones to the south. Two major cyclones are commonly observed: the largest is the Rhodes Gyre over the Rhodes Basin southeast of Rhodes; the Cretan cyclone resides at the southwest corner of Crete. A strong anticyclone called Ierepetra Gyre periodically forms near the southeast corner of Crete which is associated with a strong seasonal signal. The Mersa-Matruh anticyclone (Robinson *et al*., 1991) is a strong and persistent anticyclone located near the Egyptian coast near 28°E longitude and does not have a clear seasonal cycle (Larnicol *et al*., 1995). The Shikmona gyre complex southeast of Cyprus consists of a number of separate centers in the southeastern LB.

The wide availability of satellite data has made long-term studies of large areas of the ocean possible. Data from the Advanced Very High Resolution Radiometer (AVHRR) are now available for electronic retrieval from the NOAA Coast Watch program (Pichel *et al*., 1994) or from many different databases. Among the several available methods of analysis, Empirical Orthogonal Function (EOF) analysis is a particularly useful tool in studying large quantities of multi-variate data (Hardy, 1978; Von Storch and Hannoschock, 1984). EOF is used to decompose time-series into its orthogonal component modes. The few modes can be used to describe the dominant patterns from the variance of the time series (Preisendorfer, 1988; Gallaudet and Simpson, 1994). This method is widely used in oceanography to analyze time series of measurements of some parameters such as SSTs or currents (Lagerloef and Bernstein, 1988; Paden *et al*., 1991). EOF analysis unlike the more familiar Fourier analysis do not require a predetermined form but depends upon the inter-relationships within the data to be analyzed (Weare, 1976).

In this study EOF analysis is used to decompose a time series consisting of 36 monthly mean AVHRR SST images of the Levantine Basin of the Eastern Mediterranean.

EMPIRICAL ORTHOGONAL FUNCTION ANALYSIS

Empirical Orthogonal Function analysis is a statistical method used to decompose a multivariate data set into an uncorrelated linear combination of separate functions of the original variables. It is used to determine the dominant patterns of residual variance in the AVHRR image sequences. As applied in this study, the original multi-variate data set is a time series of images. In order to obtain a two- dimensional matrix for analysis, the column of each matrix are stacked so that the image becomes a column vector. When these column vector images are placed together as sequential columns, an $M \times N$ matrix $T(x, t)$ is formed, where M represent the number of elements in the special dimension (pixels in an image), and N represents the number of elements in the temporal dimension (the number of images). EOF analysis separates the data sets into eigenmodes. Each mode has an associated variance, dimensional spatial pattern, and nondimensional time series. The data matrix *T (x, t)* can be represented by a linear combination of the eigenvectors ϕ_n

$$T(x,t) = \sum_{n=1}^{N} a_n(t)\phi_n(x)$$

where a_n are the temporal amplitudes, and the eigenvectors carrying the unit of temperature (ºC) can themselves be viewed as 2D pictures, giving a visual representation of the variance of each mode.

In order to extract more detailed information from the EOF analysis, temporal and spatial demeaning of the data matrix is performed prior to the EOF analysis (Lagerloef and Bernstein, 1988). The removal of the temporal mean allows features that vary with time to be revealed. The temporal mean is removed by finding the mean over the time series at each pixel (*i.e*. in each raw of *T*(*x, t*)), and then subtracting the mean from each pixel in that row:

$$T'_{mn} = T_{mn} - \frac{1}{N}\sum_{n} T_{mn}$$

Persistent features such as fronts and eddies are better described in an EOF analysis if the spatial mean is removed from *T (x, t)* by calculating the mean of each image (column of *T* (*x, t*)), and subtracting it from each pixel in that image:

$$T'_{mn} = T_{mn} - \frac{1}{M}\sum_{m} T_{mn}$$

Following (Paden *et al*. 1991) we will refer to temporally demeaned EOFs as ''covariance'' EOFs and spatially demeaned EOFs as ''gradient'' EOFs. The method of EOF construction used in this study is the singular value decomposition (SVD) of T' (Kelly, 1985). The SVD method does not require the construction or storage of the covariance matrix. SVD decomposes the data matrix $T'(x,t)$ into three matrices containing the orthogonal function, the eigenvalues, and the amplitudes in a single step:

$$T'(x,y) = USV^T$$

where *U* is an $M\times M$ matrix, *V* is an $N\times N$ matrix, and *S* is an $M\times N$ matrix. The scalars $s_1 > s_2 > \ldots > s_N > 0$ of the matrix *S*, called the singular values of *T,* are arranged in descending order of magnitude in the first N positions of the matrix. The singular values are equal to the square roots of the eigenvalues (Kelly, 1988). The elements of matrix U are the eigenvectors and the amplitudes are the eigenvectors of the transposed problem multiplied by the singular values. SVD ranks the modes in order of decreasing variance. The size of the mode's eigenvalue gives the amount of variance in that mode. It is usually expressed as a percentage of the total variance.

EOF ANALYSIS ON SST PATTERNS IN THE LEVANTINE BASIN

The data used in this study are AVHRR monthly mean sea surface temperatures covering the LB between 26.18º E and 36.25º E retrieved electronically from the German Remote Sensing Center. The images obtained span the time period from January 1998 to

December 2000. In order to fill the missing data and to reduce the computation time the number of grid points was reduced by interpolating data on a grid of 11Km spacing.

The 36 LB monthly-averaged SST images were combined into a data matrix as described in Section II. This was then separately demeaned temporally and spatially. EOF analysis was performed for both cases. The mean temperature field derived from the original images is shown in Figure 1. The temporal variability of this smoothed data set is presented in Figure 2, where a strong seasonal signal is clearly visible. The temporal mean SST field over the LB shows a unique significant feature corresponding to the Rhodes gyre located southeast of the island of Rhodes.

Figure 1. Temporal mean SST field compiled from the 36 AVHRR images.

Figure 2. Time series of spatially averaged sea surface temperature for monthly mean images.

Figure 3. The first three covariance and gradient EOFs modes.

represents a sea surface temperature above the mean for the time series, and a positive eigenvector represents a temperature below the mean. The time-series begins in January 1998, when the temperatures are colder and the temporal amplitude is positive. The mode 1 temporal amplitudes show the seasonal change in temperature: maximum surface temperature of LB occurring in August, with minimum temperature in March. This mode describes patterns associated with the dominant seasonal cycle of the sea surface temperature. The second covariance mode explains 0.9 of the total variance (41.5% of the non-seasonal variance), portraying coherent variations in the region between south of Rhodes and Cyprus. It has positive values in the northern part of LB. The corresponding temporal amplitude is positive in the spring and summer months of the year, and negative during fall and winter. Mode 3 represents 0.3% of the total variability (13.4% of the nonseasonal variance), with the northeastern part of LB out of phase with respect to the southwestern part of LB. The behaviour of the temporal amplitude does not repeat in the second year of data, suggesting that this mode is not related to seasonal variations in the forcing fields as observed for modes 1 and 2. In Kabbara *et al*. (2002) covariance EOFs were used to study the variability of SST in the Levantine Basin.

Figure 5. Amplitude time series for the covariance and gradient EOFs.

B. Gradient EOFs

To examine the large-scale SST gradients in the LB, the spatially averaged SST was subtracted from each monthly mean image before calculating EOFs. The spatial mean SST exhibits a seasonal cycle (Fig. 1) with a maximum in August of 28.1 ºC and a minimum in March of approximately 17.3 ºC. However these temperatures do not reflect the absolute temperature extremes in LB, which range from 15 ºC in March to over 30 ºC in August.

The percentage and cumulative percentages of the total variance explained by the six empirical orthogonal functions are given in Table 1; this table suggests that three functions are probably adequate to describe the seasonal variation of LB. The dominant eigenfunction or first mode (*i.e.* the function with the largest eigenvalue) explains the largest portion of the temporal variability and is often associated with a seasonal signal in the data. The first gradient mode accounts for 67.12% of the SST variance with positive values in the western part of LB, and negative values in the eastern part of LB, implying that these regions are quite strongly anticorrelated. Gradient mode 1 is similar in pattern to the temporal mean and distinguishes the behaviour of the cold water of Rhodes Gyre. The temporal amplitudes of the gradient EOF functions are presented in Fig. 5. The mode 1 amplitudes are positive with a bi-modal distribution. The first maximum occurs in July, with a smaller second maximum in November. The gradient mode 2 explains 14.5 % of the spatial variability. Gradient mode 2 temporal amplitudes have a sinusoidal behaviour with maximum positive amplitudes in June and maximum negative amplitudes in December. It also illustrates the colder than normal periods of 1999-2000. Gradient mode 3 explains 4.2 % of the spatial variability. It is essentially identical to mode 3 of the covariance analysis with the northeastern basin out of phase with the rest of the basin. In addition, the shapes of the regions clearly suggest the Rhodes, Mersa Matruh and other gyres. The EOF gradient analysis suggests that the SST patterns are repeatable from year to year and very likely reflect the seasonal forcing of the upper ocean.

TABLE 1

Percent and Cumulative Percent of the Total Variance Explained by the First 6 Gradient EOF's

Gradient EOFs	Percent	Cumulative %
1	67.1	67.1
2	14.5	81.6
3	4.2	85.8
4	1.9	87.7
5	1.8	89.6
6	1.3	91.0

The most important empirical orthogonal functions have physical interpretations in the sense that they have spatially coherent patterns and can be associated qualitatively with known phenomena. The most obvious known phenomenon in our results is the seasonal variation which dominates the amplitude time series for mode 1. This can be clearly seen from Figure 6 showing the monthly average of air and sea surface temperatures measured by a buoy of the Department of Meteorology of Beirut Airport: Beirut-Gulf, stationed south of Beirut, for the year 2000. The amplitude time series for gradient mode 1 agrees well with the SST and air temperature measured at this buoy location.

Figure 6. Comparison of the amplitude time series for gradient mode 1 with the monthly average air temperature (dashed curve) and sea surface temperature (solid curve) in °C at buoy Beirut-Gulf.

CONCLUSION

The temporal and spatial demeaning of the data set produces more information about the variability of SST only for the first two modes, and produces similar results for the other modes. The results of the EOF analysis of the Levantine Basin time series provided more information into the seasonal patterns of variability. The first covariance mode is overwhelmingly dominant and reflects the annual temperature cycle. It is largest in the northwest part of LB, thus indicating that this is the region with the largest seasonal variations. It is smallest south of Antalia Bay and north of Cyprus Island. The temporal amplitude of this mode lagged the temporal amplitude of the first gradient mode by about 30 days. The first-mode time series describes an annual modulation cycle which peaks in August. The second spatial variance mode is consistent with recurring eddies in the Levantine Basin.

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