Evaluation of Technology for the Analysis and Forecasting of Precipitation Using Cyclostationary EOF and Regression Methods

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**Evaluation of Technology for the Analysis and Forecasting of Precipitation Using Cyclostation-
ary EOF and Regression Methods**

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ABSTRACT

Precipitation time series exhibit complex fluctuations and statistical changes. We investigate and forecast precipitation variations in South Korea from 1973 to 2019 using cyclostationary empirical orthogonal function (CSEOF) and regression methods. First, empirical orthogonal function (EOF) and CSEOF analyses are used to examine the periodic changes in the precipitation data. Then, the autoregressive moving average (ARMA) method is applied to the principal component (PC) time series derived from the EOF and CSEOF precipitation analyses. The fifteen leading EOF and CSEOF modes and their corresponding PC time series clearly reflect the spatial distribution and temporal evolution characteristics of the precipitation data. Based on the PC forecasts of the EOF and CSEOF models, the EOF-ARMA composite model and CSEOF-ARMA composite model are used to obtain quantitative precipitation forecasts. The comparison results show that both composite models have good performances and similar accuracies. However, the performance of the CSEOF-ARMA model is better than that of the EOF-ARMA model under various measurements. Therefore, the CSEOF-ARMA composite forecast model can be considered an efficient and feasible technology representing an analytical approach for precipitation forecasting in South Korea.

Key words: Precipitation forecasting; Empirical orthogonal function (EOF); Cyclostationary empirical orthogonal function (CSEOF); Seasonal cycle; Autoregressive moving average (ARMA); Climate change.

Introduction

Global climate and environmental changes have become major worldwide issues in recent years. In particular, interactions between the atmosphere and slowly changing oceans will have profound and long-term effects on humans. Because agricultural production and hydrological management are heavily influenced by the climate, meteorologists are interested in the effects of climate and environmental changes, such as variations in periodic meteorological phenomena (Trenberth 1990).

Precipitation is an important variable in climate change research. It is the main component of the water cycle and has a great influence on surrounding environments and hydrological systems. Changes in the timing and amount of precipitation in a given area can lead to serious flood hazards or agricultural failures

42 due to floods and droughts. Because human-induced climate change accelerates the hydrological cycle
43 of the ecosystem, forecasting precipitation on the decadal scale is becoming increasingly important for
44 long-term water resource management (Huntington 2006; Oki and Kanae 2006). Advanced precipitation
45 forecasting technologies and timely precipitation diagnoses can help improve the operation of water stor-
46 age facilities and prevent potential flood disasters. The latest Intergovernmental Panel on Climate Change
47 report indicated that there is growing concern in the scientific community regarding the significant in-
48 creases observed in the amount and intensity of precipitation and regarding the corresponding variations
49 (Nicholls and Alexander 2007).

50 Much research has been conducted regarding forecasting precipitation, with many studies highlighting
51 that the trends observed in the annual and monthly precipitation of different regions depend on the region
52 of interest and the time period examined (Becker et al. 2006; Lim and Kim 2006; Zhou and Wang 2006).
53 Several studies have focused on seasonal predictions of precipitation at the regional level using different
54 technologies, such as regional climate models (Kim et al. 2000), in conjunction with other climate vari-
55 ables (Higgins et al. 2004; Wang et al. 1999). Some studies have improved the approaches used to fore-
56 cast climate index values, such as projections with teleconnection indices (Silverman and Dracup 2010)
57 and the development other ensemble forecasting models (Block and Rajagopalan 2007; Peel and Wilson
58 2008). In addition, many studies have closely investigated the various trends and spatiotemporal charac-
59 teristics of precipitation in South Korea (Chang and Kwon 2007; Jin et al. 2005; Kim and Kim 2004;
60 Wang et al. 2006).

61 In general, traditional statistical methods are typically used for long-range forecasting, with the incor-
62 poration of dynamical methods contributing improvements. Some successful approaches have involved
63 performing climate forecasting using multiple regression and correlation analysis methods (Barnston et
64 al. 1999; Vautard et al. 1999; Waliser et al. 1999; Waliser et al. 2003; Webster and Hoyos 2004). Many
65 climatic variables, such as precipitation, surface temperature, and solar flux, are known to exhibit peri-
66 odic (annual, monthly, daily, etc.) variations in their statistical features. Analyses of such datasets per-
67 formed using stationary approaches often yield meaningless statistical characteristics, representing the
68 weak error correction performances of these methods and their inaccuracy in obtaining long-term

69 predictions. Therefore, it is both appropriate and advantageous to adopt a cyclostationary methodology
70 for statistical analyses of climatic phenomena that display strong cyclical trends.

71 Precipitation has typical cyclical variations with statistical fluctuations and seasonal tendencies. Par-
72 ticularly when a precipitation dataset covers several weather stations or spans different seasons, station-
73 ary methods can be used to obtain only the most obvious statistical trends. In climate studies, empirical
74 orthogonal function (EOF) analyses are often used to study possible spatial patterns of variability and
75 how these patterns change with time. Some studies have used EOF models to analyze precipitation data.
76 Cahalan analyzed monthly precipitation data over the US and Canada based on EOFs and their variances
77 (Cahalan et al. 1996). Singh compared major rainfall patterns using the main modes of OLR data (Singh
78 2004). Svensson showed that most of the variance observed in rainfall in four periods could be explained
79 by an elongated spatial rainfall pattern (Svensson 1999). As such, EOF analyses are sometimes classified
80 as multivariate statistical techniques. However, EOF analyses are not based on physical principles. Thus,
81 to adequately analyze a comprehensive dataset, we use a cyclostationary empirical orthogonal function
82 (CSEOF) analysis technique; this approach is useful for extracting evolving spatial patterns.

83 This study primarily focuses on the analysis of the most dominant component of the seasonal cycle of
84 precipitation in South Korea. Empirical orthogonal function (EOF) and CSEOF analyses are conducted
85 to extract individual modes in the observed precipitation data to obtain the temporal and spatial evolution
86 of individual synoptic fields. We use EOF and CSEOF analyses as the primary techniques to analyze the
87 temporal evolution of the variability in precipitation and demonstrate the physical mechanism associated
88 with each mode of precipitation variability. The autoregressive moving average (ARMA) model is used
89 to examine and forecast the evolution of the temporal modes of precipitation variability derived from the
90 EOF and CSEOF. Precipitation forecasts are generated from the regressed temporal and spatial patterns.
91 The present study provides a detailed explanation of the observed changes in precipitation variables and
92 explores a feasible statistical methodology for forecasting precipitation in a monsoon climate.

93 The data used in this study are described in Section 2. The EOF and CSEOF analysis methods used to
94 analyze precipitation variability and the ARMA model are also explained in Section 2. The cyclical sea-
95 sonal characteristics of precipitation variability are presented in Section 3. The forecasting performance
96 and related mechanisms are discussed in Section 4. Conclusions are presented in Section 5.

97 **Data and Methodology**

98 **Data**

99 The primary data used in the present study were precipitation measurements taken over South Korea by
100 the Korea Meteorological Administration (KMA). A real-time quality control system was developed for
101 meteorological data measured by integrated meteorological sensors based on a comparison of quality
102 control procedures developed for meteorological data by the World Meteorological Organization and the
103 Korea Meteorological Administration (KMA). The 56 weather stations from which the data analyzed in
104 this study were collected are generally well distributed across the mainland, as shown in Fig. 1, while
105 data from Jeju Island and Ulleungdo as well as some missing data were excluded from the analysis. The
106 dataset represents the longest and most consistent precipitation observations available in South Korea,
107 spanning 47 years (1973-2019). In this study, the data from the first 42 years (1973-2014) of the time
108 series are used to generate the forecasting model, while the last five years (2015-2019) of precipitation
109 records are used to validate the model.

110 **Methodology**

111 The statistical techniques used in this study include the application of EOFs and CSEOFs for decompos-
112 ing the data and ARMA models for forecasting precipitation.

113 *Empirical orthogonal function*

114 Empirical orthogonal function analyses (Lorenz 1956) are among the most widely applied techniques in
115 oceanography and atmospheric science research. In this method, a spatiotemporal dataset is decomposed
116 into orthogonal basis functions determined by the data. The method is similar to principal component
117 analysis; however, EOFs can detect both temporal and spatial patterns.

118 In EOF analyses, spatiotemporal data $X(r,t)$ are represented in terms of loading vectors (L) and their
119 principal component (PC) time series, as follows:

$$120 \quad X(r,t) = \sum_n PC_n(t) L_n(r) \quad (1)$$

121 where $L_n(r)$ represents a specific spatial pattern and $PC_n(t)$ represents the temporal evolution of $L_n(r)$.

122 This equation signifies a decomposition of a given dataset into a number of spatial and temporal patterns.

123 The spatial patterns are orthogonal to each other and are ordered by magnitude; the temporal patterns

124 oscillate over time. The loading vectors represent the independent patterns of variability in the dataset

and are often interpreted as a physical model of the system from which the data were derived (Hannachi et al. 2007).

Cyclostationary empirical orthogonal function

A CSEOF is the basic function in a cyclostationary process and is a cyclostationary analog of an EOF obtained using a stationary approach (Kim et al. 1996). The CSEOF analysis method is described in detail by Kim and North (Kim and North 1997). In CSEOF analyses, spatiotemporal data are represented as follows:

$$X(r, t) = \sum_{k=0}^{d-1} c_k(r, t) e^{2\pi i k t / d} = \sum_{k=0}^{d-1} \sum_m c_{km}(t) F_l(r) e^{2\pi i k t / d} \quad (2)$$

where $F_l(r)$ is any basis function and d is the nested period representing the inherent periodicity in the data.

By calculating the covariance function and the Bloch function, the space-time CSEOFs can be obtained using the following equation:

$$X(r, t) = \sum_n PC_n(t) CL_n(r, t) \quad (3)$$

where $CL_n(r, t)$ is a cyclostationary loading vector (CSLV) and $PC_n(t)$ is the corresponding PC time series.

In contrast to EOF analyses, the CSLVs are time-dependent. The temporal evolution of a spatial pattern also depends on periodic data with period d , calculated as follows.

$$CL_n(r, t) = CL_n(r, t + d) \quad (4)$$

Thus, CSLVs are periodic, time-dependent eigenfunctions of the covariance statistics.

An essential component in CSEOF analyses is determining the nested period. Selecting a proper nested period requires an adequate understanding of the physical and statistical characteristics of the dataset being analyzed (Kim and Chung 2001).

The CSEOF technique is conceptually similar to the EOF technique in that both extract sequences of spatial patterns as eigenfunctions based on the spatiotemporal structure of the covariance function. However, the major difference between EOF and CSEOF is that, in CSEOF analyses, each CSLV represents a set of spatial patterns. The critical motivation for the temporal dependence of CSLVs is that the spatial patterns of many known phenomena in climate science and geophysics evolve over time with recognizable periods while exhibiting slow fluctuations over longer time scales. A comparison of studies that used EOF and CSEOF techniques can be found in Kim and Wu (Kim and Wu 1999). Recent studies

have demonstrated the efficacy of CSEOFs in extracting robust modes representing climate variabilities (Kim and Roh 2010; Kim et al. 2004; Kim et al. 2013; Sun and Kim 2016).

2.2.3. Autoregressive moving average

The general autoregressive moving-average (ARMA) model was introduced by Box and Jenkins (Box and Jenkins 1971). This model is usually applied to estimate related values in a time series. An ARMA(p, q) model includes two types of terms: an autoregressive AR(p) term of order p and a moving-average MA(q) term of order q . The autoregressive component involves regressing the studied variable on its own lagged values. The moving-average component involves modeling the error term as a linear combination of error terms occurring contemporaneously and at various times in the past. Thus, the model can be written as follows:

$$X_t = \sum_{i=1}^p \alpha_i X_{t-i} + \sum_{j=1}^q \beta_j e_{t-j} + e_t \quad (5)$$

where X_t is the time series value, α and β are the parameters of the model, and e is white noise.

The key difficulty in applying the ARMA model is identifying the orders of the model. Numerous available tests can be used to determine the orders of an ARMA model. Two common proposed methods include the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Akaike 1974; Schwarz 1978).

Results and Discussion

Seasonal cycle of precipitation

The spatial distribution of mean precipitation in South Korea are shown in Fig. 2, where the distribution represents the precipitation interpolation at each weather station. The means of precipitation in Fig. 2 indicate the primary variabilities in precipitation. As expected, the mean (Fig. 2) is large in the north and south because of seasonal fluctuations in precipitation in the summer. The annual precipitation is approximately 1305 mm (1973-2019 average), with more than 60% of the annual rainfall occurring between June and August. Boxplots of the monthly precipitation from 1973 to 2015 are plotted in Fig. 3. The annual periodicity involves obvious precipitation increases in the summer, with maximums occurring in July and August corresponding to the summer monsoon in Asia; precipitation is lower at other times of the year.

The precipitation data are decomposed into individual modes using EOF and CSEOF analyses. The main motivation for using these techniques is to investigate the mechanisms associated with changes in the variability of precipitation. A scree plot of the accumulated percents obtained in the EOF and CSEOF analyses is shown in Fig. 4 to show how they cumulatively rise. We present the two leading EOF and CSEOF modes to illustrate the temporal and spatial variations in precipitation.

Fig. 5 shows the first and second EOF modes, which explain 77.07% and 8.13% of the total variance, respectively. The PCs and loading patterns corresponding to the two leading modes are described in Fig. 5a and Fig. 5b by homogeneous correlation maps. The loading patterns in Fig. 5c and Fig. 5d come from interpolation based on dispersion points.

The PC time series of the first and second modes of the EOF analysis (Fig. 5a and Fig. 5b) both represent special cycles with slight fluctuations over longer time scales than those seen in the CSEOF modes. The amplitude of the first PC (Fig. 5a) fluctuates over an annual cycle, similarly to the original precipitation data. The loading patterns of the first EOF mode (Fig. 5c) exhibit obvious symmetry between the north and south regions, and those of the second mode (Fig. 5d) exhibit an increase from north to south.

The advantage of the CSEOF analysis is demonstrated by the PC time series. The nested period d is set to 12 months in the CSEOF analysis because the seasonal cycle is to be extracted. The first CSEOF mode of precipitation explains 73.55% of the total variance (Fig. 6). The PC time series of the first mode (Fig. 6a) and the cyclostationary loading patterns (Fig. 6b) are shown for 12 months, from January to December. The loading patterns are interpolated based on the dispersion points. This mode denotes the seasonal cycle. The most pronounced feature of the CSLVs is the slowly varying precipitation throughout the year: the vectors indicate low rainfall from January to May, plenty of rainfall from June to September, and decreasing rainfall from October to December. The corresponding PC time series exhibits interannual and decadal variations in the seasonal cycle, as well as an increasing trend that is significant but not conspicuous, with stronger natural variability.

The second CSEOF mode shown in Fig. 7 explains 5.28% of the total variance after omitting the seasonal cycle (the first mode) and adjusting for the seasonal cycle. The precipitation diminishes in April and then increases until July, decreases significantly in August and then increases until December. The

PC time series of the second mode shows a positive phase shift in approximately 2006. Compared with the years before 2006, more recent precipitation tends to be more extensive. Thus, the second mode indicates slightly less precipitation in August and relatively large increases in precipitation in July.

In the EOF and CSEOF analyses, the 13 leading EOF modes and 15 leading CSEOF modes account for 95.15% and 95.01% of the total variance, respectively; these modes are statistically significant and distinct from the other modes; thus, they are selected for forecasting according to the rule of thumb (North et al. 1982). The thirteen leading temporal modes from the EOF and fifteen modes from the CSEOF can account above 95% of total variance are interpreted as the primary conditions for the formation of precipitation, the remaining modes are considered as noise of data.

Forecasting of precipitation

Once the precipitation data have been decomposed into EOF and CSEOF modes, an ARMA model is applied in the EOF and CSEOF space to derive precipitation variations in the PC time series. This composition of analysis and regression methods results in two combined forecasting models: a combined EOF-ARMA model and a combined CSEOF-ARMA model.

Forecasts of the temporal patterns and timescales of the PCs can be estimated using these combined models. Fig.8 shows the forecasts for the four leading PCs of the precipitation data. The forecasts for the first PC obtained using the EOF-ARMA model adequately capture the annual fluctuations, and the forecasts for the other PCs also exhibit cyclical fluctuations (Fig. 8a) with smaller amplitudes. The forecasts obtained using the CSEOF-ARMA model continue the interannual and decadal trends observed in the CSEOF analysis (Fig. 8b). The amplitudes of the fluctuations are continuations of the past PCs; this is the goal of the CSEOF-ARMA model.

Based on the PC forecasts, precipitation forecasts can be easily extrapolated using the loading vectors (spatial patterns) of the EOF and CSEOF. Quantitative precipitation forecasts are calculated for 56 weather stations over five years using the EOF-ARMA and CSEOF-ARMA models, and the results are then checked against the observed precipitation data. Fig. 9 shows scatter plots of the observations and the forecasts resulting from the two models. The forecasts from the EOF-ARMA model are slightly underestimated and are more dispersed than those obtained with the CSEOF-ARMA model (Fig. 9a). In

contrast, the forecasts from CSEOF-ARMA fit the observations well (Fig. 9b), with most points clustered around the $y = x$ line. This demonstrates the effectiveness of the combined CSEOF-ARMA model.

The mean monthly values of the precipitation forecasts obtained from the two combined models are compared with the observations, as shown in Fig. 10. Because of the effect of the Asian monsoon, rainfall is uneven, with most rainfall occurring in the summer. The EOF-ARMA forecasts are not particularly good, especially for the summer months. However, the CSEOF-ARMA forecasts not only capture the seasonal variations in precipitation but also give confident quantitative predictions of the precipitation amounts.

The mean deviations of the forecasts obtained for the summer monsoon season (June, July, August and September) at each weather station are shown in Fig. 11. The EOF-ARMA model gives higher forecasts in June and September but relatively low forecasts in July and August (Fig. 11a). In contrast, the mean deviation of the forecasts obtained from the CSEOF-ARMA model are much smaller, with small overestimations in June and July and small underestimations in August and September (Fig. 11b).

When the EOF method is used to analyze precipitation time series data, it cannot provide temporal variation responses in the spatial domain when decomposing the time components; thus, some errors result in the distribution analysis. The use of the CSEOF method can make up for this deficiency.

In the spatial distribution of the mean deviation (Fig. 11a and Fig. 11b), the errors spread over the north in June and over the south in July are higher than those in other parts of the study area. We considered that the reason for this result is that precipitation in the south increases obviously and the distribution changes greatly in July, leading to increased errors and causing the June and July deviation characteristics to almost flip between the two methods.

Several statistical measures are used to evaluate the performances of the forecasting methods: the mean absolute error (*MAE*), the root mean squared error (*RMSE*) and the coefficient of determination (R^2). Table 1 provides a comparison of these measures applied for the two combined models. The results show that both models achieve good performance and that their accuracies are similar. However, the performance of the CSEOF-ARMA model is better than that of the EOF-ARMA model under every measure. The overall results indicate that the CSEOF-ARMA model is an effective approach to precipitation forecasting.

Conclusions

We investigated the spatiotemporal variability in precipitation data in South Korea using EOF and CSEOF analyses and proposed an effective methodology for precipitation forecasting. Of the total variance in the spatial distribution and temporal evolution of the studied precipitation data, the 13 leading EOF modes accounted for 95.15% and the 15 leading CSEOF modes accounted for 95.01%. The EOF modes represented cycles with longer time scales than the CSEOF modes; the CSEOF modes represented interannual and decadal variations in the seasonal cycle with stronger natural variabilities than those seen in the EOF modes.

We estimated precipitation forecasts using a regression method. The PC forecasts obtained from the EOF-ARMA model exhibited clear cyclical fluctuations, and those obtained from the CSEOF-ARMA model represented extensions of the interannual and decadal variations observed in the CSEOF analysis. Based on the PC forecasts, quantitative precipitation forecasts were calculated for 56 stations over five years using the EOF-ARMA and CSEOF-ARMA models; these forecasts were then checked against the observed precipitation data. The results showed that the CSEOF-ARMA model performed better than the EOF-ARMA model. The combined CSEOF-ARMA forecasting model gave the best approximation performance and captured the variational trends, temporal evolution and recurrent seasonal cycles in the precipitation data. These results indicate that the use of the CSEOF-ARMA model is an accurate and efficient approach to precipitation forecasting in Korea.

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Compliance with ethical standards

Conflict of interest The authors declare no conflicts of interest.

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400 **Table 1** Quantitative statistical verification measures of forecasts

Index	MAE (mm)	RMSE (mm)	R ²
EOF-ARMA	40.79	57.56	0.64
CSEOF-ARMA	25.39	38.71	0.84

Fig. 1 Location of 56 precipitation stations in South Korea.

Fig. 2 Spatial distribution of mean monthly precipitation data totals from 1973 to 2019 in South Korea

Fig. 3 Boxplots of monthly precipitation data totals from 1973 to 2019 in South Korea, The upper and lower boundaries of each box indicate the upper and lower quartiles of the distribution, the median values are shown by the cross and line within the box, and the extreme upper data values are shown by dots above and below the box.

Fig. 4 The scree plot of the Accumulated Percent of EOF and CSEOF analysis, 13 leading modes from the EOF, 15 modes form the CSEOF can account above 95% of total variance.

Fig. 5 First and second EOF modes of precipitation: (a) principal component time series of 1st EOF mode, (b) principal component time series of 2nd EOF mode, (c) loading vectors of 1st EOF mode, (d) loading vectors of 2nd EOF mode

Fig. 6 First CSEOF modes of precipitation: (a) principal component time series, (b) Cyclostationary loading vectors (CSLV)

Fig. 7 Second CSEOF modes of precipitation: (a) principal component time series, (b) Cyclostationary loading vectors (CSLV)

Fig. 8 Forecasts of principal component time series based on EOF and CSEOF analysis

Fig. 9 Scatter plots on observation and forecasts of EOF-CCA and CSEOF-ARMA: (a) EOF-CCA forecasts, (b) CSEOF-ARMA forecasts

Fig. 10 Temporal mean of observation with EOF-CCA and CSEOF-ARMA forecasts

Fig. 11 Mean deviation distribution of forecasts of EOF-ARMA and CSEOF-ARMA in June, July, August and September, (a) EOF-ARMA forecasts mean deviation distribution, (b) CSEOF-ARMA forecasts mean deviation distribution