2. Defining Drought Regimes in Japan and How Climatic Drivers Affect Them

Ke SHI[1]＊・Yoshiya TOUGE[1]・So KAZAMA[1]

[1] Department of Civil and Environmental Engineering, Tohoku University (〒980-8579, 6-6-06 Aramakiaza Aoba, Aoba, Sendai, Miyagi, Japan)

＊ E-mail: *shi.ke.s5@dc.tohoku.ac.jp*

Droughts are widespread disasters and are concurrently influenced by multiple large-scale climate signals. Regional heterogeneity poses challenges for drought prediction and management. Teleconnection analysis between climate signals and the principal components of the classified drought regimes provides a method for overcoming this difficulty. This study took Japan with diverse ecosystems and drought characteristics as the research area.

As a result, nine natural clusters were identified based on cluster analysis. Then, how climatic drivers affect these nine drought regimes were discussed using wavelet analysis. The most influential climatic drivers varied with the drought regimes due to different drought spatiotemporal characteristics.

Key Words : *drought regimes, climatic drivers, cluster analysis, principal component analysis, teleconnection*

1. Introducion

Drought is recognized as the most complex and impenetrable extreme natural disaster[1]. Additionally, considering the probability distribution, duration, and seasonality of drought, drought can have various characteristics in different drought regimes[2]. These spatiotemporal characteristics and multiple causes of drought have led to the heterogeneity of drought in different climate zones or even in the same geographic location.

Japan, as a heterogeneous region with diverse ecosystems and drought characteristics, is a unique research area for exploring homogeneous drought regimes. Seventy percent of Japan is covered by mountains, and the rain flows quickly to the ocean after falling, leading to unique drought characteristics in Japan. For different drought regimes, the relationship between climate and drought varies from region to region, which is forced by land-sea-atmosphere interactions[3]. Defining different homogeneous drought regimes could provide a reference to managers regarding which strategies may be most effective for drought risk reduction.

How to describe the long-term variation inherent in drought regimes in a given region and connect with climatic drivers, is a crucial issue in understanding and predicting regional drought. First, this study attempted to provide an approach for defining drought regimes in Japan and then evaluated how large-scale climate signals affect these drought regimes. Second, identifying the dominant climate signals of different drought regimes contributes to the understanding of climatic causes of drought over Japan. This approach could also improve drought prediction by accounting for the influence of large-scale climate signals.

2. Materials and Methodology

(1) Study area

The study area comprises all of Japan, which is a heterogeneous region mostly characterized by steep mountainous terrain. The heterogeneity of the climate in Japan is mainly determined by the monsoon, mountains, ocean circulations and climatic zones.

Changeable climate and complex topography pose challenges to the identification of homogeneous drought regimes in Japan.

(2) Describing drought

The soil moisture data used in this study are derived from simulations using the Simple Biosphere including Urban Canopy (SiBUC) developed by Tanaka[4]. This model has been utilized not only for regional-scale analysis but also for global-scale analysis, such as Turkey[5], Japan[6] and Southeast Asia[7]. Notably, the soil moisture simulated by SiBUC is the saturation ratio. After obtaining the daily soil moisture, the monthly minimum soil moisture was extracted to show the driest situation every month.

For SiBUC forcing data, the precipitation data were taken from the Asian Precipitation Highly Resolved Observational Data_Japan (APHRO_JP)[8-10] gridded dataset. Other meteorological forcing data with high resolution (5 km × 5 km) come from the Dynamical Regional Downscaling Japanese 55-year Reanalysis (DSJRA-55) dataset[11]. Land use and land type data come from the Global Land Cover Characterization[12] and Ministry of Land, Infrastructure, Transport and Tourism, Japan. Soil parameters come from ECOCLIMAP[13].

(3) Large-scale climate signals

Four large-scale climate signals (Arctic Oscillation, North Atlantic Oscillation, El Niño-Southern Oscillation, Pacific Decadal Oscillation) were chosen to analyze the teleconnections between the large-scale climate signals and drought in Japan[14-17]. All large-scale climate signals data sources come from the internet and are freely available.

(4) Comprehensive approach

This study provides a comprehensive approach to define drought regimes and connect with climatic drivers. Firstly, the drought regimes is obtained by cluster analysis. Then principal component analysis is carried out to obtain the first principal component of each drought regime. Finally, by inputting the first principal component of each drought regime and climatic drivers, teleconnection analysis is performed to quantify the climatic causes.

For cluster analysis, a comprehensive dataset with the probability distribution, duration, and seasonality of drought based on monthly minimum soil moisture and the distance between regions was assembled. The specific information of each variable is described in Table-1. The expectation-maximization (EM) algorithm[18-19] was adopted in this study, which was an unsupervised clustering approach that discovers the underlying structure of the data without preconceived labels or definitions.

After obtaining the cluster analysis results, the distinct empirical orthogonal function (DEOF) decomposition[20] was used to identify the principal components of homogeneous drought regimes, preparing for analyzing teleconnections with large-scale climate signals. Among each drought regimes, DEOF decomposition was apply to a gridded space-time matrix of soil moisture, which can decompose the space-time matrix into the distinct spatial function part (DEOFs) and the temporal function part (distinct principal components, DPCs).

Through the DEOF decomposition in each drought regimes, the most dominant DPCs were extracted in each regimes. Then wavelet analysis was used for exploring the teleconnection between large-scale climate signals and the most dominant DPCs in each drought regimes. To measure the extent of climatic influence on wildfire burned area anomalies, the percent area of significant coherence (PASC) relative to the wavelet scale-location domain was adopted[21]. The global wavelet coherence coefficient[22] was defined to evaluate the coherence between two time series at different scales while neglecting the influence of time. The PASC is used to identify the most significant coherent variable, and the global wavelet coherence coefficient is used to quantitatively judge the level of coherence.

Table-1 Variables used in the clustering of drought regimes in Japan.

Category	Data type
Probability distribution	Average soil moisture
	Coefficient of variation (CV)
	Coefficient of skewness (CS)
Duration	Length of drought period
	Return period of drought
Seasonality	Average soil moisture in spring
	Average soil moisture in summer
	Average soil moisture in autumn
	Average soil moisture in winter
Distance	Latitude
	Longitude

3. Results and Discussions

(1) Defining drought regimes

Nine drought regimes with different characteristics were defined and quantified using unsupervised cluster analysis at a 5 km resolution across Japan, as shown in Figure-1. Among the nine drought regimes, regime-1 was dominated by extreme drought events and included the mesh with the largest length of drought period, the largest return period of drought, and the largest coefficient of variation. Drought regime-2 and regime-6 were typical representatives of spring droughts, and regime–6 was the region with the lowest average soil moisture. Under the influence of the Ou Mountains, the Tohoku region of Japan was divided into two parts: drought regime-3 and regime-5. The Hokkaido region, where summer droughts often occur, was divided into wetter drought regime-4 and drier drought regime-9. There was the longest left tail in the probability distribution curve of soil moisture in regime-7 among the nine drought regimes, indicating that this regime was wet for most of the period. Drought regime-8 is covered by high mountains and often experiences weak drought events with a short drought period and return period of drought.

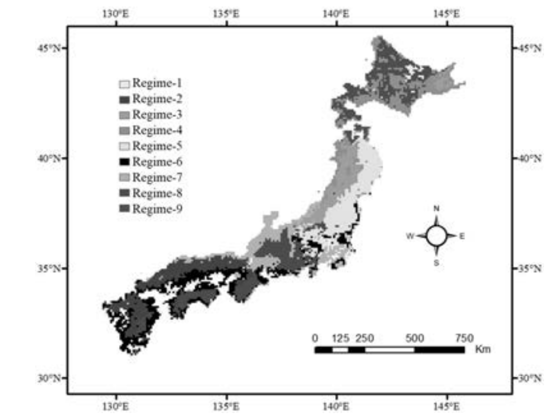

Figure-1 Spatial distribution of drought regimes across Japan.

(2)Teleconnections between drought regimes and climatic drivers

To analyze the impact of large-scale climate signals on these nine drought regimes, DEOF was first adopted to reduce multiple time series in each drought regimes into one principal component. The first DPC time series of the nine drought regimess are shown in Figure-2. The larger the explained variance is, the greater the degree of DPC representing the drought regimes. The explained variance in the DPC reached more than 60% in all nine drought regimes, except for regime-1. The high explained variance indicated the high level of homogeneity within each clustered regime, especially regime-3 and regime-5, where the explained variance even reached more than 80%. The distribution of regime-1 spanned all of Japan, and regime-1 often experienced extreme droughts with long recurrence periods, so it was difficult to find a significant principal component to represent this regime. Except for regime-4 and regime-9, which were mainly distributed in Hokkaido, the 1994 drought that covered almost all Japan was detected in other drought regimes. In this study, 1994 is considered to be the driest year since 1958, which is consistent with the study by Lee et al.[23]. For regime-4 and regime-9, 1985 was detected as the driest year.

Figure-3 shows the global coherence coefficients, providing an evaluation of average coherence between drought regimes and four large-scale climate signals over different timescales. By plotting all large-scale climate signals together, it became possible to compare the relative coherence significance of each climate signal in each drought regimes at all time scales. Except for regime-8 and regime-9, all other regions had high global coherence coefficients with the NAO on the 10-year scale. The impact of ENSO on the 15-year scale was mainly reflected in regime-1, regime-2, regime-5, and regime-6. The global coherence coefficients between regime-1, regime-3, regime-6, and regime-8 and the AO showed a continuously increasing trend on the scale of decades, while the coherence between other drought regimes and the AO had already reached the maximum values on the scale of approximately 10 or 15 years. Similar to the AO, the maximum values of the global coherence coefficients between the PDO and regime-1, regime-2, and regime-6 had been reached, but those between the PDO and regime-3, regime-4 and regime-9 were still increasing on the scale of decades.

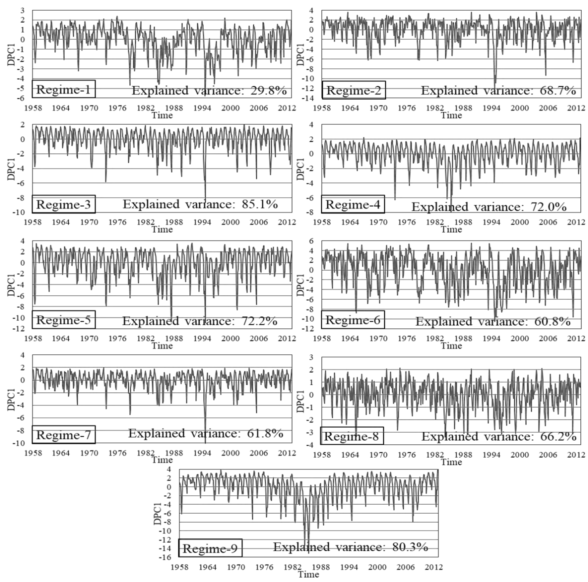

Figure-2 First distinct principal component (DPC) of nine drought rigimes. The explained variance in distinct principal component-1 in drought regimes is at the bottom right of the figures.

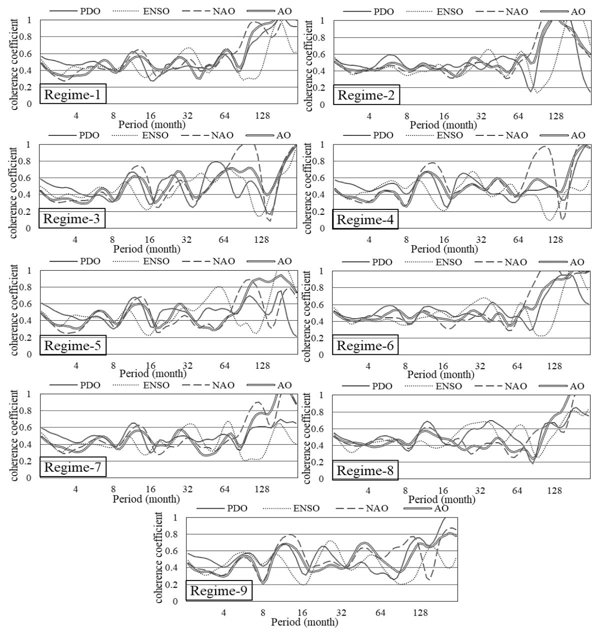

Figure-3 The global coherence coefficients between large-scale climate signals and distinct principal component-1 (DPC1) of nine drought regimes.

4. Summary and Conclusions

This paper establishes the teleconnections between large-scale climate signals and drought regimes across Japan for the first time and explores the physical mechanism behind clustering. The results of this paper are conducive to a better understanding of the homogeneity in the temporo-spatial characteristics of drought across Japan. Due to the changing climatic, atmospheric and oceanic scenarios, focusing on global climate drivers provides an efficient and promising reference for predicting drought. The conclusions will also be valuable for drought management and drought prevention.

5. Acknowledgments

This research was partially supported by the Grant-in-Aid for Scientific Research (B), 2020-2023 (20H02248, Yoshiya Touge) and Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Exploratory Research, 2019-2021 (19K21982, So Kazama). The authors declare no conflicts of interest.

Reference

1) Dai A.: Drought under global warming: A review. *Wiley Interdisciplinary Reviews: Climate Change*, 2, 45–65, 2011.

2) Herrera-Estrada J. E., Satoh Y., and Sheffield J.: Spatiotemporal dynamics of global drought. *Geophysical Research Letters*, 44, 2254–2263, 2017.

3) Sheffield J., Andreadis K. M., Wood E. F., and Lettenmaier D. P.: Global and continental drought in the second half of the twentieth century: Severity-area-duration analysis and temporal variability of large-scale events. *Journal of Climate*, 22, 1962–1981, 2009.

4) Tanaka K.: Development of the new land surface scheme SiBUC commonly applicable to basin water management and numerical weather prediction model, 2005.

5) Fujihara Y., Tanaka K., Watanabe T., Nagano T., and Kojiri T: Assessing the impacts of climate change on the water resources of the Seyhan River Basin in Turkey: Use of dynamically downscaled data for hydrologic simulations. *Journal of Hydrology*, 353(1-2), 33-48, 2008.

6) Kotsuki S., Takenaka H., Tanaka K., Higuchi A., and Miyoshi T: 1-km-resolution land surface analysis over Japan: Impact of satellite-derived solar radiation. *Hydrological Research Letters*, 9(1), 14-19, 2015.

7) Kotsuki S., and Tanaka K.:Uncertainties of precipitation products and their impacts on runoff estimates through hydrological land surface simulation in Southeast Asia. *Hydrological Research Letters*, 7(4), 79-84, 2013.

8) Kamiguchi, K., Arakawa O., Kitoh A., Yatagai A., Hamada A., and Yasutomi N.: Development of APHRO_JP, the first Japanese high-resolution daily precipitation product for more than 100 years. *Hydrological Research Letters*, 4, 60–64. 2010

9) Kamiguchi K., Arakawa O., and Kitoh A.: Long-term Changes in Japanese Extreme Precipitation Analyzed with APHRO_JP_EX. *Global environmental research*, 15, 91–99, 2011

10) Yatagai A., Kamiguchi K., Arakawa O., Hamada A., Yasutomi N., and Kitoh A.: Aphrodite constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Bulletin of the American Meteorological Society*, 93, 1401–1415, 2012.

11) Kayaba N., Yamada T., Hayashi S., Onogi K., Kobayashi S., Yoshimoto K., Kamiguchi K., and Yamashita K.: Dynamical regional downscaling using the JRA-55 reanalysis (DSJRA-55). *Scientific Online Letters on the Atmosphere*, 12, 1–5, 2016.

12) Loveland T. R., Reed B. C., Ohlen D. O., Brown J. F., Zhu Z., Yang L., and Merchant J. W.: Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing*, 21, 1303–1330, 2000.

13) Champeaux J. L., Masson V., and Chauvin F.: ECOCLIMAP: A global database of land surface parameters at 1 km resolution. *Meteorological Applications*, 12, 29–32, 2005.

14) Aizen E. M., Aizen V. B., Melack J. M., Nakamura T., and Ohta T.: Precipitation and atmospheric circulation patterns at mid‐latitudes of Asia. *International Journal of Climatology*, 556, 535‐556, 2001.

15) Hu Z. Z., Wu R., Kinter J. L., and Yang S.: Connection of summer rainfall variations in South and East Asia: Role of El Niño-southern oscillation. Int. J. Climatol., 25, 1279–1289, 2005

16) Lee M. H., Ho C. H., Kim J. H., and Song H. J.: Low-frequency variability of tropical cyclone-induced heavy rainfall over East Asia associated with tropical and North Pacific sea surface temperatures. *Journal of Geophysical Research: Atmospheres*, 117, 1–11, 2012.

17) He S., Gao Y., Li F., Wang H., and He Y.: Impact of Arctic Oscillation on the East Asian climate: A review. *Earth-Science Reviews*, 164, 48–62, 2017.

18) Bradley P. S., Fayyad U. M., and Reina C.: Scaling EM (Expectation Maximization) Clustering to Large Databases. *Microsoft Research*, 194–198, 1998.

19) Dempster A. P., Laird N. M., and Rubin D. B.: Maximum Likelihood from Incomplete Data Via the EM Algorithm. *Journal of the Royal Statistical Society*, 39, 1–22, 1977

20) Dommenget, D.: Evaluating EOF modes against a stochastic null hypothesis. Climate Dynamics, 28, 517–531, 2007

21) Hu W., and Si B. C.: Technical note: Multiple wavelet coherence for untangling scale-specific and localized multivariate relationships in geosciences. *Hydrology and Earth System Sciences*, 20, 3183–3191, 2016.

22) Partal, T., and Küçük M.: Long-term trend analysis using discrete wavelet components of annual precipitations measurements in Marmara region (Turkey). Physics and Chemistry of the Earth, 31, 1189–1200, 2006.

23) Lee S. M., Byun H. R., and Tanaka H. L.: Spatiotemporal Characteristics of Drought Occurrences over Japan. *Journal of Applied Meteorology and Climatology*, 51, 1087–1098, 2012.