Global burned area patterns and climatic influence analysis during 2001-2019

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1. INTRODUCTION

Wildfire is a critical component of the natural earth system's ecological process at scales ranging from local to global. Higher temperatures, more rain-free days, more wildfire events, and more wildfire-affected areas induce significant wildfire danger variations (Vitolo, 2020). Determining a suite of global climatic drivers that explain most of the variations in different homogeneous wildfire regions will be of great significance for wildfire management and wildfire prediction. Until now, previous studies have not filled gaps in exploring the spatiotemporally homogeneous regions of global burned areas and multiple climatic influences. Therefore, the main aim of this study was to analyze the relationships between major wildfire patterns and various global climatic drivers. First, the distinct empirical orthogonal function (DEOF) was applied to identify the spatiotemporally homogeneous regions of burned area around the world. The cross wavelet transform (XWT) and wavelet coherence (WCO) were used to analyze the relationships between wildfire burned area in major patterns and various global climatic drivers based on global burned area patterns.

2. MATERIALS AND METHODS

2.1. Data source

We used Fire CCI v5.1 dataset for burned area. Chuvieco et al. developed the Fire CCI v5.1 burned area dataset during 2001~2019 based on a hybrid approach that combines a MODIS highest resolution (250 m) near-infrared band and active wildfire information from thermal channels (Chuvieco et al., 2007). In addition, Fire CCI v5.1 was considered to perform better than other fire dataset, especially in terms of small wildfire detection capacity. And, to avoid local variations, we performed the data aggregation and changed the spatial resolution of the original data. Therefore, to obtain better homogeneous burned area results, the Fire CCI v5.1 dataset was processed to a 1°×1° resolution based on the monthly scale. And the monthly log-transformed burned area anomalies (logBAA) were calculated to increase attention to wildfire-sensitive ecosystems.

Also, sixteen global climatic drivers that may have impacts on wildfires were selected: Polar/Eurasia Pattern(POL), Dipole Mode(DMI), Arctic Oscillation(AO), Antarctic Oscillation(AAO), Western Pacific Pattern(WP), East Atlantic/Western Russia Pattern(EA/WR), Pacific/North American Pattern (PNA), Pacific Decadal Oscillation(PDO), East Pacific/North Pacific Oscillation(EP/NP), Multivariate ENSO Index(MEI), Oceanic Niño Index(ONI), Atlantic multidecadal Oscillation(AMO), North Atlantic Oscillation(NAO), East Atlantic Pattern(EA), Tropical Northern Atlantic Pattern(TNA), Tropical Southern Atlantic Pattern(TSA).

2.2. Distinct Empirical Orthogonal Function

The empirical orthogonal function (EOF), which deals with temporal and spatial functions, is used to extract the spatiotemporal modes based on the data variance representations. The EOF analysis method can decompose the time-varying variable fields into the space function part (EOFs) that does not change with time and the time function part (principal components, PCs) that depends only on time. The distinct EOF (DEOF) analysis was subsequently introduced to overcome problems in the EOF analysis (Dommenget, 2007). In the DEOF, a continuous spectrum of spatial patterns resulting from a stochastic process can be represented by EOF modes, where some spatial structures will be more dominant than others. Based on the isotropic diffusion null hypothesis, the EOF modes (DEOFs) can be found by rotating the leading EOF modes, corresponding to the distinguished principal components (DPCs). These DPCs take up a large part of the total variance in all the variables in the original field, which is equivalent to the main information of the original field concentrated on a few main components. The higher the eigenvalues, the more typical the corresponding modes, and the more significant the contribution to the total variance.

2.3. Wavelet analysis

The continuous wavelet transform (CWT) is widely used for analyzing the frequency domain of hydrometeorological time series. The spectral and temporal features of the time series can be projected onto a time-frequency plane by CWT, where the dominant cycle period and its duration can be identified. The square modulus of the CWT defines the wavelet power spectrum (WPS), which represents the signal energy at a specific scale (period) and time. In this paper, the time-frequency domain of DPCs was analyzed by CWT. The specific calculation process for the CWT can be found in Torrence et al. Notably, CWT brings about a cone of influence (COI) that delimits a region of the WPS beyond which the edge effects become significant, which means that outcomes outside COI should be suspected (Torrence et al., 1998).

3. RESULTS AND DISCUSSION

The DEOF calculation used the logBAA time series of each 1°×1° grid cell on a monthly scale. The first eight DEOFs represented 30.0% of the total variance. **Fig. 1** displays the spatial patterns of DEOF1~8 and location distribution of the top three global climatic drivers with the strongest influence on DEOF patterns. Different DEOFs represented different abnormal characteristics of wildfire burned areas. Specifically, the top 20% of the largest (smallest) DEOF values are considered high positive (low negative) loading values. For example, in DEOF2, the spatial distribution illustrated that low negative loadings occurred in Part of Russia and Ukraine. Meanwhile, the high positive loadings were mainly concentrated in northern Kazakhstan, which also meant that these regions had opposite characteristics as those of the negative loading regions.

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Some regions frequently appeared in different DEOF patterns. Region-1 (around Ukraine and Kazakhstan) was found in DEOF1~3. Although the three most dominant global climatic drivers changed with the DEOF patterns, AMO, EP/NP and PNA were the strongest influencing drivers among these five climatic drivers, indicating that these three global climatic drivers had a relatively strong impact on region-1. For DEOF3, DEOF5 and DEOF8, there were three different combinations of global climatic drivers affecting region-2 (Australia): MEI-DEOF3, AO-DEOF5 and EA/WR-DEOF8. The global climatic drivers that affect region-3 (Brazil) have become very diverse, where they were found to be affected by ten different global climatic drivers. Affected by ten climatic drivers, PNA, AO, POL and EA/WR were the dominant global climatic drivers in region-3 of DEOF4~7.

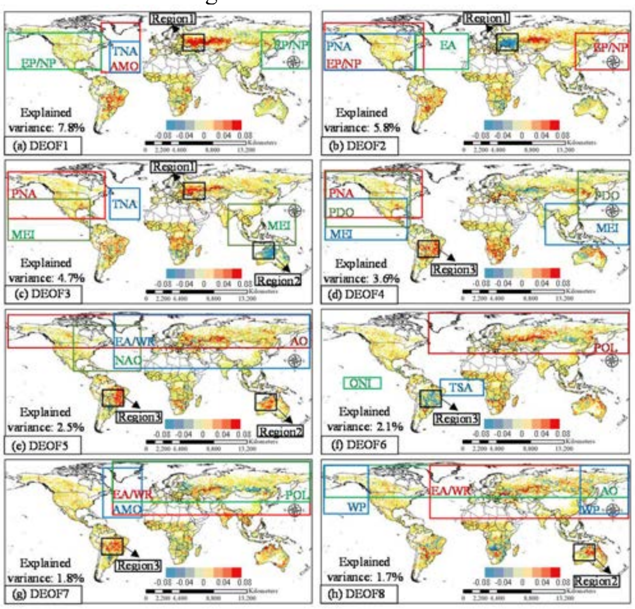

Fig. 1. The location distribution of the top three global climatic drivers with the strongest influence on DEOF patterns. The red, blue and green rectangles indicate the strongest, second-strongest and third-strongest global climatic drivers on the DEOFs, respectively. The black circle indicates the common region in different patterns.

Fig. 2 shows the global coherence coefficients, providing an evaluation of averaged coherence between monthly DPCs and the top three global climatic drivers over different timescales. By plotting the top three indices together, it becomes possible to compare the relative coherence significance of each index in each logBAA pattern under all-time scales. Only DPC1 had high coherence coefficients with global climatic drivers on the annual scale and multiyear scale simultaneously. For DPC3, there were high global high coherence coefficients on an approximately two-year scale and more than a four-year scale. These results indicated that certain global climatic drivers could have strong effects on both large and small time scales. However, other DPCs only showed high coherence coefficients on time scales larger than 32 months. In particular, some global climatic drivers did not reach high global coherence coefficients on all time scales, such as PNA-DPC2 and ONI-DPC6, indicating that these global climatic drivers have only limited impacts on these DEOF patterns.

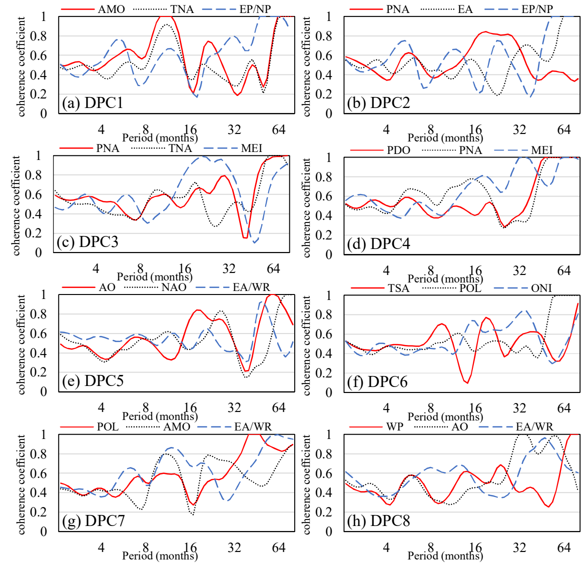

Fig. 2. The global coherence coefficient between global climatic drivers and the temporal patterns of DPC1~8.

4. CONCLUSIONS

The main conclusions obtained from this paper are summarised as follows: (1) Eight patterns with different spatiotemporal characteristics were identified. (2) The most significant global climatic drivers that strongly impacted each of the eight major wildfire patterns were identified. (3) The most significant combinations of hotspots and climatic drivers were Atlantic multidecadal Oscillation-East Pacific/North Pacific Oscillation (EP/NP)-Pacific North American Pattern (PNA) with the pattern around Ukraine and Kazakhstan, El Niño/Southern Oscillation-Arctic Oscillation (AO)-East Atlantic/Western Russia Pattern (EA/WR) with the pattern in Australia, and PNA-AO-Polar/Eurasia Pattern-EA/WR with the pattern in Brazil.

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The authors declare no conflict of interest. All datasets utilized to perform this study are freely available on the internet.

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