Fractional contribution of global warming and regional urbanization to intensifying regional heatwaves across Eurasia

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Abstract

Increasing frequency and intensity of heatwaves (HWs) in a warming climate exert catastrophic impacts on human society and natural environment. However, spatiotemporal variations of HW and their driving factors still remain obscure, especially for HW changes over Eurasia, the region with the largest population of the world. Here we provide a systematic investigation of the HW changes over Eurasia and quantify the contributions of different natural and anthropogenic factors to these changes. Increasing frequency, duration and intensity of HW are observed in most parts of Eurasia, and the occurrence of the first HW event tends to be earlier as well, especially in Europe, East Asia, Central Asia, Southwest Asia, and the Mediterranean region. These intensified HW activities are particularly stronger and more widespread after 1990s. The spatial pattern of the increasing HW trend is closely tied to the interdecadal changes of sea surface temperature in the North Pacific. More intense hot airmass convection, atmospheric circulation obstruction over the Mediterranean region and the enhanced Mongolian high hinders the southward movement of cold air and cold and wet airmass exchange. Further analyses suggest that the intensifying Eurasian HW tendency is a combined result of both climate change and human activities. Overall, the fractional contributions of climate warming, urbanization, standardized precipitation evaporation index, and Atlantic Multi-decadal Oscillation to the frequency of Eurasian HWs are 30%, 25%, 21% and 24%, respectively. It is also suggested that the relative influential rate of different driving factors for HW varies over time and differs in different areas.

Key words: Heatwaves; Spatiotemporal variability; Driving factors; Urbanization; Eurasia.

1 Introduction

As kind of extreme high temperature events, heatwave (HW) generally refers to a durative overheating phenomenon being characterized by intensity, frequency, and duration (Perkins 2015; Perkins and Alexander 2013; Perkins and Lewis 2020). Impacts of warming climate on natural ecosystems and socioeconomics and the frequency of extreme weather have been drawing increasing human concerns in recent years (Easterling et al. 2000; Williams et al. 2014; Perkins 2015; Russo et al. 2015; Wang et al. 2020). Unprecedented HWs have been frequently witnessed in Europe, North America, Asia, and Oceania (Coumou and Rahmstorf 2012; Knowlton et al. 2009; Sun et al. 2014). Frequent HWs inflict serious risks on human health and safety (Perkins et al. 2015; Xu et al. 2018b; Xu et al. 2016; Ye et al. 2012) and wildfire (Pezza et al. 2012), droughts, and on the energy and power sectors as well (Larcom et al. 2019). Therefore, it is of practical and theoretical significance to understand the spatiotemporal pattern and driving factors of HWs, so as to improve human mitigation to adverse impacts of HWs (Bobb et al. 2014; Yang et al. 2019).

Recent years have seen many record-breaking HWs in many parts of the world. Recent studies have revealed that regional and global heat wave events are experiencing a rapid increase in frequency, duration and intensity (Perkins et al. 2020). For instance, modelling outputs suggest that the risk of summer heat waves in Europe and China is growing rapidly, monthly Heat Extremes has also experienced a doubling in growth over the last century (Fischer and Schär 2010; Rohini et al. 2016; Sun et al. 2014). Eurasia (0-75°N, 20°W-180°E) covers approximately 70% of the global population and 36.3% of the global land area (Gu et al. 2019). Eurasia also has undergone severe HWs. For example, the 2003 HW in western Europe caused more than 70000 deaths (Barriopedro et al. 2011; Coumou and Rahmstorf 2012; Knowlton et al. 2009; Luterbacher et al. 2004), and severe HWs in Russia in 2010 caused 54000 deaths (Barriopedro et al. 2011). In

2013, HWs and droughts in China caused direct economic losses of around 59 billion RMB (Sun et al. 2014). Besides, in 2019, recorded most severe HWs occurred in western Europe (Ma et al. 2020). Climate simulations projected more intense HWs in regions such as East Asia and Europe (Ma et al. 2020; Sun et al. 2018; Wang et al. 2021). Meanwhile, water shortage and land degradation in the interior of Eurasia (Howard and Howard 2016; Yu et al. 2020), and dense population density in the developed regions of Europe and Asia may further deteriorate the negative impacts of HWs. It is, therefore, of great significance to advance HW studies by revealing potential causes behind spatiotemporal patterns of HWs.

The mechanism HW formation is complex and influenced by various factors. Our current understanding of the evolutionary characteristics and drivers of HWs in Eurasia is still limited. Zhou and Wu (2016) found that mega-ENSO and Atlantic Multidecadal Oscillation have potential modulation effects on Eurasian HWs. Luo and Lau (2017) studied the characteristics of HWs in southern China and concluded that urbanization may advance the onset of HW events. Based on station data, Wu et al. (2021) suggested that climate warming and anthropogenic activities contributed 75% of HW in the North China Plain. Previous studies have also attempted to analyze HWs and related attributions, while few efforts have quantified the fractional contribution of natural variability and human activities to HWs over Eurasia. Su and Dong (2019) found that greenhouse gases (GHGs) and atmospheric aerosols have significant impacts on HWs in China, with GHGs exacerbating HWs through terrestrial atmospheric and circulation feedbacks. The importance of aerosols was also highlighted by Xu et al. (2018a) when studying global HWs. A recent study of the 2010 Russian HW noted that a combination of natural climate change and anthropogenic increases in GHGs forcing led to HWs (Dole et al. 2011; Coumou and Rahmstorf 2012; Otto et al. 2012). As a result, the relative influential rates and explanatory rates of natural variability and human activity in the occurrence of HW events in Eurasia have yet to be revealed (Wu et al. 2021).

Overall, there are relatively few systematic analyses of the spatial and temporal variabilities of summer HWs in Eurasia, constrained by the low resolution or short time series of global temperature datasets, or by a focus on individual regions rather than continental scales. Some studies have also discussed the dominant or influencing factors of HWs in specific regions (Wu et al. 2021), but few have discussed the relative influence of dynamics change on HW, and somewhat neglected that the influence of the dominant factors of HWs also varies dynamically over time. Therefore, it is of great significance to gain an in-depth understanding of the interannual variability of HWs in Eurasia, to reveal the formation of the physical mechanism and influencing factors of HWs, and to detect the dynamics of HWs factors for human science to adapt to climate extremes and respond to climate change.

Here we present spatiotemporal patterns of HWs over Eurasia and related driving factors, thus contributing to deepening our understanding of HWs over Eurasia and improve the mitigation to HWs in a warming climate. In this research, we attempt to: (a) highlight changing properties of HWs across Eurasia since the 1950s, (b) investigate the potential mechanisms behind HW variability over Eurasia and their linkages to atmospheric circulations, and (c) uncover the relationships between HWs and relevant driving factors, and quantify the fractional contribution of global climate change and regional urbanization to HWs.

2 Data and Methods

2.1 Datasets

2.1.1 Daily temperature data

The HW metrics are calculated for the period of 1950-2018 based on the Berkeley Earth global land surface air temperature grid dataset (http://berkeleyearth.org/data). The Berkeley Earth dataset is a newly-released temperature dataset that adopts a new mathematical framework for temperature data generation (Perkins and Lewis 2020), integrates more than 10 observational data sets including CHCN-Daily (Global Historical Climatology Network). Finally, the land surface temperature data with high temporal and spatial resolution are generated (Richard et al. 2013). A study of global HWs finds that the well quality of Berkeley Earth data helps to improve our understanding of global and regional HW variability (Perkins and Lewis 2020). In this study, we use the daily maximum (Tmax) and daily minimum (Tmin) temperatures of this dataset with a spatial resolution of 1° × 1° covering the period of 1950-2018.

2.1.2 Atmospheric circulation pattern

Atmospheric circulation patterns associated with the long-term changes of HWs over Eurasia are examined based on monthly geopotential heights and wind at 850 hPa and 250 hPa levels. These variables are obtained from the NCEP/NCAR reanalysis dataset, which has a spatial resolution of 2.5°×2.5° and is available at https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.pressure.html. The NCEP/NCAR reanalysis dataset is one of the first reanalysis data released using an advanced analysis/prediction system that assimilates data from multiple sources from 1948 to the present, and was widely used in meteorological analysis studies (Kalnay et al. 1996; Gu et al. 2019).

2.1.3 Potential influencing factors behind HWs

We subdivide these potential influencing factors into four categories (Wu et al. 2021): climate change factors, anthropogenic factors, land-surface interactions, and atmospheric circulation indices. Climate change factors include global mean temperature, precipitation, and downward shortwave radiation. Anthropogenic factors include urbanization and aerosol optical thickness. Land-surface interactions include soil water, Standardized Precipitation Evapotranspiration Index (SPEI), and surface albedo. Atmospheric circulation indices include Nino3.4 (http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.anom.data) and Southern Oscillation (SOI) Index (http://www.bom.gov.au/climate/current/soihtm1.shtml), the IOD index (https://psl.noaa.gov/gcos_wgsp/Timeseries/DMI), North Atlantic Oscillation (NAO) index (https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml), Arctic Oscillation (AO) index (https://www.cpc.ncep.noaa.gov/products/precip/CWlink/ daily_ao_index/ao.shtml), the Atlantic Multidecadal Oscillation (AMO) (http://www.psl.noaa.gov/data/timeseries/AMO), and the Pacific Decadal Oscillation (PDO) (https://psl.noaa.gov/gcos_wgsp/Timeseries/PDO/).

Monthly temperature data is obtained from the Global Historical Climate Network/Climate Anomaly Monitoring System (GHCN_CAMS) 2m-grid surface air temperature dataset (https://psl.noaa.gov/data/gridded/data.ghcncams.html) at a spatial resolution of 0.5°×0.5°, which is used for representing the global warming. Monthly precipitation data with a spatial resolution of 0.5°×0.5° is derived from the Global Precipitation Climate Center (GPCC V2018) (https://psl.noaa.gov/data/gridded/data.gpcc.html). The monthly downward shortwave radiation data is from the MERRA-2 reanalysis dataset released from NASA (https://disc.sci.gsfc.nasa.gov/), which has Aerosol Optical Depth (AOD) data, surface albedo (Albedo) data, and soil water data. The SPEI03 index with a spatial resolution of 0.5°×0.5° is from the Spanish National Research Council (CSIC) (http://spei.csic.es/database.html) to represent seasonal drought conditions. The impervious surface area is accepted as an indicator of urbanization (Weng 2012; Zhang et al. 2020). In this current study, we use the newly-released 30m spatial resolution global artificial impervious area (GAIA) data (Gong et al. 2020) with an average accuracy of more than 90% for multiple years (http://data.ess.tsinghua.edu.cn/gaia.html/).

It is worth noting that data for the period 1985-2016 are chosen to analyze the driving factors and relative influence of HWs, considering the availability of all data. Preceding winter soil water affects temperature extremes in some way (Perkins et al. 2015), and a mature El Niño (La Niña) event is usually defined by the previous winter Niño3.4 index (Luo and Lau 2020), so we calculated the average soil water during February-May and the average Niño3.4 during the preceding winter (December- February of the last year), and the rest of the factors (air temperature, precipitation, downward shortwave radiation, aerosol optical thickness, SPEI, surface albedo, SOI, NAO, AO, IOD, PDO and AMO) use the average values from May to September.

2.2 Definition of HWs

Previous studies defined HW by different indicators (Perkins 2015), e.g., based on daily temperature (e.g., 90%, 95%), wet-bulb globe temperature (WBGT), and heat index (HI), making difficult the inter-regional comparisons and integrated analyses (Chen et al. 2019b; Li et al. al. 2018; Perkins et al. 2012). Here we use the Excess Heat Factor (EHF) to define HWs (Loughran et al. 2017; Perkins et al. 2012).

A specific definition of EHF was given by Nairn and Fawcett (2014). EHF has the advantage of considering both historical averages and current conditions by quantifying the degree of thermal anomalies in the three days prior to the event versus the previous month, and is used to study the effects of HWs on human health (Varghese et al. 2019). EHF is calculated as:

$$EHI_{\text{sig}} = \frac{Tm_i + Tm_{i-1} + Tm_{i-2}}{3} - Tm_{90i} \tag{1}$$

$$EHI_{\text{accl}} = \frac{Tm_i + Tm_{i-1} + Tm_{i-2}}{3} - \frac{Tm_{i-3} + \cdots\cdots + Tm_{i-32}}{3} \tag{2}$$

$$EHF = EHI_{\text{sig}} \times \max\left(1, EHI_{accl}\right) \tag{3}$$

T_{m} denotes the mean temperature, which is the average of the daily maximum and daily minimum temperatures, and an HW event is started given EHF > 0 for three or more consecutive days. EHI_{sig} denotes the difference between the previous 3-day mean T_{m} and the 90th percentile of T_{m} during the warm season (Tm_{90i}), EHI_{accl} denotes the difference between the previous 3-day mean T_{m} and the preceding 30-day mean T_{m} (Loughran et al. 2017).

Based on the above definition, we derive six metrics to represent the attributes of HW frequency, intensity and duration (Fischer and Schär 2010; Luo and Lau 2017; Perkins et al. 2012) (Table 1), including highest temperature (amplitude) of the hottest HW event (HWA), average magnitude of the yearly HW events (HWM), total number of the yearly HW events (HWN), yearly sum of all participating HW days (HWF), length of the longest yearly HW event (HWD) and first day of the first yearly HW event (HWT). In addition, Eurasia has been regionalized following the SREX (IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation) (Field et al. 2012) (Table 2).

2.3 Statistical Methods

2.3.1 Trend detection, probability distribution and explanatory rates

Decadal trends of HW metrics were calculated by Sen's slope (Hipel and McLeod 1994; Sen 1968) for 1950-2018. The generalized extreme value (GEV) distribution can well describe regional changes of HW indices (Siliverstovs et al. 2010; Sparrow et al. 2018), and the study period is subdivided into three segments: 1950-1989, 1990-2018, 1950-2018, based on the evolutionary trend of the HW index. The maximum likelihood method is used to estimate the parameters of GEV distribution function for each time segment.

The correlations between the potential influencing factors and HW indicators are first calculated using the Pearson's correlation. The advantage of stepwise regression is to select the most important factors by establishing the optimal multiple linear regression equation, and the explanatory rates (i.e., adjusted R^2) for each type of driving factors are calculated using the stepwise regression (Wu et al. 2021).

2.3.2 Estimation of the relative influential rates of driving factors

Before we calculate the relative influential rates, we should select the dominant driving factors. The impact factors that are significantly correlated are first selected. We then calculate the explanatory rates or importance of each factor using stepwise regression, random forest, and hierarchical partitioning. Based on the results of the above calculation, we rank the importance or explanatory rates of each impact factor from high to low, and assign the size of rank to scores. Then, the scores obtained from the three methods are summed to get the total score. By ensuring that there is only one driving factor in each category, four factors (corresponding to four categories), which have the smallest values are then selected as dominant driving factors for HWs.

The relative influential rates of these selected driving factors on HWs in Eurasia are estimated by the random forest method. The random forest algorithm is a machine learning algorithm based on training samples and feature sets with decision trees as the basic classifier (Breiman 2001). The algorithm is characterized by high accuracy, high efficiency, and stable performance, and is widely used in assessing the importance of independent variables (Luo et al. 2020; Xiong et al. 2020;

Yang et al. 2020). The random forest algorithm draws training samples by bagging and constructs multiple cart decision trees and forms a random forest by randomly selecting a subset of each node variable after splitting within *N* decision trees according to the principle of minimization of Gini coefficients. Based on an out-of-bag data term, the mean decrease in Gini (MDG) is used as a statistical measure to calculate the relative importance of the variables (Behnamian et al. 2017).

Here we put four factors selected above as input variables in the random forest model. Then we use the new formula proposed by Xiong et al. (2020) to quantify the relative rate of impact of the driving factors on HWs:

$$\eta_i = \frac{MDG_i}{\sum_1^i MDG_i} \times 100\% \qquad (4)$$

where *i* represents the number of input factors, η_i represents the relative influential rates of each factor, and MDG_i represents the mean decrease of Gini purity.

3 Results

3.1 Long-term changes of HWs

Based on GHCN_CAMS monthly temperature dataset, Fig. 1 illustrates the spatial pattern of annual mean temperature trend in Eurasia. The period of 1950-2018 witnessed a rapid increase in air temperature with the continental average temperature of 8.97°C in Eurasia, especially after the 1980s. During 1950-2018, the largest trends were mainly over Europe, Mediterranean, Southern Indian Peninsula and Middle East Peninsula. These extreme regions were growing at a rate of more than 1°C/10yr. The annual average temperature increased at a rate of 0.29°C/10yr. The annual average temperature in 2015 is 10.21°C in Eurasia, which is also the highest annual average temperature in recent decades (Fig. S1). The warm season average temperature is remarkably higher than the annual average temperature with an increased rate of 0.22°C/10yr and a maximum temperature of 19.20°C in 2016. The average temperature during the warm season of the period of 1950-2018 is 17.96°C. The average temperatures in the EAS (East Asia), SAS (South Asia) and CEU (Central Europe) and the Middle East Peninsula regions are higher than the other regions. EAS and Europe are highly urbanized regions (Table S1) with high population exposure under HW events, and TIB, being highly sensitive to global warming (Wang et al. 2020).

Fig. 2 shows the temporal variation of six different HW metrics in Eurasia and its subregions during 1950-2018. In most regions of Eurasia, nearly all HW metrics are increasing, except for HWT that shows a decreasing trend. Decreasing HWT indicates that the first HW event of the calendar year tends to occur significantly earlier in most of Eurasia; whereas, the frequency, duration and intensity of HWs are increasing and almost all regions are exposed to intensifying HW risks. Fig. 2 also shows moderate HW changes until the 1990s and significant increases in HW after the 1990s with a remarkable decrease in HWT. Particularly, we observe increasing trends in the HW frequency and duration in Mediterranean (MED), East Asia (EAS), North Asia (NAS), and Northern Europe (NEU) regions (Perkins and Lewis 2020). We also calculate the difference in the HW indices between 1950-1989and 1990-2018 (i.e., denoted as cold and warm subperiods, respectively). From the cold to the warm periods, the average temperature in Eurasia increased, leading to an increase in above-threshold high temperature events and the genesis of HWs tends to be ahead of time. HWA increased from 4.14 $°C^2$ to 6.49 $°C^2$, HWD increased from 7.79 days to 14.84 days, HWF increased from 9.81 to 30.27, HWM increased from 1.50 $°C^2$ to 1.72 $°C^2$, HWN increased from 1.66 times to 3.74 times, and HWT increased from 56.41 days to 36.64 days, with change rates of 56.76%, 90.5%, 208.56%, 16.67%, 125.3%, and -35.05%, respectively. Marginal changes in HWs in recent decades appear in South Asia (SAS).

Besides, we also calculate their linear trends and the corresponding significance (Table 3). The growth rates of regional mean HWA, HWN, HWF, HWM, HWD, and HWT over Eurasia are 0.64°C^2/10yr, 0.61/10yr, 5.8days/10yr, 0.07°C^2/10yr, 1.83days/10yr, and -4.93days/10yr, respectively. The tendencies of mean HW intensity since the 1950s are not significant over most regions, consistent with previous studies (Perkins and Lewis 2020). Regionally, HWA is subjected to the highest growth rate in the NAS region (1.19 °C^2/10yr), HWN exhibits the highest growth rate in the MED region (0.83 times/10yr), HWF is of the highest growth rate in the WAS region (11.75 days/10yr), HWM is of a weak increase with the highest growth rate observed in the NAS region (0.22°C^2/10yr), and both HWD and HWT are subjected to the highest growth rates in the WAS region (1.83 days/10yr and -4.93 days/10yr).

The HW behaviors during cold (1950-1989) and warm periods (1990-2018) exhibit distinct features, as shown by the probability density distribution functions (PDFs) of various HW metrics using the GEV model (Fig. 3). It is interesting to find that all HW metrics show similar variabilities and relatively consistent trends. Except for HWT, all other PDF curves are skewed rightward, suggesting that the HW events are significantly intensified in the warm subperiod, compared to the cold subperiod. After 1990, the number of high values for HWA, HWD, HWF and HWN does not become greater, meaning that the magnitude of the HW indicators becomes more homogeneous. For HWM, the values became more concentrated after 1990 and the magnitude of the variation in values decreased.

Spatially, western Asia and western Europe suffer the highest number and frequency of HW attacks, especially in the Middle East peninsula of West Asia (Fig. 4). Meanwhile, the maximum and the fastest growth rate of HWM (23.24 days and 51.96 days, respectively) are found in the Middle East peninsula, while the lowest HWF (4.87days) is found along the Himalayas of the

Tibetan Plateau. For HWN, the maximum number of HWs was 5 with an average of 2.33. The minimum trend is also found in the southern Himalayan region (-0.37/10yr), showing a slight decrease, while the highest growth trend continues to occur in WAS at 1.66 /10yr. The average growth trend in Eurasia is 0.43 times/10yr, and more than 50% of the regions have a growth trend greater than 0.38 times/10yr. Southeast Asia, East Asia, the Mongolian Plateau region, West Asia and Western Europe suffer the most frequent HW events. Other HW indices show consistent findings.

3.2 Physical mechanisms underlying the HW changes over Eurasia

Here we proceed to investigate the climatic dynamics behind the HW changes over since the 1950s, by examining the atmospheric circulation anomalies associated with HWs (Alizadeh et al. 2020; Loughran et al. 2017). Fig. 5 shows the difference in horizontal wind and geopotential height at the 250hPa and 850hPa levels between 1950-1989 and 1990-2018, with the significance of the difference tested by the Two-Sample Test. At the upper level (Fig. 5a), anomalous anticyclonic flow and high pressure are formed along the regions of Europe-Middle East Peninsula-North India-Northwest China-Northeast Mongolia. At the lower level, atmospheric circulation anomalies are found mainly in the Mongolian plateau of Eurasia, central and western Europe and northern Africa. Besides, a profound positive difference in geopotential height appears over the Mongolian plateau (over 40 m) (Fig. 5b). Whereas, the vertical profile along 105°E shows that the resistance to direct southward diffusion of cold air from high latitudes such as western Siberia became greater after 1990 (Fig. 5d), and this sinking motion associated with high pressure anomalies inhibits cloud formation, thus increasing the incoming solar radiation received at the surface (Li et al. 2019; Wu et al. 2012). The northeasterly winds over China weaken the monsoon flow from the Pacific Ocean, resulting in less precipitation (Wu et al. 2021). Thus, the frequency and intensity of HW events in eastern Asia are increasing. The anomalous high pressure over northern India is influenced by subtropical high pressure (Rohini et al. 2016). The atmospheric circulation over mid-latitudes, such as the Mediterranean and Europe, is controlled by persistent anticyclones with a near "positive pressure" structure from high altitude to near the ground (Fig. 5c), thus resulting in cloud-free conditions and hot air convection (Schumacher et al. 2019). Therefore, warm and humid air cannot spread and is prolonged to be trapped in the low-pressure region, where hot air cannot be exchanged, and regional temperatures increase year by year. While Fig. 5b shows that the combined influence of the three clusters of positive geopotential height anomalies near the Mediterranean Sea made this circulation condition more intense after 1990 than earlier, further intensifying the intensity, frequency and duration of HWs.

3.3 Relationship between HW and driving factors

The correlations and explanatory rates of the possible driving factors with various HW metrics are quantified (Table 4, Table S2-12). As expected, climate change factors show the highest explanatory rate for HWs in almost all sub-regions. The explanatory rates of most climatic factors exceed 50% for HWN and HWF, and the explanatory rates of climate factors for HWN, HWA, HWF, HWD and HWT in Eurasia are 84.62%, 17.15%, 84.31%, 64.32%, 64.32% and 36.18%, respectively. For HWN, HWA, HWF, HWD and HWT in the CEU region, the explanatory rates of climate factors are 73.26%, 35.56%, 59.12%, 45.64%, and 14.93%, respectively, and they are 48.2%, 12.34%, 38.99%, 27.2%, 16.05% and 6.54%, respectively, in the EAS region. The increases in air temperature and net downward short-wave radiation correspond to significant positive correlations of air temperature with radiation factors and with HWN, HWA, HWF and HWD in most regions as well. In EAS, HWT is significantly negatively correlated with temperature (R^2=-0.19), indicating that as temperatures rise, the local climate exceeds the threshold earlier, leading to an earlier onset of the first HW event (Fig. 2). Similar results can also be found in other parts of Eurasia. Precipitation, on the other hand, has less impact on the HW events and shows a weak correlation with HWs (Hirschi et al. 2011; Wu et al. 2021).

The explanatory rates of anthropogenic factors for HW indicators are relatively higher, i.e., 67.64%, 15.76%, 68.67%, 52.36% and 41.24% for HWN, HWA, HWF, HWD and HWT, respectively. Therefore, human activities have more influences on the frequency and duration of HWs. In the CEU region, the explanatory rates for HWN, HWA, HWF, HWD and HWT are 67.89%, 40.49%, 45.28%, 12.75% and 5.09%, respectively. In the EAS region, the explanatory rates for HWN, HWF, HWD and HWT are 35.29%, 27.7%, 18.44% and 3.4%, respectively. The rapid growth of global economy in recent years and the change of land use types by human activities are becoming increasingly obvious (Yang et al. 2019). The rapid development of cities caused dramatic expansion of impervious areas in Asia. In 2018, the impervious area in East Asia alone is close to North America, which makes the urban heat island effect more obvious (Gong et al. 2020). Also, atmospheric aerosols can influence the radiative balance by altering the physical properties of clouds and thus can regulate climate (Lyamani et al. 2006). The decreasing AOD in Europe increases the energy transfer of solar radiation (Wild et al. 2007), which favors the occurrence of HWs and thus has a significant negative correlation with HW events. In East Asia, due to the continuous improvement and development of industrial infrastructures and automobile emissions, atmospheric aerosols have been increasing, showing a significant negative correlation with HWs. This may be attributed to the fact that aerosols reduce the diurnal temperature difference through the radiation effect, resulting in a thermal insulation effect on the local area and thus positively influencing the occurrence of HW events (Wu et al. 2021).

Land-surface interaction causes changes in the energy exchange between the surface and the atmosphere, and surface albedo and SPEI of surface interaction factors show significant correlation with Eurasia HWs. The explanatory rates of land-surface interaction factors for HWN, HWA, HWF, HWD and HWT in Eurasia are 58.98%, 22.61%, 52.58%, 28.03% and 24.03%, respectively. In the CEU area, the explanatory rates for HWN, HWA, HWF, HWD, HWM and HWT are 48.58%, 30.24%, 50.14%, 20.8%, and 4.41%, respectively. In the EAS region, the explanatory rates of HWN, HWA, HWF, HWD, HWM and HWT are 43.97%, 25.62%, 34.87%, 22.28%, 4.56% and 15.56%, respectively. Surface albedo is significantly and negatively correlated with the frequency, intensity and duration of HW events in most regions, suggesting that a decrease in surface albedo is somehow associated with an increase in HW events. This is due to the widespread shift from agricultural land, wetlands or lakes to urban land use (Zhou and Chen 2018), which changes surface albedo and leads to significant perturbations to the Earth's surface energy balance (Du et al. 2016; Zhang et al. 2020). For example, the increase in urban land use reduces the surface albedo and stores more radiant energy than before (Zhao et al. 2014), while HW events are further enhanced by the urban heat island effect. Droughts are usually caused by a combination of extreme heat and moisture deficit, and the positive feedback effect between drought and extremely hot weather also increases the probability of simultaneous HWs and droughts (Sharma and Mujumdar 2017). Antecedent soil moisture does not present a significant correlation with HWs in most parts of the region, but shows a relatively significant correlation in the SEA region.

Atmospheric circulation factors have either strong or weak teleconnections with HWs. Such a signal can cross regions and affect weather patterns on the continents. It is found that the atmospheric circulation factors explained 63.97%, 22.49%, 67.8%, 64.21%, 22.48% and 33.36% for HWN, HWA, HWF, HWD, HWM and HWT, respectively. In the CEU region, the explanatory rates for HWN, HWA, HWF, HWD, HWM and HWT are 33.65%, 13.43%, 31.95%, 10.88%, 12.68% and 11.72%, respectively. In the EAS region, the explanatory rates of HWN, HWA, HWF, HWD and HWM are 41.44%, 9.35%, 38.92%, 37.54%, and 8.41%, respectively. Comparatively, PDO shows a high and significant negative correlation (R^2=0.73, $p<0.05$) with HW metrics in most regions (e.g., EAS, CAS, MED, TIB). The AMO index has a significant correlation with HWN, HWF and HWD in Eurasia, with correlation coefficients reaching above 0.7. Previous studies suggested that Atlantic SSTs influence HWs in northern China through Atlantic-Eurasian teleconnection (Deng et al. 2019), and positive AMO caused circulation anomalies that warm parts of Eurasia and increase HWF there, becoming the most important factor dominating the increase of HWs in Eurasia (Choi et al. 2020; Zhou and Wu 2016).

3.4 Relative influential rate of dominant driving factors

HWs involve many impact factors (Xiong et al. 2020; Luo and Lau 2017), but not all influencing factors have significant effects on HWs changes, and an excessive number of indicators also tends to increase computational redundancy and even cause dimensional disasters in the analysis. Therefore, here we use stepwise regression, random forest, and hierarchical partitioning to identify HWF key influencing factors from the 12 candidate factors (Tables S13-15). Table 5 shows the total scores obtained by the three methods mentioned above. Taking Eurasia as an example, the four selected driving factors are temperature (Tas), urbanization, SPEI, and AMO. We find that the input factors for the new random forest models built for Eurasia and its 10 sub-regions all include temperature and urbanization, suggesting that global warming and urbanization are strongly associated with severe HW events (Luo and Lau 2017).

We calculate the relative importance of each driving factor using a random forest model and calculate the relative influential rate (see Eq. 4). Fig. 6 shows the relative influential rate of each driving factor to HWs over Eurasia and sub-regions during 1985-2016. The relative influential rates of temperature, urbanization, SPEI and AMO on the change of HWF in Eurasia are 30%, 25%, 21% and 24%, respectively. Meanwhile, the relative influential rate of temperature is the highest in Eurasia, NAS, SAS and SEA, while the relative influential rate of urbanization is significantly higher than the other factors in some regions, such as EAS and WAS, where developing countries are concentrated and urbanization is rapid. The Qinghai-Tibet Plateau is particularly sensitive to global warming response (Fan et al. 2019), and the increase in local temperature and thermal anomalies can cause serious harm to the local and surrounding ecological environment. The TIB region is in high altitudes, with a year-round snowpack much larger than that of urban, so the relative influential rates of temperature and albedo reach 27% and 28%. AMO also accounts for the dominant effect on the changes in HWF on CAS, SAS, and SEA.

The decadal changes of the relative influential rate of each driving factor over the period 1985-2016 are also examined using 10-, 15-, and 20-year time windows. As shown in Fig. 7, temperature shows a decreasing-rising-decreasing pattern during the study period, and reaches a maximum value of 33.55% in 2008, while the relative influential rate of AMO is persistently decreasing, e.g., from 27.71% in 1999 to 22.44% in 2002. The urbanization contribution exhibits decreasing tendency and then changes to increase. In recent years, drought frequently occurred in both MED and SAS (Im et al. 2017; Ma et al. 2020), and the relative influential rates of SPEI in both regions have also increased sharply, i.e., from 19.29% to 35.13% and from 18.36% to 28.32%, respectively. At the regional scale, the relative influential rate of urbanization is decreasing in many regions, especially in the EAS and CEU regions. In the case of EAS, while the urban area has been expanding, and even the rate of expansion has increased after 2000 (Fig. S2) causing a "warming" effect (Wang et al. 2017). China has been implementing the concept of sustainable development, which has led to an increase in green space (Chen et al. 2019a) and caused a "cooling" effect (Peng et al. 2014). The increase of urban impervious surface will make the surface albedo increase, and the increase of green area will make the surface albedo decrease. The constraint between these two makes the change pattern of surface albedo similar to that of HW, which leads to a dynamic increase in the relative impact rate of surface albedo., makes the characteristics of the change of surface albedo rate (Fig. S2) fit better with the change of HWs, which leads to a dynamic increasing trend of the relative influential rate of surface albedo rate. Figs. S4-5 also provide the temporal dynamics for the 10- and 20-year time windows. We find that the results vary considerably when using different time windows, but for the overall trend, the results are similar for most regions.

4 Conclusions and discussion

In this study, we investigate the spatiotemporal characteristics and identify dominant driving factors for HWs in Eurasia, with the climate dynamics mechanisms behind HW changes highlighted. We obtain the following important and interesting findings and conclusions:

(1) Rapidly rising air temperatures in Eurasia since the 1950s trigger earlier occurrence of the first HW. Amplifying HWs can be detected by increased frequency, duration, and intensity of HWs, and it is particularly the case after the 1990s. Specifically, increased HW frequency and duration can be observed in MED, EAS, WAS, NAS, and NEU regions. HWs in SAS are subjected to little

changes than other regions of Eurasia. Southeast Asia, East Asia, the Mongolian Plateau region, West Asia, and Western Europe suffer the most frequent HW events. Atmospheric circulation anomalies and persistent anticyclone control at mid-latitudes contribute to the increasing occurrence of HW events in Eurasia, and the more intense atmospheric circulation obstruction and increased Mongolian high pressure after the 1990s hinder the convection of warm airmass from spreading and cold air from entering the HW centers for temperature exchange, explaining the increasing frequency of HW events. This long-term atmospheric circulation anomaly eventually leads to an increase in the intensity and duration of HWs.

(2) The climatic factor explains the highest rate of HW events in almost all regions of Eurasia, and increased temperature makes the local climate exceed the threshold state earlier and hence earlier occurrence of HWs annually. Anthropogenic factors also have a high explanation rate for HW metrics, with urban expansion and AOD emissions by human activities contributing to intensifying HW events over Eurasia. Decreasing surface albedo and increasing drought provide favorable conditions for the occurrence of HW events. AMO and PDO as representatives of atmospheric circulation factors are found to be significantly correlated with HW events in most Eurasian regions.

(3) Temperature and urbanization are the dominant driving factors modulating HWs in Eurasia and its sub-regions. The relative influential rates of warming climate, urbanization, SPEI and AMO on HWF variations in Eurasia are 30%, 25%, 21% and 24%, respectively. The relative influential rate of different driving factors for Eurasia HW varies over time, and the relative influence rate of urbanization decreases in EAS and CEU, and the time windows of different sizes also introduce uncertainty into the analysis of driving factors.

Our results are consistent with the major findings of previous studies (Zhou and Wu 2016; Luo and Lau 2017; Perkins and Lewis 2020), Although the rate of change of each HW metrics is different, the overall trend remains consistent, reflecting that HWs in the Eurasian have increased significantly over the past few decades. We analyze the background of large-scale circulation anomalies associated with the occurrence of HWs, and the relationship between dominant factors (temperature, impervious area, surface albedo and soil moisture, etc.) and HWs. The findings we obtained can help to enhance our understanding of the occurrence of heat waves and their varying trends, and to respond accordingly to the different factors. For example, as AMO is an important climate driver in the northern hemisphere, it has been found that circulation anomalies drivcd by AMO in the warm season will strengthen surface radiation and contribute to the increase of HWF over Eurasia (Zhou and Wu 2016). Our study reaches similar conclusions through correlation analysis and extends this relationship to indicators such as the duration and intensity of HWs. We also demonstrate statistically that urbanization and global warming have contributed to the intensification of HWs in recent decades, raising alarm bells about rampant urban expansion and greenhouse gas emissions. Further global temperature increases in the future projection of global climate models (Wang et al. 2020), posing challenges to regional water security, food security and power supply, among others. Therefore, further work using the latest CMIP6 model should be conducted to quantitatively attribute human activities and climate change to the HW variability. The study provided here can move forward to research on future trends in the HW changes and risk assessment based on different climate change scenarios and shared socio-economic pathways. The populations and lands exposed to future HW events, and the likely economic losses, will also be the focus of future research.

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Declarations

Conflict of interest All authors declared no conflict of interests.

Data availability

The daily gridded land surface air temperature from Berkeley Earth were acquired from their website at http://berkeleyearth.org/data. The NCEP/NCAR reanalysis dataset can be available from https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.pressure.html. Nino3.4 index was obtained from http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.anom.data. Southern Oscillation Index was obtained from https://www.bom.gov.au/climate/current/soihtm1.shtml. IOD index https://psl.noaa.gov/gcos_wgsp/Timeseries/DMI. North Atlantic Oscillation https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml. Arctic Oscillation index https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao.shtml. Atlantic Multidecadal Oscillation http://www.psl.noaa.gov/data/timeseries/AMO. Pacific Decadal Oscillation https://psl.noaa.gov/gcos_wgsp/Timeseries/PDO. GHCN_CAMS 2m-grid surface air temperature dataset can be available from https://psl.noaa.gov/data/gridded/data.ghcncams.html. The monthly gridded precipitation from GPCC were acquired from https://psl.noaa.gov/data/gridded/data.gpcc.html. The monthly downward shortwave radiation, Aerosol Optical Depth, surface albedo and soil water data were from the MERRA-2 reanalysis dataset released from https://disc.sci.gsfc.nasa.gov/. The SPEI03 index from CSIC can be available from http://spei.csic.es/database.html. The GAIA data were obtained from http://data.ess.tsinghua.edu.cn/gaia.html/.

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Figure captions:

Fig. 1 Spatial distribution of annual mean temperature trend in Eurasia from 1950 to 2020 and the sub-regions across Eurasia. The embedded line shows the corresponding time series of the regional mean temperature in Eurasia. CAS: Central Asia, CEU: Central Europe, EAS: East

Asia, MED: Mediterranean, NAS: North Asia, NEU: North Europe, SAS: South Asia, SEA: South East Asia, TIB: Tibet, WAS: West Asia.(Based on GHCN_CAMS monthly temperature dataset)

Fig. 2 Time series of (a) HWA, (b) HWD, (c) HWF, (d) HWM, (e) HWN and (f) HWT in Eurasia and its sub-regions during 1950-2018. CEU: Central Europe, EAS: East Asia, NEU: North Europe, SAS: Asia, TIB: Tibet

Fig. 3 Fitting distribution of the GEV probabilities for (a) HWA, (b) HWD, (c) HWF, (d) HWM, (e) HWD, and (f) HWT in Eurasia during the periods of 1950-1989 (green), 1990-2018 (pink), and 1950-2018 (orange). The embedded dot plots denote the corresponding distribution of HWs value

Fig. 4 Spatial distribution of (a) HWF in Eurasia and (b) its trend during 1950-2018, (c) and (d) for HWN. The embedded line graph in (a) and (c) represents the yearly series of the regional mean HWF and HWN in Eurasia

Fig. 5 Maps of the difference of geopotential height (shading) and horizontal wind (vector) at (a) 250 hPa and (b) 850 hPa levels, and vertical profile of the cross-section along 20°E (c) and 105°E (d)during the warm seasons of 1950-1989 and 1990-2018. The red dashed contours and gray slash respectively denote the differences of geopotential height and wind that are significant at the 0.05 level

Fig. 6 Relative influential rates of the dominant driving factors for HWF in Eurasia and its sub-regions during 1985-2016. Tas: near-surface temperature, Urban: urbanization, SM: soil moisture, AMO: Atlantic Multidecadal Oscillation, NAO: North Atlantic Oscillation, PDO: Pacific Decadal Oscillation, SPEI: Standardized Precipitation Evapotranspiration Index, Albedo: albedo of the land surface

Fig. 7 Temporal evolution of the relative influential rates of the dominant driving factors for HWF in Eurasia and its sub-regions based on sliding 15-year time window.

Table captions:

Table 1 Definition of heat wave indicators

Table 2 Division of Eurasia based on SREX classification criteria

Table 3 Regional decadal trends in Eurasia and its different subregions during 1951-2018, with an bold font indicating the significance at the 0.05 level.

Table 4 Results of stepwise regression analysis and correlation analysis of the driving factors for HWF and HWN in Eurasia

Table 5 The total scores summed by the results of three methods (stepwise regression, random forest, and hierarchical partitioning)