Early-onset trend in European summer caused by Greenland topographic effect

Jun-Hyeok Son1,∗, Nam-Hoon Kim1, Go-Un Kim1, Jung-Eun Chu2,©, Jae-Heung Park1, Jae-il Kwon1 and Ki-Young Heo1,∗

1 Korea Institute of Ocean Science & Technology, Busan 49111, Republic of Korea
2 Low-Carbon and Climate Impact Research Centre, School of Energy and Environment, City University of Hong Kong, Hong Kong, People’s Republic of China
3 Pohang University of Science and Technology, Pohang 37673, Republic of Korea

∗ Authors to whom any correspondence should be addressed.
E-mail: j-hson@kiost.ac.kr and kyheo21@kiost.ac.kr

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Abstract

Global heating, which is considered irreversible at least for the near future, causes various climate crises directly affecting human life. Accordingly, European countries have been afflicted by frequent heatwaves in summer. Convolutional neural network deep learning models have revealed the lengthening of the European summer over the past 42 years. Here we show that the early onset of summer is responsible for this climatic trend. In late May, an anti-cyclonic circulation anomaly strengthens over the United Kingdom, Ireland, and the adjoining Atlantic Ocean, causing significant temperature increases across Western Europe, Iceland, and around the Barents Sea. The intensification of the mid-latitude westerly wind impinging on Greenland seems to be responsible for strengthening the anomalous circulation change via topographically forced stationary Rossby wave responses. As the westerly wind intensification is ensued by further global heating, summer will begin earlier, and thus more frequent European heatwaves are expected to occur.

1. Introduction

A large proportion of the human population is distributed across the mid-latitude in the Northern Hemisphere, where the environment varies significantly according to the season change. The seasonal transition is one of the most important climate phenomena influencing directly to human livelihood across various aspects such as health, leisure, economy, and culture (Oh et al 2021, 2022, Ulrike et al 2021), as accompanying precipitation rate and temperature changes (Gemmell et al 2000, Seo et al 2015).

Seasons in the Northern Hemisphere are conventionally divided into four based on calendar months: March–May (MAM) as spring, June–August (JJA) as summer, September–November (SON) as autumn, and December–February (DJF) as winter. In addition, the astronomical definition states that summer and winter are the period from solstice to equinox, which is similar to the JJA and DJF. Alternatively, the seasons can be defined as an empirical concept by considering the hot period as summer and the cold season as winter, which roughly coincides with the former calendar methods. However, currently, global warming increases the global mean surface air temperature, altering inter- and intra-seasonal thermodynamic characteristics, culminating in complex cascade of changes influence the feature of seasons finally. Overall, these changes cause anomalous climate patterns that are incongruent with various frameworks used to characterize seasons historically.

In 2021, global temperatures were approximately 1.1 °C warmer than those seen in the 1800s. This trend is concurrent with the increase of global surface temperatures that has characterized every year since the industrial revolution. Throughout the 21st century, in particular, Europe has seen a drastic rise in temperatures (Twardosz and Kossowska-Cezak 2013, Christidis et al 2015, Dunn et al 2020). For example, in 2003, France, Germany, and Italy were affected by heatwaves, a phenomenon not characteristic of these regions. Moreover, so far, heat waves are intensifying.
across Europe (García-León et al. 2021); the hot temperature extremes are strengthening in Switzerland (Scherrer et al. 2016), the number of heatwave events is increasing in Ukraine (Shevchenko et al. 2014). Particularly in 2019, the severe heatwaves occurred in France, Germany, the United Kingdom (Sousa et al. 2020), and caused heat records being broken at Netherlands (Xu et al. 2020).

As mentioned above and reported in many previous research articles, Europe has been shown to be particularly vulnerable to the extremely hot temperature during summer. Since a duration of summer is critical for the more frequent occurrence of heatwaves, the prediction of the onset and withdrawal of summer is important for forecasting and responding to heat disasters. Despite the importance, ironically, there is no precise meteorological framework to define summer. Since long-term meteorological data such as the atmospheric reanalysis dataset from the European Center for Medium-Range Weather Forecasts has been made available to the public, it is now possible to build an observational data-driven deep learning model for climatic research (Ham et al. 2019, 2021). Capitalizing on the availability of such data, we have built a deep learning model—convolutional neural network (CNN)—to characterize the summers in Europe based on daily temperature data of the past 42 years. After characterizing summer periods in terms of temperature, we were able to show congruence between the model prediction and reality. The basis of our artificial intelligent model is firmly rooted in a factor that encapsulates summer. In this study, we have detected the European summer through CNN modeling, and shown the possible dynamical and physical mechanisms for the anomalous early onset of summer signal.

2. Methods and data

2.1. CNN model

In Europe (20°W–60°E, 30°–75°N), winter, spring, summer, and autumn are set as DJF, MAM, JJA, and SON, respectively. Furthermore, spring and autumn were framed as transient seasons that separate summer and winter. The five day running average of daily 2 m air temperature from 1979 to 1988, taken from the ERA5 dataset, was used as the input data with a dimension of 32 (longitude) × 18 (latitude) × 3650 (day), to remove high-frequency weather fluctuation. The horizontal resolution was set to 2.5° by 2.5°. Using this calendar-based definition of seasons, the CNN model was constructed, with stochastic optimization conducted using the Adam algorithm (Kingma and Ba 2015). Here, the three convolutional layers were prescribed in the CNN model: the first two convolutional layers were constructed with the kernel and max-pooling size of a 2 × 2 grid in each layer, whereas the third layer had a 1 × 1 filter size (Szegedy et al. 2016). The first, second, and third convolutional layers had maps of 64, 128 and 256 feature maps, respectively. The third convolutional layer was then linked to the fully connected layer, which was needed to classify the data into the three classes via a softmax function. The classes were prescribed as winter, summer, and transient periods, and the softmax calculated a probability for the final individual class. The number of an epoch was set to 20, and the batch size to 30. The batch size is the number of training images in one forward pass for the computational speedup, and the term ‘epoch’ refers the iteration number of an individual process all images forward to the network. After each process of the convolution layer, the rectified linear unit (Relu) was applied to prevent the vanishing gradient problem (Dahl et al. 2013). After the Relu application, the dropout process was applied with the value of 0.1 in each convolutional layer to reduce overfitting (Srivastava et al. 2014). Consequently, the CNN model shows above 90% accuracy as shown in figure S1. However, the CNN prediction results do not represent the unique solution, because of a randomized process in the training step. Therefore, to confirm whether the CNN model predicted consistent results, we separately repeated its training and prediction 1000 times. Subsequently, we were able to confirm the consistency of the results, as most predictions were similar (not exactly the same) to the representative result shown in figure 1.

The training period is the initial ten years, from 1979 to 1988, and the CNN model validation is performed in the same period. While the season prediction was conducted using data representative of the period 1989–2020. In figure 1, the validation and prediction results are illustrated serially from 1979 to 2020. The overall results are not sensitive to small perturbations of the training period; however, when the training period extended to 20 years (1979–1998) the early onset trend of summer was vanished, because the global heating effect was already included to the characteristics of spring (not shown). For the construction of the CNN model, we refer the flowchart as shown in previous study (Ham et al. 2019); however, the model was builted up to match up the purpose of this study using the Python library TensorFlow (www.tensorflow.org).

2.2. Surface heat budget analysis

To show the detailed thermodynamic process causing the early onset of summer, we analyzed the surface heat budget. The thermodynamic equation is as follows (Seo et al. 2016):

$$\frac{\partial T}{\partial t} = -V \cdot \nabla HT + S_p \omega + Q + \text{Res} \quad (1)$$
Figure 1. Architecture of the CNN model for the prediction of European seasons. The seasons (input) are labeled as winter, summer, and transient periods based on the calendar. The CNN model is trained with three convolutional layers using the surface 2 m air temperature in Europe (20° W–60° E, 30°–75° N), from 1979 to 1988. The validation of the CNN model is performed in the same period as the training data, and the prediction is conducted for 32 years from 1989 to 2020. The red (blue) color shows the summer (winter) and white shows spring and autumn together in the model prediction and validation.

where $T$ is surface air temperature, $V_H$ is the horizontal wind, and $\omega$ is the vertical velocity in pressure coordinates. The stability parameter $S_p = \left( \frac{R}{C_p} \right) \left( \frac{T}{P} \right) - \left( \frac{\partial T}{\partial P} \right)$, where the gas constant for dry air $R = 287.058 \text{ J/(KgK)}$, and the specific heat of dry air at constant pressure $C_p = 1004 \text{ J/(KgK)}^{-1}$. $Q$ is diabatic heating, which is consistent with the surface sensible (SHF) and latent heat flux (LHF; Jm$^{-2}$ per day). Res refers to the residuals.

Taking the long period integration, each term in equation (1) has units of temperature (K). The 2011–2020 minus 1979–1988 is denoted as $\Delta$ in equation (2)

\[
\Delta T = -\Delta \left( u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} \right) + \Delta \left( S_p \omega \right)
+ \Delta \left( \frac{1}{C_p \cdot sfc_{layer}} \text{SHF} \right) + \Delta \left( \frac{1}{C_p \cdot sfc_{layer}} \text{LHF} \right) + \text{Res.} \tag{2}
\]

Over mid-latitudes, the planetary boundary layer (PBL) average depth is hundreds of meters, and the surface layer is about 10% of PBL depth (Stull 1988).
In this study, the atmospheric surface layer (sfc_layer) is assumed to be ~20 m, which can be converted to approximately 200 Pa from the mean sea level pressure. Note that 1 Pa is assumed as 0.1 kg m\(^{-2}\).

In figure 2, \(T\) is temperature difference between 22–31 May in 2011–2020 and in 1979–1988; \(T_{\text{pre}}\) is temperature calculated from the heat budget analysis; \(U_{\text{ad}}\) is zonal temperature advection; \(V_{\text{ad}}\) is meridional temperature advection; \(W_{\text{ad}}\) is vertical advection of temperature; \(\text{SHF}\) is sensible heat flux; \(\text{LHF}\) shows latent heat flux; \(\text{Res}\) is the residual term.

2.3. Wave activity flux (WAF)

To estimate the propagation path of atmospheric Rossby waves, the WAF was calculated (Takaya and Nakamura 2001). The WAF analysis can be used to detect stationary Rossby wave propagation characteristics superimposed on a basic westerly flow in regions other than the equator.

2.4. Topographically forced stationary Rossby wave theory

The stationary Rossby wave response equation induced by topographic forcing is expressed as follows (Held 1983):

\[
\psi_n = \frac{f_0 h_n}{H (K^2 - K_i^2 - i\beta r K^2/k\bar{u})}
\]

where \(\psi_n\) is the streamfunction, \(f_0\) is the Coriolis parameter (10\(^{-4}\) s\(^{-1}\)); \(h_n\) is the topographical height (km); \(H\) is the scale height (8 km); \(K^2 = k^2 + l^2\) is the total wavenumber, where \(k = \frac{2\pi \times \cos(\frac{\pi n}{m})}{\bar{r}}\) is the zonal wavenumber, and \(l = \frac{2\pi}{\bar{a}}\) is the meridional wavenumber, where \(\bar{r}\) means a meridional half-wavelength of 35°; \(K_i^2 = \beta/\bar{u}\) is the stationary wavenumber; \(i = \sqrt{-1}\) is the imaginary unit number; \(a\) is the radius of the Earth (6371 km); \(r\) is the inverse of the spin-down time (1/7 d\(^{-1}\)); and \(\bar{u}\) is the zonal wind speed (m s\(^{-1}\)) at the higher level measured over the upstream region of Greenland (500–150 hPa; 80°–50° W, 50°–75° N). The height of Greenland reaches almost 3000 m, and the height of the PFL over the Greenland ice sheet is estimated to be 1000 m (von Engeln and Teixeira 2013); therefore, the zonal wind is selected from \(\geq 500\) hPa. Using a Fourier transform, the forced topographic wave is determined by calculating \(h_n\), here \(n\) denotes a natural number from one to a total number of the zonal grid points.

The theoretical prediction of streamfunction was calculated using westerly wind speed impinging on Greenland during 22–31 May in 1979–1988 and 2011–2020, respectively. To show the difference between the two periods, we subtracted the streamfunction of 1979–1988 from the one averaged in 2011–2020. Based on the theoretical results, the mechanism of stationary Rossby waves causing European summer early onset trend was validated.

3. Dataset

Data used in this study is publicly available via the following link: the fifth generation of the atmospheric reanalysis dataset from the European Center for Medium-Range Weather Forecasts (ERA5; Hersbach et al. 2020). The surface air temperature, horizontal wind at pressure level, total cloud cover fractions are used in daily from 1979 to 2020 (www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5). The Hadley center sea ice concentration data are downloaded via www.metoffice.gov.uk/hadobs/hadisst/ (HadirSST; Rayner et al. 2003). The ETOPO5 5 min gridded elevation data (National Geophysical Data Center 1988) are interpolated to a 2.5° × 2.5° horizontal resolution for the calculation of the topographically forced stationary Rossby wave equation (www.ngdc.noaa.gov/mgg/global/etopo5.HTML).

4. European current climate change detected by the CNN model

We divided European seasons into three categories based on the simplest calendrical definition: summer (JJA), winter (DJF), and transition seasons (MAM, and SON). Using these season definitions, the 2 m air temperature was used as training input data for the CNN model. The dataset encompassed a large part of Europe (20° W–60° E, 30°–75° N), and included daily data from 1979 to 1988. The CNN model revealed that the duration of winter in Europe has shortened, whereas, summer has lengthened since 1979 (figure 1). The model classifies summer conditions through a series of steps shown in figure 1. Regions showing characteristics corresponding to summer conditions, were classified and represented using a heatmap (Wang et al. 2015) (figure S2). Note that this artificial intelligence model is currently an irreplaceable technology to automatically identify the characteristics of the summer on the daily timescale and even to perform the season prediction.

The region including Portugal, Spain, and France are highly referenced in the CNN model, and some arctic regions are also used to declare summer. Consistent with the heatmap analysis, during 22–31 May for the most recent ten years (2011–2020), the temperature has increased by more than +2 °C around Portugal, Spain, and France. This is significantly higher than the temperatures seen in 1979–1988 (figure 2(b)), and is a result of gradual warming rather than abrupt climate change (not shown). In addition, the warming is also observed over Iceland and around the Barents Sea. The surface air temperature composite difference result based on the CNN technique (figure S2) is consistent with the past and present ten year mean difference.

Interestingly, these areas (western Europe, Iceland, and around the Barents Sea; green box in figure 2(b)) correspond to the region with significant
positive temperature tendency (figure 2(c)) which causes season transition from spring to summer, from 22–31 May to 1–10 June during 1979–1988 (CNN training period). This implies that warming tendency in above mentioned three regions is essential for the transition to the summer from spring. Therefore, if anomalous warming occurs during late May over these regions due to global heating, there is great impact in the forward shift of summer onset. The CNN model captures these characteristics well, and thus the model finally predicts the earlier onset trend of summer.

5. Physical mechanisms of the early onset trend of summer

According to the heat budget analysis, the warming trend over western Europe in late May is primarily owing to the SHF (black box plots in figure 2). However, Iceland is mainly affected by a meridional temperature advection, while an LHF primarily influences the region around the Barents Sea. It is seen that the warming of each region appears to be caused by different thermodynamic processes; however, the above mentioned phenomena are broadly linked to a large-scale anti-cycloic circulation anomaly covering western Europe and the northern Atlantic Ocean (figure 3(d)). Note that the anti-cycloic wind speed anomaly is similar or even more intense than the climatological horizontal wind (figures 3(a) and (d)).

The cloud cover over Western Europe is significantly reduced; therefore, the more solar radiation is directly absorbed in the surfaces contributing the increase of the surface SHF. The cloud decrease may be due to the dry advection from higher latitudes and adiabatic sinking in the high-pressure region. On Iceland, the southwesterly wind generated by the anti-cycloic circulation anomaly transports heat from lower latitudes (figures 3(b) and (e)). The anomalous southwesterly flow transports heat to the higher latitudes in the atmosphere and also via the ocean. As a result, sea-ice concentration is reduced in the Barents Sea, further strengthening the surface LHF (figures 3(c) and (f)).

Now, it is clear that the occurrence of anomalous anti-cycloic circulation over the Eastern North Atlantic to the Western Europe has a significant role on the early transition from spring to summer. Consistent with this result, the anti-cycloic circulation is developed similarly but more widely from 22–31 May to 1–10 June during 1979–1988 (figure S4). One
of the possible mechanisms for the early development of the anti-cyclonic circulation anomaly is the poleward expansion of the Bermuda/Azores High, in association with a sinking branch of the local Hadley circulation, due to global heating (Lu et al 2007, Schwendike et al 2015). Specifically, the poleward expansion of the local Hadley circulation induces that a westerly jet stream moves to the north via northward angular momentum transport (Held and Hou 1980). In the Atlantic Ocean during 1979–1988, the mid-latitude westerly jet is located at 40°–50° N; however, the westerly jet gradually shifts northward (figure S5). As a result, the westerly wind speed over the upstream region of Greenland (70°–50° W, 50°–72.5° N, 500–150 hPa) has strengthened from 6.86 m s⁻¹ in 1979–1988, to 8.33 m s⁻¹ in 2011–2020. As the jet stream flows eastwards, it impinges huge topography in Greenland, generating downstream stationary Rossby waves (Son et al 2020, 2021, Son and Seo 2022). The WAF shows the Rossby wave propagation path (Seo et al 2011), as it moves from Greenland to the southeast, as shown in figure 4. Following the thick purple arrows with a latitudinal 40° window, the eddy stream function was calculated both in observations and using the Rossby wave theory (figure 4(b)). Overall, we show the occurrence of anomalous anti-cyclonic circulation, as represented by the positive eddy streamfunction, is in line with
In addition to the early onset of summer, a shortening of winter was also detected via the CNN model prediction, as shown in figure 1. The shortening of winter is presumed to be a direct result of global heating. Based on the INM-CM5-0 future simulation using ssp585 scenario (figure S6), European historical winter is projected to vanish by the end of the 21st century. The primary emphasis of our study has been of summer-related changes, as warmer winters are currently not an urgent climate crisis. However, the changes in winter dynamics could be incremental and exponential, having the potential to rapidly and unexpectedly alter ecological dynamics to a large extent; such changes could have catastrophic implications. This is especially true if the changes are mainly tied to the anthropogenic heating of the planet. Therefore, studies dedicated to this phenomenon, in conjunction with its continuous monitoring, are of utmost importance.

Interestingly, based on the CNN model, the early onset of summer is not evident in any other region, except for Europe (not shown). The observed regional response to the global heating is not homogeneous due to regionally working internal variations (Wentz 2007, Dai 2013, Fu et al 2013, Seo et al 2013, Zhou et al 2014, Jiang et al 2019, Papalexiou and Montanari 2019). This result could emphasize the drastic nature of the consequences of global heating, prompting a sense of urgency in addressing the issue at hand. However, the main limitation of this study is that only temperature fields were used to demarcate seasons. It is possible to simply characterize summer as a hot period, but there is an array of region-specific factors that result in there being subtle differences in seasonal instances that can be universally classified as summer. These factors include wind direction, humidity, or a deviation in precipitation dynamics. Therefore, for future studies, it will be important to apply the CNN method to regions other than Europe and to include more parameters, instead of only applying an approach that is narrowed down to temperature; these studies would also include sensitivity tests, to ensure that the most important variables are used.

Data availability statement

The data that support the findings of this study are openly available. All raw datasets can be accessed via the links provided in the section of Dataset.

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Conflict of interest

The authors declare no competing interests.

Code availability

All the code associated with this paper are available from the corresponding authors upon request.
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Author contributions statement

J S, K H, G K, and J K conceptualized the paper. J S performed the analyses and wrote the most of the manuscript. N K and J S constructed the deep learning model. J S, N K, G K, J C, J P, J K, and K H discussed the results and contributed to the writing of the paper.

ORCID iDs

Jun-Hyeok Son  https://orcid.org/0000-0002-7004-8814
Jung-Eun Chu  https://orcid.org/0000-0003-2088-4758

References

Christidis N, Jones G S and Stott P A 2015 Dramatically increasing chance of extremely hot summers since the 2003 European heatwave Nat. Clim. Change 5 46–50
Dahl G E, Sainath T N and Hinton G E 2013 Improving deep neural networks for LVCSR using rectified linear units and dropout Proc. 2013 IEEE Int. Conf. on Acoustics, Speech and Signal Processing pp 8609–13
Dai A 2013 Increasing drought under global warming in observations and models Nat. Clim. Change 3 52–58
Deser C, Knutti R, Solomon S and Phillips A S 2012 Communication of the role of natural variability in future North American climate Nat. Clim. Change 2 775–9
Dunn R J et al 2020 Development of an updated global land in situ–based data set of temperature and precipitation extremes: HadEX3 J. Geophys. Res. Atmos. 125 e2019JD032863
Fu R et al 2013 Increased dry-season length over southern Amazonia in recent decades and its implication for future climate projection Proc. Natl Acad. Sci. USA 110 18110–5
García-León D, Casanueva A, Standardi G, Burgstall A, Flouris A D and Nyboe L 2021 Current and projected regional economic impacts of heatwaves in Europe Nat. Commun. 12 5807
Gemmell I, McLoone P, Boddy F A, Dickinson G J and Watt G C M 2000 Seasonal variation in mortality in Scotland Int. J. Epidemiol. 29 274–9
Ham Y-G, Kim J-H, Kim E-S and On K-W 2021 Unified deep learning model for el Niño/Southern Oscillation forecasts by incorporating seasonality in climate data Sci. Bull. 66 1358–66
Ham Y-G, Kim J-H and Luo J J 2019 Deep learning for multi-year ENSO forecasts Nature 573 568–72
Held I M 1983 Stationary and quasi-stationary eddies in the extratropical troposphere: theory Large-Scale Dynamical Processes in the Atmosphere ed B J Hoskins and R P Pearce (New York: Academic) pp 127–68
Held I M and Hou A Y 1980 Nonlinear axially symmetric circulations in a nearly inviscid atmosphere J. Atmos. Sci. 37 515–33
Hersbach H et al 2020 The ERA5 global reanalysis Q. J. R. Meteorol. Soc. 146 1999–2049
Jiang Y, Zhou L, Tucker C J, Raghavendra A, Hua W, Liu Y Y and Joiner J 2019 Widespread increase of boreal summer dry season length over the Congo rainforest Nat. Clim. Change 9 617–22
Kingma D P and Ba J J 2015 Adam: a method for stochastic optimization Int. Conf. on Learning Representations pp 1–13
Lu J, Vecchi G A and Rechler T 2007 Expansion of the Hadley cell under global warming Geophys. Res. Lett. 34 L06805
Oh J, Ha K J and Jo Y H 2022 A predictive model of seasonal clothing demand with weather factors Asia-Pac. J. Atmos. Sci. 1–12
Oh J, Jo Y H and Ha K J 2021 The effect of anomalous weather on the seasonal clothing market in New York Meteorol. Appl. 28 e1982
Papalexiou S M and Montanari A 2019 Global and regional increase of precipitation extremes under global warming Water Resour. Res. 55 4901–14
Rayner N A, Parker D E, Horton E B, Folland C K, Alexander L V, Rowell D P, Kent E C and Kaplan A 2003 Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century J. Geophys. Res. 108 4407
Scherer S C, Fischer E M, Posselt R, Liniger M A, Croci-Maspoli M and Knutti R 2016 Emerging trends in heavy precipitation and hot temperature extremes in Switzerland J. Geophys. Res. Atmos. 121 2626–37
Schwendike J, Berry G J, Reeder M J, Jakob C, Govekar P and Wardle R 2015 Trends in the local Hadley and local Walker circulations J. Geophys. Res. Atmos. 120 7599–618
Seo K-H, Lee H-J and Frierson D M W 2016 Unraveling the teleconnection mechanisms that induce wintertime temperature anomalies over the Northern Hemisphere continents in response to the Madden-Julian oscillation J. Atmos. Sci. 73 3557–71
Seo K-H, Oh J, Son J-H and Cha D-H 2013 Assessing future changes in the East Asian summer monsoon using CMIP5 coupled models J. Clim. 26 7662–75
Seo K-H, Son J-H, Lee J-Y and Park H-S 2015 Northern East Asian monsoon precipitation revealed by air mass variability and its prediction J. Clim. 28 6221–33
Seo K-H, Son J-H, Lee S-E, Tomita T and Park H 2011 Mechanisms of an extraordinary East Asian summer monsoon event in July 2011 Geophys. Res. Lett. 38 1–6
Shevchenko O, Lee H, Snizhko S and Mayer H 2014 Long-term analysis of heat waves in Ukraine Int. J. Climatol. 34 1642–50
Son J-H, Kwon J-I and Heo K-Y 2021 Weak upstream westerly wind attracts western North Pacific typhoon tracks to west Environ. Res. Lett. 16 124041
Son J-H and Seo K-H 2022 East Asian summer monsoon precipitation response to variations in upstream westerly wind Clim. Dyn. 59 77–84
Son J-H, Seo K-H and Wang B 2020 How does the Tibetan Plateau dynamically affect downstream monsoon precipitation? Geophys. Res. Lett. 47 095043
Souza P M, Barriopedro D, García-Herrera R, Ordóñez C, Soares P M M and Trigo R M 2020 Distinct influences of large-scale circulation and regional feedbacks in two exceptional 2019 European heatwaves Commun. Earth Environ. 1 48
Srivastava N, Hinton G, Krizhevsky A, Sutskever I and Salakhutdinov R 2014 Dropout: a simple way to prevent neural networks from overfitting J. Mach. Learn. Res. 15 1929–58
Stull R B 1988 An Introduction to Boundary Layer Meteorology (Dordrecht: Springer)
Szegedy C, Vanhoucke V, Ioffe S, Shlens J and Wojna Z 2016 Rethinking the inception architecture for computer vision Proc. IEEE Conf. on Computer Vision and Pattern Recognition pp 2818–26
Takaya K and Nakamura H 2001 A formulation of a phase-independent wave-activity flux for stationary and
migratory quasigeostrophic eddies on a zonally varying basic flow J. Atmos. Sci. 58 608–27
Twardosz R and Kossowska-Cezak U 2013 Exceptionally hot summers in Central and Eastern Europe (1951–2010) Theor. Appl. Climatol. 112 617–28
Ulrike P H, Claudia H, Kathrin G and Florian B 2021 Climate change: impacts on outdoor activities in the summer and shoulder seasons J. Outdoor Recreat. Tour. 34 100344
von Engeln A and Teixeira J 2013 A planetary boundary layer height climatology derived from ECMWF reanalysis data J. Clim. 26 6575–90
Wang L, Ouyang W, Wang X and Lu H 2015 Proc. IEEE Int. Conf. on Computer Vision pp 3119–27 (available at: www.cv-foundation.org/)
Wentz F J, Ricciardulli L, Hilburn K and Mears C 2007 How much more rain will global warming bring? Science 317 233–5
Xu P, Wang L, Liu Y, Chen W and Huang P 2020 The record-breaking heat wave of June 2019 in Central Europe Atmos. Sci. Lett. 21 e964
Zhou L et al 2014 Widespread decline of Congo rainforest greenness in the past decade Nature 509 86–90