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Comparison of health risks by heat wave definition: applicability of wet-bulb globe temperature for heat wave criteria

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Abstract

Despite the active applications of thermal comfort indices for heat wave definitions, there is lack of evaluation for the impact of extended days of high temperature on health outcomes using many of the indices. This study compared the impact of heat waves on health outcomes among different heat wave definitions based on thermal comfort and air temperature. We compared heat waves in South Korea (cities and provinces) for the warm season for 2011-2014, using air temperature, heat index (HI), and web-bulb globe temperature (WBGT). Heat waves were defined as days with daily maximum values of each index at a specified threshold (literature-based, the 90th and 95th percentiles) or above. Distributed lag non-linear models and meta-analysis were used to estimate risk of mortality and hospitalization for all-causes, cardiovascular causes, respiratory causes and heat disorders during heat wave days compared to non-heat wave days. WBGT identified 1.15 times longer maximum heat wave duration for the study periods than air temperature when the thresholds were based on 90th and 95th percentiles. Over the study period, for heat waves defined by WBGT and HI, the Southwestern region showed the highest total number of heat wave days, whereas for air temperature the longest heat wave days were identified in the southeastern region. The highest and most significant impact of heat waves were found by WBGT for hospitalization from heat disorders (Relative risk=2.959, 95% CI: 1.566 – 5.594). In sensitivity analyses

using different structure of lags and temperature metrics (e.g., daily mean and minimum), the impacts of heat waves on most health outcomes substantially increased by using WBGT for heat wave definitions. As a result, WBGT and its thresholds can be used to relate heat waves and heat-related diseases to improve the prevention effectiveness of heat wave warnings and give informative health guidelines according to the range of WBGT thresholds.

Abbreviations

AT, Apparent Temperature; COMS, Communication, Ocean and Meteorological Satellite; HI, Heat Index ;GAM, generalized additive model; HHWS, Heat-Health Warning System ; NMSC, National Meteorological Satellite Center; WBGT, Wet-bulb globe temperature;WMO, World Meteorological Organization; WHO, World Health Organization

Keywords

Heat wave, temperature, climate change, mortality, morbidity

1. Introduction

The significant associations between high temperature and mortality (Anderson and Bell, 2011; Guo et al., 2017) and morbidity have been studied in many parts of the world. Particularly, the harmful effect of high temperature on cardiovascular and respiratory mortality (Burkart et al., 2011; Guo et al., 2011; Urban et al., 2014) and morbidity (Michelozzi et al., 2009; Turner et al., 2012; Urban et al., 2014) have been widely reported. Climate change is expected to increase the frequency, intensity, and duration of heat waves, which will exacerbate heat-related health problems (Gasparrini et al., 2017; Jianyong et al., 2014; Lee et al., 2014; Schoetter et al., 2015). South Korea faces this concern as the total heat wave disease burden in 2008 (5.19 disability-adjusted life years /1,000 population) is expected to double in 2100 (9.53 disability-adjusted life years/1,000 population) (Yoon et al., 2014). Thus, understanding associations between heat waves and various health outcomes is essential to prevent the current and future burden of heat impacts on human health.

Many countries and organizations have made efforts to prevent the risk of heat-related health problems (Lowe et al., 2011). One such preventive measure is to implement a heat-health warning system (HHWS). A HHWS composes a series of actions: developing the system including selecting the heat wave metric to use, forecasting heat waves, predicting and monitoring the occurrence of diseases, and alerting health service organizations and specific target population (Heo et al., 2016). HHWSs announce a heat wave warning to the public for a number of consecutive days when temperature exceeds a particular threshold, generally a temperature at which excess deaths are predicted (WHO and WMO, 2015).

In many cases, HHWSs adopted thermal comfort indices, which quantify a combined effect of a series of meteorological factors (e.g., air temperature, humidity, and wind) on perceived temperature, to represent the actual human thermal situation during heat waves (Lowe et al., 2011; WHO and WMO, 2015). For example, the governments of Germany and Switzerland use a Perceived Temperature and Heat Index (HI) to set national heat wave warning definitions, respectively (Lowe et al., 2011). The Korean Meteorological Administration (KMA) formerly used HI for the national heat wave definition for a few years, but the current national definition of a heat wave is days for which the daily maximum temperature is at or above 33◦C for two or more consecutive days. HI and corresponding health risk categories defined by the US National Oceanic and Atmospheric Administration (NOAA) are currently provided as life-related weather service by the KMA.

Despite the well-known association between high temperature and health outcomes, the health implications of different heat wave definitions and temperature metrics are not fully understood (Zhang et al., 2014b). Varied levels of risk of heat-related mortality for the same study period in a population can be seen among thermal indices due to their different formula to calculate human thermal stress (Kim et al., 2006, 2011; Urban and Kyselý, 2014). Some research has suggested that which thermal index is used for a HHWS influences the number of heat wave days, the severity of those days (Hajat et al., 2010), and the association between heat waves and health on those days (Vaneckova et al., 2011). Therefore, the effectiveness of a HHWS using a thermal index (including ambient temperature) depends on how properly the heat wave definition can relate heat wave periods and related health problems, and choice of which thermal index to use is a critical public health issue for policy.

Wet-bulb globe temperature (WBGT) is one of the most commonly used indices by many organizations since the 1960s (Blazejczyk et al., 2012). This index was originally invented in the 1950s in efforts to lower the risk of heat disorders during the training of the US Army and Marine troops (Budd, 2008; D'Ambrosio Alfano et al., 2014). Since that time, WBGT has been applied in other settings, and is widely used for the evaluation of occupational heat stress exposure (D'Ambrosio Alfano et al., 2014). WBGT is a weighted average of dry-bulb (air) temperature, natural wet-bulb temperature and black globe temperature. Black globe temperature is a function of radiant heat, temperature, and wind while natural wet-blub temperature measures the amount of cooling by humidity and wind (Budd, 2008). By incorporating black globe temperature, WBGT considers radiation effect whereas many other simplified thermal comfort indices do not. In sunny conditions, the weighting coefficients are 0.7, 0.2, and 0.1 for natural wet temperature, globe temperature, and dry-bulb temperature, respectively. At other times, the weighting coefficients are 0.7 and 0.3 for natural wet temperature and dry-bulb temperature, respectively, while the globe temperature is not considered in the calculation. Until recently, several approximation formulas of WBGT using readily available meteorological data (e.g., temperature, humidity, wind, and radiation) have been suggested for practical use as the original components for calculating WBGT are not standard meteorological monitoring data.

Despite the active applications of WBGT by several organizations in the field of industrial hygiene (Lucas et al., 2014) and the military (Budd, 2008), there is a lack of studies that evaluate the impact of

WBGT on health. Although a previous study has assessed the level of black globe temperature for a small region (Park & Park, 2008) in South Korea, there are few cases that study the distribution and trends of WBGT for the whole country. Likewise, very few studies examined applicability of WBGT for heat wave definitions compared to the number of studies on air temperature for a HHWS.

This study aims to assess the implication of WBGT on heat wave warning systems, by comparing heat-related health impacts during heat wave days compared to non-heat wave days across regions in South Korea. The health impact of heat waves was compared among various heat wave definitions considering air temperature, HI, and WBGT. The assessment for impact of heat waves was based on the total effect of heat and heat waves obtained from analyses with different adjustment for the delayed heat effects through various lag structures. To define heat waves' criteria for air temperature, HI, and WBGT, we applied different threshold temperatures. We targeted mortality and morbidity causes from previously studied heat-related health outcomes such as cardiovascular, respiratory diseases and heat disorders. As our study applied a WBGT approximation formula in the analyses, we aimed to examine the applicability of the equation through comparison between approximated and observed WBGT values. Our study gives insight to decision-makers regarding the effectiveness of WBGT for a HHWS to inform on which indices best protect the public from health risks from heat waves.

2. Materials and Methods

2.1. Study area and period

Study regions include seven metropolitan cities (Seoul, Busan, Daegu, Incheon, Gwangju, Daejeon and Ulsan) and nine provinces (Gyeonggi, Gangwon, Chungbuk, Chungnam, Jeonbuk, Jeonnam, Gyeongbuk, Gyeongnam and Jeju) in South Korea. The climate of South Korea is temperate and there are four distinctive seasons with the coolest weather from December to February and the hottest weather from June to September. The study period covers the warm season (June through September) for 2011–2014.

2.2. Data description

Mortality data were collected from the Korean National Statistical Office for the study period. The data were coded by age, sex, address and cause of death according to the International Classification of Diseases, Injuries and Causes of Death, 10th version (ICD-10 code). The daily all-cause mortality except for deaths caused by accidents (V00-V99), mortality from cardiovascular causes (I00-I99), and mortality from respiratory causes (J00-J99) were calculated for each study region (cities and provinces).

Morbidity data of cardiovascular diseases (I00-I99), respiratory diseases (J00-J99) and heat disorders (T67) in 2011-2014 were collected from the National Emergency Department Information System (NEDIS) of the National Emergency Medical Center, and appropriate Institutional Review Board approval for use of pre-existing data involving human subjects was obtained. NEDIS is an electronic system that records medical information of the patients in real time and assesses the quality of the treatments of institutions in South Korea. The data have information on patients including age, sex, symptom coded by ICD-10 code, result of examination at emergency room, and admission date. Hospitalizations were defined as admissions for patients whose result of examination at emergency room was ‘hospitalization’ code. The daily cause-specific numbers of hospitalization were aggregated for each study region.

Daily 24-hour data of air temperature (℃), relative humidity (%) and wind speed (m/s) were obtained from 284 monitoring stations of the KMA for each summer season (June to September). We used 4 km x 4 km binary data of solar insolation from the Communication, Ocean and Meteorological Satellite (COMS), which is a Korean geostationary satellite. Solar insolation data represents the amount of solar energy reaching per unit area of body surface (W/m^2). The COMS computes solar insolation based on the Kawamura model (Kawamura et al., 1998), which uses separate algorithms for locations with and without clouds. The gridded insolation values were linked to the weather monitoring data.

HI attempts to represent the human perceived temperature by the impact of humidity. The equation used by the National Weather Service of the NOAA, as applied by Rothfusz (Rothfusz, 1990) and Steadman (Steadman, 1979a), was applied to estimate HI values in our study.

$$\begin{aligned}\mathrm{HI} = &-42.379 + 2.04901523 \times RH - 10.14333127 \times RH - 0.22475541 \times T \times RH \\ &- 0.00683783 \times T^2 - 0.05481717 \times RH^2 + 0.00122874 \times T^2 \times RH \\ &+ 0.00085282 \times T \times RH^2 - 0.00000199 \times T^2 \times RH^2\end{aligned} \tag{1}$$

, where T is temperature in ºF and RH is relative humidity in percent.

The equations suggested by Ono and Tonouchi (Ono and Tonouchi, 2014) and the Australian Meteorological Bureau were applied to the available existing data for the current study. We applied the validation process, as described in the statistical analysis section, for the WBGT estimates calculated from the equation of the Australian Meteorological Bureau, and found overestimation of the WBGT estimates (Bias = 3.076, root mean squared error (RMSE) = 11.162, mean absolute error (MAE) = 3.076, and index of agreement (IOA) = 0.998). Based on this larger overestimation of the method by the Australian Meteorological Bureau compared to that of Ono and Tonouchi (Ono and Tonouchi, 2014), we applied the Ono and Tonouchi approach. The estimation of WBGT based on the approximation formula developed by Ono and Tonouchi was applied to hourly data of each ground monitoring site of the study regions.

$$\begin{aligned}\mathrm{WBGT} = &\, 0.735 \times \mathrm{Ta} + 0.0374 \times RH + 000292 \times \mathrm{Ta} \times RH + 7.619 \times SR - 4.557 \times SR^2 - \\ &0.0572 \times WS - 4.064\end{aligned} \tag{2}$$

, where *Ta*, *RH*, *SR*, and *WS* are air temperature (℃), relative humidity (%), solar insolation (kW/m^2) and wind speed (m/s), respectively. Daily mean air temperature and WBGT were averaged from hourly values on a given day for each monitoring site. Region-specific maximum and mean of air temperature, HI, and WBGT were calculated by averaging daily measurements from multiple stations within a study region. For the validation of approximation of WBGT using equation 2, we obtained WBGT measurements from a local representative ground monitoring station in the city of Seoul located at 37º34’17” N and 126º57’57” E. This WBGT data were measured as a weighted average of the three original weather components mentioned in the Introduction. Black globe temperature was measured by a 150 mm black globe thermometer and natural wet-bulb temperature (T_w) was calculated by Stull's estimation formula: $[T_w = Ta \cdot \arctan[0.151977(RH + 8.313659)^{1/2}] + \arctan(Ta + RH) - \arctan(RH - 1.676331) + 0.00391838(RH)^{3/2}\arctan(0.023101RH) - 4.686035]$ (arctan=the arctangent function) (Stull, 2011). The observed WBGT values were available from April 14-30, 2016.

2.3. Definition of heat waves

We compared the trends of heat waves in the study regions between those identified by air temperature, HI, and WBGT using several heat wave definitions. First, we defined heat waves of each study region using air temperature, HI, and WBGT as days with daily maximum values ≥ the selected thresholds for 2 or more consecutive days. This threshold was derived from the piece-wise analysis described in the statistical analysis section 2.4.2, which applies separated segmented regression lines for the dose-response relationship between the index and health risks built on a Generalized Additive Model and is used to identify the statistically significant minimum mortality temperature (MMT) where the risk of mortality is at a minimum (Muggeo, 2008).

For the equivalent comparison between air temperature, HI, and WBGT, we also defined region-specific heat waves using 90th and 95th percentiles of each index's distribution in each study region.

2.4. Statistical analysis

2.4.1. Data validation

The solar insolation of COMS and estimated WBGT values were validated by comparing these values to observed data. Validation of the WBGT values calculated from the equation 1 is needed for verifying agreement with observed WBGT values. As equation 1 is based on the solar radiation on a flat horizontal plane (i.e., global horizontal radiation) measured at a ground-based monitoring station (Ono and Tonouchi, 2014), the solar radiation data from different types of data sources need to be validated as well. For the comparison of estimated (M_i) and observed (O_i) values for value i, we used parameters that previous studies (Baek et al., 2013; López and Batlles, 2013; Weihs et al., 2012) used: computed correlation coefficient, bias $[\{\sum(M_i - O_i)\}/N]$ and root mean square error (RMSE) $[\sqrt{\{\sum(M_i - O_i)^2\}/N}]$, mean absolute error (MAE) $[(\sum|M_i - O_i|)/N]$, and IOA $[1 - \{\sum(M_i - O_i)^2/\sum(|M_i - \bar{M}| + |M_i - \bar{O}|)^2\}]$ ($\bar{M}$ = mean value of M_i across all values, $\bar{O}$ = mean value of O_i, N = the number of samples). For Bias, RMSE and MAE, zero indicates the absence of error and consistency of estimated data and observed data. The closer to one for IOA, the more similarity between estimated and observed data. A value of one for IOA indicates complete similarity between estimated and observed variables.

2.4.2. Estimation of minimum mortality temperature

To identify the thresholds where the number of health outcomes increase against temperature (i.e., the minimum mortality temperature, MMT), a generalized additive model (GAM) with a link function and a Quasi-Poisson distribution and piecewise regressions were separately built for each region, each index and each health outcome. Generalized additive models allow non-linear relationships between dependent and independent variables by applying natural cubic splines (Schwartz and Schwartz, 2016). The GAMs were first built for temperature as follows;

$$\ln[E({Y^c}_t)] = {\beta^c}_0 + a^c {T^c}_t + y^c DOW_t + {\gamma^c}_i AP_{it} + ns(Time_t, df = 2) + \mathrm{ns}\left({Humidity^c}_t, df = 2\right) + B_t^c \quad (3)$$

, where $E({Y^c}_t)$ = the expected number of cause-specific death counts (or hospitalizations) for region c on day t; ${\beta^c}_0$ = the model intercept, a^c = the vector of regression coefficients for the mortality (or hospitalization) against heat for region c; ${T^c}_t$ = the temperature (or thermal index); DOW_t = the categorical variable of day of the week on day t; AP_{it} = the individual variable of the daily mean of air pollutants (particulate matter with diameter ≤ 10μm (PM_{10}) (μg/m^3) and ozone (ppm)); $ns(Time_t)$ = the natural cubic spline of calendar time with 2 degrees of freedom per summer season (June to September); $\mathrm{ns}\left({Humidity^c}_t\right)$ = the natural cubic spline of relative humidity with 2 degrees of freedom, and ${B^c}_t$ = offset term of region-specific (region c) annual population on day t. The natural cubic spline of temperature was included in the model to separate the estimated effect of extended days of exceptional heat from those of high temperature alone. For the GAMs of HI and WBGT, the term $\mathrm{ns}\left({Humidity^c}_t\right)$ was excluded because the formulation of these indices includes relative humidity.

Piece-wise regression models were applied to each GAM to apply segmented regression lines for the thermal index and to identify the statistically significant threshold where the risk of mortality starts to increase against the temperature. We applied iteration for fitting GAMs for 2 or 3 segmented lines for the relationship between heat and health outcomes with testing of different break points. We regressed 3 segmented lines for the relationship when the left segment among the three lines showed significantly different slope based on the Davies test (Davies, 1987; Muggeo, 2008) for the final converged model. When 3 segmented lines were applied and the Davies test for the left segment did not show significance for the difference in slopes, we applied 2 segmented lines (i.e., 1 break point) to the relationship between temperature and health outcomes. Also, when the middle segment and the left segment showed both positive or both negative slopes in the model with significant results from Davies test, we applied 2 segmented lines. For the models with 2 segmented lines applied, the difference in the slopes was tested and every model showed significance for the identified break point (i.e., threshold) and the difference in slopes. This analysis was conducted for each index's GAM for the entire study region. The analysis also was conducted separately for daily maximum, mean, and minimum indices. As shown in equation 3, the process of identifying thresholds considers exposure to heat as estimated by an index on a given day, 2 degrees of freedom for calendar time per summer season, and 2 degrees of freedom for humidity were considered during the process of identifying thresholds.

When fitting the distributed lag non-linear models (DLNMs) with specific settings for lag structure and degrees of freedom for natural cubic splines, reliability of the applied threshold can be assessed by model fitting. However, the identified temperature based on model fitting is sensitive to the specification of the incorporated variables. Before fitting DLNMs with segmented lines for the assumption of the non-linear relationship between heat and health outcomes, we first considered the significance of non-linearity and the threshold making that significant difference for the segmented lines. Piece-wise analysis with the Davies test was applied to test the non-linearity of applied segmented lines using the R 'segmented' package. The identified thresholds were applied to the distributed lag models using GAMs described below in section 2.4.3.

2.4.3. Distributed lag non-linear models and meta-analysis for risk estimation

The impact of heat and heat waves were assessed separately for different heat wave thresholds of daily maximum indices (T_{max}, HI_{max}, and $WBGT_{max}$) to examine if the impact of heat waves varies by the type of index. The effect of heat on a single day is distributed across several subsequent days (lag)

(Schwartz and Schwartz, 2016) and the DLNMs were widely used to address displacement of effect. Risk estimation of heat is sensitive to modeled delayed heat effects. Thus, we applied four methodologies to estimate the overall multi-day impact of heat through delayed effects and heat wave days separately on cause of mortality (or hospitalization) by heat wave definitions (i.e., the 90th and 95th percentiles of each study region, the MMT) of each index and study regions: 1) distributed lag non-linear models (DLNMs) with polynomial function for the previous 20 days (lag 20), 2) DLNMs with stratified intervals for lag 20 (e.g., lag 0-1, lag 2-4, lag 5-8, lag 9-13, lag 14-20), 3) distributed lag models using a 2-day moving average of temperature (thermal index), and 4) unconstrained distributed lag models using single temperature on the lag 0 and the lag 1. The results present the overall effect of heat for multi-day lags of the four methodologies: 21 days (lag 0 – lag 20) for the first two methodologies and 2 days (lag 0 – lag 1) for the others. Distributed lag non-linear models allow constraint for the shape of the heat effect on a day for a range of lags with some models (e.g., polynomial functions, lag-stratified models). The model is based on a 'cross-basis', which is a bi-dimensional space of functions that describe the simultaneous relationship of both heat and the lag dimension on the dependent variable (i.e., health outcome) (Gasparrini, 2014; Gasparrinia et al., 2010). The cross-basis function with different assumption on lag structure were applied to GAMs and the basis for temperature (thermal index) was centered at the thresholds obtained from the piecewise regression analyses. The DLNMs require setting the degrees of freedom for the distributed lag patterns (Gasparrinia et al., 2010), and we used 4 degrees of freedom for the polynomial function. We investigated lag effects over 20 days to address any potential long-term delayed heat effects (Guo et al., 2013). All models were built with a link function and a Quasi-Poisson distribution and included the categorical variable of heat wave on a given day, day of the week, daily mean of PM_{10} and ozone, $ns(Time_t, df=2)$, and $ns(Humidity^c{}_t, df=2)$, and offset term of annual population. We conducted sensitivity analyses applying 3 degrees of freedom for calendar time per summer season.

As single variables of temperature on days close together can be substantially correlated, we evaluated the Variance inflation factor (VIF) of variables in the unconstrained distributed lag models to examine the potential of multicollinearity among the variables. The impact of heat and heat waves were expressed as Relative Risks (RRs) with 95% confidence intervals (CIs). For sensitivity analyses, we applied DLNMs and GAMs for daily mean values of air temperature (T_{mean}), HI (HI_{mean}), and WBGT ($WBGT_{mean}$).

We estimated the overall risk across all the study regions for heat and heat waves, by applying a meta-analysis with each region-specific risk estimate (a^c). Assuming heterogeneity among study regions, a random-effect model was fitted to combine the risks. A random-effect model assumes that:

$$\theta_c = \mu + u_c + e_c, e_c \sim N(0, \sigma_c), u_c \sim N(0, \tau^2), \mathrm{i} = 1, \cdots, \mathrm{N} \quad (4)$$

, where θ_c is the region-specific risk for region c, μ is the corresponding true overall effect, e_c is the sampling error, σ_c is the within-region variance, τ^2 is the between-region variance, and N is the number of regions. (Viechtbauer, 2010). The goal of the meta-analysis was to estimate μ, the pooled heat wave risk across study regions, and its uncertainty, thereby reflecting risk across the entire study area. The DerSimonian-Laird estimator was applied to estimate the amount of heterogeneity among regions (τ^2). The DLNM analysis and meta-analyses were conducted using R 'mgcv', ‘dlnm’, and 'metafor' packages.

To compare the capability of the thermal indices for detecting health risks due to heat waves, we examined the Akaike Information Criterion (AIC) of the DLNMs and GAMs and the risk estimates of heat and heat waves among air temperature, HI, and WBGT.

3. Results

The averages of the daily T_{max}, $WBGT_{max}$, and HI_{max} of all study cities and provinces during the warm season (June through September) for 2011–2014 were 27.3ºC, 25.7ºC, and 29.4ºC, respectively. The interquartile ranges of each index were 4.5ºC, 4.4ºC, and 6.2ºC, respectively. The correlation coefficients of the T_{max} with $WBGT_{max}$ or HI_{max} were both 0.90. Table 1 shows descriptive statistics of each study region (cities and provinces). Average daily maximum temperatures ranged from 26.0ºC in Incheon to 29.6ºC in Daegu. Average daily maximum WBGT ranged from 24.7ºC in Gangwon to 27.1ºC in Daejeon. The range of HI_{max} was 27.9ºC to 30.9ºC.

Supplemental Table S8 shows the results of validation for estimated solar radiation values from remote sensing data and estimated WBGT. WBGT showed more similar data distribution (r=0.990, 95% CI: 0.987–0.992) to the observed values than solar radiation (0.903, 95% CI: 0.875–0.925). The bias for the estimated solar radiation and WBGT were -0.026 MJ/m^2 and -0.042 ºC, respectively, which indicates underestimation of each variable. High agreements were shown between the estimates and the monitored values: the IOA for solar radiation and WBGT were 0.893 and 1.000, respectively.

Fig. 1 shows the number of days identified as heat wave events during the study period (2011-2014) at weather monitoring stations based on different heat wave indices. The number of heat wave days ranged from 0 to 159 out of the 488 study days among the stations when heat waves were defined as ≥ 2 consecutive days with T_{max} at or above the 90th percentile of the distribution. When the 95th percentile of T_{max} was used for the definition, the number of heat wave days ranged from 0 to 96. For heat wave days defined as ≥ 2 consecutive days with daily $WBGT_{max}$ at or above the 90th and 95th percentiles, the number of days ranged from 0 to 157 and 0 to 120 across the stations, respectively. The number of heat waves days for the 90th and 95th percentiles of HI_{max} were similar to those of $WBGT_{max}$. The geographical patterns of the number of days differed among the heat wave definitions of $WBGT_{max}$, HI_{max}, and T_{max}; southern regions showed higher total number of heat wave days for the heat wave definitions based on T_{max} whereas a higher number of heat wave days were observed in western regions for definitions based on $WBGT_{max}$ and HI_{max}.

Fig. 2 shows the different geographic heat distributions for T_{max}, $WBGT_{max}$, and HI_{max} on the three hottest days of 2011 to 2014. Based on T_{max}, high level of heat exposure was distributed across the whole country whereas western coastal regions showed lower heat exposure level of $WBGT_{max}$ and HI_{max} compared to other regions on August 5, 2012 (Fig. 2, the first row). On August 11, 2012 (Fig. 2, the second row), the highest category of T_{max} (e.g., $T_{max} \geq 34.9$ºC) was distributed to southern regions whereas $WBGT_{max}$ and HI_{max} showed the highest category of heat exposure for a wider spatial range including western and southern regions. The geographic pattern of heat distribution on August 1, 2014 (Fig. 2, the third row) was similar between $WBGT_{max}$ and HI_{max} but T_{max} showed a slightly broader spatial pattern of the highest heat exposure level.

The number of heat wave events and the heat wave duration (the length of a heat wave in number of days) were compared between air temperature, WBGT, and HI (Table 2). The average of the maximum duration of a heat wave event among study regions were 18, 28, and 33 days for T_{max}, $WBGT_{max}$, and HI_{max}, respectively. The increase in the number of days with heat waves for $WBGT_{max}$ and HI_{max} were particularly higher in southern regions (i.e., Jeonnam). On the other hand, $WBGT_{max}$ with the threshold of 28°C (the MMT of WBGT for all-cause mortality) resulted in longer and more frequent heat wave events during the study period compared to the KMA's national heat wave definition ($T_{max} \geq 33$°C for 2 or more days); the total number of heat wave days was on average 6 times higher (Supplementary Fig. S1). According to the $WBGT_{max}$ definition of heat wave days as shown in Supplementary Fig. S1, southern regions showed relatively higher number of days with heat waves than northern regions during the study periods.

The RRs of mortality and hospitalization calculated from the DLNMs with polynomial function for the lag structure up to lag 20 days and the model with moving average of lag 0-1 are shown in Tables 3 and 4. The cumulative RRs of a 1°C increase in temperature over 20 days of lag were larger than that obtained from the moving average of lag 0-1. The constrained model using moving average of lag 0-1 had relatively higher risks for heat wave days compared to the DLNMs.

In the DLNMs, air temperature showed significant heat effects for all-cause mortality with heat wave definitions based on the 90th and 95th percentiles but no significant heat wave effects were found

(Table 3). HI_{max} and $WBGT_{max}$ showed significant heat wave effects but without significant heat effects.

The results for the risk estimation for heat and heat waves with different models (Table 3-4) were robust to the sensitivity analyses using 3 degrees of freedom per season for time trend except for hospitalization due to respiratory diseases (Supplementary Table S5-S6). For hospitalization due to all respiratory causes, significant heat wave effects were found for some indices only from the model with moving average of lag 0-1 (Table 4). In contrast, significant deleterious heat wave effects on respiratory hospitalizations were observed from the models considering distributed non-linear lag effect up to the 20 previous days for T_{max} and $WBGT_{max}$ when time trend was adjusted using 3 degrees of freedom per season (Supplementary Table S5-S6).

Regardless of whether the RRs were statistically significant, central estimates for the RRs were mostly higher for daily maximum indices compared to daily mean indices for all types of health outcomes except for respiratory hospitalization (Supplementary Table S3). The RRs for respiratory hospitalizations were relatively higher for the daily minimum index (Supplementary Table S4) compare to the other metrics.

For hospitalization due to heat disorders, the DLNMs with polynomial lag structures and the moving average showed significant risks for both heat and heat wave effects for HI_{max} and $WBGT_{max}$. The DLNM with polynomial (Table 4) showed the highest heat wave effect on hospitalization due to heat disorders for $WBGT_{max}$ with the 95th percentile (RR=2.339 (95% CI: 1.364 – 4.010)) compared to other heat wave definitions. Although the RRs were not significant, the central RRs of heat and heat waves tended to be higher for WBGT than air temperature or HI for all types of health outcomes except for hospitalization from all cardiovascular causes.

Supplementary Table S2 shows that the cumulative RRs obtained from the DLNMs with stratified intervals for lag effects (e.g., lag 0-1, lag 2-4, lag 5-8, lag 9-13, lag 14-20) were similar to the cumulative RRs of the DLNMs with polynomial lag structure with 4 degrees of freedom (Table 3-4). The cumulative RRs from the model using each of lag 0 and lag 1 heat variables (i.e., unconstrained model) were slightly lower than the RRs obtained from the constrained model using lag 0-1 moving average shown in Table 3-4 but the differences were negligible. The VIF values of the variables included in the unconstrained distributed lag models were less than 7 indicating a lack of multicollinearity among the variables. According to the I^2 statistics of meta-analysis, the daily maximum indices used in DLNMs and unconstrained models did not show particularly more or less heterogeneous estimates for heat wave effects among the study regions (Supplementary Table S7).

Akaike Information Criterion (AIC) values of the models using daily maximum air temperature and thermal indices are shown in Supplementary Fig. S2. The differences in the AIC values indicate a lack of substantial evidence for a better model fitting among the indices. Also, particularly lower AIC values for an index were not found among study regions.

4. Discussion

Which metric is selected for HHWSs can impact their effectiveness. However, the health implications of different heat wave definitions and temperature metrics are not fully understood. A heat wave is defined using several methodologies in terms of a threshold defining the heat wave intensity and the duration defining the minimum required number of consecutive days for continued heat exposure. In addition to the metrics used here (maximum temperature and WGBT), many thermal comfort indices such as Heat Index and Perceived Temperature have been used to define heat wave alerts around the world. A few studies have examined the dose-response relationship between ambient temperature itself and human health outcomes using thermal comfort indices in various parts of the world (Chung et al., 2009; Gronlund et al., 2014; Kim et al., 2011; Lin et al., 2012; Michelozzi et al., 2009), and the performance of thermal comfort indices on risk estimation of health outcomes was inconsistent among studies and according to geographical region and disease types. Only a few studies have assessed various health effects of extended days of high temperature (heat wave periods) designated by different thermal indices (Kent et al., 2013; Smith et al., 2013; Zhang et al., 2012).

We aimed to investigate how estimates of the health impacts of heat waves can be affected when WBGT was used for heat wave definitions instead of air temperature or HI. Several epidemiological studies have used other thermal comfort indices such as Apparent Temperature, but studies using WBGT are distinctively scarce. Although WBGT has been considered as one of standard indices for heat stress in occupational settings, expensive instrumentation and time-consuming attention for the maintenance of instruments have limited the use of WBGT in practice for other applications (Liljegren et al., 2008). The challenges of measuring WBGT have led to various estimation methods for WBGT: estimation formulas using standard meteorological variables (Liljegren et al., 2008; Ono and Tonouchi, 2014), physical modelling of black-globe temperature and natural wet-bulb temperature (Gaspar and Quintela, 2009), and methods using bio-geophysical variables (e.g., solar radiation) and satellite remote sensing data (Akatsuka et al., 2014). The published WBGT estimation formulas using meteorological components were reviewed by Lemke and Kjellstrom (Lemke and Kjellstrom, 2012). Among the published equations, those for modelling of black-globe temperature and natural wet-bulb temperature (Liljegren et al., 2008) could not be applied in our study due to lack of available data (e.g., solar zenith angle). After conducting data validation for the equations suggested by Ono and Tonouchi and the Australian Meteorological Bureau, which were applicable to the available existing data in this study, we decided to apply the method suggested by Ono and Tonouchi in our study.

Radiation is a critical source of heat load on human heat stress outdoors and indoors (Thorsson et al., 2014). As solar radiation is often not a standard monitoring variable, most epidemiological studies relied on other commonly monitored weather components from meteorological stations. For example, although some major thermal indices such as Apparent Temperature (Steadman, 1984, 1979b) were developed to consider the effect of radiation in the equations, previous studies tended to use a simplified version of Apparent Temperature or WBGT, which only use two parameters (e.g., air temperature and dewpoint temperature) (Gronlund et al., 2014; Lin et al., 2012; Vaneckova et al., 2011). A few other studies used an equation considering radiation for estimation of Apparent Temperature for health risk assessments (Kent et al., 2013; Morabito et al., 2014), but studies examining WBGT, which incorporates radiation effect in the equation, are rarer. The recent developments in approximation methods of WBGT and remote sensing data provided novel opportunities to evaluate spatial and temporal trends of outdoor thermal stress incorporating radiant heat for wide geographical regions.

When establishing heat wave criteria, choices must be made regarding which daily variable (e.g., daily average, maximum and minimum values) is the most appropriate in terms of the dose-response relationship and prediction for heat-related health outcomes (Morabito et al., 2014). For instance, a previous study using data for Detroit, Michigan used minimum temperature and humidity to identify heat wave days (Zhang et al., 2012), whereas a study assessing heat wave days in U.S. and European cities used mean values of temperature and thermal indices (Hajat et al., 2010). Another study reported that daily mean and maximum temperatures had similar capability to define heat waves, in contrast to minimum temperature (Guo et al., 2017). Daily maximum, mean and minimum values of air temperature, WBGT and HI were compared in our analysis. We focused on the results of daily maximum indices as WBGT showed slightly higher central estimates for the RRs for most health outcomes compared to daily mean or minimum indices (Supplementary Table S3-S4).

The health risk assessment is subject to the designated heat wave periods, and more extreme heat wave definitions with the higher thresholds generally identify fewer heat waves of shorter duration and higher intensity. Thus, the definitions with higher thresholds, which reflect the most intense heat waves but also lead to the shortest heat wave periods and fewer designated heat waves, may not necessarily result in the strongest or the most significant health effect estimate. This can be seen with the results of decreasing patterns of risk estimates with higher thresholds (i.e., 95th percentile vs. 90th percentile) across the heat waves definitions in our study.

Our study assessed heat effect on cause-specific mortality and morbidity across South Korea, whereas most other studies have targeted several metropolitan regions (Ha et al., 2011; Kim et al., 2006; Son et al., 2014). A previous study estimated total mortality increases during heat wave days in seven cities in South Korea in 2000 – 2007 and showed significant heat effects with various heat wave definitions (Son et al., 2012). The combined risks for mortality in our study were slightly lower than that of the above study, which may relate to the large study area and the differences of heat wave definitions. Evidence for the relationship between high temperature and hospitalization in South Korea is more limited than the studies assessing the risk in heat-related mortality. A previous Korean study used 98th percentile of daily mean temperature to define heat waves and observed significant estimated effects of heat waves on hospital admissions from cardiovascular and respiratory diseases (Son et al., 2014). In our analyses, significant heat wave effects were found for all-cause and cardiovascular mortality, respiratory hospitalization, and hospitalization due to heat disorders. No index showed significant heat wave effects for respiratory mortality or cardiovascular hospitalization. The model using moving average (lag 0-1) of T_{mean} (Supplementary Table S3) showed significant heat wave effects of air temperature for hospitalization due to cardiovascular diseases. According to previous studies, adverse effect of high temperature was observed more for mortality than morbidity for cardiovascular diseases due to rapid biological progression of cardiovascular effects to death before being admitted to a hospital (Åström et al., 2011). Whereas a previous study reported significant effects of heat on both hospitalization and mortality due to respiratory causes, our results did not show significant heat wave effects on respiratory mortality but on respiratory hospitalizations. The heat wave effects on hospitalization due to respiratory diseases were sensitive to adjustment of time trend in our study. For example, DLNMs using 3 degrees of freedom per season for time trend showed significant heat wave effects based on air temperature, whereas heat wave effects based on air temperature were not significant in the DLNMs using 2 degrees of freedom for time trend.

Several approaches have been applied to examine if a thermal index is reasonable for identifying health impacts of heat waves. We focused on the approach of risk estimation as the difference of model fitting based on AIC was insignificant in our study. The magnitude of risk estimates are one of the criteria for capacity of heat wave warnings for identifying heat wave days that pose significant health effects (Urban and Kyselý, 2014; WHO and WMO, 2015) in addition to AIC (Kim et al., 2006; Morabito et al., 2014) and cross-validated residual (Barnett et al., 2010). However, the actual selection of an index for heat wave warning systems depends on tradeoffs of many factors including model reliability of risk estimation through heat wave periods. The full criteria for selecting an index also could consider other factors such as the balance between sufficient warnings and how the public responds to the frequency of warnings, as well as the availability of data to estimate an index.

In our study, the central risk estimates of heat waves defined by WBGT were higher than that of air temperature or HI for risk of hospitalization due to heat disorders. Similarly, a Japanese study used daily maximum WBGT and found that the heat disorder incidence rate was more associated (i.e., higher risk) with WBGT than air temperature in some regions (Akatsuka et al., 2016). This may be because our WBGT better reflected outdoor heat exposure, which is a major cause of heat disorders, by considering solar radiation.

In the context of magnitude of risk estimates, $WBGT_{max}$ served as a reasonable predictor for the health outcomes for which significant heat wave effects were observed in our results, as it showed relatively higher central estimates of heat wave effects compared to T_{max}. $WBGT_{max}$ performed less was in predicting respiratory mortality or hospitalizations from cardiovascular diseases in our study. When daily minimum indices were used to estimate heat wave effects in our study, the health outcomes other than hospitalization due to heat disorders showed stronger heat wave estimated effects with T_{min} than T_{max}. $WBGT_{max}$ showed higher heat wave effect than $WBGT_{min}$ for most of health outcomes, whereas respiratory hospitalizations showed higher heat wave effects with $WBGT_{min}$ than $WBGT_{max}$. Daily minimum temperature has been used a proxy of nighttime temperature (Murage, Hajat, &

Kovats, 2017) and days with prolonged exposure to high minimum temperature are considered as tropical night phenomenon. As prolonged nighttime heat exposure implies lack of cooling during the nighttime, daily minimum temperature was associated with substantial effects on health outcomes including cardiovascular and respiratory diseases (Murage et al., 2017). The health effects of nighttime heat exposure might be more accurately measured by air temperature as WBGT would more represent heat exposure during the daytime by considering radiation effect. Our study did not fully elucidate the reason for the larger sensitivity of respiratory hospitalization to $WBGT_{min}$ and further research is necessary. Unlike other health outcomes such as mortality due to cardiovascular diseases, less severe progression from exacerbation of respiratory symptom to death is likely to contribute to the observation of nighttime heat effects on respiratory hospitalization. Our results suggest thermal comfort indices should be used with careful consideration of dose-response relationships that can differ by geographical region (Morabito et al., 2014) or disease types. Also, the current study suggests that the most effective HHWS may be developed by considering WBGT rather than air temperature alone to forecast heat waves and to warn of the risk of health outcomes for populations that are particularly vulnerable to outdoor heat discomfort.

The threshold value for the definition of WBGT based on our piece-wise models was 28°C. This threshold was similar to the cutoff temperature for 'warning' signs of the standard risk categories of WBGT for heat disorders: <21°C safe, 21≤WBGT<25°C caution, 25≤WBGT<28°C warning, 28≤WBGT<31°C severe warning, and ≥31°C danger (The Japanese Ministry of Environment, 2016). These risk categories were designed to provide guidelines for physical activities and rest times in everyday environments for preventing heat disorders by the Japanese Society of Biometeorology in 2008 (Japanese Society of Biometeorology, 2013). These categories are also similar to those of the WBGT reference guidelines with work and rest times published by the US Army (e.g., 26 – 27.9°C, 28 – 28.9°C, 29 – 30.9°C, 31 – 31.9°C, ≥32°C) (Department of the Army, 1980), which have been applied to health guidelines for occupational heat stress from the National Institute for Occupational

Safety and Health (Blazejczyk et al., 2012). The guidelines of the Japanese WBGT risk categories are particularly meaningful for population-based purposes as the guidelines from the US Army or occupational hygiene aim to protect workers who are typically healthier than average persons. Research may be needed to verify the categorization of WBGT's risk ranges and the range-specific health guidelines, and explore alternate categorizations, in relation to the status of heat-related health risks of Korean and other population.

Major stress, particularly for the cardiovascular system, constituted by excessive heat exposure can cause heat disorders (Kong et al., 2016). Even though heat waves have critical effects on heat disorders such as heat stroke, most health studies have evaluated the association between heat waves and morbidity using cardiovascular and respiratory diseases. This is driven partly by the tendency of heat disorders to be coded as cardiovascular and respiratory diseases in primary diagnoses and the corresponding underestimation of the number of heat disorders (Ye et al., 2012). Studies evaluating heat effects on heat disorders are mostly limited to those conducted in Western countries (Bobb et al., 2014; Dematte, 1998; Jones et al., 1982; Knowlton et al., 2009; Lippmann et al., 2013; Rydman et al., 1999; Semenza et al., 1999). Recent studies in Asian countries (Akatsuka et al., 2016; Bai et al., 2014) added findings of significant risks of heat disorders during heat waves in other regions, yet scientific evidence is still lacking on vulnerability and risk patterns in relation to demographic status (e.g., age), urban environment (e.g., urban and rural), and job status. For instance, different age structures in Japan and South Korea can contribute to different patterns for prevalence of heat disorders; for those age >65 years, the percent of deaths from heat disorders was 67% in South Korea during 2011-2014 (KCDC, 2014), whereas in Japan for those >60 years, 80% of deaths were from heat disorders in 2011 (Japanese Society of Biometeorology, 2013). Continuous increases in the number of heat-related hospitalizations, particularly from heat disorders (KCDC, 2014) during the summer season over time, raises the need for evaluation of the current health risks for evaluation of the predominant risk factors for heat disorders by different geographical locations.

Several studies reported that geographical patterns of heat stress and characteristics of heat waves during the same period varied according to the different heat wave definitions. In a previous study (Smith et al., 2013), various combinations of thresholds and indices including air temperature, HI, and Apparent Temperature showed that the region identified as the one with the highest frequency of heat waves varied by heat wave definition. In our study, different spatial patterns of heat distributions were observed between the indices for short-term (Fig 2) and long-term (Fig 1) periods. The numbers of days with heat waves were higher in southeast regions when using air temperature, whereas west and southwest regions showed higher numbers of days with heat waves based on WBGT. The geographic pattern of WBGT is consistent with the Korean Climate Change Evaluation Report (KMA, 2014); the number of days with heat waves was higher in lowland areas in the south eastern and southern regions. The geographic patterns of heat exposure during the hottest days of each year in this study indicated that daily outdoor heat exposure could be highly different based on which heat stress index is used.

The number of heat wave events and the heat wave duration varied by the heat wave definitions in our study. Interestingly, the heat wave definitions using WBGT estimated 54 heat wave days for the Gangwon prefecture, although the national heat wave definition using air temperature (based on the threshold 33°C) identified no heat wave days in this region. When a lower threshold, the 90th percentile of air temperature based on the distribution across all cities, was applied for the heat wave definition, this threshold temperature (32.2°C) was exceeded for 1 day in the Gangwon prefecture. This region is a mountainous area and the average altitude is higher than that of the other regions in the study area. Thus, this region is considered the coolest region among the prefectures and cities in South Korea. Our results imply that even a region with cool temperatures might experience considerable heat exposure, which likely causes heat-related health risks.

While we examined WBGT and HI, there exist alternative indices to air temperature that could be considered when examining heat stress. During the past decade, a thermal index considering not only weather components such as radiation but physiological thermal regulation has been suggested for valid assessment of outdoor thermal stress in the fields of public health. For instance, a Universal Thermal Climate Index was suggested by international collaborative working groups, and this advanced index incorporates including body thermoregulation models and heat exchange theory (Bröde et al., 2013). This index has been examined in few studies assessing patterns of heat exposure (Kong et al., 2016; Nastos and Matzarakis, 2012). However, it was suggested that subjective elements in calculation of the Universal Thermal Climate Index, such as clothing or physical activity, were not eligible for epidemiological studies over wide geographical regions with variability of such elements (Morabito et al., 2014). It is important to consider comparison of indices based on weather components to sophisticated indices such as Universal Thermal Climate Index in regards to applicability for heat wave warnings. Current national weather monitoring stations in South Korea do not monitor the variables needed for approximation of Universal Thermal Climate Index (e.g., mean radiant temperature), which makes the Universal Thermal Climate Index calculation impossible with our data at this time. This issue could be considered by future studies.

Effectiveness of a HHWS to prevent health risks from heat exposure is subject to the precision of weather forecast (Lowe et al., 2011; Zhang et al., 2014a). Temperature tends to be more accurately forecast than other weather components (Hajat et al., 2010), which may hinder the use of thermal indices that use other weather components for heat wave warnings. Currently, historical forecast data are available through an open data source for everywhere for components including temperature, humidity and wind speed. Before a practical use of WBGT for a HHWS, validation for forecast data of weather elements used for approximation of WBGT should be conducted. Consideration for cost of implementation and timely notification of heat wave warnings based on WBGT should be undertaken as well.

This study has several strengths. To the best of our knowledge, this is the first study to use WBGT for the estimation of increases in mortality and morbidity during heat wave periods for various heat-related health outcomes including cardiovascular diseases, respiratory diseases, and heat disorders.

Secondly, we studied a large number of geographical locations across South Korea using nationwide mortality and hospitalization data whereas previous studies of Korea have focused on smaller study areas with several regions. Third, the weather data including temperature and thermal indices had good quality and very low amounts of missing values as we used data from multiple monitoring stations and satellite remote sensing data.

A key limitation of this study, and many studies on related topics, is that exposure assessment of heat estimated for the study regions may not accurately represent the actual heat exposure of each individual in that area. A main source of this kind of measurement error is the use of local stationary monitoring data for exposure assessment. However, this limitation is thought to bias health risk estimates toward the null value (Hong et al., 2002). When heat exposure was assessed in terms of body heat stress, individual conditions such as clothing, acclimatization, and daily activity patterns can affect the actual level of exposure.

Secondly, validation of the approximation formula of WBGT developed in Japan was only available for one of our study regions across the country since the official monitoring data for WBGT from the KMA was limited. Although the estimation equation performed well in Seoul based on our results, further validation with monitoring data for more regions would aid future work.

Third, morbidity was measured by hospital admissions in our study. Future work could examine other acute health outcomes such as emergency room visits, which are considered to be less severe than hospital admissions but may also capture heat effects at the early stage (Ye et al., 2012).

Fourth, different threshold values can be applied and tested in the DLNMs based on assessment for model fitting, but we only considered one threshold obtained by piecewise analysis for each index. We identified thresholds from the piecewise models including limited specifications for variables (i.e., heat with lag 0, 2 degrees of freedom per season for calendar time and humidity). However, in this study the piecewise analysis was primarily conducted to test non-linearity of the heat-mortality relationship before assigning thresholds to the DLNMs.

5. Conclusion

The designation of heat wave characteristics and the health risks from heat waves are influenced by the choice of which thermal comfort index is used for a heat wave definition. As a consequence, the effectiveness of heat wave warnings depends on the capability of the index for detecting the association between heat wave periods and related health outcomes properly. In our study, the number of heat wave days, frequency of heat waves, and the heat risks for mortality and morbidity from various causes were compared between WBGT, HI, and air temperature in order to identify the capability of WBGT. Our findings of different geographical patterns in the number of heat wave days identified between heat wave definitions using WBGT, HI, and air temperature had implications for identifying vulnerable regions to heat exposure. Applying various thresholds for each index, we identified that WBGT was associated with significant risks for all-cause mortality, hospitalization due to respiratory diseases, and hospitalization due to heat disorders, across the heat wave definitions considered. Adopting a thermal index should be thoroughly considered in the development of heat wave warning systems to provide the best protection to public health. Additional studies are needed for specific geographic regions and susceptible populations using heat wave definitions under a range of thermal indices to improve heat wave warning systems.

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Conflict of interest

The authors declare no conflict of interest.

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Table 1. Summaries of daily maximum temperature, HI, AT, and WBGT, and demographic characteristics in study regions (warm seasons of 2011-2014).

Region	T_{max} (°C)*		$WBGT_{max}$ (°C)		HI_{max} (°C)		Population size	Number of mortalities (all-cause)
	Mean (SD)	Min – Max	Mean (SD)	Min – Max	Mean (SD)	Min – Max		
Seoul	28.1 (3.3)	18.0 – 36.2	25.0 (2.8)	15.2 – 32.3	29.9 (4.3)	17.7 – 43.2	10,249,679	46,787
Busan	28.2 (3.1)	20.1 – 36.2	26.4 (3.1)	17.3 – 32.6	27.9 (4.3)	17.3 – 39.2	3,550,963	22,671
Daegu	29.6 (3.7)	20.1 – 37.8	26.5 (3.1)	16.8 – 32.9	30.5 (4.6)	17.2 – 42.4	2,507,271	27,874
Incheon	26.0 (2.8)	15.4 – 33.2	25.0 (3.0)	14.7 – 31.5	27.8 (4.1)	17.2 – 40.9	2,801,274	14,739
Gwangju	28.8 (3.2)	20.1 – 37.1	26.6 (3.0)	18.0 – 33.2	30.9 (4.7)	20.7 – 45.3	1,463,464	7,623
Daejeon	28.3 (3.2)	18.0 – 36.9	27.1 (3.3)	16.8 – 33.9	31.0 (5.1)	15.8 – 46.3	1,515,603	7,159
Ulsan	27.9 (3.8)	18.4 – 38.4	25.7 (3.3)	17.0 – 33.0	27.9 (5.0)	17.0 – 40.9	1,135,494	5,294
Gyeonggi	27.7 (3.1)	18.2 – 35.5	25.5 (3.0)	15.4 – 31.8	29.6 (4.2)	18.6 – 43.2	11,937,415	55,935
Gangwon	27.0 (3.1)	17.1 – 34.3	24.7 (2.9)	15.2 – 31.0	28.1 (4.0)	17.5 – 40.8	1,536,448	12,031
Chungbuk	27.7 (3.2)	17.0 – 35.6	25.2 (3.0)	15.5 – 31.6	29.7 (4.4)	17.8 – 43.2	1,562,903	11,330
Chungnam	27.9 (3.0)	18.7 – 35.8	26.1 (3.0)	16.6 – 32.6	29.7 (4.5)	17.6 – 44.1	2,101,284	15,265
Jeonbuk	28.1 (3.1)	19.0 – 35.9	25.8 (2.9)	17.3 – 31.9	30.1 (4.6)	18.7 – 44.1	1,874,031	14,997
Jeonnam	27.6 (2.9)	20.1 – 34.6	26.2 (3.0)	18.1 – 32.5	29.5 (5.0)	17.9 – 44.6	1,914,339	17,969
Gyeongbuk	27.9 (3.4)	19.1 – 35.4	25.4 (3.1)	16.6 – 32.1	29.0 (4.4)	18.3 – 42.6	2,699,195	22,486
Gyeongnam	28.2 (3.2)	19.9 – 36.0	26.1 (3.1)	17.7 – 32.7	29.4 (4.4)	19.3 – 42.3	3,308,765	22,330
Jeju	27.3 (3.6)	18.5 – 35.7	27.0 (3.3)	19.2 – 34.1	28.7 (5.4)	18.1 – 43.5	576,156	3,512

Notes. T_{max}: daily maximum air temperature, $WBGT_{max}$: daily maximum wet-bulb globe temperature, HI_{max}: daily maximum of Heat Index, AT_{max}: daily maximum of Apparent Temperature.

Table 2. Heat wave characteristics defined by the minimum mortality temperature (MMT) in Korea, warm season (June to September) in 2011-2014.

	$T_{max} \geq 30.3$ºC			$WBGT_{max} \geq 28.0$ºC			$HI_{max} \geq 31.5$ ºC		
Region	Number of heat wave event	Total number of heat wave days	Mean (range) of heat wave days per event	Number of heat wave event	Total number of heat wave days	Mean (range) of heat wave days per event	Number of heat wave event	Total number of heat wave days	Mean (range) of heat wave days per event
Seoul	23	86	3.8 (2 – 18)	11	50	4.5 (2 – 17)	25	125	5.0 (2 – 29)
Busan	6	24	4.0 (2 – 13)	20	146	7.3 (2 – 21)	15	114	7.6 (2 – 27)
Daegu	36	188	5.2 (2 – 25)	21	152	7.2 (2 – 47)	22	174	7.9 (2 – 47)
Incheon	5	18	3.6 (2 – 8)	24	114	4.8 (2 – 21)	13	66	5.1 (2 – 17)
Gwangju	29	142	4.9 (2 – 21)	23	146	6.3 (2 – 26)	25	184	7.4 (2 – 47)
Daejeon	24	114	4.8 (2 – 22)	31	167	5.4 (2 – 36)	27	181	6.7 (2 – 36)
Ulsan	8	43	5.4 (2 – 15)	21	125	6.0 (2 – 26)	18	115	6.4 (2 – 22)
Gyeonggi	19	78	4.1 (2 – 17)	15	74	4.9 (2 – 21)	24	119	5.0 (2 – 25)
Gangwon	8	37	4.6 (2 – 9)	10	54	5.4 (2 – 17)	17	76	4.5 (2 – 18)
Chungbuk	18	84	4.7 (2 – 18)	12	71	5.9 (2 – 22)	21	135	6.4 (2 – 25)
Chungnam	12	72	6.0 (2 – 22)	21	122	5.8 (2 – 26)	19	135	7.1 (2 – 30)
Jeonbuk	18	100	5.6 (2 – 20)	22	119	5.4 (2 – 26)	17	153	9.0 (2 – 45)
Jeonnam	14	66	4.7 (2 – 17)	15	131	8.7 (2 – 45)	18	147	8.2 (2 – 45)
Gyeongbuk	17	80	4.7 (2 – 18)	19	102	5.4 (2 – 23)	22	127	5.8 (2 – 21)
Gyeongnam	20	99	5.0 (2 – 25)	19	135	7.1 (2 – 26)	17	142	8.4 (2 – 47)
Jeju	7	40	5.7 (2 – 19)	21	177	8.4 (2 – 55)	13	143	11.0 (2 – 52)

Notes. The minimum mortality temperature values used to this analysis were estimated from the relationship between the daily maximum values of each index and all-cause mortality.

Table 3. Estimated relative risks of mortality from 1°C increase in daily maximum temperature and heat wave days from the distributed lag model with polynomial and the model with 2-day moving average.

Disease	Index*	Distributed lag with polynomial (up to lag 20)		Moving average (lag 0-1)	
		Heat effect	Heat wave effect	Heat effect	Heat wave effect
All-cause	$T_{max} \geq$ MMT (30.3ºC)	**1.061 (1.015 – 1.109)**	0.977 (0.948 – 1.006)	**1.035 (1.012 – 1.059)**	0.979 (0.954 – 1.006)
	$T_{max} \geq$ 90PCT	**1.075 (1.027 – 1.125)**	0.964 (0.935 – 0.994)	**1.051 (1.021 – 1.082)**	0.970 (0.944 – 0.997)
	$T_{max} \geq$ 95PCT	**1.138 (1.035 – 1.252)**	0.975 (0.938 – 1.014)	**1.088 (1.031 – 1.148)**	0.982 (0.948 – 1.018)
	$WBGT_{max} \geq$ MMT (27.0ºC)	**1.017 (1.003 – 1.030)**	1.006 (0.994 – 1.018)	**1.013 (1.003 – 1.023)**	1.004 (0.992 – 1.016)
	$WBGT_{max} \geq$ 90PCT	**1.057 (1.012 – 1.105)**	1.014 (0.998 – 1.031)	**1.035 (1.005 – 1.066)**	**1.021 (1.006 – 1.036)**
	$WBGT_{max} \geq$ 95PCT	1.076 (0.978 – 1.185)	**1.064 (1.015 – 1.115)**	1.026 (0.974 – 1.081)	**1.060 (1.019 – 1.104)**
	$HI_{max} \geq$ MMT (31.5ºC)	**1.010 (1.003 – 1.016)**	1.004 (0.986 – 1.023)	**1.007 (1.002 – 1.012)**	1.002 (0.986 – 1.019)
	$HI_{max} \geq$ 90PCT	1.015 (0.999 – 1.032)	**1.033 (1.006 – 1.061)**	1.007 (0.997 – 1.016)	**1.038 (1.013 – 1.065)**
	$HI_{max} \geq$ 95PCT	**1.043 (1.001 – 1.086)**	1.007 (0.973 – 1.041)	**1.023 (1.005 – 1.041)**	1.006 (0.970 – 1.043)
All cardiovascular	$T_{max} \geq$ MMT (30.3ºC)	**1.036 (1.002 – 1.071)**	0.994 (0.937 – 1.055)	1.022 (0.997 – 1.048)	0.995 (0.944 – 1.049)
	$T_{max} \geq$ 90PCT	**1.051 (1.012 – 1.091)**	0.994 (0.965 – 1.024)	**1.026 (1.001 – 1.051)**	1.000 (0.970 – 1.032)
	$T_{max} \geq$ 95PCT	1.093 (0.996 – 1.199)	1.003 (0.941 – 1.070)	1.042 (0.985 – 1.102)	1.007 (0.943 – 1.074)
	$WBGT_{max} \geq$ MMT (27.0ºC)	1.007 (0.990 – 1.024)	1.023 (0.983 – 1.066)	1.008 (0.987 – 1.029)	1.022 (0.983 – 1.062)
	$WBGT_{max} \geq$ 90PCT	1.026 (0.971 – 1.083)	1.021 (0.973 – 1.072)	1.018 (0.982 – 1.055)	1.032 (0.986 – 1.080)
	$WBGT_{max} \geq$ 95PCT	1.000 (0.859 – 1.163)	1.090 (0.979 – 1.214)	0.935 (0.838 – 1.045)	**1.119 (1.007 – 1.242)**
	$HI_{max} \geq$ MMT (31.0ºC)	1.001 (0.995 – 1.007)	1.025 (0.990 – 1.061)	1.001 (0.996 – 1.007)	1.030 (0.992 – 1.070)
	$HI_{max} \geq$ 90PCT	0.990 (0.970 – 1.011)	**1.083 (1.012 – 1.158)**	0.990 (0.972 – 1.008)	**1.076 (1.012 – 1.145)**
	$HI_{max} \geq$ 95PCT	1.018 (0.960 – 1.079)	1.022 (0.974 – 1.073)	0.998 (0.972 – 1.024)	1.045 (0.995 – 1.097)
All respiratory	$T_{max} \geq$ MMT (29.7ºC)	1.061 (0.997 – 1.129)	1.019 (0.949 – 1.093)	1.042 (0.979 – 1.109)	0.997 (0.942 – 1.054)
	$T_{max} \geq$ 90PCT	1.071 (0.985 – 1.165)	1.065 (0.932 – 1.216)	1.048 (0.958 – 1.147)	1.032 (0.929 – 1.148)
	$T_{max} \geq$ 95PCT	1.071 (0.877 – 1.307)	1.066 (0.912 – 1.247)	1.048 (0.899 – 1.221)	1.053 (0.907 – 1.221)
	$WBGT_{max} \geq$ MMT (28.0ºC)	**1.078 (1.009 – 1.152)**	0.986 (0.917 – 1.060)	**1.044 (1.008 – 1.081)**	0.985 (0.922 – 1.051)
	$WBGT_{max} \geq$ 90PCT	1.055 (0.931 – 1.197)	1.094 (0.949 – 1.262)	1.043 (0.919 – 1.184)	1.075 (0.941 – 1.229)
	$WBGT_{max} \geq$ 95PCT	1.099 (0.815 – 1.484)	1.104 (0.954 – 1.278)	1.031 (0.826 – 1.287)	1.072 (0.941 – 1.223)

	HI_{max} ≥ MMT (32.0ºC)	**1.032 (1.005 – 1.060)**	0.965 (0.904 – 1.030)	**1.021 (1.004 – 1.038)**	0.962 (0.903 – 1.025)
	HI_{max} ≥ 90PCT	1.028 (0.980 – 1.078)	1.056 (0.921 – 1.211)	1.017 (0.976 – 1.061)	1.040 (0.910 – 1.189)
	HI_{max} ≥ 95PCT	1.081 (0.979 – 1.194)	0.977 (0.840 – 1.137)	1.029 (0.963 – 1.100)	1.010 (0.860 – 1.185)

Notes: Daily mean of PM_{10} and ozone on a given day were adjusted for in the models. Heat wave days were defined as two or more days with each thermal index at or above the selected thresholds. *T_{max}: daily maximum air temperature, $WBGT_{max}$: daily maximum web-bulb globe temperature, HI_{max}: daily maximum Heat Index. The MMT, 90PCT, and 95PCT indicate the minimum mortality temperature, 90th percentile, and 95th percentile, respectively.

Table 4. Estimated relative risks of hospitalization from 1°C increase in daily temperature and heat wave days from the distributed lag model with polynomial and the model with 2-day moving average.

Disease	Index*	Distributed lag with polynomial (up to lag 20)		Moving average (lag 0-1)	
		Heat effect	Heat wave effect	Heat effect	Heat wave effect
All cardiovascular	T_{max} ≥ MMT (34.6ºC)	0.959 (0.370 – 2.482)	0.927 (0.796 – 1.079)	0.935 (0.626 – 1.396)	0.944 (0.817 – 1.089)
	T_{max} ≥ 90PCT	0.979 (0.893 – 1.073)	1.025 (0.929 – 1.130)	1.011 (0.966 – 1.057)	1.036 (0.952 – 1.128)
	T_{max} ≥ 95PCT	1.029 (0.800 – 1.324)	0.945 (0.818 – 1.090)	1.072 (0.933 – 1.232)	0.969 (0.870 – 1.079)
	$WBGT_{max}$ ≥ MMT (32.5ºC)	1.057 (0.789 – 1.416)	0.921 (0.825 – 1.027)	1.065 (0.957 – 1.186)	0.972 (0.899 – 1.050)
	$WBGT_{max}$ ≥ 90PCT	0.977 (0.894 – 1.069)	1.010 (0.932 – 1.096)	**1.077 (1.013 – 1.146)**	1.013 (0.963 – 1.066)
	$WBGT_{max}$ ≥ 95PCT	0.936 (0.699 – 1.253)	1.023 (0.895 – 1.170)	1.103 (0.997 – 1.220)	1.023 (0.948 – 1.103)
	HI_{max} ≥ MMT (30.1ºC)	0.990 (0.974 – 1.007)	1.002 (0.961 – 1.046)	1.009 (0.999 – 1.018)	1.012 (0.964 – 1.062)
	HI_{max} ≥ 90PCT	1.000 (0.962 – 1.039)	0.973 (0.894 – 1.059)	**1.023 (1.002 – 1.045)**	1.001 (0.933 – 1.074)
	HI_{max} ≥ 95PCT	0.998 (0.929 – 1.073)	1.008 (0.911 – 1.115)	1.022 (0.992 – 1.053)	1.010 (0.946 – 1.079)
All respiratory	T_{max} ≥ MMT (30.0ºC)	0.806 (0.708 – 0.917)	1.025 (0.963 – 1.092)	1.010 (0.987 – 1.034)	**1.070 (1.005 – 1.140)**
	T_{max} ≥ 90PCT	0.767 (0.641 – 0.917)	0.983 (0.917 – 1.053)	0.996 (0.949 – 1.046)	1.055 (0.985 – 1.131)
	T_{max} ≥ 95PCT	0.591 (0.393 – 0.889)	0.951 (0.879 – 1.028)	0.967 (0.885 – 1.057)	1.034 (0.962 – 1.111)
	$WBGT_{max}$ ≥ MMT (26.7ºC)	0.818 (0.714 – 0.935)	**1.098 (1.024 – 1.177)**	1.023 (0.988 – 1.059)	**1.144 (1.037 – 1.262)**
	$WBGT_{max}$ ≥ 90PCT	0.709 (0.550 – 0.912)	1.027 (0.972 – 1.084)	0.969 (0.912 – 1.029)	**1.124 (1.038 – 1.217)**
	$WBGT_{max}$ ≥ 95PCT	0.597 (0.387 – 0.922)	0.955 (0.845 – 1.079)	0.984 (0.919 – 1.055)	1.026 (0.937 – 1.124)
	HI_{max} ≥ MMT (29.9ºC)	0.937 (0.899 – 0.977)	1.037 (0.978 – 1.099)	**1.018 (1.005 – 1.031)**	1.055 (0.991 – 1.124)
	HI_{max} ≥ 90PCT	0.885 (0.806 – 0.971)	1.011 (0.942 – 1.086)	0.987 (0.963 – 1.011)	**1.131 (1.028 – 1.245)**
	HI_{max} ≥ 95PCT	0.799 (0.663 – 0.962)	1.004 (0.926 – 1.088)	0.971 (0.935 – 1.008)	1.056 (0.975 – 1.144)

Heat disorders	$T_{max} \geq$ MMT (29.0ºC)	1.329 (0.999 – 1.767)	**1.600 (1.075 – 2.382)**	**1.380 (1.156 – 1.648)**	**1.775 (1.124 – 2.803)**
	$T_{max} \geq$ 90PCT	1.263 (0.876 – 1.821)	**1.784 (1.226 – 2.594)**	**1.331 (1.116 – 1.588)**	**2.084 (1.356 – 3.202)**
	$T_{max} \geq$ 95PCT	0.781 (0.346 – 1.763)	**1.701 (1.174 – 2.464)**	**1.432 (1.089 – 1.883)**	**1.895 (1.247 – 2.880)**
	$WBGT_{max} \geq$ MMT (26.5ºC)	**1.776 (1.243 – 2.540)**	**2.076 (1.280 – 3.365)**	**1.607 (1.224 – 2.109)**	**2.017 (1.301 – 3.125)**
	$WBGT_{max} \geq$ 90PCT	**2.073 (1.139 – 3.772)**	**1.989 (1.252 – 3.159)**	**1.663 (1.180 – 2.343)**	**2.363 (1.382 – 4.038)**
	$WBGT_{max} \geq$ 95PCT	2.007 (0.634 – 6.358)	**2.339 (1.364 – 4.010)**	1.320 (0.822 – 2.119)	**2.959 (1.566 – 5.594)**
	$HI_{max} \geq$ MMT (31.7ºC)	**1.236 (1.071 – 1.428)**	**1.945 (1.241 – 3.046)**	**1.234 (1.106 – 1.378)**	**1.826 (1.211 – 2.753)**
	$HI_{max} \geq$ 90PCT	**1.259 (1.005 – 1.578)**	**2.008 (1.257 – 3.208)**	**1.207 (1.062 – 1.373)**	**2.409 (1.420 – 4.087)**
	$HI_{max} \geq$ 95PCT	1.278 (0.858 – 1.903)	**2.381 (1.386 – 4.090)**	**1.145 (1.007 – 1.301)**	**2.905 (1.544 – 5.463)**

Notes: Daily mean of PM_{10} and ozone on a given day were adjusted for in the models. Cardiovascular and respiratory hospitalizations were assessed for the period between 2013-2014 years and hospitalization of heat disorders was assessed for 2011-2014 years. Heat wave days were defined as two or more days with each thermal index at or above the selected thresholds. *T_{max}: daily maximum air temperature, $WBGT_{max}$: daily maximum web-bulb globe temperature, HI_{max}: daily maximum Heat Index. The MMT, 90PCT, and 95PCT indicate the minimum mortality temperature, 90th percentile, and 95th percentile, respectively.

Fig. 1. The number of days with heat waves for monitoring stations under different heat wave definitions (warm seasons for 2011-2014). T_{max}: daily maximum air temperature, $WBGT_{max}$: daily maximum wet-bulb globe temperature, HI_{max}: daily maximum of Heat Index.

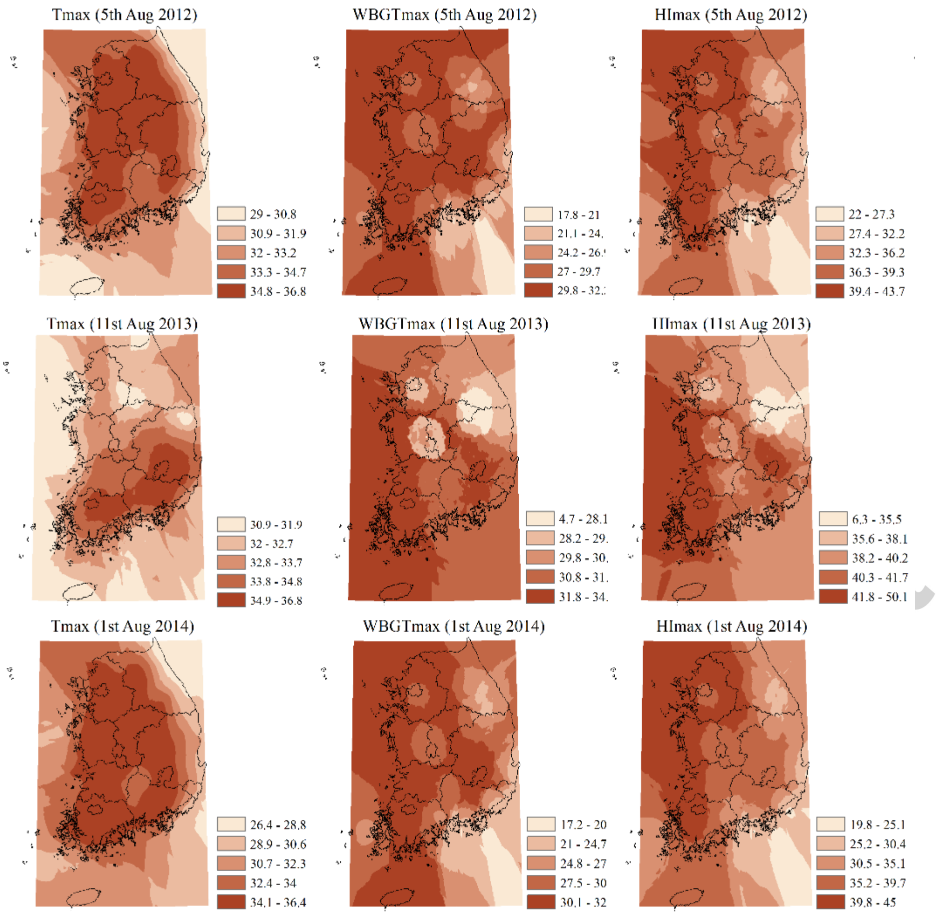

Fig. 2. Distribution of heat (°C) for the thermal indices on the three hottest days (2011-2014). T_{max}: daily maximum air temperature, $WBGT_{max}$: daily maximum wet-bulb globe temperature, HI_{max}: daily maximum of Heat Index.

Highlight

- This is one of few studies to assess the health impact of heat waves using wet-bulb globe temperature (WBGT).
- We used a novel approach that incorporated satellite remote sensing data and stationary meteorological data for estimating WBGT.
- Patterns of heat waves identified by WBGT substantially differed with those identified by air temperature.
- The difference between the risk of air temperature and WBGT was higher for particular disease: heat disorders.