Evaluation of heat effect on all-cause mortality in Japan using two temperature indices

（二つの気温指標を用いた日本の総死亡に与える暑熱の影響）

By

馬　超辰

Chaochen Ma

MBA

A thesis submitted for the degree of Doctor of Philosophy in Human Care Science

Graduate school of Comprehensive Human Sciences

The University of Tsukuba

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Key words

Climate Change

Global warming

Heat effect

All-cause mortality

Wet-bulb globe temperature

Temperature

Heat warnings

Epidemiology

Distributed lag nonlinear model

Abstract

Heat effects on mortality have been drawing much attention in recent years. Many studies have assessed this issue. Some of them examined heat-mortality from single cities, and some conducted multi-country / multi-city studies. However, most studies so far only used daily temperature (daily mean, minimum and max temperatures) as the exposure indices. The effects of other heat temperature indices on mortality should also been investigated. This thesis tends to investigate this issue by using wet bulb globe temperature (WBGT), which is widely around the world.

Chapter one analyzed the association between WBGT and mortality, and compared WBGT with mean temperature for evaluating mortality risk in 47 Japanese prefectures using data from 1972–2012. Firstly, the prefecture-specific effect of WBGT on mortality using a time series regression model combined with a distributed lag non-linear model was calculated. Secondly, the minimum mortality WBGT (MMW) and minimum mortality (mean) temperature (MMT) for all the prefectures were compared.

Chapter two checked the reliability of WBGT estimation method used by the Bureau of Meteorology of Australia and compared it with another WBGT estimation method which was proved to be accurate in Japan, for evaluating the mortality in 47 Japanese prefectures.

Declaration

I declare that this thesis is my own work, and that I have acknowledged all results and quotations from the published and unpublished work of other people.

Acknowledgement

I am grateful to many people who contributed in various ways to the completion of this thesis. First and foremost, I would like to thank my dedicated supervisors, Prof. Yasushi Honda, Prof. Ichiro Okubo and Prof. Masahide Kondo.

I owe a great deal of gratitude to Prof. Yasushi Honda, my Principal Supervisor, for his support throughout my PhD journey. He has been supportive not only academically, but also financially and spiritually. He always revised my draft in time despite his busy schedule. He is generous to buy me many books which are very important and classic in the field. His mentorship and guidance have truly helped me along over the past three years, and I am very grateful to have had the opportunity to learn from his knowledge, experience and insights.

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Chapter 1: Introduction

1.1 Climate change and health

In recent years, the impact of extreme temperatures on the human health has been drawing an increasing number of concern. According to the 4th assessment report of the Intergovernmental Panel on Climate Change, the global mean surface temperature at the end of this century could increase 1.0–3.7 °C compared with the level during 1986–2005 (IPCC, 2007), and it is projected to rise by 0.3–4.8°C by the end of 2100 (IPCC, 2014). In general, global climate change affects human health via diverse ways, including landslide, drought, heavy snow disease vectors, rising sea level, air pollution, occupation diseases, malnutrition and psychological diseases (IPCC, 2014).

The temperature-mortality (both all-cause mortality and specific-specific mortality) appear J-, V-, U-shaped, which means, exposure to both extreme high and low temperatures increases mortality (Goldberg, Gasparrini, Armstrong, & Valois, 2011; Guo, Barnett, Pan, Yu, & Tong, 2011; Guo et al., 2014; Patz, Campbell-Lendrum, Holloway, & Foley, 2005; Yang, Ou, Ding, Zhou, & Chen, 2012). The minimum point of the temperature-mortality relationship curve is the temperature where the mortality rate is the lowest. The optimum temperature varies across regions and populations and it is generally higher in warmer areas since people can get accustomed to the climates, which is also called adaptation (Patz et al., 2005).

Some epidemiological evidences showed the negative heat effects actually caused more deaths than lightning, earthquakes, floods, landslides, hurricanes and many other natural disasters

(Luber & McGeehin, 2008). Extreme heat can affect human health either in the form of separate hot days, or some consecutive hot days (i.e. heat waves). Many previous researches quantified the negative effect of heat on health (Basu, 2009; Basu & Samet, 2002; Huang et al., 2011; Luber & McGeehin, 2008; Stafoggia et al., 2006; Turner, Barnett, Connell, & Tong, 2012). Comparatively, there are less studies on the negative effect of cold (Analitis et al., 2008; Anderson & Bell, 2009; Group, 1997; Huynen, Martens, Schram, Weijenberg, & Kunst, 2001; Keatinge & Donaldson, 2001; Wilkinson et al., 2004). Previous studies also found several factors can modify the effect of temperature on mortality. For example, Women (B. G. Armstrong, 2003; Bobb, Peng, Bell, & Dominici, 2014); having low education level (Antonio Gasparrini et al., 2016; Medina-Ramon, Zanobetti, Cavanagh, & Schwartz, 2006), people with chronical disease (Li, Zhou, Cai, Zhang, & Pan, 2011; Zanobetti, O'Neill, Gronlund, & Schwartz, 2013) , the elderly (Bai et al., 2014; Basu & Malig, 2011), blacks (Gronlund, 2014; Reid et al., 2009), living in the houses without good ventilation (Loughnan, Carroll, & Tapper, 2015; Maller & Strengers, 2011), living in the city (Hondula, Davis, Rocklov, & Saha, 2013; Ma et al., 2015) and having no access to air conditioning (Kovats & Hajat, 2008) were more susceptible to the hot weather. However, the modification effects of these factors are not consistent.

1.2 Time series analysis in environmental epidemiology

Both time series regression and case-crossover design are popular to quantify the heat-mortality relationship. However, the latter is mainly more popular in case the data are individual level records. Time series analysis has been popular in many fields, such as finance and econometrics. In recent years, most of the studies which explored the adverse impact of both hot and cold temperatures on health are also based on a time series design (Guo et al., 2011; Luber &

McGeehin, 2008; Turner et al., 2012). The purpose of using time series model is to quantify short-term associations of exposures, such as temperature, air pollution and health outcomes, such as mortality, morbidity and hospitalizations on the same day and on previous days (i.e. lag-effects) after controlling for the potential confounders. There are some features in this kind of studies worth noting which have been well addressed in previous studies (Bhaskaran, Gasparrini, Hajat, Smeeth, & Armstrong, 2013; Gasparrini & Armstrong, 2010). Firstly, in general, time series is just a sequence of measurements that are equally spaced through time. For example, daily mean temperature and daily mortality, both of which are regularly measured every day. Secondly, the unit of the time series analysis is the day (e.g. annual, monthly, weekly, or hourly), not the individual. Thirdly, the outcome is a count, such as the number of mortality, morbidity or hospitalizations. Figure 1.1 shows an example of how time series data look like.

Table 1.1 Example of time series data (Hokkaido (Japan), Jan 1972–Dec 2012)

Date	Temperature	Relative humidy	ISCHHD
1972.01.01	-1.4	87	9
1972.01.02	-5.3	83	2
1972.01.03	-4.7	66	8
1972.01.04	1.5	79	7
1972.01.05	-1.6	91	4
1972.01.06	-6.1	79	6
1972.01.07	-4.2	75	2
1972.01.08	-1	70	11
1972.01.09	-2.9	70	6

Since the aim of time series regression is to find if there is an association between day-to-day variation in exposure and daily risk of health outcome. To do this, it is necessary to remove the long-term and seasonal patterns (Analitis et al., 2008). Figure 1.1 gives a simple visual explanation. There are many common ways to achieve this, such as Fourier series (Zeger, Dominici, & Samet, 1999), LOESS (Schwartz & Zanobetti, 2000).

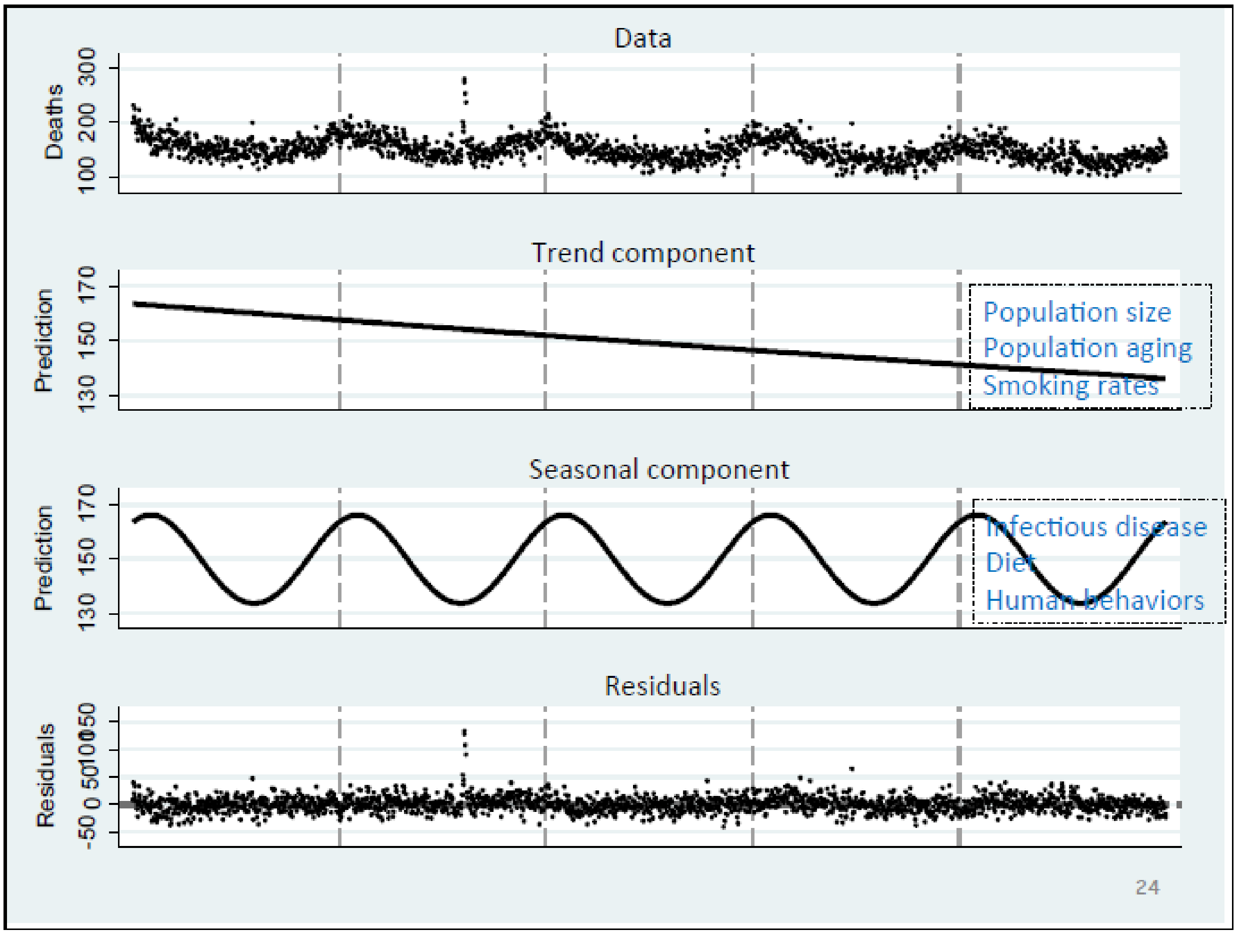

Fig. 1.1 Decomposition of time series

(Bhaskaran et al., 2013).

1.3 Limitations of current studies

Various temperature indices have been used to assess the association between mortality and temperature around the world (Gasparrini, Guo, Hashizume, Lavigne, et al., 2015; Guo et al., 2017). In addition, some studies have already determined which index is optimal to describe temperature-mortality association in some countries. For example, Lin et al. compared 8 high-temperature indices to evaluate all-cause mortality and outpatient in Taiwan and found the performance of each temperature index was inconsistent in different areas and in estimating diverse types of mortality (Lin, Chang, Li, Wu, & Wang, 2012). A study conducted in Korea showed that heat index and mean temperature are replaceable when assessing mortality (Kim, Ha, & Park, 2006). However, few similar studies have been done in Japan.

WBGT is also used for heat warnings and restrict activities at school in Japan, though it also has some limitations, such as high humidity and low wind speed yields high stress, but WBGT is not that high. It should be overcome by different indices. Despite this limitation, WBGT would be better than temperature alone in describing heat stress. However, there is no comparison made so far between WBGT and daily mean temperature for assessing heat related mortality.

1.4 Research aim

The thesis aims to fill the gap by comparing daily mean temperature and WBGT for assessing all-cause mortality in 47 Japanese prefectures using data from 1972–2012.

Chapter 2: Heat stress indices

2.1 Some frequently heat related disasters

People may suffer health problems if they are exposed to the heat, especially the abnormal heat. There are many accidents caused by the heat in history. In Chicago in July 1995, at least 700 deaths were caused by the heat wave (Semenza et al., 1996). During August 2003 in France, over 15,000 excess deaths were due to the record high temperatures (Filleul et al., 2006). In 2010, an exceptional heat wave in summer caused 55,000 in Russia (Barriopedro, Fischer, Luterbacher, Trigo, & Garcia-Herrera, 2011).

2.2 Classification of Heat stress indices

Heat should not be considered equal to high temperatures. Therefore, heat stress indices should account for all possible aspects of heat sources and pathways (McGregor & Vanos, 2017). A heat stress index is a number that integrates the effects of the basic parameters in any human thermal environment such that its value would change with the thermal strain experienced by the individual exposed to the hot environment (Parsons, 2002a).

The heat stress indices can be divided into three groups: rational indices, empirical index and direct indices. Rational indices are based on the calculations involving heat balance equations. Empirical indices are based on building equations considering human subjective strain. Direct indices are based on the direct measurement of environmental variables, such as temperature and humidity (Epstein & Moran, 2006; Parsons, 2002b). Some of the examples of heat stress indices are given in table 2.1. compared with the first two groups, the indices of the third group are more practicable since they are based on fewer assumptions and measured values in real.

Table 2.1 Some main heat stress indices
(Parsons, 2002c).

Index name	Abbreviation	Indices classification	Equation	Variables used
Heat stress index (Belding & Hatch, 1955)	HSI	Rational	Ereq / Emax * 100 Ereq: Required sweat loss Emax: Maximum evaporative loss	Required sweat loss Metabolic heat production Radiation loss Convection loss Maximum evaporative loss
Index of thermal stress (Givoni, 1964)	ITS	Rational	$(H - (R + C) - R_s) / 0.37\ \eta$ H: Metabolic heat production R: Radiation loss C: Convection loss Rs: Solar load	Required sweat loss Metabolic heat production Radiation loss Convection loss Maximum evaporative loss
Heat rate prediction (Fuller & Brouha, 1966)	HR	Empirical	22.4 + 0.18M + 0.25 (ta + 2Pa) M: Metabolic rate T_a: Air temperature P_a: vapor pressure	Metabolic rate Air temperature Vapor pressure
Wet-bulb globe temperature (Yaglou & Minaed, 1957)	WBGT	Direct	$0.7t_{nwb} + 0.2t_g + 0.1t_a$ (outdoor) $0.7t_{nwb} + 0.3t_g$ (Indoor)	t_{nwb}: Wet bulb temperature t_a: Air temperature t_g: Black globe thermometer
Oxford index (Lind, Hellon, Jones, Weiner, & Fraser, 1957)	WD	Direct	$0.85\ t_{wb} + 0.15\ t_{db}$	t_{wb}: Aspirated wet bulb temperature t_{db}: dry bulb temperature

Chapter 3: Study 1

Comparison of wet-bulb globe temperature (WBGT) and mean temperature for assessment of heat-related mortality: evidence from 47 Japanese prefectures

3.1 Aim

This study aims to compare WBGT and mean temperature in evaluating heat related mortality in 47 Japanese prefectures during 1972–2012.

3.2 Methods

3.2.1 Data collection

Data on the daily number of deaths and weather variables were collected from all 47 Japanese prefectures, during the period 1972–2012 (except for Okinawa, which was 1973–2012). Mortality data included two age groups: 0–64 and over 65 years old. Mortality was represented by daily counts of death from all causes. The mortality data were obtained from the Ministry of Health, Labor, and Welfare with special permission. The weather data were collected from the Japan Meteorology Agency. Daily mean values of temperature (°C) and water vapor pressure (hPa) were calculated from the 24 h average.

3.2.2 Estimation of WBGT

Many equations have been proposed for estimating WBGT (Gaspar & Quintela, 2009; Maia, Ruas, & Bitencourt, 2015). In this study, the method followed the Bureau of Meteorology of Australia (WBGT = 0.567 * temperature + 0.393 * water vapor pressure + 3.94). This method does not consider variations in the intensity of wind speed or of solar radiation, and assumes a moderately high radiation level in light wind conditions. Use of this approximation may be inaccurate in cases of cloudy and windy conditions (Meteorology, 2010). Because most of the days when a heat warning would be issued are bright days without strong wind, this assumption is supposed acceptable.

In this study, daily mean temperature and daily mean vapor pressure were used to calculate daily mean WBGT. In the case of temperature, daily maximum temperature and daily mean temperature have a very high correlation, and temperature impact evaluation can be done using either daily maximum temperature or daily mean temperature. In this study, daily mean WBGT was used as the main exposure index, and daily mean temperature for comparison. For brevity, "WBGT" is used instead of daily mean WBGT from here.

3.2.3 Statistical analysis

In this study, a quasi-Poisson regression model combined with a distributed lag nonlinear model (DLNM) (B. Armstrong, 2006) were used to estimate WBGT– and temperature–mortality relationships for each prefecture. The main advantage of DLNM is the ability to simultaneously estimate the nonlinear association of mortality with present day exposure, and its lag (Gasparrini

& Armstrong, 2011; Gasparrini, Armstrong, & Kenward, 2010). The key issue is to describe the relationship in each dimension based on functions, like polynomials, double threshold, simple stratification and so on. Among all of them, cubic spline functions are better to describe the flexible relationship. In the models, A natural cubic spline of time with eight degrees of freedom (df) per year was used to control for long term and seasonal trends, and the week was controlled for as a categorical variable after examining the parameter settings of some representative studies (Gasparrini, Guo, Hashizume, Lavigne, et al., 2015; Vicedo-Cabrera et al., 2016).

the exposure–response curve was modelled for both mean temperature and WBGT with a natural cubic spline with three internal knots placed at the 10th, 75th and 90th percentiles of prefecture specific WBGT and temperature distributions. For the lag–response curve, a natural cubic spline was used with an intercept and five internal knots at equally spaced values on the log scale. A maximum lag of 21 days was used to capture the long delay of the cold effect (Guo et al., 2011; Guo et al., 2014; Tong, Ren, & Becker, 2010; Vicedo-Cabrera et al., 2016). The minimum mortality WBGT (MMW) and the minimum mortality temperature (MMT) were used as reference values to calculate the relative risks. Each lag day has its own risk, but, for easier understanding, overall cumulative risk was shown, which is the sum of the contributions for 21 days across the lag, unless otherwise stated. To obtain MMW and MMT and their confidence intervals (CIs), a newly proposed method (Tobias, Armstrong, & Gasparrini, 2017) was implemented. In cases that there were multiple local minimum risks, the highest value was chosen (Rocklov, Ebi, & Forsberg, 2011). After obtaining the MMWs and MMTs, the relations between the two were explored.

3.3 Results

Table 3.1 shows the statistical summary on the daily total mortality, mean temperature, and WBGT distributions from the 47 Japanese prefectures. The daily total mortality ranged from 15 in Tottori to 204 in Tokyo. The prefectures include different climate zones, from subpolar Hokkaido to subtropical Okinawa. As expected, the daily mean temperature was lowest in Hokkaido (8.8 °C) and highest in Okinawa (22.9 °C). These were consistent with daily WBGT, reaching the lowest in Hokkaido (12.5 °C) and highest in Okinawa (25.5 °C).

Figure 3.1 shows the overall cumulative mortality effect of WBGT and temperature (95% CI) for five prefectures. These prefectures were selected to show the north–south difference. The graphs of the other prefectures are reported in the supplemental materials. The common shape of the patterns of the results for these prefectures can be regarded as inverse J, with some differences. These differences are explored in more detail in the discussion section. Table 3.2 shows estimates of MMT and MMW, and their corresponding percentile values (MMTP, MMWP). In general, the MMT increased from north to south, and the ranges were about 21 °C and 29 °C for most prefectures (with the exception of Kochi: 32.1 °C). The MMTP ranges were at about the 80th and 90th percentiles for most prefectures, with the exception of Kochi (100th) and Okinawa (44.6th). The MMW was consistent with MMP, increasing from north to south except for Kochi (19.6 °C). The MMWP ranges were at about the 80th and 90th percentiles for most prefectures except for Kochi (51.4th) and Okinawa (42.6th).

Figure 3.2 shows the relationship between MMW and MMT for each prefecture. There is a high correlation between MMT and MMW after removing Kochi. Figure 3.3 shows the associations between temperature– and WBGT–mortality for the outlier (Kochi). The estimated MMT is at the maximum of its temperature range.

The identical methods were implemented among two age groups (younger than 64 and older than 65 years old). Supplementary Figures S2 and S3 show the overall risk curves for both two groups. In general, the curves of the older group were more similar to the whole population than the younger group because most of the deaths were from the 65+ population.

Table 3.1 Distribution of daily mean temperature and daily WBGT in 47 Japanese prefectures (1972–2012).

“r” indicates the Pearson correlation coefficient between daily mean temperature and WBGT in each prefecture.

Prefecture	Study period	Daily mean death	Daily mean temperature						Daily WBGT						r
			Mean	Min	P25	P50	P75	Max	Mean	Min	P25	P50	P75	Max	
Hokkaido	1972-2012	109	8.8	-14.1	0.1	9.2	17.2	30.1	12.7	-3.6	5.7	12.1	19.2	32.1	0.99
Aomori	1972-2012	33	10.3	-8.7	2.1	10.6	17.9	30.1	14.1	0.1	7.2	13.4	20.2	32.4	0.99
Iwate	1972-2012	33	10.2	-8.9	1.6	10.3	18.3	29.6	14.0	-0.2	6.8	13.3	20.7	31.8	0.99
Miyagi	1972-2012	43	12.4	-5.2	4.8	12.8	19.1	31.2	15.7	2.1	8.8	15.0	21.6	32.9	0.99
Akita	1972-2012	30	11.7	-6.4	3.3	11.6	19.6	31.6	15.2	1.2	7.9	14.4	21.7	32.8	0.99
Yamagata	1972-2012	31	11.7	-7.4	3.0	11.9	19.7	31.5	15.2	1.0	7.8	14.4	21.8	32.5	0.99
Fukushima	1972-2012	48	13.0	-5.2	4.8	13.3	20.2	31.4	16.0	2.1	8.8	15.4	22.2	33.0	0.99
Ibaraki	1972-2012	57	13.6	-3.8	6.1	14.1	20.2	31.3	17.0	3.0	9.9	16.6	23.1	34.2	0.99
Tochigi	1972-2012	40	13.7	-4.5	5.8	14.3	20.8	31.4	16.8	2.6	9.5	16.5	23.1	33.7	0.99
Gunma	1972-2012	41	14.5	-3.8	6.7	14.8	21.5	32.6	17.0	2.9	9.9	16.6	23.4	33.7	0.99
Saitama	1972-2012	96	14.9	-2.8	7.1	15.3	21.8	33.7	17.5	3.3	10.3	17.1	23.9	34.3	0.99
Chiba	1972-2012	89	15.7	-1.4	8.6	16.1	22.0	32.2	18.4	4.4	11.5	18.2	24.4	34.0	0.99
Tokyo	1972-2012	204	16.1	-0.6	9.0	16.5	22.5	33.1	18.4	4.8	11.5	18.1	24.3	34.1	0.99
Kanagawa	1972-2012	119	15.7	-1.0	8.8	16.1	21.9	30.9	18.3	4.4	11.5	18.1	24.3	33.9	0.99
Niigata	1972-2012	56	13.8	-3.9	5.8	13.9	21.2	32.6	16.8	3.2	9.7	16.1	23.3	33.6	0.99
Toyama	1972-2012	25	14.0	-4.4	6.1	14.3	21.3	33.8	17.3	2.9	10.2	16.7	23.9	34.1	0.99
Ishikawa	1972-2012	24	14.6	-3.9	6.9	14.9	21.8	32.3	17.5	3.2	10.6	16.9	23.9	33.3	0.99
Fukui	1972-2012	18	14.5	-3.8	6.4	14.9	22.0	32.1	17.6	3.3	10.4	17.2	24.2	33.2	0.99
Yamanashi	1972-2012	19	14.5	-4.4	6.5	15.1	22.1	31.8	17.1	2.6	9.8	16.9	23.9	33.2	0.99
Nagano	1972-2012	50	11.9	-7.7	3.0	12.4	20.3	30.7	15.2	0.7	7.8	14.8	22.1	31.3	0.99
Gifu	1972-2012	42	15.7	-3.0	7.9	16.2	23.1	32.9	18.3	3.5	11.1	17.9	25.1	34.4	0.99
Shizuoka	1972-2012	70	16.6	-0.9	9.9	17.0	22.7	31.9	19.1	4.4	12.5	18.8	25.2	33.8	0.99
Aichi	1972-2012	112	15.7	-2.9	7.9	16.2	22.9	32.7	18.2	3.5	11.0	17.9	24.9	33.9	0.99
Mie	1972-2012	39	15.8	-2.4	8.3	16.1	22.8	33.5	18.6	3.3	11.4	18.1	25.2	35.2	0.99
Shiga	1972-2012	24	14.6	-3.2	6.8	14.8	22.0	31.4	17.8	3.3	10.6	17.2	24.4	33.0	0.99
Kyoto	1972-2012	52	15.8	-3.4	7.9	16.2	23.2	32.8	18.2	2.9	11.1	17.8	24.6	34.0	0.99
Osaka	1972-2012	152	16.8	-2.1	9.1	17.2	23.9	32.9	18.9	3.5	11.8	18.5	25.3	34.4	0.99
Hyogo	1972-2012	106	16.3	-4.3	8.8	16.8	23.2	32.0	18.7	2.2	11.7	18.4	25.2	33.9	0.99
Nara	1972-2012	26	14.8	-3.7	6.9	15.1	22.1	31.7	17.8	2.6	10.6	17.4	24.5	32.7	0.99
Wakayama	1972-2012	27	16.6	-2.7	9.1	17.0	23.5	31.9	19.0	3.3	11.9	18.7	25.5	34.7	0.99
Tottori	1972-2012	15	14.8	-5.6	7.3	15.0	21.9	32.3	17.8	2.0	10.9	17.3	24.1	33.5	0.99
Shimane	1972-2012	21	14.8	-5.3	7.5	15.0	21.6	32.2	18.1	2.0	11.2	17.5	24.3	33.9	0.99
Okayama	1972-2012	44	15.9	-4.8	7.9	16.2	23.2	32.3	18.5	2.1	11.2	18.0	25.2	34.2	0.99
Hiroshima	1972-2012	59	15.9	-5.8	8.3	16.2	23.0	32.7	18.5	1.9	11.5	18.0	25.1	33.7	0.99
Yamaguchi	1972-2012	38	15.3	-5.4	7.7	15.7	22.6	31.2	18.3	2.1	11.3	17.9	24.9	33.7	0.99
Tokushima	1972-2012	21	16.5	-4.0	9.2	17.0	23.3	32.3	18.9	2.5	11.9	18.7	25.4	33.9	0.99
Kagawa	1972-2012	24	16.1	-3.3	8.5	16.4	23.2	32.3	18.7	2.9	11.5	18.2	25.3	34.1	0.99
Ehime	1972-2012	36	16.3	-3.1	9.1	16.6	23.1	31.9	18.7	3.0	12.0	18.3	25.1	33.1	0.99
kochi	1972-2012	22	16.9	-2.3	10.1	17.6	23.6	32.1	19.4	3.7	12.6	19.2	26.0	33.9	0.99
Fukuoka	1972-2012	97	16.9	-3.2	9.9	17.1	23.3	32.4	19.3	3.2	12.7	18.9	25.6	34.2	0.99
Saga	1972-2012	21	16.5	-3.6	9.2	16.9	23.6	32.2	19.2	3.0	12.3	18.8	25.9	34.3	0.99
Nagasaki	1972-2012	36	17.1	-2.5	10.5	17.6	23.5	32.2	19.7	3.8	13.1	19.4	26.0	34.4	0.99
Kumamoto	1972-2012	42	16.8	-3.2	9.5	17.5	24.0	31.5	19.4	3.2	12.5	19.2	26.3	34.9	0.99
Oita	1972-2012	29	16.3	-3.4	9.4	16.7	22.9	31.6	19.0	3.1	12.3	18.6	25.3	33.7	0.99
Miyazaki	1972-2012	26	17.5	-1.0	11.0	18.1	23.8	32.0	20.3	4.4	13.7	20.3	26.9	34.5	0.99
Kagoshima	1972-2012	46	18.3	-2.1	12.0	18.9	24.8	31.1	20.8	4.4	14.4	20.8	27.4	34.4	0.99
Okinawa	1973-2012	19	22.9	9.1	19.2	23.3	27.2	31.1	25.5	11.9	20.9	25.7	30.9	34.9	0.98

Table 3.2 Estimations of minimum mortality temperature (MMT), minimum mortality temperature percentile (MMTP), minimum mortality WBGT (MMW) and minimum mortality WBGT percentile (MMWP).

"-" indicates that limits were not identified.

Prefecture	MMT (℃)	MMTP (%)	MMW (℃)	MMWP (%)
Hokkaido	21.0 (20.4, 21.5)	89.5 (87.3, 91.2)	23.3 (22.6, 23.8)	89.7 (87.4, 91.3)
Aomori	21.6 (0.9, 22.0)	88.6 (19.7, 89.8)	24.5 (7.0, 24.9)	89.2 (24.1, 90.4)
Iwate	22.1 (-8.9, 29.6)	88.4 (-, -)	25.1 (-0.2, 29.1)	89.5 (-, 96.6)
Miyagi	23.4 (22.5, 24.7)	89.6 (86.9, 93.5)	26.0 (25.1, 26.9)	88.5 (86.2, 90.9)
Akita	23.1 (22.4, 23.6)	88.5 (86.0, 90.3)	25.5 (24.7, 26.1)	87.9 (85.2, 89.5)
Yamagata	23.4 (22.8, 23.9)	87.7 (85.9, 89.2)	25.6 (24.8, 26.2)	87.1 (84.9, 88.8)
Fukushima	24.1 (5.6, 25.1)	87.8 (28.1, 90.6)	26.6 (9.6, 27.5)	88.2 (28.9, 90.5)
Ibaraki	24.5 (23.8, 25.7)	89.2 (87.1, 92.8)	27.6 (26.8, 28.6)	88.6 (86.5, 91.2)
Tochigi	24.2 (9.9, 24.9)	86.6 (38.0, 88.8)	26.7 (13.2, 27.5)	85.9 (39.5, 88.1)
Gunma	25.0 (23.7, 25.7)	86.6 (82.7, 88.9)	26.6 (25.3, 27.5)	84.9 (81.0, 87.5)
Saitama	25.3 (24.8, 25.6)	86.6 (85.2, 87.7)	27.3 (26.7, 27.8)	85.5 (83.7, 86.6)
Chiba	25.8 (25.2, 26.4)	88.0 (86.0, 90.0)	28.8 (28.1, 29.8)	87.8 (85.8, 91.0)
Tokyo	26.1 (25.8, 26.4)	86.8 (85.7, 87.6)	28.1 (27.7, 28.4)	86.2 (85.2, 86.9)
Kanagawa	25.4 (25.0, 25.9)	86.5 (85.3, 88.4)	28.1 (27.5, 28.7)	86.4 (84.6, 88.0)
Niigata	24.6 (24.1, 25.1)	87.7 (86.0, 89.2)	26.7 (25.9, 27.2)	86.2 (83.7, 87.7)
Toyama	24.1 (13.3, 25.4)	85.2 (46.7, 89.5)	26.8 (23.2, 28.4)	84.0 (72.7, 88.7)
Ishikawa	25.1 (24.1, 25.8)	86.7 (83.6, 88.8)	27.1 (25.9, 27.9)	84.9 (81.1, 87.1)
Fukui	26.3 (25.2, 28.3)	89.7 (86.5, 95.5)	28.6 (27.7, 30.2)	88.6 (85.6, 94.7)
Yamanashi	25.7 (24.8, 27.1)	88.6 (85.1, 93.8)	28.3 (26.8, 33.1)	90.2 (84.2, -)
Nagano	24.4 (23.9, 25.0)	89.7 (88.2, 91.4)	26.2 (25.5, 26.8)	88.3 (86.2, 90.4)
Gifu	26.6 (26.0, 27.1)	87.7 (85.7, 89.5)	28.6 (28.0, 29.2)	86.2 (84.2, 88.4)
Shizuoka	26.2 (25.8, 26.8)	87.9 (85.9, 91.0)	29.0 (28.3, 29.8)	87.7 (84.9, 90.9)
Aichi	25.9 (25.4, 26.3)	85.5 (83.9, 87.0)	27.5 (26.8, 27.9)	83.0 (80.9, 84.3)
Mie	25.3 (13.8, 26.5)	84.0 (43.0, 88.8)	27.9 (19.7, 29.4)	83.3 (55.8, 88.2)
Shiga	25.9 (24.4, 29.5)	88.3 (83.2, 99.2)	27.9 (25.1, 32.9)	85.6 (77.1, -)
Kyoto	26.5 (25.5, 27.3)	86.4 (83.0, 88.9)	27.5 (18.6, 28.6)	83.2 (53.0, 86.8)
Osaka	26.6 (25.8, 27.1)	84.4 (81.8, 86.1)	28.0 (18.6, 28.6)	82.5 (50.2, 84.4)
Hyogo	26.9 (9.7, 28.8)	88.1 (28.4, 96.2)	28.9 (14.1, 30.9)	85.9 (35.2, 94.3)
Nara	25.6 (10.4, 26.6)	87.3 (36.6, 91.1)	27.8 (26.6, 28.8)	84.7 (80.9, 88.6)
Wakayama	25.8 (19.7, 27.2)	82.7 (60.2, 88.2)	27.5 (24.2, 28.7)	80.7 (70.9, 84.1)
Tottori	25.1 (20.9, 26.4)	86.4 (71.5, 90.0)	27.4 (20.5, 31.4)	84.6 (62.3, 98.4)
Shimane	26.6 (25.6, 32.2)	91.7 (88.9, -)	29.8 (28.4, 33.9)	91.7 (87.2, -)
Okayama	28.2 (27.2, 32.3)	91.9 (88.7, -)	30.0 (29.0, 34.2)	89.3 (85.8, -)
Hiroshima	26.3 (25.4, 27.0)	86.3 (83.7, 89.1)	27.7 (21.1, 28.8)	82.4 (61.5, 85.9)
Yamaguchi	25.5 (11.9, 26.4)	85.7 (39.1, 89.0)	28.2 (14.9, 29.3)	84.7 (40.1, 88.6)
Tokushima	26.3 (12.4, 32.3)	86.5 (36.1, -)	24.3 (17.5, 28.3)	71.6 (46.1, 83.3)
Kagawa	26.3 (15.4, 27.6)	85.8 (47.1, 90.9)	27.4 (20.8, 29.2)	80.7 (59.6, 86.4)
Ehime	26.8 (11.5, 28.9)	88.1 (34, 96.7)	28.6 (15.2, 31.3)	85.9 (39.0, 98.6)
Kochi	32.1 (13.9, 32.1)	100 (38.4, -)	19.6 (16.7, 33.8)	51.4 (41.0, -)
Fukuoka	26.9 (26.2, 27.4)	87.5 (85.1, 89.1)	29.2 (28.6, 29.7)	85.7 (83.6, 87.3)
Saga	26.3 (17.8, 28.3)	85.6 (52.6, 93.5)	26.9 (18.7, 28.9)	77.9 (49.6, 83.8)
Nagasaki	28.5 (26.4, 32.2)	95.5 (85.5, -)	30.1 (21.5, 34.3)	87.2 (58.6, -)
Kumamoto	27.9 (26.4, 31.5)	91.1 (84.3, -)	29.2 (19.9, 30.7)	83.7 (52.5, 91.2)
Oita	26.6 (25.5, 27.9)	89.0 (84.3, 94.5)	29.2 (16.5, 31.7)	87.0 (42.5, 98.7)
Miyazaki	26.1 (24.9, 26.7)	83.5 (78.6, 86.5)	28.6 (23.0, 29.4)	79.7 (61.1, 82.4)
Kagoshima	27.3 (26.0, 28.9)	84.5 (79.3, 94.1)	29.7 (22.6, 31.1)	81.7 (57.7, 89.2)
Okinawa	22.3 (20.4, 28.3)	44.6 (32.7, 85.4)	24.3 (22.7, 27.2)	42.6 (34.2, 56.9)

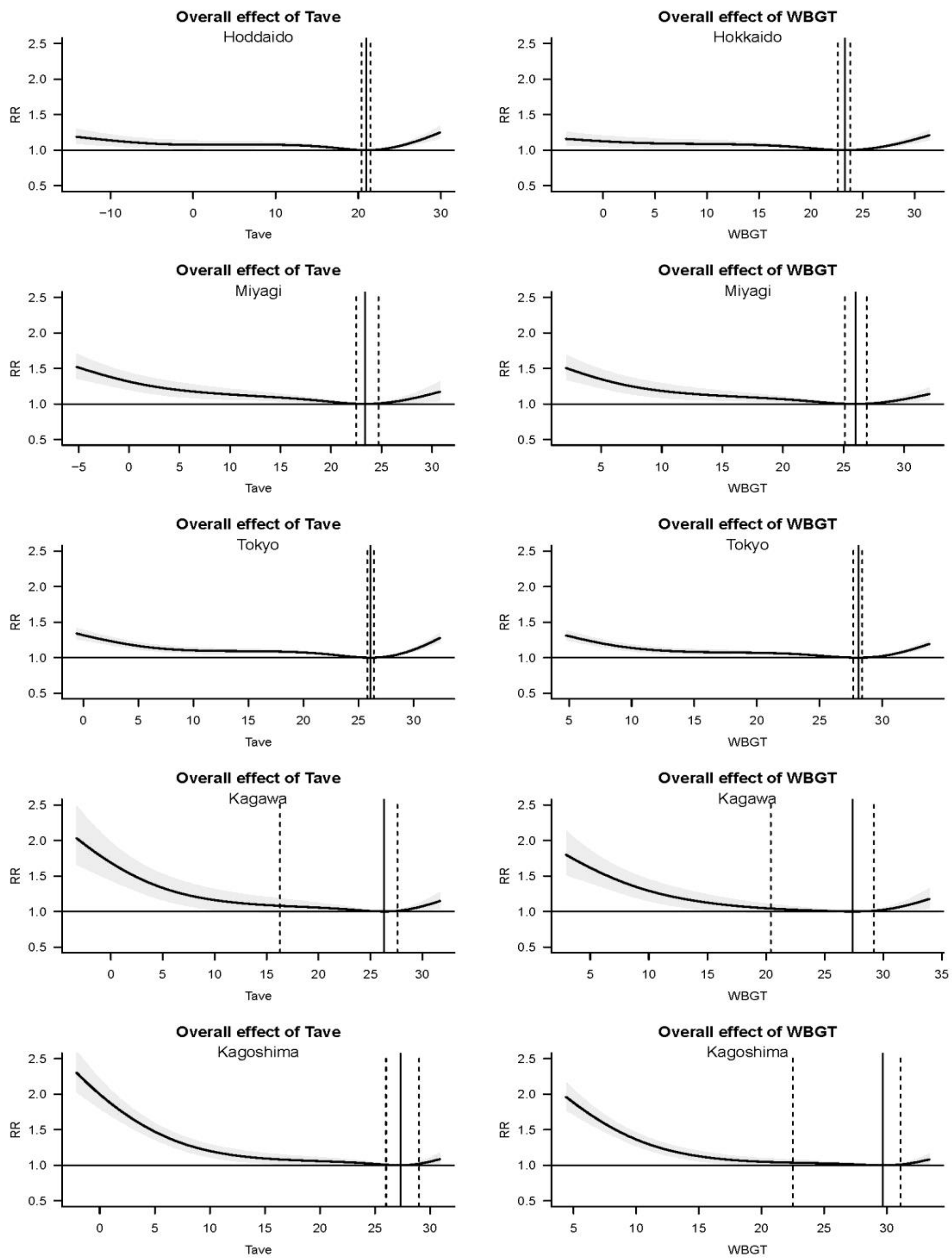

Fig. 3.1 Comparison of the associations between WBGT– and temperature–mortality for five selected prefectures at different latitudes in Japan, 1972–2012.

All show unconstrained minimum mortality temperature and solid vertical lines are minimum mortality temperature or minimum mortality WBGT, and dashed vertical lines are their 95% confidence intervals. RR indicates the relative risk. Tave is daily mean temperature.

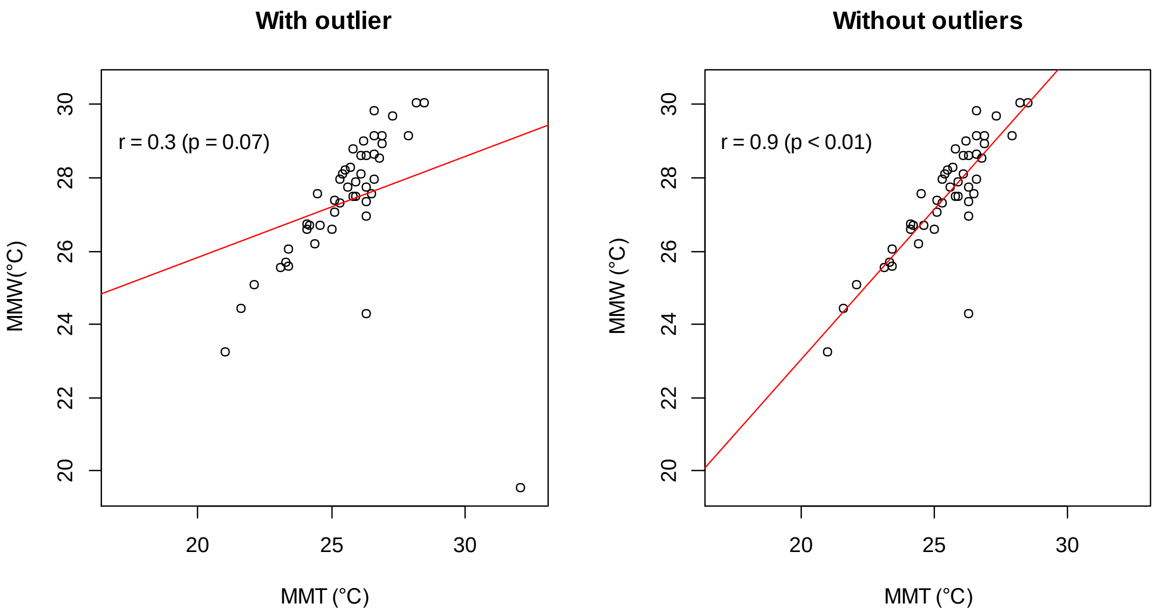

Fig. 3.2 Comparison of the associations of MMW–MMT with and without outlier. “r” is Pearson correlation coefficient.

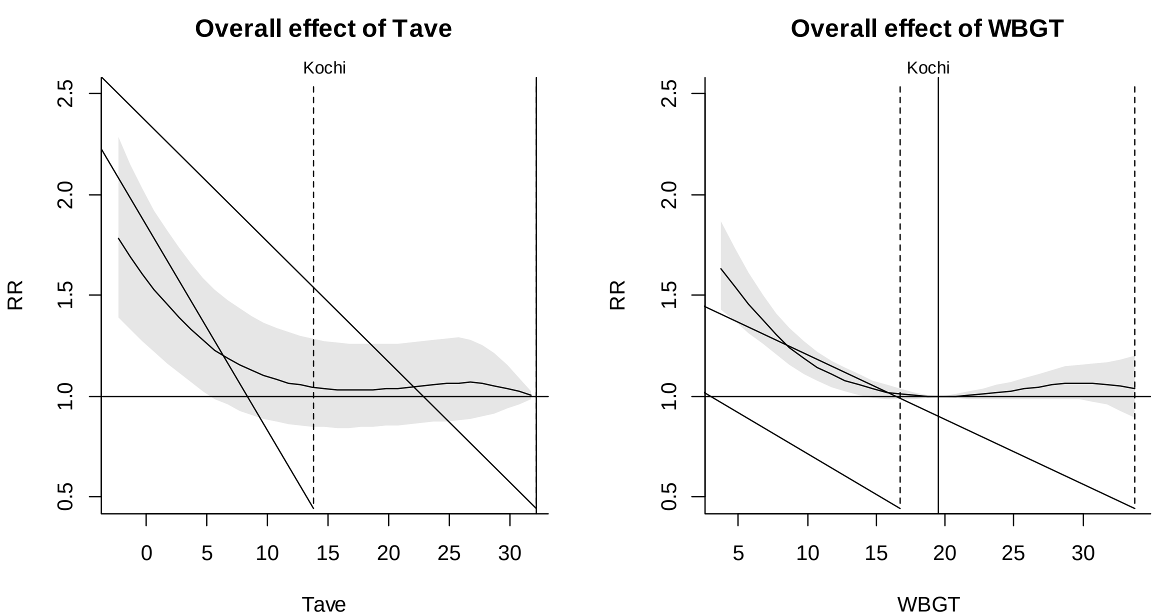

Fig. 3.3 Associations between WBGT– and temperature–mortality for Kochi.

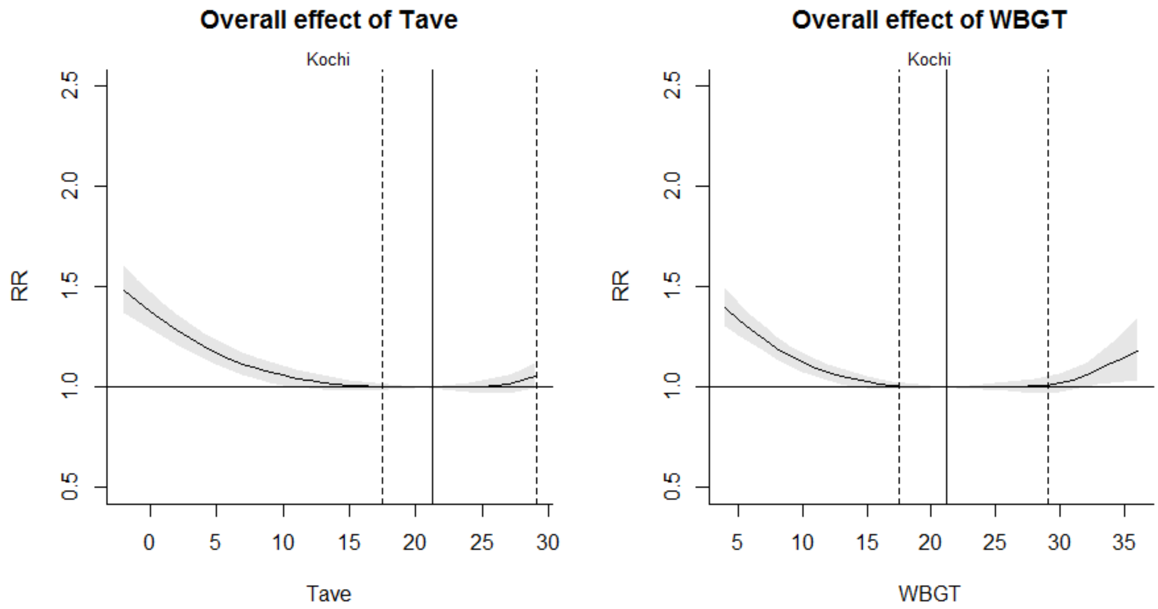

Fig. 3.4 Overall effect of temperature– and WBGT–mortality in Kochi when the lag was set to seven days.

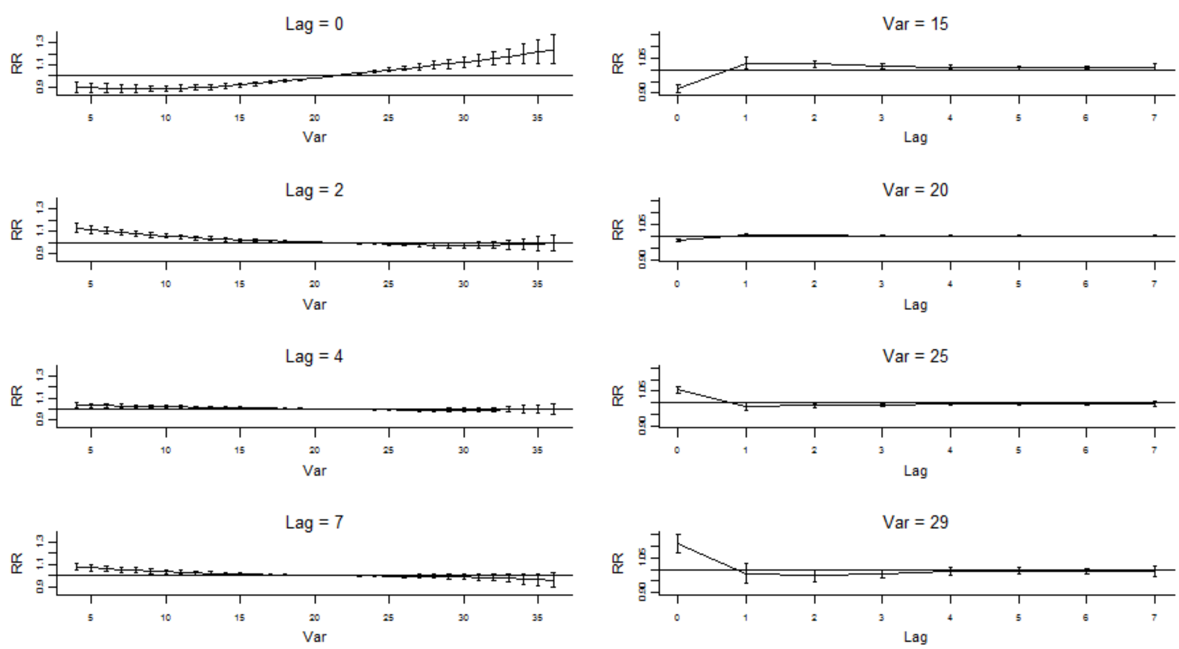

Fig. 3.5 Estimated effects at different WBGTs and lags for Kochi.

3.4 Discussion

In this study, the effects of WBGT on all-cause mortality were examined and compared it with the effects from mean temperature using data from 47 Japanese prefectures. To the best of our knowledge, this is the first study to systematically compare WBGT and temperature for all of Japan.

As was shown in previous studies, we also observed that, overall, the pattern of WBGT mortality was generally inverse J-shaped, and the north–south differences were in line with the results from previous studies (Chung et al., 2015; Gasparrini, Guo, Hashizume, Lavigne, et al., 2015). Although some prefectures showed inconsistent patterns, like Iwate, that may be due to its small population and other unknown extraneous factors. Moreover, in terms of Iwate, although the colder part showed a strange pattern, usual definition of MMT / MMW is the highest temperature among multiple local minimum mortality risks (Rocklov et al., 2011), and the MMT / MMW appeared similar to the neighboring prefectures. It was found extreme cold temperatures and WBGT had stronger effects than did extreme hot temperatures and WBGT in most of the prefectures. The cold effects were more apparent in southern areas, while the heat effects were more pronounced in northern areas; which is also in line with results from previous studies (Gasparrini, Guo, Hashizume, Lavigne, et al., 2015; Ma et al., 2015). As with MMT, MMW increased from north to south. In summary, the mortality patterns associated with mean temperature and WBGT showed similar patterns. In this regard, either measure could be used in risk evaluations, at least in Japan.

Kochi and Tokushima were outliers in the pattern when comparing MMW and MMT. However, unlike the extreme pattern of Kochi, Tokushima's relation appeared acceptable. Since the curves in Tokushima showed a very low risk over a wide range, which means a small statistical difference could change MMT and MMW drastically. Therefore, although Tokushima looked like an outlier, it was accepted. In terms of Kochi, one of the reasons could be the relatively small population, but another possibility could be the extraneous confounding effect from using a too long lag time. Previous studies suggested that cold effects can last for 2–4 weeks, while the heat effects were limited within a few days (Braga, Zanobetti, & Schwartz, 2002; Gasparrini, Guo, Hashizume, Lavigne, et al., 2015; Ma et al., 2015). 21 lag days was firstly used to capture the longer lag effect for cold, but the lag effect for heat was considered to be much shorter. Although in a simulation study (Gasparrini, 2016)) DLNM appropriately captured both short and long lag effects, in some real cases, due to accident or disaster; a long lag effect could be erroneous. To explore this issue, an identical analysis was conducted for Kochi, except for setting a shorter lag of seven days. As shown in Figure 2.4, with this adjustment, the estimated set of MMT and MMW became non-outliers. In addition, Figure 2.5 shows that there was virtually no heat effect for lag days close to Day 7. This implies that, in this case, it is not necessary to use a lag longer than seven days to evaluate the heat effect.

There are limits to this study. First, the formula used to estimate WBGT assumes moderately high radiation in light wind, and constant wind speed or solar radiation. This partly explains why temperature and WBGT yielded similar results, but at least it was showed that humidity did not systematically alter the relation. Because a more sophisticated method for WBGT estimation was used in a study of a limited number of areas in Japan, our next step will be to evaluate the use of this sophisticated method. However, this involves hourly measurements of radiation and would be difficult to use in a multi-country study. On the other hand, our simple WBGT method could be used in such settings.

3.5 Conclusions

Mean temperature and WBGT were highly correlated when evaluating mortality in most prefectures. Therefore, the mean temperature is a good index to use when obtaining WBGT for a heat warning is difficult.

3.6 Acknowledgement

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Chapter 4: Study 2

Comparison of two WBGT estimation methods for assessment of heat-related mortality: evidence from 47 Japanese prefectures

4.1 Aim

This study aims to test the reliability of WBGT estimation method used by the Bureau of Meteorology of Australia (BMA), a comparison is made between this and another method (Ono & Tonouchi, 2014), which is proved to be accurate in Japan for evaluating the mortality risk in 47 Japanese prefectures.

4.2 Methods

4.2.1 Data collection

Data were collected on the daily number of deaths and weather variables from 47 Japanese prefectures, during the period 2006–2012. The data were restricted to the warmest months of the year (May–October). Mortality was represented by the daily counts of deaths from all-cause mortality. The mortality data were obtained from the Ministry of Health, Labor, and Welfare with special permission. The weather data were collected from the Japan Meteorology Agency. The daily mean values of temperature (°C) and water vapor pressure (hPa) were calculated from the 24 h average. In addition, the estimated values by the method (Ono & Tonouchi, 2014) were provided by the authors. In this study, the estimated values by the method (Ono & Tonouchi, 2014) were regarded as observed WBGT values.

4.2.2 Ono and Tonouchi (2014)

Ono and Tonouchi developed WBGT estimation equation and proved that the equation could be applied for different years and for different cities with good accuracy (Ono & Tonouchi, 2014).

$$WBGT = 0.735 * T_a * 0.0374 * RH * 0.00292 * T_a * RH + 7.619 * SR - 4.557 * SR^2 - 0.0572 * WS - 4.064$$

Where T_a refers to the air temperature; RH is relative humidity; SR represents solar radiation.

4.2.3 Statistical analysis

In this study, the quasi-Poisson regression model combined with a distributed lag nonlinear model (DLNM) was implemented to estimate WBGT-mortality relationships by using the two estimation methods in each prefecture. In the models, seasonality was controlled for by using natural cubic B-splines with equally spaced knots and 4 degrees of freedom (df). And interaction between the spline function and indicators of summer of the year was specified to allow the different seasonal trend. In addition, a natural cubic B-spline with equally spaced knots and approximately 1 df per decade were included to control for long-term trends. Day of the week variable is also included in the model. In specific, the quadratic B-splines for the exposure-response with 1 internal knot at the 75th percentile of each prefecture's WBGT distribution and natural cubic B-splines for the lag-response with an intercept and 2 internal knots placed at equally spaced values in the log scale. The lag period was extended to 5 days to capture the delay of the heat effects. These modelling choices were motivated by the previous studies (Gasparrini, Guo, Hashizume, Kinney, et al., 2015; A. Gasparrini et al., 2016).

4.3 Results

Table 4.1 shows the statistical summary on the daily total mortality WBGT distribution using two estimation methods and the correlation coefficients between mean values using two estimation methods from the 47 Japanese prefectures. The daily total mortality ranged from 17 in Tottori to 257 in Tokyo. As expected, the daily mean WBGTs by both methods were lowest in Hokkaido and highest in Okinawa. The estimated WBGT values by BMA were generally higher than the values by Ono's method, especially in the southern prefectures. The correlation coefficient between daily mean WGBT using two methods was around 0.95.

Figure 4.1 shows the overall cumulative mortality effect of WBGT by two methods. These prefectures were selected to show the most densely populated areas with geographical difference. The graphs of the other prefectures are reported in the supplemental materials (Fig.S5). The common shapes of these curves are U or inverse J, with some difference. The reference value of the curves was either the estimates of minimum mortality WBGT (MMW) or 50th percentile values of WBGT distribution if the MMW was at the extreme WBGT. Table 4.2 shows the estimates of MMW and minimum mortality WBGT percentile (MMWP) by using the two methods. In general, the difference between the estimates of MMW and MMWP was significant in many prefectures. Figure 4.2 shows the comparison of MMW by using two WBGT estimation methods for each prefecture.

Table 4.1 Distribution of daily mortality and estimated WBGT values by using two methods in May–October of 2006–2012 in 47 Japanese prefectures.

"*r*" represents the Pearson correlation coefficient between WBGT estimates by using two methods.

Prefecture	Daily mean death	Australian Bureau of Meteorology						Ono (2014)						*r*
		Mean	Min	P25	P50	P75	Max	Mean	Min	P25	P50	P75	Max	
Hokkaido	143	19.8	8.0	16.0	19.9	23.5	30.7	19.7	5.4	15.7	20.2	23.6	30.5	0.96
Aomori	41	21.0	9.5	17.0	20.6	24.7	32.4	21.1	6.2	17.3	21.1	25.1	32.0	0.96
Iwate	39	21.2	8.3	17.2	21.0	25.2	31.8	21.4	4.2	17.7	21.3	25.5	31.5	0.95
Miyagi	54	22.7	10.5	18.8	22.3	26.7	32.9	22.2	6.2	18.5	21.8	26.2	32.7	0.96
Akita	36	22.4	10.1	18.2	22.2	26.4	32.8	21.8	5.4	18.1	22.0	25.5	32.3	0.95
Yamagata	36	22.3	10.0	18.4	22.0	26.5	31.8	22.6	5.8	18.8	22.6	26.9	32.4	0.95
Fukushima	56	23.0	10.5	19.2	22.6	27.0	32.8	23.0	6.9	19.5	22.8	27.0	32.5	0.95
Ibaraki	70	23.8	12.1	20.2	23.5	27.9	33.3	23.9	8.1	20.3	23.7	28.0	34.3	0.92
Tochigi	48	24.1	12.2	20.4	23.7	28.3	33.7	24.0	8.9	20.4	23.6	28.2	33.8	0.95
Gunma	49	23.9	11.9	20.1	23.5	28.0	32.9	23.8	9.0	20.2	23.6	28.0	32.6	0.94
Saitama	135	24.8	12.7	20.8	24.5	29.0	34.3	24.9	8.9	21.2	24.7	29.2	35.2	0.92
Chiba	123	25.2	13.5	21.6	24.8	29.5	33.9	24.8	9.6	21.3	24.6	28.9	34.6	0.92
Tokyo	257	25.0	13.1	21.4	24.6	29.3	34.1	23.5	9.9	20.1	23.3	27.4	32.5	0.97
Kanagawa	168	25.0	13.3	21.4	24.6	29.1	33.7	24.4	9.0	21.0	24.1	28.6	32.7	0.93
Niigata	66	23.8	12.2	19.7	23.7	27.7	33.6	22.9	8.3	19.4	23.0	26.6	32.2	0.97
Toyama	30	24.8	12.6	20.7	24.6	29.1	34.1	24.6	10.7	20.9	24.6	28.6	33.6	0.96
Ishikawa	29	24.1	12.0	20.2	23.9	28.3	32.8	24.1	10.8	20.7	24.0	28.1	34.4	0.93
Fukui	21	24.6	12.7	20.7	24.6	29.0	32.8	24.4	11.3	20.9	24.3	28.5	33.0	0.95
Yamanashi	22	24.1	12.3	20.3	24.3	28.1	32.3	24.2	9.4	20.7	24.3	28.2	32.7	0.94
Nagano	58	22.4	9.7	18.5	22.5	26.7	30.7	23.4	7.1	19.5	23.6	27.7	33.2	0.93
Gifu	50	25.1	13.8	21.2	25.2	29.3	33.4	25.2	12.3	21.6	25.2	28.9	34.7	0.91
Shizuoka	88	25.7	15.4	22.0	25.7	29.6	33.5	25.0	14.2	21.7	24.7	28.8	32.6	0.95
Aichi	45	25.6	13.7	21.7	25.7	29.9	34.0	24.7	10.8	21.2	24.9	28.7	32.5	0.94
Mie	45	25.6	13.7	21.7	25.7	29.9	34.0	25.3	12.6	21.8	25.5	29.0	34.5	0.98
Shiga	28	24.8	13.7	20.8	24.8	29.2	33.0	24.4	12.2	20.8	24.3	28.6	32.7	0.96
Kyoto	60	24.8	13.7	21.0	24.7	29.1	32.6	25.1	12.5	21.6	25.3	29.0	34.2	0.91
Osaka	190	25.6	14.0	21.9	25.5	29.9	33.2	24.9	12.3	21.7	25.0	28.8	32.3	0.96
Hyogo	126	26.0	14.2	22.3	25.9	30.4	33.9	25.3	13.6	22.1	25.4	29.1	32.5	0.97
Nara	32	24.6	13.3	20.8	24.7	28.9	32.2	25.0	10.9	21.7	25.1	28.8	32.3	0.95
Wakayama	30	25.4	14.1	21.7	25.4	29.6	32.7	25.0	12.7	21.8	25.0	29.0	32.6	0.94
Tottori	17	24.6	13.2	20.7	24.5	29.1	32.9	24.8	13.0	21.4	24.7	28.8	33.2	0.92
Shimane	23	24.8	13.3	20.9	24.6	29.2	33.6	23.5	10.2	19.9	23.4	27.2	33.0	0.93
Okayama	49	25.6	13.4	21.6	25.6	30.0	33.2	25.3	12.5	21.9	25.4	29.4	33.5	0.93
Hiroshima	69	25.4	13.2	21.5	25.5	29.7	33.3	24.1	9.7	21.0	24.2	27.5	33.4	0.94
Yamaguchi	44	25.0	13.4	21.2	25.2	29.5	33.0	22.5	10.3	19.5	22.8	25.8	29.1	0.97
Tokushima	23	25.7	14.5	21.9	25.7	29.9	32.9	25.4	12.9	22.1	25.4	29.4	34.0	0.92
Kagawa	27	25.7	14.2	21.8	25.7	30.1	33.7	25.1	11.6	21.6	25.2	29.1	32.6	0.96
Ehime	40	25.3	13.7	21.6	25.5	29.4	32.4	25.0	13.0	21.8	25.0	28.9	31.9	0.95
kochi	24	26.6	14.8	22.8	26.8	30.7	33.9	25.9	14.1	22.8	25.9	29.6	32.5	0.95
Fukuoka	117	26.0	14.5	22.3	26.0	30.3	33.5	25.2	13.5	22.2	25.2	28.8	33.1	0.95
Saga	23	25.7	14.4	21.9	26.0	30.0	33.1	25.3	13.3	22.1	25.3	29.1	32.3	0.93
Nagasaki	41	26.3	15.1	22.5	26.4	30.6	33.8	25.4	14.3	22.2	25.5	29.3	32.7	0.95
Kumamoto	48	26.4	15.1	22.6	26.8	30.5	33.8	26.0	14.5	22.9	26.2	29.7	33.0	0.94
Oita	33	25.5	14.7	21.8	25.7	29.7	32.3	25.0	11.6	21.7	24.8	28.9	32.0	0.95
Miyazaki	31	26.7	15.8	23.1	27.2	30.7	33.5	25.9	14.1	22.8	26.4	29.6	32.6	0.95
Kagoshima	51	27.4	16.5	23.9	27.9	31.3	34.4	26.4	15.5	23.5	26.7	30.0	32.7	0.95
Okinawa	26	30.3	21.2	28.3	31.2	32.6	34.8	28.3	18.8	26.5	29.3	30.5	32.5	0.94

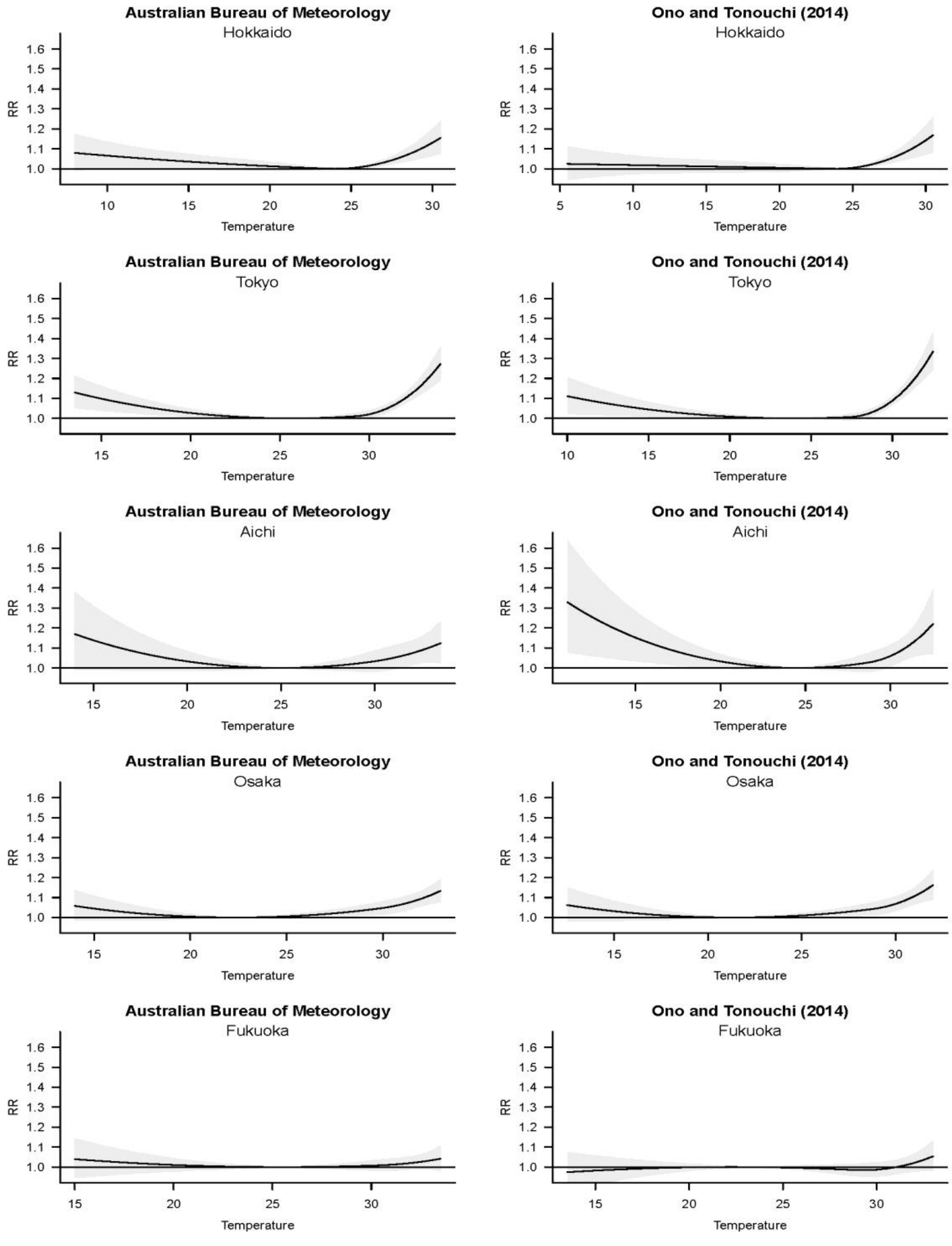

Fig. 4.1 Comparison of the associations of WBGT-mortality by using two WBGT estimation methods for five selected prefectures at different latitudes in May–October of 2006–2012.

RR indicates the relative risk.

Table 4.2 Estimations of minimum mortality WBGT (MMW) and minimum mortality WBGT percentiles (MMWP) by using two methods.

Prefecture	BMA	MMWP (%)	Ono (2014)	MMWP (%)
Hokkaido	24.0	79.5	24.0	78.4
Aomori	25.0	77.1	25.0	74.8
Iwate	26.0	78.8	26.5	81.6
Miyagi	22.5	51.2	21.5	47.8
Akita	27.0	79.2	22.0	50.0
Yamagata	27.0	77.8	27.0	75.9
Fukushima	24.0	58.0	21.5	41.8
Ibaraki	22.5	44.0	22.0	38.4
Tochigi	25.0	56.4	23.5	49.5
Gunma	23.5	49.9	9.0	0.1
Saitama	13.0	0.1	25.0	53.0
Chiba	26.5	59.1	26.0	58.7
Tokyo	25.5	54.7	24.0	55.5
Kanagawa	24.0	45.8	23.5	45.7
Niigata	24.5	55.0	22.5	46.7
Toyama	29.5	77.6	11.0	0.1
Ishikawa	25.0	55.8	23.5	46.7
Fukui	29.5	77.9	28.5	75.1
Yamanashi	23.5	45.8	13.0	0.6
Nagano	24.0	58.2	23.5	49.8
Gifu	21.0	24.0	22.0	28.0
Shizuoka	25.0	46.5	23.5	39.9
Aichi	25.0	46.9	24.5	48.5
Mie	25.0	46.9	24.5	43.9
Shiga	24.5	48.7	12.5	0.2
Kyoto	25.0	52.2	24.5	44.4
Osaka	22.5	29.9	21.5	24.4
Hyogo	27.0	54.4	27.0	60.7
Nara	27.5	64.3	11.0	0.1
Wakayama	32.5	99.7	32.5	99.9
Tottori	26.5	60.2	13.0	0.2
Shimane	30.0	79.7	10.5	0.1
Okayama	30.5	79.4	30.5	85.1
Hiroshima	21.0	21.1	23.0	41.1
Yamaguchi	32.5	99.9	24.5	63.8
Tokushima	14.5	0.1	13.0	0.1
Kagawa	28.5	63.2	26.0	56.1
Ehime	25.0	47.2	22.0	26.7
kochi	28.0	55.2	25.0	43.3
Fukuoka	25.5	47.0	13.5	0.1
Saga	23.0	33.0	24.0	41.1
Nagasaki	15.5	0.1	14.5	0.1
Kumamoto	26.5	48.3	14.5	0.1
Oita	29.5	73.2	26.0	56.9
Miyazaki	33.5	99.9	32.5	99.9
Kagoshima	34.0	99.9	32.5	99.8
Okinawa	29.0	29.6	26.6	25.9

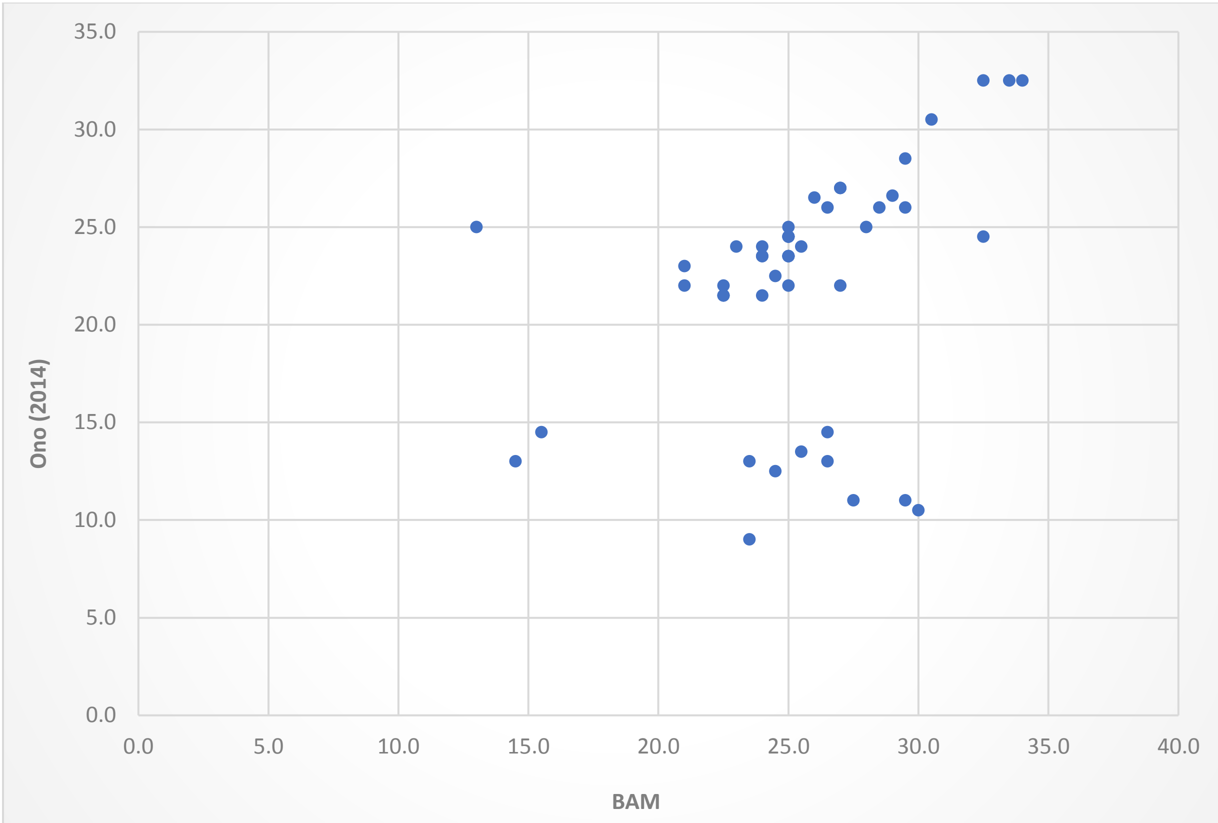

Fig. 4.2 Comparison of MMW estimated by two WBGT estimation methods for each prefecture.

4.4 Discussion

In this study, the effects of WBGT on all-cause mortality were examined and compared between two WBGT estimation methods. WBGT-mortality relationships were found non-linear for both methods.

WBGT estimates by using BAM's method were higher than by Ono's method. In addition, the comparison of MMW by using two WBGT estimations showed that the MMW estimates were very inconsistent. The difference is supposed to be due to the assumption of fixed solar radiation and wind speed of BAM's method. Therefore, at least it is safe to say considering the variation of solar radiation and wind speed is necessary when evaluating WBGT-mortality relationships in Japan.

There are several limitations in this study. First, due to the availability, only 6-month data were used in this study. In future, the full year data should be analyzed by the same method. Second, WBGT estimated by BAM's method may apply better in Australia than in Japan. Therefore, the same comparison should also be made in the Australian setting to check if the result is still very different. Third, since the assumption of BAM's method is mild and constant radiation and wind speed, it is necessary to do the analysis stratified by the location of the death (indoor and outdoor).

Chapter 5: General discussion

As far as I know, this is the first study to assess relationships between temperature and mortality in Japan. Daily mean temperature is the most frequently used temperature index to assess the temperature effects. WBGT is a type of apparent temperature invented during 1950s and used by United States Army and Marine Corps to prevent from heat illness, and since then it has been adopted by athletes to control work out hours (Budd, 2008). For example, WBGT is taken as ISO7243 standard for controlling exposure to hot temperature (Epstein & Moran, 2006). WBGT was found a better and more comprehensive index than other indices (Hyatt, Lemke, & Kjellstrom, 2010). Hoshi et al. (Hoshi, Inaba, & Murayama, 2007) suggested that the heat stress risk for emergency risk would be similar if WBGT is used even when the risk is different if daily maximum temperature is used. Thus, it is interesting to see the relation between WBGT and mortality across the prefectures in Japan.

The present thesis shows that WBGT and daily mean temperature are highly correlated. In study 2, the comparison was made between two WBGT methods in terms of estimating WBGT-mortality associations. The results showed that the assumption of constant and mild solar radiation and wind speed may cause problems when assessing WBGT effect on health outcomes.

This thesis may have implications for public health and clinical trials. For example, MMW is different depending on the climate of the area. We may need to take MMW difference into account in implementing heat-health warning depending on different climate zones, or we need to ask them to be aware of heat related illnesses for frail patients, who may be well off if the WBGT is low enough but may die due to the high WBGT, such as construction workers.

The future direction could be: (1) to use more systematic and scientific methods to calculate WBGT; (2) to include more heat indices, such as maximum temperature, minimum temperature, heat index, humidex, temperature humidity index, apparent temperature; (3) to stratify the mortality by occupations and ages. (4) to expand the study period to the whole year; (5) to add the air pollutants to evaluate the interactions between WBGT and air pollutants.

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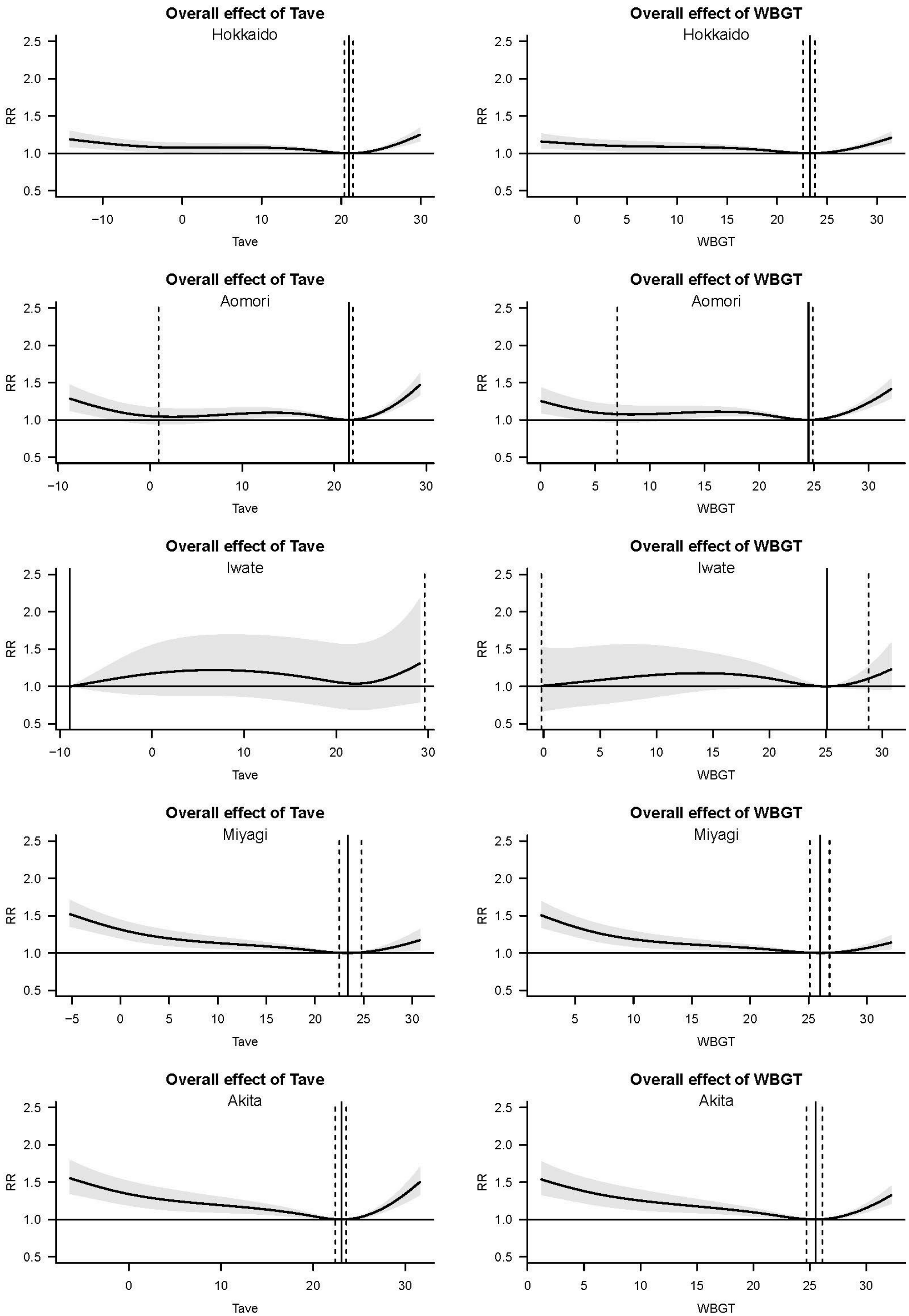
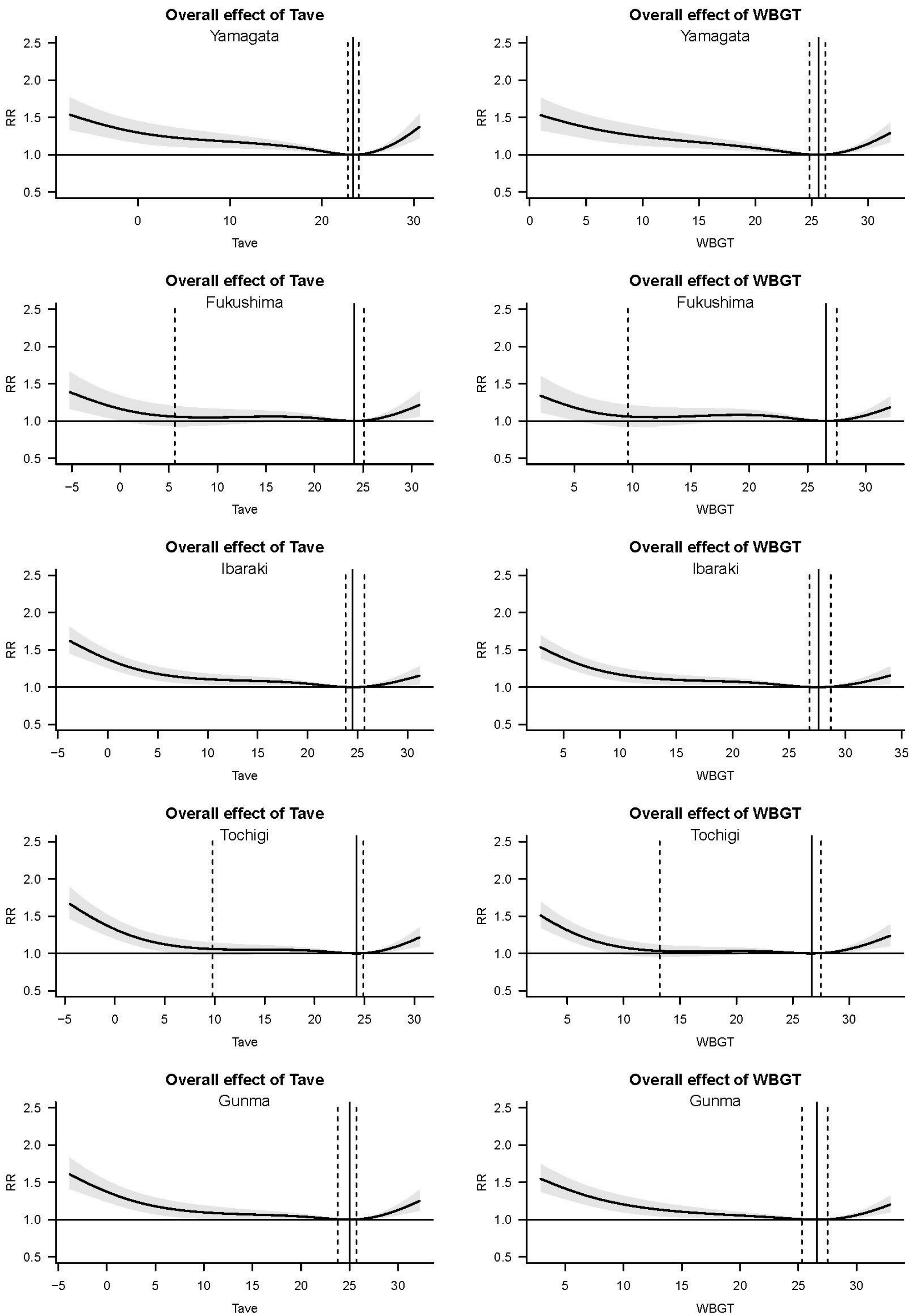
Supplemental materials

Fig. S1

The overall cumulative mortality effect of WBGT and temperature in 47 Japanese prefectures, 1972–2012: All show unconstrained minimum mortality temperature and solid vertical lines are minimum mortality temperature or minimum mortality WBGT, and dashed vertical lines are their 95% confidence intervals. RR indicates the relative risk. Tave is mean temperature.


Overall effect of Tave
Hokkaido
Overall effect of WBGT
Hokkaido
Overall effect of Tave
Aomori
Overall effect of WBGT
Aomori
Overall effect of Tave
Iwate
Overall effect of WBGT
Iwate
Overall effect of Tave
Miyagi
Overall effect of WBGT
Miyagi
Overall effect of Tave
Akita
Overall effect of WBGT
Akita
RR
Tave
WBGT


Overall effect of Tave
Yamagata
Overall effect of WBGT
Yamagata
Overall effect of Tave
Fukushima
Overall effect of WBGT
Fukushima
Overall effect of Tave
Ibaraki
Overall effect of WBGT
Ibaraki
Overall effect of Tave
Tochigi
Overall effect of WBGT
Tochigi
Overall effect of Tave
Gunma
Overall effect of WBGT
Gunma
RR
Tave
WBGT
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2.0
2.5
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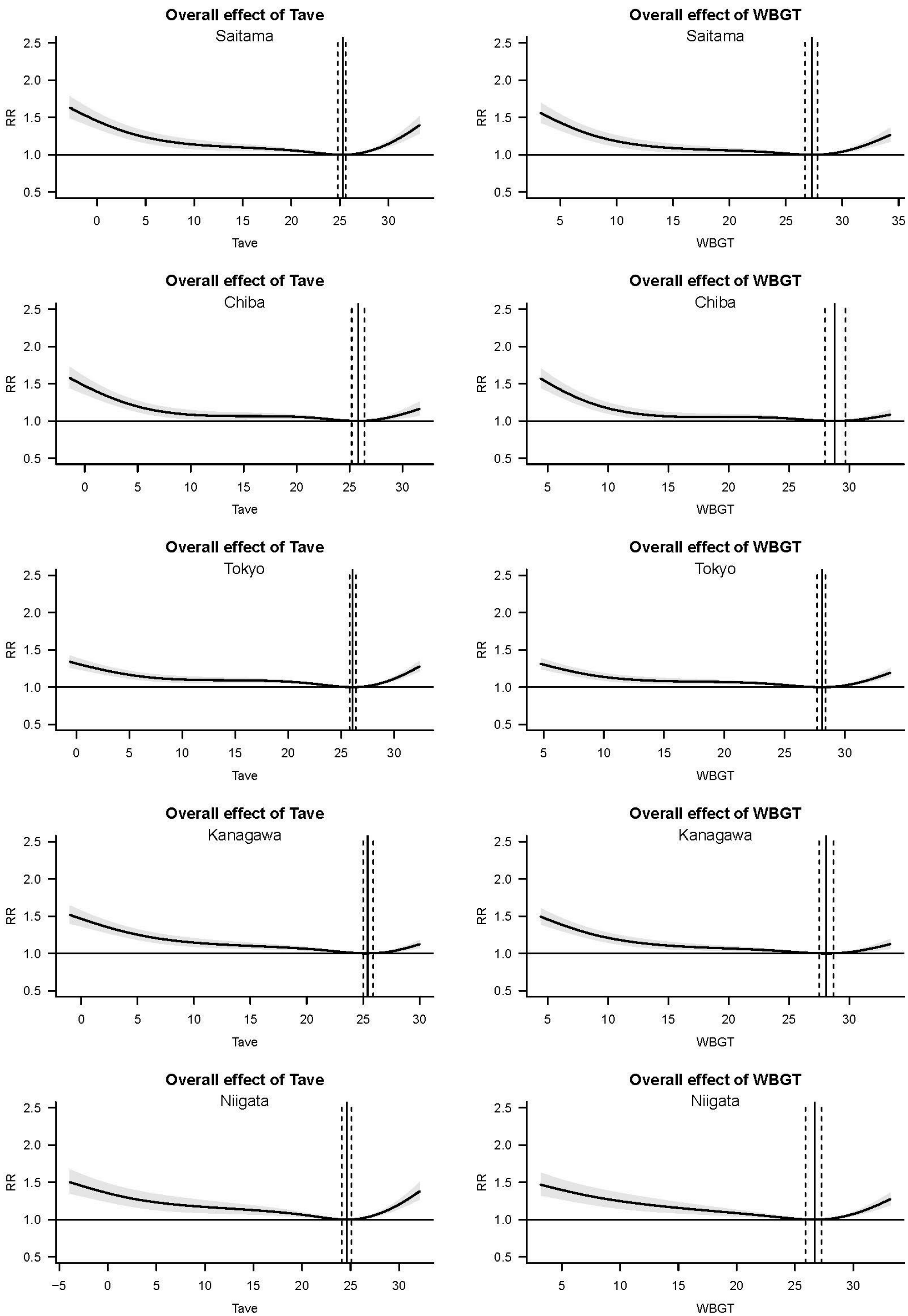
15
20
25
30
35



Overall effect of Tave
Saitama
RR
2.5
2.0
1.5
1.0
0.5
0
5
10
15
20
25
30
Tave
Overall effect of WBGT
Saitama
RR
2.5
2.0
1.5
1.0
0.5
5
10
15
20
25
30
35
WBGT
Overall effect of Tave
Chiba
RR
Tave
Overall effect of WBGT
Chiba
RR
WBGT
Overall effect of Tave
Tokyo
RR
Tave
Overall effect of WBGT
Tokyo
RR
WBGT
Overall effect of Tave
Kanagawa
RR
Tave
Overall effect of WBGT
Kanagawa
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Niigata
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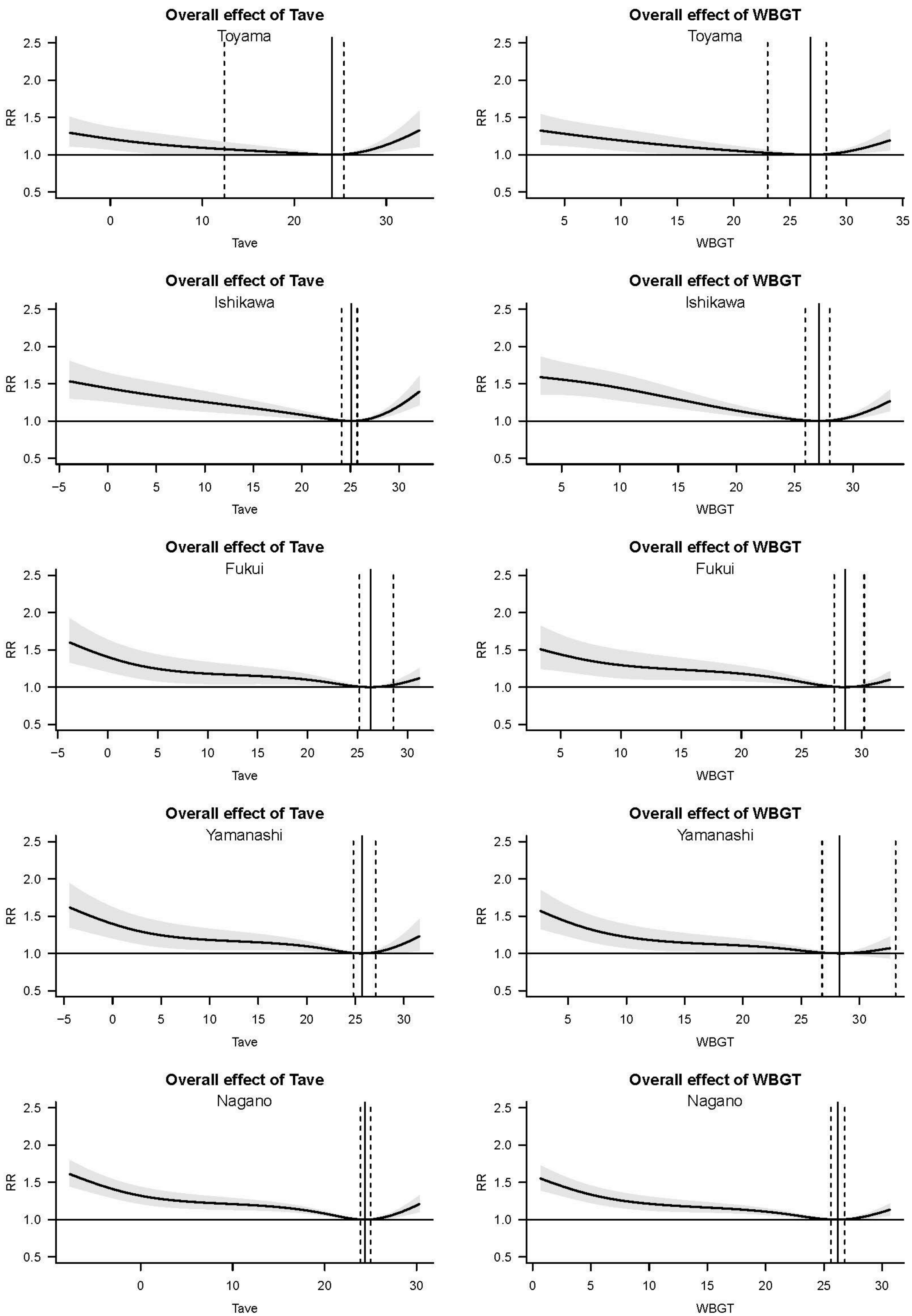
Overall effect of WBGT
Niigata
RR
WBGT


Overall effect of Tave
Toyama
RR
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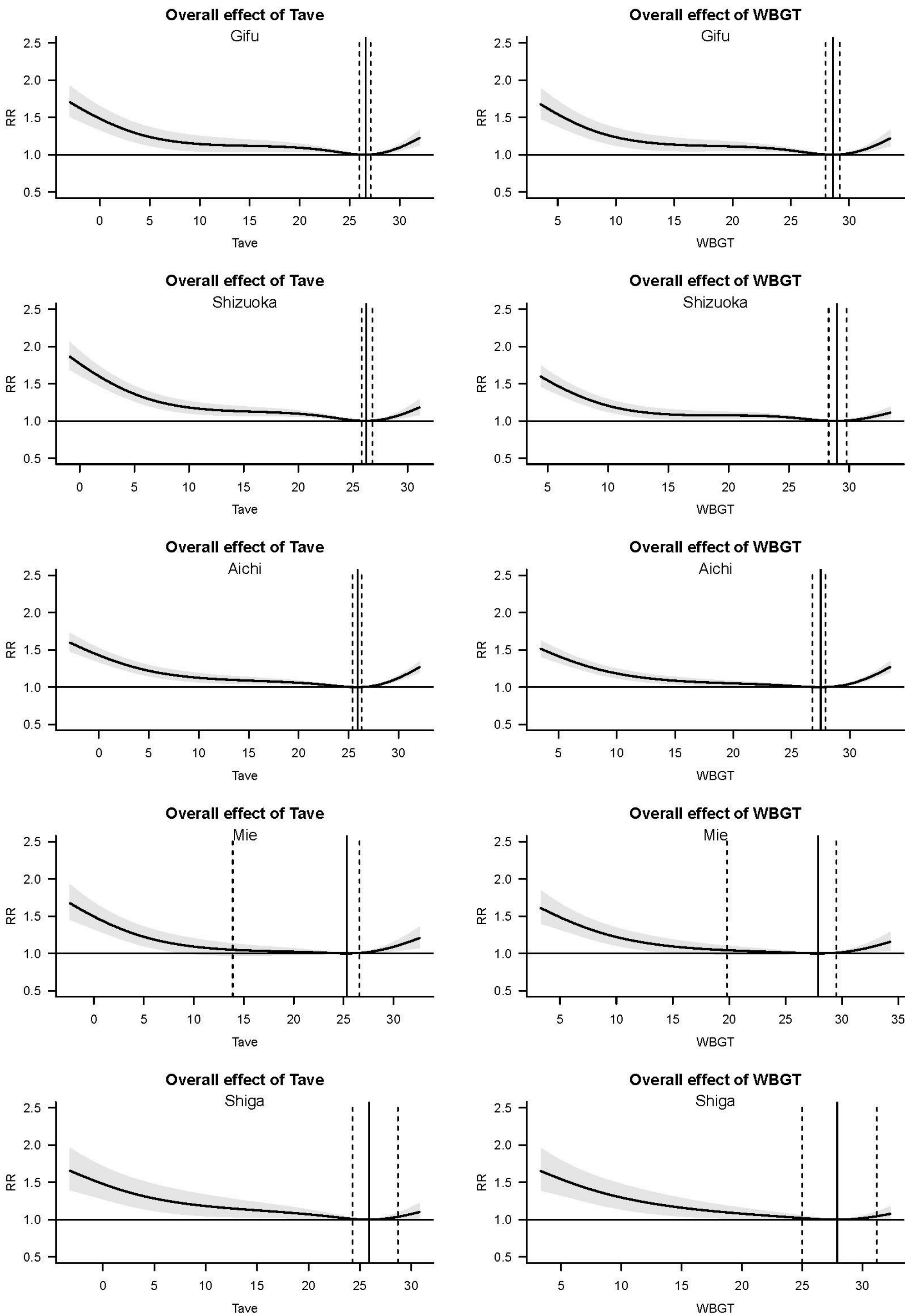
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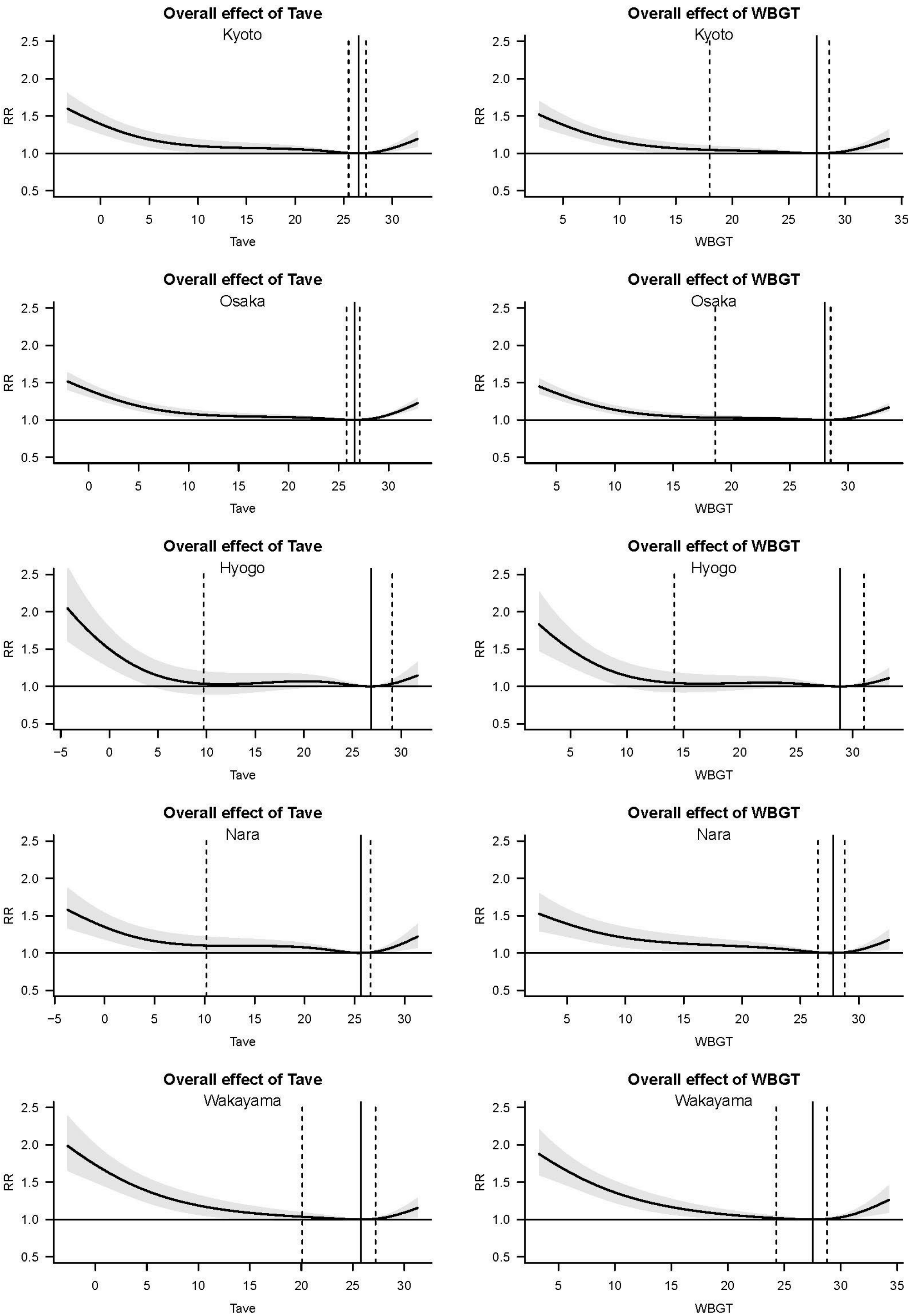
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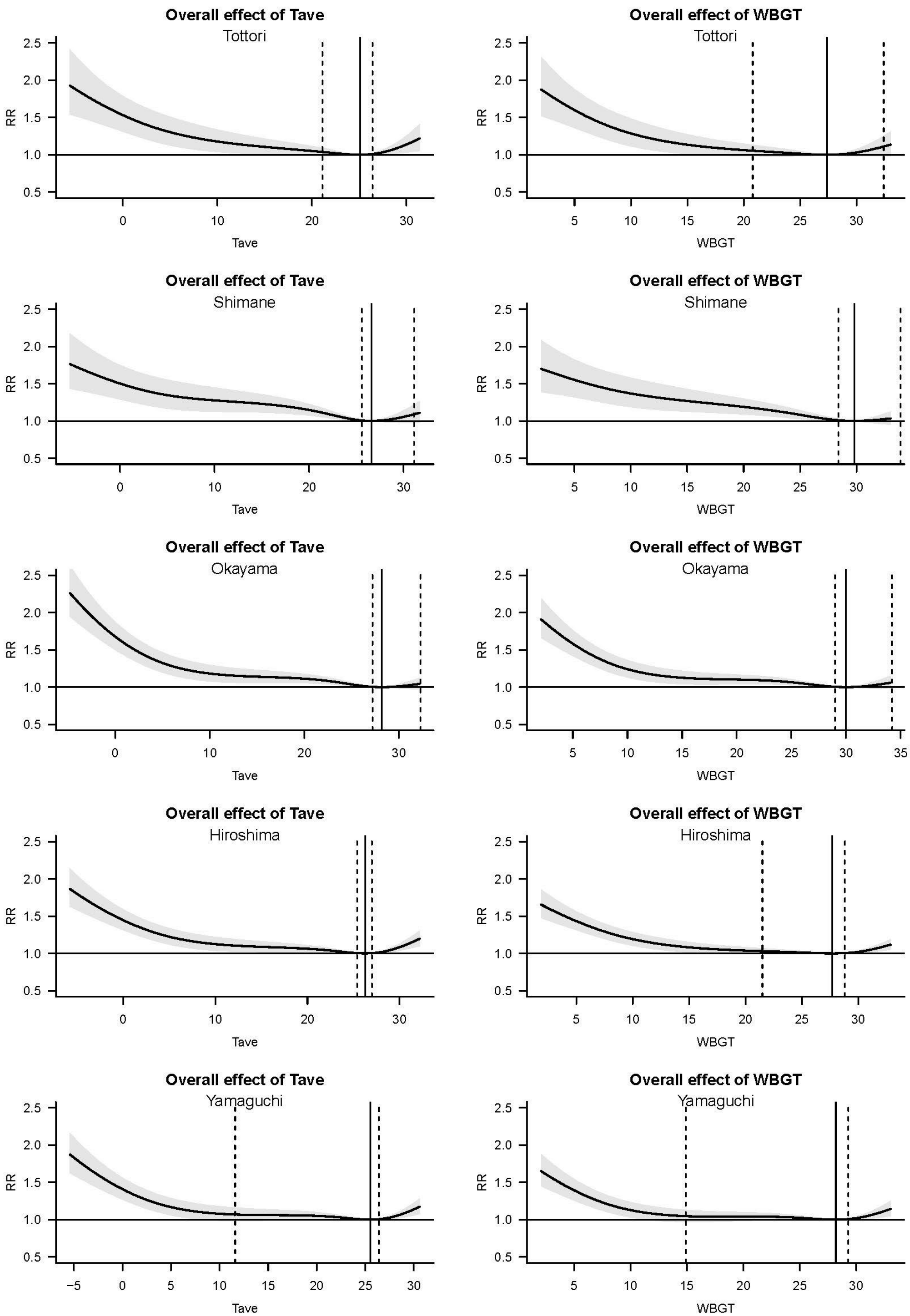
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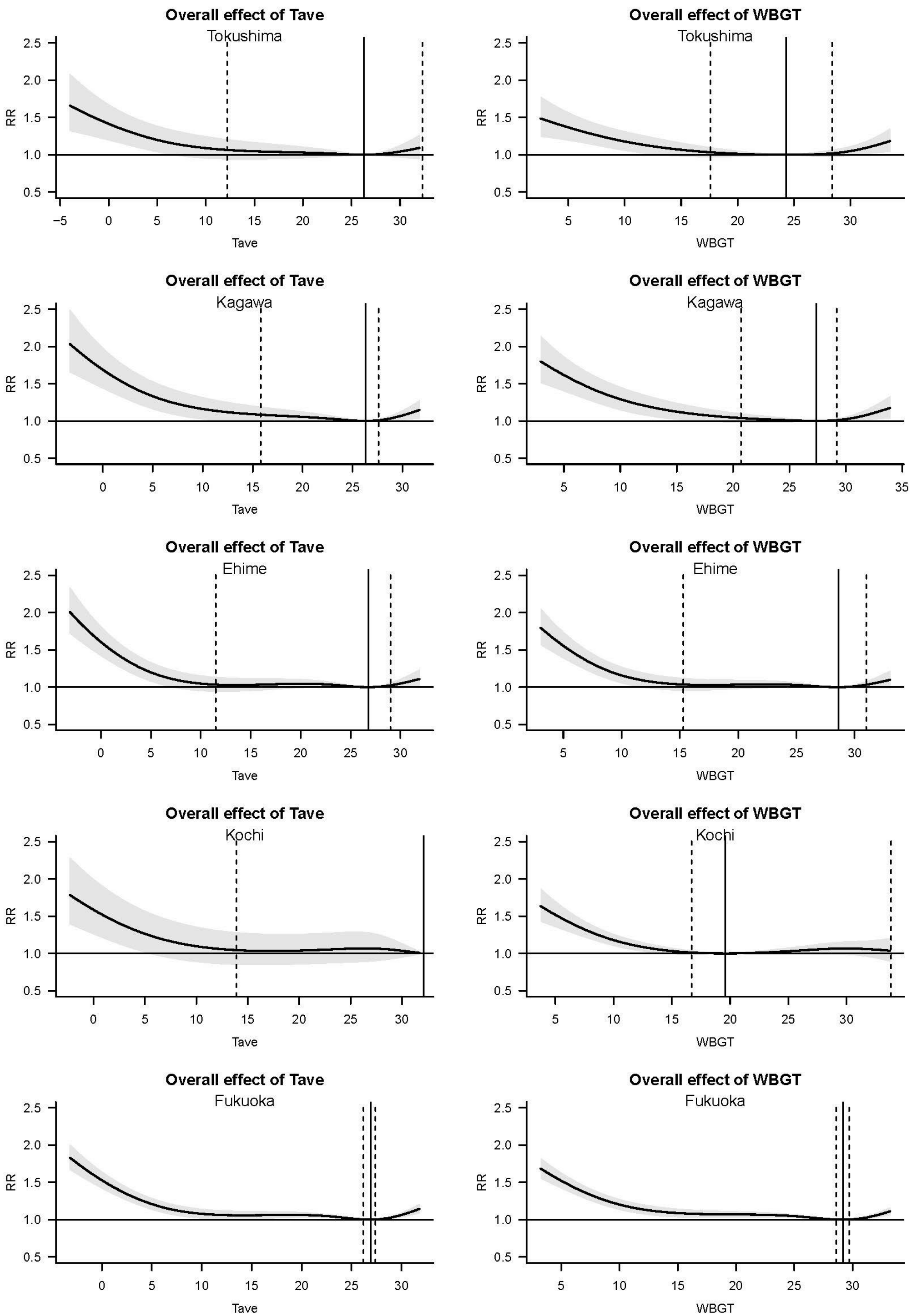

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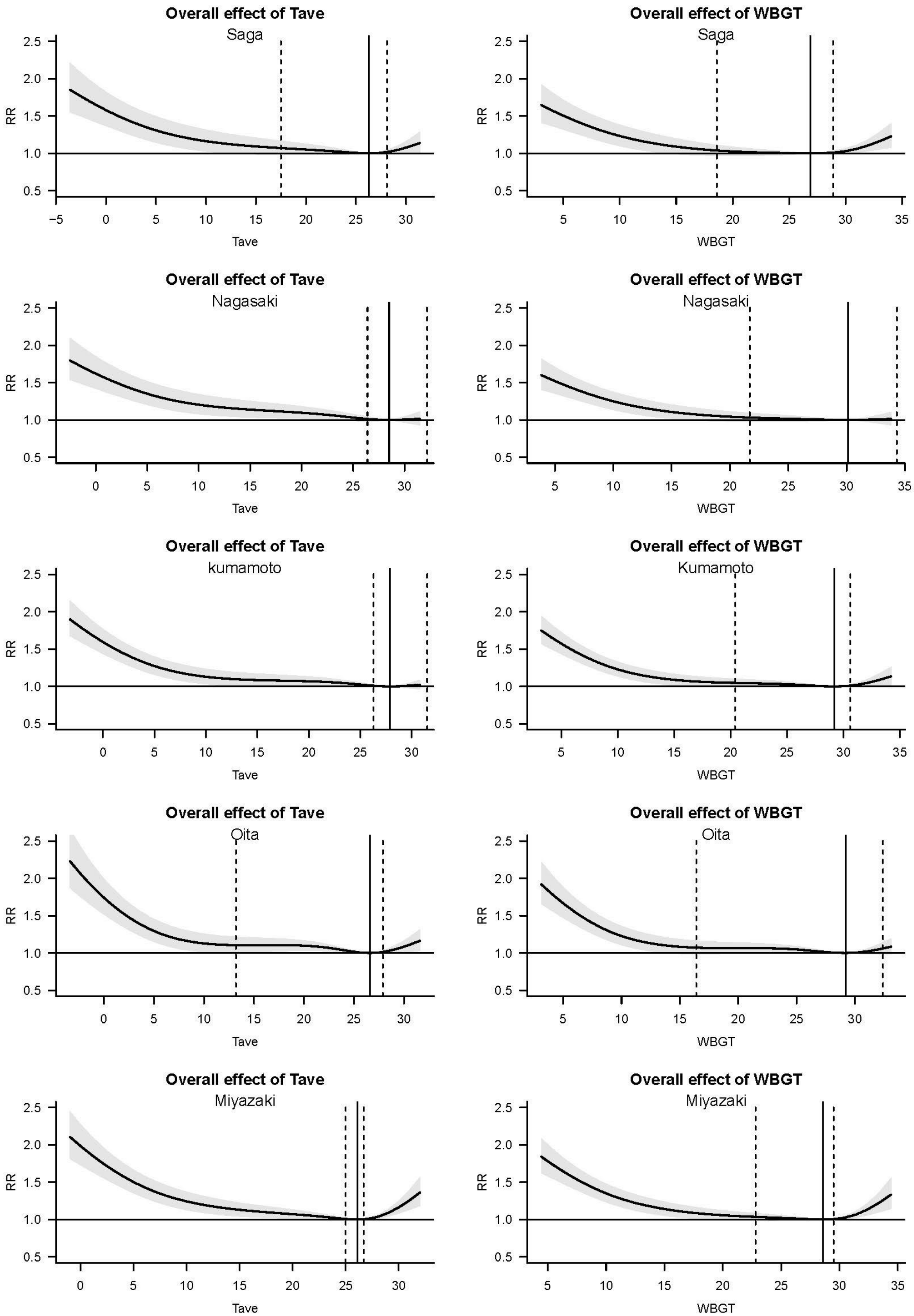

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Oita
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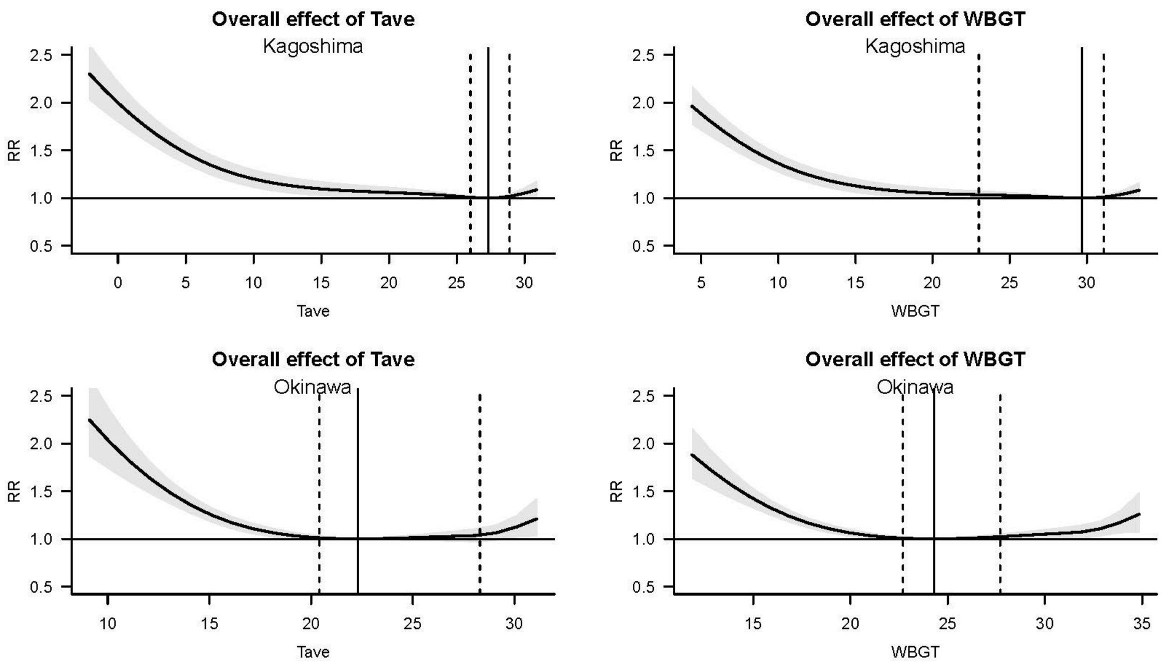
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S Table 1

Estimation of minimum mortality temperature (MMT), minimum mortality temperature percentile (MMTP), minimum mortality WBGT (MMW) and minimum mortality WBGT percentile (MMWP) among people of 0–64 years old.

"-" indicates that limits were not identified.

MMT (℃)	MMTP (%)	MMW (℃)	MMWP (%)	MMT (℃)
Hokkaido	20.3 (-2.6, 21.5)	86.8 (14.3, 91.2)	22.7 (8.4, 24)	87.8 (37, 91.9)
Aomori	20.7 (-3.71, 22.2)	85.5 (3.6, 9-.5)	24.1 (0.1, 25.6)	87.9 (-, 92.2)
Iwate	-8.9 (-8.9, 29.6)	- (-, -)	-0.2 (-0.2, 30.5)	- (-, 99.7)
Miyagi	18.0 (-5.2, 31.2)	7-.2 (-, -)	20.7 (2.1, 32.9)	71.2 (-, -)
Akita	23.5 (22.5, 24.4)	9- (86.4, 92.4)	25.9 (9.4, 26.9)	89 (32, 91.6)
Yamagata	23.7 (-7.4, 31.5)	88.6 (-, -)	1.0 (1, 32.4)	- (-, -)
Fukushima	-5.2 (-5.2, 31.4)	- (-, -)	2.1 (2.1, 32.9)	- (-, -)
Ibaraki	31.3 (-3.7, 31.3)	- (-, -)	18.2 (3.0, 34.2)	55.7 (-, -)
Tochigi	17.2 (5.8, 24.4)	6-.4 (24.9, 87.2)	20.4 (8.6, 26.7)	64.6 (2-.4, 85.9)
Gunma	25.5 (-3.7, 32.6)	88.2 (-, -)	26.3 (2.9, 33.7)	84.1 (-, -)
Saitama	25.0 (11.5, 26)	85.7 (39.-, 89.-)	27.0 (12.6, 28.4)	84.6 (35.1, 88.5)
Chiba	8.3 (6.1, 32.2)	24.2 (13.9, -)	12.9 (10.8, 34.0)	3-.8 (21.4, -)
Tokyo	26.5 (25.9, 27.3)	88 (86.1, 9-.7)	28.5 (27.8, 29.4)	87.2 (85.4, 89.9)
Kanagawa	26.1 (24.6, 30.9)	89.1 (84.2, -)	28.9 (14.4, 33.8)	88.7 (37.1, -)
Niigata	24.5 (-3.9, 25.7)	87.4 (-, 9-.7)	26.3 (3.2, 27.9)	85 (-, 89.6)
Toyama	-4.4 (-4.4, 24.3)	- (-, 85.8)	22.1 (2.9, 26.7)	68.7 (-, 83.7)
Ishikawa	26.9 (20.8, 32.3)	91.7 (7-.9, -)	28.1 (23.9, 33.3)	87.8 (75, -)
Fukui	32.1 (-3.7, 32.1)	- (-, -)	33.1 (3.4, 33.1)	- (-, -)
Yamanashi	26.3 (-4.4, 31.8)	9-.9 (-, -)	30 (2.7, 33.1)	97.1 (-, -)
Nagano	30.7 (14.8, 30.7)	- (56.7, -)	28.3 (11.6, 31.2)	95.9 (4-.2, -)
Gifu	26.8 (24.3, 28.3)	88.4 (79.4, 93.6)	29.1 (26.5, 34.4)	88 (79.6, -)
Shizuoka	25.9 (5.6, 27.4)	86.8 (6.9, 93.9)	29 (4.5, 33.7)	87.7 (-, -)
Aichi	25.5 (8.4, 26.5)	84.2 (26.9, 87.8)	27.2 (12.6, 28.1)	82.1 (32.1, 84.9)
Mie	28.4 (-2.3, 33.5)	95.6 (-, -)	29.6 (3.3, 35.2)	89 (-, -)
Shiga	19.8 (9.09, 31.4)	67.1 (33.5, -)	21.9 (16.6, 32.9)	66.8 (48.1, -)
Kyoto	25.6 (10, 27.5)	83.3 (32.3, 89.7)	26.6 (2.9, 28.9)	8-.6 (-, 87.8)
Osaka	27.1 (11.1, 28)	86.1 (32.2, 89.3)	28.4 (13.7, 29.4)	83.7 (33.2, 87.1)
Hyogo	9.6 (6.4, 32.0)	28.1 (15.5, -)	28.2 (10.8, 33.9)	83.5 (2-.6, -)
Nara	31.7 (4.6, 31.7)	- (14.5, -)	32.7 (11.3, 32.7)	- (28.1, -)
Wakayama	26.7 (23.9, 31.9)	86.1 (76.6, -)	28 (24.1, 34.6)	82 (7-.5, -)
Tottori	32.3 (13.7, 32.3)	- (45.5, -)	33.5 (17.3, 33.5)	- (5-.1, -)
Shimane	27.8 (-5.2, 32.2)	95.- (-, -)	33.9 (2.1, 33.9)	- (-, -)
Okayama	27.4 (10.4, 32.3)	89.5 (33.5, -)	29.5 (10.8, 34.2)	87.5 (22.8, -)
Hiroshima	10.6 (-5.7, 26.4)	33.4 (-, 87.-)	15.5 (1.9, 27.4)	41.7 (-, 81.6)
Yamaguchi	26.3 (7.4, 31.2)	88.5 (24.2, -)	29.5 (11.5, 33.7)	89.5 (25.9, -)
Tokushima	3.7 (-4.0, 32.3)	3.2 (-, -)	2.6 (2.6, 33.9)	- (-, -)
Kagawa	29 (-3.2, 32.3)	95.9 (-, -)	3.0 (3.0, 34)	- (-, -)
Ehime	31.9 (7.1, 31.9)	- (16.5, -)	15.7 (11.5, 33)	4-.7 (22.6, -)
kochi	32.1 (-2.2, 32.1)	- (-, -)	20 (3.8, 33.8)	52.9 (-, -)
Fukuoka	26.4 (9.0, 27.5)	85.8 (21.3, 89.4)	28.7 (13.1, 29.8)	83.9 (27.2, 87.7)
Saga	15.5 (-3.6, 32.2)	45.5 (-, -)	15.4 (3.1, 34.3)	38.3 (-, -)
Nagasaki	32.2 (27.2, 32.2)	- (89, -)	34.3 (12.8, 34.3)	- (23.2, -)
Kumamoto	31.5 (8.6, 31.5)	- (21.8, -)	30.1 (10.4, 34.8)	87.8 (15.5, -)
Oita	26.9 (7.7, 31.6)	9-.2 (17.5, -)	29.6 (11.5, 33.7)	88.7 (21.1, -)
Miyazaki	26.6 (13.1, 32.0)	86.- (32.8, -)	29.2 (16.1, 34.4)	81.7 (34.6, -)
Kagoshima	31.1 (13.7, 31.1)	- (31.6, -)	34.3 (16.3, 34.3)	- (32.9, -)
Okinawa	19.3 (17.8, 31.1)	25.9 (17.9, -)	21.9 (20.0, 25.9)	29.9 (2-.3, 5-.9)

S Table 2

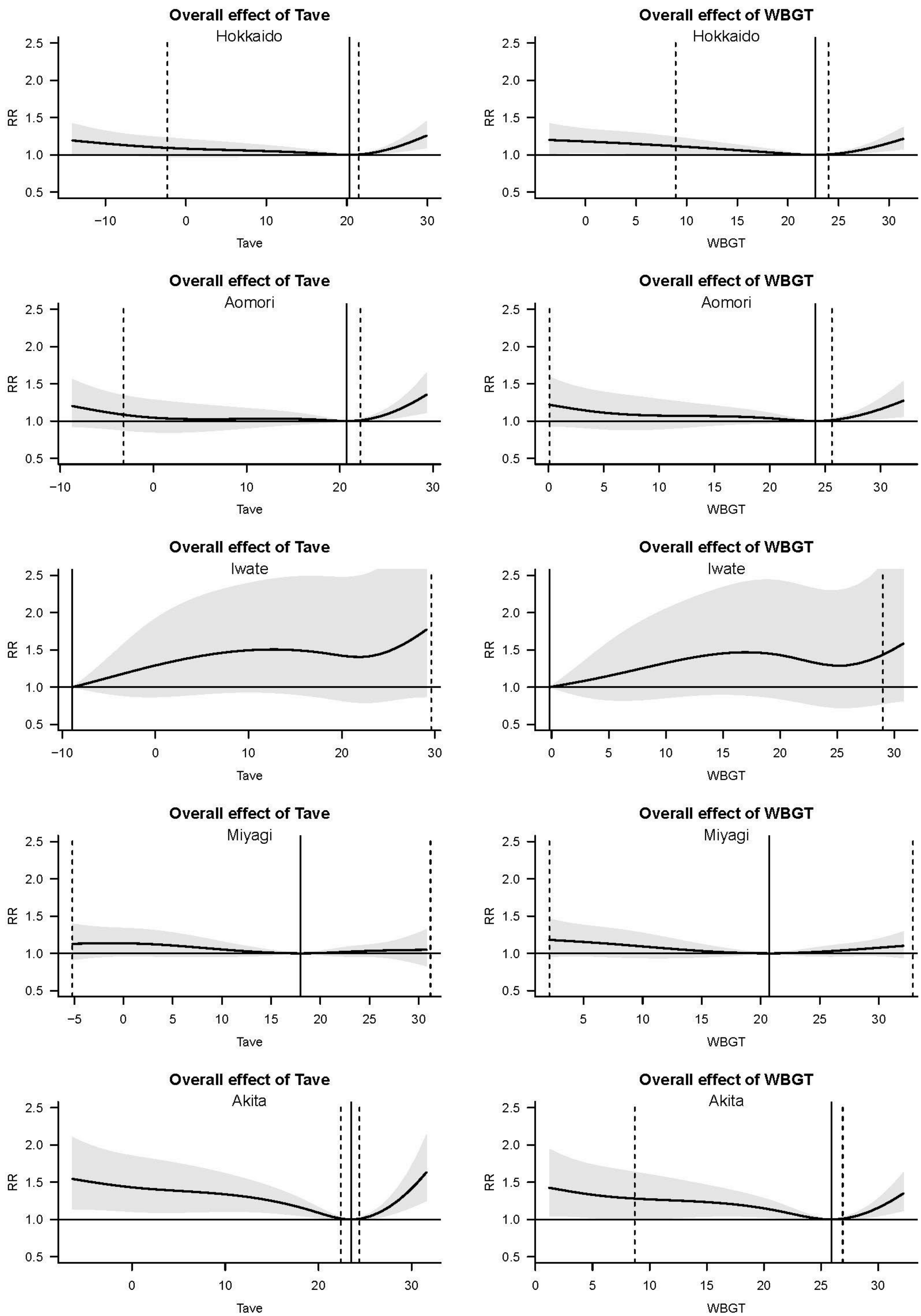
Estimation of minimum mortality temperature (MMT), minimum mortality temperature percentile (MMTP), minimum mortality WBGT (MMW) and minimum mortality WBGT percentile (MMWP) among people 65+ years old.

"-" indicates that limits were not identified.

Prefectures	MMT	MMTptl	MMW	MMWptl
Hokkaido	21.2 (20.3, 21.7)	90.2 (86.8, 91.7)	23.4 (22.5, 24.0)	90 (87.0, 91.9)
Aomori	21.7 (0.5, 22.1)	88.9 (18.0, 90.2)	24.5 (6.5, 25.0)	89.2 (21.0, 90.7)
Iwate	22.2 (-8.9, 29.6)	88.7 (-, -)	25.0 (-0.2, 27.8)	89.2 (0, 95.7)
Miyagi	23.5 (22.9, 24.6)	89.8 (87.8, 93.2)	26.3 (25.6, 27.1)	89.3 (87.5, 91.3)
Akita	22.9 (21.8, 23.6)	87.8 (83.7, 90.3)	25.3 (24.2, 26.0)	87.3 (83.4, 89.3)
Yamagata	23.3 (22.7, 23.9)	87.4 (85.6, 89.2)	25.6 (24.9, 26.2)	87.1 (85.1, 88.8)
Fukushima	24.1 (6.6, 24.9)	87.8 (31.4, 90.0)	26.6 (10.6, 27.4)	88.2 (33.5, 90.2)
Ibaraki	24.6 (24, 25.3)	89.7 (87.7, 91.8)	27.7 (27.1, 28.5)	88.8 (87.3, 91.0)
Tochigi	24.5 (10.2, 25.3)	87.4 (38.5, 90.2)	27.2 (13.1, 28.1)	87.2 (39.1, 89.9)
Gunma	24.9 (23.4, 25.6)	86.2 (81.9, 88.6)	26.6 (25.4, 27.4)	84.9 (81.3, 87.1)
Saitama	25.3 (24.9, 25.7)	86.6 (85.5, 88.0)	27.4 (26.8, 27.9)	85.7 (84.0, 86.9)
Chiba	25.6 (25, 26.3)	87.3 (85.4, 89.7)	28.5 (27.8, 29.4)	87.0 (85.0, 89.5)
Tokyo	26.0 (25.7, 26.3)	86.4 (85.5, 87.3)	27.9 (27.5, 28.3)	85.7 (84.6, 86.6)
Kanagawa	25.3 (24.8, 25.7)	86.1 (84.8, 87.7)	27.9 (27.2, 28.5)	85.7 (83.8, 87.4)
Niigata	24.7 (24.1, 25.1)	88.1 (86, 89.2)	26.7 (25.9, 27.3)	86.2 (83.7, 88.1)
Toyama	24.9 (19.8, 26.4)	87.8 (68.7, 91.8)	27.6 (24.9, 29.3)	86.4 (78.1, 91.6)
Ishikawa	24.9 (23.8, 25.5)	86 (82.6, 87.8)	26.9 (25.6, 27.8)	84.3 (80.2, 86.8)
Fukui	26.1 (25.2, 27.4)	89.1 (86.5, 92.9)	28.5 (27.7, 29.7)	88.3 (85.6, 92.6)
Yamanashi	25.5 (10.8, 27.1)	87.8 (38, 93.8)	28.1 (15.8, 33.1)	89.4 (46.2, 100)
Nagano	24.2 (23.8, 24.7)	89.2 (87.9, 90.6)	26.1 (25.6, 26.7)	88.0 (86.5, 90.1)
Gifu	26.5 (25.6, 27.1)	87.4 (84, 89.5)	28.5 (27.8, 29.2)	85.8 (83.6, 88.4)
Shizuoka	26.3 (25.8, 27)	88.4 (86.3, 92.1)	29.0 (28.2, 30.1)	87.7 (84.5, 92.3)
Aichi	26 (25.5, 26.4)	85.9 (84.2, 87.5)	27.5 (26.8, 28.1)	83.0 (80.9, 84.9)
Mie	24.1 (13.8, 25.8)	80 (43, 85.9)	27.3 (19.0, 29.0)	81.4 (53.2, 86.9)
Shiga	26.1 (25.1, 27.6)	89 (85.5, 94.3)	28.3 (27.0, 30.0)	86.8 (82.6, 93.3)
Kyoto	26.7 (11.8, 27.6)	87 (37.9, 90.1)	27.8 (15.7, 29.1)	84.2 (43.0, 88.5)
Osaka	26.3 (17.1, 26.9)	83.4 (49.6, 85.4)	27.8 (19.7, 28.5)	81.9 (54.4, 84.0)
Hyogo	27 (10.7, 28.2)	88.5 (31.6, 93.7)	29.1 (15.0, 30.6)	86.5 (38.5, 92.6)
Nara	25.4 (9, 26.2)	86.5 (32.5, 89.5)	27.4 (18.6, 28.3)	83.2 (54.3, 86.7)
Wakayama	25.1 (14.4, 27.1)	80.4 (41.8, 87.8)	27.3 (20.0, 28.8)	80.2 (55.4, 84.5)
Tottori	25.0 (20.0, 26.0)	86.1 (68, 89)	27.4 (19.0, 29.0)	84.6 (56.6, 89.4)
Shimane	26.4 (25.4, 30.6)	91.1 (88.4, 99.9)	29.6 (28.3, 33.9)	90.9 (86.9, -)
Okayama	28.6 (27.1, 32.3)	93.7 (88.3, 100)	30.2 (29.0, 34.2)	90.2 (85.8, -)
Hiroshima	26.6 (25.9, 27.4)	87.7 (85.3, 90.7)	28.3 (26.7, 29.5)	84.2 (79.7, 88.3)
Yamaguchi	25.3 (11.5, 26.3)	85.1 (37.9, 88.5)	27.7 (14.8, 29.0)	83.0 (39.8, 87.6)
Tokushima	26.4 (13.1, 32.3)	86.9 (38.2, 100)	24.0 (18.0, 28.3)	70.6 (47.7, 83.3)
Kagawa	26.2 (14.5, 27.3)	85.4 (44, 89.7)	27.4 (20.5, 29.0)	80.7 (58.5, 85.6)
Ehime	26.7 (11.7, 28.1)	87.6 (34.6, 93.7)	28.6 (15.5, 30.1)	85.9 (40.0, 93.4)
kochi	32.1 (14.2, 32.1)	100 (39.3, 100)	19.6 (16.8, 33.8)	51.4 (41.3, -)
Fukuoka	27 (26.3, 27.6)	87.8 (85.5, 89.8)	29.3 (28.7, 30.0)	86.0 (83.9, 88.5)
Saga	26.6 (24.9, 27.9)	86.6 (80, 91.8)	28.1 (24.5, 29.3)	81.3 (70.8, 85.2)
Nagasaki	27.2 (21.6, 32.2)	89 (67.5, 100)	28.3 (20.5, 34.3)	81.1 (54.5, 100)
Kumamoto	27.4 (25.6, 31.5)	88.5 (81.2, 100)	29.1 (22.5, 30.4)	83.3 (62.4, 89.5)
Oita	26.5 (12.8, 28.2)	88.6 (37.6, 95.6)	29.1 (16.6, 33.7)	86.5 (42.8, 100)
Miyazaki	25.9 (22.6, 26.6)	82.6 (70, 86)	28.3 (21.2, 29.4)	78.9 (53.8, 82.4)
Kagoshima	27 (25.5, 28)	83.1 (77.5, 88.5)	29.5 (22.9, 30.5)	81.1 (59, 85.2)
Okinawa	23.9 (21.4, 28.8)	54 (38.9, 90.5)	25.5 (23.3, 34.8)	48.9 (37.3, 100)

Fig. S2

The overall cumulative mortality effect of WBGT and temperature among people of 0–64 years old in 47 Japanese prefectures, 1972–2012: All show unconstrained minimum mortality temperature and solid vertical lines are minimum mortality temperature or minimum mortality WBGT, and dashed vertical lines are their 95% confidence intervals. RR indicates the relative risk. Tave is mean temperature.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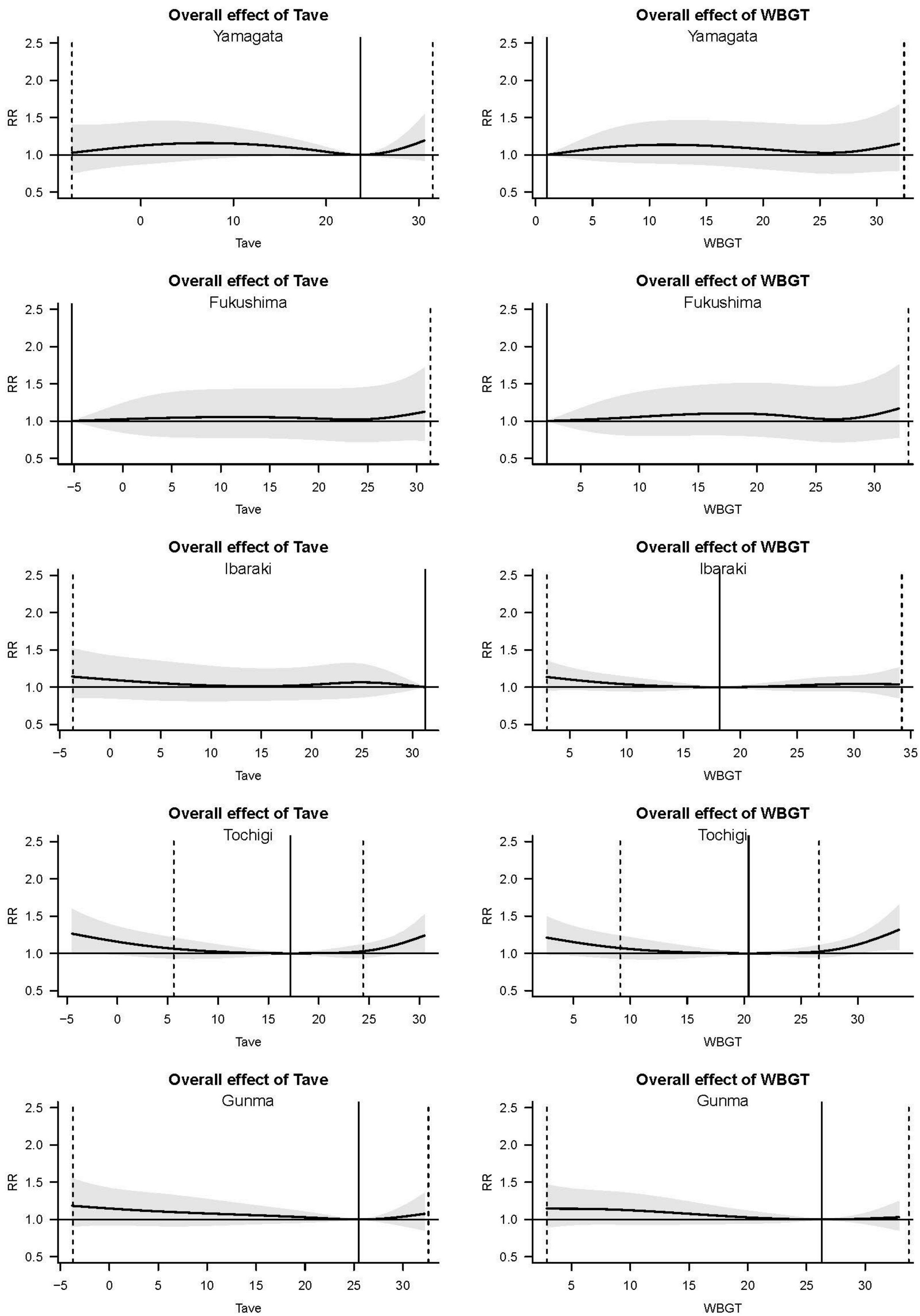

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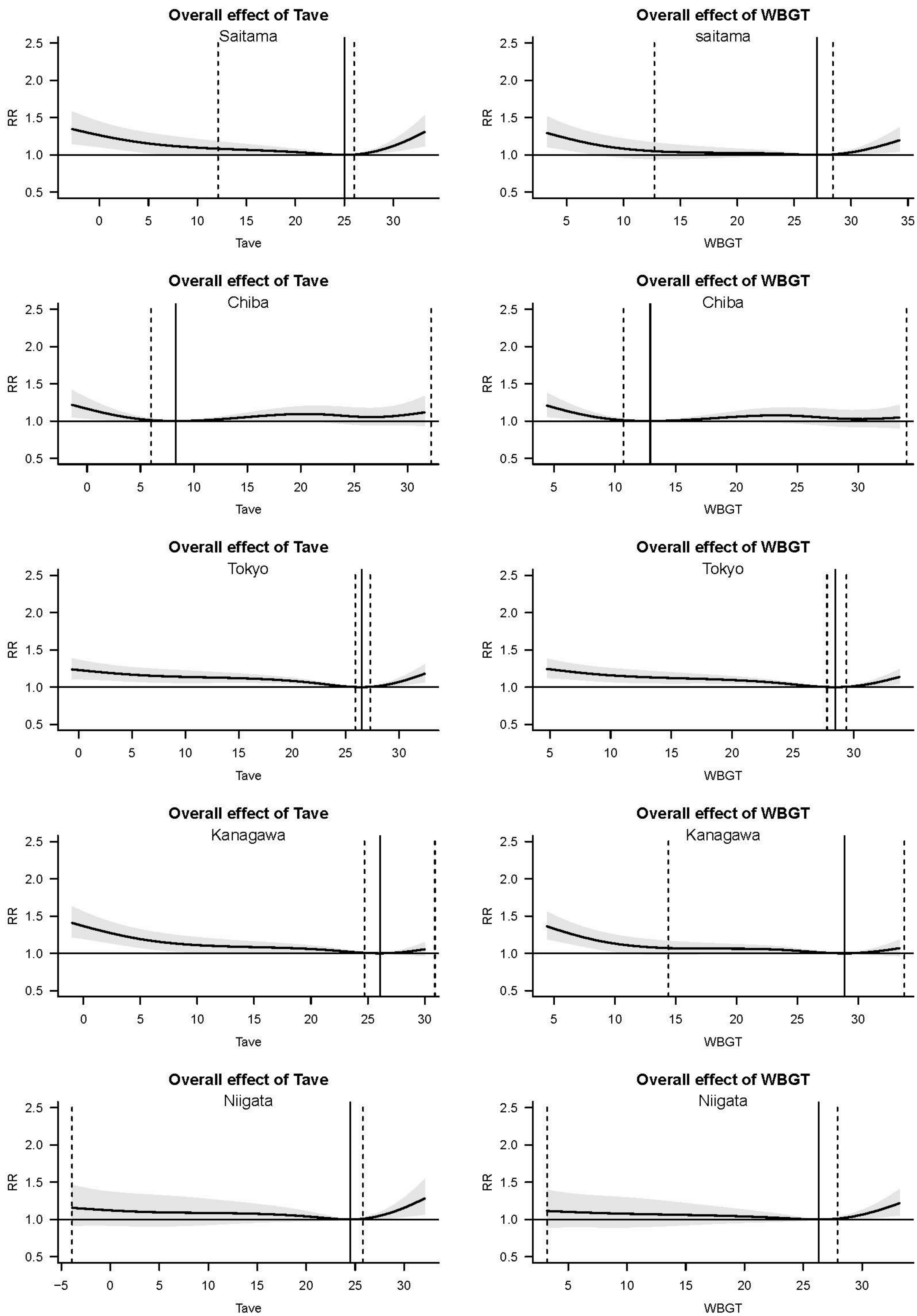
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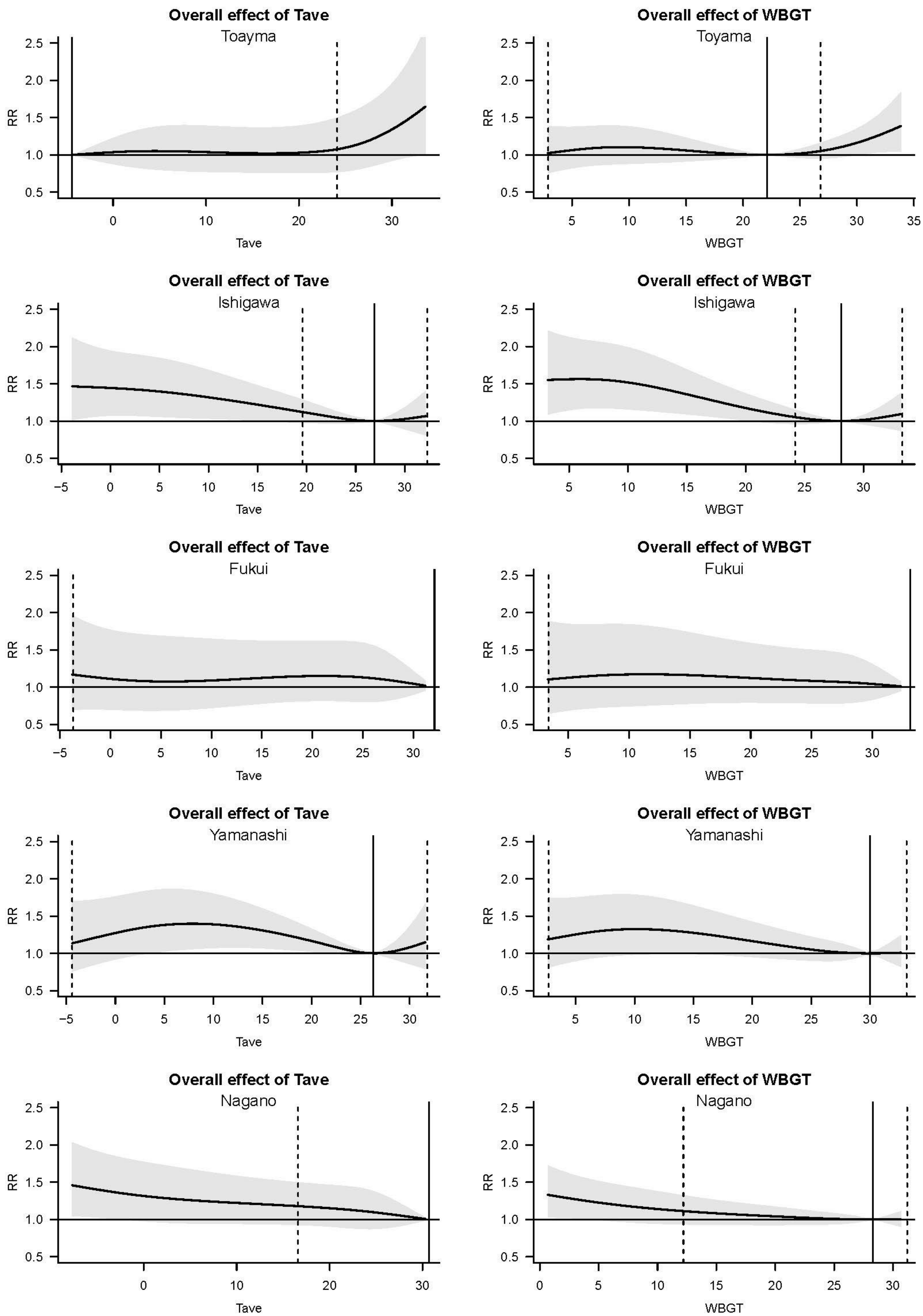
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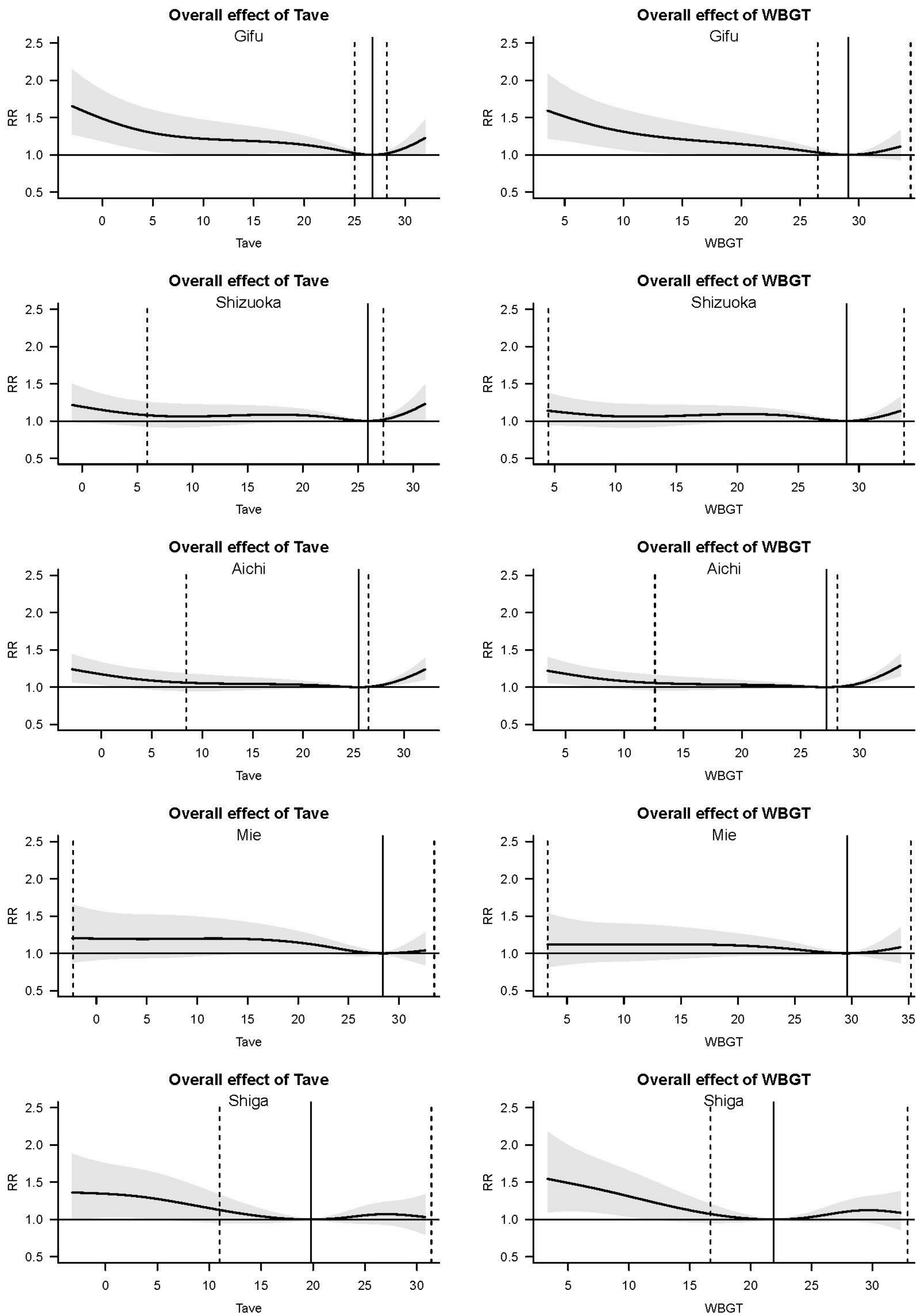
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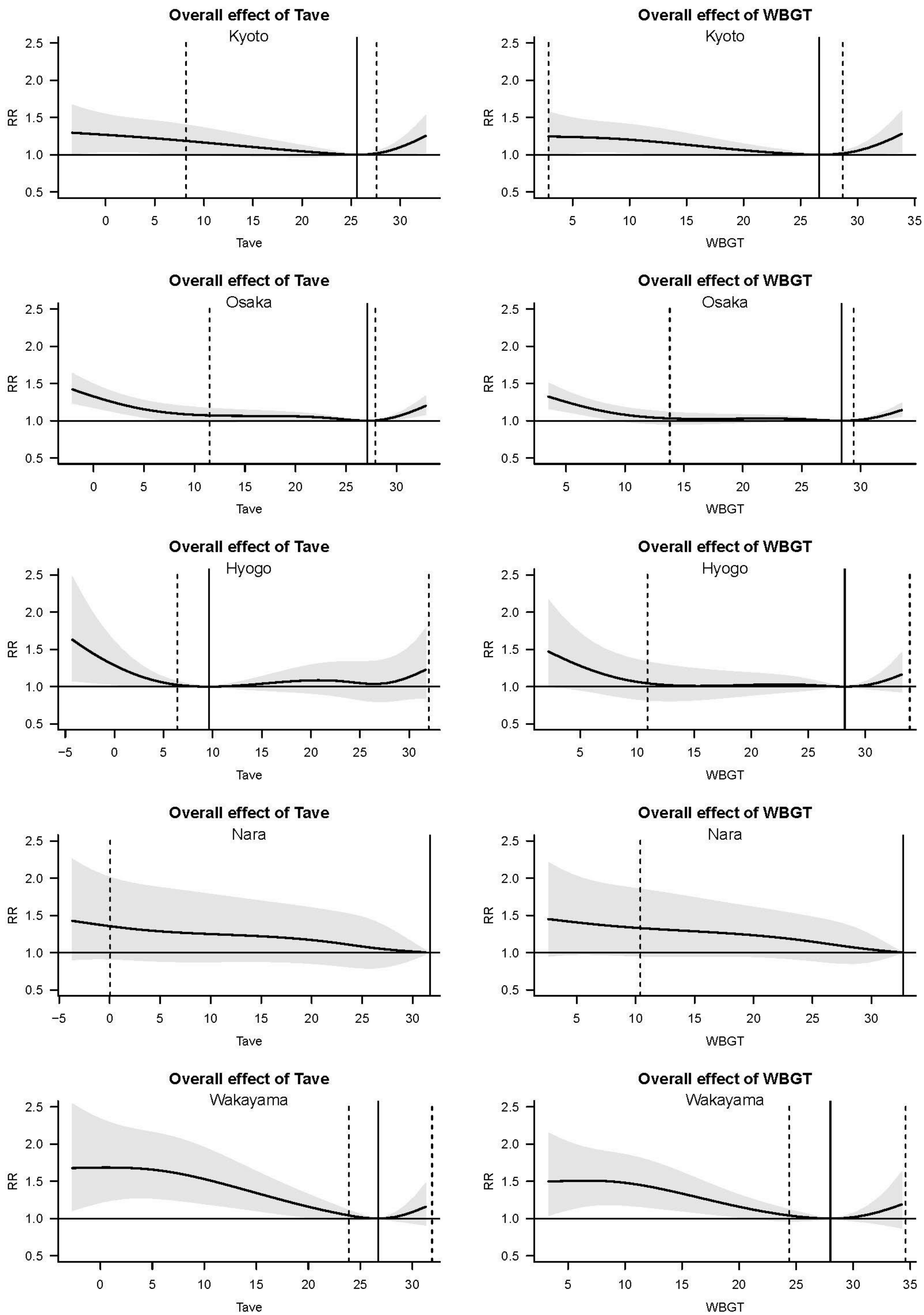
Shiga
RR
Tave
WBGT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Osaka
RR
WBGT
Overall effect of Tave
Hyogo
RR
Tave
Overall effect of WBGT
Hyogo
RR
WBGT
Overall effect of Tave
Nara
RR
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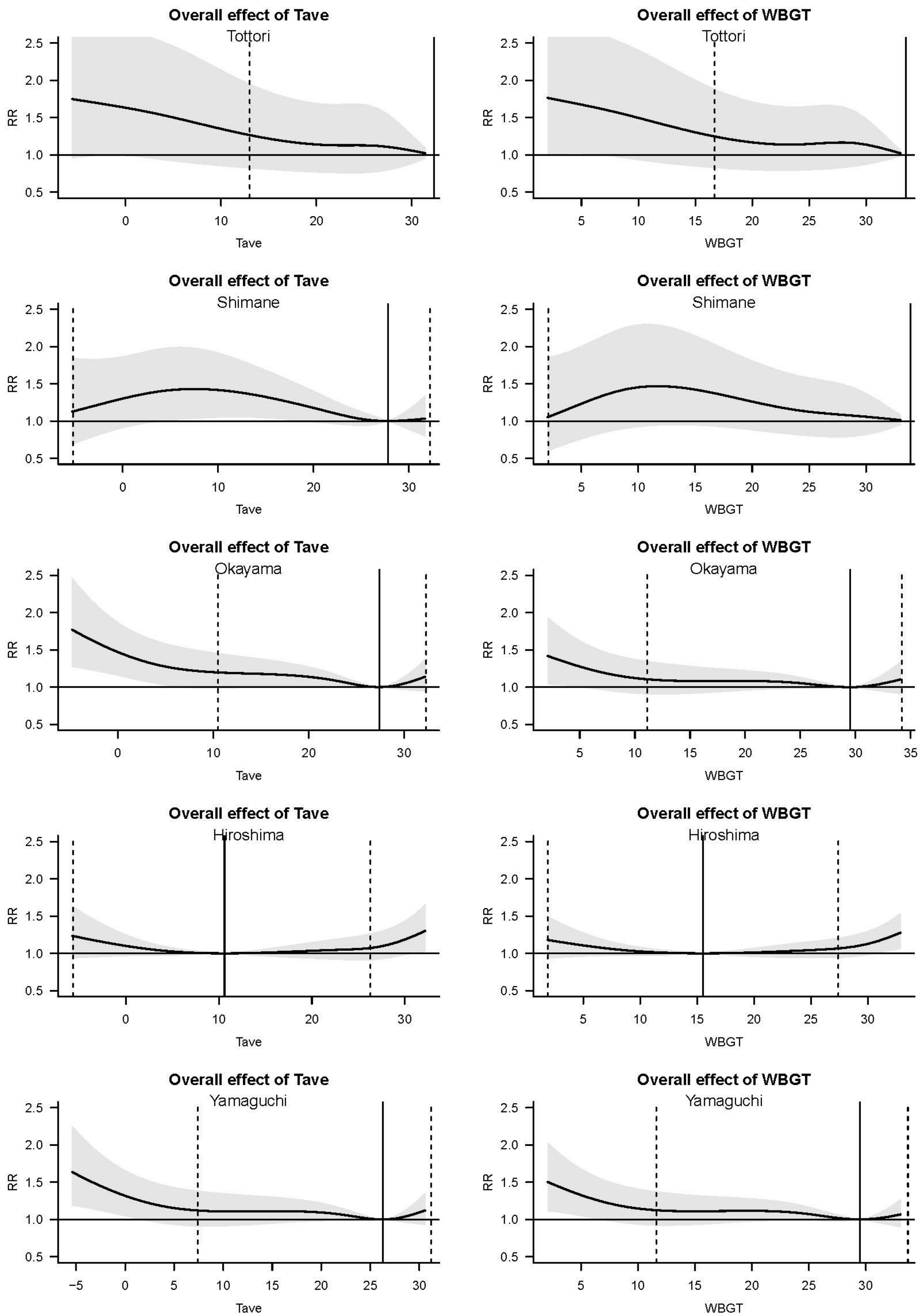
RR
Tave
Overall effect of WBGT
Wakayama
RR
WBGT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Tottori
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Overall effect of WBGT
Okayama
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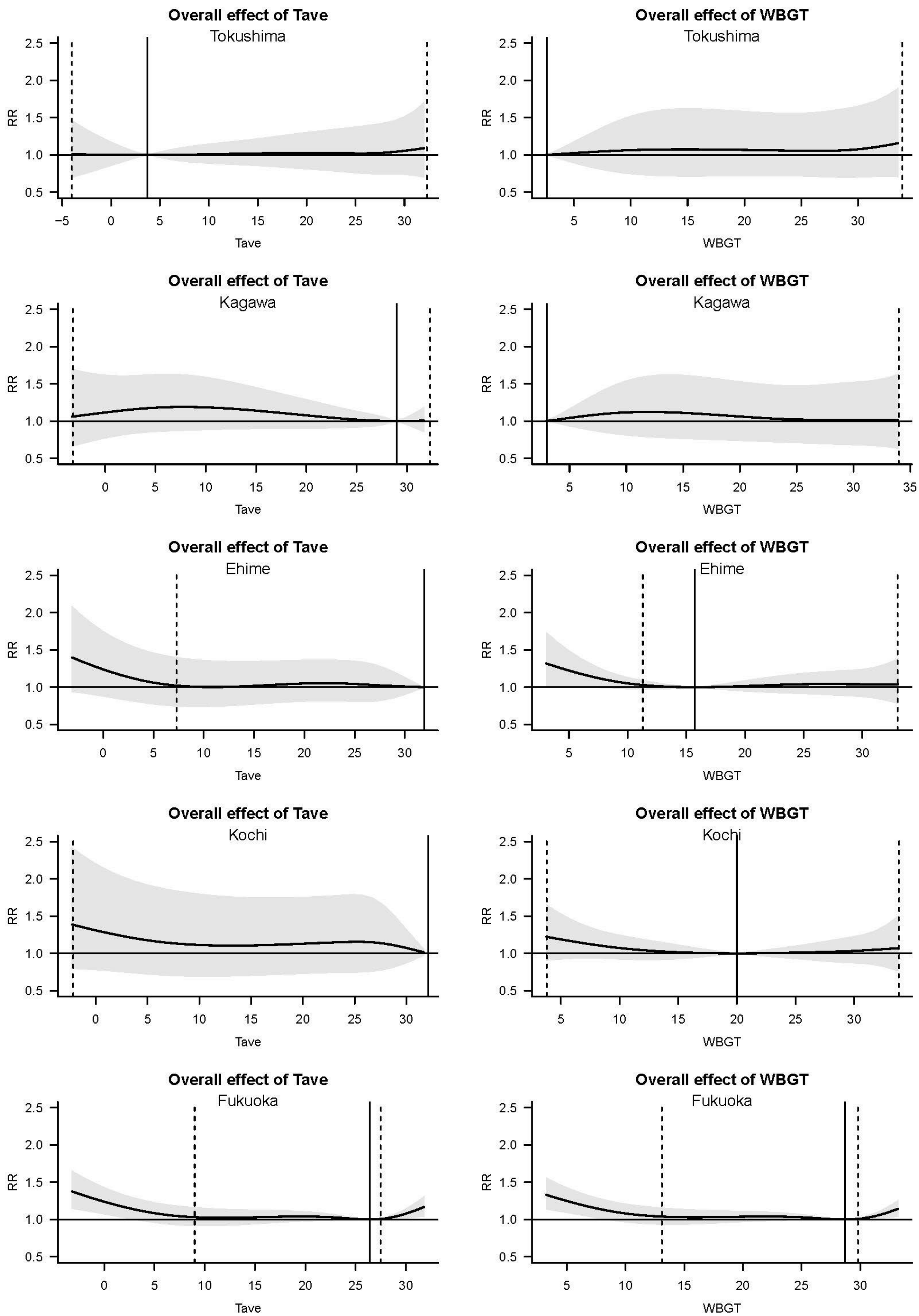
Overall effect of Tave
Yamaguchi
Overall effect of WBGT
Yamaguchi
RR
Tave
WBGT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WBGT
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RR
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RR
WBGT
Overall effect of Tave
Ehime
RR
Tave
Overall effect of WBGT
Ehime
RR
WBGT
Overall effect of Tave
Kochi
RR
Tave
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RR
WBGT
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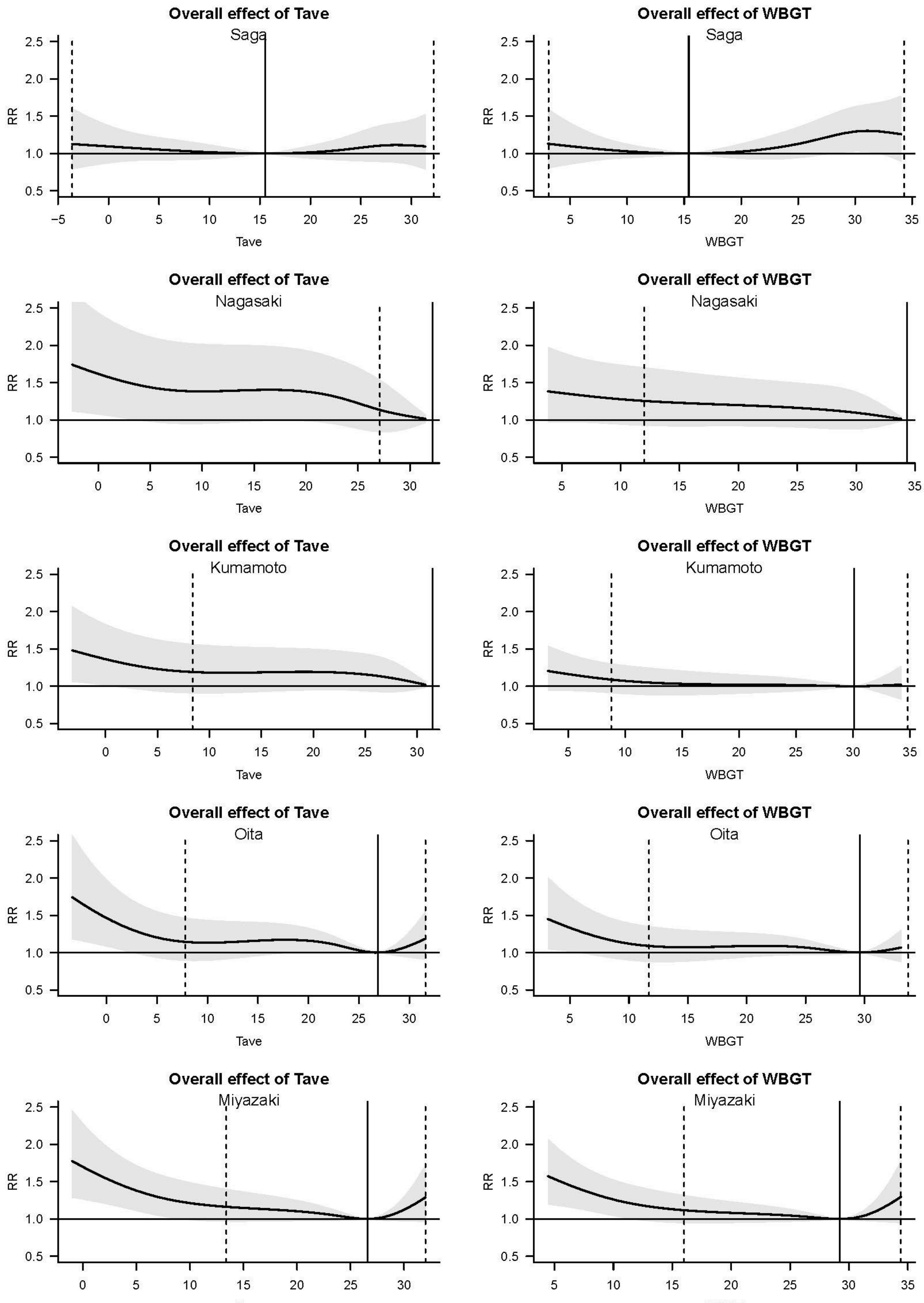
Fukuoka
RR
Tave
Overall effect of WBGT
Fukuoka
RR
WBGT



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Overall effect of WBGT
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Overall effect of WBGT
Kumamoto
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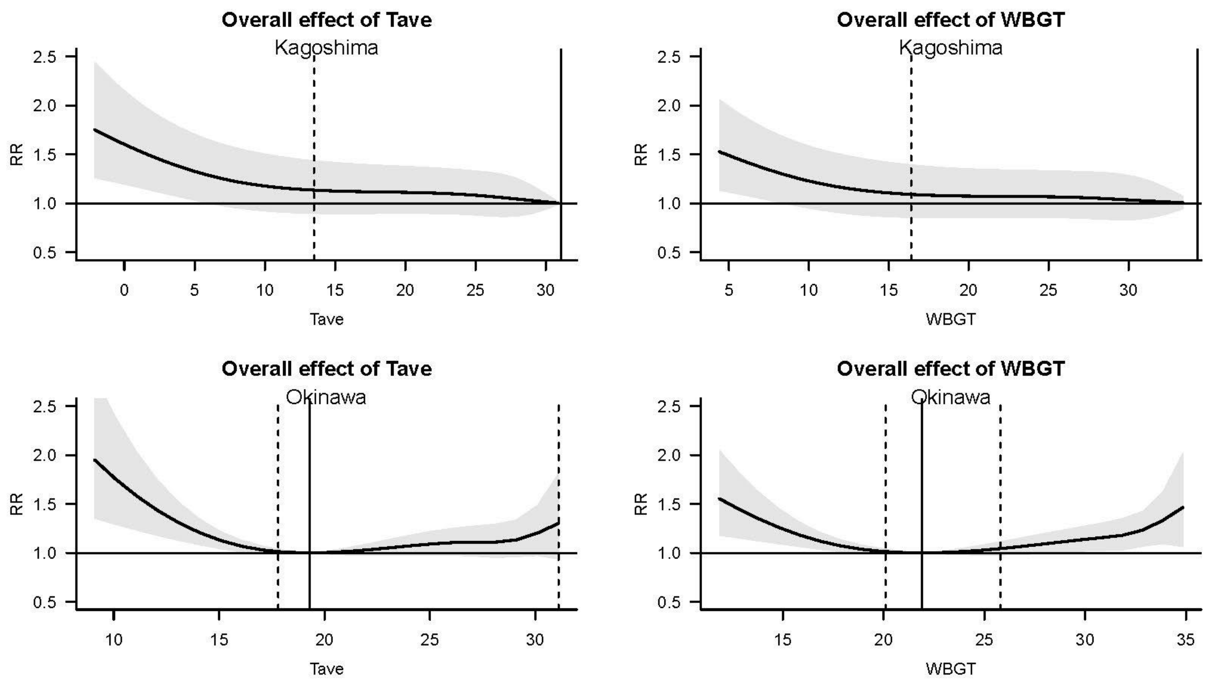
Oita
Overall effect of Tave
Miyazaki
Overall effect of WBGT
Miyazaki
RR
Tave
WBGT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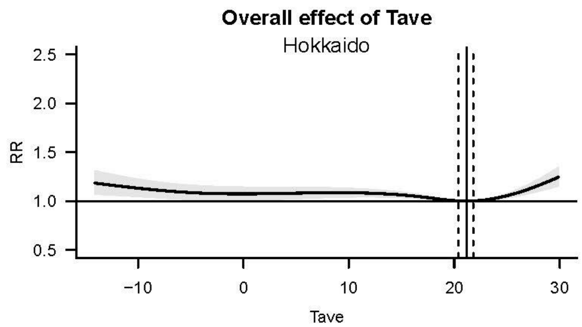
Overall effect of WBGT
Kagoshima
Overall effect of Tave
Okinawa
Overall effect of WBGT
Okinawa
RR
Tave
WBGT

Fig. S3

The overall cumulative mortality effect of WBGT and temperature among people of 65+ years old in 47 Japanese prefectures, 1972–2012: All show unconstrained minimum mortality temperature and solid vertical lines are minimum mortality temperature or minimum mortality WBGT, and dashed vertical lines are their 95% confidence intervals. RR indicates the relative risk. Tave is mean temperature.


Overall effect of Tave
Hokkaido
RR
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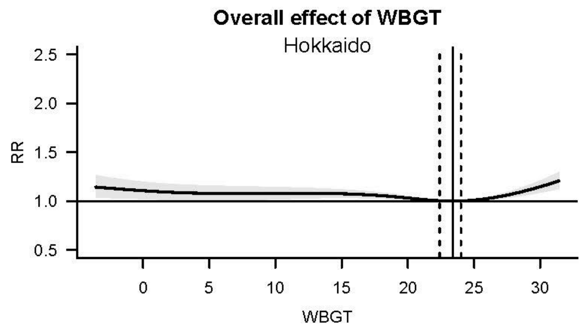
Tave


Overall effect of WBGT
Hokkaido
RR
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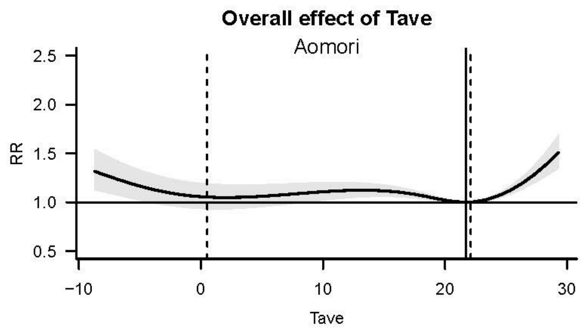
WBGT


Overall effect of Tave
Aomori
RR
2.5 2.0 1.5 1.0 0.5
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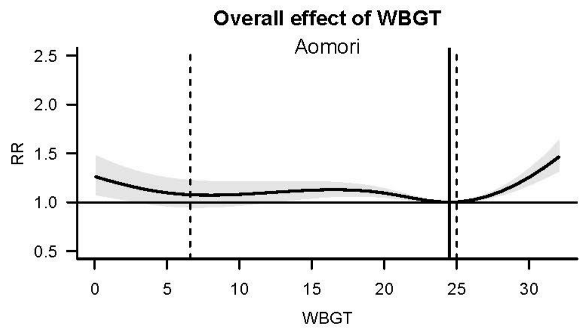
Tave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Aomori
RR
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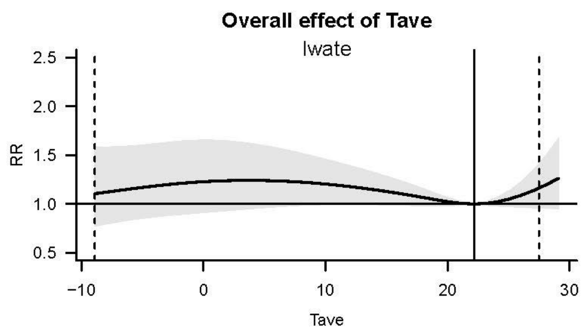
WBGT


Overall effect of Tave
Iwate
RR
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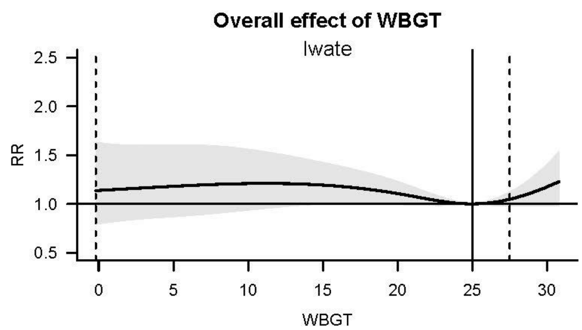
−10 0 10 20 30
Tave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Iwate
RR
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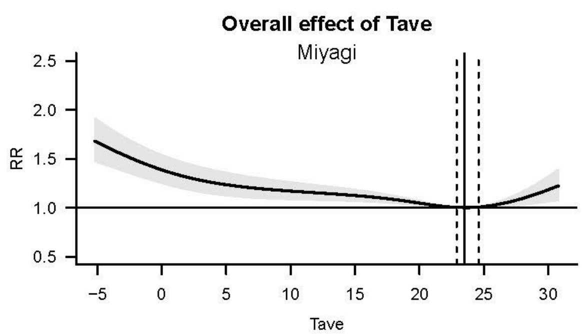
0 5 10 15 20 25 30
WBGT


Overall effect of Tave
Miyagi
RR
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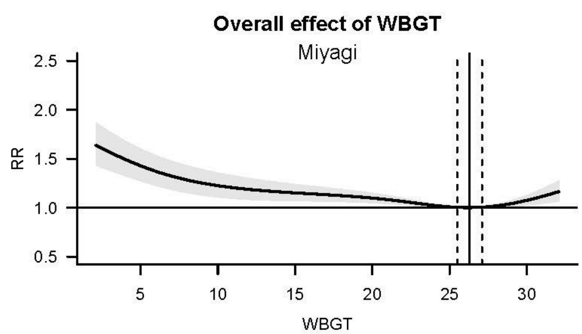
Tave


Overall effect of WBGT
Miyagi
RR
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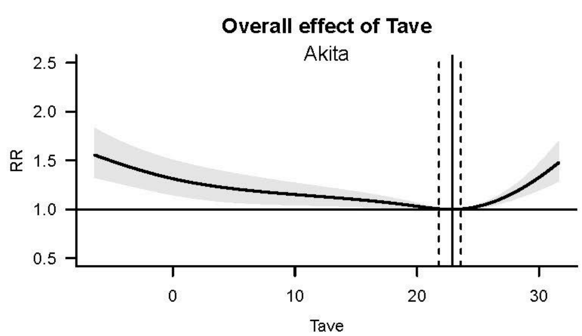
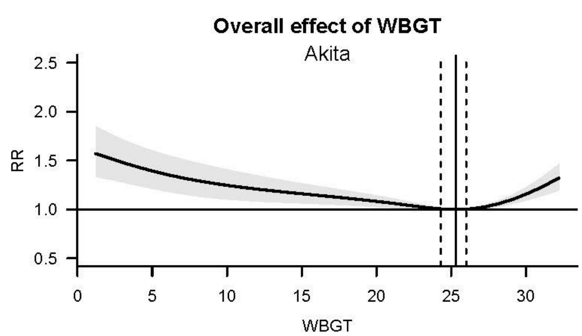
WBGT


Overall effect of Tave
Akita
RR
2.5 2.0 1.5 1.0 0.5
0 10 20 30
Tave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Akita
RR
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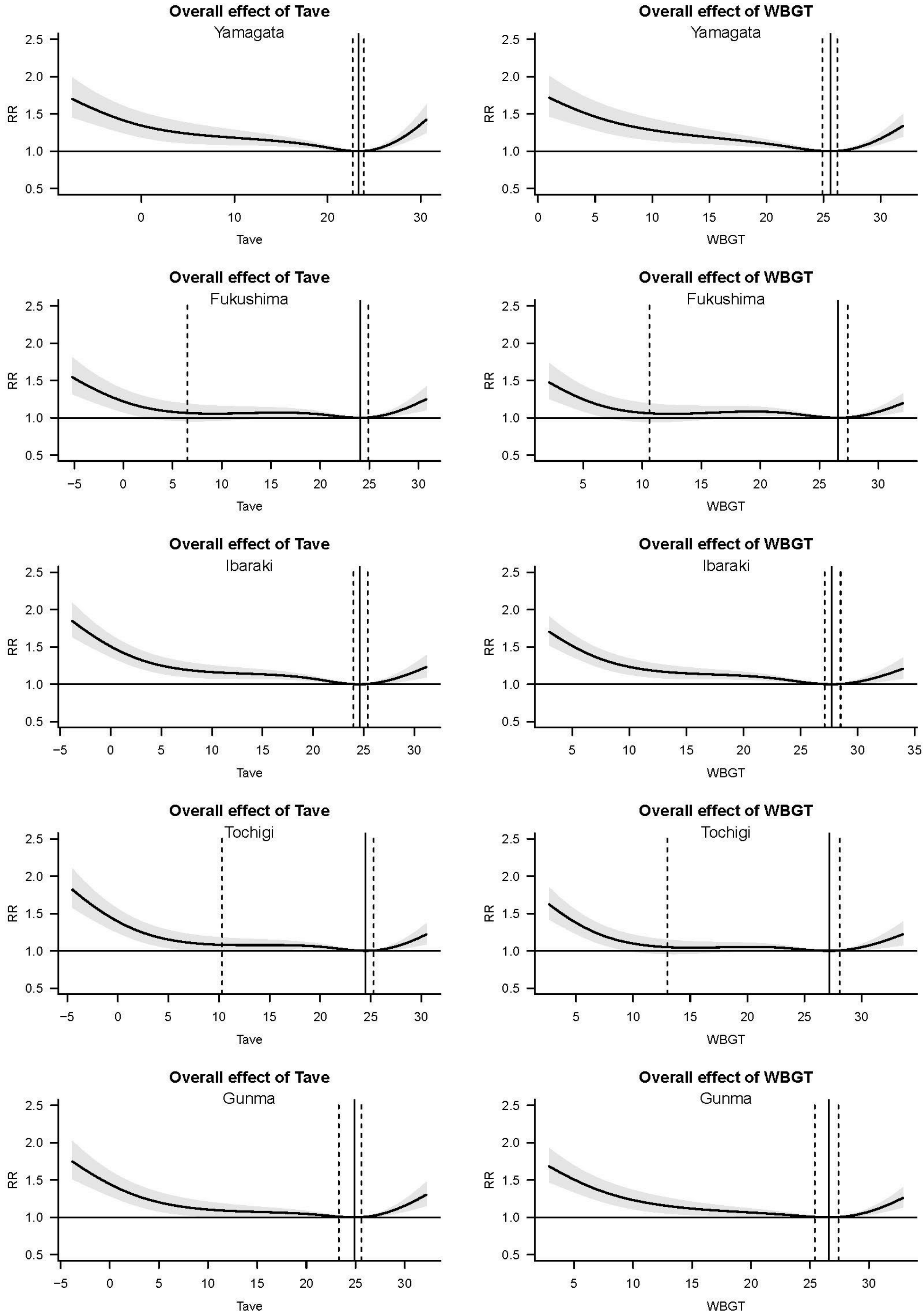
0 5 10 15 20 25 30
WBGT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Overall effect of Tave
Fukushima
Overall effect of WBGT
Fukushima
Overall effect of Tave
Ibaraki
Overall effect of WBGT
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Overall effect of WBGT
Tochigi
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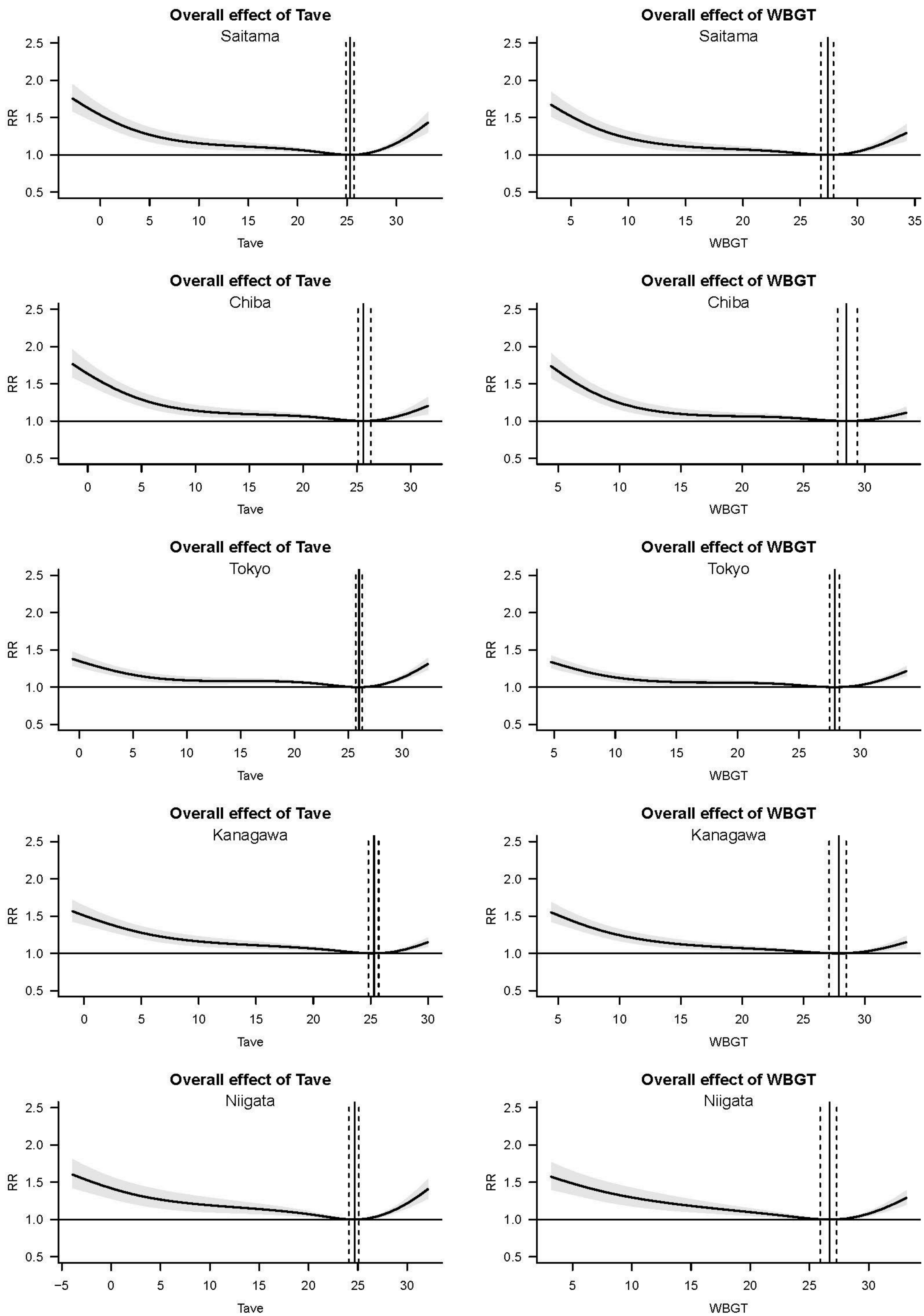
Gunma
Overall effect of WBGT
Gunma
RR
Tave
WBGT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Saitama
RR
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1.5
1.0
0.5
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Tave
Overall effect of WBGT
Saitama
RR
5 10 15 20 25 30 35
WBGT
Overall effect of Tave
Chiba
RR
0 5 10 15 20 25 30
Tave
Overall effect of WBGT
Chiba
RR
5 10 15 20 25 30
WBGT
Overall effect of Tave
Tokyo
RR
0 5 10 15 20 25 30
Tave
Overall effect of WBGT
Tokyo
RR
5 10 15 20 25 30
WBGT
Overall effect of Tave
Kanagawa
RR
0 5 10 15 20 25 30
Tave
Overall effect of WBGT
Kanagawa
RR
5 10 15 20 25 30
WBGT
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Niigata
RR
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Tave
Overall effect of WBGT
Niigata
RR
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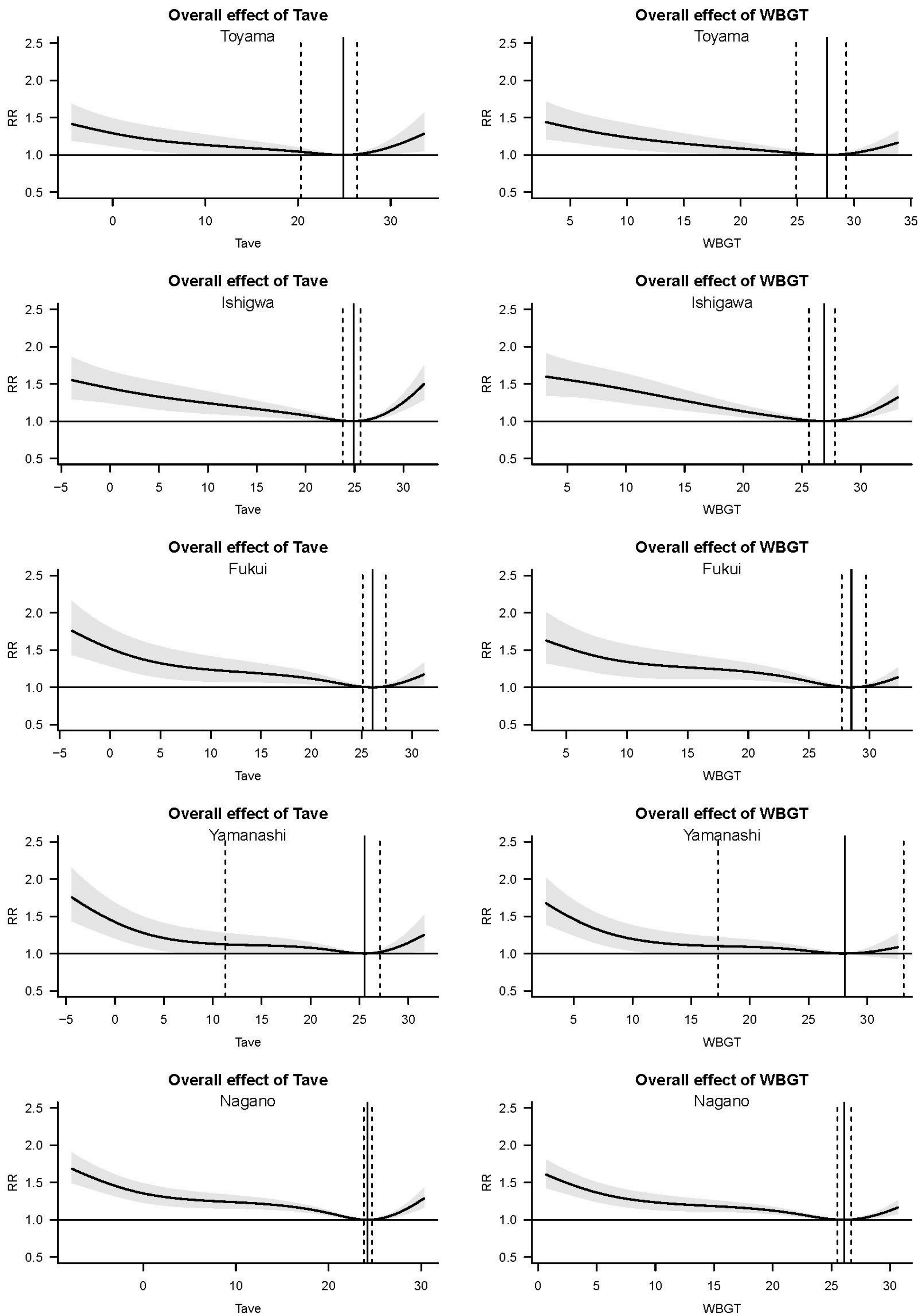
WBGT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Overall effect of WBGT
Ishigawa
Overall effect of Tave
Fukui
Overall effect of WBGT
Fukui
Overall effect of Tave
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Overall effect of Tave
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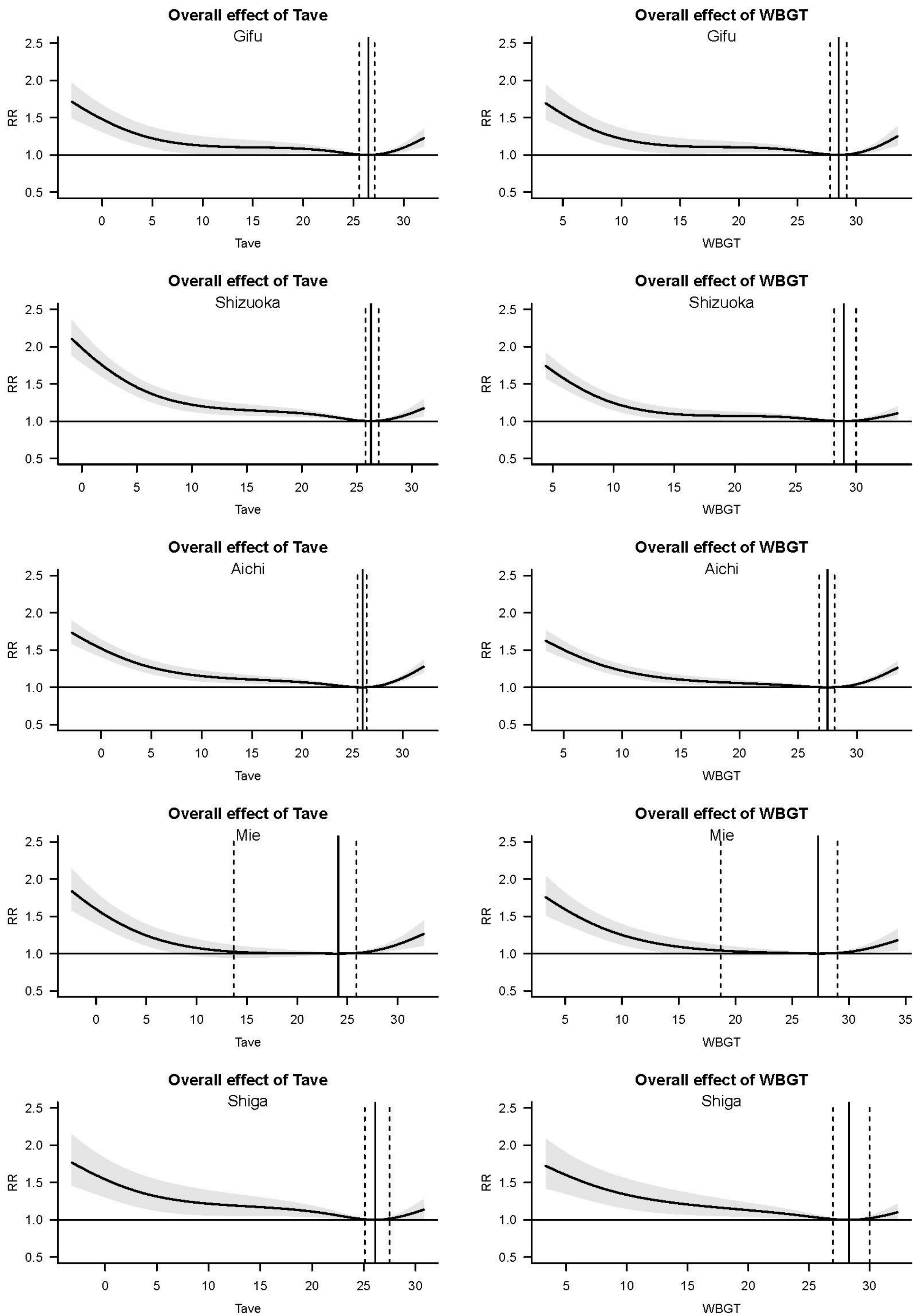
Overall effect of WBGT
Nagano
RR
Tave
WBGT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Gifu
Overall effect of Tave
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Overall effect of WBGT
Shizuoka
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Aichi
Overall effect of WBGT
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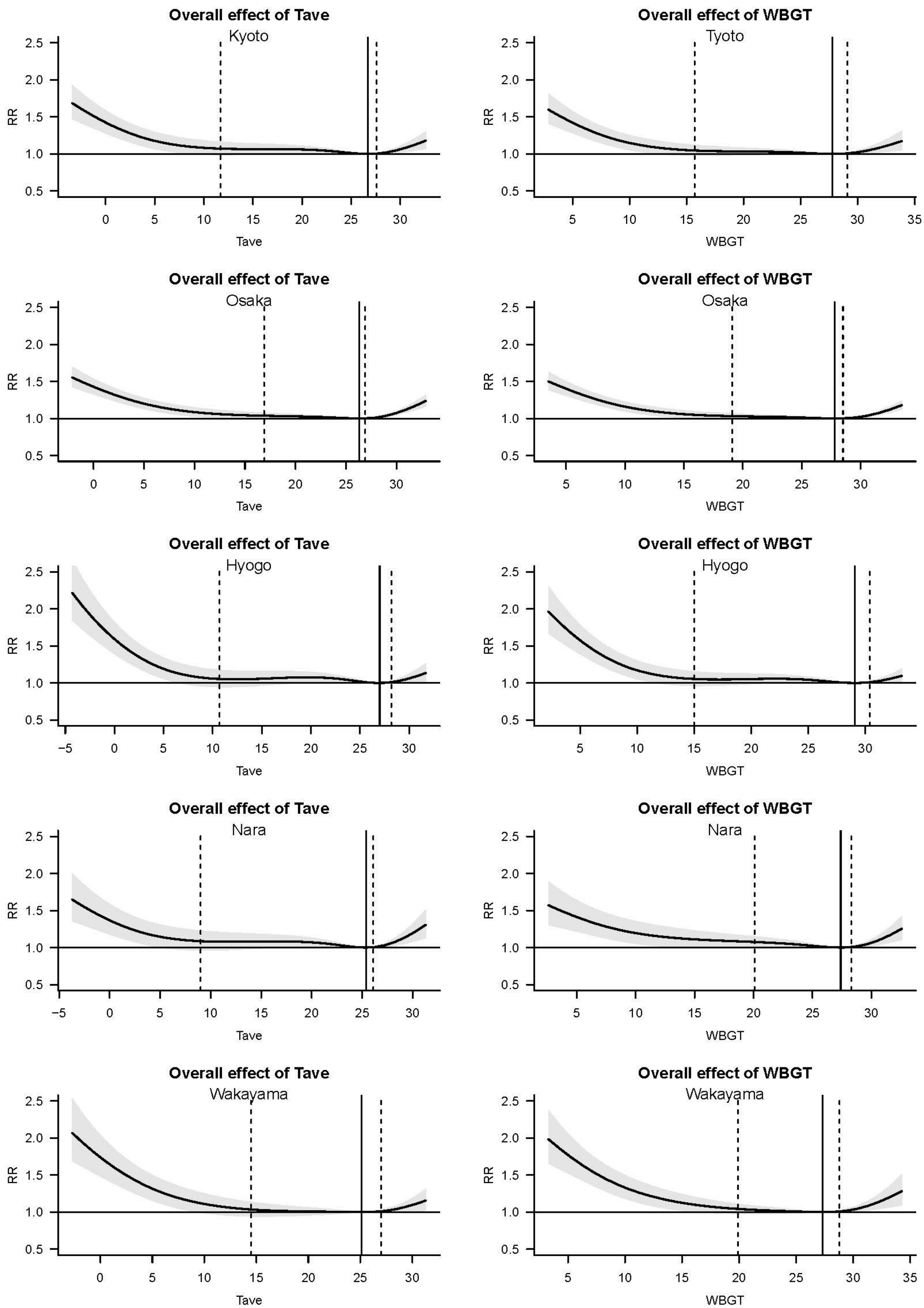
Shiga
Overall effect of WBGT
Shiga
RR
Tave
WBGT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RR
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Osaka
RR
WBGT
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Hyogo
RR
Tave
Overall effect of WBGT
Hyogo
RR
WBGT
Overall effect of Tave
Nara
RR
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RR
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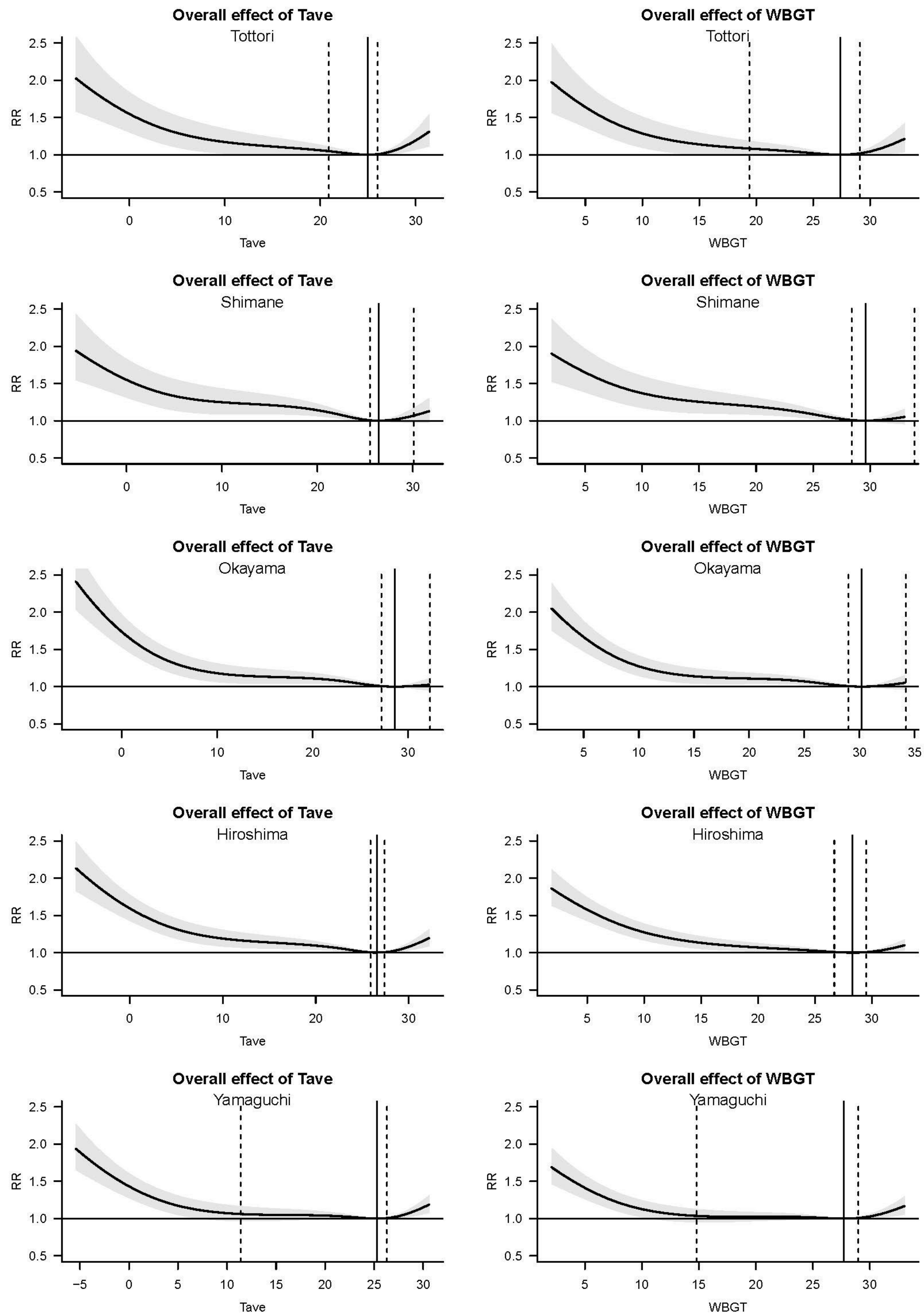
RR
WBGT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RR
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WBGT
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Shimane
RR
WBGT
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Okayama
RR
Tave
Overall effect of WBGT
Okayama
RR
WBGT
Overall effect of Tave
Hiroshima
RR
Tave
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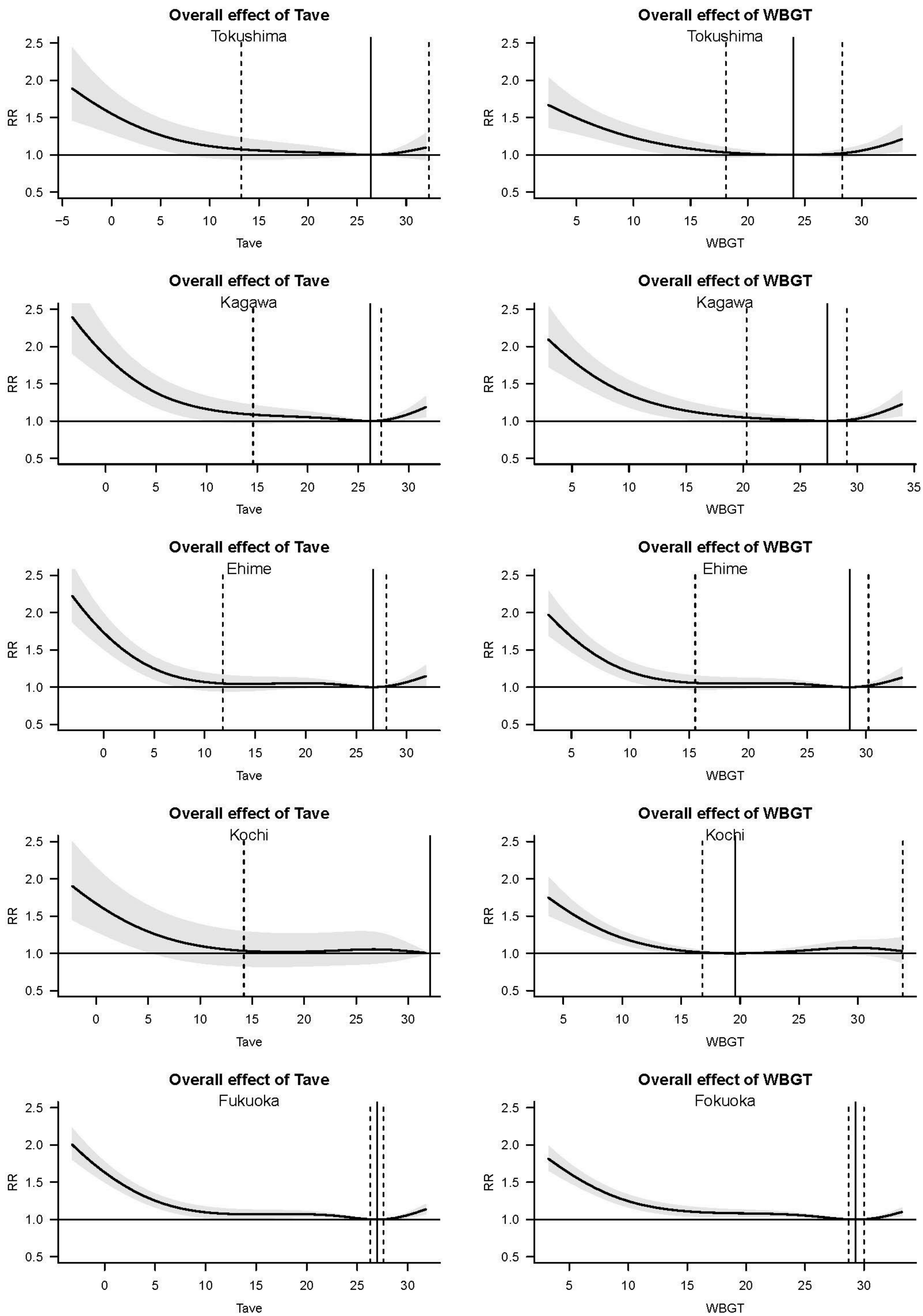
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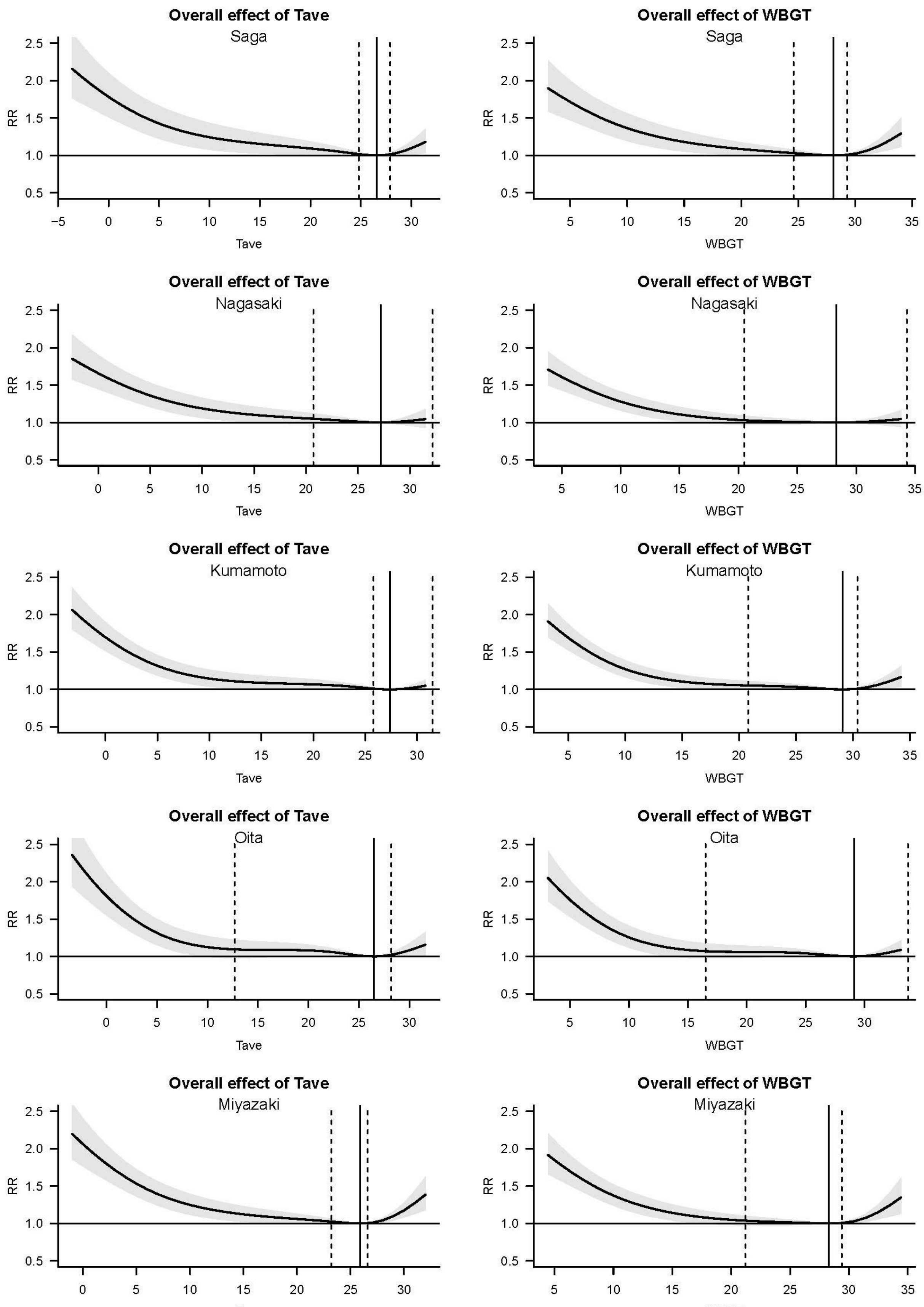
Tave
WBGT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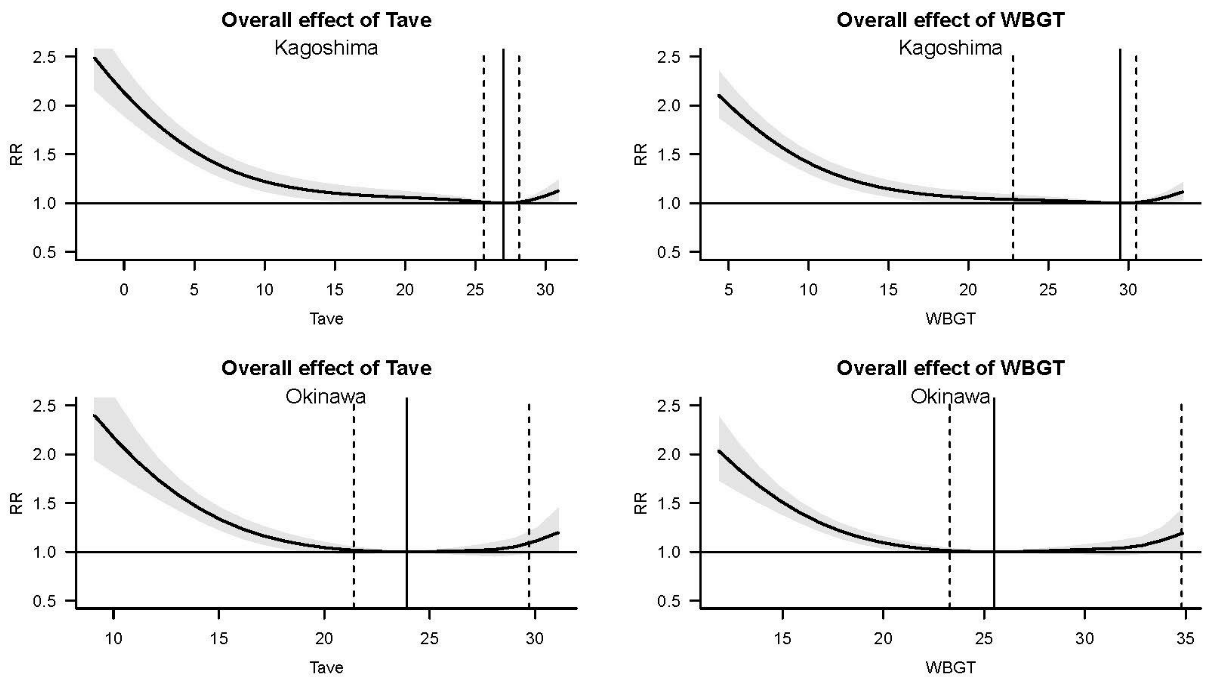
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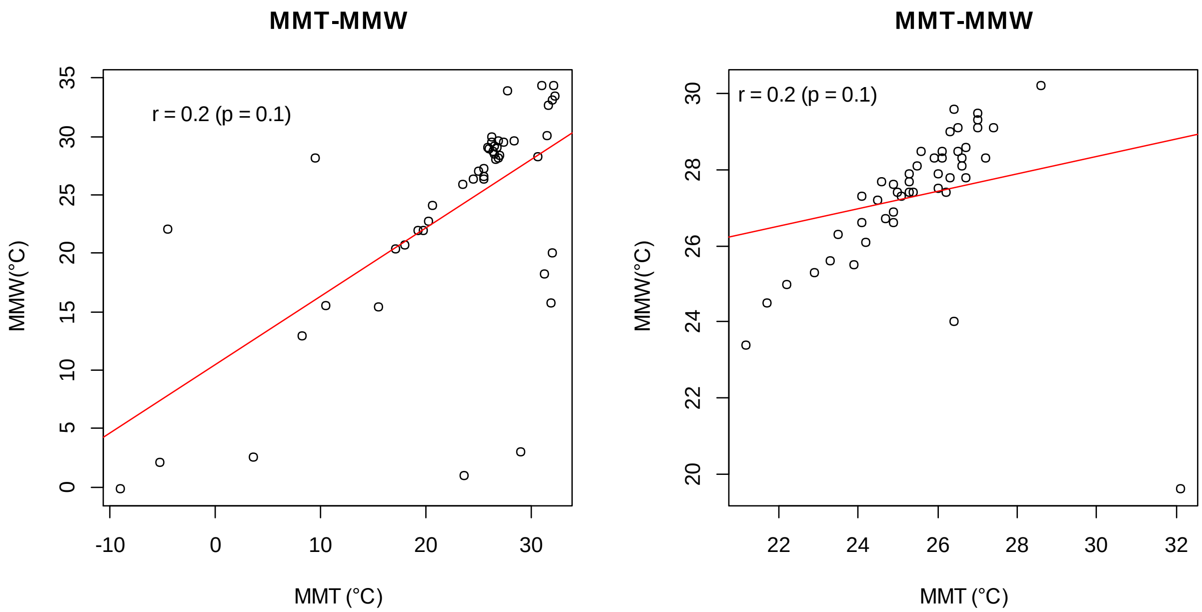
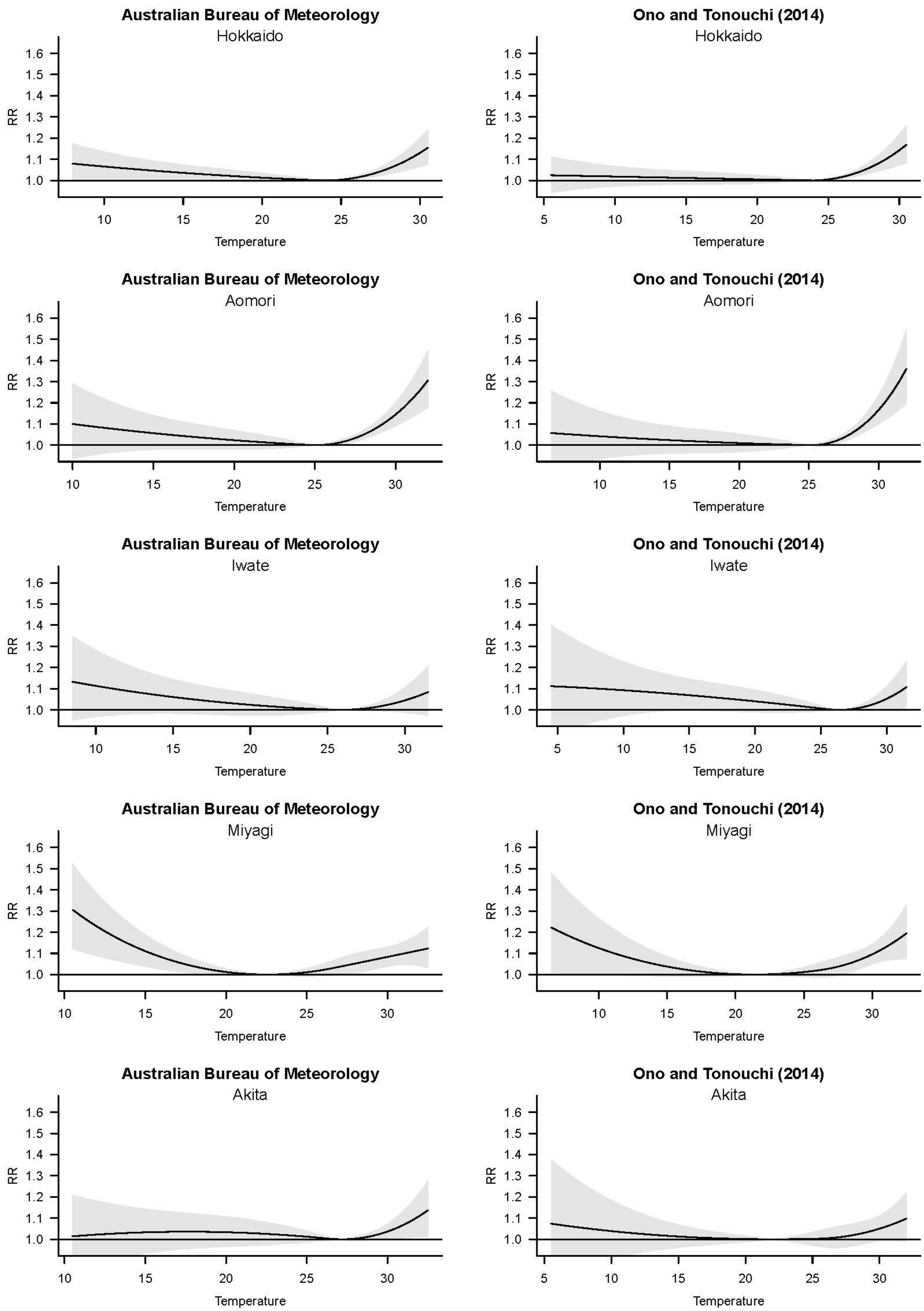


Fig. S4.

Comparison of the associations of MMW-MMT among people of 0–64 years old (left) and 65+ years old (right).

Fig. S5.

Comparison of the associations of WBGT-mortality by using two WBGT estimation methods for 47 Japanese prefectures in May–October of 2006 – 2012. RR indicates the relative risk.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Australian Bureau of Meteorology
Iwate
Ono and Tonouchi (2014)
Iwate
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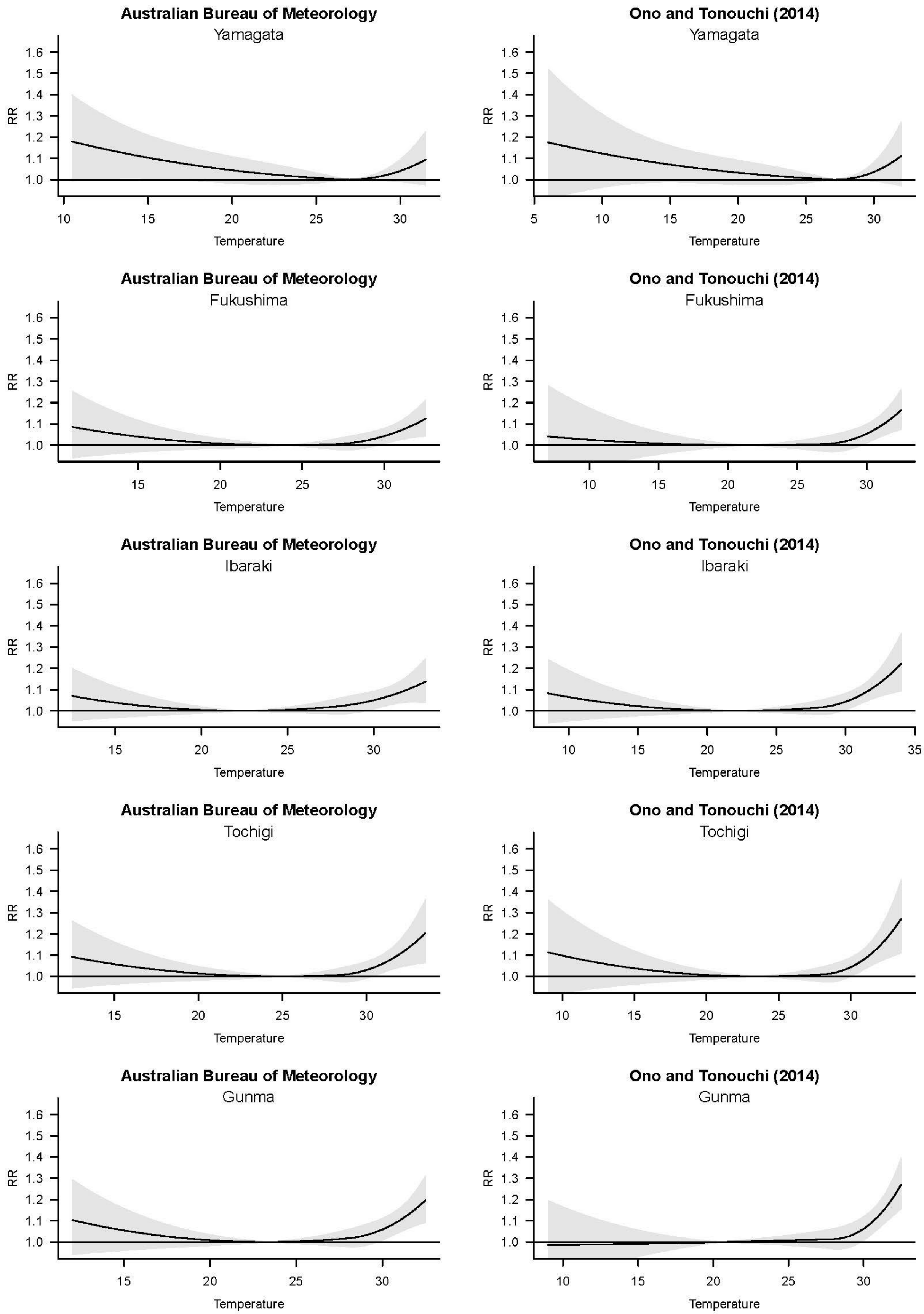
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Temperature
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Yamagata
RR
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Temperature
Australian Bureau of Meteorology
Fukushima
RR
15 20 25 30
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RR
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RR
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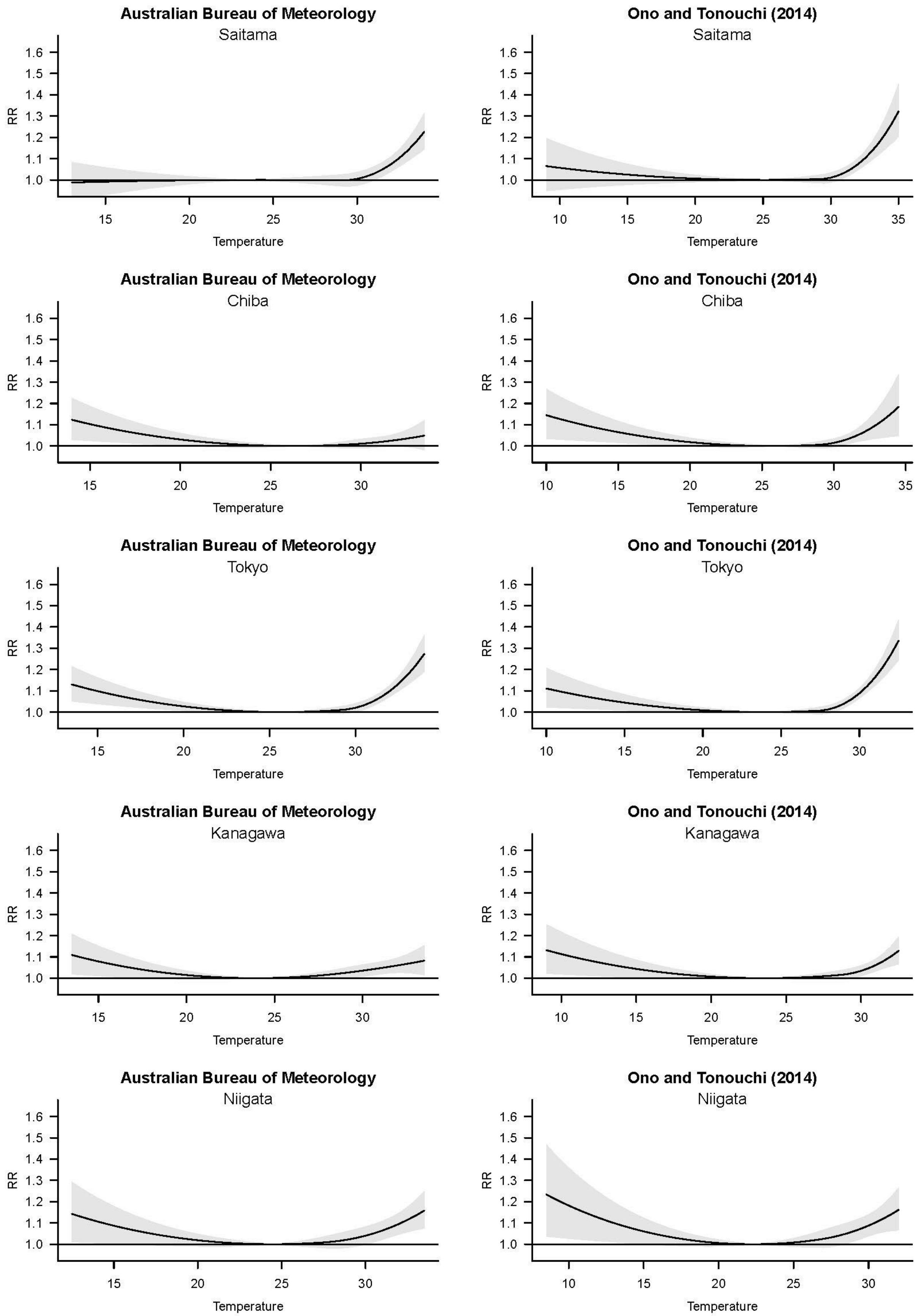
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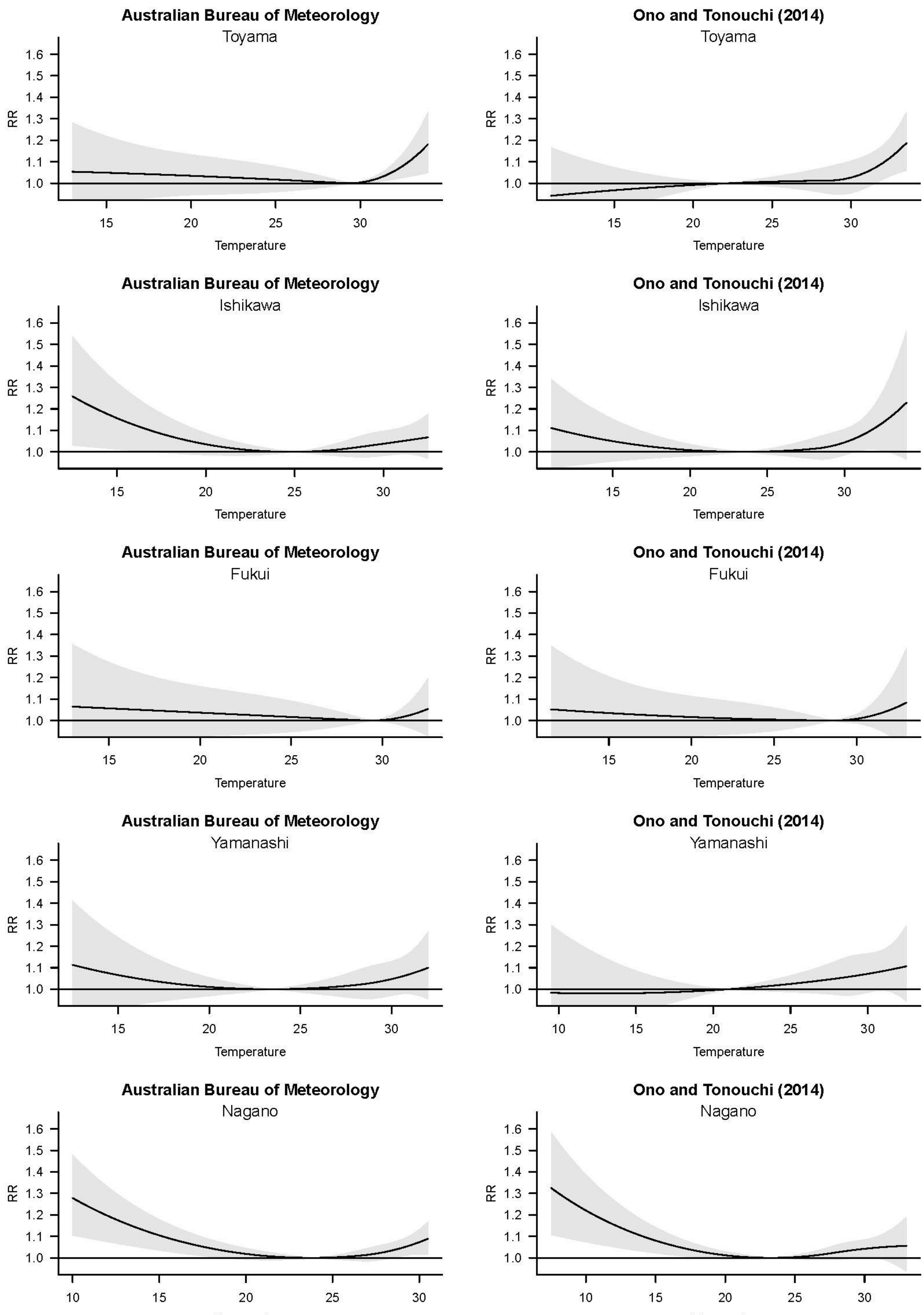
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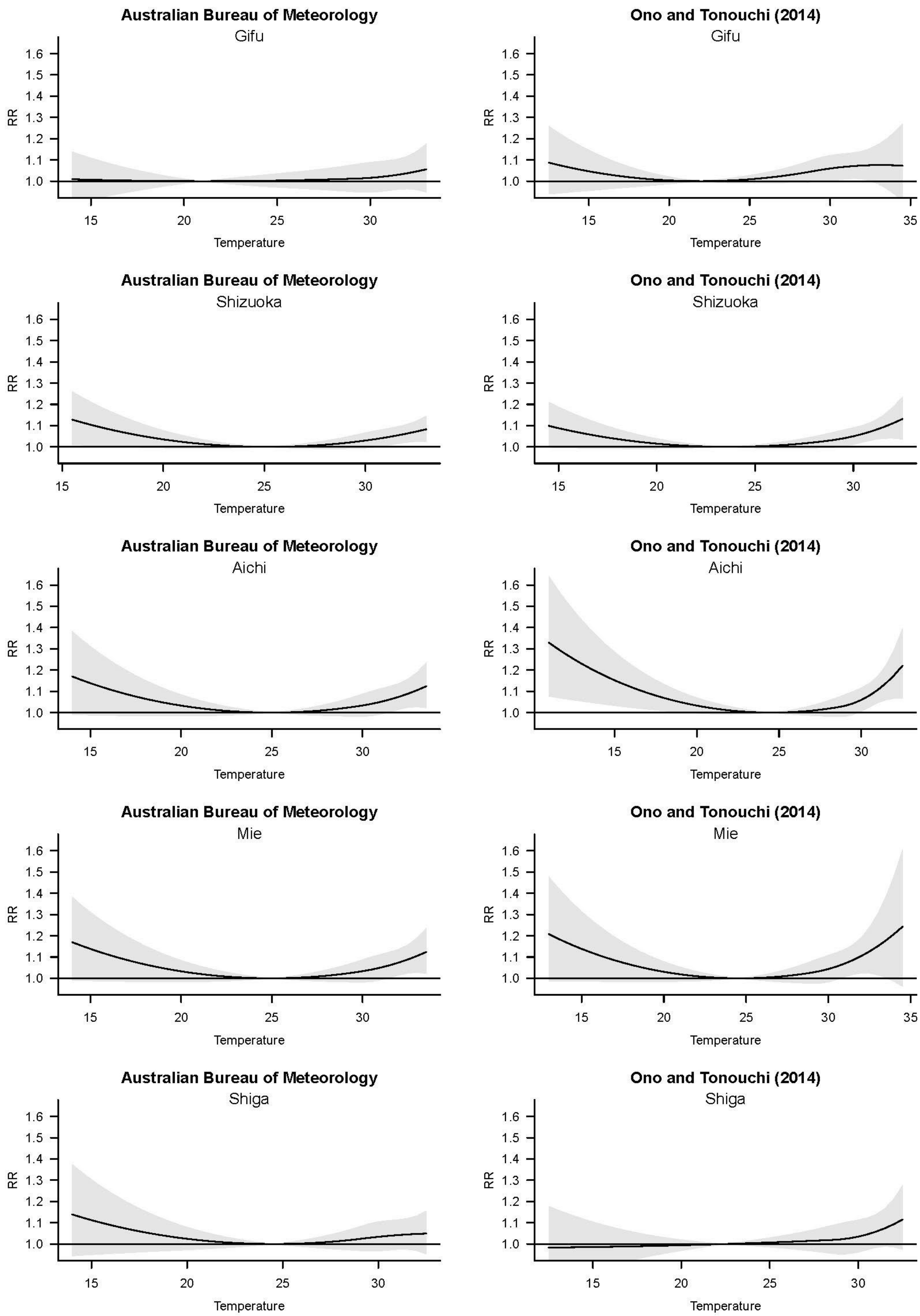
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Ono and Tonouchi (2014)
Aichi
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Mie
Ono and Tonouchi (2014)
Mie
Australian Bureau of Meteorology
Shiga
Ono and Tonouchi (2014)
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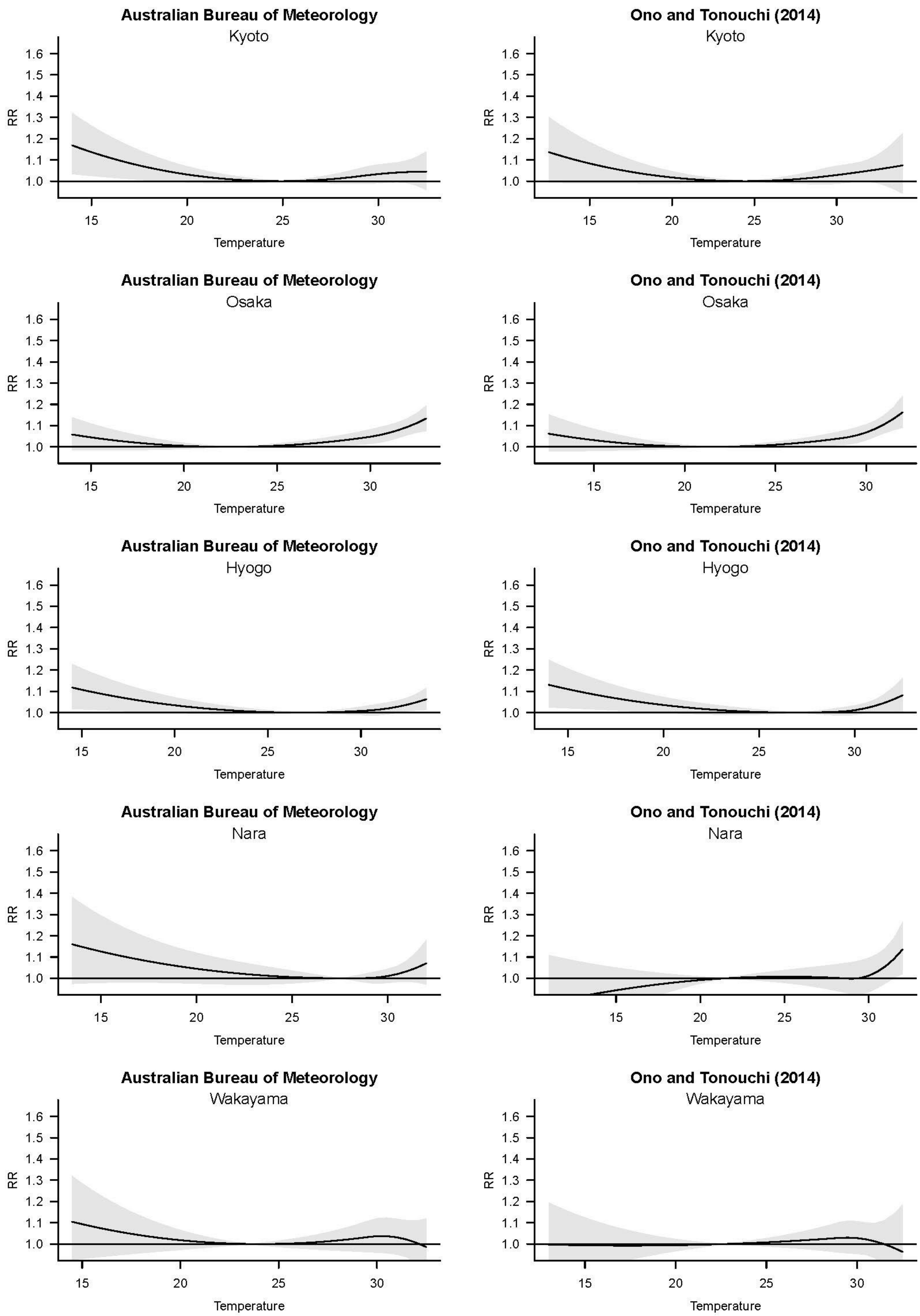
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Nara
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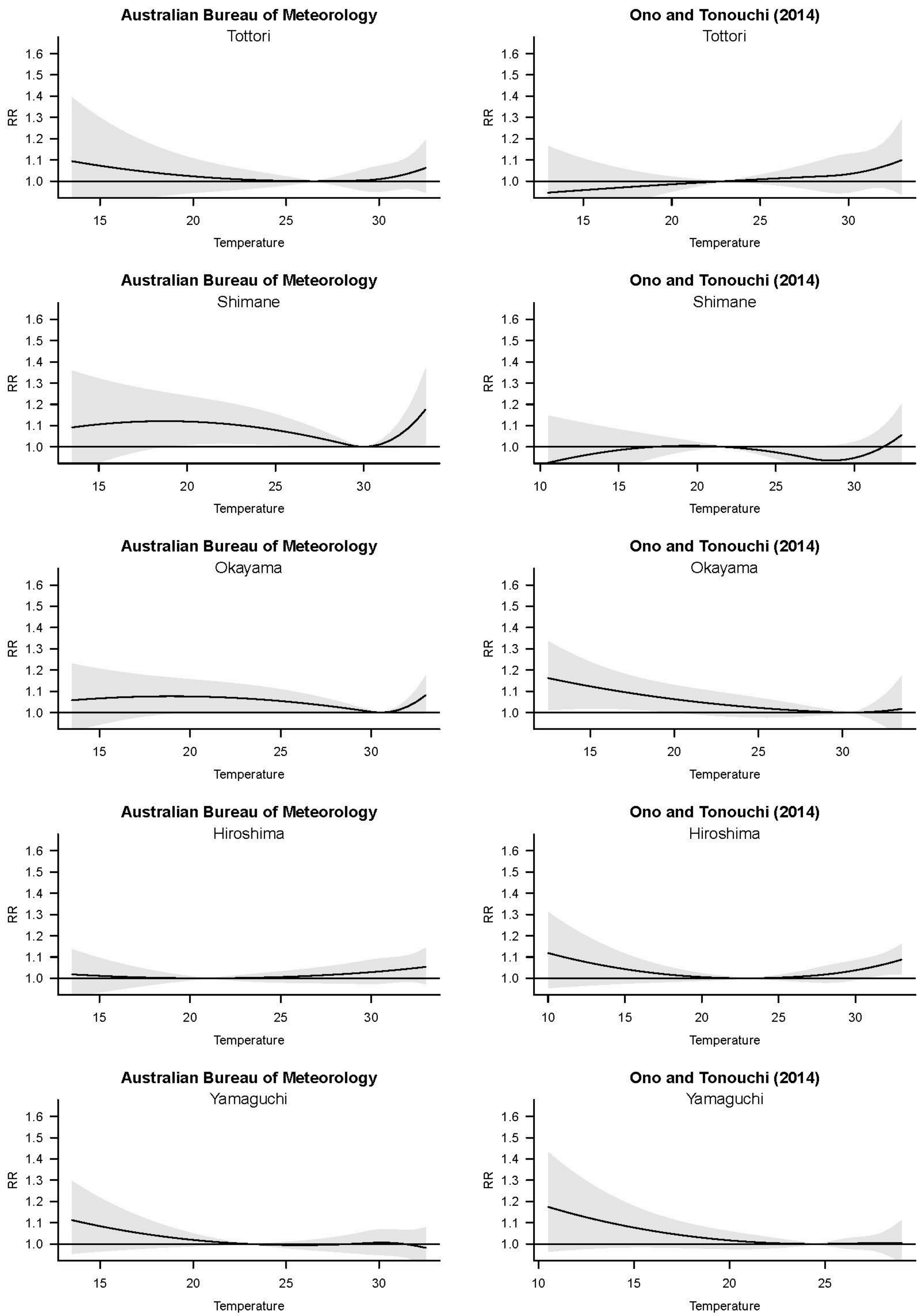
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Hiroshima
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Ono and Tonouchi (2014)
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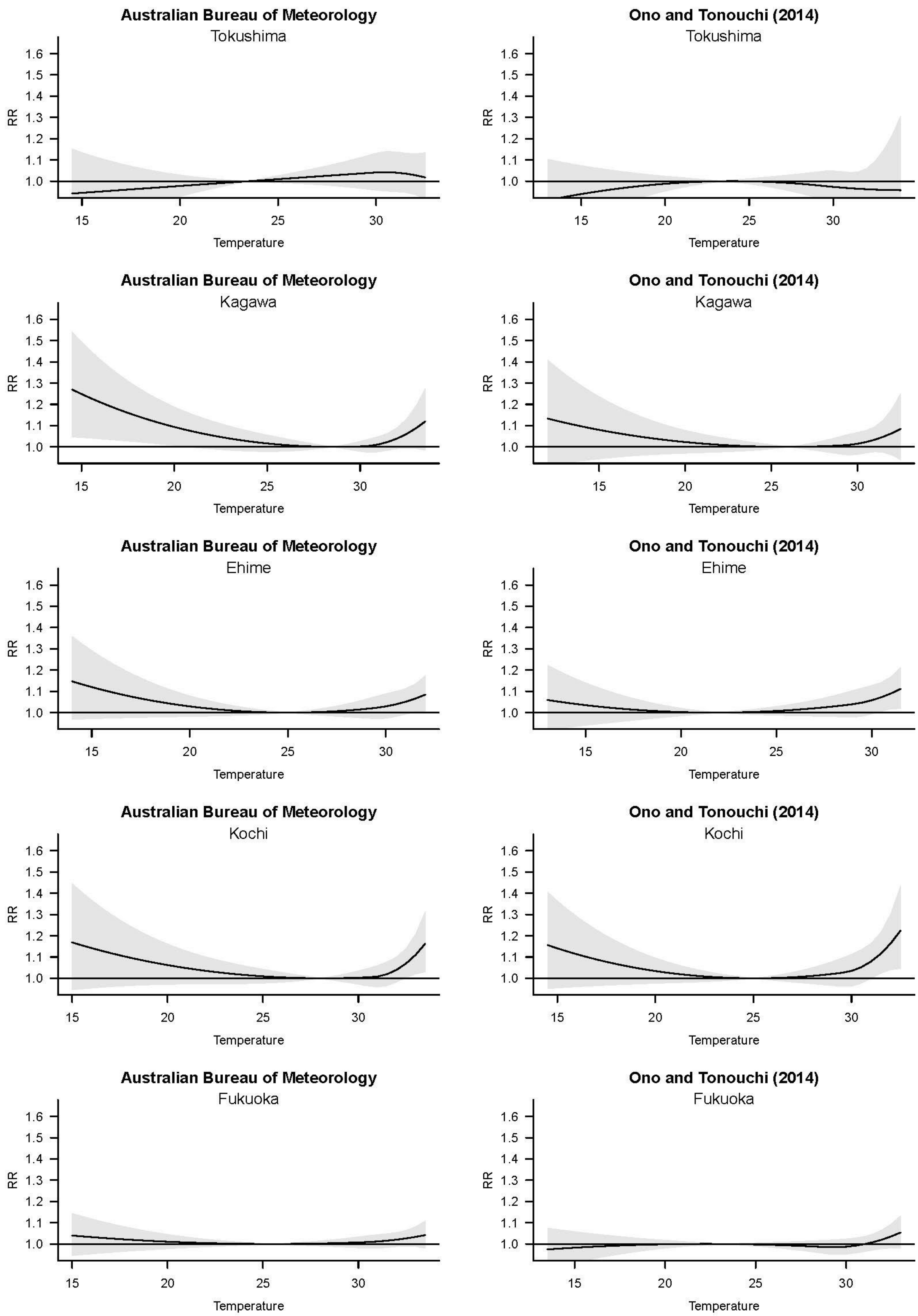
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Ono and Tonouchi (2014)
Kochi
Australian Bureau of Meteorology
Fukuoka
Ono and Tonouchi (2014)
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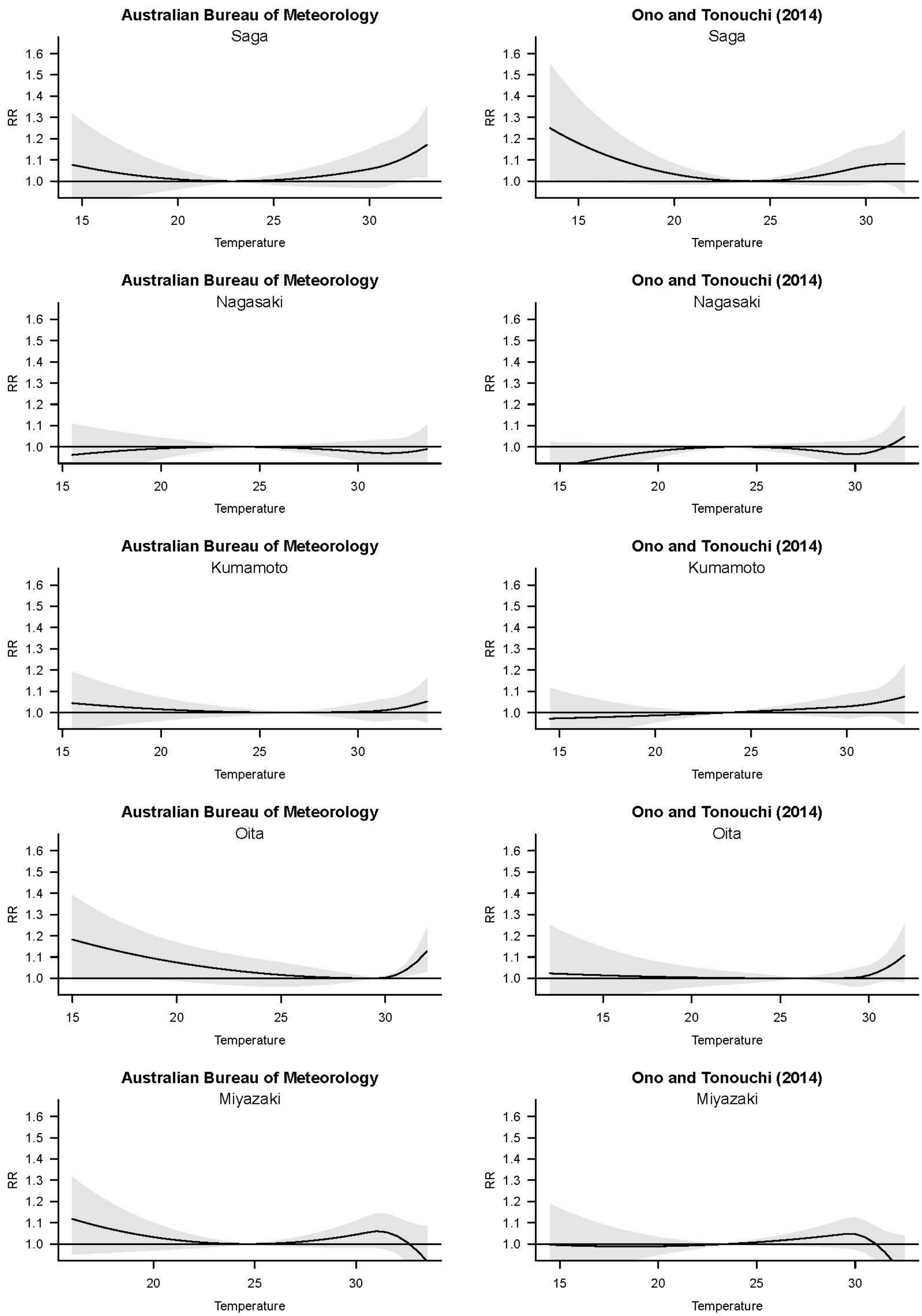
Temperature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Kumamoto
Ono and Tonouchi (2014)
Kumamoto
Australian Bureau of Meteorology
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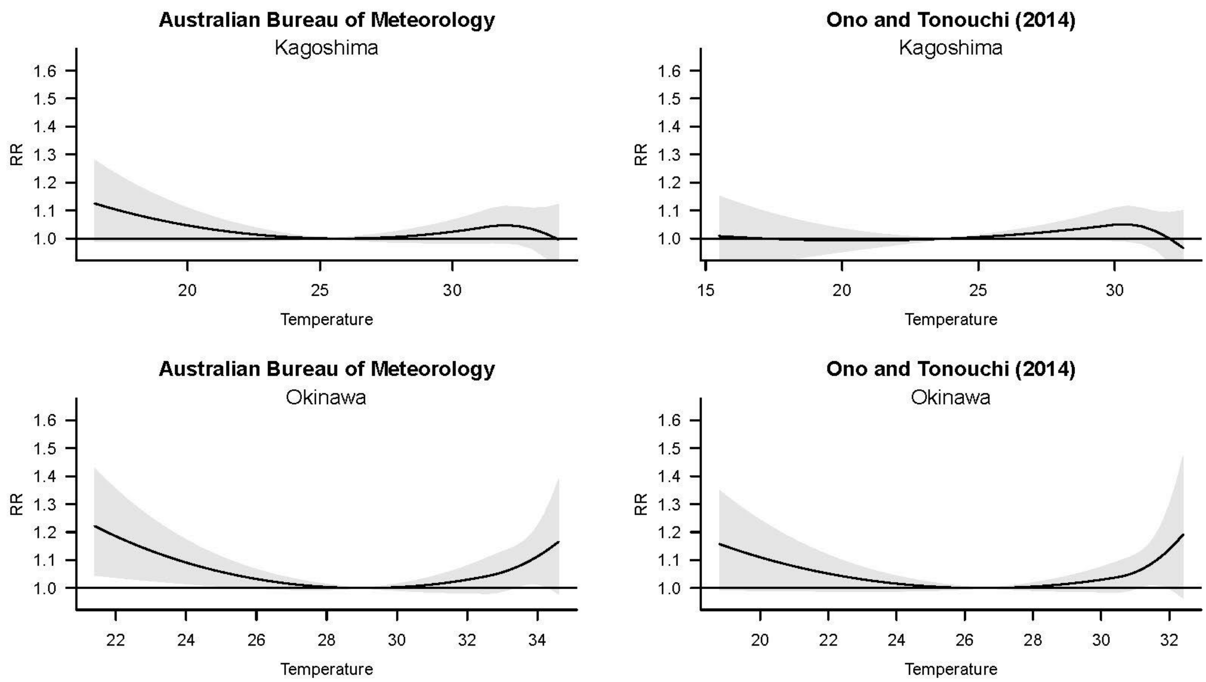
Ono and Tonouchi (2014)
Miyazaki
RR
Temperature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RR
Temperature