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Tembata, Kaori

Takeuchi, Kenji

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The impact of climate variability on drought management: Evidence from Japanese river basins

Kaori Tembata*

Graduate School of Economics, Kobe University

2-1, Rokkodaicho, Nadaku, Kobe, Hyogo 657-8501 Japan

E-mail address: kaoritembata@stu.kobe-u.ac.jp

Kenji Takeuchi

Graduate School of Economics, Kobe University

2-1, Rokkodaicho, Nadaku, Kobe, Hyogo 657-8501 Japan

E-mail address: takeuchi@econ.kobe-u.ac.jp

* Corresponding author

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Abstract

This study examines the effect of climate variability on water resource management during droughts. We use data from local droughts in Japan over three decades to investigate how variability in precipitation and temperature affects water restrictions implemented by drought coordination councils. We find that climate variability is significantly related to water restrictions in terms of both intensity and duration. The regression results show that a 100-mm decrease in annual precipitation is associated with a 0.2% increase in the water withdrawal restriction rate and an increase of one day in the restriction period. Our findings suggest that climate variability might induce more stringent water restrictions, implying negative consequences for water availability. This study thus shows the importance of strategically building adaptive capacity to climate change due to the risks of extreme weather events, such as prolonged droughts and extended summer seasons.

Keywords: Climate variability; Water resource management; Drought; Climate change; Urban water management; Japan

JEL Classification: Q25; Q54

1. Introduction

Climate change can affect the hydrological cycle of river basins, making water availability more uncertain across time and space (World Bank, 2016). The uncertain availability of water may lead to serious economic consequences because it is essential for various human activities. The impact of climate variability on water resources can have many dimensions, such as population growth, agricultural yield, energy production, human health, urbanization, migration, and conflicts over resources (Dell et al., 2014; WWAP, 2015). Researchers have shown that weather variability induces unfavorable outcomes (Barrios et al., 2006; Chen et al., 2016; Dell et al., 2009, 2012; Hsiang and Narita, 2012; Marchiori et al., 2012; McDermott and Nilsen, 2014; Miguel et al., 2004; Nordhaus, 2010). These social and economic concerns are not only diverse but also important issues that require policy responses. The *Fifth Assessment Report of the Intergovernmental Panel on Climate Change* discusses how climate change is linked to water-related sectors in terms of its impacts, vulnerabilities, and risks (IPCC, 2014). Facing such challenges, the importance of effective water resource management is strongly emphasized in order to alleviate negative impacts of climate change (World Bank, 2016).

This study contributes to the literature on the socio-economic impacts of climate variability. Chen et al. (2016) analyze the impact of climate change on crop production in China. According to their estimation, economic losses in China's corn and soybean production amounted to $595-858 million over the past decade. McDermott and Nilsen (2014) investigate environmental impact on energy production. Focusing on the issue of thermal pollution by cooling water used for thermal power generation, they examine how water scarcity and river temperature affect electricity prices. Their study reveals the potential risks of climate change to the energy sector. It is also well known that precipitation shocks and lack of water resources may provoke social disturbances and political instability (World Bank, 2016). Evidence of such issues has been provided by researchers studying the impact of climate variability on violent conflict and crime (Maystadt et al., 2014; Maystadt and Ecker, 2014; Miguel et al., 2004; Takahashi, 2017). There is also growing literature regarding the link between climate variability and migration (Barrios et al., 2006; Dallmann and Millock, 2017; Marchiori et al., 2012).

The objective of this study is to evaluate the impact of climate variability on water resource management. Specifically, we examine how climate variability affects water restrictions in local communities during droughts. Our dataset includes records of water restrictions implemented in river basins in Japan over the last three decades. It allows us to investigate the impact of weather variability on urban water supply in the face of extreme weather events. Our analysis also uses drought-related climate variables based on precipitation and temperature. Although the high dependence of water restrictions on weather conditions is expected because of their impact on the water cycle, the extent of such effects has not been studied extensively. This study thus examines changes in precipitation and temperature to evaluate the extent to which they affect water restrictions during droughts.

Several studies include weather variability as a determinant of residential water use (Hoyos and Artabe, 2017; Schleich and Hillenbrand, 2009). These studies suggest that weather conditions affect water consumption. While water consumption simply refers to how much water is used, it does not represent how much water can be used when the availability of water is limited. Our study, on the other hand, focuses on water restrictions during droughts and examines how they are affected by weather. Such drought response actions are taken in order to enhance water availability under extreme weather. Therefore, our approach directly investigates decision making for climate change adaptation. Addressing the risks of climate change has become an important policy task for sustainable water management. The results of our study may provide useful information for a better understanding of climatic impacts on urban water management, thereby leading to an effective adaptation strategy for climate change.

The results of our empirical analysis show that climate variability is significantly correlated with water restrictions. We find that a decrease in annual precipitation raises the restriction rate of water withdrawals and extends the duration of water restrictions. This study also investigates the effect of weather shocks by measures of weather anomalies, which have been proposed in the relevant literature (Barrios et al., 2010; Marchiori et al., 2012). The results from this weather indicator show that a decrease in precipitation anomalies is associated with higher restriction rate and longer restriction period. Moreover, another precipitation measure shows that an additional day without rainfall during a year also affects water restrictions. These findings suggest that changes in rainfall patterns may disturb the management of water resources, leading to more severe water restrictions.

The remainder of the paper is organized as follows. Section 2 provides an overview of drought conditions in Japan and response actions taken in river basins. Section 3 describes the method and data. The estimation results are presented and discussed in Section 4, and Section 5 concludes.

2. Droughts and the drought response in Japan

Although Japan receives relatively abundant precipitation and seasonal typhoons, the country has suffered droughts and water shortages. One of the reasons for the insufficiency of water resources lies in its geographical conditions. The gradient of Japanese rivers is steeper and its length is shorter compared to rivers around the world (Water Resource Department, Land and Water Bureau, MLIT, 2015). Runoff from precipitation therefore quickly drains to an outlet that eventually flows into the ocean. Consequently, this prevents runoff from remaining in streams and reservoirs. In addition to geographical difficulties, population growth and economic development have boosted water consumption in the last century (Akiyama, 2011). High demand for urban water use caused an imbalance in water supply and demand, particularly during periods of high economic growth. Recently, water resource management is facing an additional challenge from climate change, which is becoming one of the greatest concerns as it triggers extreme weather events including droughts.

Droughts occur in various parts of Japan almost every year, with various degrees of severity. While a drought can be defined in many ways depending on the context, this study refers to a drought as a period of dry weather that causes diminishing water supply and thus requires restrictions on water withdrawals from reservoir dams. Drought-vulnerable areas include many economically important and/or highly populated cities in Japan, including the Tokyo metropolitan area. Recently, in the summer of 2016, Tokyo and its large suburban area experienced a drought for the first time since 2013. Concerns over a water shortage began in the spring of 2016 when the region received substantially lower precipitation than usual, followed by a lack of snowpack in winter. After the storage level of reservoirs dropped low enough to threaten water supply, the region implemented restrictions on water withdrawals from dams in June. The drought persisted for about three months until September. Before 2013, seasonal droughts also occurred in the Tone River Basin, Tokyo's largest watershed, in 2012, 2001, and 1997. The Tone River Basin has implemented water restrictions 16 times between 1972 and 2016.

The impact of droughts may spread to various aspects in communities, resulting in social, economic, and environmental consequences. In the Tone River Basin mentioned above, water from dams is used for several purposes: water supply for residential, agricultural, and industrial sectors, and hydroelectric power generation. In addition, these dams are also used for controlling floods and stabilizing water flows in rivers. Because almost every river basin in Japan has such multipurpose dams, regional droughts can be a threat to water use in various sectors. Moreover, issues related to droughts and water shortages may significantly affect how local communities collectively manage water resources.

To address droughts at the river basin level, local communities in Japan implement water restrictions as one of the drought response actions. For instance, the Tone River Basin curtails water use from their eight dams located upstream.[1] Water restrictions are introduced via the drought coordination council, which is organized in a river basin in response to a drought. The council originated from the notification issued by the former Japanese Ministry of Construction in 1974, in which the implementation of a council is suggested in river basins facing droughts (Kasenho Kenkyu Kai, 2011). Members of the council include water users such as representatives of water utilities, farmers' groups, and electric power companies, together with river administrators and related government agencies.[2] In addition to sharing information on drought conditions, the council makes collective decisions on water restrictions. Therefore, the introduction of the council is not only a way to facilitate communications among council members but also to involve water users in the decision-making process for drought management. From this point of view, water restrictions implemented through the drought coordination council can be characterized as collective action in river basin communities.

3. Empirical analysis

3.1. *Estimation framework*

Our empirical analysis aims to examine whether and to what extent weather variability affects drought management, with a focus on the relationship between water restrictions and weather variability. The analysis explores

[1] However, this is a rather exceptional case, as water restrictions in most cases involve only one dam. Even in cases in which water restrictions are imposed jointly on multiple dams, only two or three dams are usually involved.

[2] Note that the groups of stakeholders actually participating in the council depends on the community in question.

river basins that experienced droughts and implemented water restrictions in Japan, which gives us the panel dataset of 60 river basins with the time period from 1984 to 2014. For drought events included in the analysis, the water restrictions that were implemented concern water withdrawals from dams.[3] Therefore, we collect climate variables using point data from weather stations based on the locations of dams. Figure 1 shows the site of each reservoir dam used in the analysis. The specification of our estimation model is as follows:

$$WaterRestrictions_{it} = \beta_0 + \beta_1 Weather_{it} + \gamma_i + \delta_t + \varepsilon_{it}. \tag{1}$$

The dependent variable $WaterRestrictions_{it}$ represents drought response measures, i.e., water restrictions, implemented by a drought coordination council in river basin i in year t. Drought coordination councils are usually organized on the basis of river basins or sub-river basins. Therefore, the cross-sectional unit is defined according to river basins. The explanatory variable, $Weather_{it}$, is a set of climate variability that captures the severity of drought conditions. River basin dummies are captured by γ_i. These time-constant variables control for any unobserved heterogeneity across areas divided by river basins, such as geographical characteristics and cultural background in terms of water use. The other fixed effects δ_t are year-fixed effects, which are time-specific variables controlling for any external event common to all river basins. Finally, ε_{it} is an error term.

[3]For this reason, the panel dataset is unbalanced as we only include observations of each river basin after the completion of dams that were subject to the restrictions.

3.2. *Data and variable description*

Table 1 summarizes the variables used in the regression analysis. Table 2 presents descriptive statistics of these variables. Two variables are used as dependent variables: the rate of water restrictions on residential water supply and the duration of water restrictions. The former measures the percentage of water that was curtailed during the restriction period, and the latter measures how long such restrictions continued.

Figure 2 depicts these two drought response actions, using the 2008 drought in Matsuyama City as an example. The figure shows at what level water restrictions were implemented and revised as daily rainfall changed over the period. In response to a drought, river basin communities collectively make decisions on water restrictions via the drought coordination council. In the case of the 2008 drought in Matsuyama City, the Ishitegawa Drought Coordination Council organized meetings and set water restrictions from August 4. At the early stages of drought, restrictions are usually imposed with lower rates of withdrawal reduction. The restriction rates are gradually increased as drought conditions worsen. As shown in Figure 2, the highest restriction rate (25%) was applied in late September. The restrictions were then relaxed as drought conditions ceased.

Our dataset is composed of the maximum rates of water restriction issued during each drought event. Water restrictions described in this study are associated with reductions of water intake by water utilities. Therefore, the restriction rate of 25% does not imply that percentage of reduction in water supply to citizens. During the drought in 2008, Matsuyama City implemented different types of measures to curtail water use. For instance, the city regulated residential water use by reducing water pressure and closing school and community swimming pools. The duration of water restrictions means the period between the day of implementation and the day of lifting of the restrictions, which is illustrated in the shaded area in Figure 2. In this example, the duration of water restrictions is 64 days, from August 4 to October 6.

Data on water restrictions are obtained from *Water Resources in Japan* published by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism. This annual report provides the records of regional drought, including the maximum rates of water restrictions issued during each drought event.[4] We collect data on these regional droughts and water restrictions, which comprise 301 drought events for models estimating restriction rates and 356 drought events for models estimating restriction duration. Data on restriction rates and duration are used for each river basin in the drought years when water restrictions were issued. Non-drought years in any river basin are assigned a value of zero.

The variables of interest in this study are a series of weather variability. We compute several types of climate measures based on precipitation and temperature. By including these alternative variables, we intend to capture the weather variability that may affect water availability and drought management. Data on precipitation and temperature are available from the online database of the Japanese Meteorological Agency.[5] We collect daily

[4]The document does not report other measures related to the rates of water restrictions.
[5]Available at http://www.jma.go.jp/jma/indexe.html.

data on precipitation and temperature at weather stations geographically closest to each dam, which are calculated with GIS software by using point data of weather stations and reservoir dams.[6] The data are then aggregated at the annual level. In cases where multiple dams were jointly subject to water restrictions, we average the values of the weather data.

We first use the level measure of weather variables, represented as *Rain* and *Temp*. *Rain* indicates the annual amount of precipitation, whereas *Temp* indicates the average daily temperature during a year. We then construct alternative variables based on these level measures of precipitation and temperature variables. Following Barrios et al. (2010) and Marchiori et al. (2012), we construct the weather anomaly variables, *Rain anomalies* and *Temp anomalies*, by taking the deviation from the long-run mean and dividing it by its long-run standard deviation. The weather anomaly variables are thus computed as follows:

$$Weather\ anomalies_{it} = \frac{Weather_{it} - \mu_i^{LR(Weather)}}{\sigma_i^{LR(Weather)}}, \tag{2}$$

where $Weather_{it}$ is the level of precipitation or temperature for river basin i in year t, $\mu_i^{LR(Weather)}$ is the long-run mean for river basin i, and $\sigma_i^{LR(Weather)}$ is its long-run standard deviation.[7] The normalized measure defined as weather anomalies in Equation (2) has been used in the literature on the relationship between climate variability and socio-economic activities (see Barrios et al., 2010; Dallmann and Millock, 2017; Marchiori et al., 2012; Maystadt and

[6] Data on the locations of the dams are obtained from the *National Land Numerical Information download service* run by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism and are available at http://nlftp.mlit.go.jp/ksj-e/index.html.

[7] We take the long-run to be a period from 1983 to 2014.

Ecker, 2014). With this approach, weather conditions are captured in a relative sense because anomaly variables take into account weather variations in a particular area. In other words, the anomaly measures indicate how weather conditions of a region in any given year deviate from the average weather conditions (Marchiori et al., 2012).

For precipitation, we use the amount of rainfall, in either absolute or relative terms. In addition to these variables, we further examine three types of variables related to precipitation: *Dry days*, *Avg. consecutive dry days*, and *Max. consecutive dry days.* These variables indicate the number of days without rainfall a river basin had in a year. A dry day is defined as a day with precipitation less than 1 mm. We construct the variable *Dry days* by calculating the annual number of such days without rainfall. Consecutive dry days are defined as the sequence of days without rainfall. *Avg. consecutive dry days* is calculated as the average annual number of consecutive dry days, while *Max. consecutive dry day* is taken as the longest spell of dry days in a given year.

Analogous to the precipitation variables, three temperature variables are also constructed, based on the maximum daily temperature. *Hot days* indicates the total number of days with maximum daily temperature above 30°C (86°F) threshold in a year. Then we calculate the mean number of consecutive hot days to obtain *Avg. consecutive hot days. Max. consecutive hot days* is the longest spell of days with maximum daily temperature above 30°C threshold in a given year.

4. Results

4.1. *Main results with precipitation variability*

The main results from the regression analysis are presented in Tables 3 and 4. The panel structure of the data allows us to use alternative estimation approaches; i.e., fixed-effects model and random-effects model. First, we test the validity of these models by using an F-test for the fixed-effects model and the Breusch-Pagan Lagrange multiplier test for the random-effects model. Both tests confirm that these models are more appropriate than the OLS model. Then, we also conduct the Hausman test to compare the fixed-effects and random-effects models. The tests in all models do not reject the null hypothesis that the regressors are uncorrelated with river basin-specific effects. This suggests that the random-effects model is more appropriate; however, the estimates of the fixed-effects model do not considerably differ from those of the corresponding random-effects model. We present the estimation results of both fixed-effects (FE) and random-effects (RE) models, as shown in the tables.

The estimation results using precipitation variability show that the variables have significant impacts on water restrictions. The coefficients of *Rain* are negative and statistically significant as shown in the first and sixth columns in Table 3. The estimation results suggest that the restriction rate increases by 0.2% as the level of annual precipitation decreases by 100 mm. The coefficients of *Rain anomalies* in the second and seventh columns are also negative and statistically significant. These coefficients indicate that a one-point decrease in precipitation anomalies leads to an increase in the restriction rate by 1.4%. Moreover, we find that *Dry days* is correlated with the water restriction rate. The coefficients in the third and eighth columns are positive and statistically significant at the 1% level, suggesting that more days without rainfall may lead to stricter water restriction rates. However, we find that the coefficients of *Avg. consecutive dry days* and *Max. consecutive dry days* are not statistically significant. A spell of dry days may not affect the levels of water restrictions if it rains substantially in a short period of time. Potentially, one typhoon with heavy rain brings large amount of water that can be stored in reservoirs.

While the results above show that precipitation affects the intensity of water restrictions, we also find that precipitation variables have significant effects on the duration of water restrictions. In Table 4, the coefficients of *Rain* are negative and statistically significant at the 1% level. The findings suggest that a decrease in annual precipitation by 100 mm is associated with an increase in the restriction period by 0.7–0.9 days. Similarly, *Rain anomalies* is also correlated with the duration of water restrictions. The coefficients show that a one-point decrease in precipitation anomalies increases the duration by 5.6 days. Furthermore, the coefficients of *Dry days* are statistically significant and indicate that one additional dry day increases the duration of water restrictions by 0.2 days. The positive sign of the coefficients suggests that more dry days may lead to extended water restrictions. The coefficients of *Avg. consecutive dry days* are also positive and statistically significant. While both variables of the average and maximum consecutive dry days do not show a significant effect on the restriction rate, we find that the average number of consecutive dry days may induce prolonged water restrictions. On the other hand, we do not find the correlation between *Max. consecutive dry days* and the duration of water restrictions.

The results from Tables 3 and 4 show that variability in precipitation affects both the rate and duration of water restrictions. This suggests that changes in rainfall may bring an adverse impact on drought management. In other words, lower precipitation can cause stringent water restrictions during a drought, in terms of higher restriction rates and longer restriction period. The impacts of precipitation variability have also been observed in other studies. Schleich and Hillenbrand (2009) investigate residential water demand and find that that the number of days with rainfall in the summer months affects water consumption, which is similar to our findings on the dry days variable. However, in contrast to our results, they find no significant effect of the amount of rainfall. Barrios et al. (2010) use precipitation anomalies and find that lower rainfall negatively affects the growth rate of GDP per capita in sub-Saharan African countries. In another study, Miguel et al. (2004) use rainfall measures as instrumental variables and show that rainfall shocks have a significant impact on the economic growth rate in sub-Saharan Africa. Although the focuses of their analyses are different, our findings are in line with the relevant literature examining the impact of precipitation variability.

In the bottom row of Tables 3 and 4, we provide the standardized coefficients of the weather variable included in each model. Both the dependent and independent variables are standardized, meaning that the coefficients are estimated as standard deviation changes in the dependent variable, i.e., the rate or duration of water restrictions, for a one standard deviation change in the weather variable. The standardized coefficients are useful for comparing variables with different metrics. Because variables are measured by the same metric when standardized, it makes the impacts of variables more comparable to each other. According to the results, for instance, a decrease in the annual precipitation by one standard deviation raises the rate of water restrictions by 0.12–0.18 standard deviations and the duration by 0.19–0.26 standard deviations. The standardized coefficients of the anomaly variable also show that a one standard deviation decrease in precipitation anomalies increases the restriction rate by 0.14 standard deviations and the duration by 0.21 standard deviations. Although the magnitude of the (unstandardized) coefficients of *Rain* are substantially smaller than those of *Rain anomalies* and *Dry days*, the standardized coefficients suggest that the impact of *Rain* is as large as those of the other two precipitation variables.

4.2. *Temperature variability*

The regression results using temperature variables are shown in Tables 5 and 6. The models in Table 5 examine the effect on the restriction rate, while the models in Table 6 examine the effect on the duration. In Table 5, none of the temperature variables are statistically related to the water restriction rate, except *Avg. consecutive hot days*. The coefficients in the fourth and ninth columns are positive and statistically significant at the 10% level, suggesting that a one-day increase in the average spell of dry days is associated with an increase in the restriction rate by 0.2%. While precipitation variables in Table 3 are found to be correlated with the restriction rate, we find little evidence of temperature impacts. The findings suggest that water restrictions, in terms of intensity, are affected by precipitation rather than temperature. The results seem reasonable since precipitation is more directly related to water use, storage, and shortage.

Regarding the duration of water restrictions, however, we find significant effects of temperature more clearly. The coefficients of *Temp* are statistically significant as shown in the sixth column in Table 6. The coefficients are positive, indicating that a $1°C$ increase in daily temperature prolongs the duration of water restrictions by 0.7 days. We also find that *Hot days* is statistically correlated with the duration of water restrictions. The coefficients in the eighth column in Table 6 show that an additional hot day extends water restrictions by 0.1 days. Likewise, *Avg. consecutive hot days* is statistically related to the duration of water restrictions. The coefficients suggest that the duration of water restrictions increases by 0.8–0.9 days with a one-day increase in the average spell of hot days.

The findings show that water restrictions are affected by higher temperature measured by both levels and frequencies. Although precipitation may be a more robust predictor for drought response actions, temperature conditions are also expected to affect water restrictions. This may be because of the potential demand for water in the hot year: higher temperature induces more water consumption for drinking, gardening, taking showers, etc. Another possible explanation may be that higher temperature results in larger water loss in reservoirs through evaporation. These concerns could cause a river basin to restrict water use in the hot year. The results from temperature variables suggest that potential extreme weather events caused by climate change, such as heat waves and longer summer seasons, could lead to more stringent drought response actions being implemented.

4.3. *Robustness checks*

We test the robustness of our estimation results by examining alternative weather indicators. We introduce alternative measures of weather anomalies in this section. In the main analysis, weather anomalies are included as a proxy for climatic conditions. To check the validity of the main results, we use alternative definitions of weather variables constructed as follows:

$$\mathit{Rain\ ratio}_{it} = \frac{\mathit{Rain}_{it}}{\mu_i^{LR(Rain)}}, \tag{3}$$

$$\mathit{Rain\ deviation}_{it} = \mathit{Rain}_{it} - \mu_i^{LR(Rain)}. \tag{4}$$

The definitions of the variables used to compute *Rain ratio* and *Rain deviation* are the same as those in *Weather anomalies*, explained in Section 3.2.[8] Similar to the anomaly variable, the ratio and deviation variables consider the long-run mean value. The rain ratio in Equation (3) is computed as the level of the precipitation variable, divided by the long-run mean. The rain deviation in Equation (4) is taken as the deviation from the long-run mean precipitation. The Japanese Meteorological Agency regularly releases the ratio and deviation of precipitation and temperature calculated in a similar manner to capture long-term climatic trends. Moreover, the ratio and deviation measures have also been examined in previous literature (Barrios

[8]We also compute and test the ratio and deviation variables using temperature. The coefficients of these variables are both statistically insignificant (results not shown); therefore, they do not alter the results presented in Section 4.2.

et al., 2010; Levine and Yang, 2014).[9] Thus, these variables are suitable for use as alternative indicators.

Table 7 presents the estimation results of the ratio and deviation measures. Columns 1–4 provide the results for the restriction rate model, and columns 5–8 provide the results for the duration model. The results of models using alternative variables do not largely differ from the main results in Section 4.1. The coefficients of *Rain ratio* are statistically significant and negative as expected. The standardized coefficients in the bottom rows indicate that a one standard deviation decrease in *Rain ratio* increases the restriction rate by 0.13 standard deviations and the duration by 0.21 standard deviations. Likewise, *Rain deviation* is also negatively correlated with both the restriction rate and duration. The standardized coefficients show that a decrease in the deviation measure of precipitation is associated with a 0.11 standard deviation increase in the restriction rate and a 0.16 standard deviation increase in duration. The magnitudes of these standardized coefficients are similar to those of the level and anomaly variables.

5. Conclusion

This study investigate the impact of weather variability on community-based water management during droughts. To explain how drought management is affected by weather conditions, we analyze water restrictions that were implemented in response to droughts in Japanese river basins from 1984 to

[9] Barrios et al. (2010) study the effect of precipitation on economic growth in Africa using the ratio measure along with its interaction terms. Levine and Yang (2014) examine the impact of rainfall on rice production with the deviation measure by taking the log of rainfall and the log of mean rainfall.

2014. The analysis uses climatic indicators relevant to precipitation and temperature. We construct alternative variables to examine whether and to what extent weather conditions affect water resource management during droughts.

Our study shows that weather variability is significantly related to water restrictions. We find that changes in weather conditions affect not only the amount of water being curtailed but also the duration of restriction implementation. The regression results show that the rate of water withdrawal restriction increases by 0.2% and the restriction period extends by almost a day when annual precipitation decreases by 100 mm. In addition, the impact of weather shocks is estimated using weather anomalies, which capture regional weather variations relative to the average conditions. The results show that a one-point decrease in precipitation anomalies intensifies the restriction rate by 1.4% and the duration by 6 days. These findings suggest that precipitation, measured by both absolute and relative terms, is associated with drought response actions. When we use dry days, i.e., the number of days without rainfall, as a weather indicator, we also find evidence of a negative impact of weather shocks that cause an increase in the rate and duration of water restrictions. The results of our study suggest that lower precipitation may result in the implementation of more stringent water restrictions.

Furthermore, the regression results show that temperature variability is correlated with water restrictions. The findings suggest that the negative impact of temperature variability on water restrictions may be amplified as temperature conditions become more intense. This has important policy implications regarding drought management in local communities. As climate change is expected to cause more extreme weather events, the potential risks of heat waves or extended summer seasons should be considered in drought management. In addition to concerns for human health, crop losses, environmental damages, etc., the occurrences of such extreme events may have a serious impact through the water supply. Drought coordination councils in Japan can facilitate the management of water supply under drought conditions by providing opportunities to coordinate the water demand of local stakeholders.

We believe that this is one of the few studies that investigate the impact of climate variability on water resource management under extreme weather conditions. Despite the urgent need for adaptation to future climate variability and change, there are few attempts to empirically analyze the topic, especially in the context of drought issues in Japan. Our study provides empirical evidence of climatic impact on water availability under drought conditions. The findings of our study suggest an important role of coordination body in enhancing an institutional capacity to adapt to severe weather events. On the other hand, we do not consider how the restrictions on water availability affect the livelihood of water users in river basins. Economic activities and actual water consumption may also be affected by such restrictions under droughts. Future research should thus focus on these aspects to investigate economic consequences of extreme weather events.

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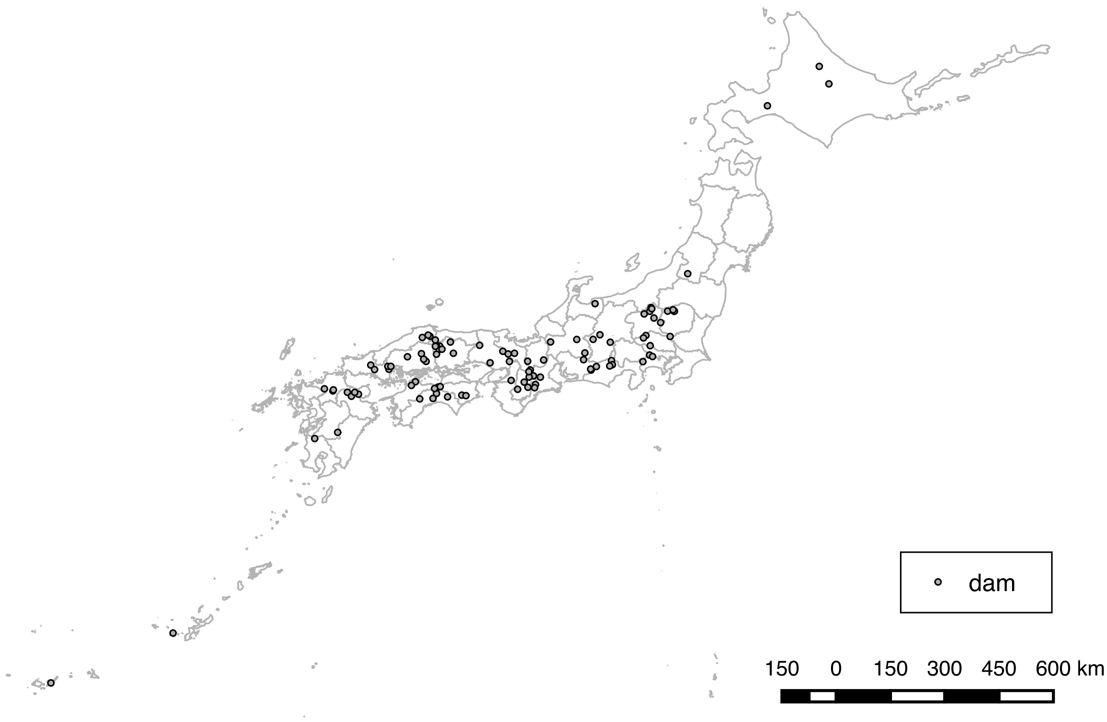

Figure 1. Location of dams subjected to water restrictions

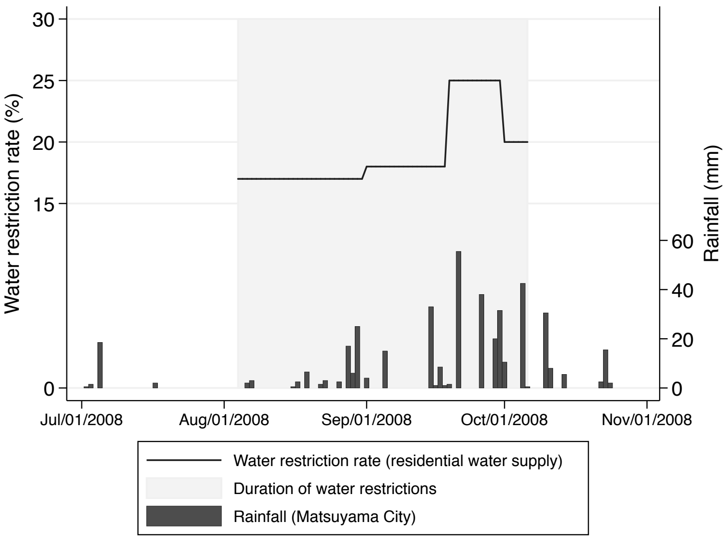

Figure 2. Water restrictions during the 2008 drought in Matsuyama city
Source: Matsuyama City

Table 1. Descriptions of variables

Variable	Unit	Description
Restriction rate	%	Rate of water withdrawal restrictions on residential water supply
Duration	day	Duration of water restrictions
Rain	mm	Annual precipitation
Rain anomalies	-	Deviations of precipitation from the long-term (1983-2014) mean precipitation, divided by its long-term standard deviation
Dry days	day	Annual number of days with precipitation less than 1mm
Avg. consecutive dry days	day	Average annual number of consecutive days with precipitation less than 1mm
Max. consecutive dry days	day	Maximum annual number of consecutive days with precipitation less than 1mm
Temp	°C	Average daily temperature
Temp anomalies	-	Deviations of temperature from the long-term (1983-2014) mean temperature, divided by its long-term standard deviation
Hot days	day	Annual number of days with maximum daily temperature above 30°C threshold
Avg. consecutive hot days	day	Average annual number of consecutive days with maximum daily temperature above 30°C threshold
Max. consecutive hot days	day	Maximum annual number of consecutive days with maximum daily temperature above 30°C threshold

Table 2. Descriptive statistics

Variable	Mean	S.D.	Min	Max
Restriction Rate	3.12	9.69	0.00	100.00
Duration	9.22	25.92	0.00	190.00
Rain	1926.44	703.65	661.00	5892.00
Rain anomalies	-0.00	0.98	-3.21	3.97
Dry days	232.64	25.51	133.00	294.00
Avg. consecutive dry days	4.76	0.71	2.86	7.83
Max. consecutive dry days	18.28	7.05	6.00	59.00
Temp	13.67	3.04	3.50	25.38
Temp anomalies	0.02	0.98	-4.69	3.51
Hot days	42.09	23.28	0.00	138.00
Avg. consecutive hot days	5.48	3.80	0.00	34.50
Max. consecutive hot days	15.18	11.23	0.00	80.00

Table 3. Main regression results with rain variables (Dependent variable: water restriction rate)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Rain	-0.002*					-0.002**				
	(0.001)					(0.001)				
Rain anomalies		-1.428***					-1.423***			
		(0.398)					(0.397)			
Dry days			0.076***					0.059***		
			(0.022)					(0.016)		
Avg. consecutive dry days				0.479					0.552	
				(0.482)					(0.453)	
Max. consecutive dry days					0.062					0.061
					(0.056)					(0.052)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.06	0.07	0.06	0.06	0.06					
Within R^2	0.08	0.09	0.08	0.07	0.07	0.08	0.09	0.08	0.07	0.07
Overall R^2	0.04	0.07	0.06	0.06	0.06	0.04	0.07	0.07	0.06	0.06
Standardized coef.	-0.180	-0.144	0.200	0.035	0.044	-0.118	-0.143	0.156	0.040	0.043

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 4. Main regression results with rain variables (Dependent variable: duration of water restrictions)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Rain	-0.009***					-0.007***				
	(0.002)					(0.002)				
Rain anomalies		-5.565***					-5.552***			
		(0.919)					(0.918)			
Dry days			0.243***					0.198***		
			(0.056)					(0.048)		
Avg. consecutive dry days				2.581*					2.786*	
				(1.501)					(1.514)	
Max. consecutive dry days					0.121					0.124
					(0.085)					(0.082)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.14	0.15	0.14	0.13	0.13					
Within R^2	0.16	0.17	0.15	0.14	0.14	0.16	0.17	0.15	0.14	0.14
Overall R^2	0.09	0.13	0.12	0.12	0.11	0.10	0.13	0.13	0.12	0.11
Standardized coef.	-0.257	-0.210	0.240	0.070	0.032	-0.185	-0.209	0.195	0.076	0.033

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 5. Regression results with temperature variables (Dependent variable: water restriction rate)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Temp	0.373					0.131				
	(0.731)					(0.160)				
Temp anomalies		0.501					0.483			
		(0.566)					(0.555)			
Hot days			0.069					0.047		
			(0.051)					(0.032)		
Avg. consecutive hot days				0.209*					0.216**	
				(0.111)					(0.107)	
Max. consecutive hot days					0.016					0.020
					(0.048)					(0.042)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.06	0.06	0.06	0.06	0.06					
Within R^2	0.07	0.07	0.08	0.08	0.07	0.07	0.07	0.08	0.08	0.07
Overall R^2	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Standardized coef.	0.116	0.050	0.167	0.083	0.018	0.041	0.048	0.113	0.086	0.023

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 6. Regression results with temperature variables (Dependent variable: duration of water restrictions)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Temp	0.936					0.727*				
	(2.299)					(0.441)				
Temp anomalies		0.960					0.940			
		(1.941)					(1.925)			
Hot days			0.124					0.125**		
			(0.083)					(0.060)		
Avg. consecutive hot days				0.775**					0.854**	
				(0.379)					(0.366)	
Max. consecutive hot days					0.077					0.123
					(0.082)					(0.083)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.12	0.13	0.13	0.13	0.13					
Within R^2	0.14	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.15	0.14
Overall R^2	0.12	0.11	0.12	0.13	0.12	0.12	0.11	0.12	0.13	0.12
Standardized coef.	0.108	0.036	0.111	0.115	0.033	0.084	0.035	0.113	0.126	0.053

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 7. Robustness checks

	Restriction rate				Duration			
	FE		RE		FE		RE	
	1	2	3	4	5	6	7	8
Rain ratio	-6.623***		-6.615***		-27.525***		-27.454***	
	(2.357)		(2.348)		(4.564)		(4.554)	
Rain deviation		-0.002*		-0.002**		-0.010***		-0.010***
		(0.001)		(0.001)		(0.002)		(0.002)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.07	0.06			0.15	0.14		
Within R^2	0.08	0.08	0.08	0.08	0.17	0.16	0.17	0.16
Overall R^2	0.06	0.06	0.06	0.06	0.13	0.13	0.13	0.13
Standardized coef.	-0.134	-0.109	-0.133	-0.109	-0.207	-0.158	-0.207	-0.158

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.