Decadal and Monthly Change of an Empirical Coefficient in the Relation between Solar Radiation and the Daily Range of Temperature in Japan: Implications for the Estimation of Solar Radiation Based on Temperature

Sonia Hossain, Koki Homma and Tatsuhiko Shiraiwa

(Graduate School of Agriculture, Kyoto University, Kyoto 606-8502, Japan)

Abstract: The need for solar radiation \( (R_s; \text{MJ m}^{-2} \text{d}^{-1}) \) estimation remains a common concern for agronomists. Evaluation of crop productivity is primarily based on \( R_s \) data, which are difficult to collect because of cost and calibration requirements. Generally, historical \( R_s \) data are more difficult to obtain. This study focused on an estimation model based on the daily range of temperature and evaluated its accuracy from the viewpoint of crop productivity analysis. The variability of an empirical coefficient in the model \( (K_{Rs}) \), which was derived from the relation between \( R_s \) and daily range of temperature \( (T_{max} - T_{min}) \), was analyzed using climatic data observed in Japan considering data availability and quality. \( K_{Rs} \) had significant monthly differences, and it significantly increased from 1981 – 1985 to 2003 – 2007 at all 10 locations. Period-month interactions were not significant, except for in Utsunomiya, suggesting that the seasonal pattern did not change during the period. Weather data indicated that the increase in \( K_{Rs} \) was caused not only by increased solar radiation but also by a decrease in \( T_{max} - T_{min} \). The substantial differences in \( K_{Rs} \) produced considerable bias for the estimated \( R_s \) when the estimation was conducted with a constant \( K_{Rs} \) (0.16). Despite the bias, the model is considered to perform well given the present availability of \( R_s \) data. The results of this study suggest that the evaluation of the seasonal pattern of \( K_{Rs} \) greatly improves the model accuracy.

Key words: Daily range of temperature, Decadal change, Empirical coefficient, Hargreaves and Samani model, Seasonal pattern, Solar radiation.

Solar radiation \( (R_s; \text{MJ m}^{-2} \text{d}^{-1}) \) is a driving factor in all physical and biochemical processes on the earth’s surface. Crop production also depends fundamentally on the amount of intercepted \( R_s \). Although \( R_s \) data has been collected for its significance (WRDC, 2013; Kuwagata et al., 2011), the number of weather stations that collect \( R_s \) data is still limited in the world due to the cost, maintenance and calibration requirements (Ball et al., 2004; Liu et al., 2009). Even where \( R_s \) data have been routinely measured, there are often significant gaps as a result of instrument errors or failures. Moreover, historical data are strongly recommended to evaluate the effects of climatic change on crop production, and these data typically lack \( R_s \) information. Hence, empirical models estimating \( R_s \) from commonly available climate data have been required.

One common approach to predicting \( R_s \) is the product of extraterrestrial radiation \( (R_a; \text{MJ m}^{-2} \text{d}^{-1}) \) and an estimated atmospheric transmissivity coefficient \( (T_t) \) as follows:

\[
R_s = R_a \times T_t
\]  

This model is based on the assumption that the difference

Received 24 September 2013. Accepted 15 April 2014. Corresponding author: K. Homma (homma@kais.kyoto-u.ac.jp, fax +81-75-753-6065).

Abbreviations: \( \text{Alt} \), altitude; ANOVA, analysis of variance; DOY, day of the year; \( K_{Rs} \), empirical coefficient in the estimation model for solar radiation; \( R_s \), extraterrestrial radiation; RMSE, root-mean-square error; \( R_s \), solar radiation; \( T_{max} \), daily maximum temperature; \( T_{min} \), daily minimum temperature; \( T_t \), transmissivity coefficient.
between daily maximum and minimum temperatures provides a general indication of cloudiness. Compared to clear skies, cloud cover usually decreases the maximum air temperature due to lower solar radiation levels and increases minimum air temperature due to increased downward emission and reflection of longwave radiation by clouds at night (Allen, 1997). Although other important factors, e.g., wind speed, humidity, elevation, precipitation and available soil water for evaporation, also affect transmissivity, these factors are not included in the model by assuming that the effects are fairly constant over a period of as long as one month (Hargreaves and Samani, 1982). Accordingly, the model is commonly applied to estimate monthly $R_s$ based on weekly or monthly averages of daily temperature ranges (Meza and Varas, 2000; Samani, 2000). Despite the inaccuracy caused by the assumption, the advantage in estimating $R_s$ using the model is greater because temperature data are available for wider areas and over longer periods around the world (Homma et al., 2007; JMA, 2013; GHCN, 2013).

Annandale et al. (2002) set $K_{Rs}$, an empirical coefficient in the model, to 0.16 for inland sites and 0.19 for coastal sites. However, Ball et al. (2004) and Fletcher and Moot (2007) reported that model performance is improved when the $K_{Rs}$ value is not fixed (0.16 or 0.19) and is instead calibrated to each site. Not only location differences but also seasonal differences in $K_{Rs}$ are important when using the model for the estimation of climate on crop production because the seasonal pattern of $R_s$ has a significant meaning in crop production. Historical changes in $K_{Rs}$ are also important when the evaluation is conducted using historical data. However, many studies have used constant $K_{Rs}$ (e.g. Irmak et al., 2012; van Wart et al., 2013), which could be a source of error in the $R_s$ estimates. This study aimed to evaluate seasonal and historical changes in $K_{Rs}$ and their effects on the estimation of $R_s$ to evaluate effects of climate on crop production because the seasonal pattern of $R_s$ has a significant meaning in crop production. Historical changes in $K_{Rs}$ are also important when the evaluation is conducted using historical data. However, many studies have used constant $K_{Rs}$ (e.g. Irmak et al., 2012; van Wart et al., 2013), which could be a source of error in the $R_s$ estimates. This study aimed to evaluate seasonal and historical changes in $K_{Rs}$ and their effects on the estimation of $R_s$ in order to characterize the error derived from the Hargreaves and Samani (1982) model. The effects on the estimation of $R_s$ were evaluated by setting $K_{Rs}$ as a constant. We used daily weather data because daily values are sometimes recommended when analyzing the effects of climate on crop production, e.g., analysis using a crop simulation model (van Wart et al., 2013). Data quality is of prime importance in the analysis of the above mentioned topics. Accordingly, we selected the dataset in Japan that included $R_s$ strictly certified by a certain standard (JMA, 2012), and yet covered a range of climatic and geographical conditions.

Materials and methods

1. Database and data sources

We selected 10 locations, which are representative agricultural areas widely distributed in Japan (Fig. 1). The locations were classified into Cfa, Dfa and Dfb of the Köppen-Geiger climate classification (Peel et al., 2007). The daily maximum temperature ($T_{max}$), minimum temperature ($T_{min}$) and solar radiation ($R_s$) data over the periods of 1981–1985 and 2003–2007 were collected from the Japan Meteorological Agency (JMA, 2012). Extraterrestrial radiation ($R_a$) was calculated using standard geometric methods for any given day of the year (DOY) based on latitude, solar constant, sunset hour angle and solar declination angle. The dataset was used for the estimation of $K_{Rs}$ and model validation.
2. Estimation of $K_{Rs}$

The transmissivity coefficient ($T_t$) was estimated using the following equation:

$$T_t = K_{Rs} \times (1 + 2.7 \times 10^{-5} \times Alt)^{(T_{max} - T_{min})^{0.5}}. \quad (3)$$

The equation was modified by Annandale et al. (2002) to include a correction factor for altitude ($Alt$; m). By combining Equation (1) and (3), $Rs$ is expressed as follows:

$$Rs = K_{Rs} [Ra (1 + 2.7 \times 10^{-5} \times Alt)^{(T_{max} - T_{min})^{0.5}}]. \quad (4)$$

Depending on the equation, $K_{Rs}$ was obtained as a regression coefficient where $[Ra (1 + 2.7 \times 10^{-5} \times Alt)^{(T_{max} - T_{min})^{0.5}}]$ is an independent variable and $Rs$ is a dependent variable with the intercept equal to 0 (as shown in Fig. 2).

The $K_{Rs}$ value for each month and each prefecture was estimated. Differences in $K_{Rs}$ between the periods of 1981 – 1985 and 2003 – 2007 as well as for each month were tested using two-way analysis of variance (ANOVA).

3. Model testing and assessment

To evaluate the effect of differences in $K_{Rs}$ on $R$, we used two-way analysis of variance (ANOVA). The results for each location are shown in Table 1.

Table 1. Comparison of location-wise $K_{Rs}$ variation for 1981 – 1985 and 2003 – 2007.

| Location     | Year          | Obihiro | Sapporo | Morioka | Utsunomiya | Niigata | Matsumoto | Nagoya | Hikone | Hiroshima | Fukuoka |
|--------------|---------------|---------|---------|---------|-------------|---------|-----------|--------|--------|-----------|---------|
| Latitude     | 42.92 N       | 43.06 N | 39.70 N | 36.55 N | 37.91 N     | 36.25 N | 35.17 N   | 35.28 N| 34.40 N| 33.58 N   |
| Longitude    | 143.21 E      | 141.33 E| 141.17 E| 139.87 E| 139.05 E    | 137.97 E| 136.97 E  | 136.24 E| 132.46 E| 130.38 E  |
| Altitude     | 38.4 m        | 17.2 m  | 155.2 m | 119.4 m | 1.9 m       | 610.0 m | 51.1 m    | 87.3 m | 3.6 m  | 2.5 m     |
| Distance from sea | 45 km      | 14 km   | 69 km   | 67 km   | 2 km        | 81 km   | 19 km     | 46 km  | 6 km   | 2 km      |
| $K_{Rs}$     | 1981 – 1985   | 0.151   | 0.163   | 0.146   | 0.144       | 0.147   | 0.151     | 0.154  | 0.161  | 0.162     |
|              | 2003 – 2007   | 0.160   | 0.176   | 0.151   | 0.152       | 0.157   | 0.156     | 0.165  | 0.160  | 0.165     |
|              | Whole         | 0.155   | 0.166   | 0.149   | 0.148       | 0.152   | 0.153     | 0.160  | 0.161  | 0.163     |

ANOVA Period (P) < 0.01 < 0.01 < 0.05 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 | < 0.01 | < 0.05 | < 0.01 |
Math (M)   < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 < 0.01 | < 0.01 | < 0.01 | < 0.01 |
P × M      0.71 0.55 0.47 < 0.01 0.26 0.52 0.74 0.31 0.29 0.20 |

Table 2. Comparison of location-wise daily range of temperature ($T_{max} - T_{min}$, ºC) and $R$ (MJ m$^{-2}$ d$^{-1}$) variation for 1981 – 1985 and 2003 – 2007.

| Location     | Year          | Obihiro | Sapporo | Morioka | Utsunomiya | Niigata | Matsumoto | Nagoya | Hikone | Hiroshima | Fukuoka |
|--------------|---------------|---------|---------|---------|-------------|---------|-----------|--------|--------|-----------|---------|
| $T_{max} - T_{min}$ | 1981 – 1985   | 10.65   | 7.86    | 9.31    | 10.08       | 6.85    | 11.07     | 8.72   | 7.73   | 7.86      | 7.44    |
|              | 2003 – 2007   | 10.45   | 7.50    | 8.86    | 9.59        | 7.03    | 11.21     | 8.73   | 7.56   | 8.50      | 7.25    |
|              | Whole         | 10.55   | 7.68    | 9.09    | 9.84        | 6.94    | 11.14     | 8.72   | 7.64   | 8.18      | 7.34    |
| Period (P)   | < 0.01        | < 0.01  | < 0.01  | < 0.01  | < 0.01      | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    | < 0.01  |
| ANOVA        | < 0.01        | < 0.01  | < 0.01  | < 0.01  | < 0.01      | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    | < 0.01  |
| P × M        | 0.52          | 0.65    | 0.77    | < 0.01  | 0.02        | 0.13    | 0.02      | 0.14   | 0.86   | 0.61      |
| $R$          | 1981 – 1985   | 12.52   | 12.18   | 12.03   | 12.45       | 11.39   | 14.46     | 12.84  | 12.98  | 13.11     | 13.16   |
|              | 2003 – 2007   | 13.17   | 12.52   | 12.27   | 12.89       | 12.24   | 15.09     | 13.83  | 12.97  | 13.88     | 13.71   |
|              | Whole         | 12.84   | 12.35   | 12.15   | 12.67       | 11.81   | 14.77     | 13.33  | 12.97  | 13.50     | 13.43   |
| Period (P)   | < 0.01        | 0.12    | 0.34    | 0.13    | < 0.01      | < 0.01  | < 0.01    | < 0.01 | 0.95   | 0.01      | < 0.05  |
| ANOVA        | < 0.01        | < 0.01  | < 0.01  | < 0.01  | < 0.01      | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    | < 0.01  |
| P × M        | 0.37          | 0.38    | 0.28    | 0.39    | 0.52        | 0.57    | 0.40      | 0.72   | 0.60   | 0.33      |
prediction, we estimated daily \( R_s \) using Eq. 3 with \( K_{Rs} = 0.16 \) and compared with the observed \( R_s \). Bias and root-mean-square error (RMSE) were used as measures of the estimated \( R_s \) accuracy as follows:

\[
\text{bias} = \frac{\sum (\text{estimated} \ R_s - \text{measured} \ R_s)}{n}, \quad (5)
\]

\[
\text{RMSE} = \left( \frac{\sum (\text{estimated} \ R_s - \text{measured} \ R_s)^2}{n} \right)^{0.5}. \quad (6)
\]

Bias shows the over- or under-estimation, and RMSE shows the magnitude of error. Two-way ANOVA was also conducted to quantify the bias and RMSE.

**Results**

1. **Effect of locations, periods and seasons on \( K_{Rs} \)**

The \( K_{Rs} \) value varied from 0.148 (Utsunomiya) to 0.166 (Sapporo and Fukuoka) during the entire study period (1981 – 2007; Table 1). The values generally decreased with the distance from sea, except Niigata (Table 1 and Fig. 3). At almost all locations, except Hikone and Hiroshima, \( K_{Rs} \) significantly increased from the 1981 – 1985 period to the 2003 – 2007 period (note: the probability of period...
between the months of January and March followed by a steep decline between May and July (0.12 to 0.14) and a gradual increase from August to December (Fig. 4). However, Niigata showed an opposite pattern of KRs values, i.e., higher values in the middle of the year and lower values in the late and early months of the year. The KRs values for Hikone, Hiroshima and Fukuoka did not show a clear pattern for any given year. The pattern appeared similar in both time periods (1981 – 1985 and 2003 – 2007) because the period and month interactions for KRs values...
were not significant, except for Utsunomiya (Table 1).

2. Errors in $R_s$ estimation with a constant $K_{Rs}$ value

A constant value of $K_{Rs}$ ($= 0.16$) produced bias in the $R_s$ estimation in both periods in a pattern that was somewhat similar but inverse to the monthly variation pattern of $K_{Rs}$ (Fig. 5). Bias for the entire period was the highest in November to March (Fig. 5). Bias for the entire period was the highest in November to March from April to July in comparison with the estimation from a seasonal variation, i.e., the model tended to overestimate the relation between measured and estimated $R_s$.

The relation between measured and estimated $R_s$ ($-0.35$ MJ m$^{-2}$) and RMSE (MJ m$^{-2}$) for 1981 – 1985 and 2003 – 2007 periods. Solar radiation was estimated by setting $K_{Rs} = 0.16$.

$$T_{max} - T_{min}$$

| Location     | Year       | Obihiro | Sapporo | Morioka | Utsunomiya | Niigata | Matsumoto | Nagoya | Hikone | Hiroshima | Fukuoka |
|--------------|------------|---------|---------|---------|------------|---------|-----------|--------|--------|-----------|---------|
| 1981 – 1985  | 3.79       | 3.91    | 4.20    | 3.95    | 4.26       | 4.03    | 4.06      | 4.33   | 3.90   | 4.77      |         |
| 2003 – 2007  | 3.98       | 4.11    | 4.26    | 4.12    | 4.81       | 3.97    | 4.52      | 4.52   | 4.16   | 5.01      |         |
| **Whole**    | **3.89**   | **3.96**| **4.23**| **4.04**| **4.53**   | **4.00**| **4.19**  | **4.42**| **4.03**| **4.89**  |         |

**ANOVA**

| Period (P)   | < 0.01  | < 0.01  | < 0.01  | < 0.01  | < 0.01    | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    | < 0.01  |
|--------------|---------|---------|---------|---------|-----------|---------|-----------|--------|--------|-----------|---------|
| Month (M)    | < 0.01  | < 0.01  | < 0.01  | < 0.01  | < 0.01    | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    | < 0.01  |
| **P × M**    | 0.61     | 0.14    | 0.04    | 0.17    | 0.15      | 0.79    | 0.51      | 0.69   | 0.35   | 0.27      |         |

**RMSE**

| Period (P)   | < 0.05  | < 0.01  | 0.54    | 0.18    | < 0.01    | 0.59    | < 0.05    | 0.09   | < 0.05 | < 0.05    |         |
|--------------|---------|---------|---------|---------|-----------|---------|-----------|--------|--------|-----------|---------|
| Month (M)    | < 0.01  | < 0.01  | < 0.01  | < 0.01  | < 0.01    | < 0.01  | < 0.01    | < 0.01 | < 0.01 | < 0.01    |         |
| **P × M**    | 0.21     | 0.94    | 0.17    | 0.33    | < 0.01    | 0.64    | 0.57      | 0.13   | < 0.01 | < 0.01    |         |

Discussion

Solar radiation ($R_s$) is one of the major determinant factors of crop production, but the observations have locational and historical limitations (WRDC, 2013). Accordingly, the estimation of $R_s$ is quite important when the relation between weather and crop production is historically analyzed in a wide range of locations. Among many methods to estimate $R_s$, models based on sunshine hours are most reliable (Angstrom, 1924; Kondo et al., 1991). However, sunshine hours have the same problem as $R_s$ in terms of data availability (Homma et al., 2007). This study focused on the estimation method based on temperature, which is historically collected in a large number of locations (JMA, 2013; NOAA, 2013).

The Hargreaves and Samani (1982) model has been tested and accepted as a reasonable method for estimating solar radiation by several previous studies (Ball et al., 2004; Fortin et al., 2008; Bandyopadhyay et al., 2008) for a wide range of locations. Some studies have modified the original model by adding one more coefficient (De Jong and Stewart, 1993; Hunt et al., 1998; Chen et al., 2004), which commonly produces better results but only for a specific location because the goals did not encompass the examination of diverse locations (Liu and Scott, 2001). In fact, Liu et al. (2009) showed that the original Hargreaves and Samani (1982) model (with or without the Annandale et al., 2002 modification) is still more accurate than the complex modified model for a wide range of locations. Although an alternate method, which estimates $R_s$ based on temperature, has also been proposed (Bristow and Campbell, 1984 and modified by Weiss et al., 2001), Ball et al. (2004) concluded that the Hargreaves and Samani (1982) model with the Annandale et al. (2002) modifications is better than the Bristow and Campbell (1984) model modified by Weiss et al. (2001). We selected the model according to Ball et al. (2004).

To characterize the bias variability, we first calculated the
empirical constant ($K_{Rs}$) in the model. The recommended values by Annandale et al. (2002) for $K_{Rs}$ are 0.16 for inland sites and 0.19 for coastal sites. Although the $K_{Rs}$ estimated in this study also tended to decrease along with the distance from the sea (Fig. 3), the values seemed lower than the recommendation by Annandale et al. (2002). Further study might be necessary to determine the accurate value of $K_{Rs}$ in the worldwide range. Other weather factors, such as humidity and precipitation, might be necessary to estimate $K_{Rs}$ more accurately, (Thornton and Running, 1999). However, such modification requires other weather data and decreases the applicability of the model. In this study, we did not modify the model, and we set $K_{Rs}$ to 0.16 to estimate $R_s$ because $K_{Rs}$ was approximately 0.16 and 0.16 was one of the recommended values by Annandale et al. (2002). The difference in $K_{Rs}$ between the constant (0.16) and actual values produced bias. Accordingly, the average $K_{Rs}$ ranged from 0.166 at Fukuoka to 0.148 at Utsunomiya, which corresponded to the average bias ranging from $-0.35$ MJ m$^{-2}$ at Fukuoka to 1.72 at Utsunomiya. $K_{Rs}$ values showed a distinct seasonal pattern in most areas studied (Fig. 4) and the difference of the seasonal pattern against $K_{Rs} = 0.16$ created seasonal bias differences.
(Fig. 5). In this study, most locations tended to have a lower \( K_{\text{R}} \) and higher bias in the summer, but Niigata had a higher \( K_{\text{R}} \) and lower bias in the summer. The difference in monthly bias between the largest and smallest was largest at Obihiro (6.3 MJ m\(^{-2}\)) and smallest at Hikone (2.3 MJ m\(^{-2}\)). Abraha and Savage (2008) also reported that the Hargreaves and Samani (1985) model, which was taken from the Hargreaves and Samani (1982) model, tends to overestimate in the summer. Apart from the seasonal pattern, \( K_{\text{R}} \) also changed with the period (Fig. 4). Therefore, reproducing the results of this study suggested that the estimation of \( R_s \) from April to September (Fig. 5). The increase in RMSE was mainly due to increased RMSE negative, and RMSE tended to increase over the decades. The interaction between month and period was small overestimation area in the figure, which was one of the distributed from April to July than from August to March.

RMSE showed a more distinct seasonal pattern than bias (Fig. 5). The pattern showed the maximum around June and the minimum around December, which correspond with the extraterrestrial radiation \( (R_s) \). Several studies have indicated that the global warming trend commonly decreases the daily range of temperature because the increase in daily minimum temperature is commonly larger than that of daily maximum temperature (Karl et al., 1991; Kawatsu et al., 2007). Urbanization also decreases the daily range of temperature (Suzuki et al., 2001). Although historical changes in solar radiation are not obvious (Pinkier et al., 2005; Wild et al., 2007), the decreasing trend in the daily range of temperature itself produces an increasing trend in \( K_{\text{R}} \). The interaction between month and period was small for \( K_{\text{R}} \), thereby suggesting that the seasonal pattern of \( K_{\text{R}} \) is location-specific and less affected by global warming.

The increase in RMSE was mainly due to increased RMSE from April to September (Fig. 5).

Although the Hargreaves and Samani (1982) model is widely used (e.g. Irmak et al., 2012; van Wart et al., 2013), the results of this study suggested that the estimation of \( R_s \) using the Hargreaves and Samani (1982) model has a considerable problem with bias when analyzing crop production, i.e., bias changes depending on the location, year and, especially, month. However, use of this model may be the best method in the present situation in which obtaining adequate and qualified data for \( R_s \) around the world is quite difficult, especially in developing countries (Thornton and Running, 1999; Homma et al., 2007; Liu et al., 2009). Accordingly, the difference in bias must be considered when the estimation of \( R_s \) by the model is applied to analyze crop productivity. For example, the maximum location-wise difference in bias was 2 MJ m\(^{-2}\) in this study corresponding to approximately 15% of \( R_s \). The maximum periodic difference was 1 MJ m\(^{-2}\) corresponding to 7%, and the maximum monthly difference was 6.5 MJ m\(^{-2}\) corresponding to 50%. These values may suggest that the method is not suitable to discuss seasonal changes in productivity. The relatively smaller periodic difference together with the smaller interaction between period and month for bias (Table 3) suggest that the evaluation of seasonal pattern of \( K_{\text{R}} \) in the present situation improved the estimation accuracy of \( R_s \) for the past decades.

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* In Japanese with English abstract.

** In Japanese.