Impacts of temperature effect removal on rainfall estimation from soil water content by using SM2RAIN algorithm

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Abstract. Rainfall data is the most basic and essential input for many studies in hydrology, climatology, or water management. However, rainfall data is quite limited in poorly equipped regions such as high mountain regions, developing countries, and savannahs. In recent years, a new approach named SM2RAIN that has been proposed to assess rainfall amount on a daily scale. This method uses the relative saturation of soil (Se) as the input to infer rainfall. Some of these studies showed promising results in evaluating rainfall by using SM2RAIN. Over past decades, however, some other studies have also found that the soil water content (SWC), which is used to calculate the Se, has errors associated with diurnal temperature fluctuation. As soil water content is the primary input variable of SM2RAIN, this error must have impacts on the performance of SM2RAIN. In this study, the authors have assessed and cleared the impact of temperature on SM2RAIN performance. Thus, an effective temperature correction method has been applied to remove the impact of temperature on soil water content at 19 sites over the United States, Africa (Senegal) and Europe (Romania) in varies climatic conditions to assess the impact of temperature effect removal on results of SM2RAIN algorithm. The criteria to evaluate the program such as Nash-Sutcliff has increased up to 53% depending on the initial results and climatic condition. The correlation coefficient has positive change as well. As a result, this removing makes the performance of the algorithm better.

1. Introduction
Rainfall is one of the key variables controlling the water cycle of the earth and energy exchange between the land surface and atmosphere. Its data also plays a crucial role in various hydrological models, water management, and planning. Nowadays, there are two major sources to collect rainfall data, including rainfall stations and satellite sensors. Nevertheless, they still suffer from some limitations [1-3]. Collecting accurate rainfall data at a global scale is facing many challenges, especially the observed rainfall from the gauges and weather radars, which is known as the most accurate data currently. Usually, the limitations have come from poorly equipped regions such as high mountain or savannah areas or developing countries.

Recent studies suggested another efficient method for rainfall estimation from the relative saturation of soil, a product derived from SWC, which is called SM2RAIN algorithm [4]. Moreover, this method can apply to the global scale by using satellite soil moisture data as well [5]. However, in other researches, Brocca \textit{et al} [6] also showed that this algorithm has some limitations in arid climates, which causes worse performance than humid temperate climates.

On the other hand, existing researches indicated that measured SWC, especially in situ soil moisture sets hosted by ISMN networks, suffer errors related to the temperature fluctuations regardless
of the sensor types [7,9-10]. These errors may be the limitation of rainfall estimation models using the product from SWC such as SM2RAIN. Indeed, after removing temperature effects from SWC by using the automated general temperature correction method proposed by Kapilaratne and Lu [10] to calculate the relative saturation of soil, we found that the SM2RAIN algorithm’s performances have positive changes.

By investigating the changes of SM2RAIN’s performance after removing temperature effects from SWC, this study determines the importance of temperature effects removal on the applications which using soil water content or its derivation as the primary input such as SM2RAIN algorithm. The soil moisture data using for this study has been obtained from ISMN networks [11,12], which is one of the biggest global in situ soil moisture database. Some results of this study have shown that it is necessary to remove temperature effects from SWC as a preprocessing step for applications which using the soil moisture data as essential input, especially in arid climates.

2. The study area and data description

2.1. Study area

Table 1. Description of the monitoring networks used for this study. The climates are classified followed Peel et al [13] where: B: arid, C: Temperate, D: Cold, W: desert, s: dry summer, S: Steppe, f: Without dry season, a: hot summer, b: Warm summer, h: Hot, k: Cold.

| The network name and Country | Station name | Location (long/lat) | Climate classification | Soil type          |
|-----------------------------|--------------|---------------------|------------------------|--------------------|
| USCRN – The United States of America [14] | Redding-12-WNW | -122.61, 40.65 | Csa | Sandy Clay |
| USCRN – The United States of America [14] | Las-Cruces-20-N | -106.74, 32.61 | BSk | Loam |
| USCRN – The United States of America [14] | Fallbrook-5-NE | -117.19, 33.44 | BSk | Loam |
| USCRN – The United States of America [14] | Socorro-20-N | -106.89, 34.36 | BSk | Clay Loam |
| USCRN – The United States of America [14] | Goodwell-2-SE | -101.61, 36.57 | BSk | Loam |
| USCRN – The United States of America [14] | Williams-35-NNW | -112.34, 35.76 | Dsb | Loam |
| USCRN – The United States of America [14] | Riley-10-WSW | -119.69, 43.47 | BWk | Loam |
| USCRN – The United States of America [14] | Stovepipe-Well-1-SW | -117.14, 36.60 | BWk | Loam |
| USCRN – The United States of America [14] | Yuma-27-ENE | -114.18, 32.83 | BWk | Sandy Loam |
| USCRN – The United States of America [14] | Bronte-11-NNE | -108.50, 37.25 | Dfa | Loam |
| USCRN – The United States of America [14] | Cortez-8-SE | -115.43, 15.40 | BSh | Sand |
| DHARA – Senegal [15] | Dhara | -21.54, 14.05 | Dfb | Loam |
| RSMN – Romania | Alexandria | -23.35, 43.98 | Cfa | Loam |
| RSMN – Romania | Bacles | -11.61, 44.48 | Dfb | Clay |
| RSMN – Romania | RosioriideVede | 24.98, 44.11 | BWk | Silty Clay Loam |
| SCAN – The United States of America | FordDryLake | -115.10, 33.65 | BWk | Sandy Loam |
| SCAN – The United States of America | MonoclineRidge | -110.55, 36.54 | BWk | Clay |
| SCAN – The United States of America | PineNut | -115.20, 36.57 | BWk | Sandy Loam |

To assess the results of temperature effect removal from soil water content (SWC) at various climatological conditions and soil type, the authors chose the soil moisture monitoring networks as shown in table 1 for this study. Most of these networks located in the United States, where cover many types of climate and soil; two of them are in Europe (Romania) and Africa (Senegal). Due to the conditions of SM2RAIN algorithm and temperature effect removal methods [6,9-10], these selected networks consist of three main climates (as classified in Köppen-Geiger climate classification [13]) and seven major soil types. The primary climates of monitoring networks in the USA can be listed as follows: arid, temperate, and cold. The network in Romania (Europe) is under cold, arid, and temperate conditions. Meanwhile, the African site (Senegal) covers the arid area. The dominant soil types of the selected sites range between sandy and clay soils. More details about the location, networks, climates, and soil types of each monitoring stations are described in table 1. All the
monitoring sites were selected based on three criteria. The first and foremost is the availability of three long continuous data sets: the dielectrically measured near-surface SWC along with temperature measurement as the same depth and observed precipitation as the same investigating period. The longer data using for estimation, the better result will be reflected [6,10]. Secondly, to eliminate the possible effect of the wet condition of the soil (in saturated), the sites with the annual precipitation less than 800 mm were chosen. Thirdly, to estimate the impacts of temperature effect removal on SM2RAIN in many sides, the sites with both horizontally and vertically inserted soil moisture probes were selected.

2.2. Data description
The data used in this study were downloaded from the website of the International Soil Moisture Network (ISMN) and assessed from 04/07/2018 to 07/05/2019; where the USCRN and DHARA were obtained from 04/07/2018 to 04/12/2018 and the remain sites were gotten on 07/05/2019.

The ISMN currently hosts 59 soil moisture networks in global scale which consist of in-situ soil moisture database of more than 1400 stations. Although there are many soil moisture stations which match to the criteria conditions, only 19 stations from 4 networks were used for this study (refer to table 2 and figure 1). During the first assessment to conduct this study, it was found that some soil moisture datasets contain errors such as spikes, breaks, and valleys, as mentioned by Dorigo et al [8]. These erroneous data were excluded during the process of this study. The SWC and temperature of 19 stations were measured using four commercially available dielectric sensors combined with temperature sensors. Table 2 describes the information of those sensors in detail. The temporal resolution of all data sets is hourly and available for at least three consecutive years.

All the investigating sites display the spurious diurnal fluctuation of SWC as proposed by Cobos and Cambell [16], Lu et al [9], Saito et al [17] and Schanz et al [18]. This fluctuation is the effect of temperature on SWC regardless of climatic conditions, probed directions, sensor, or soil types [9,10].

Table 2. Description about sensor setups of soil moisture monitoring stations.

| Station name       | Soil moisture sensor | Measurement depth (m) | Direction probes | Period       |
|--------------------|----------------------|-----------------------|------------------|--------------|
| Redding-12-WNW     | Stevens Hydaprobe II | 0.05 – 0.05           | Horizontal       | 2012-2014    |
| Las-Cruces-20-N    | Sdi-12               |                       |                  | 2012-2014    |
| Fallbrook-5-NE     |                      |                       |                  | 2012-2014    |
| Socorro-20-N       |                      |                       |                  | 2012-2014    |
| Goodwell-2-SE      |                      |                       |                  | 2012-2014    |
| Williams-35-NNW    |                      |                       |                  | 2012-2014    |
| Riley-10-WSW       |                      |                       |                  | 2012-2014    |
| Stovepipe-Wells-1-SW |                    |                       |                  | 2012-2014    |
| Yuma-27 -ENE       |                      |                       |                  | 2012-2014    |
| Bronte-11-NNE      |                      |                       |                  | 2012-2014    |
| Cortez-8-SE        |                      |                       |                  | 2012-2014    |
| Dhara              |                      | 0.05-0.05             | Horizontal       | 2012-2014    |
| Alexandria         |                      |                       |                  | 2016-2018    |
| Bacles             |                      | 0.0508-0.0508         | Vertical         | 2016-2018    |
| RosioriiodeVede    |                      |                       |                  | 2016-2018    |
| SannicolauMare     |                      |                       |                  | 2016-2018    |
| FordDryLake        |                      |                       |                  | 2013-2016    |
| MonoclineRidge     |                      | 0.0508-0.0508         | Horizontal       | 2015-2017    |
| PineNut            |                      | (2.5 Volt)            |                  | 2015-2017    |
Figure 1. The location of soil moisture monitoring networks used in this study (a) and ISMN database (b).

3. Methodology

3.1. Generality method
To deeply assess the impacts of temperature effect removal on rainfall estimation from soil water content, the authors do two critical experiments: the first experiment to estimate how the correction work for full data series and the second one to understand how the regulation makes the results change on removing period only. The solution was then assayed for the assessment using both the automated general temperature correction method [10] and SM2RAIN algorithm [4] in two cases: removing temperature effect and keeping the raw data.

As the first step, the SWC has been corrected by using the general automated method as the reprocessing data. The second step was to use corrected SWC for calculating the relative saturation of the soil, which is the essential input of SM2RAIN algorithm. A comparison between doing the first step and not doing the first step was conducted to evaluate the effect of temperature effect removal on SM2RAIN algorithm.

3.2. The automated general temperature correction method
This method was established by Lu et al [9] and developed by Kapilaratne and Lu [10], they successfully removed the temperature effects from SWC in both wet and dry conditions. Equation (1) was used to express the relationship between measured and actual SWC at corresponding observed and reference temperature, respectively.

$$\theta_{ref} = \frac{\theta}{1 + \alpha(T - T_{ref})} \quad (1)$$

where $\theta$ and $\theta_{ref}$ are measured and reference SWC at $T$ and $T_{ref}$ respectively; $\alpha$ stands for temperature correction coefficient; $T$ is actual soil temperature and $T_{ref}$ represents a temperature where the calibration curve was created.

Concurrently, the equation (2) expresses the temperature effects on measured SWC by analyzing the correlation of measured SWC and temperature data. Also, the coefficient $\alpha$ of equation (1) is obtained from equation (2) [9].

4
\[ A_{\theta} = \alpha \theta_{d} A_{T} \]  
\[ \text{where } A_{\theta} \text{ and } A_{T} \text{ represent the daily amplitudes of SWC and temperature, respectively; } \alpha \text{ stands for temperature correction coefficient; } \theta_{d} \text{ is daily mean SWC.} \]

In equation (1), the reference SWC, \( \theta_{ref} \) is known as the SWC after correction, is considered to be true SWC without temperature effect. Lu et al [9] had shown that temperature effects might cause a 16\% relative error in SWC. According to Kapilaratne and Lu [10], the days with daily rainfall amounts higher than 0.1 mm along with the following days have to be removed to avoid the abrupt increases in soil moisture amplitudes due to rainfall events. Notably, this step is crucial to estimate rainfall from SWC. The model can realize the abrupt increase as a heavier rainfall event. Additionally, the negative soil temperature has to exclude from the analysis to get rid of the effects of drastic changes in the bulk dielectric permittivity of the soil when the water freezes [19].

3.3. SM2RAIN algorithm

The SM2RAIN algorithm was proposed by Brocca et al [4]. The idea of this method is to estimate rainfall amount by using the soil moisture as a natural rain gauge. The basic concept depends on soil water balance equation. The rainfall was derived from the relative saturation of soil by inverting the soil water balance equation. The inversion equation was shown as below:

\[ P(t) \equiv Z \frac{ds(t)}{dt} + as(t)^{b} \]  
\[ \text{where } Z \text{ is a layer depth of soil [L]; } s(t) \text{ (also known as Se) stands for the relative saturation of the soil [-]; } t \text{ is time [T]; } as(t)^{b} \text{ represents the drainage rate in which } a \text{ [L/T] and } b \text{ [-] are two parameters expressing the nonlinearity between drainage rate and soil saturation.} \]

In equation (3), the evaporation rate was neglected whenever it rains [20]. Also, a strong assumption that all precipitation infiltrates into the soil. As a result, the runoff is equal to zero. This assumption is the most significant limitation of this algorithm when the soil comes to saturate. This limitation will be discussed in another study. Fourth-order Runge-Kutta method was applied to solve equation (3) for reducing the error. A schematic of the SM2RAIN procedure is shown in figure 2. The relative saturation of soil in equation (3) was converted from SWC by the following equation:

\[ S_{e} = \frac{\theta - \theta_{r}}{\theta_{s} - \theta_{r}} \]  
\[ \text{where } S_{e} \text{ presents the relative saturation of the soil; } \theta \text{ and } \theta_{s} \text{ stands for SWC and soil saturation, respectively; } \theta_{r} \text{ is residual saturation. In this study, the } \theta_{s} \text{ was referred from each of monitoring network database, } \theta_{r} \text{ was assumed equal to zero since its value is so small that being able to neglect [19].} \]
Figure 2. Schematic of the SM2RAIN procedure.

Table 3. The changes in the evaluation index after removing temperature effects on SWC.

| Station name          | \( \alpha \) (°C\(^{-1}\)) | Annual rainfall (mm) | Nash-Sutcliffe (NS) | % change | The correlation coefficient (R) | % change |
|-----------------------|-----------------------------|---------------------|---------------------|----------|--------------------------------|----------|
| Redding-12-WNW        | 0.0224                      | 879                 | 0.810               | 0.814    | 0.5                             | 0.902    | 0.902 | 0   |
| Las-Cruces-20-N       | 0.0137                      | 248                 | 0.477               | 0.500    | 4.2                             | 0.722    | 0.734 | 1.7 |
| Fallbrook-5-NE        | 0.0107                      | 406                 | 0.592               | 0.723    | 22.1                            | 0.796    | 0.857 | 7.7 |
| Socorro-20-N          | 0.0161                      | 261                 | 0.444               | 0.500    | 11.9                            | 0.724    | 0.759 | 4.8 |
| Goodwell-2-SE         | 0.0111                      | 435                 | 0.415               | 0.431    | 3.9                             | 0.646    | 0.658 | 1.9 |
| Williams-35-NNW       | 0.0125                      | 568                 | 0.501               | 0.530    | 5.8                             | 0.726    | 0.744 | 2.5 |
| Riley-10-WSW          | 0.0164                      | 289                 | 0.240               | 0.265    | 10.4                            | 0.507    | 0.521 | 2.8 |
| Stovepipe-Wells-1-SW  | 0.0230                      | 61                  | 0.363               | 0.510    | 40.5                            | 0.756    | 0.765 | 1.2 |
| Yuma-27-ENE           | 0.0144                      | 78                  | 0.201               | 0.309    | 53.7                            | 0.478    | 0.600 | 25.5 |
| Bronte-11-NNE         | 0.0131                      | 615                 | 0.631               | 0.646    | 2.4                             | 0.831    | 0.832 | 0.1 |
| Cortez-8-SE           | 0.0120                      | 319                 | 0.335               | 0.344    | 2.7                             | 0.585    | 0.589 | 0.7 |
| Dhara                 | 0.0139                      | 100                 | 0.638               | 0.699    | 8.5                             | 0.801    | 0.837 | 4.5 |
| Alexandria            | 0.0127                      | 358                 | 0.483               | 0.500    | 3.3                             | 0.703    | 0.710 | 1   |
| Baches                | 0.0090                      | 578                 | 0.525               | 0.534    | 1.7                             | 0.730    | 0.735 | 0.7 |
| RosioriideVede        | 0.0075                      | 447                 | 0.630               | 0.659    | 4.6                             | 0.795    | 0.815 | 2.5 |
| SannicolauMare        | 0.0100                      | 504                 | 0.584               | 0.602    | 3.1                             | 0.766    | 0.780 | 1.8 |
| FordDryLake           | 0.0208                      | 215                 | 0.440               | 0.472    | 7.3                             | 0.689    | 0.720 | 4.5 |
| MonoclineRidge        | 0.0123                      | 208                 | 0.164               | 0.177    | 7.9                             | 0.481    | 0.481 | 0   |
| PineNut               | 0.0194                      | 285                 | 0.438               | 0.454    | 3.7                             | 0.686    | 0.694 | 1.2 |

4. Results and discussions

The overall purpose of this study was to evaluate the effect of SWC correction on another program which using soil moisture data as an essential input, such as SM2RAIN for rainfall estimation. The proposed automated general method was developed by Kapilaratne and Lu [10]. The findings indicated that the removing had improved SM2RAIN performance regardless of the soil type or climatic conditions. However, the significance of improvement is varying depending on the initial results and climatological conditions.

4.1. The first experiment: the impact of temperature effect removal on SM2RAIN for full data series

The first experiment was carried out by using consecutive soil moisture data to estimate rainfall from SM2RAIN algorithm. In this experiment, the SWC during periods to which the automated general temperature correction method is applicable are corrected, and the raw data are kept in remained
periods to make a consecutive data series for SM2RAIN. This SWC is known as corrected data and used for calculating the relative saturation of soil, which is input of the first simulation. The results of this simulation stand for “after correcting result”. The second simulation completely follows steps of Brocca et al [4], and it is known as “before correcting results”.

In this study, the evaluation methods used included Nash-Sutcliffe efficiency, which described in the equation (5) and the correlation coefficient (R).

\[
NS = 1 - \frac{\sum_i (O_i - P_i)^2}{\sum_i (O_i - \overline{O})^2}
\]

where NS is Nash-Sutcliffe efficiency; \(O_i\) and \(P_i\) stand for the observed and simulated value, respectively; \(\overline{O}\) is the mean of the observed data.

According to Guppta et al [21], the model simulation can be judged as satisfactory if \(NS \geq 0.5\).

The results of the first experiment have been presented in table 3. Three main factors have shown in table 3 to make the temperature effect removal judgment, including \(\alpha\) value, annual rainfall, and performance of SM2RAIN algorithm (Nash-Sutcliffe and correlation coefficient)

As shown in table 3, obviously, the performance of SM2RAIN had become better after removing. The NS efficiency had grown up to 53% after correction. On average, the Nash-Sutcliffe of SM2RAIN had increased about 10.4% when using the corrected SWC for calculating the relative saturation of soil. Four of eleven underestimated sites have changed to be judged. The least change is at Redding-12-WNW site, where the annual rainfall amount is highest (879 mm) although the \(\alpha\) value of this site is large. In contrast, the two highest improvements are at Yuma-27-ENE and Stovepipe-Wells-1-SW, where are recognized as desert and the annual rainfall is lowest (78 mm and 61 mm for Yuma and Stovepipe-Wells, respectively). These results indicate that no significant impact of temperature effect removal on rainfall estimation under the humid temperate climates. This finding also agrees with the previous study of Brocca et al [6].

Most of the sites having the percentage change larger than 5% have the annual rainfall lower than 500 mm and alpha higher than 0.01. The higher alpha value, the stronger effects of temperature on SWC [10]. Neglecting the other factors which impact on the performance of SM2RAIN such as freezing time of soil or snowing period, it can be seen that the temperature effect removal had improved the rainfall estimation from soil moisture data.

4.2. The second experiment: how the results change on removing period

This experiment was conducted to deeply understand how the removing temperature effects work on SM2RAIN to better its performance. In this investigation, the SWC during periods to which the automated general temperature correction method is applicable are corrected and the remained periods are set up as NaN value; that is mean the experiment only used the SWC after removing temperature effects for simulation. Similar to the first experiment, this data reveals for the “after correcting results”.

The results of the second experiment are presented in figure 3. Six of 19 stations are selected to show the results. Figure 3 reveals that there has been a significant decrease in simulating noise after removing temperature effects during the dry period due to reducing the fluctuation of SWC, which may cause false rainfall events. Before the correction, many small rainfall events which should be equal to zero as actual are obtained from SM2RAIN. After removing the temperature effects, the fluctuation of SWC is gone down; the outcome of rainfall tends to zero as observed data. Brocca et al [6] also mentioned from their study that the performance of SM2RAIN is better for sites in humid temperate climates. In this study, it can be improved the performance of the algorithm for sites in arid conditions.
Figure 3. The comparison of monthly simulating rainfall between before and after removing temperature effects along with observed data at (a) RosioriideVede, (b) SannicolauMare, (c) FordDryLake, (d) Fallbrook-5-NE, (e) Yuma-27 –ENE, (f) Socorro-20-N; in this figure, the straight lines with triangle makers present for the observed rainfall (Pobs); the dash lines with square makers stand for the simulated rainfall which using the corrected SWC (Psim_corr); finally, the long dash lines with diamond makers are simulated rainfall which using the raw SWC (Psim).

5. Conclusions
As shown in the previous section, the implicit influence on rainfall estimation from soil data has been detected. The performance of rainfall estimation has grown up after applying the temperature effect removal method. At all station. The Nash-Sutcliffe efficiency improved, and the highest one is 53%. These findings have significant implications for the understanding of how the temperature effect removal work for the model which using soil moisture data as an essential input. Furthermore, this study strengthens that it is necessary to remove the temperature effect on the SWC before applying the program which using soil moisture data as basic input.

Besides, the results have also shown that there are two primary factors impact on the efficiency of removal for rainfall estimation including the annual rainfall amount along with the frequency of rainfall events and the strength of temperature effects on SWC. The higher annual rainfall amount along with the frequency of rainfall events, the less impact of temperature effect removal on the performance of rainfall estimation.
The limitation of this study is that the impacts of snowing and freezing periods have not eliminated from the simulation of SM2RAIN algorithm. Further studies will carry out to check the snowing and freezing time impact on both the temperature effect removal and rainfall estimation.

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