Evaluation of Temperature-Soil Moisture Dryness Index for Surface Soil Moisture and Evapotranspiration Analysis

Thai Minh-Tin and Liou Yuei-An

December 3, 2021

Evaluation of Temperature-Soil Moisture Dryness Index for Surface Soil Moisture and Evapotranspiration Analysis

Minh-Tin Thai [1]and Yuei-An Liou [1*]
[1] Center for Space and Remote Sensing Research, National Central University, 300 Jhongda Road, Jhongli District, Taoyuan City 320317, Taiwan
[*]Email: yueian@csrsr.ncu.edu.tw

***Abstract*[+]—In the context of climate change, the surface soil moisture (SSM) assessment is crucial for the precise irrigation of crops and the economical use of water resources. The recently developed Temperature-Soil Moisture Dryness Index (TMDI) has shown better potentials in the assessment of SSM. The TMDI is empirically calculated by the Land Surface Temperature (LST) and Normalized Difference Latent Heat Index (NDLI) derived by Landsat-8 data. In the current study, SSM assessment was carried out using the TMDI to analyze the dryness conditions and water availability for irrigation over southwestern Taiwan on October 11, 2017. To evaluate the TMDI applicability in SSM monitoring, this study used two indices, Temperature Vegetation Dryness Index (TVDI) derived by Sandholt's concept and Evapotranspiration (ET) product obtained by the Surface Energy Balance Algorithm for Land developed within Google Earth Engine platform (geeSEBAL). Meanwhile, the geeSEBAL-based ET was taken as the reference data to evaluate the sensitiveness of the TMDI and TVDI for observing the SSM and ET at the regional extent. The outcomes showed a good correlation (negative) between the TMDI and ET with R (-0.90), while a relatively lower R-value (-0.83) was found between TVDI and ET. Hence, the TMDI application for the extraction of SSM will be better due to its strong correlation with the ET.**

***Keywords*—Evapotranspiration (ET), Landsat-8 data, geeSEBAL, surface soil moisture (SSM), Temperature-Soil Moisture Dryness Index (TMDI)**

I. INTRODUCTION

Since the 1960s, severe droughts have occurred in Taiwan due to the downward trend of rainfall [1, 2]. The drought has emerged as a noticeable issue with an increase in frequency and intensity [3]. Such trends can lead to water scarcity and will affect the crop yield in the future [4]. Thus, the drought condition assessment is needed to prevent its unexpected consequences. Theoretically, surface soil moisture (SSM) is an indicator of surface water and energy exchanges [5]. Hence, accurate assessment of SSM is crucial for the drought severity assessment, which can play an essential role in easing the drought threat and ensuring food security [3].

Recently, Remote Sensing (RS) data has been widely used in the spatio-temporal analysis that eliminates the limitation of in-situ measurements [6]. In this study, the RS data was adequately exploited to depict the SSM distribution for drought observation at the regional scale. Particularly, the Temperature Vegetation Dryness Index (TVDI) is a common drought index obtained by the integration of Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI). However, certain limitations are always attached to the application of TVDI. Notably, the SSM assessment for the less or no vegetation areas using TVDI still has uncertainties [5]. The Evapotranspiration (ET) is identified as a drought indicator and closely correlated with SSM [5-7]. The Surface Energy Balance Algorithm for Land (SEBAL) is a reliable model for simulating ET distribution [6]. In addition, the recently proposed Normalized Difference Latent Heat Index (NDLI) has been demonstrated as an effective index to examine the water availability, which can be utilized further to examine the SSM and ET at a regional scale [8]. Later, Le and Liou [6] introduced a new dryness index named Temperature-Soil Moisture Dryness Index (TMDI) derived by the simplified LST-NDLI triangle space. This study aims to investigate the TMDI ability in SSM and ET monitoring for specific agriculture areas. The analysis of TMDI was carried out and compared with the traditional TVDI to investigate the drought severity and ET variation. The results have shown the ability of TMDI to sufficiently evaluate the water stress information. This will help to ameliorate crop failure and refine crop management.

II. STUDY AREA

The study area, Yun-Chia-Nan plus Kaohsiung City (YCNK), is located in the tropical climate zone. It is characterized by a monsoon climate with relatively high year-round rainfall [2].

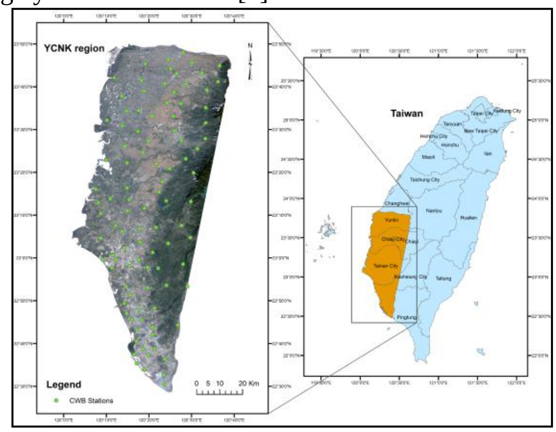

Figure 1. The YCNK region with a true-color image was extracted by Landsat-8 image.

Due to spatial variations in the terrain elevation, the rainfall distribution is uneven, and this creates difficulties in storing water for irrigation [9]. In the absence of the storage capacity and uneven distribution of rainfall, this region is prone to severe droughts and needs more attention [1, 2].

III. METHODOLOGY

In this study, Landsat 8 OLI/TIRS satellite data provided by the National Aeronautics and Space Administration (NASA) was used to calculate spectral indices (NDVI and NDLI) and LST. Additionally, the Split Window Algorithm (SWA) was also used to retrieve the LST. The air temperature data were collected from 98 Center Weather Bureau (CWB) stations (https://www.cwb.gov.tw/eng/) to validate the LST. The NDLI is calculated using the equations:

$$\mathrm{NDLI} = \frac{\rho_{\mathrm{Green}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{Green}} + \rho_{\mathrm{Red}} + \rho_{\mathrm{SWIR1}}} \qquad (1)$$

where ρ_{Green}, ρ_{Red}, and ρ_{SWIR1} are the reflectance of green, red, and shortwave-infrared bands, respectively.

It is well known that the LST and NDLI are significantly sensitive to SSM. In particular, the LST directly affects the ET and SSM [10]. Meanwhile, the NDLI is sensitive to the energy release or absorption without temperature change [8]. Therefore, Le and Liou [6] proposed the TMDI derived by combining the LST and NDLI to assess the SSM. The TMDI can be calculated using the equations:

$$\mathrm{TMDI} = \frac{\mathrm{LST} - \mathrm{LST_{Cold}}}{\mathrm{LST_{Hot}} - \mathrm{LST_{Cold}}} \qquad (2)$$

$$\mathrm{LST_{Hot}} = a_1 + b_1 \times \mathrm{NDLI} \qquad (3)$$

$$\mathrm{LST_{Cold}} = a_2 + b_2 \times \mathrm{NDLI} \qquad (4)$$

where a_1, b_1, a_2, and b_2 represent the intercept and slope of the hot and cold boundaries, respectively.

These baselines were defined by linear regression of LST and NDLI. The upper and lower limits of the given pixels are hot and cold baselines, respectively. The cold pixels represent the wettest status, while the hot pixels feature the driest status [6].

The spatial analysis of the ET is carried out using the geeSEBAL tool [12] provided at the webpage: https://etbrasil.users.earthengine.app/view/geesebal. The SEBAL formula is expressed as:

$$\lambda \mathrm{ET} = R_n - G - H \qquad (5)$$

where ET is the Evapotranspiration (mm h^{-1}), λ is the latent heat of vaporization (J/kg), λET is the latent heat flux, R_n is the net radiation, G is the soil heat flux, and H is the sensible heat flux (Wm^{-2}). The ET analysis is later used to check the reliability of TMDI and also compared with the TVDI for the assessment of SSM.

IV. RESULTS AND DISCUSSION

A. Calculations of NDLI and LST

The NDLI is an effective index to obtain the information on the Earth's skin, like, the available water and potential latent heat flux [8]. The NDLI map (Fig. 2a) depicts the spatio-temporal extent of surface water availability and latent heat flux on October 2017 across the YCNK area. The dark blue regions show the water bodies with high positive NDLI, while the fully vegetated patterns featured by the bright blue correspond to a low positive NDLI value. In contrast, the negative NDLI values, with bright yellow pixels, illustrate the status of water scarcity in dry soil and urban areas.

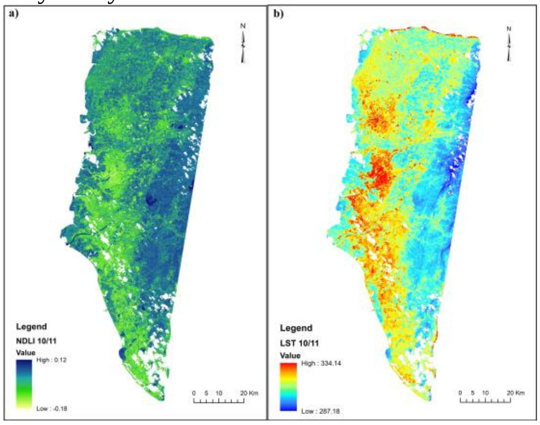

Figure 2. NDLI (a) and LST (b) over YCNK region.

We found a strong agreement between the LST and air temperature (from 98 CWB stations) with an acceptable correlation (R = 0.55). Thus the remotely sensed LST data can be used for further analysis. In the mountain area of the YCNK region, the LST values are lower than the other zones. Meanwhile, the driest areas in the central zone are found due to sparse or no vegetation and rapid urbanization.

B. Estimations of TMDI and TVDI

NDLI may be utilized to infer the surface water availability [8], and NDVI is used to indicate the status of surface vegetation, while the LST is one of the indirect indicators of SSM [10]. Hence, the advantage of these variables would be integrated to better characterize the SSM. The scatterplots of LST-NDLI and LST-NDVI are used to calculate the triangle spaces, and later TVDI and TMDI are shown in Figures 3 a and b, respectively.

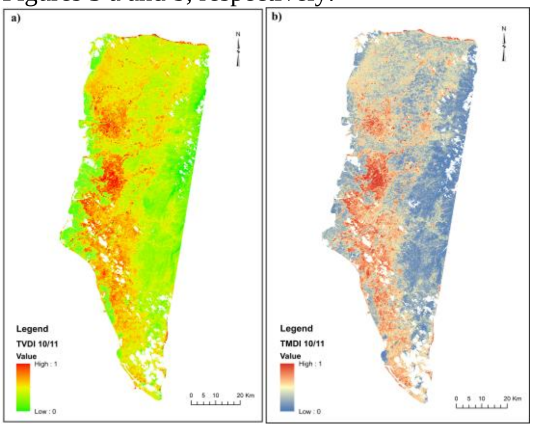

Figure 3. TVDI (a) and TMDI (b) over the YCNK region.

Notably, the TMDI value substantially differs in the different land-cover types. Specifically, the lowest TMDI values are mainly found in the eastern side, which is the dense vegetation-covered area. This area has higher water availability with lower temperature leading to the wettest status. In contrast, the driest regions are mainly found in the middle area due to scant precipitation and poor vegetation. Higher temperatures and lower water availability are found in these areas.

C. Evaluation of TMDI performance

The available ET product provided by the geeSEBAL platform is exploited to evaluate the reasonableness of TMDI and TVDI for assessing SSM. It is found that the correlation between the geeSEBAL-derived ET product and two indicators (TMDI and TVDI) has been significantly different at regional extent (all land covers) and agriculture areas. To identify the agriculture area, we have used the Global Land Cover provided by the Copernicus program [11] (https://lcviewer.vito.be/2017). The correlation coefficients of ET with TMDI and TVDI are -0.89 and -0.82 for the agriculture area, respectively.

We find that the correlation coefficient of ET and TVDI is -0.83 for all land cover types, whereas the new dryness index TMDI expresses a strong correlation with the ET (R = -0.90). The results show that the newly developed index TMDI has high efficiency for capturing SSM and ET compared to the TVDI. These advantages of TMDI are entirely based on the NDLI and LST derived by Satellite data with no additional in-situ measurements. Thus, the TMDI can be disseminated as an alternative and potential approach for determining the SSM and ET variabilities.

V. Conclusion

The SSM and ET are important factors to analyze the crop water stress and drought conditions. The analysis of drought and dryness indices (TVDI and TMDI) using satellite image provides better spatio-temporal coverage over the in-situ measurements. In the current study, the new dryness index TMDI has been evaluated and compared with the commonly used drought index TVDI for the derivation of SSM and ET. The results show the superiority of TMDI over the TVDI in assessing the ET and monitoring the SSM status. The TMDI will be a new base for the study of SSM and surface ET and will provide a fast and precise method to assess the drought severity. The application of TMDI will also help in crop water management issues and sustainable agriculture development in the current climate change crisis.

Acknowledgment

This study was supported by the Ministry of Science and Technology of Taiwan (Grant No. MOST109-2923-E-008-004-MY2). This study used the Landsat-8 image supported by United States Geological Survey (USGS) and the air temperature data provided by the Taiwanese CWB.

References

[1] S. T. Chen, C. C. Kuo, and P. S. Yu, "Historical trends and variability of meteorological droughts in Taiwan," *Hydrol. Sci. J.*, vol. 54, no. 3, pp. 430-441, 2009.

[2] H. F. Yeh and H. L. Hsu, "Stochastic model for drought forecasting in the Southern Taiwan Basin," *Water*, vol. 11, no. 10, pp. 2041-2056, 2019.

[3] S. Shi, F. Yao, J. Zhang, and S. Yang, "Evaluation of Temperature Vegetation Dryness Index on drought monitoring over Eurasia," *IEEE Access*, vol. 8, pp. 30050-30059, 2020.

[4] S. T. Chen, T. C. Yang, C. M. Kuo, C. H. Kuo, and P. S. Yu, "Probabilistic drought forecasting in Southern Taiwan using El Niño-Southern oscillation index," *Terrestrial, Atmospheric and Oceanic Sciences*, vol. 24, no. 5, pp. 911-924, 2013.

[5] M. S. Le and Y.-A. Liou, "Temperature-Soil Moisture Dryness Index for Remote Sensing of Surface Soil Moisture Assessment," *IEEE Geoscience and Remote Sensing Letters*, pp. 1-5, 2021.

[6] M. S. Le and Y.-A. Liou, "Spatio-Temporal Assessment of Surface Moisture and Evapotranspiration Variability Using Remote Sensing Techniques," *Remote Sensing*, vol. 13, no. 9, 2021.

[7] I. Sandholt, K. Rasmussen, and J. Andersen, "A simple interpretation of the Surface Temperature/Vegetation Index space for assessment of surface moisture status," *Remote Sens. Environ.*, vol. 79, no. 2-3, pp. 213-224, 2002.

[8] Y. A. Liou, M. S. Le, and H. Chien, "Normalized Difference Latent Heat Index for Remote Sensing of Land Surface Energy Fluxes," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 3, pp. 1423-1433, 2019.

[9] M. H. Yen, D. W. Liu, Y. C. Hsin, C. E. Lin, and C. C. Chen, "Application of the deep learning for the prediction of rainfall in Southern Taiwan," *Sci. Rep.*, vol. 9, no. 1, pp. 12774-12783, Sep 4 2019.

[10] Y. A. Liou and S. Kar, "Evapotranspiration estimation with Remote Sensing and various Surface Energy Balance algorithms-A review," *Energies*, vol. 7, no. 5, pp. 2821-2849, 2014.

[11] M. Buchhorn, M. Lesiv, N.-E. Tsendbazar, M. Herold, L. Bertels, and B. Smets, "Copernicus Global Land Cover Layers—Collection 2," *Remote Sensing*, vol. 12, no. 6, 2020.