A new spectral index to characterize solar photovoltaic panels for Sentinel-2 data

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Abstract: Solar Photovoltaic (PV) is one of the most popular methods of producing renewable energy around the world. As more and more PV panels are installed, the necessity for the accurate mapping of existing assets is increased for better monitoring and management of those facilities. Many studies that try to map the PVs using remotely sensed images and machine-learning techniques are already done. However, those machine learning-based solar PV detection studies haven't utilized a spectral index which is common in other satellite image classification studies such as water body extraction, vegetation monitoring, and soil mapping. Spectral indices are helpful to emphasize the locations of targets in a satellite image to help manual training data production processes, and they could also improve the detection of the solar PVs. There is an experimental spectral index for solar PVs using a hyper-spectral sensor which has hundreds of available bands (Ji, Chaonan, *et al*, 2021). Though it was concluded that the hyper-spectral solar PV index performs well to characterize PV materials, the availability of the data is limited. Therefore, a spectral index based on the fewer spectral band data for solar PVs is needed. This study aims at developing a new spectral index for characterizing solar PV materials in multispectral Sentinel-2 imagery.

The Sentinel-2 level-2A surface reflectance data on the Google Earth Engine (GEE) platform is used for the study. Cloud contaminated pixels are removed by using the "Sentinel-2 cloud probability" product. Two different seasonal periods are examined. 2021/06/01 to 2021/09/01 and 2021/11/01 to 2022/02/01 are defined as the summer season and the winter season, respectively. The median values for each season are calculated for further analysis. A test site is chosen around Ibaraki-prefecture and Chiba-prefecture, Japan. Those areas are selected since there are typical land-use-land-cover (LULC) classes namely forests, paddy fields, urban areas, and water. To find appropriate bands for solar PV index, at least 100 sample points are manually collected from the test site at five different LULC covers. Those are "Barren land", "Forests", "Croplands", "Solar PVs", and "Water". A photovoltaic spectral index (PVSI) is defined as follows. The first term catches the solar PV characteristics that the reflectance at B11 is usually higher than B12 and B8. The other three terms are intended to refine the index values at bare lands, shadow, and boundary areas between lands and water.

$$PVSI = \frac{2.3 * B11 - 1.1 * B12 - B8}{2.3 * B11 + 1.1 * B12 + B8} + 0.5 * (B2 - B4 - B8) + signum\left(1.3 - \frac{B6}{B8}\right) - 1$$

This formula indicates a sign function that takes values of 1, 0, and -1 if the input values are greater than 0, equal to 0, and less than 0, respectively. PVSI takes positive values at solar PV pixels, and

negative values are expected in other LULC classes. To test the performance of PVSI quantitatively, four sites are selected from the test area. Reference PV shapes are manually digitized using the QGIS software. The thresholding values for the solar PV detection process are decided by taking the lower 15% percentile of the extracted solar PV index values using the 400 manually collected points outside the four test solar PV sites. The solar PVs are predicted by PVSI>thresholding value. The predicted PV panels from PVSI are compared to the reference PV shapes, and set operations are performed to calculate the accuracy assessment metrics, namely kappa-coefficient, overall accuracy, specificity, precision, recall, IOU, and F-value.

Solar PV classes tended to take positive PVSI values, while other LULC classes were in negative values, as expected both in winter and summer. An example of PVSI imagery is shown in Fig.1. It is notable that based on the PVSI are well separated. The predicted solar PV extent using PVSI thresholding was compared to the manually made PV exterior polygons, and the accuracy metrics were evaluated. The proposed solar PV index generally performed well to characterize the PV materials in Sentinel-2 imagery. The difference among B11, B12, and B8 emphasized the locations of PV panels while additional components of the index refined the index values. However, the general applicability of the PVSI has not been tested yet in various conditions. The numerical weighting values included in the definition of the PVSI formula could be different if the imagery from different areas is used. In addition to this point, the type of solar panel was not considered. There are many types of solar panels in the market so the reflectance characteristics should be different among them. Therefore, it is necessary to test the proposed formula for a larger test site, and a detailed investigation of the PVSI performance should be done depending on the type of solar PV on the ground.

In a conclusion, this study proposed a new spectral index for solar PV detection based on the Sentinel-2 multispectral imagery. It was shown that the index performed well to distinguish PV materials from other LULC classes. The scale of the test site in this study is still limited and the type of solar PV material is not considered yet, so those points are further investigated in the future study.

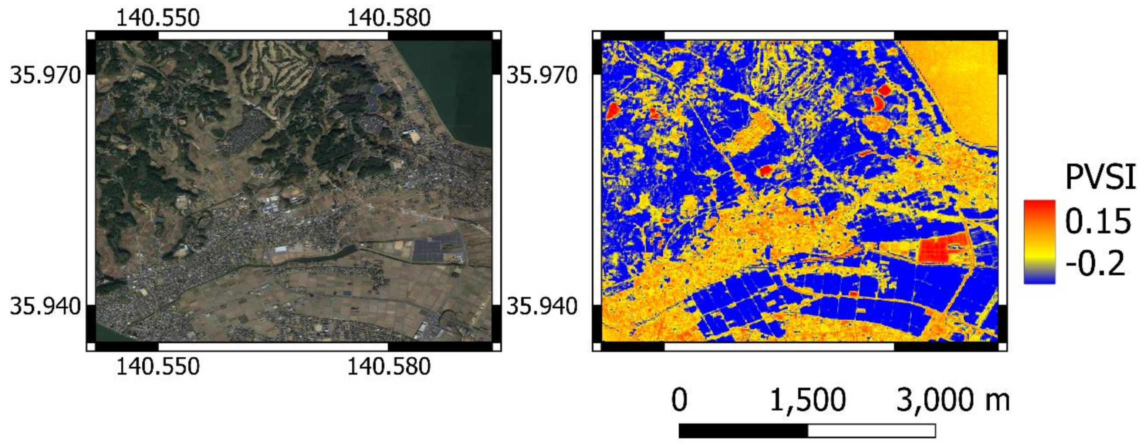

Fig.1. An example of PVSI imagery where the solar PVs are highlighted with high PVSI values.

Reference: Ji, Chaonan, *et al*. "Solar photovoltaic module detection using laboratory and airborne imaging spectroscopy data." Remote Sensing of Environment 266 (2021): 112692.

Keywords: Solar photovoltaics, renewable energy, remote sensing, spectral index