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Spatiotemporal Variations of Satellite Microwave Emissivity Difference Vegetation Index in China Under Clear and Cloudy Skies

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Abstract In this study, we used data from multiple sensors onboard NASA Aqua satellite to conduct a 10-year (2002–2011) remote sensing of microwave emissivity difference vegetation index (EDVI) over China. We investigated the spatial and temporal variations of EDVI in tropical and subtropical evergreen forest, deciduous forest, rice and wheat farmlands, grassland, and montane vegetation regions. The average of China’s EDVI is positive in dense vegetation regions and negative in sparse vegetation regions, depending on the proportion of bare soil and open water. In all selected studying regions, the seasonal variation of EDVI follows the trend of vegetation phenology, even in regions with large proportion of open water. EDVI is positively correlated to the greenness of vegetation (normalized difference vegetation index [NDVI]) with certain phase difference in their seasonal cycle. In autumn, EDVI begins to decline earlier and faster than NDVI. In tropical rainforest, EDVI also starts to increase earlier than NDVI in spring. The large-scale spatial distribution of EDVI under clear sky and cloudy sky is similar. In montane vegetation regions, EDVI under heavy clouds (90% fraction) condition is significantly greater than that under clear sky (10% fraction), indicating a possible cloud induced enhancement of vegetation water content. In forests and croplands in the plains, such effect is not remarkable.

1. Introduction

Vegetation plays a key role in the water and carbon cycle of the Earth’s climate system. The uptake of one mole of carbon dioxide from the atmosphere is coupled with the loss of about 500 moles of vegetation water in plants (Taiz & Zeiger, 2006). The vegetation water content (VWC) is one of the most important controlling factors of photosynthesis and transpiration processes, by which plants interact with atmosphere and modulate cloud formation, rainfall, and climate (Wright et al., 2017). VWC can also affect the emission of biogenic volatile organic components (BVOCs) from vegetation (Zhang et al., 2019). And BVOC changes the concentration of atmospheric greenhouse gases and secondary order aerosols and exerts strong effects on the shortwave and longwave radiative transfer in atmosphere directly and indirectly (Riipinen et al., 2012; Topping et al., 2013). In addition, VWC can induce changes of surface albedo and surface emissivity affecting the surface radiation balance (Copeland et al., 1996). From the viewpoint of satellite remote sensing, VWC is important to determine the surface radar backscattering coefficients (Xu et al., 2010), the attenuation of microwave emission through vegetation (Njoku & Li, 1999), and the background microwave brightness temperature, which is crucial to estimate precipitation over land (Li & Min, 2013). In terms of practical applications, VWC is important in agricultural and forestry management such as irrigation scheduling, yield estimation, drought assessment, and fire risk assessment (Penuelas et al., 1996; Peñuelas et al., 1993; Pyne et al., 1996; Tucker, 1980). In spite of its importance in multiple aspects of scientific researches and applications, the direct in situ measurement of VWC is very limited. However, remote sensing offers a feasible and economic way to obtain VWC at broad and long-term scale.
The absorption, scattering, and emission of microwave (wavelength 1 mm to 1 m) radiation by vegetation are sensitive to its water content and canopy structure (Li & Min, 2013; Min & Lin, 2006a). In addition, microwave has good capabilities of penetrating cloud and is independent of sunlight illumination. Series of satellite microwave vegetation index (VIs), such as the normalized microwave polarization difference index (MPDI) (Becker & Choudhury, 1988), the polarization index (Macelloni et al., 2003), the microwave vegetation indices (MVIs) (Shi et al., 2008), and the microwave emissivity difference vegetation index (EDVI) (Min & Lin, 2006a), have been developed.

Among them, the EDVI is defined as $2(MLSE_{f1} - MLSE_{f2})/(MLSE_{f1} + MLSE_{f2})$, where $MLSE_{f1}$ and $MLSE_{f2}$ are the Microwave Land Surface Emissivity (MLSE) at two frequencies of $f_1$ and $f_2$, respectively ($f_1$ and $f_2$ equal to 18.7 and 36.5 GHz in this study). Generally, the upwelling microwave radiation at lower frequency 18.7 GHz receives less attenuation than that at higher frequency 36.5 GHz when transferring through the vegetation canopy. Based on microwave radiation transfer modeling results, the MLSE$_{18.7}$ is larger than MLSE$_{36.5}$, and EDVI increases with VWC over a certain dynamic range in forest (Min & Lin, 2006a). In addition, Li and Min (2013) found that MLSE in Amazon rainforest had mixed responses to underneath soil moisture, canopy interception water, and precipitation.

Studies showed great potential of EDVI in estimating the water and carbon exchange between vegetation and atmosphere, which is beneficial to the study of atmospheric greenhouse gases (Jeong et al., 2012; Zhao et al., 2009). For very dense vegetation, EDVI at regional scale represents well the spatiotemporal changes of Amazon rainforest and does not saturate, as optical VIs do (Min et al., 2010). Zhang et al. (2019) revealed the relationship between EDVI and atmospheric formaldehyde (HCHO) in South America. Particularly, EDVI is closely related to the evapotranspiration (ET) process. The temporal correlation coefficient between satellite observed EDVI and ground measured evapotranspiration fraction can be as high as 0.79 (Min & Lin, 2006a). Using EDVI as dynamic variable in the vegetation productivity and environmental stress function, satellite algorithms for retrieving ET rate have been developed for Harvard forest site (Li et al., 2009) and East Asia forest sites (Wang, Li, Min, Fu, et al., 2019; Wang, Li, Min, Zhang, et al., 2019).

Instantaneous satellite retrieved ET under all sky conditions are found to have a bias of 16.5 W/m$^2$ (13.7%) and a root mean square error of 63.6 W/m$^2$ (52.5%) over East Asia forest sites.

EDVI is a very promising tool for studying the vegetation and its interactions with climate. However, EDVI is based on tree model with important crown layer and high VWC. For lower vegetation such as grasses, crops, bare soil, and open waters, the absolute value and even the sign of EDVI are different from forest. Particularly, the performance of EDVI over the relatively big footprint of satellite microwave radiometry (typically tens of kilometers) mixed with multiple types of land surface is unknown. This is a critical issue that needs to be addressed before further applications of EDVI (such as ET estimation) on a regional and global scale.

China shows a complex terrain and diverse vegetation, including evergreen and deciduous forests, savanna, farmland, grassland, and deserts regions, providing different vegetation conditions to investigate the behavior of EDVI. In this study, we combined observations from the Advanced Microwave Scanning Radiometer-EOS (AMSR-E) and Moderate Resolution Imaging Spectroradiometer (MODIS) on Aqua satellite to perform 10 years of EDVI estimation in the central, eastern, and southern China. Then we investigated the spatial and temporal variations of EDVI over multiple vegetation regions in China, with comparisons to NDVI. Particularly, we examined the EDVI under clear-sky and cloudy-sky conditions to reveal the potential impacts of clouds.

2. Data and Method
2.1. Study Area
We selected 10 regions (Table 1 and Figure 3a) from the vegetated territory in China of 95–130°E, 5–40°N (Figure 3). To exclude those samples with heavy snow or with very sparse vegetation, we used land surface temperature (from ERA) warmer than 0 °C and NDVI greater than 0.25 (refer to data description in section 2.2).

In terms of vegetation zone, based on Hou (Hou, 1981; Wu & Wang, 1985), the Regions 1–4 and 6 are subtropical evergreen broadleaf forest zones; Region 5 is tropical rainforest zone; Regions 7 and 8 are temperate...
deciduous broadleaf forest zones; Region 9 is temperate grassland zone; and Region 10 is Qinghai-Xizang Plateau vegetation zone containing alpine meadows and forests. Each region (vegetation zone) contains multiple land cover types. The proportions of these types are listed in Table 1. There are 52.5% and 92.7% crop lands in Regions 6 and 7, respectively. And we know that the middle and lower reaches of Yangtze River are an important grain producing area in China (Liu et al., 2013) and Region 7 is one of the most important wheat producing areas in China (Zhao, 2010). Therefore, we chose these two regions to discuss the behavior of EDVI in farmlands.

### Table 1

| Vegetation zone                      | Longitude (E)/latitude (N) | Proportions of different land types (%) | Urban and build-up |
|--------------------------------------|----------------------------|----------------------------------------|--------------------|
|                                      |                           | Water body | Barren area | Forests | Crop and wet lands | Grass and shrubs | Savannas |                        |
| **1** Subtropical evergreen broadleaf forest | 104°–108°/28°–31°          | <0.01      | <0.01      | 4.2     | 43.4               | <0.01          | 51       | 1.31                   |
| **2** Subtropical evergreen broadleaf forest | 110°–115°/28°–32°          | 1.96       | <0.01      | 9.9     | 32                 | 0.2            | 54.6     | 1.31                   |
| **3** Subtropical evergreen broadleaf forest | 103°–108°/24°–27°          | 0.01       | <0.01      | 0.8     | 14.6               | 1.4            | 82.9     | 0.24                   |
| **4** Subtropical evergreen broadleaf forest | 110°–115°/24°–27°          | 0.05       | <0.01      | 23.5    | 6.34               | 0.2            | 69.5     | 0.42                   |
| **5** Tropical rain forest           | 108°–113°/18°–20°          | 2.53       | <0.01      | 18      | 10.1               | 5.7            | 63.2     | 0.4                    |
| **6** Subtropical evergreen broadleaf forest | 116°–120°/30°–33°         | 4.24       | <0.01      | 5.4     | 52.5               | <0.01          | 34.2     | 3.66                   |
| **7** Temperate deciduous broadleaf forest | 116°–119°/34°–38°         | 1.54       | 0.46       | <0.01   | 92.7               | 1.1            | 0.2      | 4                      |
| **8** Temperate deciduous broadleaf forest | 110°–115°/33°–37°         | 0.08       | 0.04       | 11.7    | 58.4               | 14.5           | 12.4     | 2.84                   |
| **9** Temperate grassland           | 107°–110°/36°–40°          | 0.01       | 0.67       | 2.4     | 0.36               | 96.1           | 0.4      | <0.01                  |
| **10** Qinghai-Xizang Plateau vegetation | 97.5°–102.5°/30°–35°      | 0.22       | 0.72       | 5.1     | <0.01              | 90.5           | 3.5      | <0.01                  |

*a* It also contains large area of rice. *b* It also contains large area of wheat.

As shown in the flow chart in Figure 1, to retrieve the microwave land surface emissivity (MLSE) and EDVI, we used multiple data inputs (July 2002 to October 2011). These include the AMSR-E global swath spatially

![Figure 1](https://example.com/flowchart.png)

**Figure 1.** The flow chart of retrieving MLSE and EDVI.
resampled brightness temperatures (Ashcroft & Wentz, 2013) at the top of atmosphere, AMSR-E rain product (Adler et al., 2004) to exclude rainy pixels, Aqua MODIS cloud product (Platnick et al., 2015) to do cloud correction, and ERA-interim reanalysis of atmosphere temperature, pressure, relative humidity, and land surface temperature (Dee et al., 2011). The MicroWave Radiative Transfer (MWRT) model (Liu, 1998) and the Community Radiative Transfer Model (CRTM) (Han, 2006; Weng et al., 2001) were used to simulate the upwelling brightness temperature at the top of atmosphere (TB\text{Mod}_\text{TOA}). Cloud properties were adopted from MODIS cloud products (MYD06L2), which was based on combined visible and infrared measurements at 1- to 5-km resolution. Specifically, cloud fraction, cloud phase, cloud top temperature, cloud water path (CWP), and ice water path (IWP) were projected into the AMSR-E field of view (FOV) in the retrievals. To deal with the sub-FOV horizontal inhomogeneity, a Gaussian weighting function of each individual MODIS pixel within the AMSR-E FOV was applied. The calculation of microwave radiation transfer accounts for the absorption, emission, and scattering from gases and clouds, especially the temperature and pressure dependences of those radiative properties (Liu, 1998). By iterating the MLSE at 18.7 and 36.5 GHz until TB\text{Mod}_\text{TOA} matched the satellite observed TB\text{Obs}_\text{TOA}, we obtained the best estimation of MLSEs and EDVI at each AMSR-E footprint at ~20-km resolution. The EDVI product is available online (at http://rse.ustc.edu.cn/products/EDVI).

In data analysis, we used monthly normalized difference vegetation index from MODIS standard products of MYD13C2 with 0.05° resolution (Huete et al., 2002), GPCC monthly precipitation data with 0.5° resolution (Schneider et al., 2011), Global Land One-kilometer Base Elevation (GLOBE) data with 1-km resolution (Hastings et al., 1999), and AMSR-E monthly open water fraction data with 0.25° resolution (Jones et al., 2009).

We used MODIS land cover products of MCQ12 (Sulla-Menashe et al., 2019) with International Geosphere-Biosphere Programme (IGBP) classification of land type (Loveland & Belward, 1997) at 0.05° resolution to calculate the proportion of different types of land cover in each selected region (Table 1). To study the impacts of cloud on EDVI, we defined samples with MODIS retrieved cloud fraction less than 10% as clear-sky group, those with cloud area fraction larger than 90% as heavy cloudy-sky group. Previous studies have shown that cloud fractions over the selected regions in this study are around 60-80% (roughly 70%) (Yang et al., 2020; Zhao et al., 2019). Thus, the use of two threshold values is reasonable.

2.3. MLSE Modeling

We used microwave radiation transfer modeling to understand the behavior of EDVI over pure water and/or bare soil. For EDVI over water, the conditions of wind speed, salinity, and temperature are the major controlling factors for microwave emissivity (Schluessel & Luthardt, 1991). In China, from 1969 to 2005, the mean near-surface wind speed was 2.2–2.8 m/s (Guo et al., 2011), so we set wind speed...
to a constant of 2.5 m/s. Salinity was set to 0.01% to indicate fresh water. In addition, the CRTM model was used to simulate the EDVI of bare soil as a function of soil moisture content (SMC) from 0 to 0.8 m$^3$/m$^3$ over nine soil types. Please note that all settings were based on experience and are not representative of the real case.

Figure 3. Distribution of (a) long-term mean (July 2002 to October 2011) microwave emissivity difference vegetation index (EDVI) and (b) normalized difference vegetation index (NDVI), (c) elevation, (d) open water fractional coverage, (e) precipitation at surface, and (f) air temperature at 2-m height. Black boxes numbers refer to regions; see Table 1.
3. Results and Discussions

3.1. Modeling of EDVI Over Water and Bare Soil

Min and Lin (2006a) discussed the relationship between EDVI and VWC in a 100% vegetated area, which was confirmed in the studies by Li et al. (2009) and Li and Min (2013). EDVI generally shows positive values and increases with increasing vegetation water content in dense forest. However, in partially vegetated area, a footprint of Aqua AMSR-E may contain a mixture of vegetation, bare soil, and open water. To understand the combined effects of multiple components on the footprint-mean EDVI, we first need to understand the EDVI of 100% bare soil and open water.

Figure 2a shows the relationship between EDVI over water and a function of water temperature because the dielectric constant of water mainly changes with temperatures in different seasons. Figure 2b shows the EDVI over bare soil as a function of soil moisture. In terms of soil texture, it only shows results for sandy-clay soil (50% sand and 43% clay). The relationship for other eight types of soil was similar to this result.

In contrast to positive EDVI on vegetation, it is not surprising that EDVI on water and bare soil are negative, which confirms the fact that the MLSE for water and bare soil increases with frequency. With the water temperature from 0 to 30 °C, the EDVI of pure water (EDVI_{water}) increases from −0.14 to −0.10. As soil moisture decreases, the EDVI of bare soil (EDVI_{soil}) decreases from 0 to −0.018 (the differences among different soil types are small).

The EDVI over vegetation (EDVI_{veg}, refer to Li & Min, 2013, and later discussion) is typically from −0 to 0.01. Therefore, the absolute value of EDVI_{water} (negative) is about an order larger than those of EDVI_{soil} (negative) and EDVI_{veg} (positive). Consequently, EDVI over inhomogeneous land surface is very sensitive to the area fraction of open water and bare soil. Small open water proportion (e.g., 10–20%) can completely offset the signals of EDVI from positive (for vegetation) to negative. Meanwhile, for AMSR-E footprints without open water, about 50% of bare soil also can make satellite-observed EDVI negative. These modeling results are consistent with the actual performances of satellite-retrieved EDVI (Figure 3a).

3.2. Spatial Distribution of EDVI

The spatial pattern of multiple year mean (July 2002 to October 2011) EDVI (Figure 3a) shows that China’s vegetation water content (VWC) decreases from Southeast to Northwest, which is consistent with the greenness of vegetation reflected by NDVI (Figure 3b). Vegetation regions in China are highly controlled by
climatic conditions, especially by precipitation and temperature (Figures 3e and 3f, Piao et al., 2003). The abundant water moisture from the Pacific Ocean and the warm and mild temperatures in south and southeast China favor dense and high vegetation with high VWC (i.e., EDVI). For example, Hainan and Taiwan

Figure 5. Time series of monthly mean EDVI and NDVI over selected Regions 1 to 5. Correlation coefficients (R) between EDVI and NDVI are also showed.
have the highest EDVI. From the coastal area to inland, and from subtropics to middle-high latitudes, precipitation and temperature in China decline generally, and vegetation becomes sparse, short, and with smaller EDVI.

Figure 6. Time series of monthly mean EDVI and NDVI over selected Regions 6 to 10. Correlation coefficients ($R$) between EDVI and NDVI are also showed.
The Qinling and Taihang (Q-T) Mountains (35°–40°N, 110°–115°E) impede the transport of water vapor from east to west, which leads to a drastic reduction in precipitation required for vegetation growth in the west. Therefore, a remarkable northeast-southwest ecotone associated with the Q-T Mountains can be seen from the EDVI map. The Q-T Mountains are also the dividing line between "the North" and "the South" in terms of climate regime in China. Meanwhile, it should be noted that in the selected Regions 7, 8, 9, and 10, annual mean precipitation is relatively low, so water is the primary limiting factor for vegetation growth in those regions.

Long-term mean EDVI is negative and shows strong spatial heterogeneity in regions with large lakes such as Dongting Lake (29°19'N, 112°57'E), Poyang Lake (29°05'N, 116°17'E), Hongze Lake (33°18'N, 118°43'E), Taihu Lake (31°14'N, 120°8'E), and Chaohu Lake (31°30'N, 117°30'E). As we discussed in the model analysis in section 3.1, this is mainly due to the contribution of open waters, coastal areas, and farmlands with high soil moisture. Actually, in Regions 1, 2, and 6 with open waters greater than 20%, the monthly mean

Figure 7. Normalized seasonal cycles of EDVI and NDVI comparison for the Regions 1 to 10.
EDVI changes with the dynamic open water proportion (%), and the temporal correlation coefficients were −0.92, −0.43, and −0.42, respectively.

The seasonal variation of EDVI (Figure 4) depends on total biomass and internal water content. For evergreen forest (Regions 1–5), the seasonal changes in greenness are relatively small. EDVI shows stronger seasonal variation than NDVI. For example, EDVI declines more significantly from summer to autumn in the boxed region, Hainan and Taiwan Islands. This indicates that leaves in evergreen forest may be dry out in boreal during autumn and winter seasons but still with its greenness unchanged. In the Sichuan Basin and territory with large lakes, the greenness (NDVI) of vegetation is similar to its nearby regions. However, EDVI in those regions are significantly lower than its neighbors. This is caused by bare soil and open water, which only affect the microwave emissivity rather than visible reflectance.

### 3.3. The Temporal Variations of EDVI at Monthly Scale

Time series of monthly mean EDVI in the 10 selected regions are shown in Figures 5 and 6. Overlapped are associated time series of NDVI, land surface temperature (LST), and precipitation (vertical bars).

In most regions, the monthly EDVI increases sharply in the spring and early summer growing season, reaches a maximum in summer, falls in autumn, and gets to a minimum in winter. This is caused by two primary factors. One is the seasonal change in vegetation biomass, particularly for deciduous forests and farmlands with significant leaf growth cycle. The other is the seasonal variations of the moisture content.
inside vegetation, which should dominate the evergreen forests. As a result, EDVI is positively correlated with NDVI in most regions, even in those regions with a large area of open water (i.e., Regions 1, 2, and 6). EDVI shows a very strong positive correlation with NDVI (correlation coefficients equal to 0.92, 0.93, and 0.88, respectively). This demonstrates that the coarse spatial resolution EDVI can be used to study the seasonality of vegetation in mixed vegetated area, even if it contains a large area with open water (e.g., over 20%) and/or bare soil. The main cause for this may be explained by the seasonal changes in vegetation water content that are more pronounced than the signals from open water and bare soil.

In addition to the consistency, in most regions, particularly in tropical rainforest and temperate grassland area in autumn, comparison between monthly EDVI and NDVI shows a large time lag. In tropical rainforest of Region 5, the monthly EDVI peaks during the months of maximum rainfall. However, NDVI peaks in the latter months of rainy season and shows a remarkable delay compared to EDVI. This implies that the EDVI in tropical rainforest is mainly controlled by precipitation, while the greenness of vegetation favors the rich sunlight after the rainy season, as suggested by previous studies (Cheng et al., 2008; Myneni et al., 2007; Saleska et al., 2007; Zhang et al., 2016). In Region 9, the temperate grassland contains meadow and shrubs with low VWC and small leaf area (Piao et al., 2006). EDVI begins to decrease from the peak in June or July, while NDVI begins to decrease in August or September. The original correlation coefficient between EDVI and NDVI is only 0.3, and the 2-month lag correlation between them reaches 0.7. This indicates that the temperate grassland starts to dry out (VWC decreases) 1–2 months before its leaves turn yellow.

To show the phase differences in seasonal cycles between EDVI and NDVI, the normalized seasonal variations of them are shown in Figure 7. In most regions, EDVI starts to decline earlier and faster than NDVI during autumn season. And in rainforest Region 5, EDVI also increases earlier than NDVI in spring. We speculate that the moisture may change earlier than chlorophyll inside the leaves in transition seasons.

EDVI has the potential capability to represent the growing status of rice and wheat and may be used as an index to estimate the agricultural yield. The middle and lower reaches of Yangtze River are an important grain producing area in China (Liu et al., 2013). In Region 6 (Figure 6), EDVI is never positive at any season and varies from zero in summer to about −0.014 in winter. This is due to the territory’s well-developed river
systems and large irrigated farmlands. Despite its negative values in all seasons, the time series of EDVI in this region is still strongly positively correlated with NDVI ($R = 0.88$). This indicates that EDVI in rice region, even if perturbed by signals from bare soil and open waters, still correctly represents the seasonality of crops.

Region 7 is one of the most important wheat producing areas in China (Zhao, 2010). Because the open water fraction in wheat area is smaller than that of rice area, the monthly EDVI here is positive from April to September. The time series of EDVI is also very consistent with that of NDVI ($R = 0.77$).

### 3.4. The Possible Impacts of Cloud on EDVI

As we discussed in the introduction, clouds may exert significant influences on vegetation evapotranspiration and carbon dioxide sequestration. And the emission of water vapor and organic vapor from the vegetation may also influence the formation of clouds. Most of these kinds of studies rely on ground-based in situ measurements. To study the large-scale response of vegetation to clouds, we need to coexist satellite observations of cloud and vegetation properties. AMSR-E EDVI and MODIS cloud provide us such opportunities.

By comparing the long-term mean EDVI under clear sky (upper row in Figure 8) and heavy cloudy sky (middle row in Figure 8), we found that the large-scale spatial distribution of EDVI in China, including the southeast-northwest gradient and the mean values at different vegetation regions, was not changed significantly. This indicates that the possible impact of clouds on VWC is mild. From the perspective of satellite remote sensing evaluation, it demonstrates that the cloud correction in current EDVI retrieving process is correct and does not introduce systematic bias into the results.

In the eastern Tibetan Plateau and Qinling-Taihang (Q-T) Mountains area (e.g., Regions 9 and 10), EDVI values under cloudy skies are greater than those under clear-sky conditions in all seasons except winter (refer to the positive difference in bottom row of Figure 8). From the point of view of statistics, the probability distribution function (PDF) of EDVI shifts to the high end from cloudy to clear-sky conditions in these two regions (Figure 9). This phenomenon may reflect the cloud enhancement of vegetation water content in montane cloud forest reported by Berry et al. (2015). If cloud is low enough to reach the vegetation over mountain, the fog can improve water potential of both branches and leaves due to enhanced foliar uptake of water and weakened transpiration (Berry et al., 2014; Reinhardt & Smith, 2008; Schreel & Steppe, 2019). Further studies which relate detailed cloud properties (such as cloud top height, cloud thickness, and cloud water content) to vegetation will further improve our understanding about the cloud-vegetation interactions.

In addition, in subtropical forests (e.g., Regions 1–4), EDVI are smaller under cloudy condition comparing to clear-sky condition in spring and winter. The cloud-related changes of EDVI in other regions and seasons are not clear.

### 4. Conclusions

As a new microwave vegetation index, the microwave emissivity difference vegetation index (EDVI) can well represent the vegetation water content (Min & Lin, 2006a, 2006b) in dense and tall vegetation areas under both clear and cloudy conditions. A series of studies in midlatitude forest and Amazonian rainforest have confirmed its validity (Li & Min, 2013; Min et al., 2010; Min & Lin, 2006b). Recently, it has also been used to estimate the evapotranspiration rates at some forest sites in East Asia (Wang, Li, Min, Fu, et al., 2019; Wang, Li, Min, Zhang, et al., 2019). However, its spatiotemporal features over large-scale complex land cover mixed with vegetation (forest, crops, and grass), bare soil, and open water were not clear yet. In this study, we investigated the features of EDVI of multiple vegetation regions including tropical and subtropical evergreen forests, deciduous forest, rice and wheat cropland, grassland, and montane forests in China.

The long-term mean EDVI shows that the vegetation water content (VWC) in China decreases from the Southeast to the Northwest with the Qinling and Taihang (Q-T) Mountains acting as a remarkable northeast-southwest transition zone from moist (dense) vegetation to dry (sparse) vegetation. This is generally consistent with the vegetation greenness represented by NDVI.

Unlike the EDVI in Amazonian rainforest, which is always positive, China’s EDVI is positive in dense vegetation area and negative in sparse vegetation areas, depending on the proportion of bare soil and open waters. According to the microwave radiation transfer modeling, about 10–20% of open water or 50% of
bare soil area in the satellite footprint can completely offset the signal of EDVI from vegetation, from positive to negative.

The temporal variation of EDVI on monthly scale is mainly determined by vegetation phenology although the signals from water and bare soil can significantly affect the absolute value of EDVI. EDVI can also represent the growing status of rice and wheat and thus may be used as an index to estimate the agricultural yield.

In most regions, even in the case of negative EDVI, the time series of monthly mean EDVI shows positive correlations with NDVI. Meanwhile, it can be found that there is a clear phase difference between them, particularly in tropical rainforest and temperate grassland regions. In autumn, EDVI begins to decline earlier and faster than NDVI. In rainforest, EDVI also starts to increase earlier than NDVI in spring. We speculate that during the transition season, water may change earlier than chlorophyll inside the leaves.

Cloud may make impacts on vegetation, and such impacts can be reflected by the spatiotemporal variations of EDVI. In the Qinling-Taihan Mountains and the Eastern Tibetan Plateau areas, we found that under cloudy sky, the mean value of EDVI is greater than that under clear sky, and the probability distribution function of EDVI shifts to the higher end under cloudy condition. We speculate that this is due to the enhanced foliar uptake of cloud/fog water and weakened transpiration. The differences between EDVI under clear sky and cloudy sky provide us with new tool to study the large-scale vegetation-cloud/air interactions, and further studies are needed.

The main purpose of this study was to conduct a comprehensive investigation of the large-scale characteristics of EDVI on China’s complex land cover. The great potential of using EDVI to study the physiology and phenology processes of vegetation has been confirmed. However, to answer the detailed questions raised by this study, including the phase difference of seasonality between EDVI and NDVI and the impacts of cloud on different vegetation types in different seasons, we need to combine more observations and help with associated vegetation modeling.

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