Integrating satellite-based passive microwave and optically sensed observations to evaluating the spatio-temporal dynamics of vegetation health in the red soil regions of southern China

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ABSTRACT
Attentions over the health of evergreen vegetation are increasing owing to frequently occurrence of recent disturbance events (i.e. soil erosion, logging activities, and afforestation). However, vegetation indices that characterize canopy greenness have limitations in spectral saturation for representing the growth states of densely vegetated areas, and the continuous acquisition of satellite-derived vegetation functional metrics depends on the availability of clear image observations. This study investigated the vegetation health dynamics (1993–2012) in the red soil regions of southern China using satellite observations based task-oriented metrics, including the Normalized Difference Vegetation Index (NDVI), Vegetation Water Content (VWC), and Aboveground Biomass Carbon (ABC). The results indicated that the total number of pixels with significant changes (SC) was 214, 1,186, and 794 for the NDVI, VWC, and ABC indices, respectively. More than 90% of the SC pixels in the three metrics exhibited increasing trends, which were primarily observed in mountainous areas. Pixels that exhibited a continuously declining trend were discretely distributed throughout the entire study area. Among the SC pixels, vegetation in major parts of the study area was disturbed by abrupt events. In the NDVI, VWC, and ABC, the frequency of abrupt changes increased after 2000, coinciding with the launch of the Natural Forest Conservation Program (NFCP) in 2000–2001. For regions with abrupt changes, four patterns were further observed based on the indices: the continued increases (pattern-1), sustained decreases (pattern-2), recovery growth after an initial decline (pattern-3), and significant decreases after initial growth (pattern-4). Pattern-1 appeared more frequently than the other three patterns. This study indicates that vegetation in most areas was optimally developed and exhibited a healthier tendency compared with previous growth states. Notably, the presence of an increasingly unhealthy vegetation state was observed in the northeastern region of the study area. Satellite derived datasets and synergetic use of indicators contribute to understanding the changes in the vegetation health in the entire red soil regions in southern China. Thus, this study acts as a reference for forest management and soil erosion control.

1. Introduction
A healthy ecological system refers to the self-regulating ability of the system to maintain its structures and functions after experiencing a disturbance, while sustainably providing ecosystem services (Costanza 2012; Costanza et al. 2014). In recent decades, research on vegetation health has received increasing attention because of its significant role in the global hydrological cycle, carbon budget, and energy balance (Zhu et al. 2016; Piao et al. 2020). In the 2000s, the subtropical forests of southern China gradually developed into timber production bases (Zhang et al. 2000; Liu et al. 2008). Continuous deforestation in these regions could lead to a drastic increase in the disturbance intensity (i.e. wide-ranging deforestation and the rapid regeneration of monoculture plantations). Particularly, the red soil regions in subtropical China have suffered from long-term pressure owing to soil erosion, climate change, insect attacks, and logging activities (Li, Tian, and Li 2011; Liu et al. 2021). Here, vegetation plays an important role in alleviating regional soil and water losses. Despite growing evidence of the impacts of external pressures on vegetation distribution, structure, and...
function (Zhao, Huang, and Wang 2015; Wu, Dai, and Lin 2018), there is still a lack of a comprehensive evaluation on changes in the vegetation health throughout the entire red soil region.

To assess the ecosystem health, numerous studies have focused on the construction of integrated metric models using statistical and geographical methods (Wiegand et al. 2010; Sun et al. 2016; Pan et al. 2021; Ran et al. 2021); however, most of these studies use dual-phase images or discontinuous multi-temporal images, which cannot capture the critical abrupt events and the restoration process that could alter the vegetation structures and functions during the long-term evolution process. Continuous image collections and remotely sensed indices aid in obtaining the detailed information (i.e. location, direction, and time) on external disturbances (Zhu et al. 2014; Mariano et al. 2018). Recently, several studies resort to characterizing the vegetation health based on multidimensional measurements, such as resilience, resistance, and variability, utilizing single spectral indices (SIs) (Harris, Carr, and Dash 2014; Liu et al. 2021; Meng et al. 2020). However, most of these studies do not effectively exhibit the effects that disturbances have on vegetation structure and function. Additionally, previous studies on vegetation health have focused extensively on fragile ecoregions that have experienced drastic changes in vegetation cover, for example, in the karst region in southern China and the Loess Plateau in northwest China (Liao et al. 2018; Fang et al. 2019). However, single canopy greenness used in aforementioned regions is not enough to describe the changes in the vegetation health of evergreen forests in southern China. Particularly, vegetation in subtropical China does not entirely display a seasonal behavior (i.e. emergence and senescence), as they grow rapidly owing to warm and humid climates (Dai et al. 2016). Therefore, the integrated spectral metrics that highlight the impacts of disturbances on vegetation physiological functioning should be further examined for this region.

Studies have noted that the vegetation health is related to the structures and functions of an ecosystem (Costanza 2012). Canopy greenness is especially suitable for characterizing the presence and vitality of plants in regions with apparent seasonal events and substantial land cover changes (Richardson et al. 2018; Chen et al. 2019). Increasing disturbances (i.e. logging activities) may cause massive loss of trees within a certain period, thereby resulting in the loss of vegetation cover. Normalized Difference Vegetation Index (NDVI), derived from satellite observations, is an index that can effectively retrieve the physical and physiological properties (i.e. chlorophyll and leaf area) of vegetation (Tucker et al. 1985; Carlson and Ripley 1997). This index, which has been widely used to evaluate the changes in the vegetation cover (Velasco et al. 2017; Wen et al. 2017; Zhao et al. 2021). In addition to the changing chlorophyll abundance and canopy greenness (represented by the NDVI), the vegetation water content (VWC) is another essential factor that constrains plant growth and productivity (Gitelson et al. 2003; Pasqualotto et al. 2018; Jiao et al. 2021; Liu et al. 2021). Water variability in vegetation can be used to capture abrupt events (Jia et al. 2017), such as an abrupt decrease in the VWC caused by deforestation and a gradual increase in the VWC owing to the maturity of newly added plantations. Changes in the VWC can also reflect water and soil losses in the red soil region. Meanwhile, ecosystems provide a series of services that directly or indirectly benefit human livelihood (Millennium Ecosystem Assessment 2005), of which vegetation plays a dominant role in mitigating global greenhouse gases through carbon sequestration (Cook-Patton et al. 2020; Piao et al. 2020). The amount of carbon exchange primarily depends on the photosynthetic intensity of the above-ground biomass (Houghton 2005). Although remote sensing-based studies have reported the effects of disturbance on ABC (aboveground biomass carbon) stocks, these investigations are limited in the red soil regions in China (Wu, Dai, and Lin 2018; Meng et al. 2020; Liu et al. 2021).

Although optically sensed NDVI indices can highlight the greenness and vitality of vegetation in the canopy layer; NDVI values are easily saturated in areas with dense vegetation, which can lead to the underestimations of the vegetation changes from a canopy greenness perspective (Tian et al. 2016). VWC metrics can represent the dynamics of the physiological functions of vegetation in response to internal growth and external disturbances (Jackson and Schmugge 1991), and ABC stocks may show cumulative increase or gradual decline characteristics of vegetation during the entire growth stage; the latter can be also used to characterize vegetation changes in the ecological functions across a study region (Pflugmacher et al. 2014).
Accordingly, a task-oriented synergy index (NDVI-VWC-ABC), which can effectively capture the ecological issues in the red soil regions of southern China, can aid in accurately characterizing the vegetation health dynamics of an entire evergreen forest ecosystem.

Broad-scale sensors can effectively retrieve vegetation dynamics over large spatial areas (Mariano et al. 2018; Pei et al. 2018). For example, satellite observations can provide long-term (1981–2015) measurements of global vegetation greenness, such as the NDVI products from the National Oceanic and Atmospheric Administration and the Global Inventory Monitoring and Modeling System Index-3rd generation (GIMMS3g) (Pinzon and Tucker 2014). However, the availability of continuous optical images in southern China is restricted by cloud contamination, thick haze cover, and rainy weather, leading to the discontinuous VWC and ABC time series. Recently released satellite-derived passive microwave datasets with lower wavelength frequencies (~1 to18GHz) can resolve the above issues as they have higher penetration capacity and are insensitive to atmospheric effects (Jones et al. 2011; Guan et al. 2014; Konings, Rao, and Steele-Dunne 2019). Global long-term (1987–2018) vegetation optical depth climate archive (VODCA) products, which retrieve data using multiple space-borne sensors, demonstrate high correlation with the leaf water content (Moesinger et al. 2020). Another dataset is the global time-series (1993–2012) ABC, which has been widely used as an indicator of the carbon dynamics on Earth (Liu et al. 2015; Tong et al. 2018; Kong et al. 2020). Collectively, these optically sensed images and passive microwave products provide a reliable data source for the dynamic monitoring of the vegetation health of evergreen forests.

The primary objective of this study was to investigate the vegetation health dynamics (1993–2012) under continuous disturbances in the red soil regions of southern China based on coupled passive microwave and optically sensed images with a more task-oriented metric (NDVI-VWC-ABC). In this study, the overall trend features, time, hotspots, and transformation of the vegetation health were initially determined by integrating the Mann-Kendall (MK) monotonic trend test and MK rank statistic method. The spatiotemporal patterns and associated drivers were also analyzed in this study.

2. Material and Methods

2.1. Study area

The hilly red soil regions of southern China cover an area of ~1.24 million km² (12 provinces) and are situated along the middle and lower reaches of the Yangtze River (Figure 1a). The region comprises two different climates: a subtropical humid monsoon climate and tropical humid monsoon climate. Additionally, the average annual rainfall in most areas ranges from 800 to 2,000 mm. The soil types in the region mostly consist of brown soil, yellow-red soil, and red soil (http://www.stats.gov.cn/). Natural vegetation mainly consists of a mix of subtropical evergreen coniferous and broadleaf forest, where the vegetation coverage accounts for 45.16% of the overall study region (http://www.stats.gov.cn/). Pinus massoniana and Eucalyptus robusta smith dominate the plantation species (Wang et al. 2020). In this region, the plantation area increased from 0.28 million km² in 1993 to 0.32 million km² in 2012 (http://www.stats.gov.cn/). Figure 1b-d, respectively, indicate the annual average vegetation greenness (represented by NDVI), water content (represented by VWC), and carbon stocks (represented by ABC) from 1993–2012 over the study area.

2.2. Acquisition and processing of remote sensing datasets

We used three different and independent long-term datasets (Table 1) to monitor the impact of external disturbances on vegetation structures and functions: two were based on passive microwave satellite observations (ABC and VODCA), while the other was based on optical remote sensing images (NDVI).

The ABC dataset was derived from the harmonized vegetation optical depth (VOD) product, which has a spatial resolution of 0.25°. Data were obtained for the duration from 1993–2012 available at http://www.wenfo.net/wald/globalbiomass (Liu et al. 2015; Zhou, Yamaguchi, and Arjasakusuma 2018). The VOD dataset was primarily used to characterize the total water content in the aboveground vegetation, including green and non-green components (i.e. trunks and branches) (Jackson and Schmugge 1991; Zhou, Yamaguchi, and Arjasakusuma 2018). The harmonized VOD data was constructed by merging multiple bands of VOD products that derived from a series of passive
satellite sensors, including the Special Sensor Microwave Imager (SSM/I), Advanced Microwave Scanning Radiometer for Earth Observation System (AMSR-E), FengYun-3B Microwave Radiometer Imager (MWRI) and Windsat (Liu et al. 2011a). ABC estimation was performed by establishing an empirical relationship to convert the harmonized VOD to ABC, which based on the grid cells with a reported uncertainty of < 30% derived from the benchmark map around year 2000 (Saatchi et al. 2011; Liu et al. 2015). The predicted VOD-based ABC stocks have been reported to have a good correlation with the benchmark ABC map (annual $R^2 = 0.97$) (Liu et al. 2015). The predicted results in Southeast Asia (our study area included) demonstrated similarities in ABC stocks with the benchmark ABC when the uncertainty was < 10% (42.4 PgC vs. 51.1 PgC). A similar phenomenon was observed while comparing the ABC estimates reported in Pan et al. (2011) and the VOD-based ABC stocks (ABC 2000: 32.2 PgC vs. 34.2 PgC; ABC 2007: 33.7 PgC vs. 33.8 PgC) (Liu et al. 2015; Saatchi et al. 2011; Pan et al. 2011). This satellite-derived VOD-based ABC dataset has been widely utilized to estimate the carbon dynamics in vegetation, which forms the basis of our study (Tong et al. 2018; Rodríguez-Fernández et al. 2018; Kong et al. 2020).

The passive microwaves in the VODCA products are sensitive to water content changes in vegetation (Moesinger et al. 2020); thus, the value of VODCA
could be utilized as a proxy to quantify changes in the VWC. The satellite-derived VODCA is a new series of multi-band VOD datasets, which combines the latest single-sensors using a similar core methodology implemented in the VOD (Liu et al. 2011a, 2011b). Compared with the original VOD products, the new datasets contain three daily products having a resolution of 0.25° in different spectral bands based on the long-term dynamics and the unique characteristics of each frequency: Ku-band (1987–2017), X-band (1997–2018), and C-band (2002–2018) (obtained from https://zenodo.org/record/2575599) (Moesinger et al. 2020).

In this study, the VODCA Ku-band dataset was adopted as an indicator to analyze the variations in the VWC over the entire study area. Although the Ku-band has less penetration than that of the C and X bands within the canopy and soil (Brandt et al. 2018a, 2018b; Tong et al. 2018), it still maintained sensitivity toward VWC changes. Annual average, Ku-VODCA values obtained from the same period as that of ABC data were extracted for the study area.

The long-term (1981–2013) NDVI product used in the study is the latest GIMMS3g release that exhibits a bimonthly frequency and has a spatial resolution of 1/12° (Pinzon and Tucker 2014). This product was downloaded from the Google Earth Engine (GEE) platform (https://developers.google.com). To maintain a consistent spatial resolution and temporal coverage for all the datasets, all available NDVI time series overlapping with the ABC time period (1993–2012) were averaged to provide a proxy for the annual greenness of the vegetation cover. Furthermore, the acquired NDVI composite was re-projected to a 0.25°×0.25° grid using the bilinear method.

Thus, we used the optically sensed NDVI metrics as a proxy to reflect the greenness and vitality of the vegetation from the canopy layer (Table 1). The passive microwave observations in the Ku-band VODCA were utilized to represent the VWC in the green (leaves) and non-green (roots, stems, branches) components. The long-term ABC dataset was used to estimate the vegetation carbon dynamics.

The data used in this study are freely available. These data were extracted for the red-soil regions of southern China. Pre-processing steps, including generating composites, re-projecting, and image cropping were executed on open-source platforms such as the GEE (using the image collection function), Python APIs (using arcpy package), and RStudio APIs (using the raster package) (Sanner 1999; Racine 2012; Gorelick et al. 2017).

### 2.3 Auxiliary data

Climatologies at high resolution for Earth’s land surface areas (CHELSA) is a global climate data set with a spatial resolution of ~1 km (Karger et al. 2017), which is available in a raster format from the Swiss Federal Institute for Forests (https://www.wsl.ch/de/projekte/chelsa.html). This dataset can provide the monthly precipitation climatology from 1979–2018. The statistic data with related to urbanization and forest areas were obtained from the National Bureau of Statistics of China (http://www.stats.gov.cn/) and the China Forestry and Grassland Statistical Yearbook for 2003–2013 (http://www.forestry.gov.cn/), respectively.

### 2.4 Trend Analysis with Mann–Kendall Method

Given that the number of satellite images is relatively sparse and the data distribution does not satisfy homoscedasticity or prior assumptions, non-parametric statistical methods were used to derive the vegetation dynamics in the red-soil regions from 1993 to 2012. Two non-parametric statistical methods were combined to demonstrate the possible existence of trends over the study area. First, the Theil-Sen estimator and MK monotonic trend test were performed. Second, the MK rank statistic test was utilized to describe the changes that occurred in each pixel, including the change dates and trend direction after disturbance.

#### 2.4.1. Theil-Sen estimator and MK monotonic for overall trends

To obtain the overall trend of the NDVI, VWC, and ABC across the entire study area, we performed a trend analysis with the widely applied Theil-Sen estimator; this method has advantages when identifying the magnitude of the trend in the time-series data (Theil 1950; Pranab Kumar Sen 1968; Myers-Smith et al. 2020). Estimations (β) were performed by calculating the median of the slopes and intercepts of each pixel in the study area, which can be expressed as follows:

$$\beta = \text{Median} \left( \frac{x_j - x_i}{j - i} \right) \forall 1 < i < j$$  \hspace{1cm} (1)
where \( x_i \) and \( x_j \) are the observed data at times \( i \) and \( j \), respectively.

For the trends that were detected in the \( \beta \) values (\( \beta > 0 \): upward trend; \( \beta < 0 \): downward trend), the MK monotonic trend test (designated by \( Z \)) was performed to evaluate the significance of these trends in terms of the NDVI, VWC, and ABC for a 95% significance level (\( \alpha = 1.96 \)). This criterion led to the elimination of the pixels associated with fluctuations and unchanged features.

The MK monotonic trend test was first proposed by Mann (1945) and has been widely used to detect significant trends in time sequence data (Kendall 1975). The MK monotonic trend test was estimated by calculating \( Z \) as follows:

\[
Z = \begin{cases} 
\frac{S}{\sqrt{\text{Var}(S)}} (S > 0) \\
0 (S = 0) \\
\frac{S+1}{\sqrt{\text{Var}(S)}} (S < 0) 
\end{cases}
\]

where \( S \) is the statistics function, which can be defined as given below:

\[
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(x_i - x_j) 
\]

where \( n \) is the number of observations and \( \text{sign}(\cdot) \) represents the sign function. If \( x_i > x_j \) (\( i > j \)), then \( \text{sign} = 1 \); if \( x_i < x_j \) (\( i > j \)), then \( \text{sign} = -1 \); otherwise, \( \text{sign} = 0 \).

In this study, \( \beta > 0 \) and \( Z > 1.96 \) corresponded to a significant increase in the time-series metrics, which indicates a positive trend in the vegetation ecosystem. Otherwise, \( \beta < 0 \) and \( Z < -1.96 \) represented a significant decrease in the time-series metrics, which indicated a negative vegetation trend.

### 2.4.2. MK Rank Statistic Method for Abrupt Changes

Those pixels that exhibited with significant changes (SC) (\( Z > 1.96 \)) after the MK monotonic trend test were identified. Further, the MK rank statistic method was performed to obtain the specific time and direction of the NDVI, VWC, and ABC in every SC pixel. This method was proposed by Sneyers (1990) to determine the start time and duration of abrupt changes (Sneyers 1990). Particularly, the abrupt time was identified by considering the progressive and backward series.

A progressive analysis of a series based on the statistical value (\( UF(t_i) \)) was performed using equation (4):

\[
UF(t_i) = \frac{t_i - E(t_i)}{\sqrt{\text{Var}(t_i)}} (i = 1, 2, \ldots, n; UF_1 = 0)
\]

where \( t_i \) is the cumulative statistics obtained by calculating the number of values that follow the condition \( x_i > x_j \) (\( i > j \)). If the values of \( UF(t_i) \) exceeded the corresponding 95% significance thresholds (\( U_a = 1.96 \)), a significant increase or decrease in trend could be observed depending on whether \( UF(t_i) > 0 \) or \( < 0 \).

A sequential analysis was performed to locate the start of the phenomenon in the significant trend. Sneyers et al. (1990) suggested that if the trend is real, then the time of an abrupt change could be recent. Therefore, waiting for more recent observations to obtain confirmation of the timing of the abrupt change is reasonable. The backward series \( UB(t_i) \) was proposed to aid \( UF(t_i) \) in accurately locating the specific start time of an abrupt change (Sneyers 1990). This method has been widely promoted and applied in different fields (Tabari, Somee, and Zadeh 2011; Shifteh Some‘E, Ezani, and Tabari 2012).

In this case, the value of \( UB(t_i) \) for the backward series was calculated as follows:

\[
UB(t_i) = -UF(t_i) (i = n, n - 1, \ldots, 1; UB(1) = 0)
\]

where “\(-\)” indicates a calculation in the direction opposite of \( UF(t_i) \), this means \( t_i \) and \( UB(t_i) \) were calculated from back to front.

As illustrated in Figure 2, if \( UF(t) > 0 \) (green dash-dotted line) or \( UB(t) < 0 \) (blue dash-dotted line), then the original time sequence exhibited an increasing trend. Additionally, \( UF(t) < 0 \) or \( UB(t) > 0 \) corresponded to a decreasing trend. Specifically, the changes at a given time were considered significant when the value of \( UF(t) \) or \( UB(t) \) exceeded the corresponding significant thresholds (\( U_a = \pm 1.96 \)) (red-dotted line). The range that exceeded the significant value was determined as the duration of the change (covered by a green or red rectangle). Furthermore, the start time of an abrupt change was determined if the intersection pixel of \( UF(t) \) and \( UB(t) \) was within the significance level \([-1.96, 1.96]\) (see T1 in Figure 2). Otherwise, if the intersection pixel was outside the
range of -1.96 to 1.96, this particular pixel did not exhibit abrupt changes in the corresponding year (see T2 in Figure 2).

### 3. Results

#### 3.1. Overall trend in NDVI, VWC, and ABC

We applied the MK monotonic trend method on annual satellite-derived datasets (NDVI, VWC, and ABC) to map the growth dynamics of vegetation from 1993 to 2012. Table 2 summarizes the number of SC pixels (|Z|>1.96) in each index. Furthermore, illustrates the trend maps of the NDVI, VWC, and ABC. The total number of SC pixels was 214, 1,186, and 794 in NDVI, VWC, and ABC, respectively. In the NDVI, although only 214 pixels showed significant trends over the entire region, the pixels that increased significantly accounted for approximately 93.93% of the SC pixels (Table 2). The SC pixels in the NDVI were non-uniformly distributed on the edge of the red-soil regions. The pixels with a decreasing trend (13 out of 214) located in the northeastern region of the study area (Figure 3a). In the VWC dataset, the number of pixels that exhibited significant trends was 1,186, among which those with an increasing trend were significantly greater than those with a decreasing trend (91.57% vs. 8.43%) (Table 2). Similar trend changes were also observed in the ABC, although the number of SC pixels was slightly smaller than that in the VWC (794 vs. 1186). Overall, changes in the VWC and ABC in the red soil region represented an apparent positive increase. In terms of the changes in the VWC and ABC, the most conspicuous region with an increasing trend was located in the middle of the study area, especially in Guangxi, Hunan, Jiangxi, Fujian, Hebei, and Anhui. Among these adjacent areas, the spatial distribution of the VWC with significant increasing trends was more contiguous than that of the ABC (Figure 3b and Figure 3c). Regions that exhibited a significant decrease in the VWC and ABC were observed in parts of the Jiangsu province.

![Schematic diagram of the pixels with and without abrupt changes](image)

**Figure 2.** Schematic diagram of the pixels with and without abrupt changes. If the intersection pixel of UF(t) and UB(t) was within the significance level [−1.96, 1.96] (see T1), this point had abrupt features. T1 was the start time of the abrupt change. If the value of the intersection pixel exceeds the significant level (see T2), it did not represent abrupt features (pixels without abrupt changes).

| Pixels with significant changes | Increased significantly | Decreased significantly |
|--------------------------------|------------------------|------------------------|
| NDVI 214                      | 201 (93.93%)           | 13 (6.07%)             |
| VWC 1186                      | 1086 (91.57%)          | 100 (8.43%)            |
| ABC 794                       | 740 (93.20%)           | 54 (6.80%)             |

**Table 2.** Number and percentage of pixels with significant changes in the NDVI, VWC, and ABC.
Overall, the number of SC pixels in the VWC (1,186 pixels) and ABC (794 pixels) were generally greater than the NDVI (214 pixels) (Table 2). This indicates that there was a minor greening trend in the vegetation coverage, whereas the water content and carbon stocks of the vegetation experienced major changes in the red-soil regions during the study period. Generally, more than 90% of the SC pixels in each index exhibited an increasing trend, and only small parts of the region exhibited a significant decline in the NDVI, VWC, and ABC. Figure 3

### 3.2. Spatial distribution of different change types

We performed the MK rank statistic method separately for each SC pixel to estimate abrupt changes. For the NDVI, VWC, and ABC, pixels with abrupt changes in each index accounted for approximately 97.20%, 72.00%, and 66.25% of the SC pixels, respectively (Table 3). These results indicated that the changes in the vegetation ecosystem in the red-soil regions were dominated by abrupt events, suggesting that the external pressures have frequently disturbed the vegetation in this area. Figure 4 shows the timing of the latest abrupt changes estimated by our method within the NDVI, VWC, and ABC time series. We found that the vegetation in most adjacent areas was disturbed in the same year. For example, in the NDVI, the disturbance time varied in different areas (Figure 4a), among which the abrupt changes were mostly noted after 2000, and these were discretely distributed in the northern and southern marginal areas of the red-soil regions. In both the VWC and ABC (Figure 4b and Figure 4c), vegetation in parts of Jiangxi, Hunan, and

![Figure 3. Overall trend map of the (a) NDVI, (b) VWC, (c) ABC, and (d) Precipitation in the red soil regions from 1993–2012. Notes: no color indicates no statistically significant trend was observed.](image-url)

| Pixels with | Pixels with | Pixels without |
|------------|-------------|----------------|
| significant changes | abrupt trend | abrupt trend |
| NDVI | 214 | 208 (97.20%) | 6 (100%) | 0 |
| VWC | 1186 | 854 (72.00%) | 312 (94.00%) | 259 (96.64%) | 9 (3.36%) |
| ABC | 794 | 526 (66.25%) | |

Table 3. Numbers and percentages of the different disturbance types in the NDVI, VWC, and ABC from 1993–2012.
Anhui mostly suffered abrupt disturbances from 2000–2005. Furthermore, disturbances in the northern and southern regions mostly occurred after 2005. Additionally, a few disturbances occurred before 2000. For these three indices (NDVI, VWC, and ABC), the frequency of the abrupt changes that occurred each year was summarized to facilitate further analysis (Figure 5). In the red-soil region, the values of the NDVI time-series experienced abrupt changes in 2000, 2002 and 2005–2007. The values of the VWC and ABC time-series depicted the most abrupt changes from 2001–2008.

Apart from the pixels with significant abrupt changes, a small minority of the SC pixels failed to meet the requirements for determining abrupt events using the MK rank statistic method (Table 3). As listed

![Figure 4](image_url) Annual abrupt changes within the (a) NDVI, (b) VWC, and (c) ABC in every pixel.

![Figure 5](image_url) Frequency of abrupt changes that occurred each year within the NDVI, VWC, and ABC.
in Table 3, a total of 6 (2.7%), 332 pixels (28.00%), and 268 pixels (33.75%) revealed no significant abrupt trends in the NDVI, VWC, and ABC, respectively. Among the pixels that showed no significant abrupt changes, we inferred that a large proportion of them presented a steady step change during the study period. For example, in the VWC, the percentage of pixels exhibiting a gradual increase was 94.00%; this was conspicuously observed in parts of Hunan, Fujian, Hubei, and Guangxi (Figure 6a). Most of the pixels exhibited continuous growth with steady steps that began in 1993 and continued for approximately 20 years (insets of A in Figure 6a). Similarly, in the ABC, 96.64% of the pixels exhibited an increase at a gradual rate, and these pixels were mostly distributed in parts of Fujian, Jiangxi, and Yunnan (Figure 6b) Most of these pixels in the ABC data experienced a steady increase starting in 1993, which gradually exhibited significant features (insets of C in Figure 6b). A small number of pixels, located in the parts of the Jiangsu province, steadily decreased in the VWC and ABC datasets (insets of B in Figure 6a and insets of D in Figure 6b). In the NDVI, none of the pixels gradually decreased.

3.3. Analysis of abrupt changes in the NDVI, VWC, and ABC

To measure the specific processes and patterns characterizing the vegetation in the region after a disturbance, we further analyzed the variation trends of the NDVI, VWC, and ABC time-series in each pixel. In the NDVI, there were 208 pixels that experienced abrupt disturbances during the study period. The results exhibited three patterns of NDVI variation based on the $U_F(t)$ and $U_B(t)$ values during the study period (Figure 7). Most of the pixels exhibited a continuous increasing trend (193 out of 208, 92.79%) after the abrupt change.

![Figure 6](image_url). Spatial distribution of the regions without abrupt changes in the (a) VWC and (b) ABC. The insets on the right highlight corresponding examples of the continuous increase and sustained decrease in the VWC (A, B) and ABC (C, D), respectively. Note: considering only six pixels did not exhibit abrupt changes in the NDVI, we did not include them in this figure.
Additionally, a few pixels exhibited a sustained declining trend (insets of B in Figure 7) (13 out of 208, 6.25%), and two pixels (0.96%) displayed an evident upward trend after an initial decline (insets of C in Figure 7).

In the VWC data, pixels that experienced abrupt events represented four different patterns during the study period (Figure 8). For example, in the VWC time-series data, most of the pixels (632 out of 854, 74.00%) were distributed in large parts of the study region, which formed a pattern of continued increase that mostly appeared after 2000 (insets of A in Figure 8). A sustained decrease in trend (insets of B in Figure 8) was observed in a few pixels (73 out of 854, 8.64%) that were mostly distributed in the parts of Jiangsu, Hubei, Zhejiang, Taiwan, Guangdong, and Jiangxi provinces. Additionally, a small number of pixels (139 out of 854, 16.27%) recovered to an upward trend after a slight decline from 1995 to 2005 (insets of C in Figure 8). The remaining pixels (10 out of 854, 1.17%) experienced initial growth from 1995–2000, followed by a pattern of significant decrease after 2005 (insets of D in Figure 8).

In the ABC data, 526 pixels experienced abrupt disturbances during the study period. We also observed four different patterns associated with the changes in the ABC (Figure 9). For example, a large portion of the points displayed significant increasing trends after a disturbance. Among them, several points (434 out of 526, 82.51%) were distributed in the study area, forming a continuous upward trend from 1993–2012 (insets of A in Figure 9). The other points (43 out of 526, 8.175%) experienced various degree of declines from 1995–2005, finally forming a pattern of recovery growth that lasted for approximately 3–5 years (insets of C in Figure 9). This pattern was mostly observed in the parts of
Figure 8. Spatial distribution of four typical patterns associated with VWC variation (a). Insets on the right and bottom highlight corresponding examples of pattern-1 (A), pattern-2 (B), pattern-3 (C), and pattern-4 (D). The locations of A, B, C, and D are denoted in Figure 8(a) with cross symbols. Pattern-1: continued increase; Pattern-2: sustained decrease; Pattern-3: recovery growth after initial decline; Pattern-4: significant decrease after initial growth.

Figure 9. Spatial distribution of four typical patterns associated with ABC variation (a). Insets on the right and bottom highlight corresponding examples of pattern-1 (A), pattern-2 (B), pattern-3 (C), and pattern-4 (D). The locations of A, B, C, and D are denoted in Figure 9(a) with cross symbols. Pattern-1: continued increase; Pattern-2: sustained decrease; Pattern-3: recovery growth after initial decline; Pattern-4: significant decrease after initial growth.
Hubei and Guangxi provinces. Additionally, a small number of pixels, which exhibited significant decreasing trends, represented two different variation features. For example, several pixels (43 out of 526, 8.175%) appeared in small parts of Jiangsu, Guangdong, Guangxi, and Fujian provinces, presenting a pattern of sustained decrease during the study period (insets of B in Figure 9). The other points (6 out of 526, 1.14%) exhibited a clear decrease before a short-term growth from 1995–2000 (insets of D in Figure 9).

4. Discussion

4.1. Necessity and reliability of selecting multifaceted indicators

Based on the synergic use of indicators and the MK test method, we detected the vegetation health status of the red-soil regions in southern China using long-term (1993–2012) satellite datasets. Although we found that the overall trend of vegetation growth in the red soil region had a positive direction, and different responses were observed pertaining to vegetation greenness, water content, and carbon changes because of external pressures. The results showed that only a small part of the study area exhibited a significant greening trend during the study period, whereas both the VWC and ABC exhibited significant changes over most areas. The NDVI values mostly showed no significant trend, which may have been caused by the saturation problem. Therefore, the changes in the greenness could not be effectively characterized by the NDVI. In addition, apparent variations were observed with respect to their hotspot location and spatial distribution. For example, regions with significant changes in the VWC were greater than those in the ABC. The ABC may not change in the same location where there was a significant change in the VWC (and vice versa) (Figure 3b and Figure 3c). We further selected pixels where the NDVI, VWC, and ABC experienced significant changes. Only 44 pixels displayed significant trends in the entire study area. This also reflects the asynchronous features of the NDVI, VWC, and ABC after disturbance. Our analysis indicated that the different aspects reflected the response of vegetation to external disturbances. This further confirms the necessity of selecting multiple indicators to evaluate the vegetation health in the red-soil regions.

Interestingly, 97.73% of these pixels (43 out of 44) demonstrated a synchronous and significant increasing trend in the NDVI, VWC, and ABC during the study period; there were predominantly distributed in parts of the Guangxi province. Most of the significant trends occurred after 2000. These results are in consistent with historical studies that reported considerable increases in greening and carbon stock after 2000 in the Guangxi province (Brandt et al. 2018a, 2018b; Tong et al. 2018). NDVI showed minor greening trends in small parts of the study area, which were consistent with the global increase in vegetation reported by numerous studies (Fensholt et al. 2012; Zhu et al. 2016). Compared with the trend map from the original NDVI dataset (Figure 1b), the aggregate NDVI is still reliable as the characteristics of the critical trend could be extracted. There are several explanations for this phenomenon. First, locally retrieved detailed information may have been smoothed during the aggregation process, where the NDVI dataset, with a spatial resolution of ~8 km, was down-sampled to 25 km. Second, the vegetation coverage exhibited strong fluctuations (i.e. the abrupt removal of natural forests and rapidly growing trees on plantations) under frequent human-related disturbances and humid climate conditions, most of which failed to pass the significance test.

4.2. Causes of different vegetation health dynamics

As listed in Table 3, the changed areas were mostly controlled by abrupt events, and the frequency of these events gradually increased after 2000 (Figure 5). The increase in abrupt events and the abrupt date coincided with a recently implemented project (NFCP), launched in 2000/2001 to protect the natural forests of Inner Mongolia, the upper and middle reaches of the Yangtze River and the three provinces in northeast China (Zhang et al. 2000; Lu et al. 2018). The initial specific goal of the NFCP included the following three aspects: decrease the timber yield in natural forests from 32 million m$^3$ in 1997 to 12 million m$^3$ in 2003, protect approximately 90 million ha of natural forests and afforest an additional 31 million ha by 2010 (Liu et al. 2008; Cao et al. 2010; Ma, Xia, and Cao 2020). As a result, logging activities have gradually moved to the subtropical forests of southern China. Deforestation regions may be rapidly replaced by monoculture plantations,
which have increased the intensity of disturbances in this area (Wu, Dai, and Lin 2018; Zhao, Huang, and Wang 2015). Meanwhile, we observed that abrupt events did not occur in every SC pixel. Apart from pixels in the NDVI, there were a small number of pixels that did not represent abrupt changes in both the VWC and ABC time series. The change process of the VWC and ABC in most of these pixels exhibited a clear gradual increase or decrease (Figure 6), showing that the external disturbances in these regions did not alter the equilibrium state of the vegetation ecosystem.

We further evaluated the overall precipitation trends and their correlation with the VODCA, in combination with the Theil-Sen estimator, Mann–Kendall method, and CHELSA data. As illustrated in (Figure 3b and Figure 3d), although they both showed significance in certain areas, the VWC did not represent a consistent trend with precipitation. This also supports the analysis that the VWC could be used to reflect the growth status of evergreen forests. The positive trends in the VWC may have been related to the moist environment and dense vegetation in the mountainous region. Moreover, the continuous decline in the VWC was mostly observed in the Jiangsu province, which may be ascribed to two aspects. First, the vegetation growth environment may have been largely impacted by high intensity and over-exploitation activities in the Jiangsu province; this region has been reported to have experienced increased urban development (http://www.stats.gov.cn/, National Bureau of Statistics of China), such as deforestation to land reclamation and over-logging in pursuit of timber yield, thus affecting the vegetation health. Besides, compared with the other 11 provinces, the proportion of plantations in Jiangsu province accounted for more than 90% of its total forest area, according to the China Forestry and Grassland Statistical Yearbook for of 2003–2013 (http://www.forestry.gov.cn/). Previous studies have indicated that there was a significant difference in structures and functions between natural and planted forests (Guo and Ren 2014; Tyukavina et al. 2015). Additionally, our results illustrated that the regions experiencing an increase in VWC were significantly greater than those in the ABC over the entire study area. We estimated that the increases in the vegetation carbon stocks were mostly related to the long-term steady water status of the vegetation.

Our study revealed that four different dynamic patterns obtained from three remotely sensed indices (Figure 7, Figure 8, and Figure 9) enabled the identification of the specific change process and status of the vegetation health in every pixel. We observed that in the NDVI, VWC, and ABC data, the vegetation variation trends in most areas appeared to continuously increase (pattern-1) after a disturbance. The phenomenon of pattern-1 showed that the vegetation in this area not only maintained the stability of its structure and function after a disturbance, owing to its maximal genetic diversity, but also grew steadily for a specific period. These analyses indicated a “healthier” vegetation state over large parts of the study region. For pattern-3, the vegetation was initially in a fragile state (significant declines in the NDVI, VWC, or ABC); this was followed by a recovery growth period after disturbances by abrupt changes, and further, this vegetation grew in a “healthier” direction compared with its previous growth state. However, for vegetation in small regions of the study area, significant decreasing trends were observed when compared with the growth states before disturbance (pattern-2); this indicates a rise in unhealthy states during the study period. The rest of the vegetation corresponded to large landscapes planted with minimal genetic diversity in the ecosystem, resulting in an originally increasing trend in the NDVI, VWC, or ABC for a short period, but eventually showed an apparent negative tendency owing to negligible resilience to disturbances (pattern-4). In summary, apart from the frequent appearance of pattern-1 in the study area, the other three patterns solely accounted for a small proportion of each index. Based on our results, we suggest that a critical focus should be placed on several regions that are exhibiting sustained decrease without a recovery trend; the vegetation in these regions displays a significant decrease after initial growth. Although these regions are not concentrated in a certain area, they present unhealthy vegetation states.

4.3. Current advantages and limitations in this study

In this study, we analyzed the overall development trends of vegetation health, the spatial distribution of different change types, and the specific times and patterns of abrupt changes in the study area from 1993–2012. These results aid in understanding the
impact of external pressures on vegetation growth from a large-scale perspective over the entire red-soil region. The synergetic use of indicators (NDVI, VWC, and ABC) selected in our study act as a reference for the evaluation of vegetation health dynamics in the densely vegetated areas. In densely vegetated tropical or subtropical forests, the level of carbon stocks is an important factor when evaluating the services and functions of terrestrial ecosystems. In addition, VWC is another critical factor that reflects the vegetation growth status considering instantaneously cut and newly planted trees.

However, in this study, we could not identify the specific disturbance type or accurately quantify the magnitude of the change; quantifying these changes typically depends on the continuous acquisition of high-resolution remote sensing images with clear (i.e. less affected by clouds, fog, and rain) observations. Additionally, existing remote sensing methods and spectral indices have certain limitations in terms of the precise retrieval of the water content and carbon stocks for different vegetation types owing to complex vegetation growth conditions (Zhu and Woodcock 2014; Fang et al. 2017; Joiner et al. 2018). Moreover, vegetation index is prone to saturation in dense forests and is only sensitive to the vegetation canopy layer. Although passive microwave observations surpass some of these limitations, future research on the generation of high resolution and long-term time-series datasets for timely and precise estimations of the carbon and water content in vegetation is highly recommended. Besides, the correlation between the dynamics and mechanism of the NDVI, VWC, and ABC is an important research direction. Thus, future studies should focus on the dynamic mechanism and identifying the interrelations in the canopy greenness, carbon stocks, and moisture content in different vegetation types at the stand scale by constructing suitable spectral indices and fusing higher-resolution images.

5. Conclusion

In this study, we combined long-term (1993–2012) and multifaceted remotely sensed indicators (NDVI, VWC, and ABC) to examine the large-scale dynamics of the vegetation health over the entire red soil regions in southern China, which has received limited attention in previous studies. The major conclusions of this study can be summarized as follows.

First, the Theil-Sen estimator and MK monotonic test were implemented to obtain the overall trends of vegetation changes in the NDVI, VWC, and ABC data. 1) The results showed that SC pixels in the VWC (1,186) and ABC (794) were greater than those observed in the NDVI (214) over the entire study area. Thus, we inferred that the NDVI time-series only displayed minor greenness changes in small parts of areas (unlike the VWC and ABC). 2) In the NDVI, VWC, and ABC data, the pixels with increasing trends accounted for more than 90% of the SC pixels; a decreasing trend was only observed in a small number of SC pixels.

Second, based on these SC pixels, we applied the MK rank statistic method to acquire the specific type, time, and process of the changes in each indicator. 1) The percentage of SC pixels with abrupt changes was 97.20%, 72.00%, and 66.25% for the NDVI, VWC, and ABC, respectively. This indicates that the study area was largely disturbed by abrupt changes. A small portion of the SC pixels without abrupt features displayed a steady increase or decrease in the VWC and ABC time-series during the study period. 2) The frequency of these abrupt events in the three indicators increased after 2000. Specifically, despite similar abrupt dates observed in adjacent pixels, the abrupt change timing mostly varied in different regions. Across the entire study region, the SC pixels in VWC and ABC located, in the middle areas were disturbed by abrupt changes (2000–2005) earlier than those observed in the northern and southern areas (after 2005). 3) For both indicators, significant increasing trends were mostly observed in mountainous areas with the densest vegetation and moisture conditions. A significant decline was observed in small areas with increased human activities.

Third, four diverse patterns were observed in our study: continued increase, sustained decrease, recovery growth after initial decline, and significant decrease after initial growth. The SC pixels characterized by a continued increase accounted for approximately 92.79%, 74.00%, and 82.51% of the SC pixels in the NDVI, VWC, and ABC, respectively. The other three patterns accounted for only a small proportion in the study region.
In summary, although abrupt events suddenly increased after 2000, vegetation growth in the red soil regions generally followed a healthy trend during the study period. Considerable attention should be directed toward regions exhibiting continuously decreasing patterns and significantly decreased patterns after initial growth, which reflects unhealthy developments in the vegetation ecosystem.

Author contribution statement
Qin Yang: Conceptualization, Methodology, Investigation, Project administration, Writing – original draft, and Visualization. Xiangnan Liu: Funding acquisition, Resources, Supervision, and Writing-review & editing. Zhi Huang: Conceptualization, formal analysis, and Writing-review & editing. Binbin Guo: Methodology and Software. Lingwen Tian, Caiyong Wei, and Yuanyuan Meng: Visualization and Writing-review & editing. Yue Zhang: Visualization and Software.

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Data availability statement
The data and code that support the findings of this study are openly available in [Zenodo] at https://doi.org/10.5281/zenodo.5630763. These datasets were derived from the following public domain resources:
- The NOAA GIMMS3g NDVI product was download form https://developers.google.com
- The Ku-band VODCA product was obtained from https://zenodo.org/record/2575599
- The ABC product was received from http://www.wenfo.org/wald/globalbiomass
- The CHELSA data was download from https://www.wsl.ch/de/projekte/chelsa.html

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