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ORIGINAL RESEARCH ARTICLE

Identification of citrus orchard under vegetation indexes using multi-temporal remote sensing

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ABSTRACT

Citrus is widely planted in southern China. Due to cloudy and rainy weather, complex planting types, and other factors, it is difficult to use spectral information to directly identify citrus orchard information. Based on the unique phenological characteristics of citrus, this study put forward the hypothesis that “the vegetation information of citrus orchards may be weakened during the growth and expansion of citrus fruit”. According to this feature, a method of citrus orchard information identification is proposed, and the threshold of the key time window is determined. Taking Wuming District, Nanning City, and Guangxi Zhuang Autonomous Region as the research area, an empirical study on remote sensing identification of citrus orchard information is carried out. First, multi-temporal Sentinel-2 remote sensing images of the study area in 2018 were obtained, and a normalized difference vegetation index was constructed. NDVI, Green Normalized Difference Vegetation Index (GNDVI), Difference Vegetation Index (DVI), Sentinel-derived red-edge spectral indices (RESI), and other vegetation spectral indices Secondly, according to the ground sample point information, the difference in remote sensing vegetation information of different vegetation types in different periods was compared, and then the optimal features of citrus orchard identification were determined. The results showed that there was no significant difference in spectral characteristics between citrus orchards and other major crop types in the study area (such as sugarcane, banana, corn, rice, etc.), but the multi-temporal remote sensing vegetation index of the study area showed that the NDVI of citrus orchards in October was 0.47 lower than that of November, which was significantly lower than that of other crop types. In October, the GNDVI of the citrus orchard also showed a low value of 0.43, but the difference was not obvious compared with other months. However, the dispersion degree of citrus orchard DVI was low, and the separation was not strong. According to the crop phenological calendar, the period of rapid expansion of citrus fruits was from September to October, which verified the scientific hypothesis proposed in this study that the vegetation information of citrus orchards would be weakened during this period. The dispersion degree of different vegetation indexes in the citrus fruit expansion stage was obviously different, and the dispersion degree of NDVI was the highest, and the difference was the strongest. According to the phenological characteristics of the citrus orchard NDVI in October, to further build

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the normalized index, by using the threshold value method to identify the spatial distribution of the citrus orchard, the identification method had an overall accuracy of 82.75%, better than other identification results of vegetation index. The results of the study for citrus orchard information and remote sensing identification research provide better support for theory and practice.

Keywords: remote sensing; classification; phenology; citrus; vegetation index; Sentinel-2; Google earth engine

1. Introduction

China is one of the important origin countries for Citrus (Citrus reticulata Banco), with a cultivation history of more than 4000 years. As an evergreen fruit tree, citrus is very suitable for planting in southern China, and the citrus industry has also become a characteristic pillar industry in poverty alleviation and rural revitalization in southern China[1–3]. According to statistics[4,5], in 2018, the planting area of citrus in China reached 2.49×10^6 hm^2, surpassing apple to become the fruit with the highest cultivation area and yield in China. Among them, the output and planting area of Guangxi citrus orchards showed an increasing trend in recent years. In 2018, compared with the previous year, the expansion of planting was 6.67×10^4 hm^2, the planting area reached 3.88×10^5 hm^2, ranking first in China, and the output value exceeded 100 billion yuan[6]. The citrus industry expands ceaselessly and develops toward intensification and scale. It is of great significance to accurately obtain the planting area and spatial distribution information of citrus orchards and explore the changes in the area of citrus orchards and their economic, social, and ecological benefits so as to guide the healthy development of the citrus industry.

Remote sensing technology provides the possibility to obtain spatial distribution information about vegetation in a real-time, accurate, and large-scale manner[7–9]. In recent years, remote sensing mapping technology for annual crops such as rice, corn, wheat, and soybean has become increasingly mature, and remote sensing mapping research for perennial crops such as citrus is gradually emerging. Wang [10] used the Gaofen No. 1 image combined with an object-oriented method to extract citrus orchards in layers. Zhang et al.[11] and Chen et al.[12,13] respectively used Google Earth images and Landsat images to extract citrus orchard information and analyze the spatial characteristics and area changes of citrus in counties in southern Jiangxi, China. Xu et al.[14] used a Landsat image combined with a random forest algorithm to extract information about citrus orchards in spring and autumn. Crops and sparse woodland had similar spectral characteristics to young citrus orchards and were prone to mixed classification. The misclassification error between citrus orchards and cultivated land was about 20%. Most of the existing studies on remote sensing extraction of citrus orchards are concentrated in southern Jiangxi, where there are few orchards except citrus, which can theoretically simplify the complexity of remote sensing recognition objects[15]. However, these studies generally found that when the spectral information of a single period image was used to extract the distribution information of citrus orchards, the feature description of remote sensing identification of citrus orchards was insufficient.

Compared with southern Jiangxi, the planting types of orchards in Guangxi are more complex, and the spectral characteristics of different orchards are similar. Therefore, under the conditions of insufficient optical remote sensing images and complex orchard planting types, it is more challenging to use spectral information to carry out remote sensing identification of citrus orchard information in Guangxi[16]. In the case of insufficient spectral information, phenological information can be used as an important supplement to spectral information. Some studies began to pay attention to the role of multi-time window phenological information in the remote sensing classification of annual crops[17–19]. For example, rape flowers turn yellow at the flowering stage, and the color characteristics are the most obvious at the most vigorous flowering stage, while the color characteristics weaken during the fading process. Based on this, some studies have proposed a normalized yellow index to extract the spatial distribution information of rape by accurately detecting the peak at the flowering stage[20]. Some studies also try to apply phenological information to the remote-sensing classification of perennial crops. For example, Liang et al.[21] used Landsat images to identify the spatial distribution of perennial rubber trees by taking the February dormant period in the deciduous period as the key phenological period. Based on Sentinel multi-spectral images of four seasons, Li et al.[22] analyzed the phenology and spectral characteristics of tea gardens, finally determined May as the key phenological period, constructed the normalized tea garden index, and extracted the spatial distribution information of perennial tea gardens. Since the key phenological periods and characteristics of citrus are different among perennial crops, how to determine the key phenological periods and characteristics of citrus is still rarely reported.

In conclusion, considering that the citrus fruit hanging stage carries specific fruit color characteristics, it is speculated that the vegetation information before and after the citrus fruit growth expansion stage may change significantly, and then it is hypothesized that the citrus fruit growth expansion stage may become the key phenological stage for remote sensing identification of citrus orchards. Based on the scientific hypothesis, this research chose cloudy and rainy climate, orchard type complex, and citrus orchard to expand rapidly in Guangxi Zhuang Autonomous Region to carry out empirical research, through analysis of spectral characteristics of different crops in different phases, find the citrus orchard information to identify key phenological periods and the optimal vegetation index for cloudy and rainy, complex planting conditions, To explore a method of citrus orchard information recognition based on multi-temporal image data so as to provide a reference for the scientific construction of a citrus orchard remote sensing recognition index and the convenient and efficient extraction of spatial distribution information for citrus orchards.

2. Materials and methods

2.1. Overview of the study area

This study selected Wuming District of Nanning City, Guangxi Zhuang Autonomous Region as the study area (22°59' N~23°33' N, 107°49' E~108°37' E). The total area of Wuming District is 3378 km^2, surrounded by low mountains and hills, and the middle is a basin, which accounts for 63.50% of the whole area. According to the land use status[23], woodland is mainly distributed in the hills and gentle slopes around the region, while cultivated land is mainly distributed in the central basin (**Figure 1**).

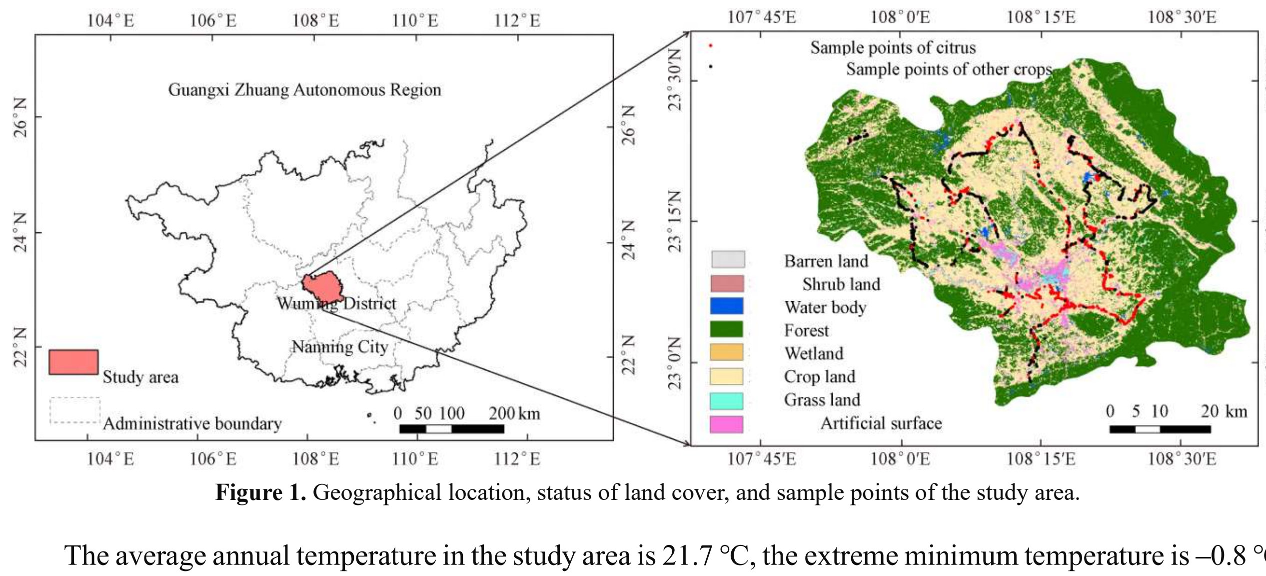

Figure 1. Geographical location, status of land cover, and sample points of the study area.

The average annual temperature in the study area is 21.7 °C, the extreme minimum temperature is –0.8 °C, the average annual rainfall is 1100–1700 mm, and the average annual total sunshine hours is 1665 h. It is a subtropical monsoon climate with abundant light and heat, abundant rainfall, uniform rainfall, and the same season of rain and heat. In autumn, the diurnal temperature difference is large, which is conducive to the accumulation of photosynthates. The cultivation structure of the study area is complex. In addition to citrus, rice, corn, sugarcane, banana and other crops are widely planted. The citrus orchards in the study area began to expand from 2012 to 2014–2015, and formed a certain scale.

2.2. Data sources and preprocessing

2.2.1. Remote sensing image data

In this study, the Level-1C product (spatial resolution 10 m) of Sentinel-2 remote sensing data was selected, and the code was written online based on the Google Earth Engineering (GEE) platform to realize remote sensing data processing and analysis. The study area is covered by six images of Sentinel-2 data. The data product used is the atmospheric apparent reflectance data, which has been ortho-corrected and subpixel-level geometric fine-tuning corrected. The platform can be used through the Application Programming Interface of the JavaScript Programming Language (API) to access the data and process the catalog (https://developers.google.com/earth-engine/datasets//COPERNICUS_S2).

Under cloudy and rainy conditions, remote sensing images of the study area in each period are easily disturbed by clouds. How to effectively remove the influence of clouds is the premise of this study. In this study, Sentinel-2 images from 2017, 2018, and 2019 were widely collected. The quality of the images was first evaluated and screened based on GEE, and then cloud removal was performed on high-quality images through Quality Assessment (QA). Finally, the median value is edited from the time series of each image pixel, that is, the synthesis of the image time series[24]. The cloud coverage of each image was statistically analyzed, and the evaluation standard for high-quality images was set as cloud coverage less than or equal to 30%. It was found that the data quality in the first half of each year was generally poor (cloud coverage was more than 30%), and the data quality in the second half of each year was generally better than that in the first half of each year. Analysis of all the data from the second half of the year revealed a significant lack of high-quality images in 2017; in the second half of 2019, the distribution of high-quality images was uneven, especially from October to November, with poor data quality and serious cloud cover. The data quality of the second half of 2018 was generally better than other years, and 2018 was finally determined as the study year. Previous studies have shown that[25] when crops enter the harvest period (that is, from October to December), the spectral characteristics of different crops differ greatly. At the same time, according to the cloud coverage analysis results of this study, the cloud pollution degree from October to December is low, and the image data quality is high, which can ensure the smooth development of the study.

In order to further obtain the image data without cloud cover and covering crop harvest in a time span, the median function was used based on GEE to reconstruct the median value of each pixel of the image in the time series from October to December 2018, so as to carry out image cloud removal processing. The mass band QA60 of Sentinel-2 is a bit mask band with cloud band information, in which different cloud bits represent different meanings. Cloud bit Bit10 represents an opaque cloud, and cloud bit Bit11 represents a cirrus cloud. In this study, the cloud bits Bit10 and Bit11 are set to 0 to obtain a cloud mask. The cloud information in the image was removed, and the cloud-free reconstructed images from October to December were obtained after cutting and stitching[24,26]. In addition, based on the evaluation of cloud cover (**Figure 2**), the four months of August, October, November, and December with a large number of high-quality images (cloud coverage less than or equal to 30%) were further selected to construct multi-temporal data sets month by month for subsequent vegetation index extraction.

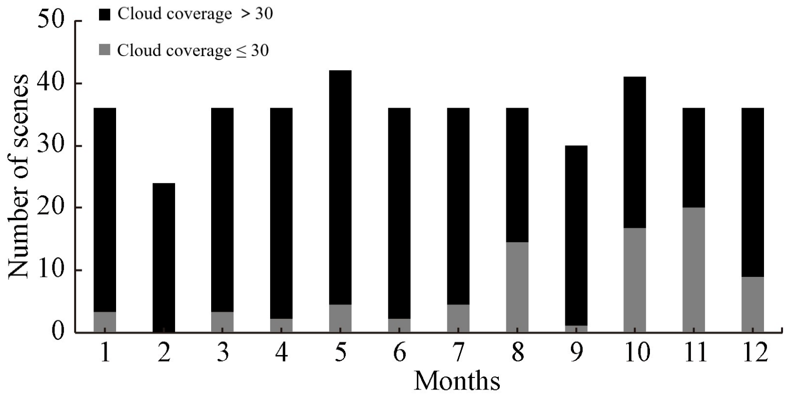

Figure 2. Cloud cover assessment of Sentinel-2 images in the study area in 2018.

2.2.2. Field survey data

The results of remote sensing image analysis need to be verified by comparing the relative truth value of the ground pixel scale. Ground-measured data are generally obtained by the ground sampling method or ground sample point method, in which ground quadrat refers to representative plots with a certain square area selected in the survey of plant communities. This method has a high cost and a complex process and is mostly used in quantitative remote sensing studies such as biomass estimation[27,28]. Ground sample points generally refer to geographical coordinates reflecting land cover types. This method has a low cost and a simple process and is mostly used in remote sensing image classification research. Considering previous studies[14–16] and sampling efficiency, this study used the ground sample point method to verify the accuracy of remote sensing classification results and completed the field ground sample point collection in the study area in December 2019. Since the spatial distribution of citrus orchards will not change significantly within one year, it is reasonable to use the ground sample data of 2019 to verify the remote sensing classification results of 2018. At the same time, referring to Google Earth image comparison and confirmation, field survey interviews, and other means[29,30], further ensure the consistency of ground data and image data.

Due to the large agricultural land area and many crop types in the central plain area, there were more sampling sites in towns and surrounding areas of the central plain. On the contrary, the surrounding mountains are mostly woodland, and the planting area of citrus and other crops is smaller, so the sampling points are smaller. In order to ensure the representativeness of the ground sample points, a total of 839 pure pixels were collected as citrus sample points, and 912 pure pixels were collected as non-citrus main crop sample points by focusing on townships and surrounding areas with large citrus planting areas in the study area (**Figure 1(b)**). The non-citrus sample sites included four main crop types, namely banana (fruit tree), sugarcane (cash crop), rice (paddy field), and maize (dry land). According to the local agricultural statistics[31], these crops accounted for a large proportion of the study area and were the main crop types except citrus.

2.3. Multi-temporal vegetation information acquisition and analysis methods

2.3.1. Phenology and spectral characteristics

Citrus belongs to the rutaceae subordinate plants and is a tropical, subtropical evergreen fruit tree, the growth cycle is long, generally planting 2–3 A can bear fruit, fruit after maturity can be as long as 3–4 months, flowers and fruits at the same time. According to the field survey and interview results of this study, the phenological calendar of citrus and other major crop types in the study area was established, and the phenological information of different crops was analyzed (**Figure 3**). The main crops (including bananas, sugarcane, rice, and maize) in the study area were all in the peak growth stage in August. According to the planting habits of the study area, the large-scale harvest period of summer bananas is generally in September–

December; rice is usually double rice; early rice is sown in March; and late rice is transplanted in July. The harvest period for late rice is from October to December. Sugarcane and corn are also harvested from October to December.

Crops	Months											
	1	2	3	4	5	6	7	8	9	10	11	12
Citrus	Flower bud differentiation stage	Spring shoot germination period	Bud stage	Flower and fruit synchronization	Summer shoot germination period	Summer shoot period	Fruit swelling period		Rapid fruit expansion period		Fruit ripening period/flower bud differentiation period	
Banana						Vigorous growth period			Harvest period			
Sugarcane		Seedling stage		Growth period	Tillering stage	Rapid growth period					Harvest period	
Rice			Early rice growth period				Harvest period	Vigorous growth period				
			Sowing period				Transplantation period	Late rice growth period			Harvest period	
Maize			Spring corn growth and harvest period				Summer maize growth period					Harvest period

Figure 3. Phenological calendar of major crops in the study area.

The phenological information of mature citrus orchards generally showed the following characteristics: Because citrus is a broad-leaved evergreen species, the vegetation information remained stable throughout the year; in the first half of the year, citrus was in the flowering and summer end stages, and the leaves often obscured the flowers. The color of the evergreen canopy was basically the same as that of the flowering stage, and the spectral characteristics of the citrus orchard did not change obviously. In July, citrus entered the fruit expansion stage, the fruit began to grow and mature, and the color gradually changed from green to mature color (orange or yellow), and the occlusion effect of fruit expansion on canopy leaves gradually increased. Since October, when citrus enters the fruit maturity stage and winter shoot stage, flower bud differentiation and fruit ripening occur at the same time, and the influence of fruit occlusion on the canopy spectrum of citrus orchards is gradually weakened[32]. Based on the above characteristics, this study proposed a scientific hypothesis from the perspective of phenological information, that is, the vegetation information of citrus orchards may weaken during fruit growth and expansion, while the vegetation information of citrus orchards may gradually recover during fruit ripening and winter shoot occurrence. Therefore, July–October may be the ideal time window to identify citrus orchards. In particular, citrus orchards have the turning point of fruit ripening and new bud germination between October and November, and October, as the end of fruit expansion, is also the period when citrus orchards are most affected by mature fruits.

According to the phenological characteristics of citrus, the reconstructed images removed the influence of clouds from October to December in the study area. Based on the main crop types in the study area, such as citrus, banana, sugarcane, rice, and maize, 30% of the ground-measured sample points were randomly selected to calculate the reflectance of each crop in each band (**Figure 4**). It was found that the overall variation trend of spectral reflectance of the five crop types in the study area was basically similar, and the numerical difference was not obvious, but there were still some differences in details. Among them, the reflectance of banana, sugarcane, and rice in red-edge band 1, red-edge band 2, and the near-infrared band was higher than that of citrus, and banana had the highest reflectance in these three bands, which were 0.01, 0.25, and 0.31, respectively. On the contrary, the reflectance of banana, sugarcane, and rice in the shortwave infrared bands 1 and 2 is lower than that of citrus, and the reflectance of banana and rice in the shortwave infrared bands 1 and 2 is the lowest, at 0.15 and 0.07, respectively. The reflectance of citrus in red band and red edge band 1 was 0.09 and 0.12, which were slightly higher than those of banana and sugarcane but basically coincided with that of rice and maize. The reflectance values of maize and citrus in nine bands were basically consistent with the trend.

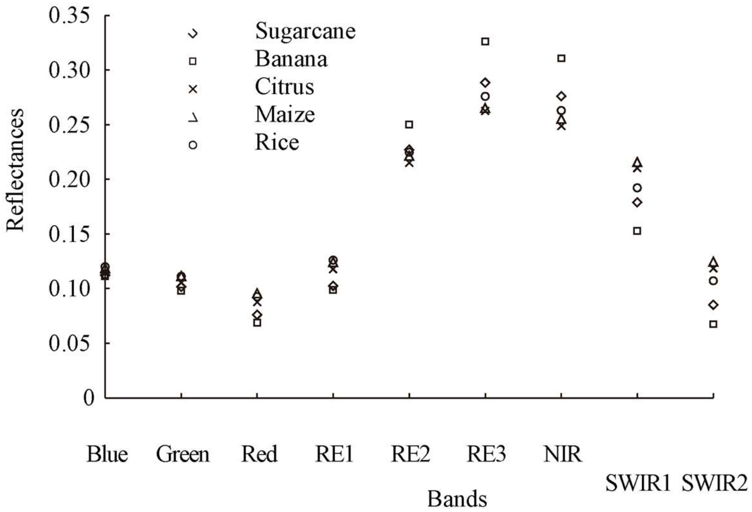

Figure 4. Spectral reflectance comparison of five major crops in the study area.

Note: RE is red edge; NIR is near infrared; SWIR is short-wave infrared.

2.3.2. Construction of vegetation index

As can be seen from **Figure 5**, the differences in the information characteristics of the original bands of different crops are not obvious enough. Therefore, this study will construct a vegetation index by band combination to enhance the spectral differences among different vegetation. Considering the growth characteristics of different crop types in the study area, vegetation indices were calculated for the Sentinel-2 image data of August, October, November, and December, which had low cloud coverage, to distinguish the differences in key phenological periods of the five major crop types in the study area. To compare the discriminating effects of different vegetation indices on citrus and other crop types, the Normalized Difference Vegetation Index was selected in this study. NDVI[33], Green Normalized Difference Vegetation Index (GNDVI)[34], Difference Vegetation Index DVI)[35]. Among them, GNDVI replaced the red band in NDVI with the green band, which had better stability. DVI can better identify vegetation and water. Meanwhile, Sentinel-2 Red-edge Spectral Indices (RESI)[36] were introduced to compare with the commonly used vegetation indices NDVI, GNDVI, and DVI. The calculation of each vegetation index and RESI is shown in Equations (1)–(4):

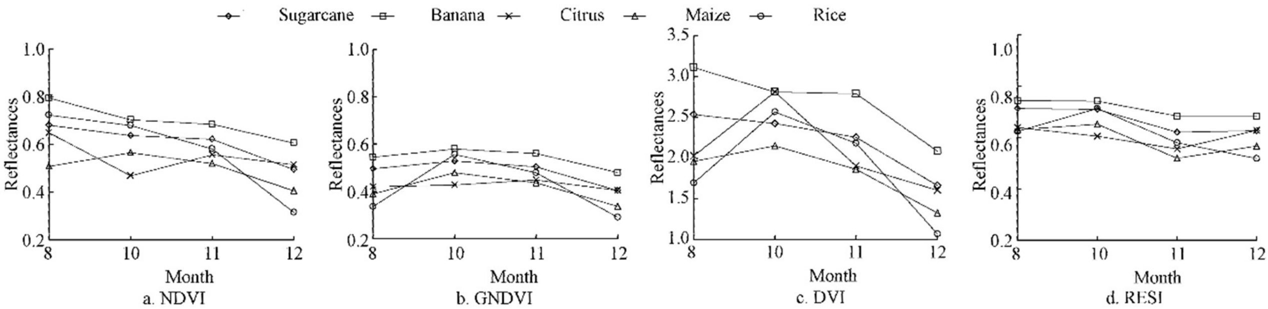

Figure 5. Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Difference Vegetation Index (DVI), and Sentinel-derived Red-edge Spectral Indices (RESI) of major crops at different time windows in the study area.

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}} \tag{1}$$

$$\mathrm{GNDVI}=\frac{\rho_{\mathrm{NRR}}-\rho_{\mathrm{GREEN}}}{\rho_{\mathrm{NRR}}+\rho_{\mathrm{GREEN}}} \tag{2}$$

$$\mathrm{DVI}=\rho_{\mathrm{NIR}}-\rho_{\mathrm{RED}} \tag{3}$$

$$\mathrm{RESI}=\frac{\rho_{\mathrm{RE3}}+\rho_{\mathrm{RE2}}-\rho_{\mathrm{RE1}}}{\rho_{\mathrm{RE3}}+\rho_{\mathrm{RE2}}+\rho_{\mathrm{RE1}}} \tag{4}$$

where ρ_{NIR} is the reflectance of near-infrared band, ρ_{GREEN} is the reflectance of green light band, ρ_{RED} is the reflectance of the red light band, ρ_{RE1}, ρ_{RE2}, and ρ_{RE3} are the reflectance of three RED edge bands respectively.

In order to further test the dispersion degree of 3 planting quilt index and RESI, the Coefficient of Variation (CV) was introduced for analysis. The coefficient of variation, namely the dispersion coefficient, is a normalized measure of the dispersion degree of the probability distribution. It is defined as the ratio of the standard deviation σ to the mean value μ, and its calculation is shown in Equation (5).

$$\mathrm{CV}=\frac{\sigma}{\mu} \tag{5}$$

2.3.3. Construction of spatial distribution identification method for citrus orchards

In this study, the spatial distribution recognition method for citrus orchards was constructed in two steps. As a first step, according to the research area of orange, banana, sugarcane, rice, and maize, five types of main crops in different phenological characteristics of the time window, using the five kinds of crop growth and harvest period, based on the idea of simple to complex hierarchical extraction[37], for bananas, sugar cane, rice, and corn, after many filters to obtain the classification of the image, The specific steps are as follows: First, distinguish vegetation from non-vegetation, retain vegetation information, and eliminate non-vegetation information. Then, based on the peak growth period in August and the harvest period in November and December, the threshold values of the vegetation index in different periods were set to classify banana, sugarcane, rice, and maize layer by layer[38], and the four crop types were initially excluded. Finally, the pre-classified images containing citrus orchard information were extracted. Second, on the basis of layer-by-layer classification, the unique characteristics and spectral changes of citrus in the phenological stage are used, and the normalized red-edge band index proposed by Xiao et al.[36] is referred to. According to the principle of "re-normalized" vegetation index in different periods to enhance phenological differences, the re-normalization of vegetation indexes (RNVI) was further constructed, and its calculation is shown in Equation (6):

$$\mathrm{RNVI}=\frac{\mathrm{VI}_a-\mathrm{VI}_b}{\mathrm{VI}_a+\mathrm{VI}_b} \tag{6}$$

where VI_a is the maximum vegetation index synthesis value in the last month of the fruit expansion period, and VI_b is the maximum vegetation index synthesis value in the first month after the end of the fruit expansion period. Based on the RNVI index, the determination rules of citrus orchards in the study area were established, and the pre-classified images containing information on citrus orchards were discriminated. If the RNVI value of the image to be determined was negative, the pixel was judged to be a citrus orchard. If the RNVI value of the image pixel to be determined is positive, the pixel is judged as a non-citrus orchard. Due to the influence of planting time and orchard management, some citrus phenophases in the study area were not synchronized, so only mature citrus orchards were identified in this study, not young ones.

2.4. Accuracy evaluation

In order to quantitatively evaluate the recognition accuracy of citrus orchards by different indexes, this study randomly acquired the confusion matrix of classification results calculated by 30% of sample points collected to obtain User accuracy (UA) and Production accuracy (UA). PA), Overall accuracy (OA) and Kappa coefficient[33]. In this study, OA and Kappa coefficients were used to evaluate the overall classification effect, and UA and PA were used to evaluate the identification accuracy of citrus orchards, and the identification area of citrus orchards was tested.

3. Results and analysis

3.1. Crop phenology and spectral feature extraction

By comparing the differences in vegetation indices of citrus orchards, bananas, sugarcane, rice, and maize in different time windows (**Figure 5**), it was found that the changes in NDVI reflectance of citrus orchards from October to November were significantly different from those of other crop types. Only the NDVI reflectance of citrus orchards decreased significantly in October to 0.47 and then increased to 0.56 in November. Corresponding to the phenological period of citrus, it was verified that October was the end of the expansion of citrus fruits, and its volume and etiolation weakened the canopy vegetation information, that is, the NDVI reflectance decreased. In November, the winter tip period began, and the canopy vegetation information of citrus orchards gradually rose; that is, the NDVI reflectance increased. In addition, during the key phenological stage of fruit ripening, there was little difference between the DVI and RESI index reflectance of citrus orchards and the other four crop types, and the GNDVI of citrus orchards was not obvious at this stage, indicating that only NDVI was highly sensitive to the characteristics of citrus fruit expansion. The variation in vegetation spectral characteristics caused by fruit growth and development is a unique feature of the fruit expansion period in citrus orchards. Different from citrus orchards, the NDVI reflectance of banana, sugarcane, and rice showed the same trend in the four-time windows. In August, the NDVI reflectance of the four crops showed the maximum value, which was 0.80, 0.68, and 0.72, respectively. However, from October to December, the NDVI reflectance of the four crops gradually decreased, and the NDVI reflectance of banana, sugarcane, rice, and maize in December was 0.60, 0.49, 0.31, and 0.41, respectively.

Furthermore, the coefficients of variation of NDVI, GNDVI, DVI, and RESI in October of the phenological stage were calculated, which were 0.16, 0.12, 0.11, and 0.08, respectively. It was found that the CV value of NDVI in October of the citrus orchard was the highest, which was 0.16, indicating that the dispersion degree of NDVI among different crop types was the highest and the difference was the strongest. It has the best differentiation effect on citrus orchards.

3.2. Identification results of spatial distribution of citrus orchards

Because the normalized vegetation index NDVI has the highest dispersion degree for various crop types and the best separation ability for citrus orchards, this study selected NDVI to further construct the RNVI index to identify citrus orchards. Meanwhile, GNDVI, a green normalized vegetation index with similar characteristics of citrus fruit swelling but poor discrimination, was selected for comparison. However, featureless DVI and RESI were not selected for citrus orchard identification. Based on the RNVI formula, NDVI and GNDVI were selected as the re-normalized variables, and the reflectance of vegetation index in October (end of fruit swelling) and November (winter tip) were respectively used to construct the re-normalized NDVI and re-normalized GNDVI. The citrus orchards in the study area in 2018 were identified by re-normalized NDVI and re-normalized GNDVI respectively (**Figure 6**). As can be seen from **Figure 6**, in terms of the overall spatial distribution of the recognition results of the two indexes, citrus orchards were mainly distributed in plain, basin, and low mountain slopes, and less in hills with high altitudes. The citrus orchards identified by normalized NDVI were relatively complete, while the citrus orchards identified by normalized GNDVI were relatively fragmented.

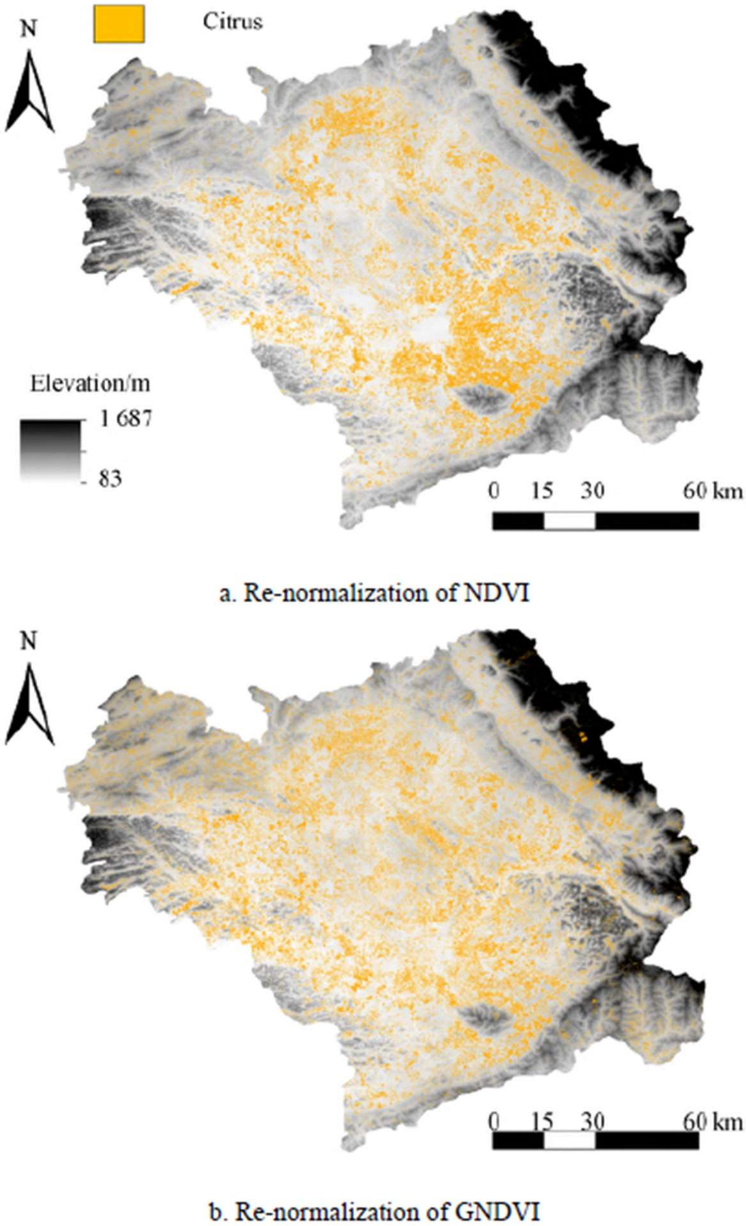

Figure 6. Identification of citrus orchards based on multitemporal vegetation indices of at the fruit expansion stage.

The area of citrus orchards in each township in the study area was statistically analyzed (**Figure 7**). The total area of citrus orchards identified by normalized NDVI in the study area was 3.42×10^4 hm^2, while that identified by normalized GNDVI was 3.47×10^4 hm^2. The two orange orchards identified by the index had almost the same area. It is basically consistent with the statistical data of 3.07×10^4 hm^2[6].

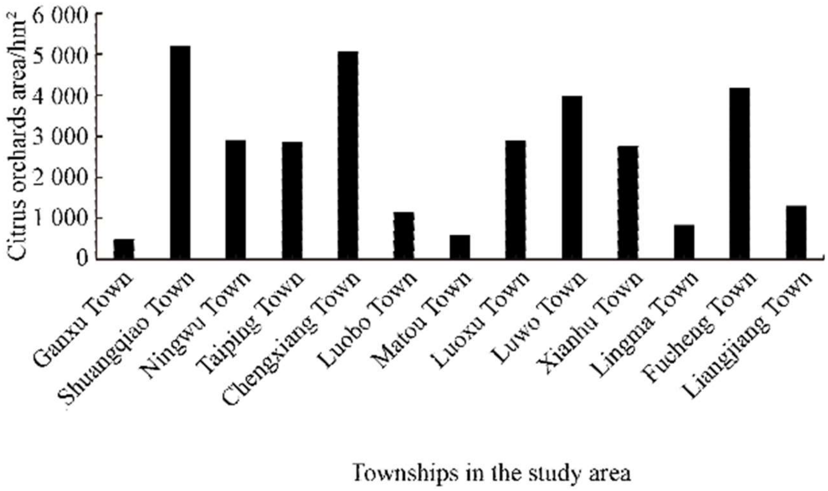

Figure 7. Statistics of citrus orchards area in the study area.

3.3. Accuracy evaluation and analysis

In this study, the overall accuracy, Kappa coefficient, production accuracy and user accuracy were used as the evaluation indexes of citrus orchard identification results[33]. The accuracy verification results showed (**Table 1**) that the overall accuracy of the normalized NDVI for citrus orchard identification was 82.75%, and the Kappa coefficient was 0.66. This indicates that the vegetation index method based on phenological information has better identification accuracy in the complex planting types and cloudy and rainy conditions. The production accuracy of citrus orchards identified by normalized NDVI was 84.86%, and the user accuracy was 80.27%, both higher than 80%. The identification effect was good. The overall accuracy of normalized GNDVI for citrus orchard identification was 75.78%, and the Kappa coefficient was 0.51, which was lower than those of normalized NDVI. In addition, the production accuracy of the re-normalized GNDVI for citrus identification was only 66.03%, and the user accuracy was 79.94%. The miss error and miss core error of the re-normalized NDVI were inferior to those of the re-normalized NDVI, especially since the miss score phenomenon was more serious.

Table 1. Comparisons of classification accuracy based on different vegetation indices.

Vegetation indices	Crop types	Overall accuracy/%	Kappa coefficient	Producer's accuracy/%	The user's accuracy/%
NDVI	Citrus orchard	82.75	0.66	84.86	80.27
	Other crops			80.81	85.30
GNDVI	Citrus orchard	75.78	0.51	66.03	79.94
	Other crops			84.76	73.06

The misclassification phenomenon can be divided into two types: sparse forest land, sugarcane land, and buildings with high reflectance. Woodland misclassification errors mainly come from hilly areas in the northwest. Studies have proved that the spectra of sparse woodland and shrubs are similar to those of citrus young orchards, which are easy to confuse confused[39]. The study area has a large area of eucalyptus plantations in hilly and mountainous areas, which may be the result of image remote sensing classification. Since eucalyptus has no fruit and its phenological characteristics are significantly different from those of citrus orchards, and citrus shows regular characteristics of row-by-row planting, similar spacing between adjacent tree species, and low plant height, subsequent studies can prioritize the distribution of eucalyptus forests[37] to exclude the interference of sparse woodland on remote sensing recognition of citrus orchards.

The phenomenon of missing scores was mainly from citrus orchards with abnormal NDVI values. Citrus orchard of spectral characteristics and the environment, tree age, human management and so on has certain relations, although the citrus orchards in the study area are mostly prostagland orchards, but part of the growth stage of sync citrus orchard of easy leakage phenomenon, such as a new species of citrus seedlings growth to guaguo prostagland fruit trees need 2~3 a, and small seedlings, tree height, leaf blade sparsely, It is difficult to identify the phenological characteristics of fruit maturity. In addition, some orchards grew more vigorously after manual management, such as branch pulling treatment, and the tree species were more closely spaced when the fruit matured, so the NDVI value was high, and it was easy to miss the score.

4. Conclusion

This study based on the characteristics of the growth of citrus orchards is presented based on the phenological characteristics of the citrus orchard information identification method and compares the different vegetation indexes to identify the effect of citrus orchard information in different periods. With the introduction of phenology information, the perennial evergreen citrus fruit trees in remote sensing recognition spectral information is insufficient, leading to the following main conclusions:

1) Confirmed the scientific hypothesis that "the expansion process of citrus fruit will lead to the gradual weakening of vegetation information". Compared with other crop types in the study area, the characteristics of citrus orchards in this period were significantly different. The volume of fruits became larger, the color became mature, and the spectral information of citrus fruit leaves was affected to a certain extent, which was an important feature for identifying citrus orchards.

2) The sensitivity differences of different vegetation indices to the changes in citrus fruit characteristics were found. Normalized Difference Vegetation Index (NDVI) was a better description of the fruit swelling characteristics, which was the weakening of vegetation information brought by fruit development; that is, the NDVI reflectance decreased significantly, the dispersion degree was large, and the separation was strong. These characteristics were significantly better than the Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Vegetation Index (Normalized Difference Vegetation Index), DVI, and Sentinel-derived Red-edge Spectral Indices (RESI).

3) The different effects of different vegetation indices on the distribution and extraction of citrus orchards were clarified. Using the key phenology to extract the spatial distribution of citrus orchards in the study area, the overall accuracy of citrus orchards identified based on multi-temporal NDVI is 82.75%, which is better than that of GNDVI, which is 75.78%. Compared with the identification results, the citrus orchards identified by GNDVI are more broken, and the phenomenon of missing points and wrong points is serious.

The key phenological period of citrus is just in the month with less cloud pollution from Sentinel-2 data, which partially solves the problem of insufficient multi-temporal data caused by cloudy and rainy weather in southern China. This method provides good theoretical and practical support for remote sensing identification of citrus orchards under complicated planting and cloudy and rainy conditions, and it also provides a reference and foundation for constructing a more universal citrus index. In this study, Sentinel-2 optical data is used, but radar data such as Sentinel-1 is not yet considered. Its main purpose is to reveal the effect of citrus fruit color change characteristics on citrus orchard identification through spectral changes. In the future, it is necessary to dig deep into the application potential of red edge band in citrus orchard information identification, introduce a variety of red edge band indices, and combine Sentinel-1 and other multi-source data with the unique phenological information of citrus orchards to find a better citrus identification method and further promote the innovation of remote sensing identification theory and method for citrus orchards.

Conflict of interest

The authors declare no conflict of interest.

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