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Dynamic estimation model of vegetation fractional coverage and drivers

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ABSTRACT

This research reveals major changes of VFC and drivers in 2000 to 2010 in Guangdong province, China. Using MODIS NDVI, VFC directly calculated. Spatial patterns of VFC changes classified into four levels such as low (<50%), medium (50-70%), high (70-90%) and very high (>90%) in 2000, 2005 and 2010 separately. Time series of VFC showed the fitting curve is a straight line of value 0.783 (78.3%). Results showed that level >90% has highest mean of change annually, with values between 3.89% to 21.44% and level <50% has the lowest mean among all levels. The values of level 50-70% are between 7.79% and 19% and values of level 70-90% are between 68.38% and 77.25%. Trend analysis of VFC showed that in the northern mountainous regions, the economy is undeveloped and there is less human disturbance, leads to having higher VFC. In the southern coastal parts, human disturbance such as industrialization and urbanization can be seen, leads to having low VFC. Plus, using DMSP/OLS, CNLI computed. The driving factors of VFC dynamics considered human activities and climatic factors and finally Pearson correlation coefficient confirmed the relationship between VFC, climatic factors and CNLI. Result showed that VFC is positively correlated with sunshine hour, but VFC is not related to CNLI indicates that at provincial scale over research period of about 10 years, Even though urbanization and industrialization had a defined impact on the change of VFC in some cases.

1. Introduction

The VFC due to increased human activities and natural environmental changes is one of the most important issues in ecological systems and climatic model simulation. VFC includes some vertical projection of vegetation such as leaves, stem and shoots (Li et al., 2014). Vegetation, including forests, bushes, grasslands, farmlands, and orchards, as important components of the ecological cycle, can maintain the ecological environment (Zhang et al., 2013), so that it has been especially considerable in the last few decades. VFC changes due to land use-land cover changes increased, and other side monitoring of VFC has a necessary significant for global energy cycle and geo-biochemical circulation of substance (Yang et al., 2010). Among many forest structure variables, vegetation fractional cover, defined as the fractional area (projected vertically) of vegetation canopy occupying a given land area (Li et al., 2009), is a key parameter for modeling the exchanges of carbon on the land surface and for monitoring urban environment and urban growth. However, it is very important to predict the dynamic of global VFC with the field sampling, GIS special analysis, artificial neural network (ANN) and especially calculation of satellites products as NDVI (normalized different vegetation index) (Potapov et al., 2015; Jiapaer et al., 2011).

Methods of calculating the VFC by spatial resolution, spectral resolution and temporal resolution of imagery that got on a different remotely sensed platforms or different sensors are dissimilar. According to scope of imagery, the satellite remotely sensed data can reflect the detail changes from local to global scale. Some methods using remotely sensed data to predict the vegetation fractional coverage have been included experiential model, vegetation index and sub-pixel decomposition (Li et al., 2003). Thus, choosing proper vegetation index is significant to predict the vegetation fractional coverage. According to different demands, the appropriate sensor was selected as various modes to simulate the vegetation fractional coverage. The result measured by remote sensing data must be verified by field survey data. Recent studies have shown that hyper spectral data enables to eliminate the scattering effect of soil and

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atmosphere on sensor reflectance (Estel et al., 2015). In addition, it can reflect the direct chlorophyll concentration and leaf area index and develop the accuracy of vegetation fractional coverage predicted by remotely sensed data (Kenneth et al., 2000). On the other side, simulating the vegetation fractional coverage using multi-scale remotely sensed data such as MODIS doesn't enable to meet different requirements to ground surface parameters of model, however to improve the accuracy of measurement on large scale, it is one of important methods of scaling research using remote sensing data (Li et al., 2003; Schneider et al., 2009; Burges et al., 2012).

Effective monitoring of VFC requires longer-term data set with fine spatial resolution-ideally at sub-hectare spatial resolutions spanning multiple decades (Sexton et al., 2013; Kim et al., 2014). In this context, satellite borne sensors can detect VFC change in the visible, thermal and mid-infrared signature during the days, nights, months and seasons (Chand et al., 2006). In this study, we are going to use one of the most common satellite systems as MODIS (2017) from NASA which provides visible and thermal images and also it can be evaluated forest cover changes. There are a lot of projects that were defined start and end of the growing season using MODIS-based 16-days NDVI profiles derived within MODIS-based forest cover mask (Potapov et al., 2015). The growing season was defined as the sum of all 16-day intervals having an NDVI equal to or above 90% of the maximum annual NDVI. The NDVI images of MODIS (1 month-Terra) from the NEO (2017) data archive can be used as based datasets. Using NDVI images are directly computed VFC and as it was mentioned above, VFC is the vertical projection of vegetation including leaves, stems, and also shoots to the ground surface and is expressed as the fraction or percentage of the reference area (Zhang et al., 2013). In fact, VFC enables to couple natural environment changes and human activities and also it is an essential index to study the ecological systems (Liu et al., 2009). In addition, vegetation changes attaches a great importance to global energy circulation and geo-biochemical cycle of substance, thus evaluating VFC contains a great significant for both ecology and society exactly (Gu et al., 2013). On the other side we applied DMSP/OLS night time lights data series to calculate CNLI. CNLI is considered as one of the most significant driving forces on VFC dynamics. DMSP/OLS data enables us to makes daily over flights and routinely collects visible images during its nighttime pass (Kharol et al., 2008). In fact, measured DMSP/OLS data is possible to detect human presence, urban people, settlements and light-demanding activities, energy, electricity consumption and gas emissions (Amaral et al., 2006; Huang et al., 2014). However, using DMSP/OLS data, there were some related studies focused on monitoring the dynamics of urbanization level for the last two decades at multiple scales in Guangdong province, especially the dynamics after 2000.

In this way, we tend to develop a quantitative approach by employing the model of CNLI to predict and mapping human activities. Even though, our finding will be more complete by dynamic modeling of the VFC changes, time series analysis of VFC, trend analysis of VFC and finally driving factors of VFC dynamics during the years of 2000 to 2010 completely.

2. Materials and methods

2.1. Study area

Fig. 1 shows the map of China with geographical collation of Guangdong province boundary. Guangdong is a province located in the south of China, and it occupies an area of 179,800 km^2 and bounded by 20°13′-25°31′ North latitudes and 109°39′-117°19′ East longitudes. Guangdong neighbors Jiangxi and Hunan provinces in the north, Fujian province in the east, and the Guangxi Zhuang region in the west. Guangdong had 106,440,000 people in 2013 and it was followed by many economic and social developments, (SBGP, 2011). More so, climatologically, the province crosses the tropical and subtropical zones from south to north, and has plenty of light, heat and rainfalls. Due to its proximity to the equator circuit, tropical and sub-tropical regions; Guangdong has a climate marked by high temperature and plentiful rainfall. It has the highest and lowest mean temperature of 28 °C in July and 13 °C in January respectively.

The greater part of the Guangdong has a mean annual precipitation of about 1,500-2,000 mm and with 140-160 rainy days. It is influenced by monsoon climate; seasonal distribution of precipitation was uneven in this province. This province also has vegetation varies from north to south. In the north, the Nanling mountain ranges is covered by the subtropical montane evergreen broadleaved forest; in the middle, it is the subtropical evergreen broadleaved forest, and in the south the tropical monsoon forest. Guangdong abounds in the rich fauna and flora resources is as follows that; there are more than 7,055 species of vascular plant there, and 4,000 species of which are woody plant in China (Wang et al., 2013). So the monitoring vegetation coverage of mentioned tropical ecosystem due to provides habitat for species of plants and animals, regular climate, to prevent soil erosion, to supply home for indigenous people and other benefits is very essential.

2.2. Data source and data process method

The selection of first images with minimizing phonological and atmospheric noise extracted from the website of NEO datasets (http://neo.sci.gsfc.nasa.gov/), by appropriate based on phonological time series of NDVI from the MODIS. The desired data was selected from the start and end of the growing season from April to October during the years 2000 to 2010. MODIS plays a vital role in the development of validated, global, interactive earth system models able to predict global change accurately enough to assists policy makers in making sound decisions concerning the protection of our environment (Lyapustin et al., 2014).

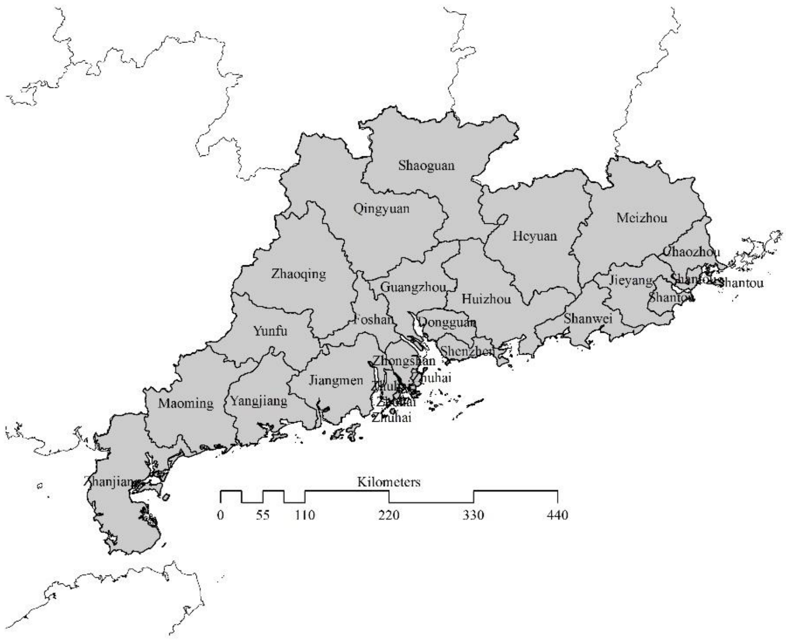

Fig. 1: Geographical location of Guangdong province, China

The second datasets derived DMSP/OLS satellites such as F14, F15 and F16 by years 2000 to 2010 in sun synchronous orbits with nighttime overpasses ranging from nearly 8 pm to 10 pm local time. Elvidge et al. (2009) concluded the time series of DMSP/OLS nighttime lights for the period of 2000–2010 were collected by individual sensors: F14 (1997–2003), F15 (2000–2007) and F16 (2004–2009). The DMSP/OLD data were obtained from the web site of NOAA (NCEI, 2017) directly. Given the sensitivity of the sensor at night, DMSP/OLS data can be used to detect a variety of VNIR emissions (Small et al., 2005). The availability of long time data with moderate spatial resolution (e.g., 1 km) has enabled researchers to explore a series of global, national and regional research subjects (Elvidge et al., 2009; Gao et al., 2015). In present paper DMSP/OLS nighttime data was used to directly calculate CNLI and to evaluate urbanization, evaluate social-economic activities (Huang et al., 2014).

2.2.1. Calculation of VFC

VFC was calculated from 2000 to 2010. NDVI$_{min}$ is minimum of NDVI value and NDVI$_{max}$ is maximum of NDVI value. The formula of VFC is as follows;

$$VFC = \frac{NDVI - NDVImin}{NDVImax - NDVImin} \quad (1)$$

2.2.2. Time series analysis of VFC

Time series analysis was calculated using annual VFC data from 2000 to 2010 using statistical software SPSS. Time series forecasting model of export was computed to fit the annual VFC data.

2.2.3. Trend analysis of VFC

Trend analysis using cubic polynomial with least root mean square error was calculated by spatial toolset of ARCGIS 9.3. VFC were classified into four levels such as low (<50 percent), medium (50-70 percent), high (70-90 percent) and very high (>90 percent). VFC trend analysis conducted distinctly.

2.2.4. Calculation of CNLI

By DMSP/OLS data, CNLI was computed at the scale of our study area using the following formula:

$$CNLI = I \times S \quad (2)$$

where I is the average night light brightness of all lit pixels in a region. It is illustrated as follows:

$$I = \frac{1}{N_L \times DN_M} \times \sum_{i=p}^{DN_M} (DN_i \times n_i) \quad (3)$$

where DN$_i$ is the DN value of the ith gray level, n_i is the number of lit pixels belonging to the ith gray level, P is the optimal threshold to extract the lighted urban area from the DMSP/OLS images. DN_M is the maximum DN value, and N_L is the number of lit pixels with a DN value between P and DN_M. S is the proportion of lit urban areas to the total area of a region. It can be showed as follows:

$$S = \frac{Area_N}{Area} \quad (4)$$

where $Area_N$ is the area of lit urban areas in a region and $Area$ is the total area of the region.

2.2.5. Driving forces analysis of VFC dynamics

Pearson correlation coefficient confirmed to calculate the relationship between VFC, CNLI and climate factors eventually.

3. Results and discussion

3.1. Time series analysis of VFC

Time series analysis conducted using annual VFC data from 2000 to 2010 supported by statistical software SPSS version 22.0. Time series forecasting module of expert modeller was applied to fit the annual VFC data. An annual VFC curve and a fitting line were generated (Fig. 2). As can be seen from Fig. 2, the fitting curve is a straight line of value 78.3 percent paralleling to the horizontal year axis. It should be noted that, during the period from 2000 to 2010, annual VFC fluctuated around the fitting straight line but showed no general trend of increase or decrease. Among eleven research years, the VFC in 2002 and 2006 was equal to the average value of 78.6 percent, while the VFC in 2000, 2001, 2005, 2008 and 2010 was below the average and the remaining years above the average. According to the data provided by the Guangdong provincial meteorological statistical yearbook in 2000 to 2010, the province was caught by a severe drought in 2003, 2004, 2007 and 2009. During these years, the precipitation was very sparse and the sunshine hour was very long, which promoted vegetation growth and increased annual VFC. On the contrary, in five years from 2000, 2001, 2005, 2008 and 2010, there were many torrential rains in Guangdong, causing a large area of crop and grass drowned to death, resulting in the decrease of VFC.

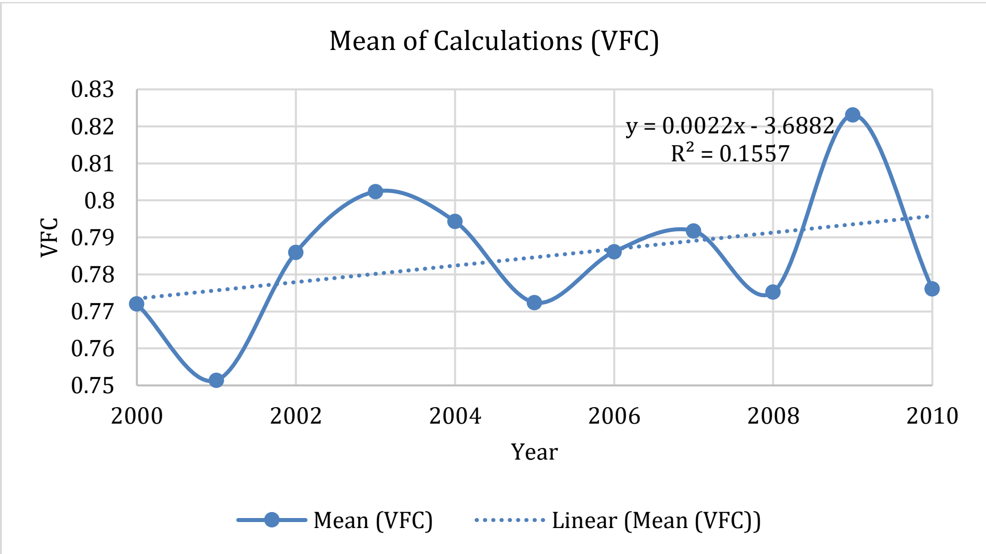

Fig. 2: Dynamics of annual VFC from 2000 to 2010 in Guangdong province

3.2. Trend analysis of VFC

Firstly, VFC in three years from 2000, 2005, 2010 were selected to do trend analysis using cubic polynomial with least RMSE supported by spatial analysis toolset of ArcGIS 9.3. Then VFC were classified into four categories: low (<50 percent), medium (50-70 percent), high (70-90 percent) and very high (> 90 percent). Finally, a VFC trend analysis map and an area change table of VFC were produced (Fig. 3). As it can be seen from Fig. 3, during the three periods of 2000, 2005 and 2010, the spatial distribution of VFC in the province generally decreased from the north to the south, showing a strip spatial distribution pattern. Surely this spatial pattern is closely related with regional differences in the level of industrialization and urbanization. The CNLI for the three mentioned categories during three periods of 2000, 2005 and 2010 were 0.1034, 0.0969 and 0.1564 respectively. In the northern mountainous regions of the province, the economy is undeveloped and there is less human disturbance, resulting in the higher VFC. In the southern coastal part of the province, especially in the Pearl River Delta region, human disturbance such as industrialization and urbanization is very strong, resulting in the low VFC.

As can be seen from Table 1, during the three periods of 2000, 2005 and 2010, both the area ratio and spatial distribution pattern of different levels of VFC changed. From the viewpoint of area ratio, during 2000 to 2010, the percentage of low and high level VFC increased gradually, while the percentage of medium level of VFC decreased rapidly. However, the percentage of very high VFC showed a more complex trend of a slight decline first (2000-2005), then upward (2005-2010). With the low-end industrial transfer from coastal area to the central and northern part of the province, the process of industrialization and urbanization in these economically underdeveloped regions was greatly accelerated. The area with medium VFC spread to the middle cities of Guangzho, Shanwei, Huizhou, Qingyuan, Zhaoqing and Yunfu. The area with high and very high VFC gradually moved to the northern and eastern part of the province. The area with a very high VFC was reduced and retreated to northern cities of Shaoguan, Heyuan, Meizhou and Chaozhou with backward economy and rich forest resources.

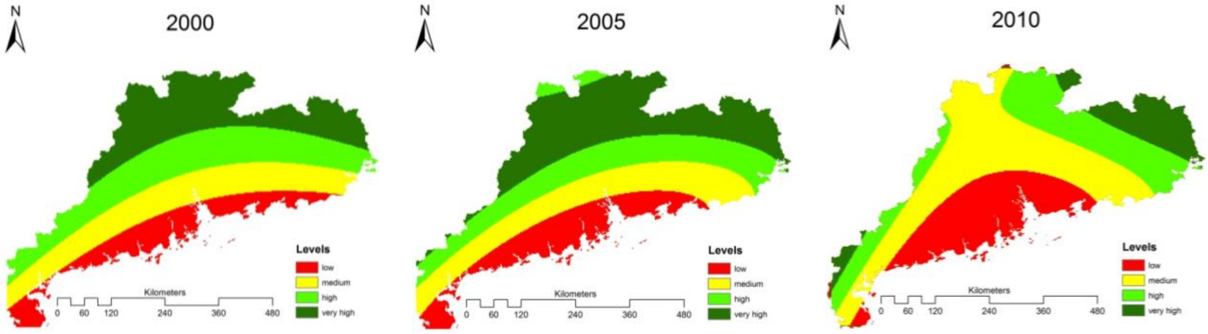

Fig. 3: Spatial trend dynamics of VFC in Guangdong province in 2000, 2005 and 2010

Table 1: Area change table of VFC of Guangdong in 2000, 2005 and 2010

Year	Low (<e.g. 50%)	Medium (e.g. 50-70%)	High (e.g. 70-90%)	Very high (>e.g. 90%)
2000	3.42	15.74	72.78	8.05
2005	4.04	13.26	75.86	6.82
2010	4.39	12.45	75.84	7.3

3.3. Driving factors of VFV dynamics

Pearson correlation coefficient calculated to analyze the relationship between VFC, climatic factors and light Index which is closed with urbanization index (Table 2).

If the correlation coefficient is | r |> 0.90, there is a significant correlation between the two variables; if | r | ≥0.8, is highly relevant; if 0.5≤ | r | <0.8, is moderately correlated; if 0.3≤ | r | <0.5, there is llow correlation; if | r | <0.3, there is a very weak relationship between two variables.

Table 2: Pearson correlation of VFC, climate factors and CNLI

Factors	VFC (e.g. %)	Mean Temp. (°C)	Mean precip.(mm)	Sunshine hour	Rainy days	CNLI
VFC (e.g. %)	1.0000					
Mean Temp. (°C)	0.1733	1.0000				
Mean precip. (mm)	-0.1550	0.3001	1.0000			
Sunshine hour	0.4642	0.2227	-0.2409	1.0000		
Rainy days	-0.8117	-0.1349	0.3374	-0.8343	1.0000	
CNLI	0.2044	-0.4183	0.1084	-0.0605	-0.1737	1.0000

As showed from Table 2, VFC is highly negatively correlated with rainy days, low positively correlated with sunshine hour, but is not correlated with average annual temperature (°C), annual precipitation (mm) and light index. The reason why VFC is positively correlated with sunshine hour lies in the fact that long sunshine hour can promote plant photosynthesis and help to increase VFC. In Guangdong Province, rain always appears in the form of rainstorm which causes large area of farmland, grassland be flooded, leading to the death of many kinds of vegetation and decrease of VFC. In rainy days, sunshine hours will be decreased, which can adversely affect the normal function of photosynthesis of plants, resulting in reduced VFC. The result that VFC is not related to light index indicates that at provincial scale over research period of about 10 years, the process of urbanization and industrialization has little impact on the change of average annual VFC.

4. Conclusion and recommendation

We could use of the MODIS NDVI images and DMSP/OLS datasets to establish models for linking vegetation fractional coverage with the compounded night light index, to predict vegetation coverage change detection of Guangdong province in the period of 2000 to 2010 dynamically. We calculated VFC levels into four classes as level I, level II, level III and IV with the pre-specified values including low percentage of VFC (<50%), medium percentage of VFC (50%-70%), high percentage of VFC (70%-90%) and very high percentage of VFC (>%90) respectively. In this way the major changes of VFC were defined annually and spatial patterns were shown dynamics of vegetation coverage by all levels of VFC completely. We could obtain areas with level I, had lowest annual changes and areas with level IV, had highest rate among all. Herein Moran's *I* statistic ruled that, during the years of 2000, 2002, 2007 and 2009, human activities such as urbanization and industrialization have been increased and land cover changes was dominated in some parts of the study area, but fortunately in the period of 2001, 2003, 2006, 2008 and 2010, we witnessed reforestation and ecological protection with reduction of human activities. In addition spatial and temporal changes of VFC with trend analysis of VFC and CNLI restated that major changes with reduction of vegetation coverage change caused by human activities and climatic factors was related to central-southern parts and coastal areas of the study area in the periods of 2000 to 2005, and on the other side we could demonstrate that north parts, east and west area with high and very high percentage of coverage, had less changes in this period fortunately. Also with the help of mentioned indicators we could show that urbanization and industrialization was stopped, and VFC could concentrate in the north and specially east areas in the period of 2005-2010. But our correlation showed that both of human activities as urbanization and climatic factors as drought and flood have influenced on VFC dynamics.

In fact the process of increasing VFC was successful in this period of our study, although we saw increasing human activities and impact of the weather factors. Indeed development of economy had increasingly aware of the importance of environment protection and also driven by ecological benefits followed reforestation and to restore land cover correctly. As a consequence an advantage of our approach is that it also allows testing alternative definitions of VFC and CNLI together dynamically. Our study provided the first Guangdong province wide maps showing the spatial patterns, Hot/Cold spots and some of the evaluation indicators of vegetation fractional coverage change detection based on the dense time series of DNVI images in relation to DMSP/OLS night-time observations and climatic data. However highlights the dynamic nature of VFC changes, human activities and climatic factors need for frequent monitoring of all lands in order to assess the forest areas, no forest areas and degraded areas.

These findings will be important for inferring the efficacy of forest resources management and for analyzing causal relationships between economic drivers, human factors, environmental and climate propellant and land-cover changes.

Accordingly a quantitative research for the 11-year variation of VFC in one of the southern provinces of China using MODIS NDVI images, DMSP/OLS datasets and meteorological data in 2000, 2005, and 2010, and by dynamically predicting the variation, the conclusion is as follows:

1) The results of the time series analysis of VFC have shown among eleven research years, the average value of VFC was 78.3%. However, the VFC in 2002 and 2006 have been equal to the average value, and while the VFC in 2000, 2001, 2006, 2008 and 2010 were less than the average value and subsequently the VFC in 2003, 2004, 2005, 2007 and 2009 were more than the average value. Mentioned fluctuations in the amount of VFC were derived from climatic factors such as drought, precipitation, sunshine hour, torrential rain and also due to increase population as well as improved urbanization annually.
2) Spatial distribution of VFC indicated that the oasis is mostly occupied by low (50%) and medium (50-70%) category, caused by human disturbance such as urbanization and industrialization were related to central and southern parts of the Guangdong during the three periods of 2000, 2005 and 2010. On the other side of the northern, northwest and northeast parts of the study area, the economy was unexploited and resulting in the high and very high of VFC.
3) CNLI was greatly indicated human disturbance and urbanization. Industrialization and urbanization have expanded form Pearl River and Delta region into inner part of the province. On the other hand VFC was not related to CNLI indicates at provincial scale, just the dynamic of urbanization and industrialization had a defined impact on the change of average annual VFC.
4) Temporal dynamic of VFC at the scale of the province is largely influence by the fluctuation of climate factors, especially sunshine hour and rainy days, which helps to increase VFC and makes many crops, or which decrease of VFC and causes land cover be flooded. VFC is positively correlated with sunshine hour which are greatly negatively correlated with rainy days. Sunshine hour maybe negatively correlated with CNLI. The reason lies in the fact that both industrialization and urbanization could cause serious air pollution, such as haze, making sunshine hour be decreased.
5) Consequently, the results showed that the VFC in Guangdong province from 2000 to 2010 had changed significantly. The average value of VFC was raised from 3.42% to 4.39% and 72.78% to 75.84% in low and high categories, and was decreased from 15.74% to 12.45% and 8.05% to 7.3% in medium and very high categories mutually. Considering the importance of VFC, for the conservation and sustainable development of the ecological environment, for further studies will be the focus on VFC research in the future.

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