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Monitoring Anthropogenic Effects on Land-surface phenologies in China from AVHRR using the Discrete Fourier Transform

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Synopsis

Remote sensing is increasingly used for investigating land-surface phenologies by capitalizing on the recent availability of spaceborne optical and radar data. This paper detects temporal changes in vegetation phenologies and attempts to attribute these changes in vegetation to some identifiable vegetation forcing factors, such as human activities, climate, and natural factors. Human activities, such as settlement, agricultural practices, and pollution, can significantly impact vegetative cycles. In the absence of human influences, vegetative growth (recurring biological cycles) is seasonally regulated and primarily a function of temperature and precipitation. Remotely sensed Normalised Difference Vegetation Index (NDVI) data from the National Oceanographic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) is used to model the impact of both anthropogenic influences and natural disturbance regimes/climate on vegetation phenologies at regional and national scales. Specifically, NDVI NOAA AVHRR data from 1982 to 2000 is used to discriminate the influence of human activities from climatic and natural factors using the Discrete Fourier transform (DFT). Harmonic analysis of temporal NDVI in southern China shows that the first harmonic is in-phase with atmospheric temperature, while the second and third harmonics capture the combined influence of human activity information and climate on vegetation. But in northern China and the Qingzang plateau, sandstorms and snow cover obfuscate the second and third harmonics, making correct interpretation difficult. In all, meteorological data from 560 observations are analyzed in order to detect changes to land-surface phenologies. This work can be extended by attempting to attribute changes in vegetation to specific climate forcing factors, such as greenhouse gases and human influences such as deforestation.

Keywords: camera-ready manuscript, PDF files, two-column text, punctuality

1. Introduction

Human and natural disturbance regimes are known to significantly impact vegetation phenologies. This paper provides a methodology for determining the degree to which land-surface changes are the result of human activities (pollution, deforestation, urbanization, etc) or the inherent randomness of natural processes. However, separating anthropogenic from natural influences on vegetation is difficult. For example, it is unknown whether the changes in the frequency or intensity of extreme weather and climate events are a function of decadal fluctuations, or "indicative of longer term trends related to anthropogenic induced climate change" (Easterling et al, 2000). While year-to-year variations in vegetation phenologies can be the result of human intervention they are also related to climate: mesoscale satellite bioclimatological analyses have highlighted relations between the functional and biophysical attributes of plant canopy (net primary production, biomass, the fraction of absorbed photosynthetically active radiation and chlorophyll concentration) and life-controlling climate variables (temperature, precipitation, and growing degree days, etc.) (Rundquist, Harrington and Goodin, 2000; Yang, Wylie, Tieszen and Reed, 1998).

Human activities may have irreversible effects on natura l systems: It is well known that biological processes may undergo bifurcations/ (sudden shifts) at particular temperature or precipitation thresholds. The distribution and abundance of plants and animals is often determined by drought and frost tolerances (Woodward, 1987). For example, an extended drought in New Mexico in the 1950s caused a 2 km shift to the boundary between the pine and pinon/juniper forest (Allen and Breshears, 1998). Finally, ecosystem structure and function are impacted significantly by disturbance events, many of which are associated with floods, tsunamis, and drought. Natural systems are expected to exhibit even more novel, unpredictable responses to modern, human dominated environments.

Based on satellite observations, long-term climate change and climatic anomalies (such as El Niño/Southern Oscillation and North Atlantic Oscillation) may also influence vegetation dynamics. One of the major concerns with a potential change in climate is that an increase in extreme temperature and precipitation events will occur. In wild plants and animals, climate-induced extinctions, distributional and phenological changes, and species' range shifts are being documented at an increasing rate.

The overall areas of the world affected by either drought or excessive wet periods have increased (Dai and Trenberth, 1998). This paper will investigate the situation in China in which a decrease in mean precipitation (Ye et al., 1996) has been accompanied by an increase in the area of droughts and a decrease in the area with excessive precipitation.

Earth observation techniques are becoming increasingly important for the monitoring of the earth environment and the detection of its temporal variations. Remote sensing data is now routinely used for operational land-surface applications, such as disaster prevention (mapping of hazardous areas, detecting landslides, and land cover mapping) and a posteriori evaluation of damaged areas. This paper focuses on the use of remote sensing using time series of Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) in southern China to monitor land cover variations and changes in vegetation dynamics. The characterization of land-surface phenologies from regional to global scales provide baseline data from which to monitor changes in vegetation associated with anthropogenic and natural processes. Accordingly, both vegetation phenologies and growth periods are important for land surface (LSM) and global climate models (GCM).

2. Background

As a self-organizing, adaptive system, the earth's climate system is highly sensitive to human-induced land use change (Ning Zeng,1999, L. BOUNOUA et al., 2000, Pielke, 2000, Bonan, 1997, Lauenroth *et al*., 1999, Pitman *et al*., 1999, Wang and Eltahir, 2000a, b, Baron *et al*., 1998, Kabat, 2001; see section A, Skinner and Majorowicz, 1999, Sisk, 1999, and Lewis, 1998). As vegetative canopies are known to influence the terrestrial climate system (through land surface processes such as the exchange of radiation and gases), both the type of vegetation (determined by its physical, chemical, and structural properties) and its scale (degree of cover) are important parameters for Land Surface Models (LSM) and changes to the vegetation surface will determine species abundance, rainfall and atmospheric/soil temperature because vegetation type is a MID-MEDIA (Dickinson, R.E., A.1993; Yongjiu Dai,,2001). (Xue, 1993; Nobre, 1991, C. S. POTTER,1998, A. KAWABATA,2001).

It is therefore unfortunate that many assessments of land-surface temperatures fail to adequately consider human-induced landscape changes. While the effects of anthropogenic landuse change have been addressed in the context of urbanization (Gallo *et al*., 1999), they have been largely ignored in the context of temperature trends and climate change assessments (Delworth and Knutson, 2000; Crowley, 2000), even though alterations in landscape cover affect both the local and regional temperature record. For example, Pielke *et al*. (1999) explain how landscape change in South Florida (from a natural to a human-dominated form) led to warmer, dryer summers. In eastern Colorado, Pielke *et al*. (2000a) document a significant spatial variation in temperature trends, some of which are clearly associated with 20th century landscape change. Segal *et al*. (1988, 1989) and Stohlgren *et al*. (1998) document the role of irrigation on the Colorado climate, including a cooling of summer maximum temperatures along the eastern slope of the Colorado Rocky Mountains.

Monitoring the impact of human activities is important because our expansive and dominant species of primate, *Homo sapiens* (so called ``man the wise'' because of unprecedented neurological development) has caused significant changes to its host ecological systems. Human-caused landscape change includes agricultural activities (such as replacing vegetation species, increasing the cropping index), deforestation, overgrazing, and urbanization. Such anthropogenic disturbances are by no means new (they probably contributed more to the collapse of earlier civilizations than military fortunes); however, most landscape disturbances have occurred in recent history – and their scope and scale is accelerating, significantly altering the balance between vegetation and climate (Leemans, 1999). Specifically, O'Brien (2000) notes the accelerating rate of tropical deforestation.

Landscape alterations can influence global climate and atmospheric circulation thousands of miles from the source of the disturbance (Pitman and Zhao, 2000; Chase *et al*., 1996, 2000; Burke *et al*., 2000): Land surface plays an important role on deep cumulus convection, leading to major shifts in the polar jet stream, with substantial higher latitude regions of warming and cooling (Pielke *et al*., 1997, Shaw *et al*. 1997, Grasso, 1996, and Ziegler *et al*., 1997). In addition, landscape alterations lead to a reduction in transpiration (of the natural landscape) and declining cumulonimbus cloud activity.

Over the past two decades, time series of AVHRR data has been used to investigate vegetation phenology. This body of research has improved our understanding of fluctuations and directional trends in the characteristics of vegetation and ecological systems (particularly inter- and intra-deviations from baseline characteristics) as influenced by climate change and other human and natural effects. However, it is often problematic to estimate some vegetation/land surface parameters for physically based models of climate, hydrology and biogeochemical cycles (Sellers et al., 1994). Due a lack of effective instrumentation, these models were unable to consider either the effect of human activities or land surface changes. However, many studies have shown that human activities, including deforestation, and urbanization significantly alter land-surface phenologies and the interaction between land surface and the interaction between land surface and the atmosphere. Abedo studies demonstrate that phenology can significantly change the distribution of solar energy (Xu Xingkui et al, 2004).

3. Data Source and Remote Sensing and Vegetation Indices

3.1 NDVI

AVHRR data provides regional and global estimates of vegetation by using the Normalised Difference Vegetation Index (NDVI), one of the most common vegetation indices derived from remotely sensed data. The NDVI is a normalized ratio of the Near Infra Red (NIR) and red bands, which is given by

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$

where ρ_y is the surface bi-directional reflectance of the y band (for y = NIR and red). Hence, the NDVI detects the presence of chrolophyll, which absorbs red light but strongly reflects infrared radiation by mesophyll tissues (Sellers 1994; G.Aasrar, 1984; J.KRISTIAN, 1986; Jing M.Chen,1996). NDVI has proven valuable in the estimating herbaceous total biomass accumulation in grasslands and steppes. Using satellite data, total dry biomass production has been estimated from time series vegetation indices (summed over the growing season, PAR and NDVI are highly related to total photosynthesis, and hence to total dry biomass).

NDVI has been used in various land cover classification and land cover monitoring applications from local to global scales, including vegetation maps in Africa (Tucker et al, 1985), North America (Goward *et al.* 1985) and the entire world (Justice *et al.* 1985, Townshend et al., 1991). AVHRR continental land surface models assume that large aggregations of land cover have various NDVI responses through time: the different NDVI magnitudes and time variations provide a means to distinguish among land surface types. Although exact boundary delineation is often difficult, particularly when multiple land cover aggregations are required over large areas.

Analyzing NDVI data, changes in vegetation cover, including the impact of climate on land surface phenologies, can be directly obtained. Because green vegetation absorbs and reflects more energy in the visible red and near infrared regions than senescent vegetation (Tucker, 1979,1991), NDVI has been used for the purposes of phenologic mapping (Benoit Duchemîn, 1998; B.DUCHEMIN ,1999;Aaron Moody, 2001; A.BONFIGLIO,2002; G.Dall'olmo,2002;), land surface monitoring (Sellers, 1996; Zhan, X, 2000). It has also been applied to determine growing season length (GROTEN,2002) and the fraction of vegetation cover (zengxubing ;Peter R.J. North，2002).

The density of green vegetation and significant fluctuations in vegetation can be revealed by NDVI because of its high positive correlation with LAI. For natural vegetation, NDVI will display an annual variation that is highly correlated with climate (once human activities are eliminated). The NDVI trend can be simulated by using atmospheric parameters such as temperature and precipitation in some dry regions, where the vegetation is highly sensitive to precipitation (Nicholson S E,1994; Malo A R,1990; William T H,1996; Grist J,1997; A. KAWABATA, 2001). However, as previously discussed, in many regions, human activities disturb the interactions between vegetation and climate, leading to phonologic changes. Accordingly, the effects of human activities must be considered to accurately simulate phonologic characteristics.

Because NOAA-AVHRR NDVI data comprises both land surface information and vegetation information, the proportion of the vegetative changes that are caused by natural processes and human activities can be determined. The following two reasons explain why NDVI can accurately account for the impact of human influences and climate on vegetation:

1) NDVI errors have minimal impact on phenologies

The sensor equipped, NOAA-AVHRR satellite circles the earth at near-polar inclination, and provides the continuous monitoring necessary for intensive data analysis on various regions of the Chinese landscape. While the spatial resolution of NOAA-AVHRR is course (1.1 km), it is capable to pass the same area twice daily (actually the monitoring period is one every six hours, two times are uncounted due to darkness). The AVHRR provides four- to six-band multispectral data from the NOAA polar-orbiting satellite series. NDVI accuracy/precision is affected by three factors: bi-directional reflection, signal degradation, and atmospheric interference. Firstly, the satellite's bi-directional reflection is a function of its azimuth angle, the solar zenith angle and illumination (Gutman, 1991). But studies have shown that even "extreme reflectance" has a relatively small influence on NDVI precision (Micheal, 1996). The second source of error is from sensor degradation (Los 1993, Rao and Chen 1996) and satellite orbit degradation (Price 1991). The extent of the error resulting from this degradation depends on the terrestrial calibration system employed. Thirdly, clouds and aerosol also interfere with NDVI quality (Gutman et al. 1994). Atmospheric calibration only can partly eliminate the effect of this interference.

The NDVI data in this study are from the GES Distributed Active Archive Center during the period from January 1982 to December 2000. All the data are processed by Gordon's atmospheric correction scheme. The composite NDVI index is formed by taking the maximum NDVI value from the daily data over a ten day period. Because a quality control flag exists for each pixel, the systemic error in the NDVI series is assumed to remain constant. This systemic error is small when compared with seasonal NDVI changes.

2) Higher temporal resolution can unveil phenologies and human activities.

In southern of China, the favorable climate allows for two or three crops annually. In general, because the NDVI monitoring interval exceeds ten days, the maximum daily NDVI (obtainted over a ten day period) can accurately reveal the relationship between vegetation cycles and climate (phenology). In addition, the NDVI can reveal valuable information on human agricultural practices such as when planting and harvesting occurs. By so doing, human activities can be distinguished from natural vegetation growth.

3.2 Climate data and GIS Database

1) The database of precipitation and air temperature.

The distribution of precipitation and temperature are two factors which impact vegetation characteristics. In order to determine the degree to which vegetation change is influenced by climatic factors and human activities diurnal meteorological observatory data is collected from 560 weather stations during the thirty year period: 1970 to 2000, as illustrated in Figure 1. Note that the concentration of weather stations is highest in eastern China. The distribution of observatories within every Chinese climatic region is shown in Table 1. Moreover, 360 of the 560 weather stations have sandstorm records.

2) The database of vegetation on the land surface

Vegetation characteristics are a function of the species type. It follows that regions with heterogeneous distributions of vegetation species possess a wide spectrum of physical vegetative features. Accordingly it was necessary to create vegetation database. The database contains vegetation data from field studies digitized by Institute of Geography Chinese Academy of Science. This database contains more than 100 types of vegetation at a resolution of 2 km by 2 km. From this data, seven vegetation categories are created: Desert or Semi-desert, One Crop Annually, Evergreen forest, Deciduous forest, Double-Cropping Rice/Three Upland Crops Annually, Two Crops Containing Upland and Rice Annually, and Steppe and Savana as shown in Figure 2.

It is important to point out the three distinct climatic regions in China: the temperate zone, subtropical zone and tropical zone. The vegetation distribution and the interactions between meteorological variables (temperature, precipitation, atmospheric pressure, radiation, etc) and vegetation vary significantly in each climatic region. These variations are not unique to China: climatic phenomena are highly variable in many parts of the world. For example, in the savannas of Southern and East Africa, rainfall can vary from more than 750 mm per annum in wet years to nil at the driest extremes. It follows that a cateogorization of climatic division (Figure 3) is valuable in order to analyze phenology and human activities.

3) The database of soil texture.

The soil texture categories include sand, loam sand, sandy loam, loam, silty loam, sandy clay loam, clay loam, silty clay loam, sandy clay, silty clay, clay, heavy clay. These distribution of these soil textures in China are shown in Figure 4.

4) The observational data of phenologies.

Phenologic data from Chinese observation stations --- including meteorological stations, agricultural and forest departments in 1352 Chinese counties --- are used to confirm the satellite results. The data is collected from the years 1980 and 1981 and cover 18 type of crops and 37 types of forest and herbage (Zhang fuchun,1987).

4. Methods

Physical models demonstrate that when the resistance is unity and the instantaneous voltage is x(t), then the instantaneous power will be $x^2(t)$ and the total energy can be expressed as:

$$\int_{-\infty}^{+\infty} x^2(t)dt \tag{1}$$

The statistical interpretation of Equation (1) is that the expected variance of x(t) is zero. The total energy or variance can be decomposed into fractional harmonic energy or variance. Suppose that

$$x(t) = \sum_{k=-\infty}^{+\infty} c_k e^{i\omega_k t} \tag{2}$$

Then, it follows that:

$$\frac{1}{T}\sum x(t)x(t)dt = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} \sum_{k=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} c_k^2 e^{i(2\omega_k)t}dt \tag{3}$$

$$\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} c_k^2 e^{i(2\omega_k)t}dt = \begin{cases} 1 & (k+k')=0 \\ 0 & (k+k')=0 \end{cases} \tag{4}$$

$$\frac{1}{T}\sum x(t)x(t)dt = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} c_k^2 \tag{5}$$

$$S_k^2 = 2\left|c_k\right|^2 = \frac{1}{2}(a_k^2 + b_k^2) \tag{6}$$

$$\begin{cases} a_0 = \dfrac{1}{T}\displaystyle\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)dt \\ a_k = \dfrac{1}{T}\displaystyle\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)\cos\omega_k tdt \\ b_k = \dfrac{1}{T}\displaystyle\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)\sin\omega_k tdt \end{cases} \tag{7}$$

From formula (6) the total variance of $x(t)$ can be decomposed into the sum of [n/2] harmonic variance terms. According to the variance test, assume that H_0: $E(a_k)=E(b_k)=0$. It follows that the statistical value

$$F = \frac{\frac{1}{2}(a_k^2 + b_k^2)/2}{\left(s^2 - \frac{1}{2}a_k^2 - \frac{1}{2}b_k^2\right)\Big/\left(n-2-1\right)} \tag{8}$$

is consistent with the distribution of F in which the numerator has 2 degrees of freedom and the denominator has n-3 degrees of freedom.

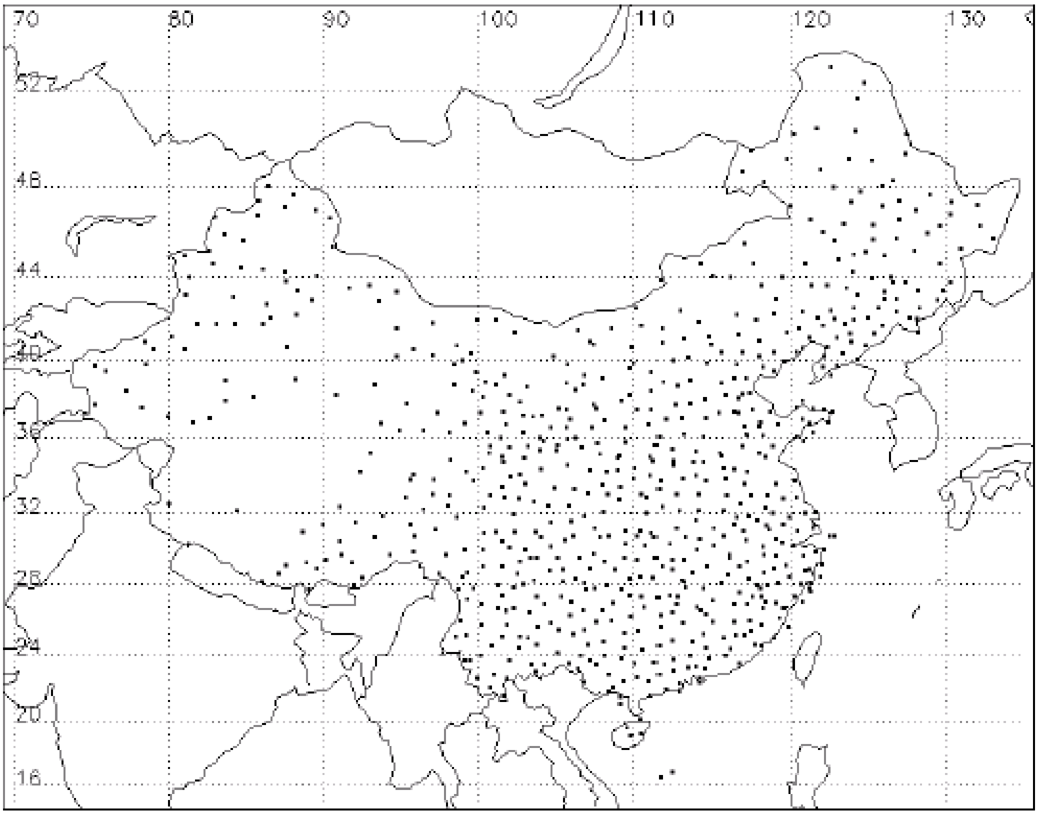

Fig.1 The distribution of observatory

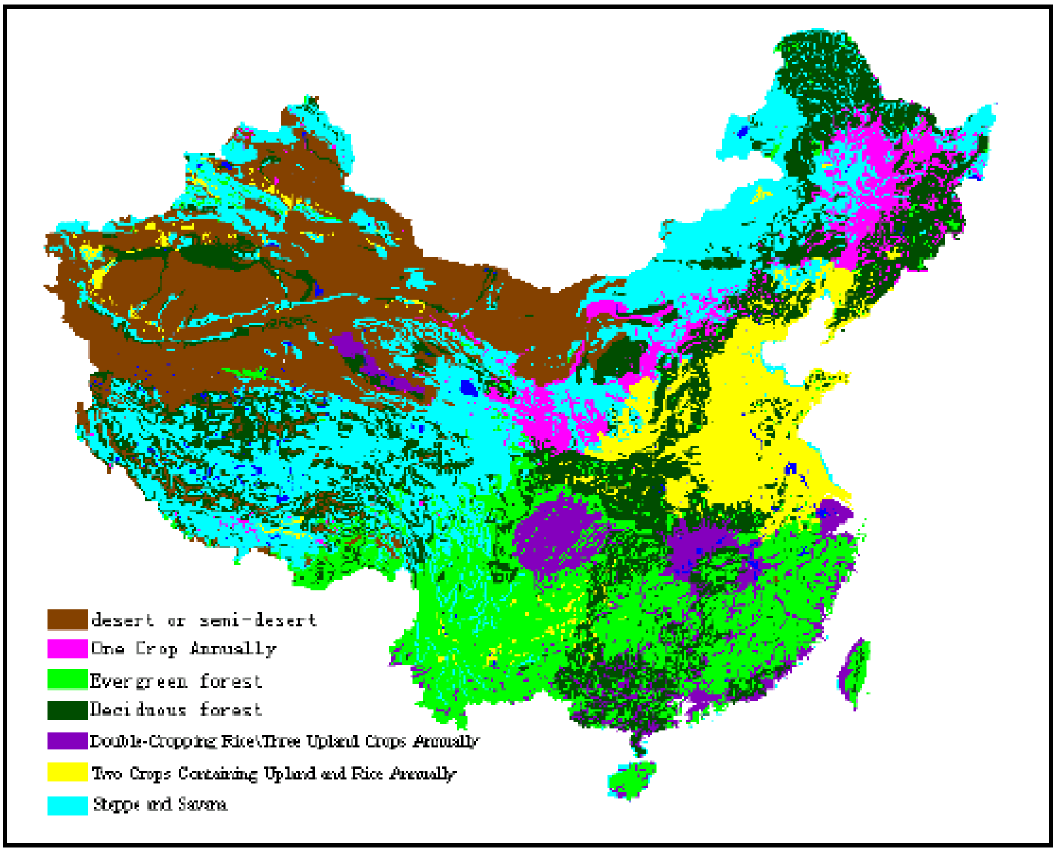

Fig. 2 The distribution of land surface cover

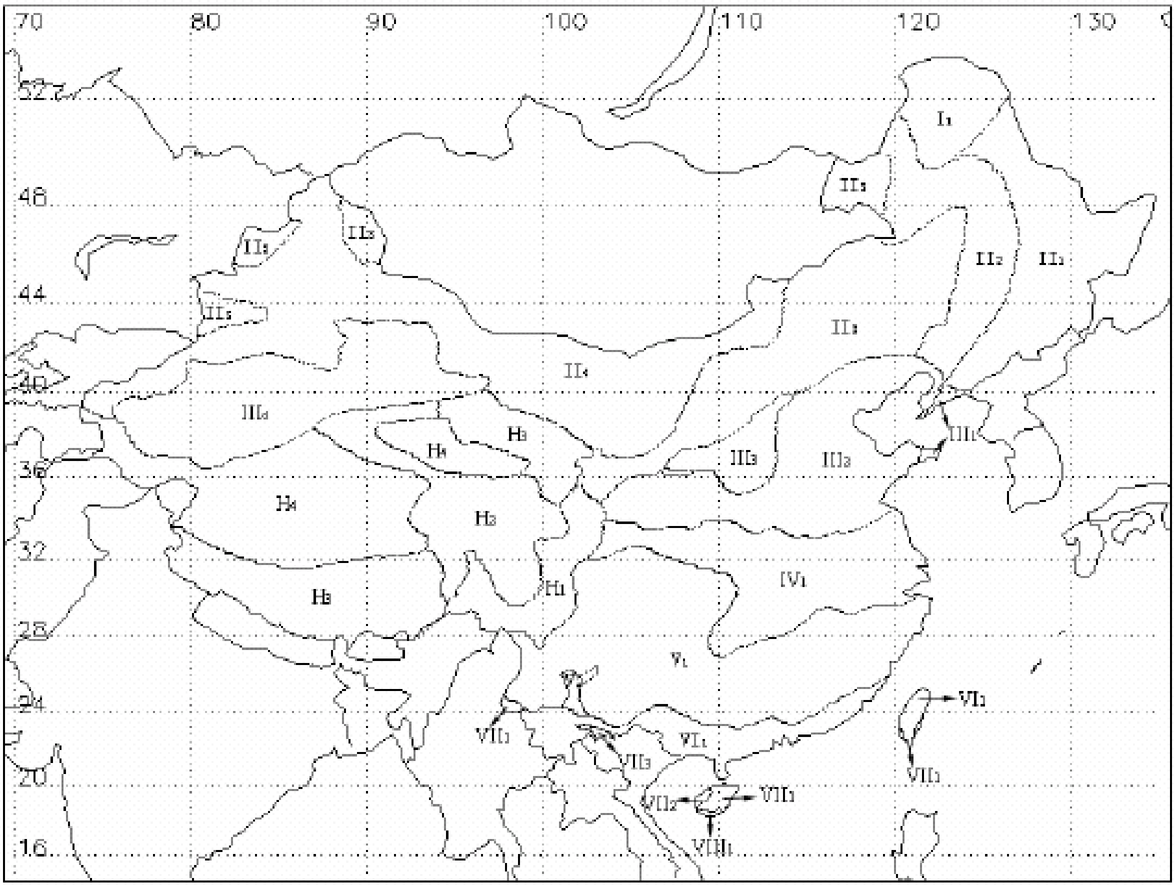

Fig. 3 Distribution of climatic region on the land-surface of China

Table1. The Climate division of China and distribution of observatory within every division

Climate division	Amount of observatory	Climate division	Amount of observatory
I_1 Humid North Temperate Zone	2	II_1 Humid Mid Temperate Zone	34
II_2 Sub-humid Mid Temperate Zone	25	II_3 Sub-dry Mid Temperate Zone	49
II_4 Dry Mid Temperate Zone	50	III_1 Humid South Temperate Zone	6
III_2 Sub-humid South Temperate Zone)	70	III_3 Sub-dry South Temperate Zone	10
III_4 Dry South Temperate Zone	16	IV_1 Humid North Subtropic	63
V_1 Humid Mid Subtropic	128	V_2 Sub-humid Mid Subtropic	2
VI_1 Humid South Subtropic	40	VII_1 Humid North Tropic	4
VII_2 Sub-humid North Tropic	1	VII_3Sub-dry North Tropic	0
VIII_1 Sub-humid Mid Tropic	2	H_1 Humid South Plateau	14
H_2 Sub-humid South Plateau	9	H_3Sub-dry South Plateau	20
H_4Dry South Plateau	8		

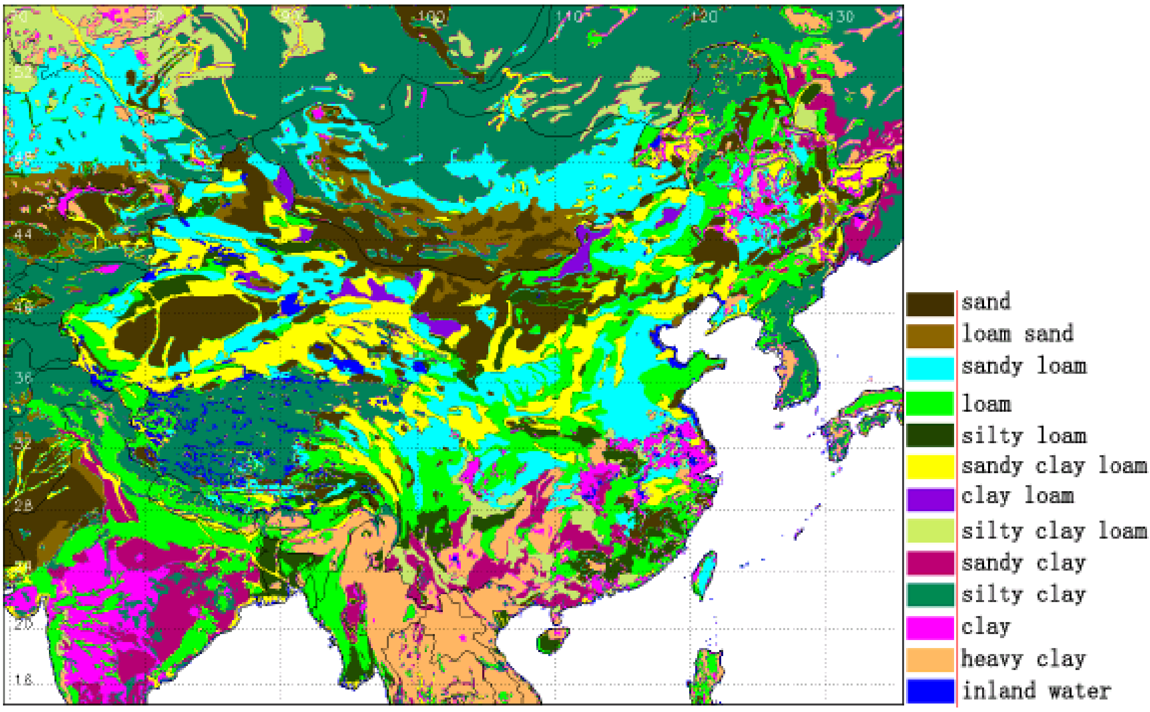

Fig. 4 The distribution of soil texture

Applying the above method (Equations 2 through 8), the NDVI data from 1982 to 2000 is decomposed into n/2 harmonic groups. In addition, every harmonic is tested. Using Equation 8 to calculate F, it follows that a 99.9 percentile confidence of the F distribution corresponds to $F_a=6.23$. Since $F>Fa$, we conclude that the harmonic is highly significant and the result is output.

5. Result and discussion

[n/2] harmonics are analyzed. The results suggest that there are three distinct vegetation periods in China. This is illustrated in Figure 5. In addition to white noise, every harmonic shall have a unique underlying characteristic/trend. The main reasons underlying each harmonic are herein described. Each harmonic will be analyzed separately. Specifically, the first harmonic of the discrete Fourier transform (DFT) is in-phase with atmospheric temperature, while the second and third harmonics are shown to concisely summarize human activity information.

5.1 The First Harmonic reflects climate influence on vegetaion

The entire area under investigation has a period of one year (is studied for a one year period), namely the first harmonic, as shown in Figure 5a.. The mean value of seasonal and climate variables determine the trends in vegetation change. Because climate occurs throughout a one year period in most regions under study, it is one of the most important factors determining vegetation change.

The vegetation type and growth period are influenced by local climate characteristics. In the event that climate is compatible with the vegetation, the period of vegetation growth is self-determined by physiological characteristics and there are higher correlations between vegetation and climate. In China, climate is relatively dry in the west, and humid in the east; northern regions of China have significantly lower temperatures that the southern parts, as illustrated in Figures 6 and 7. The land surface is primarily a function of climate characteristics.

The climatic divisions of southern China include the South Temperate Zone, Subtropic, Tropic and the Qingzang plateau; limited vegetation growth is also present in the Humid South Plateau, where the landscape is covered by sand, gravel, and bare-soil. Vegetation grows mainly in the eastern regions of China. In southern China, the growing season is longer, and the cropping index is higher, than other regions because of higher cumulative temperature. The vegetation consists mainly of evergreen forests, two crops annually, three crops in two year, two crops containing upland and rice annually, double-cropping rice or three upland crops annually. To maximize net productivity, human select the vegetation type that adapts best to the local climate presenting one year period. Accordingly, in this region, phenologies take on a one year period.

In May, the ripe winter wheat causes the correlation coefficient between NDVI and rainfall to decrease in the South Temperate Zone. Vegetation also does not depend on rainfall south of Yangtze River because of excessive rainfall. In June and July, vegetation requires more rainfall in the middle part of moist temperate zone, owing to upgrowth. Cultivation of a late autumn crop makes vegetation extremely dependent on rainfall. In the middle and lower reaches of Yangtze River, the advent of Meiyu leads to a lack of any correlation between NDVI and rainfall.

In the northern regions (which include the Humid North Temperate Zone, the Humid Mid Temperate Zone, the Sub-humid Mid Temperate Zone, and the Sub-dry Mid Temperate Zone) the annual mean temperature is relatively low and the vegetation consists of deciduous trees, grass, and one annual crop. Here, the vegetation's LAI shows a high rate of change from one month to the next. The vegetation varies, for the most part, according to the temperature.

The results show the regional characteristics of vegetation in each month. For example, vegetation does not grow in northern China in April because of low temperatures. During April, these northern regions have less rainfall but are suitable for the growth of winter wheat. Accordingly, the correlation coefficient between NDVI and rainfall is low. The regions with higher correlation coefficients are primarily located in the humid parts of the South Temperate Zone. On the other hand, the correlation coefficient in the subtropics and tropics is not high due to excessive rainfall and soil humidity (although this rainfall occurs during the vegetation period). In May, as temperature increases, the distribution of maximum correlation coefficients expands throughout northern China except for some regions with snow cover, where melting snow causes the soil to increase in humidity. However, with the exception of these areas, the correlation coefficient between NDVI and rainfall increases in all other northern regions.

The temporal lag of NDVI behind rainfall differs significantly among climatic regions with correlation coefficients higher than 0.3. In drought regions, even a limited rainfall can increase the vegetation cover significantly. Accordingly, the time lags are less than in other regions. For example, in rainy regions, precipitation supplies water continuously for vegetation growth and results in relatively long time lags.

In April the southern humid temperate zone has a relatively high correlation coefficient between NDVI and rainfall --- and rainfall occurring between day 45 and 65 is best relative to NDVI. This means vegetation will be most effected if the total precipitation occurs within days 45 to 65. In May, vegetation in the mid variable/region zones and semi-drought regions is highly sensitive to rainfall. As a consequence, rainfall occurring within day 15 to 45 is most important for vegetation. In June and July, soil moisture in northern China trend to be in stable condition. So the days of rainfall are basically limited to 25-45.

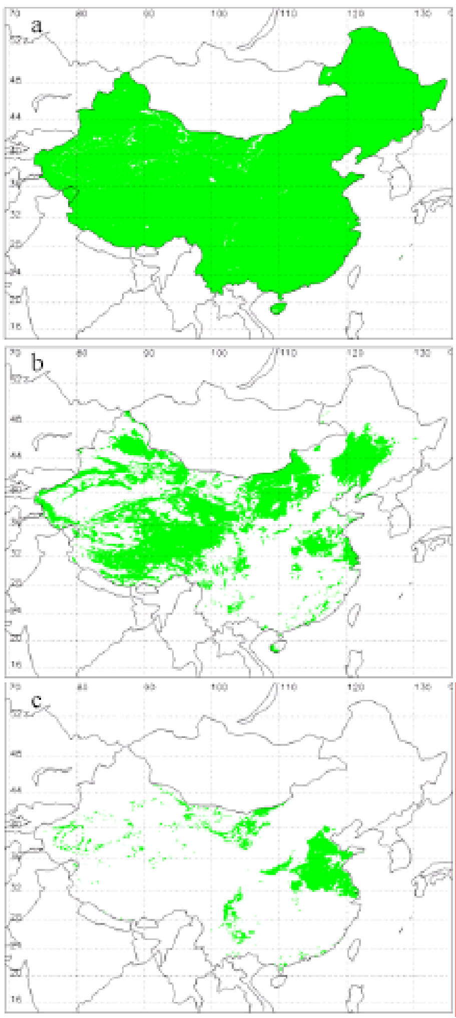

Fig. 5 The distribution of first second and third harmonic

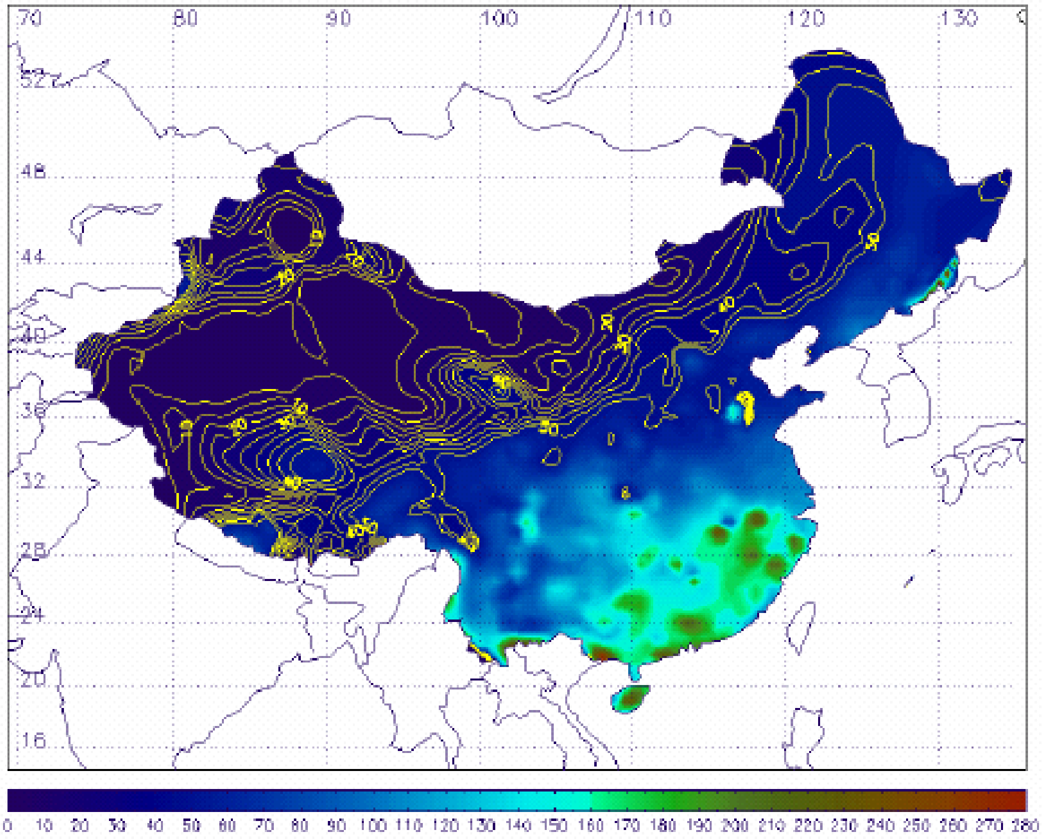

Fig 6. The distribution of annual mean amount of precipitation(cm)

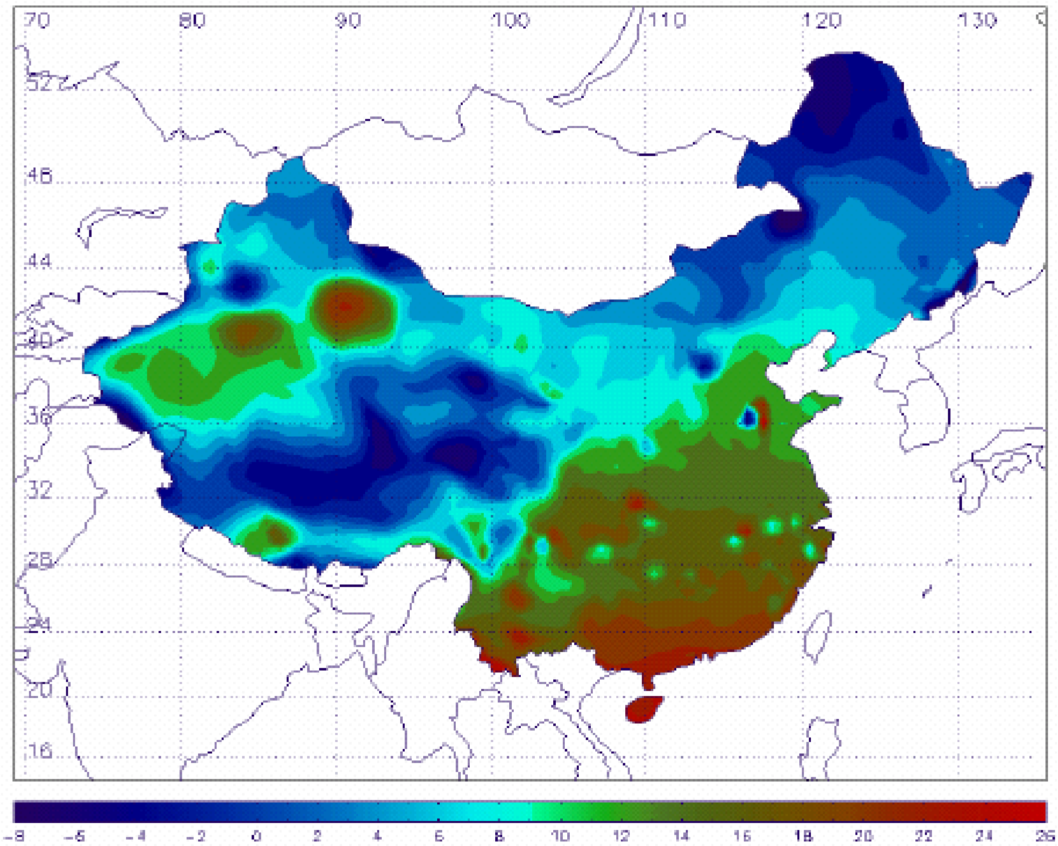

Fig 7 The distribution of annual mean temperature(℃)

The relationship between NDVI and temperature is contrary to the relationship between NDVI and rainfall due to inverse-correlation between temperature and rainfall. During the rainy season, precipitation is a primary factor inhibiting plant growth, so correlation between NDVI and temperature is, in general, higher than the correlation between NDVI and rainfall. In addition, during the wet season, vegetation growth requires higher temperatures. In the dry season, however, these correlations are not evident.

The different soil textures and vegetation types will cause heterogeneous correlation distributions between NDVI and rainfall or temperature. Consider the correlation between NDVI and rainfall: sandy texture regions will lead to higher correlations than the clay texture regions. In the context of the correlation between NDVI and temperature, sandy texture regions will lead to lower correlations than clay texture regions.

5.2 Second and Third Harmonic—reflect human activities influence on vegetation.

Climate distinctions across China from north to south lead to different distributions of vegetation and agricultural practices. In addition, the land use and cropping index also change with climate, as shown in Figure 8. In the north, the growth period is relatively short (temperature is the main factor limiting vegetation growth). Vegetation, including both naturally occurring plants and human-planted crops, are at the same phase as temperature throughout the year and take on single peak value. In northern regions, there is not an obvious distinction between the period of natural and farming vegetation.

On the other hand, in the southern provinces of China, the benign climatic condition makes it possible to plant two or three crops annually. From Figures 5b and 5c, the second or third harmonic is present in several northern AND SOUTHERN regions, such as the Humid Mid Temperate Zone (II_1), the Sub-humid Mid Temperate Zone (II_2), the Sub-dry Mid Temperate Zone (II_3), the Dry Mid Temperate Zone (II_4), the Humid South Temperate Zone (III_1), the Sub-dry South Temperate Zone (III_3), the Dry South Temperate Zone (III_4), the Sub-humid South Plateau (H_2), the Sub-dry South Plateau (H_3), and the Dry South Plateau (H_4), where the period of vegetation growth is only one year because temperature acts as a limiting factor. However, when comparing the Dry South Plateau region with areas that experience snow cover and frequently occurring sandstorms, we find that the second or third harmonic in the region is NDVI is very sensitive to land surface changes. In WHAT season, snow cover melts and sandstorms are

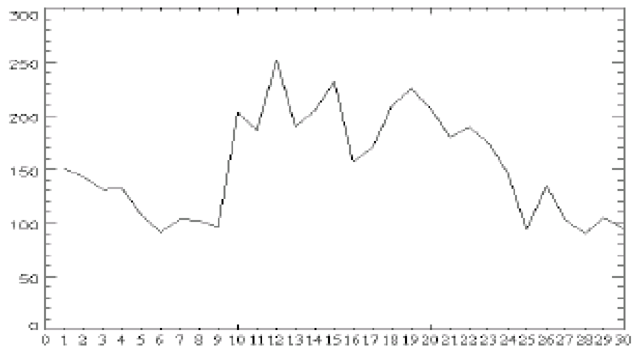

Fig8. The cropping index of china in 1987(%)

Table 2.

1	2	3	4	5	6	7	8	9	10
average	Beijing	Tianjin	Hebei	Shanxi	Inner mongolia	Liaoning	Jilin	Hei Longjiang	Shanghai
11	12	13	14	15	16	17	18	19	20
Jiangsu	Zejiang	Anhui	Fujiang	Jiangxi	Shandong	Henan	Hubei	Hunan	Guangxi
21	22	23	24	25	26	27	28	29	30
Guangxi	Sichuan	Guizhou	Yunnan	Tibet	Shan'anxi	Gansu	Qinghai	Ningxia	Xinjiang

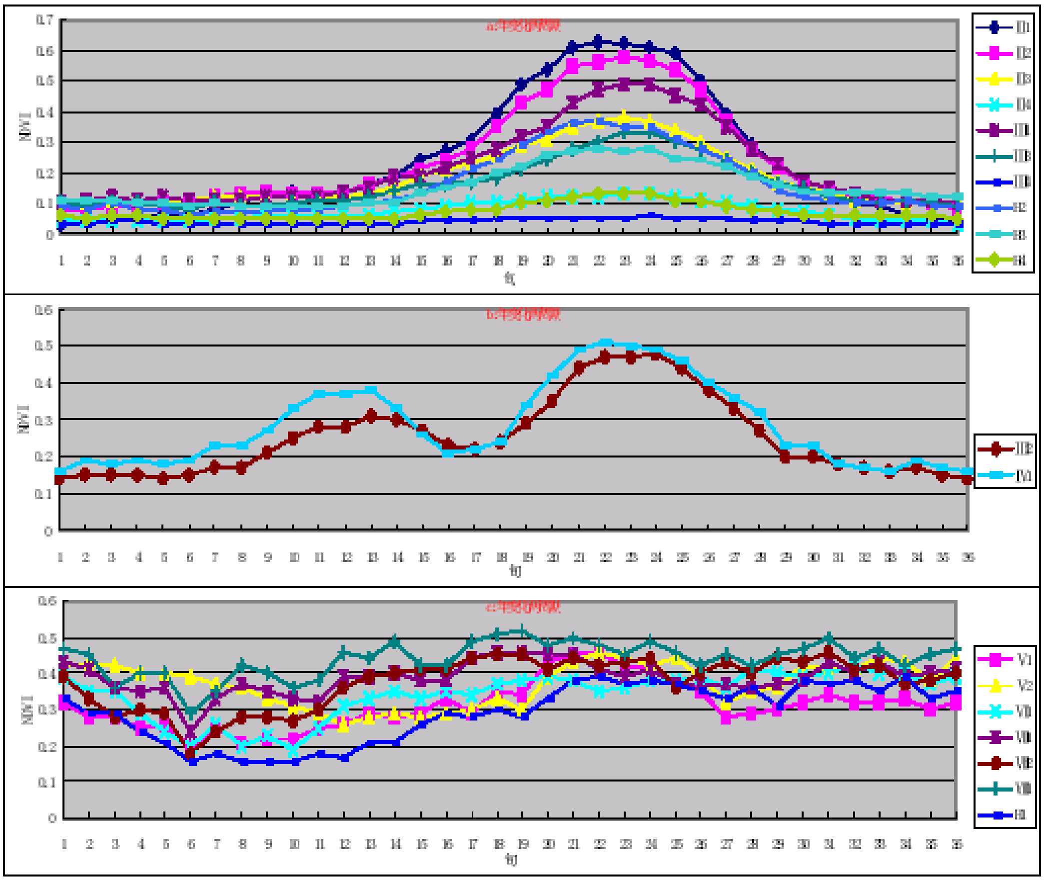

Fig 9 The NDVI characteristics in the region of second harmonic

frequent. Regardless of how much snow cover melts or how many sandstorms occur, the period (the period of WHAT!!) is still approximately the same. Melting snow cover will cause the NDVI to increase, and sandstorms will change the land surface characteristics.

Accordingly, in this region (WHAT REGION), the second or third harmonic show only a minor fluctuation when compared with other climate regions (see Figure 9a). For example, in most northern regions of China, there is little amplitude in March because of the change in snow cover. The Sub-humid South Temperate Zone (III$_2$) and Humid North Subtropic (IV$_1$), are situated on North China and Changjiang delta where most vegetation is influenced by human activities: agricultural crops and non-timber product forest dominate the landscape. For example, winter wheat is grown during the October to May period while dry farming or rice is continuously planted. Accordingly, the second harmonic is significant, as shown in Figure 9b. For other regions (Fig 9c) the NDVI exhibits a smooth change because the higher accumulated temperature and sufficient precipitation permits vegetation planting throughout the year.

The third harmonic is mainly distributed in the Humid South Temperate Zone (III$_{1)}$, the Sub-humid South Temperate Zone (III$_2$), the Sub-dry South Temperate Zone (III$_3$), the Dry South Temperate Zone (III$_4$), the Humid North Subtropic (IV$_1$), the Humid Mid Subtropic (V$_1$), the Sub-humid Mid Subtropic (V$_2$), the Humid South Subtropic (Ⅵ1), the Humid North Tropic (VII$_1$), the Sub-humid North Tropic (VII$_2$), the Sub-dry North Tropic (VII$_3$), the Sub-humid Mid Tropic (VIII$_1$), and the Humid South Plateau (H1). The common characteristics in these regions are the suitable year-round climate for vegetation growth and a higher cropping index(**Fig10**). The types of crops are “double-cropping rice” or “three upland crops annually”.

In the Humid South Temperate Zone (III$_1$), the Sub-humid South Temperate Zone (III$_2$), the Sub-dry South Temperate Zone (III$_3$), and the Humid North Subtropic (IV$_1$) farmland predominates. Zone XX has a higher amplitude than the Humid Mid Subtropic (V$_1$), the Sub-humid Mid Subtropic (V$_2$),. The Humid North

Tropic (VII_1), and the Sub-dry North Tropic (VII_3) where cropland is mixed with forest. In the Sub-dry Mid Temperate Zone (II_3) and the Humid South Plateau (H_1) vegetation exhibits a smaller amplitude because lower density of vegetation cover. The harmonic results compare favorably with the observational phonologic data.

6. Conclusion

Most land surface models (LSM) are incapable of capturing the degree to which human perturbations effect the landscape/climate system.. Human activities can have profound and unexpected consequences on natural systems due to complex feedbacks across a wide spectrum of spatio-temporal scales. To improve land surface monitoring, the impact of both human influences and phenology on vegetative canopies was considered using remotely sensed NDVI data from NOAA AVHRR and DFT analysis. Harmonic analysis of temporal NDVI in southern China shows that the first harmonic is in-phase with atmospheric temperature, while the second and third harmonic include human activity information.

Precipitation and temperature distributions allow us to accurately estimate whether land surface changes are caused by human activities or climatic variables. The temperature distribution shows that in the region of the second and third harmonics the annual minimum, mean, and maximum temperatures are more than 2°C, 8°C and 14°C higher on average. The second and third harmonics are also found to be highly dependent on the precipitation distribution. For example, there is a higher cropping index in the North-China plain and Changjiang delta than in regions to their west; these western regions possess little vegetation due to a lack of precipitation and corresponding dry climate. Even if a region has higher temperatures, giving rise to a larger cropping index, the lack of precipitation will restrict vegetation growth. As shown in Figure 6, the monthly mean precipitation in a region should exceed 50mm in order to match the cropping index of warmer regions. The results are consistent with a large body of literature which has shown rainfall to be a critical variable determining ecological health. For example, depending on rainfall variability, rangeland ecosystems have been characterized as intrinsically stable, unstable, fragile and extensively degraded, or highly resilient.

The characterization of land-surface phenologies in China can be useful for remote sensing applications including drought management, the monitoring of land use conversions and forest fire detection. However, real-time utilization of remote sensing for emergency risk management requires a dedicated system (constellation) providing day-to-day information of critical areas.

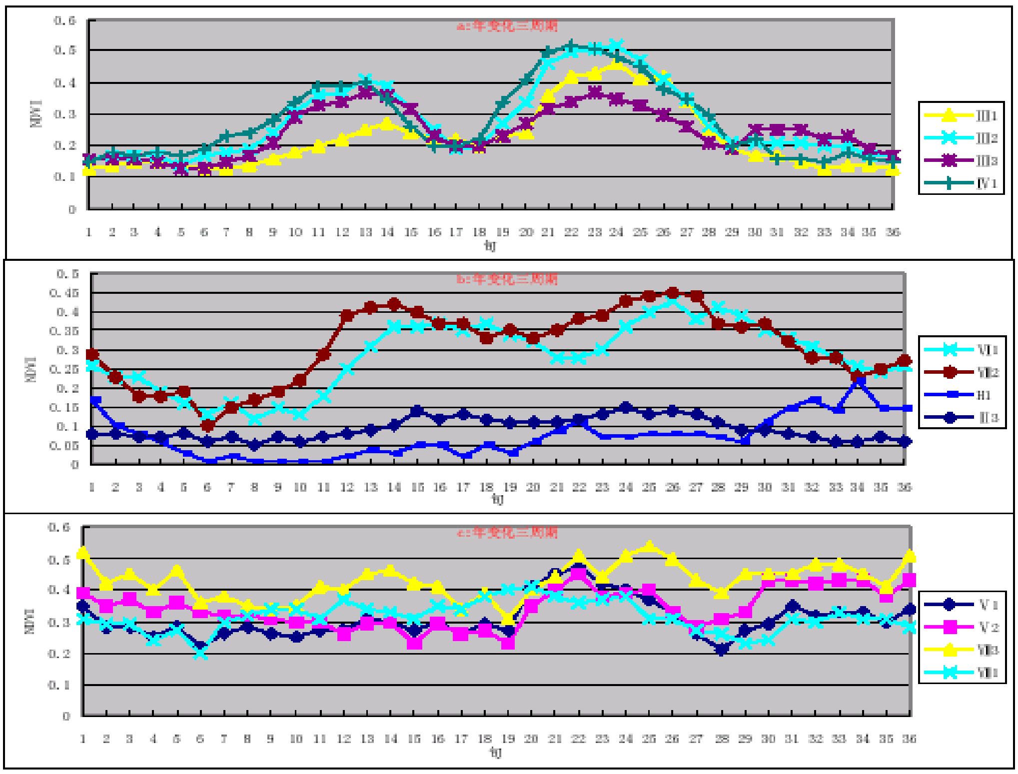

Fig 10 The NDVI characteristics in the region of third harmonic

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要旨

米国海洋大気庁（NOAA）による衛星搭載の改良型高分解能放射計（AVHRR）によって遠隔測定された正規化差分植生指数（NDVI）データは，地域的とある一国の規模での生物気候学的な植生について，人間による影響と自然の擾乱のレジーム／気候の両方の効果をモデル化するために使われる。特に，1982 年から2000 年までのNDVI NOAA AVHRR データが，離散フーリエ変換（DFT）を使用して人間活動の影響を気候，自然の因子から識別するために使われた。

キーワード: 生物気候学，衛星搭載の光学測器，中国