Identifying Scale-location Specific Control on Vegetation Distribution in Mountain-hill Region

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Abstract: The scale-location specific control on vegetation distribution was investigated through continuous wavelet transforms approaches in subtropical mountain-hill region, Fujian, China. The Normalized Difference Vegetation Index (NDVI) was calculated as an indicator of vegetation greenness using Chinese Environmental Disaster Reduction Satellite images along latitudinal and longitudinal transects. Four scales of variations were identified from the local wavelet spectrum of NDVI, with much stronger wavelet variances observed at larger scales. The characteristic scale of vegetation distribution within mountainous and hilly regions in Southeast China was around 20 km. Significantly strong wavelet coherency was generally examined in regions with very diverse topography, typically characterized as small mountains and hills fractured by rivers and residents. The continuous wavelet based approaches provided valuable insight on the hierarchical structure and its corresponding characteristic scales of ecosystems, which might be applied in defining proper levels in multilevel models and optimal bandwidths in Geographically Weighted Regression.

Key words: NDVI; Continuous wavelet transform; Characteristic scale; Mountain-hill region; Scale-location specific

Introduction

The evaluation of spatial patterns and their spatial scales of expression is very important to better understand spatial processes in ecology (Dungan et al. 2002). Spatial pattern analysis remains challenging when these spatial relationships were examined by large ecological datasets that include patterns determined by multiple processes operating at multiple scales (Holling 1992). For example, vegetation cover was influenced by individual or combined effects from climate, topography, soil properties, and anthropogenic factors. The multi-scale spatial pattern of vegetation cover has been investigated in a number of recent studies (Lookingbill et al. 2011; Nelson et al. 2007; Propastin 2011; Gao et al. 2012). Among them, the multi-scale correlation and Geographically Weighted Regression (GWR) approaches were generally applied (Nelson et al. 2007; Propastin 2011). In these studies, the multi-scale analysis was based on results from each specific scale individually, but not simultaneously and continuously. Continuous approaches are more attractive in order to identify scales of patterns in a complex hierarchical ecosystem. Identifying scale-location specific control on vegetation distribution will enrich our knowledge of the complex vegetation distribution patterns.

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Recently, the continuous wavelet transform method was utilized to investigate multi-scale spatial pattern of vegetation cover across an area (He et al. 2007; Xie and Liu 2010). The wavelet variance, calculated from local wavelet spectrum, could provide valuable information of dominant spatial variability as well as the characteristic scales of vegetation distribution. Wavelet coherency could simultaneously examine the correlation between spatio-temporal patterns of two variables at differing scales, locations, and times (Cazelles et al. 2008; Grinsted et al. 2004). Wavelet coherency has also been successfully applied to identify the location-specific correlation of soil water storage with topographic conditions (Biswas and Si 2011b) and wheat yield with topographic indices (Si and Farrell 2004). Until now, however, few studies have provided the cross-scale relationship between vegetation cover and its influencing factors (Xie and Liu 2010; Keitt and Urban 2005).

In this study, the multi-scale spatial patterns of vegetation distribution and its connections with topographic, climatic and anthropogenic factors in a mountain-hill region were investigated through a continuous wavelet analysis. The Normalized Difference Vegetation Index (NDVI) calculated from Chinese Environmental Disaster Reduction Satellite image was utilized as an indicator for vegetation cover. We asked three specific questions: (1) How many characteristic scales and scale domains are there observed from vegetation distribution patterns in a subtropical mountain-hill region? (2) For each characteristic scale and scale domain, is there any dominant influencing factors controlling the complex vegetation distribution patterns? (3) Could those phenomena examined at different scale domains be uniformly confirmed from position-specific analysis? If not, in what circumstances could be those exceptions?

1 Materials and Methods

1.1 Study area

Fujian province is located between 23°32'–28°19'N latitude and 115°50'–120°43'E longitude, in Southeast China. The widest part is around 480 km and the length is approximately 530 km. The total land area is 121,400 km². Located in the

subtropical humid areas, the annual mean temperature of Fujian fluctuates between 17 and 21°C and the yearly precipitation varies between 920–2,100 mm (Lu 1999). There is a very diverse relief with elevations of zero in the eastern coastal areas and upwards of 2,258 m in the northwest. Across this gradient, land cover varies from paddy fields near the coastal areas to evergreen hardwood forests, mixed forests, conifer forests, and meadows as elevations increase. The various plant communities contribute not only to Fujian's high plant diversity, with more than 4,700 species of vascular plants, but also to high animal diversity, with over 1,600 species of terrestrial vertebrates (Fujian 2010). For the past several decades, Fujian ranks in the first in China for its high ratio of vegetation cover. Using the threshold elevations of 500 and 50 m to distinguish between mountains, hills, and plains the mountain ratio of Fujian is 15:3:2 (Lu 1999). The central mountain is located in the west and central regions of the province, hindering the passage of cold air from the inland. To the west are the Wuyi and Shaling mountains, and in the middle are the Jiufeng and Danyun mountains.

1.2 HJ-1 satellite image and NDVI calculation

The data utilized in this study came from the Chinese Environmental Disaster Reduction Satellite (HJ-1 satellite for short), which includes A star and B star with an orbital altitude of 650 km. The HJ-1A/B satellite was launched on September, 2008. The spectrum scope covers blue light (0.43–0.52 μm), green light (0.52–0.60 μm), red light (0.63–0.69 μm), and near-infrared light (0.76–0.9 μm). The sub-satellite resolution is 30 meters and the breadth of two cameras is 710 km.

Two cloud free HJ-1 satellite images, acquired on December 17th and December 9th, 2010 respectively, were used to represent the range of vegetation greenness in Fujian province. Geometric correction was made using 1:10,000 topographic maps, while GPS route recording and ground truth data was used to guarantee that the alignment error was within one pixel. According to the experience linear transformation, the atmospheric radiation correction and the reflection conversion were obtained using the actual reflectivity of

ground calibration body and the corresponding primitive DN value of the satellite images. NDVI was calculated as: $NDVI = (\rho_N - \rho_R) / (\rho_N + \rho_R)$, where ρ_N , ρ_R are the NIR and red bands corresponding to the ETM scaled band 4 and 3 reflectance data (Figure 1). The map projection was converted to Universal Transverse Mercator using ENVI image processing software.

Two sampling lines were set along the latitudinal transect (sampling line A, starts from 26°11'48.1"N, 116°23'13.2"E and ends at 26°11'48.1"N, 119°37'48"E) and the longitudinal transect (sampling line B, starts from 27°25'20.3"N, 119°13'51.6"E, ends at 23°41'35.9"N, 117°03'0.1"E) respectively (Figure 1). The latitudinal transect runs across four regions from west to east, i.e. Wuyi Mountains, Daimao Mountains, Daiyun Mountains, and low reaches of Minjiang basin. The longitudinal transect runs across three regions from north to south, i.e. Jiufeng Mountains, Daiyun Mountains, and Zhangzhou plain.

1.3 Candidate explanatory variables

The vast diversity of environmental situations and plant hereditary conditions can cause variability of vegetation distribution. As many of the direct determinants are difficult or expensive to access (Wang et al. 2010), the physical and human geographical proxies of vegetation cover determinants were selected due to their easy collection and implementation in ArcGIS.

Numerous studies have confirmed that topographic variables, accessibility, and climate conditions play an important role in the vegetation distribution (Nie et al. 2012; Bayramov et al. 2012; Propastin 2012; Viviane et al. 2012). Candidate explanatory variables utilized in this paper included topographic variables (elevation and slope), accessibility variables (distance to nearest rivers and the distance to nearest residents) and land use intensity (LUI) calculated with reference on related study (Zhuang and Liu 1997). Forest & grass land, agricultural land, construction land, unused land & water body, were assigned with scores of 100, 200, 300 and 400 respectively.

The DEM dataset utilized was the ASTER_GDEM dataset (version 1, downloaded from <http://www.gdem.aster.ersdac.or.jp/search.jsp>), with the spatial resolution of 30 m. Topographic variables, such as slope and aspect, were calculated from DEM dataset using ArcGIS software. Climatic variables such as temperature and precipitation were not considered due to its co-linearity with elevation or very weak correlation with NDVI. Meteorological datasets were obtained from the Meteorological Information Centre of Fujian province, China. Other datasets used for this study consisted of spatially explicit land use data and forest type data. The 1:100,000 land use distribution map was collected from the Geological Mapping Bureau, and a variable of land use intensity was calculated. The accessibility variables were calculated through a standard distance

Figure 1 The spatial distribution of (a) NDVI dataset and (b) the two transects in Southeast China

operation in ESRI software ArcGIS 9.3.

1.4 Continuous wavelet transform

Wavelet analysis is a powerful signal processing tool which has been successfully applied in remote sensing image processing to extract information at various scales (Partal 2010; Biswas and Si 2011b). The Continuous Wavelet Transform (CWT) converts the analyzed signal (i.e. the NDVI data series along one transect) into sets of coefficients by scaling (scale parameters a) and shifting (space-localized parameter b) the mother wavelet function.

$$W_{\psi}(a, b) = |a|^{-\frac{1}{2}} \int_{\mathbb{R}} f(s) \psi\left(\frac{s-b}{a}\right) ds \quad (1)$$

where $\psi(s)$ is the mother wavelet function, $f(s)$ is the analyzed signal and s represents position. The wavelet coefficients are calculated at each possible scale and location. Therefore, the continuous wavelet transform turns a one-dimensional data series $f(s)$ into a two-dimensional matrix, the wavelet coefficients. The CWT coefficients ($W_{\psi}(a_i, b_j)$), $i = 1, 2, \dots, m$, $j = 1, 2, \dots, n$ constitute a 2-dimensional spectrum (i.e. an $m \times n$ matrix), where one dimension is the scale ($i = 1, 2, \dots, m$) and the other is position ($j = 1, 2, \dots, n$). The magnitude of the wavelet coefficients at a location and scale represents the local variance at that specific location and scale, and the sum of local spectrum over a certain scale range denotes the total variance within the specific scale range. Therefore, the wavelet spectrum could be applied to examine the spatial variation of vegetation properties at different scales and locations. In order to characterize the 2-dimensional wavelet spectrum, the position-averaged wavelet variances were calculated.

$$W_{\psi}(a_i) = \frac{1}{n-1} \sum_{j=1}^n (W(a_i, b_j) - \bar{w}(a_i))^2 \quad (2)$$

where $\bar{w}(a_i)$ is the computed average of the wavelet coefficients for a selected scale a_i , b_j represents different locations of the analyzed signal $f(s)$. When wavelet variances are plotted as a function of scale, it can be utilized to determine the scales of pattern in the analyzed signal. There are many basic functions with different shapes and characteristics which could be applied in the wavelet transform (mother wavelets). The Morlet wavelet was finally chosen since it has been shown

to provide satisfying results for scale analysis in geography research areas (Partal 2010; He et al. 2007). The continuous wavelet analysis was executed using the Matlab software package (The MathWorks, Natick, Massachusetts, USA). All variables were standardized by subtracting their mean and dividing by their standard variations in order to facilitate comparison between the local wavelet spectra.

1.5 Wavelet coherency analysis

The cross wavelet power spectrum between two spatial series Y and Z can be defined as (Grinsted et al. 2004; Torrence and Compo 1998).

$$|W_i^{YZ}(s)| = |W_i^Y(s) \overline{W_i^Z(s)}| \quad (3)$$

where W_i^Y and W_i^Z are the wavelet coefficients of the data series Y and Z . $\overline{W_i^Z(s)}$ is the complex conjugate of W_i^Z . While wavelet cross spectra are similar to the covariates in the spatial domain, the wavelet coherence spectra are similar to the coefficients of determination in the space-scale domain for the two variables (Biswas and Si 2011a). The wavelet coherency explains the correlation between two variables at each scale and location. Wavelet coherency between vegetation cover and its potential influencing factor is defined as (Torrence and Webster 1999).

$$R_i^2(s) = \frac{|S(s^{-1} w_i^{XY}(s))|^2}{S(s-1 |W_i^X(s)|^2) S(s-1 |W_i^Y(s)|^2)} \quad (4)$$

where S is defined as a smoothing operator that can be written as

$$S(W) = S_{scale}(S_{space}(W(s, \tau))) \quad (5)$$

where τ denotes the location, S_{scale} and S_{space} represent the smoothing along the wavelet scale axis and the spatial domain, respectively (Si and Zeleke 2005). The smoothing function is the normalized real Morlet wavelet and has a similar footprint as the Morlet wavelet:

$$\frac{1}{s\sqrt{2\pi}} \exp\left(-\frac{\tau^2}{2s^2}\right) \quad (6)$$

Therefore, the smoothing along locations can be written as (Torrence and Webster 1999):

$$S_{space}(W(s, \tau)) = \sum_{k=1}^N \left(w(s, \tau) \frac{1}{s\sqrt{2\pi}} \exp\left(-\frac{(\tau - xk)^2}{2s^2}\right) \right) \Big|_s \quad (7)$$

And the smoothing along scales can be written

as:

$$S_{scale}(W(sk, x)) = \frac{1}{2m+1} \sum_{j=k-m}^{k+m} (S_{scale} w(sj, x) \Pi(0.6sj)) \Big|_x \quad (8)$$

where Π is the rectangle function, $|_x$ means at a fixed x value, and j is the index for scales. The factor of 0.6 is the empirically determined scale decorrelation length for the Morlet wavelet (Torrence and Compo 1998).

The statistical significance of wavelet variance can be assessed relative to the null hypotheses stating that the signal is generated by a stationary process with a given background power spectrum (P_k) (Grinsted et al. 2004). Many geophysical time series have distinct red noise characteristics that can be modeled very well by a first order autoregressive (AR) process. Therefore, the red noise is modeled as a univariate lag-1 autoregressive (AR1) process (Grinsted et al. 2004). The red noise is treated as the background or the null hypothesis for the statistical test. For testing the statistical significance of wavelet coherency, one thousand realizations of a pair of spatial series were generated and the wavelet coherency of each

realization at each scale and location was calculated and sorted in ascending order. The 95th wavelet coherency value at a scale and location would therefore give the 95th confidence level at that scale and location. If the actual global wavelet spectrum is significantly greater than the red noise spectrum at a confidence level of 95%, then it can be assumed to be a significant difference from that of red noise with this confidence.

2 Results

2.1 Spearman rank correlation analysis of NDVI and its influencing factors

The NDVI, elevation, slope, land use intensity, and two accessibility variables along the latitudinal transect are provided in Figure 2. There were four main knolls (Wuyi Mountains, Daimao Mountains, Daiyun Mountains and Shou Maintains) along the latitudinal transect. Additionally, there are three main depressions (Shaxi River, Youxi River, and Minjiang River) and two small depressions (Jiulongxi River, Aojiang River) along this transect.

Figure 2 Measured values of (a) NDVI, (b) elevation, (c) slope, (d) land use intensity (LUI), (e) distance to nearest rivers, and (f) distance to nearest residents along the latitudinal transect

The elevation data presented a similar pattern: large values on the knolls and small values on the depressions. The land use intensity, however, displayed an opposite pattern, with small values on knolls and large values on the depressions. The NDVI curve along the latitudinal transect exhibits a general pattern with the elevation, and provides detailed fluctuations that represent the variations observed from land use intensity. Visual inspection revealed that the spatial variation of NDVI, elevation, land use intensity and accessibility variables exhibited non-stationarity with several localized features and trends along the transect.

Statistical analysis also confirmed that NDVI was significantly correlated with candidate influencing factors. The strongest correlation was observed between NDVI and land use intensity ($r^2 = -0.634$, $p < 0.001$). Very strong correlation was also examined between NDVI and elevation ($r^2 = 0.617$, $p < 0.001$). The topographic and accessibility variables had positive connections with NDVI, which indicated that considerably large NDVI values were observed in areas with relatively sloping altitudes away from rivers and residents.

Variables of land use intensity exhibited negative influences on the spatial distribution of NDVI, indicating that less land use intensity lead to better vegetation greenness.

2.2 Controlling factors of vegetation distribution

2.2.1 Wavelet variance of NDVI along the latitudinal transect

The position-averaged wavelet variances of NDVI, elevation, slope, land use intensity, and other accessibility variables are provided in Figure 3. Distinct spatial patterns were observed from NDVI and its candidate influencing factors at different scales. In general, four scales of variation, 0–9 km, 9–27 km, 27–45 km and above 45 km, were revealed from the position-averaged wavelet variance for NDVI, Elevation and LUI across the latitudinal transect. For the 0–9 km scales, the intensity of local wavelet spectrums of NDVI, Elevation and LUI were very weak and generally not significantly greater than the red noise. For the 9–27 km scales, the intensity of local wavelet

Figure 3 The position-averaged wavelet variance of (a) NDVI, (b) elevation, (c) slope, (d) land use intensity (LUI), (e) distance to nearest rivers, and (f) distance to nearest residents along the latitudinal transect

spectrum of NDVI, Elevation and LUI slightly increased, with local maximum values synchronously observed around 20 km. Statistical testing results indicated that the wavelet variances around 20 km are significantly different from those of the red noise. For the 27–45 km scales, the intensity of local wavelet spectrum of NDVI was generally significantly greater than the red noise, with local maximum value seen at 35 km. Nevertheless, the intensity of local wavelet spectrums of Elevation and LUI were fairly weak and generally not significantly greater than the red noise. Much greater and significant wavelet variances were synchronously detected from the local wavelet spectrums of NDVI, Elevation, and LUI at scales above 45 km. The total variances of other two large characteristic scales (60 km & 90 km) were much greater than those of observed at two smaller scales (20 km & 35 km). The characteristic scale of 60 km was also shown by the local wavelet spectrum of LUI. Another two characteristic scales, 55 km and 75 km, were also displayed by the local wavelet spectrum of Elevation and roughly corresponded to the average size of dominant mountains and hills.

Differing from those observed in NDVI, Elevation and LUI, two scales of variation were also observed from the local wavelet spectrum of slope and the two accessibility variables. In general, significant wavelet variances were only recognized at large scales (for slope, >60 km; for distance to rivers, >45 km), with local maximums roughly examined at 60 km which corresponds to maximums observed from NDVI. Different from any other candidate influencing factors, the local wavelet spectrum of distance to nearest residents displayed significant variance only at small and medium scales. The magnitude of wavelet variances at the 25–50 km scale was much greater than other scales, with the characteristic scales examined being 30 km and 45 km.

Four scales of variation were synchronously observed from the local wavelet spectrum of NDVI, Elevation, and LUI; which suggests the effect of terrain and land use intensity upon NDVI. Greater variances were observed from the local wavelet spectrum of NDVI and all its influencing factors at relatively large scales, except the accessibility variables. This indicates the strong influence of topographic conditions and land use intensity on

NDVI at large scales. The spatial variability of NDVI at 27–45 km scales possibly results from accessibility variables such as distance to the nearest resident.

2.2.2 Wavelet coherency analysis along the latitudinal transect

The scale and location specific correlation between vegetation greenness and the controlling factors was calculated using wavelet coherency. Differing intensities and patterns of wavelet coherency was revealed between NDVI and its influencing factors at different spatial scales (Figure 4). According to the dominant coherencies between vegetation greenness and its controlling factors, four principal scales of coherencies; up to 9 km (small scale), 9–27 km (medium scale), 27–45 km (large scale), and above 45 km (very large scale) were identified.

At less than 9 km, the average wavelet coherency between vegetation greenness and elevation was 0.36 with a standard derivation (SD) of 0.24. A mere 30% of locations were significantly greater than the red noise. Similarly, the small-scale average coherencies between vegetation cover and all other controlling factors (i.e. land use intensity, slope) were also relatively small. Very few locations at small scales had significant coherency between vegetation cover and its relevant influencing factors.

The 9–27 km scale average coherency was 0.62, 0.53, 0.58, and 0.48 between vegetation greenness and elevation, slope, land use intensity, and distance to nearest river respectively, with over fifty percent locations significantly greater than red noise. However, there was relatively small average coherency (less than 0.26) between vegetation greenness and distance to the nearest resident at the medium scale, with less than 16 percent of locations significantly greater than red noise.

At the 27–45 km scale, a considerably large average coherency of 0.55 was observed between NDVI and variable of the distance to the nearest resident, with over 64 percent locations significantly greater than red noise. The average coherency at a very large scale (above 45 km) was 0.82 and 0.51 between NDVI and elevation and slope, with the standard derivation of 0.13 and 0.17 respectively.

For the elevation, over 95 percent of locations

Figure 4 Wavelet coherence between NDVI and (a) elevation, (b) slope, (c) land use intensity, (d) distance to Rivers, and (e) distance to Residents along the latitudinal transect

X-axis indicates distance from west along the transect in kilometers, Y-axis indicates scale in kilometers, solid line denotes 5% significant level, color bar indicates strength of correlation, and the direction of arrow represents phase information or type of correlation (right directed—'in phase' or positive; left directed—'out of phase' or negative).

were significantly greater than the red noise. This indicated very strong coherence between vegetation greenness and altitude at a very large scale. Nonetheless, when compared with medium or large scales, relatively small average coherence was seen between NDVI and land use intensity or distance to nearest resident at very large scales.

For the relationship between vegetation cover and its influencing factors, different intensity and patterns of wavelet coherence was examined at different locations, helping to discern the characteristics of different regions. Across the latitudinal transect, very strong wavelet coherence between NDVI and its influencing factors was exhibited in the Wuyi Mountains. The Wuyi Mountains region was characterized by medium

elevations with complex topography and strong variations of land use intensity from urban land to less intensive woodland. Similar to the Wuyi Mountains region, relatively strong wavelet coherence between NDVI and nearly all its influencing factors was displayed in the Daimao Mountains region. The Daimao Mountains region was characterized by a long range of elevation (100–1,400 m) and strong variations of topographic conditions corresponding to different altitudinal gradients along the transect. Therefore, the strongest wavelet coherence across the latitudinal transect was between NDVI and the topographic variables within this region.

The Daiyun Mountains was described as relatively high elevations with relatively less

intensive land use (primary woodland). Consequently, the least wavelet coherency was observed between NDVI and its influencing factors in this region. Opposite to the Daiyun Mountains region, the low reaches of Minjiang basin was characterized with fairly low elevation with relatively intensive land use (i.e. construction land, cultivated land) and considerably strong variations of different land uses (woodland in hilly region, construction land, and cultivated land in relatively flat areas). In this area, slightly stronger wavelet coherency was observed between NDVI and the land use intensity or slope.

2.2.3 Wavelet variance and coherency analysis along the longitudinal transect

There are three main knolls (Jiufeng Mountains, Daiyun Mountains and Bopingling Mountains) and two main depressions (Minjiang River and Zhangzhou plain) synchronously observed from NDVI and elevation along the longitudinal transect (Figure 5), with large values

observed on the knolls and small values within the depressions. Similarly, the local wavelet spectrum of the NDVI exhibited four scales of variation across the longitudinal transect: 0–9 km, 9–27 km, 27–57 km and above 57 km (Figure 5). Much larger wavelet variances were observed at large scales, which corresponds to the knolls and depressions along the longitudinal transect. Four characteristic scales were detected at 8 km, 20 km, 40 km and 80 km within these four scale domains respectively.

Correspondingly, greater proportional areas with significant relationship between NDVI and its influencing factors were observed at the large scales (Figure 6). Compared with results from the latitudinal transect, less wavelet coherency was seen between NDVI and elevation, whereas stronger wavelet coherency was shown between NDVI and slope. Much more complex topographic conditions were encountered at the longitudinal transect, which varies from Zhangzhou plain with an elevation below 30 m to the Jiufeng and Daiyun Mountains with an average elevation above 800 m. The intensity and patterns of wavelet coherency

Figure 5 Measured value and corresponding wavelet variance of (a) NDVI, (b) elevation, and (c) land use intensity (LUI) along the longitudinal transect

also differed in various positions across the longitudinal transect. The correlations were relatively small in Jiufeng Mountains, and considerably strong in the Zhangzhou plain, as observed from the wavelet coherency between NDVI and topographic variables, land use intensity, and accessibility variables.

3 Discussion

3.1 The scale-location specific control on vegetation distribution

The multi-scale pattern of vegetation distribution have been disclosed in numerous studies (He et al. 2007; Lookingbill et al. 2011; Nelson et al. 2007; Propastin 2011; Gao et al. 2012). In this study, four scale domains of vegetation distribution were revealed from the local wavelet spectrum of the NDVI along both latitudinal and longitudinal transects. The scale of 20 km might be the characteristic scale of vegetation distribution in the mountainous and hilly regions. Through scale-

location specific analysis, it indicated that significantly strong wavelet coherency was rarely observed between NDVI and elevation in relatively high mountain areas (i.e. elevation > 800 m) and plains (i.e. elevation < 30 m and slope < 5°) at large scales, which were consistent with related studies conducted through geographic weighted regression approach in mountain-hill region (Qiu et al. 2012; Qiu et al. 2013b). Intensive influence from anthropogenic activities mainly occurred in areas with relatively low elevation and gentle, concave slopes, which was also indicated in other research conducted in arid regions (Liu et al. 2009). Besides, it was demonstrated that directions of the relationship between NDVI and topographic variables (elevation and slope) varied in different sites. Despite that the positive wavelet coherency generally examined at relatively large scales, negative wavelet coherency was also observed between NDVI and topographic variables in relatively high mountains areas (i.e. > 800 m) at small scales. Consequently, the continuous wavelet approaches were efficient in characterizing the

Figure 6 Wavelet coherency between NDVI and (a) elevation, (b) slope, (c) land use intensity (LUI), and (d) distance to nearest resident along the longitudinal transect

hierarchical complex vegetation pattern.

3.2 Comparison and possible combinations with other non-stationary models

Besides the wavelet based methods, GWR and multilevel models are also the commonly utilized method dealing with spatio-temporal non-stationarity in geographic databases. In vegetation distribution related studies, GWR has been most commonly applied in recent years (Propastin 2011, 2012; Zhao et al. 2010; Bayramov et al. 2012; Gao et al. 2012). The GWR framework has been proved to be efficient in characterizing the spatio-temporal non-stationary and scale-dependent relationships between vegetation distribution (or dynamic) patterns and their influencing factors (Propastin 2012; Gao et al. 2012; Bayramov et al. 2012; Propastin 2011). Nevertheless, the selection of optimal bandwidths was often iterative based on Akaike information Criteria (AIC) (Propastin 2011; Zhao et al. 2010). Results from scale-location specific analysis could contribute to define the proper bandwidths in the process of creating GWR models. Besides, original candidate variables were generally calculated and applied on one specific level in GWR models (e.g. pixel or data collection level).

On the contrary, the multilevel models could be utilized to investigate the complex interaction of the hierarchical ecosystem (Serneels et al. 2007; Qiu et al. 2013a). Under the multilevel framework, it's very flexible in the process of determining suitable analysis scale and selecting proper explanatory variables at different analysis levels (Qiu et al. 2013a). However, the different levels of hierarchical ecosystem had generally to be predefined, which relied on related scientific knowledge. The continuous wavelet-based approaches could provide valuable information on the hierarchical structure of vegetation distribution. For example, this study revealed that in subtropical mountain-hill region, the multiple scale patterns may be attributed to micro-topography, anthropogenic and accessible processes acting at different levels. The principal scales of variation and their corresponding characteristic scales could enrich our knowledge of levels in hierarchical ecosystems and the basic size at each level. This

knowledge could be applied to identifying different levels and its corresponding candidate influencing variables in multilevel models. Besides, the spatial boundaries of the hierarchical ecosystems at different levels should also be predetermined, which might be derived through two-dimensional continuous wavelet analysis (Mi et al. 2005; James et al. 2010).

4 Conclusion

The wavelet spectrum and wavelet coherency analysis provided an appropriate approach through affording valuable information on the complex vegetation distribution pattern simultaneously and continuously. Four scales of variation were identified from the local wavelet spectrum of NDVI across the latitudinal and longitudinal transects, with significant wavelet variances generally observed at considerably larger scales. The hierarchical structure of vegetation distribution in subtropical mountain-hill region has been revealed. The small and medium scale patterns may be attributed to the variations in micro-topography, landform elements, and anthropogenic processes (denoted by land use intensity). The large scale patterns may be attributed to the variation of accessibility conditions. The very large patterns might originate from the alternating knolls and depressions along the latitudinal transect, characterized by mountains cracked by big rivers. Besides, location specific analysis indicated that the magnitude and direction of connections between vegetation distribution and its influencing factors varied at different locations, and strong associations were generally examined in areas with small mountains and hills fractured by rivers and residents.

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