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Research paper

Assessing spatiotemporal eco-environmental vulnerability by Landsat data

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ABSTRACT

An indicator of quantifying eco-environmental vulnerability was established by synthesizing 12 variables, mainly retrieved from satellite data with incorporation of analytical hierarchy process (AHP). Six vulnerability levels of *potential, slight, light, medium, heavy*, and *very heavy* were graded to depict changes of vulnerability over temporal and spatial scales. The proposed approach was employed to study spatiotemporal eco-environmental vulnerability with Landsat data acquired in 1989, 2003, and 2014 for the Thua Thien – Hue Province, Vietnam. Over the time periods of 1989–2003 and 2003–2014, both *heavy* and *very heavy* vulnerability levels exhibit an increasing trend in both magnitude and spatial size: The former raised from 5.9% in 1989, to 7.9% in 2003, and 15% in 2014; and the later increased from 1.2% in 1989, to 3.2% in 2003, and 7.3% in 2014. Both levels mainly appeared on urbanized area, bare land, semi-bare land, agricultural land, and sparse forests. In contrast, there was a significant decline in *potential* vulnerability level with 36.4% in 1989, 30.9% in 2003, and 19.2% in 2014, while the remaining vulnerability levels *slight, light,* and *medium* fluctuated slightly, increased in 2003 and decreased in 2014. Supporting reasons for such changes include: *(1)* deforestation, agriculture intensification, construction of three hydro-electric projects during the period 2003–2014; and *(2)* significant expansion of urbanized area leading to differences in thermal signatures in urban areas as compared with rural areas. The findings demonstrate that eco-environmental vulnerability is primarily exaggerated by anthropogenic activities through land use/land cover (LULC) changes and further enhanced by natural processes including disasters in the Thua Thien – Hue Province of Vietnam. The correlation between land surface temperature (LST) and Normalized Difference Built-up Index (NDBI) is found to be positively correlated with 0.87, 0.89, and 0.84 for 1989, 2003, and 2014, respectively. In contrast, LST-Normalized Difference Vegetation Index (NDVI) is found negatively correlated with respect to the spatiotemporal trend of environmental vulnerability with −0.81, −0.81, and −0.76 in 1989, 2003, and 2014, respectively. In addition, areas having *potential, slight,* and *medium* thermal environmental levels are decreased from 1989 to 2003 to 2003–2014. At the regional scale, increased anthropogenic activities through land's modification have intensified the eco-environmental vulnerability in the study area. The currently proposed methodology is feasible for evaluating long-term eco-environmental changes processes by using remote sensing data, and valid for the other regions.

1. Introduction

Environmental changes and their causes increase the need to tackle their consequences on affecting the structural and functional ecosystem (Polsky et al., 2007; Turner et al., 2003). Natural ecosystem and eco-environmental vulnerability are sensitive to changes in land use/land cover (LULC) (Boori and Amaro, 2011; Xie et al., 2013; Hao and Ren, 2009; Adger, 2006; Valipour, 2015, 2016). Decision makers are increasingly pressured with challenges of pursuing social and economic developments without causing detrimental impact on the environment (Hinkel, 2011; Ostendorf, 2011; Lawley et al., 2016). While there might have strong correlations among eco-environmental health, LULC, and thermal signatures (Strand et al., 2010). The thermal signature is the apparent thermal status near surface and can be characterized by land surface temperature (Xiong et al., 2012). Urban area is a complex eco-environment involving a variety of anthropogenic activities (Zhang et al., 2006). Due to changes of LULC, including distributions of urban sprawl and vegetation, urban areas often present more significant

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thermal signatures than less disturbed rural areas. Therefore, thermal signatures are considered as important eco-environmental characteristics representing evolutions in urban micrometeorology affected by LULC changes (Adger, 2000; Mallick et al., 2013; Miller and Small, 2003). Changes in LULC have been not only recognized as a key determinant factor among a broad range of land surface parameters (e.g., land surface temperature, evapotranspiration, runoff, etc.), but also considered as the most significant in terms of affecting the Earth System functioning (Lambin et al., 2003). The eco-environmental vulnerability is defined and governed by four factors: hydro-meteorology signatures, land resource, social economics (human activities), and topography condition, which can be classified into two categories: internal and external vulnerabilities. Internal vulnerability results from the structure of eco-environment itself and is less impacted by external vulnerability, which is influenced by human activities (Nguyen et al., 2016). In view of environmental vulnerability affected by significant LULC changes, there is a strong demand of using high quality geo-spatial information to visualizing how environmental vulnerability dynamics varied with to LULC changes. Spatiotemporal eco-environmental vulnerability assessment aims to identify the trend and regions where tend to experience vulnerability, and answer the relevant questions: "what are the reasons for vulnerability and can we use this information to support environmental decision making".

In our previous study (Nguyen et al., 2016), we proposed an assessment framework to evaluate the eco-environmental vulnerability in the Thua Thien – Hue Province, Vietnam, with involvement of 16 variables including those extracted from Landsat 8 OLI, digital maps, and *in situ* measurements. However, in view of long-term environmental monitoring across the region, it often becomes a barrier by using *in situ* measurements due to their limited spatiotemporal resolution, insufficient historical data, and infeasibility to capture both natural and man-made attributes within a given place and time. Fortunately, the time series of Landsat satellites have made a significant contribution to various fields of environmental studies, such as long-term environmental monitoring; natural and man-made disaster studies; and support of the evaluation of magnitude, dynamics, and spatiotemporal distribution of land surface parameters and eco-environmental vulnerability over timespans of multiple decades (Tehrany et al., 2013; Wilson et al., 2003).

The current work intends to further apply Landsat data to monitor eco-environmental vulnerability by proposing an improved framework over our previous version (Nguyen et al., 2016). Such improved framework is more suitable for long-term eco-environmental monitoring by advancing the illustration of spatiotemporal variability of eco-environmental vulnerability using time series of Landsat data to retrieve variables for detecting surface characteristics affecting regional eco-environment. That is, the improved framework resolves the difficulties in obtaining long-term *in situ* eco-environmental measurements that are required in the previous framework. In addition, the impacts and trends of LULC on environmental vulnerability for the past 25 years were assessed as an example to demonstrate how these remote sensing data can be used to support planners to obtain objective measurements and comparative context. In addition, this study assesses the impacts of past LULC policies on spatiotemporal eco-environmental vulnerability by: *(i)* evaluating eco-environmental vulnerability changes based on variables retrieved from Landsat TM, ETM, and OLI & TIRS (Thematic Mapper, Enhanced Thematic Mapper, and Operational Land Imager & Thermal Infrared Sensor); and *(ii)* analysing the relationship between land use changes and thermal anomaly by computing correlation coefficient between land surface temperature (LST) and Normalize Difference Built-up Index (NDBI) over the past 25 years (1989–2003–2014). Deliverable products of this study can be used to assist decision makers to deal with comparative context to answer the planning questions such as how anthropogenic processes affect the environment? Does any region of concern have less harmful impacts on the physical environment as compared with the others? Although the Thua Thien-Hue Province was selected as our study area, the type of data and proposed framework used in the current study should be available and applicable in many moderate and large size regions.

2. Materials and methods

2.1. Materials

The present study used several data sets free of charge to examine eco-environmental vulnerability changes. Remote sensing data is the main source with meteorological data of three stations only used to compare with the results extracted from satellite data. The data used in the study are listed below:

(1) Remotely sensed Landsat time series images from Landsat 5 TM images (acquired on 08 May 1989; 03 December 1990), Landsat 7 ETM+ images (acquired on 21 April 2003; 06 November 2000), and Landsat 8 OLI & TIRS images (acquired on 27 April 2014; 04 October 2014). Those images acquired in summer months are used to examine the LST and land cover changes with supporting seasonal vegetation features by using the images acquired in winter months.
(2) ASTER digital elevation model (DEM) with spatial resolution of 30 m, and
(3) Meteorological data of three stations, Hue, A Luoi, and Nam Dong used to investigate the trend of temperature (Fig. 1).
(4) Photos of field survey used to correlate the LULC classification with ground features.

2.2. Methods

2.2.1. Image processing

Seven major steps were performed for image processing: *(i)* Atmospheric correction was performed for all bands by using Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) (Waner and Chen, 2001) and following the atmospheric correction, the images were geo-referenced to UTM projection, zone 48 North; *(ii)* Digital numbers (DNs) of thermal bands were converted to spectral radiance and then brightness temperatures are computed; *(iii)* Land emissivity is estimated based on NDVI method (Sobrino et al., 2008; Valor and Caselles, 1996) and brightness temperatures are converted to LST (Jimenez-Munoz et al., 2009); *(iv)* Visible bands of images (Landsat 5 TM image acquired on 08 May 1989; Landsat 7 ETM+ image acquired on 21 April 2003; and Landsat 8 OLI & TIRS image acquired on 27 April 2014) were selected to composite to be a single image and land cover classification is performed with Support Vector Machine (SVM) method (Cortes and Vapnik, 1995). There are nine classes of land cover types including *dense forest, medium forest, sparse forest, bare land, agricultural land, planted forest, mixed planted forest (semi-bare land, grassland, shrub, and young planted forest), water, and urbanized area.* The accuracy assessment was also done for the classified LULC derived from Landsat images with classification accuracy, Kappa statistics coefficients being 0.84, 089, and 0.88 for 1989, 2003, and 2014, respectively; *(v)* Urban thermal field variance index (UTFVI) representing microscale temperature variation between urban and rural areas was calculated based on LST by using Eq. (1) (Liu and Zhang, 2011):

$$UTFVI = \frac{T_s}{T_s - T_{mean}} \tag{1}$$

where UTFVI is the urban thermal field variance index; T_s is the LST of certain pixel in degree Celsius (°C); and T_{mean} is the mean LST of the whole study area in degree Celsius. To classify thermal field variance index into different levels, histograms are used to reveal the statistical distribution of calculated thermal field variance values from grid cells; *(vi)* Calculated Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water