An assessment of erosivity distribution and its influence on the effectiveness of land use conversion for reducing soil erosion in Jiangxi, China

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1. Introduction

Soil erosion is a primary cause of soil degradation throughout the world (Flanagan, 2002), and is significantly threatening the sustainable development of society and environment (Singha et al., 2006). As a complex process, soil erosion is determined by mutual interaction of numerous factors.

Land use is one of the most important factors influencing the susceptibility of a region to soil erosion (Fullen, 1998; Kosmas et al., 1997). A lack of adequate land use planning can accelerate water soil erosion and create major environmental problems (Cebecauer and Hofierka, 2008; Durán Zuazo et al., 2006). Undoubtedly, the conversion of land use can significantly influence soil erosion by changing vegetation cover, soil properties (Kosmas et al., 2000), characteristics of runoff and later the climatic conditions (Hernández et al., 2005; Wei et al., 2010a,b) in a region. Assessing the response of soil erosion to land use change is important to understand the efficiency of land use modification (e.g. ‘Grain for Green’ program) (Deng and Shang, 2012).

Soil erosion, however, is strongly affected by many other factors besides land use. Rainfall can cause soil erosion by means of rain-splash and runoff when reaching the ground (Kinnell, 2005). The erosivity index, which is usually implemented in the mathematical model (e.g. Universal Soil Loss Equation USLE and its revised form RUSLE), can effectively stand for the ability of rainfall to detach soil particles by considering rainfall amount and intensity (Sanchez-Moreno et al., 2014). Thus, soil erosion can be linked directly with rainfall characteristics by erosivity index.

The spatio-temporal heterogeneity of rainfall erosivity has a great influence on spatial distribution of soil erosion (Ma et al., 2009). In addition, classification of the erosivity distribution zones will provide a set of zones with their unique temporal and spatial distribution characteristic. Soil erosion may thus vary greatly in various zones of erosivity distribution in large scale. Addressing the response of soil erosion to different land use conversion types and different erosivity distribution zones is therefore important for land use structure adjustment and vegetation restoration. However, many studies assessed the impacts of different land use conversion on soil erosion simulated by using different models in long time scale (Muller et al., 2009; Wendt and Corey, 1980; Yuan et al., 2007; Zhang et al., 2014b). The impacts of erosivity were seldom studied because the accurate estimation of its spatio-temporal distribution over large areas is complicated and difficult.

Fortunately, entropy theory provides a possibility to delineate rainfall erosivity distribution zones on large scales. Entropy is a measure of unpredictability of information content. The entropy concept was introduced by Shannon (1948) to measure the uncertainties of random
variables. Later, the researches on applying entropy theory to quantitatively assess uncertainties of hydrologic variables have become a research focus (Liu et al., 2013; Singh, 1997). The studies on features of meteorological system demonstrated that meteorological factors of the terrestrial atmosphere have the characteristic of self-similarity (Monin and Obukhov, 1954), which exists from free troposphere to boundary layer of the atmosphere (Nieuwstadt, 1984; Shao and Hacher, 1990). In addition, information transmission between meteorological stations was found by Yang and Burn (1994). The research showed that meteorological stations can be treated as recipients of dynamic signals from hydro-meteorological parameters (e.g., precipitation) and these parameters have similar characteristics and are also spatially related across a given region. Consequently, meteorological observation system can be treated as a signal communication network. It provides the theoretical basis for the application of entropy theory in erosivity distribution zoning.

Soil erosion modeling using historic land use data offers a unique opportunity to study impacts of actual land use changes on erosion (Jordan et al., 2005). With the rapid development of GIS and RS technology, quantification modeling has become a widely accepted method that is considered the most scientific approach for future study for revealing soil erosion on a large scale (Xu et al., 2012). Some common or less common distributed hydrological models used for valuation of soil erosion are the Revised Soil Loss Equation (RUSLE) (Renard et al., 1991) (a revised method of USLE methodology), Water Erosion Prediction Project (WEPP) (Flanagan and Nearing, 1995) and the Soil and Water Assessment Tool (SWAT) (Antje and Martin, 2009). All these models study the phenomenon of soil erosion by attempting to estimate the volume of soil loss. However, RUSLE has been proved to be the one of the still most commonly used and tested methodology over many years from different researchers all over the world (Renard et al., 1997). It has been frequently applied to assess soil erosion risk and to guide development and conservation plans for soil erosion control in areas of different sizes and environmental conditions (Angima et al., 2003; Brooks et al., 2014; Fernandez et al., 2003; Zhang et al., 2014a). For example, using RUSLE and GIS, Terranova et al. (2009) conducted a comparison of soil erosion risk among four scenarios (one present scenario and three hypothesized scenarios) in the Mediterranean environment. His study highlighted the effectiveness of some antierosive measures and the increased intensity of erosive processes as a consequence of forest fires. Xu et al. (2012) carried out a risk assessment of soil erosion in different rainfall scenarios by RUSLE. It was found that greatest amount of attention should be paid to the prevention of soil erosion in July rather than September in Baohai Rim, China.

The validities and limitations of the RUSLE model are already known. The limitation is the obtained values of soil erosion must be employed

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Landsat image description.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Sensor</td>
</tr>
<tr>
<td>1988</td>
<td>TM</td>
</tr>
<tr>
<td>2013</td>
<td>OLI</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Descriptions of the land use classes identified.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class name</td>
<td>Description</td>
</tr>
<tr>
<td>Farmland</td>
<td>Areas consisting of paddy land and dry land</td>
</tr>
<tr>
<td>Forest</td>
<td>Natural forest and plantation forest (canopy density &gt; 0.3)</td>
</tr>
<tr>
<td>Open forest</td>
<td>Forest with canopy (0.1 &lt; density &lt; 0.3)</td>
</tr>
<tr>
<td>Shrub</td>
<td>Low woody plant (&lt;2 m) with multiple stems (canopy density &gt; 0.4)</td>
</tr>
<tr>
<td>Orchard</td>
<td>Area devoted to the cultivation of fruit or nut trees</td>
</tr>
<tr>
<td>Grass</td>
<td>Areas in which grasses are dominant (canopy density &gt; 0.05)</td>
</tr>
<tr>
<td>Construction land</td>
<td>Residents and transportation and industries area</td>
</tr>
<tr>
<td>Water area</td>
<td>Area covered with lakes, rivers, and ponds</td>
</tr>
<tr>
<td>Bare land</td>
<td>Areas with little or no vegetation consisting of exposed soil/rocks</td>
</tr>
</tbody>
</table>
Poyang Lake in the north central region is the largest freshwater lake in China, and Ganjiang river basin, covering an area of 79,173 km², is one of the most important tributaries of Yangtze River. The study area has many developed river systems. In brief, the key objectives in this paper are to: (i) extend the original use of entropy and construct an entropy model to delineate erosivity distribution zones in study area using daily rainfall data from 1988 to 2013. (ii) calculate the mean annual soil loss of study area for 1988 and 2013 using RUSLE model. (iii) study the response of the effective- ness of land use conversions over the period 1988–2013 for reducing soil erosion with reference to different erosivity distribution zones.

2. Study area and materials

2.1. Study area

Jiangxi province covers 166,900 km² and lies between 113°34′–118°29′E longitude and 24°29′–30°04′N latitude, surrounded by Anhui, Hubei, Hunan, Guangdong, Fujian and Zhejiang provinces (Fig. 1). This region is characterized by a typical moist, subtropical climate. It has a mean annual temperature of 17.7 °C, a maximum daily temperature of around 40 °C in summer, an annual rainfall of 1786 mm and an annual potential evaporation of 1229.1 mm. The differences in spatial and temporal distributions of precipitation are quite apparent, with about 50% of rainfall occurring in the rainy season (from March to early July). However, about 50% of evaporation occurs during the dry season from middle July to November. The study area has many developed river systems. Poyang Lake in the north central region is the largest fresh water lake in China, and Ganjiang river basin, covering an area of 79,173 km², is one of the most important tributaries of Yangtze River.

The dominant soil, widely distributed in the region, belongs to red soil developed from quaternary sediments. This type of soil has a low infiltration rate of precipitation, and is degraded and erosion-prone. About 35% of the territory, located predominantly in the mid-north, represents flat alluvial plains or smoothly undulated hilly lands. Paddy soil is mainly distributed in this part of territory, with relatively high susceptibility to soil erosion, despite the gentle slopes. The rest of territory is formed by highlands and mountains with intra-mountainous valleys. The slopes in mountains areas are somewhat longer and steeper. However, these areas have a relatively good soil and water conservation due to high coverage rate of forest, which has an efficient protection function against soil erosion (Šúri et al., 2002).

The main land use types are farmland, forest, open forest, grass, shrub, orchard and construction land. Land use has been altered by the implementation of the Grain-for-Green project of the Chinese central government during the last several decades. China implemented the ‘Grain-for-Green’ Program in 1999 for ecological reconstruction and control of the country’s soil erosion problems. The program increased the forest and grass coverage by removing lands with steep slopes and marginal farmland from agricultural production. By 2010, the program had converted most steeply sloped farmland into forest and grass. Because vegetation cover contributes greatly to soil and water conservation, the program has a positive impact on soil and water conservation and this impact is becoming more and more obvious (Deng and Shang, 2012).

2.2. Materials

Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) images were chosen to develop land use map and the Normalized Difference Vegetation Index (NDVI) for the two time periods: 1998 and 2013. A total of 34 images (17 Landsat TM images of 1988 and 17 OLI images of 2013) were provided by The Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences (CAS) (http://ids.csde.ac.cn/images/wn-top.png) (Table 1).

Preprocessing included the application of geometric and atmospheric corrections.

Remote images were geo-referenced by using digital elevation model (DEM) at a spatial resolution of 30 m (provided by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences), with at least 5 Ground Control Points (GCPs) for each TM/OLI image. The Root Mean Squared Error (RMS error) was less than 0.5 pixels. Atmospheric correction was conducted using the FLAASH module in Environment for Visualizing Images 4.7 (ENVI) software. Land use map was developed by visual interpretation method. Specialists used MGE Modular GIS Environment (MGE) software to identify the land use types based on their knowledge. This interpretation technique follows the procedure of the national database (Liu et al., 2005). Land use types were classified into nine types, including farmland, forest, open forest, shrub, orchard, grass, construction land, water area and bare land (Table 2). To support image interpretation and the validation of land use classification and soil erosion model results, we conducted an integrated field survey including land use types and soil erosion status across Jiangxi province (our study area is Jiangxi) in October 2013, with an accumulated survey length of 3063 km, a total of 92 patches and 1336 photos located with GPS facilities recorded. The validation result showed that the overall accuracy of the land use types classification is 94.3%.

The NDVI was calculated using the NDVI module in ENVI 4.7 software. Daily rainfall data from 1987 to 2013 was collected from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/cdc_en/home.dd). The soil database was provided by the Data Sharing Infrastructure of Earth System Science (http://www.geodata.cn/Portal/index.jsp). All spatial data have been converted into raster at 100 m grid cell, so that spatial analysis can be done in the same cell size and map projection.

3. Methods

3.1. Entropy of erosivity

When considering the amount of annual erosivity as a random variable given in a discrete form and taking p(x_i) as its occurrence probability in a given time series, the Shannon (1948) information entropy at meteorological station X can be estimated using Eq. (1) in units of “bit”.

\[ H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \]  

(1)

where x_i is the ith annual erosivity at station X, p(x_i) is the probability of x_i, P(X = x_i) = p(x_i) (i = 1, 2, ..., n), p(x_i) ≥ 0, \( \sum p(x_i) = 1 \), and n is the length of annual erosivity series.
If all \( p(x_i) \)s are equal, i.e. \( p(x_i) = 1/n \), then the entropy is \( H(X) = \log_2 n \) (bit), which is a monotonically increasing function of \( n \). For a given \( n \), \( H(X) \) is maximum when all \( p(x_i) \)s are equal. On the contrary, \( H(X) \) is minimum and is equal to zero when every \( p(x_i) \) but one is zero. Obviously, the value of entropy varies from minimum to maximum according to the distribution of \( p(x_i) \). According to Eq. (1), the joint entropy \( H(X, Y) \) between stations X and Y can be calculated by Eq. (2).

\[
H(X, Y) = - \sum_{i,j} p(x_i, y_j) \log_2 p(x_i, y_j)
\]  

(2)

where \( p(x_i, y_j) \) is the joint probability of erosivity \( x_i \) and \( y_j \). \( p(x_i, y_j) \), \( p(x_i) \), \( p(y_j) \) can be evaluated as follows (Fig. 2):

1. Construct a two-dimensional space graph with X and Y axes representing the magnitudes of erosivity at the two stations, ranging from the minimum value to the maximum, respectively.
2. Split up the whole range of annual erosivity of X and Y station into \( n \) and \( m \) classes at an equal interval, respectively. The entire domain is then divided into \( n \times m \) uniform grids.
3. Sample all data points in each grid each time to compute the probabilities. For example, when setting the number of data points in each grid as \( N \), \( N = N_{11} + N_{12} + \ldots + N_{nm} \), and \( N_j = N_{j1} + N_{j2} + \ldots + N_{jm} \), the joint probability \( p(x_i, y_j) \), and the probability \( p(x_i) \) and \( p(y_j) \) can be respectively computed as:

\[
p(x_i, y_j) = \frac{N_{ij}}{N}
\]

\[
p(x_i) = \frac{N_i}{N}
\]

\[
p(y_j) = \frac{N_j}{N}
\]

where \( N \) is the total number of points for the entire data series.

In order to quantify the transmission of information and clarify the dependence between two stations X and Y, a directional information transfer index (DITI) is defined as:

\[
\text{DITI}_{XY} = \frac{I(X,Y)}{H(Y)} \quad \text{DITI}_{YX} = \frac{I(X,Y)}{H(X)}
\]

(3)

where \( I(X,Y) \) is the mutual information defined as:

\[
I(X,Y) = I(Y,X) = H(X) + H(Y) - H(X,Y)
\]

(4)

\( I(X,Y) \) measures the statistical degree of dependency between X and Y. \( I(X,Y) \) is zero if station X and Y are independent. In DITI, X is named the basic point (basic station) and Y is the auxiliary point (auxiliary station). DITI varies from 0 to 1; a higher DITI value reflects a stronger information exchange between the two stations.

An index was proposed to measure the similarity between stations X and Y:

\[
\gamma_{XY} = (\text{DITI}_{XY} + \text{DITI}_{YX})/2
\]

(5)

When \( \gamma_{XY} \) is high, it indicates that the two stations have high similarity and they should be classified into the same erosivity distribution zone. On the contrary, they do not belong to the same zone. The fuzzy cluster analysis (Rao and Srinivasa, 2006) was adopted to classify stations into a series of clusters (stations belonging to the same cluster will be distributed in a same zone in space), with a basic principle: stations with high \( \gamma_{XY} \) were classified into the same cluster. A fuzzy proximity matrix \( R \) can be defined from \( \gamma_{XY} \) which stands for proximity relation between stations X and Y. Given the fact that the matrix \( R \) is not transitive, the transitive closure method was applied to transform \( R \) into a fuzzy equivalence matrix. Then a series of dynamic cluster graphs can be gained by a gradually decreasing threshold \( \lambda \). When \( \lambda \) is fixed, the number of clusters will be determined.

There are two steps to determine boundaries among erosivity zones. 1) we used point data of stations to generate Voronoi diagrams (Li et al., 2003). Therefore, study area was divided into a number of regions which are called Voronoi cells. 2) Voronoi cells belonging to the same cluster were merged into a larger zone (erosivity zone).

### 3.2. Mann–Kendall test

The Mann–Kendall test is a non-parametric analysis designed to detect trends in climatologic and hydrologic time series. It is widely used because it is simple and does not require the data to be normally distributed. Furthermore, it can handle values that are missing or below the detection limits and has low sensitivity to abrupt breaks due to inhomogeneity. This method has been highly recommended by the World Meteorological Organization (1988) as a standard procedure for detecting trends in hydrological data that are serially independent. It was assumed that, if there are no trends in time series in a given zone, precipitation is not the major driver for the changes of soil erosion (Bi et al., 2009; Gebremicael et al., 2013).
3.3. RUSLE model

RUSLE, one of the most widely-used models, provides a clear perspective from which to understand the interaction of erosion and its influencing factors.

\[
A = \frac{R}{C^2} \times \frac{K}{L^2} \times \frac{S}{C^2} \times \frac{P}{C^2}
\]

where \( A \) is the computed spatial average soil loss in the year selected for \( R \left( \text{Mg m}^{-2} \text{y}^{-1} \right) \); \( R \) is the erosivity factor (\( \text{MJ mm km}^{-2} \text{h}^{-1} \text{y}^{-1} \)); \( K \) is the soil erodibility factor (\( \text{Mg km}^{-2} \text{h}^{-1} \text{MJ}^{-1} \text{mm}^{-1} \)); \( L \) is the slope length–steepness factor (dimensionless); \( C \) is the cover management factor (dimensionless); and \( P \) is the erosion control practice factor (dimensionless, ranging between 0 and 1).

The model was implemented in GIS environment. The software ArcGIS 9.3 was used for the model factors preparation, data management, results evaluation and visualization. The datasets and performed spatial analyses have a spatial resolution of 100 m. The temporal variability of factors \( K \), \( L \) and \( S \) was not considered in this study.

3.3.1. Erosivity factor (\( R \))

The erosivity factor is a measure of the erosive force of the rainfall. It is generally determined as a function of the volume, intensity and the duration of a rainfall, and can be estimated from a series of storms to include cumulative erosivity from any time period (Prasannakumar et al., 2011). Daily rainfall dataset from 48 meteorological stations, including 29 stations located in study area and 19 stations surrounding it (Nanxiong station is treated as inside station for its special location), for 27 years (1987–2013) was collected from China Meteorological Data Sharing Service System (Fig. 4). Annual erosivity factors in the 1988–2013 period were calculated for the distribution zoning and those in 1987–1989 and 2012–2013 periods were calculated as input parameters of RUSLE model to calculate soil loss for year 1988 and 2013, respectively. The value of \( R \) factor is calculated as Eq. (7) according to Zhang and Xie (2002), which is applicable to China’s situation.

\[
M_i = \alpha \sum_{j=1}^{k} \left( D_j \right) ^{0.5}
\]

where \( M_i \) is the erosivity in ith half-month (\( \text{MJ mm km}^{-2} \text{h}^{-1} \text{y}^{-1} \)) (each month is separated into two half-months: days 1–15 and day 16 until the end of the month. Therefore, one year is divided into 24 half-months); \( D_j \) is the erosive rainfall on kth day of ith half-month (mm) (according to China standard (Xie et al., 2000), a daily rainfall is considered erosive when exceeds 12 mm); \( k \) is the number of days in ith half-month. The \( R \) can then be expressed by the summation of \( M_i \) from \( i = 1 \) to 24.
\( \alpha \) and \( \beta \) are:

\[
\beta = 0.8363 + \frac{18.177}{P_{d12}} + \frac{24.455}{P_{y12}}
\]

\[
\alpha = 21.986 \gamma^{-7.1891}
\]

where \( P_{d12} \) is daily average erosive rainfall; \( P_{y12} \) is annual average erosive rainfall.

3.3.2. Soil erodibility factor \((K)\)

\( K \) has three layers of meaning: susceptibility of soil or surface material to erosion, transportability of sediment and the amount and rate of runoff given a particular rainfall input as measured under a standard condition. The soil database as a spatial resolution of 100 m provided by the Data Sharing Infrastructure of Earth System Science (http://www.geodata.cn/Portal/index.jsp) were applied to estimated \( K \) by using the method of William et al. (Sharpley and Williams, 1990).

\[
K = \left\{ \begin{array}{c}
0.2 + 0.3 \exp\left(\frac{0.0256SAN(1 - \frac{SIL}{100})}{0.25C}\right) \\
\times \left[1 - \exp(-3.72 - 2.95SN_1)\right] + 0.7SN_1
\end{array} \right\} \times \left(\frac{SIL}{CLA + SIL}\right)^{0.3}
\]

where SAN, SIL, and CLA are respectively the subsoil sand fraction, the silt fraction and the clay fraction (%). \( C \) is the topsoil carbon content (%). \( SN_1 = 1 - SAN/100 \).

3.3.3. Slope length and steepness factor \((L)\)

Using DEM with a resolution of 30 m as basic data, LS factor is calculated by using the methods developed by Liu et al. (1994) and McCool et al. (1989). In ArcGIS 9.3 (ESRI Inc., USA), the LS data at a spatial resolution of 30 m was resampled to 100 m using Bilinear interpolation method.

\[
S = \begin{cases} 
10.8\sin\theta = 0.03, & \text{if } \theta \leq 9\% \\
16.8\sin\theta - 0.5, & 9\% < \theta \leq 18\% \\
21.91\sin\theta - 0.96, & \theta > 18\% 
\end{cases}
\]

3.3.4. Vegetation coverage and management factor \((C)\)

\( C \) is the cover management factor, which is the ratio of soil loss from an area with a specified cover and management to soil loss from an identical area in tilled continuous fallow. It takes into account variability of the vegetation cover and methods of land management, reflecting their protective function. Many methods have been developed to estimate \( C \) factor using the normalized difference vegetation index (NDVI). \( C \) is calculated according to the equation of Cai et al. (2000).

\[
C = \begin{cases} 
1 & f = 0, f \leq 0.783 \% \\
0.6508 - 0.3436gf & f > 0.783 \%
\end{cases}
\]

where \( f \) is the NDVI variation (CV) (%); \( \gamma \) is the horizontal slope length; and \( m \) is the dimensionless constant depending on \( \theta \).

3.3.5. Erosion control practices factor \((P)\)

\( P \) is usually estimated based on land use type. Referring to the research results of Shu and Jiang (2011), \( P \) of farmland, forest, open forest, and pasture are 0.064, 0.043, and 0.021, respectively. The Kendall’s rank correlation coefficient is calculated to test the relationship between DITI and distance for each zone.

\[
\text{Table 3}
\]

<table>
<thead>
<tr>
<th>Zone</th>
<th>Number of meteorological stations</th>
<th>Average annual R (MJ mm km$^{-2}$ h$^{-1}$ y$^{-1}$)</th>
<th>Coefficient of variation (CV) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone I</td>
<td>7</td>
<td>11,624.2</td>
<td>3.2</td>
</tr>
<tr>
<td>Zone II</td>
<td>7</td>
<td>8825.6</td>
<td>2.7</td>
</tr>
<tr>
<td>Zone III</td>
<td>6</td>
<td>9583.2</td>
<td>3.9</td>
</tr>
<tr>
<td>Zone IV</td>
<td>2</td>
<td>9609.7</td>
<td>1.8</td>
</tr>
<tr>
<td>Zone V</td>
<td>2</td>
<td>10,141.5</td>
<td>2.3</td>
</tr>
<tr>
<td>Zone VI</td>
<td>2</td>
<td>10,765.1</td>
<td>1.8</td>
</tr>
<tr>
<td>Zone VII</td>
<td>2</td>
<td>10,846.5</td>
<td>2.9</td>
</tr>
</tbody>
</table>

Table 4

Mann–Kendall trend tests of annual erosivity in rain gauges belonging to Zone I and Zone II.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Station</th>
<th>Kendall’s tau$^a$</th>
<th>$\gamma$</th>
<th>P-value$^c$</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Shangao</td>
<td>0.001</td>
<td>8</td>
<td>0.98</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Dexing</td>
<td>0.012</td>
<td>80</td>
<td>0.71</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Jingdezhen</td>
<td>0.043</td>
<td>18</td>
<td>0.9</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Boyang</td>
<td>0.021</td>
<td>-9</td>
<td>0.9</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Yushan</td>
<td>0.064</td>
<td>43</td>
<td>0.75</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Guxi</td>
<td>0.014</td>
<td>15</td>
<td>0.805</td>
<td>No significant change</td>
</tr>
<tr>
<td>I</td>
<td>Qiaoxian</td>
<td>-0.043</td>
<td>-134</td>
<td>0.32</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Ninggang</td>
<td>0.20</td>
<td>89</td>
<td>0.12</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Jinggs</td>
<td>0.24</td>
<td>125</td>
<td>0.03</td>
<td>Significantly increasing</td>
</tr>
<tr>
<td>II</td>
<td>Suijin</td>
<td>0.17</td>
<td>70</td>
<td>0.24</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Ganzhou</td>
<td>-0.15</td>
<td>-63</td>
<td>0.27</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Nanxiong</td>
<td>-0.13</td>
<td>-56</td>
<td>0.33</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Xunniao</td>
<td>0.024</td>
<td>11</td>
<td>0.86</td>
<td>No significant change</td>
</tr>
<tr>
<td>II</td>
<td>Longnan</td>
<td>0.064</td>
<td>43</td>
<td>0.78</td>
<td>No significant change</td>
</tr>
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$^a$ The Kendall correlation coefficient.
$^b$ The Kendall score.
$^c$ P-value of two-tailed test.
shrub, orchard, grass, construction land, water area, and bare land is set at 0.4, 1, 1, 1, 0.3, 1, 0, 0, and 1 respectively.

4. Results and discussions

4.1. Erosivity distribution

Using Eq. (1), the entropy values, in units of bits, of 48 stations were calculated. Next, the indexes rXY for evaluating the similarity between station pairs were obtained from Eq. (5).

Directional Information Transfer Index (DITI) can be used to assess the signal transmission of erosivity in space and the decrease of signal strength with increasing distance between meteorological stations. Two stations, Nanxiong and Jiujiang, were selected to show the information transfer graph with distance. There are two reasons for choosing these stations. One is that these two stations are located in the border of the region. Therefore, more auxiliary stations can be selected when a direction is extended from the basic station. The other is that they are much different in location, weather and topography, for station Nanxiong is located in the southwest mountainous area and station Jiujiang in the northeast plain area.

(1) station Jiujiang as a basic station, 8 auxiliary stations to be chosen from Northwest to Southeast.
(2) station Nanxiong as a basic station, 14 auxiliary stations to be chosen from Southwest to Northeast.

As shown in Fig. 3, DITI decreases with increasing distance in two directions. Quite logically, the signals among meteorological stations are transferable in a given region. Close stations tend to have a stronger and more frequent information transfer among them. On the other hand, signal transfer reduces or diminishes when the distance between two stations increases. The fitting equations are also presented in Fig. 3a and b. The results show that the slope for the fitted line in the southwest-northeast direction is steeper than in the northwest-southeast direction. In other words, the signal influence in the northwest-southeast direction is greater than in the southwest-northeast direction. It implies that the erosivity value is easier to change in the southwest-northeast direction. This observation coincides with the results of Ma et al. (2009).

4.2. Identification of the extreme erosivity zones

With each DITI amongst the meteorological stations computed, fuzzy cluster analysis method divided the whole area into eight zones (Fig. 4). We developed a method to test the reliability of the results. Two new stations, Yugan and Wanan, which provided daily rainfall data from 1988 to 2013, were collected as test-stations (Fig. 4). When added to the map of erosivity zones based on their coordinates, Yugen station was found in Zone I and Wanan station in Zone II. With DITI calculated, information transfer with distance between the test-stations (basic stations) and the 29 stations (auxiliary stations, located in study area) was shown in Fig. 5. As we found, DITI decreases away with increasing distance. However, as can be seen form Fig. 5a, the DITI between Yugen station and auxiliary stations located in Zone I is higher than that located in other zones, despite the influence of distance. It indicates that Yugen station has higher similarity with stations in Zone I than those in other zones and should be classified into Zone I. It is the same situation in Zone II (Fig. 5b). These findings coincide with zoning results, which illustrates that our map of erosivity zones is reliable.

The basic statistics of erosivity zones are summarized in Table 3. The coefficient of variation of each zone exhibited an insignificantly small seasonal and temporal variability. The max and min value of averaged annual erosivity occurred at Zone I and Zone II, respectively. Moreover, those two zones have more meteorological stations than others, which might guarantee a more satisfactory explanation for erosivity characteristic. Thus, Zone I and Zone II, were selected for the next step study.

In order to detect the changes of annual erosivity in Zone I and II from 1988 to 2013, Mann–Kendall tests were applied at 14 stations located in the two zones. The results are presented in Table 4, including the station names, Mann–Kendall trend test, statistical summary S, the computed P-value, and trend types. These results showed no change of annual erosivity for the last 26 years (1988–2013). All the computed probability values (P-values) except for jings were greater than the reference value at the given significance level (5%). This finding implies that inter-annual erosivity pattern is not the major driver for the trend changes of soil erosion in both the two zones. Consequently, Zone I and Zone II can safely be identified as two extremities of erosivity with their unique and stable temporal and spatial distribution characteristics. Such an identification is climatologically meaningful not only for quantitatively describing the distribution features of erosivity but also measuring the response, in term of soil erosion, to land conversion in different zones.

4.3. Soil erosion versus conversions in land use

According to Eqs. (6)–(11), soil loss (in Mg km⁻² y⁻¹) of Zone I and Zone II was both calculated using RUSLE for two time periods, 1988 and 2013. The soil loss products were classified into 6 classes from tolerable to destructive, by setting class thresholds. The ranges used for this classification were based on “Standards for classification and gradation of soil erosion SL 190-2007” (Ministry of Water Resources of the People’s Republic of China, 2007) (Table 5). In 2013, 92 field survey data were used to assess the accuracy of RUSLE model products. The accuracy was 90.3%.

Soil erosion classes and land use types for the two periods in the two zones were shown in Fig. 6. It is obvious that land use undertook great changes accompanied by significant changes of soil erosion. For example, the areas that experienced the conversion of farmland to other land use types tend to have a reduction of soil erosion. In contrast, the areas with high vegetation cover were more likely to experience soil erosion when changed to farmland. The total area under farmland has decreased in favor of other land use types. Farms were converted to grassland (19.6%), forest (15.8%), open forest (8.5%), shrub (5.4%) and orchard (1.1%) in Zone I and grassland (6.0%), forest (10.1%), open forest (14.5%), shrub (0.3%) and orchard (0.2%) in Zone II. The comparison of the soil erosion classes in 1988 and 2013 (Fig. 7) shows an increase in the tolerable, slight, medium and destructive classes (1700, 2000, 1600 and 390 km², respectively), a decrease in the strong classes and very strong (4200 and 1300 km², respectively) in Zone I. In Zone II, a slight increase occurred in all soil erosion classes except for tolerable and medium class with a 300 and 1001 km² decrease, respectively. Overall speaking, Zone I characterized by relatively higher annual erosion has severer soil erosion than Zone II.

4.4. Soil erosion versus land use and erosivity

The area percentage of erosion classes in different land use of 2013 is presented in Fig. 8. From the two images, it is safely concluded that the intensity of soil erosion among land use types is: farmland > orchard > grass/open forest > shrub > forest. This result is in conformity with previous studies indicating that farmland and orchard generated more soil loss than grass, shrub and forest (Feng et al., 2010; Wei et al., 2007; Zokaib and Naser, 2011).

<table>
<thead>
<tr>
<th>Table 5 Classification scheme of erosion values.</th>
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<tr>
<td>Erosion degree</td>
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<td>1</td>
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L. Xiao et al. / Catena 125 (2015) 50–60
The present study divided forestland into two types: forest (canopy > 0.3) and open forest (0.1 < canopy < 0.3). Open forest had significantly more soil loss than forest in 2013. The reason for this phenomenon may be due to the canopy standing for the vegetation cover, which is the key factor affecting soil erosion (Peter and d’Oleire-Oltmanns, 2014; Zhang et al., 2004). Zhang et al. (2010) found that, when initial forest coverage rate is below 45%, sediment yield decreases dramatically as forest coverage rate increases. Furthermore, the effects of land use types on soil erosion in different erosivity zones were also captured. Open forest and orchard showed a more sensitive response to erosivity than farmland, forest, grass and shrub. The most likely explanation is that, in comparison to other land use types (except farmland), open forest and orchard has lower vegetation cover and failed to intercept rainfall drops and reduces surface runoff effectively (Woo and Luk, 1990) and thus is more sensitive to erosivity. As for the farmland, the impact of rainfall erosivity might be weakened by human activities, such as terrace building (Zhang et al., 2010).

4.5. Response of soil erosion to land use conversion and rainfall erosivity

From 1988 to 2013, complicated land use conversions occurred in the two erosivity zones. Five land use conversion types (farmland–forest,
farmland—open forest, farmland—grass, farmland—shrub and farmland—orchard) were selected to analyze their effectiveness for reducing soil erosion (Fig. 9). Those five land use conversion types belong to de-intensification of land use (the conversion of an erosion-prone land use to a non-erosion-prone land use) (Bakker et al., 2008), which often implies the regeneration of vegetation cover in natural succession and thus is beneficial with respect to reduce soil erosion (Kosmas et al., 1997). This was confirmed by the results of the present study. However, when considering rainfall erosivity, which is a destructive force to the land surface making the soil prone to erosion (Dijk et al., 2002), the reduction of soil erosion in different land use conversion types varied greatly between various rainfall erosivity zones. For instance, it was found that the positive effects of farmland—forest conversion for reducing soil erosion showed no significant difference between two rainfall erosivity zones, as well as the farmland—shrub conversion type. While the conversion of farmland—open forest and farmland—grass played a greater role in reducing soil erosion in Zone II than that in Zone I.

Kateb et al. (2013) found that soil loss on grass land was 19 times higher than forest by constructing experimental plots in Shaanxi province, China. However, the present study argued that, in relatively low erosivity zone, farmland—grass conversion performed as well as farmland—forest conversion for soil erosion reduction. Certainly, after several decades of development, forestland converted from farmland may have a better soil conversation than grass (Wei et al., 2007). Taking into account the socio-economic cost and effectiveness for reducing soil erosion, however, land use conversions of farmland—grass and farmland—open forest are important supplements to conversion of farmland—forest in low erosivity areas. Nevertheless, in high erosivity zone, the farmland—forest conversion was considered as the most effective land use conversion type to reduce soil erosion. Slope has a considerable impact on soil erosion (Koulouri and Giourga, 2007; Li et al., 2010). Previous studies showed that the soil erosion reduction by land use conversion was often amplified on steeper slopes (Bakker et al., 2008; Feng et al., 2010). Since the maximum permissible slopes for farmland are limited to be only about 20–25% in China, in the present study, all conversion of farmland to other land use types occurred under 0–16° slope areas. Nevertheless, according to the results, the effect of slope on soil erosion reduction is not significant in that slope scope.

5. Conclusion

Using entropy theory, eight zones were delineated with their unique and stable temporal and spatial distribution characteristics of erosivity. Zone I and Zone II were considered as two extreme zones for the study area. Zone I in the northeast of study area has such feature as high erosivity. Zone II in the southwest is characterized by low erosivity. These two zones were selected to analyze the response of soil erosion to land use conversion (de-intensification) in the 1988–2013 period. Soil erosion was assessed by using RUSLE model for 1988 and 2013 years.

It was found that comprehensive inter-relationships exits between land use, erosivity and soil erosion. Generally, Zone I has severer soil erosion than Zone II. Farmland and orchard generated more soil loss than grass, shrub and forest. The effectiveness of farmland—forest conversion for reducing soil erosion showed no difference between the two zones, as well as farmland—shrub. However, conversion of farmland—open forest and farmland—grass both performed better in low annual erosivity zone than in high annual erosivity zone. These results may assist our understanding of soil erosion dynamics and the relation with land use conversions and rainfall. These findings also imply that different practical plans of land use conversion for reducing soil erosion should be laid out according to erosivity zones. In order to reduce soil erosion in Jiangxi province, China, farmland—forest conversion is strongly recommended when land use conversion is implemented. When considering the economic cost, the conversions of farmland—grassland and farmland—open forest can be used as important supplements to conversion of farmland—forest in low erosivity areas. The effect of slope on soil erosion reduction by land use conversion has no obvious regulation in the scope of 0°–16°.

Acknowledgments

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Fig. 9. Interaction of land use conversion, slope, and erosion change within two erosionity zones.