Quantitative assessment model of ecological vulnerability of the Silk Road Economic Belt, China, utilizing remote sensing based on the partition–integration concept

Bing Guo\(^a,b,c,d\), Yewen Fan\(^c\), Fei Yang\(^e\), Lin Jiang\(^a\), Wenna Yang\(^a\), Shuting Chen\(^a\), Rui Gong\(^a\) and Tian Liang\(^a\)

\(^a\)School of Civil Architectural Engineering, Shandong University of Technology, Zibo, Shandong, China; \(^b\)Key Laboratory of Geographic Information Science (Ministry of Education), East China Normal University, Shanghai, China; \(^c\)State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China; \(^d\)Hubei Key Laboratory of Regional Development and Environmental Response (Hubei University), Wuhan, China; \(^e\)State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research of Chinese Academy of Sciences, Beijing, China

ABSTRACT
The various patterns of spatial heterogeneity in the eco-environment of the Silk Road Economic Belt of China differ greatly. In this study, a partition–integration concept was introduced to assess the ecological vulnerability of the Silk Road Economic Belt in China. To confirm the comparability of ecological vulnerability among different sub-regions, the net primary productivity (NPP) was utilized to determine the ecological vulnerability thresholds for different sub-regions. The results indicated that: (1) the new assessment model of ecological vulnerability based on the partition–integration concept was strongly operational and practical for the study region; (2) NPP was conducive to the continuous expression of ecological vulnerability, which can ensure better comparison and analysis of ecological vulnerability among the three sub-regions; (3) the spatial patterns of zones at different vulnerability levels differed greatly. The mild vulnerability zone was the most widely distributed, whereas the zone of slight vulnerability covered the smallest area. (4) Specific environmental protection and treatment measures should be conducted in the three sub-regions with different dominant ecological problems. These results can provide decision-making support in realizing the great strategy of the “one belt and one road” idea.

1. Introduction
Ecological vulnerability refers to the sensitivity and resilience of a landscape or ecosystem toward disturbances of the external environment on a specific spatial-temporal
scale (Chuvieco et al. 2014; Beroya-Eitner 2016). Since the twentieth century, environmental temperatures have increased worldwide, causing significant changes in the global climate and environment. Feedbacks to ecosystem changes, such as loss of species diversity, frequent occurrences of extreme weather events, intensified desertification, and melting of the polar glaciers all greatly threaten the survival of human beings and the sustainable development of a social economy (Farley and Voinov 2016; Heltberg et al. 2009). Moreover, with the rapid expansion of population and unreasonable exploitation and utilization of resources, the restorative and self-purification abilities of ecosystems have been declining; thus, both human living and natural environments have become more fragile (Li et al. 2007; Nandy et al. 2015; Liang et al. 2017). Ecological vulnerability assessment has become an important means for recognizing ecological conditions, which can aid sustainable development and ecological restoration of fragile ecological areas (Song et al. 2010; Shao et al. 2015; Sahoo et al. 2016). In September 2013, a strategic vision of the ‘Silk Road Economic Belt’ was proposed by President XI; subsequently, the Silk Road Economic Belt has become a relevant topic both at home and abroad (Li et al. 2017). The Silk Road Economic Belt of China, with a fragile ecological environment, is an important energy base, extending the advanced provinces of East China eastward, and linking Central Asian countries westward (Liu and Hao 2018). However, eco-environmental problems, including drought, desertification, salinization, and soil and water loss, have greatly restricted the sustainable development of the regional economy and society. Therefore, quantitative assessment of the ecological vulnerability of the Silk Road Economic Belt of China is of great importance in realizing the great strategy of ‘one belt and one road’.

The first assessment of ecological vulnerability performed in China dates back to the 1980s; since then, numerous empirical investigations and analyses have been conducted at varying scales (national, regional, and municipal) in different regions (Linder et al. 2010; Zhang et al. 2015). Through field investigation of ecological conditions in the Bosten Lake basin, the driving mechanisms of ecological vulnerability for the Bosten Lake wetland were analyzed and discussed by combining qualitative and quantitative methods (Ye et al. 2017). A pressure-support-state-response model (PSSR) was proposed for ecosystem vulnerability assessment, which had been applied to analyze the spatial patterns of the ecological vulnerability of wetlands in the Yellow River Delta (Zhang et al. 2017). Considering ecological sensitivity, pressure, and resilience, an ecological vulnerability assessment indicator system comprising nine elements and 12 indicators was established by Hong et al. (2016) and applied to finding the range of ecologically vulnerable areas in a highly urbanized region. Using remote sensing and geographic information system (GIS) technology, the wetlands of the Yellow River Delta were measured and the influence of human activities on wetland degradation was discussed (Wang et al. 2008). During recent decades, various ecological vulnerability assessment frameworks have been proposed, such as the vulnerability scoping diagram assessment framework (Polsky et al. 2007), the environmental sensitivity index (Amiri et al. 2014; Kang et al. 2018), and the pressure-state-response assessment framework (Zhang et al. 2017). In addition, specific vulnerability assessment methods have often been utilized as follows: the principal component analysis method (Li et al. 2006), the analytic hierarchy process (AHP) method (Guo
et al. 2016; Shen et al. 2016; Topuz and van Gestel 2016), the fuzzy comprehensive evaluation method (Enea and Salemi 2001; Adriaenssens et al. 2004) and the entropy method (Amiri et al. 2014; Hou et al. 2015). With its development, aeronautical remote sensing has become one of the most important technologies available for collecting biological parameters (Liu et al. 2006; Rogers and Xue 2015). Despite its advantages, such as the spatially explicit nature of measurements and the consistency across political borders, there were also some disadvantages that needed improvement.

Over recent decades, various investigations have been conducted to qualitatively or quantitatively evaluate ecological vulnerability, on varying scales, of the Silk Road Economic Belt of China (Liu et al. 2006; Hou et al. 2015; Jin and Wang 2016). However, spatial heterogeneity patterns of the eco-environment have not been considered in previous research. Further, how to determine a reasonable threshold to ensure the comparability of ecological vulnerabilities among the different regions should also be investigated. Therefore, fully considering the diversity of ecosystems in the Silk Road Economic Belt of China, the partition–integration concept has been introduced to assess the ecological vulnerability of the study region. In addition, the net primary productivity (NPP) and natural breaks methods have been utilized to determine the threshold for confirming the spatial consistency of ecological vulnerability among the different sub-zones.

2. Materials and methods

2.1. Study area

Historically, the Silk Road was an ancient network of routes that facilitated trade, culture, knowledge, and enhanced relations between people and between countries (Liu and Hao 2018). Geographically, the Silk Road Economic Belt in China...
(73°41′–121°57′E, 29°41′–49°33′N; Figure 1) covers an area of about 3.40 million km², including Jiangsu Province, Anhui Province, Henan Province, Shanxi Province, Gansu Province, Qinghai Province, the Ningxia Hui Autonomous Region, and the Xinjiang Uygur Autonomous Region (Xu et al. 2017). The terrain is complex and diverse, comprising the North China Plain, Loess Plateau, Tarim Basins, Qinghai-Tibetan Plateau, Altay Mountains, and the Tianshan and Kunlun Mountains (Deng et al. 2008). The altitude difference of the whole study region can reach 7000 m. Influenced by the East Asian monsoon, there is an increasing trend in the annual average precipitation from the southeast (1000 mm) to the northwest (50 mm). The annual temperature ranges from –2.5 °C to 10 °C. The climate type is diverse, including a temperate monsoon climate and temperate continental climate (Li et al. 2014). Owing to the singular structure of the ecosystem and low vegetation coverage, the ecosystem of the western part is extremely fragile, and the area of soil salinization and desertification is widely distributed (Wang et al. 2011).

2.2. Materials

The meteorological data during 2011–2015, including daily precipitation (mm), daily mean temperature (°C), daily highest temperature (°C), daily lowest temperature (°C), and daily and average wind velocity (m/s), were obtained from the Climatic Information Center of China (available at http://data.cma.cn/). The 342 meteorological stations are unevenly distributed over and around the whole study region, particularly in the western part (Figure 2). Thus, 176 interpolated stations were constructed according to the dataset of TRMM3B42 (Guo et al. 2016). The statistical spatial downscaling algorithm of TRMM (Equation 1) was used in this study (Guo et al. 2017):

Figure 2. Spatial distributions of the meteorological and interpolated stations. Source: Author
where \( P_d \) is the daily precipitation of the meteorological stations, and \( P_{trmm} \) is the daily precipitation calculated using the 3-hourly precipitation from TRMM3B42.

First, each 3-hourly precipitation rate was multiplied by 3 h to calculate the precipitation for each 3-h period, using FORTRAN. Then, the daily precipitation was obtained by accumulating all 3-hourly precipitation data as defined for the 24-h period.

Land use types from 2013 at 1:100,000 were obtained from the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences. This dataset was obtained by combining the computer-automated and manual interpretations with Landsat TM/ETM+/OLI. The digital elevation model data were downloaded free of charge from the National Geospatial-Intelligence Agency and the National Aeronautics and Space Administration (NASA) (available at http://srtm.csi.cgiar.org). The normal differential vegetation index (NDVI) data obtained from the MOD13A2 satellite were produced at a pixel resolution of 1000 m, with a 16-day interval. The annual net primary production (NPP) data derived from MOD17A3 was produced at a spatial resolution of 1000 m. The above mentioned datasets can be collected from NASA-EOS (National Aeronautics and Space Administration Earth Observing System) (https://ladsweb.modaps.eosdis.nasa.gov). Detailed information regarding soil types for the study region, such as soil organic carbon (%), soil particle size distribution (% sand, silt, and clay content), and calcium carbonate (%), was acquired from the Institute of Soil Science, Chinese Academy of Sciences; the spatial resolution of this dataset is 1000 m. The statistical social and economic data, including population, gross domestic product, and the Engel coefficient, were collected from the national and provincial statistical yearbooks.

2.3. Methods

2.3.1. Weighted linear combinations method

Integrated multiple factors into one index could indicate the condition of the eco-environment (Song et al. 2010; Guo et al. 2016). The method of weighted linear combinations (Equation 2), widely used in the vulnerability or quality assessment of an ecosystem, was used herein to calculate the ecological vulnerability index:

\[
EVI = \frac{\sum_{j=1}^{n} w_j I_j}{\sum_{j=1}^{n} w_j},
\]

where EVI refers to the ecological vulnerability index; \( w_j \) refers to the weight of factor \( j \); and \( I_j \) refers to the standardized factor \( j \).

2.3.2. Fuzzy analytic hierarchy process

Various methods have been applied to assess ecological vulnerability in different regions, such as the entropy-weight method (Amiri et al. 2014), the fuzzy comprehensive assessment (Enea and Salemi 2001; Adriaenssens et al. 2004), the AHP method (Mikhailov and Tsvetinov 2004; Sahoo et al. 2016), the landscape evaluation method (Linder et al. 2010), and the principal component method (Li et al. 2006). Among these methods, the AHP method is one of the most widely used evaluation tools,
which can determine the weights of the evaluated factors based on expert experience. However, the subjective judgment in AHP cannot fully consider the inherent uncertainty and ambiguity. Thus, the membership function (Equation 3) was introduced to establish the fuzzy analytic hierarchy process (FAHP) with AHP (see Figure 3):

\[ MF_{xi} = \frac{1}{1 + \left(\frac{x_i - b}{d}\right) \times 2}, \]

where \( MF_{xi} \) refers to the membership value of factor \( i \); \( x_i \) refers to the value of factor \( i \); \( d \) is the width of the transition interval; and \( b \) refers to the factor value, whereas the membership value is 1.

2.3.3. ISODATA algorithm

The ISODATA algorithm is an unsupervised classification method, which is used to simultaneously classify raster grids (various layers) into several categories (Li et al. 2017; Zhang et al. 2018). The detailed steps of the ISODATA algorithm are listed as

Figure 3. Technical process of the fuzzy analytic hierarchy process (FAHP).
follows (see Figure 4). The detailed information of the evaluation system and weights is listed in the following table (Table 5).

2.3.4. Standardization for assessment variables
As the evaluated factors are measured in different units, they must be standardized to a uniform scale (Guo et al. 2016; Zhou et al. 2016; Guo et al. 2017). Therefore, in the process of ecological vulnerability assessment, the first step is to establish a standardized measurement system for all factors. For this case, variables can be processed using Equations 4 and 5 to change them into unitless variables (0–1):

$$I_i = \frac{Var - Var_{\min}}{Var_{\max} - Var_{\min}} \text{ (Positive)},$$

Figure 4. Technical process of the ISODATA algorithm.
\[ I_i = \frac{Var_{\text{max}} - Var}{Var_{\text{max}} - Var_{\text{min}}} \text{(Negative)}, \]  

(5)

where \( I_i \) refers to the standardized factor of \( Var \); \( Var_{\text{min}} \) refers to the minimum value of factor \( Var \); and \( Var_{\text{max}} \) refers to the maximum value of factor \( Var \).

### 3. Evaluation system of the sub-regions of the silk road economic belt in China

#### 3.1. Partition of the eco-environment

Owing to the vast territory of the Silk Road Economic Belt, there are significant differences in the ecosystems among the different sub-regions (Liu and Hao 2018). Moreover, the dominant eco-environmental problems affecting the vulnerability of the regional ecosystems differ greatly (Zhou and Ren 2011). Partitioning of the eco-environment is essential for large-scale ecological vulnerability assessment. Expert integration methods have been widely used to construct the eco-environmental sub-regions, which cannot be repeatedly operated owing to the overreliance on expert experience and knowledge.

In this study, spatial autocorrelation analysis was performed among various factors affecting eco-environmental vulnerability by combining the GIS and remote sensing. The result thus obtained showed that correlations among various factors are significant. In addition, the number of factors is vast, which is not conducive to the partitioning of the eco-environment (Table 1). Thus, the principal component analysis method was introduced to obtain the main components of the multi-factors, which could largely eliminate the correlation among different factors. Furthermore, the top four principal components with an information contribution of more than 96% were extracted (Table 2, Equations (6–7)).

\[
\text{PC1} = -0.06x_1 + 0.03x_2 - 0.17x_3 - 0.07x_4 - 0.16x_5 + 0.42x_6 - 0.25x_7 - 0.05x_8
\]

\[
-0.25x_9 - 0.30x_{10} - 0.27x_{11} - 0.16x_{12} - 0.39x_{13} - 0.53x_{14}
\]  

(6)

### Table 1. Factors for partitioning the eco-environment.

| Clustering factors | First level | Second level |
|--------------------|-------------|--------------|
|                    | Climate     | Precipitation, Temperature, Sunshine hour, Aridity, Wind velocity, Accumulated temperature (>10 °C) |
|                    | Topography  | Altitude, Slope, Aspect |
|                    | Vegetation  | NDVI, NPP |
|                    | Soil        | Soil erosion, Salinization, Desertification |

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**Table 1. Factors for partitioning the eco-environment.**
where $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, $x_7$, $x_8$, $x_9$, $x_{10}$, $x_{11}$, $x_{12}$, $x_{13}$, and $x_{14}$ refers to precipitation, temperature, sunshine hour, aridity, wind velocity, accumulated temperature ($>10^\circ C$), altitude, slope, aspect, NDVI, NPP, soil erosion, salinization, and desertification, respectively.

Then, the ISODATA was utilized to obtain the sub-regions of the study region (Figure 5). Four partition schemes (Figure 5(a–d)) were obtained based on four components. Figure 5(a) showed that there were two sub-regions (sub-region I and sub-region II), mainly resulting from the climate and vegetation factors. Sub-region I was primarily distributed in the humid and semi-humid area, whereas Sub-region I covered the arid and semi-arid zones. Sub-region I in Figure 5(a) was divided into two parts because of the topography and soil factors; Sub-regions I and II in Figure 5(c) were divided into two parts, mainly according to the climate factors. In Figure 5(d), there were four sub-regions. Then, fully considering the dominant eco-environmental problems (desertification, wind erosion, salinization, freeze–thaw erosion, and soil and water erosion) and previous researches of the Silk Road Economic Belt in China, the study region was finally divided into three sub-regions (Figure 6).

3.2. Construction of an evaluation system for the three sub-regions

Considering the spatial heterogeneity patterns of the eco-environments of the Silk Road Economic Belt, different evaluation systems can be constructed for different
sub-regions. Moreover, the factors to be evaluated must be chosen according to dominance, adaptability, and rationality principles.

3.2.1. Evaluation system of the arid desert ecological region

The Arid Desert Ecological Region is located in the northwest of China, which is slightly influenced by the humid monsoon. The annual precipitation in this area is

![Figure 5](image1.png)

Figure 5. Different partition schemes for the Silk Road Economic Belt in China. (a) Two sub-regions; (b) Three sub-regions; (c) Four sub-regions; (d) Five sub-regions. Source: Author

![Figure 6](image2.png)

Figure 6. The three sub-regions of eco-environments. Sub-region I refers to the Arid Desert Ecological Region; Sub-region II refers to the Alpine Ecological Region; Sub-region III refers to Humid and Semi-humid Ecological Regions. Source: Author
generally less than 200 m and the vegetation is low (Jin and Wang 2016). The surface landscape is dominated by deserts, including the Gobi, and wind-eroded hills. The eco-environmental characteristics of the Arid Desert Ecological Region are sandstorms, drought, desertification, wind erosion, and salinization (Deng et al. 2008). Based on field investigations of the eco-environmental background characteristics of the Arid Desert Ecological Region, the evaluation system herein has been established in conjunction with the National Main Function Zone Planning and Implementation Plan, the Technical Standard for Ecological Environment Status Assessment (Trial Implementation), and related previous studies. Next, the weight for each factor in the evaluation system was determined via the FAHP. Table 3 provides detailed information regarding the same:

### Table 3. Evaluating the system and weight of each factor for the Arid Desert Ecological Region.

| First Grade | Second Grade |
|-------------|--------------|
| **Factor**  | **Weight**   | **Factor**  | **Weight** |
| Evaluation system of Arid Desert Ecological Region | | WR | 0.5 | 0.13 |
| Water       | 0.25         | WCD | 0.5 | 0.13 |
| Climate     | 0.16         | AAP | 0.26 | 0.04 |
|             |              | AT  | 0.14 | 0.02 |
|             |              | NDWV| 0.18 | 0.03 |
|             |              | AR  | 0.16 | 0.03 |
|             |              | SH  | 0.07 | 0.01 |
|             |              | NEHTD | 0.11  | 0.02 |
|             |              | NELTD | 0.08  | 0.01 |
| Vegetation  | 0.2          | BI  | 0.42 | 0.08 |
|             |              | NPP | 0.47 | 0.09 |
|             |              | SHEI| 0.06 | 0.01 |
|             |              | SHDI| 0.06 | 0.01 |
| Soil        | 0.27         | SWAE| 0.17 | 0.05 |
|             |              | SSA | 0.22 | 0.06 |
|             |              | DES | 0.35 | 0.09 |
|             |              | SWIE| 0.26 | 0.07 |
| Human activities | 0.12 | PD  | 0.38 | 0.05 |
|             |              | GDPD| 0.38 | 0.05 |
|             |              | EC  | 0.12 | 0.01 |
|             |              | PCNIFH| 0.12  | 0.01 |

**Notes:** WR refers to water resource; WCD refers to water channel density; AAP refers to average annual precipitation; AT (>10 °C) refers to the accumulative temperature of ≥10 °C; NDWV (>6 m/s) refers to the number of days with wind velocity ≥6 m/s; AR refers to aridity index; SH refers to sunshine hour; NEHTD refers to the number of extremely high temperature days; NELTD refers to the number of extremely low temperature days; BI refers to biodiversity index; NPP refers to NPP; SHEI refers to the Shannon evenness index; SHDI refers to the Shannon diversity index; SWAE refers to soil water erosion; SSA refers to soil salinization; DES refers to desertification; SWIE refers to soil wind erosion; PD refers to population density; GDPD refers to gross domestic product density; EC refers to Engle’s Coefficient; PCNIFH refers to the per capita net income of farmers and herdsmen.

3.2.2. Evaluation system of the alpine ecological region

The Alpine Ecological Region is located in the Qinghai-Tibet Plateau. Owing to the spatial-temporal distributions of water and heat, the climate of the Alpine Ecological Region is characterized by strong wind, drought, hypoxia, cold, strong radiation, and large temperature differences between day and night (Guo et al. 2016). Based on field investigations of the eco-environmental background characteristics of the Arid Desert Ecological Region, the evaluation system herein has been established in conjunction with the National Main Function Zone Planning and Implementation Plan, the Technical Standard for Ecological Environment Status Assessment (Trial Implementation), and related previous studies. Next, the weight for each factor in the evaluation system was determined via the FAHP. Table 3 provides detailed information regarding the same:
the weight for each factor was similar to that of the Arid Desert Ecological Region. The detailed information of the evaluation system and weights is listed in Table 4.

### 3.2.3. Evaluation system of the humid and semi-humid ecological region

The Humid and Semi-humid Ecological Region is located in the Loss Plateau and the Huang-Huai-Hai Plain, and its climate is significantly affected by the marine monsoon in summer and the Siberian High in winter. Majority of the precipitation occurs during summer (Li et al. 2009; Wang et al. 2011; Fan et al. 2015). The ecosystem of this sub-region was greatly disturbed by rainstorms, soil and water erosion, and human activities (Jiao et al. 2012). The process of selecting the evaluating factors and determining the weight for each factor was similar to that of the Arid Desert Ecological Region. The detailed information of the evaluation system and weights is listed in the following table:

### 4. Results

#### 4.1. Quantitative assessment of the Sub-regions

The weighted linear combinations method was adopted to calculate the ecological vulnerability index of the three sub-regions based on Tables 1, 2, and 3. However, the comparison and analysis were difficult to conduct owing to the differences in evaluation systems and weights of the factors for the three sub-regions. NPP had a clear ecological meaning, which was conducive to the continuous expression of ecological vulnerability in the different sub-regions (Guo et al. 2016). In this study, NPP has been introduced to help determine the thresholds of ecological vulnerability. The steps can be listed as follows: (1) the NPP of the whole study region was first divided

### Table 4. Evaluating system and the weight of each factor for the Alpine Ecological Region.

| Evaluation system of Alpine Ecological Region | Weight | Factor | Weight | Factor | Weight |
|-----------------------------------------------|--------|--------|--------|--------|--------|
| Water                                         | 0.21   | WR     | 0.5    | WCD    | 0.5    |
|                                               |        |        |        | AAP    | 0.21   |
|                                               |        |        |        | AT     | 0.17   |
|                                               |        |        |        | NDWV   | 0.19   |
|                                               |        |        |        | AR     | 0.15   |
|                                               |        |        |        | SH     | 0.11   |
|                                               |        |        |        | NEHTD  | 0.07   |
|                                               |        |        |        | NELTD  | 0.1    |
|                                               |        |        |        | BI     | 0.42   |
|                                               |        |        |        | NPP    | 0.47   |
|                                               |        |        |        | SHEI   | 0.06   |
|                                               |        |        |        | SHDI   | 0.06   |
|                                               |        |        |        | SWAE   | 0.22   |
|                                               |        |        |        | SFTE   | 0.35   |
|                                               |        |        |        | SSA    | 0.27   |
|                                               |        |        |        | SWIE   | 0.16   |
|                                               |        |        |        | PD     | 0.38   |
|                                               |        |        |        | GDPD   | 0.38   |
|                                               |        |        |        | EC     | 0.12   |
|                                               |        |        |        | PCNIFH | 0.12   |

Notes: SFTE refers to soil freeze–thaw erosion; Other definitions of abbreviations are identical to those in Table 3.
into four categories using the tool of natural breaks of ArcGIS 10.2; (2) the categorized NPP were then extracted for the three sub-regions; (3) the average vulnerability index of each NPP category for the three sub-regions was calculated; (4) finally, the vulnerability thresholds of the three sub-regions were determined using the statistical average value of the vulnerability indices. Based on the vulnerability thresholds for the three sub-regions (Table 6), the spatial distribution of different levels of ecological vulnerability for the Silk Road Economic Belt of China was obtained (Figure 7).

### 4.2. Spatial patterns of the ecological vulnerability of the Silk Road Economic Belt

As shown in Figures 7 and 8, the spatial patterns of the zones at different vulnerability levels differed greatly. The mild vulnerability zone was the most widely distributed and accounted for 25.9% of the entire study region. This zone was concentrated in the middle part of the Three River Source Region (including southern Zhiduo and northern Maqin), the western margin of Tarim Basin (including the middle of Kashi, Southern Hetian), the southern part of the North China Plain, and the Qinling Mountains region. The zone of severe vulnerability, covering the second largest area (accounting for 24.2%), was mainly distributed across Junggar Basin, Qaidam Basin, and the western part of the Inner Mongolia Plateau. The zone of intense vulnerability was mostly distributed across Tarim Basin (including Korla and northern Hetian), the southeastern part of the Qaidam Basin (including Wulan), and the western part of the Loess Plateau. The moderate vulnerability zone was discontinuously distributed across the northern part of the Three River Source Region and the eastern part of the Loess Plateau. Of all the vulnerability levels, the zone of slight vulnerability covered the smallest area and accounted for 7.3%. This zone was mostly concentrated in the

### Table 5. Evaluating system and the weight of each factor for the humid and semi-humid ecological regions.

| First Grade | Second Grade |
|-------------|--------------|
| Water       | WR          |
| WR          | Water       |
| 0.18        | 0.5         | 0.09 |
| WCD         | 0.5         | 0.09 |
| AAP         | 0.3         | 0.04 |
| AT          | 0.18        | 0.02 |
| SH          | 0.12        | 0.02 |
| NEPD        | 0.15        | 0.02 |
| NEHTD       | 0.13        | 0.02 |
| NELTD       | 0.12        | 0.02 |
| BI          | 0.42        | 0.12 |
| NPP         | 0.47        | 0.13 |
| SHEI        | 0.06        | 0.02 |
| SHDI        | 0.06        | 0.02 |
| SWAE        | 1           | 0.30 |
| PD          | 0.28        | 0.04 |
| GDPD        | 0.36        | 0.05 |
| PAP         | 0.12        | 0.02 |
| EC          | 0.12        | 0.02 |
| PCNIFH      | 0.12        | 0.02 |

Notes: NEPD refers to the number of extreme precipitation days; PAP refers to the proportion of agricultural population; Other definitions of abbreviations are identical to those in Table 3.
Table 6. Vulnerability thresholds for the three sub-regions.

| Vulnerability Levels | SR1     | SR2     | SR3     |
|----------------------|---------|---------|---------|
| Slight               | ≤0.55   | ≤0.49   | ≤0.57   |
| Mild                 | 0.55–0.73 | 0.49–0.64 | 0.57–0.73 |
| Moderate             | 0.73–0.87 | 0.64–0.78 | 0.73–0.85 |
| Intensive            | 0.87–0.98 | 0.78–0.95 | 0.85–0.97 |
| Severe               | ≥0.98   | ≥0.95   | ≥0.97   |

Notes: SR1 refers to the Arid Desert Ecological Region; SR2 refers to the Alpine Ecological Region; SR3 refers to the Humid and Semi-humid Ecological Region.

Figure 7. Spatial distribution of the different levels of ecological vulnerability. Source: Author

Figure 8. Area percentages of the different levels of ecological vulnerability.
southeast part of the Three River Source Region, the Ili River Valley, and the Altay Mountains.

5. Discussions

5.1. Analysis of the method presented

The partition–integration concept has been introduced to establish the evaluation system of the ecological vulnerability of the Silk Road Economic Belt of China, combing the FAHP, RS, and GIS. Similar studies have not been reported in the field of ecological vulnerability evaluation. The Silk Road Economic Belt of China covers about 3.40 million km$^2$, which comprises eight provinces (Xu et al. 2017). The terrain and climate are complex and diverse. The dominant ecological problems significantly differ over the whole study region (Liu and Hao 2018). In addition, the relative importance of factors considerably varies across the different sub-regions. This method fully considered the spatial pattern differences of the ecological environments, and different evaluation systems were developed. The determination of weights for factors played an important role in the process of vulnerability evaluation. The method of FAHP brought the triangular fuzzy number of the fuzzy set theory into the pair-wise comparison matrix of the AHP, which solved the vague problems that occurred during the analysis of criteria and the judgment process (Adriaenssens et al. 2004; Li et al. 2009; Topuz and van Gestel 2016). Thus, FAHP should tolerate vagueness or ambiguity and be more appropriate and effective than conventional AHP in dynamic estimations of eco-environmental vulnerability.

5.2. Major problems of the three sub-regions

The predominant problems of the three sub-regions considerably differed over the whole study region:

1. The Arid Desert Ecological Region is located in the northeastern inland area, which is a typical arid region with an annual precipitation of 146 mm (Deng et al. 2008). In addition, this sub-region is one of the most severely affected regions by meteorological disasters (Zhang et al. 2008). Various disasters, including cold waves, strong winds, snowstorms, sandstorms, heavy rain, early frost, drought, and continuous extreme heat, are widely and unevenly distributed across this entire sub-region (Xu et al. 2017). The composition of the vegetation ecosystem is extremely poor, and the community is homogeneous. The structure of the regional ecosystem is mostly monolayer while the biological productivity is extremely low (Guo et al. 2017). Therefore, the stability of the ecosystem is low and its self-regulating ability is poor. During the past decades, owing to excessive economic activities, the balance of the ecosystem has been destroyed, and processes of change have occurred in originally non-desert areas (mainly desert grasslands with sparse vegetation), where the surface pattern is similar to the desert landscape (Jin and Wang 2016). Desertification is another major environmental problem due to the abundant sources of sand and wind. Moreover, excessive human activity, such as indiscriminate reclamation,
logging, digging, cutting, and blind deforestation has greatly destroyed the natural vegetation and gradually transformed non-desert land into desert land (Deng et al. 2008). Salinization is one of the most widely distributed ecological problems in this zone owing to the arid climate that can bring the salt of deep soils to the ground surface (Guo et al. 2017). In addition, improper agricultural measures, such as blocked drainage systems, have greatly exacerbated this ecological problem.

2. The Alpine Ecological Region is located in the northeastern part of the Qinghai-Tibetan Plateau. Desertification is the most serious ecological problem in this sub-region owing to its dry and cold climate and human activity (Guo et al. 2016). The desertified land types mainly comprise mobile dunes, semi-fixed dunes, and fixed dunes. Moreover, an increasing trend has been observed in the area’s desertification with increasing global warming and human activity (Nandy et al. 2015). Freeze–thaw erosion was widely distributed throughout the Qilian Mountains, directly affecting and restricting floral succession and further accelerating the degradation process of the grassland (Shao et al. 2015). Soil wind erosion and salinization is widely distributed in Qaidam Basin, causing great loss of arable land resources (Liu et al. 2006). Soil water erosion is mainly concentrated in the eastern part of the study region, particularly in the loess hilly region. During recent decades, an increasing trend has been observed in the frequency of drought, snowstorms, and sandstorms, which has brought great loss to farmers and herdsmen (Yang et al. 2004; Guo et al. 2016).

3. The Humid and Semi-humid Ecological Region is mostly located in the Loess Plateau and North China Plain. The dominant ecological problems in this region constitute drought, catastrophic floods, rainstorms, sandstorms, and soil water erosion (Hou et al. 2015). Owing to the increase in population, the scope and intensity of reclaimed land have been continuously spread, and the vegetation has been seriously damaged (Fan et al. 2015). The Loess Plateau has become one of the most serious soil erosion areas in the world, with the erosion area accounting for 80% of the total area (Li et al. 2009). Long-term, severe soil erosion has led to the fragmentation and fissuring of the Loess Plateau. In recent centuries, human activity has strongly influenced the evolution of the ecological environment in the Loess Plateau. Furthermore, the soil erosion process has dominated the whole Loess Plateau system (Jiao et al. 2012). Sandstorms have become a common natural phenomenon, caused by meteorological factors (including drought, high temperatures, and strong wind) and human factors (including increasing population, poor sense of environmental protection, overcutting of trees, and overgrazing) (Wang et al. 2011). The Loess Plateau is located in the arid and semi-arid regions of the middle latitudes. The Loess Plateau is mostly covered by sandy land, sparse grassland, and dry farmland. The plateau has become more easily prone to sandstorms in such areas, where surface vegetative coverage is low and weather conditions are conducive, particularly in spring (Jiao et al. 2012). The dust storm process has significantly destroyed the ecosystem, accelerating the land’s desertification (Fan et al. 2015). The Loess Plateau is the oldest known area of loess accumulation in the world. However, the development of loess accumulation indicates a general trend toward a dry climate in northern China (Hou et al. 2015). Thus, drought is also one of its major ecological problems. In addition, the rainy season in the Loess Plateau is concentrated, making it flood prone owing to frequent rainstorms.
5.3. Conservation implications

The objective of environmental assessment is to assist policy makers and practitioners of environmental protection. Zones of severe ecological vulnerability should receive more attention than others, and appropriate measures such as ‘convert slope farmland into forest or pasture’ should be established and implemented. However, the dominant ecological problems of the Silk Road Economic Belt of China differ greatly. Therefore, different conservation systems should be applied to protect specific regional eco-environments.

1. First, for the Arid Desert Ecological Region, the shelterbelt and artificial grasslands should be constructed to reduce damage to ecosystems from wind erosion and sandstorms. Second, the oasis should be expanded to optimize the desert ecosystem. In an oasis, owing to expansion of surface irrigation and the enhancement of evapotranspiration, the relative humidity is increased, whereas the maximum surface temperature is decreased (Zhang et al. 2008). Therefore, the desert’s water and heat conditions are changed to establish the water and heat balance of the oasis (Deng et al. 2008). Third, the efficiency of water resource use should be enhanced to mitigate the water resource deficit over the whole sub-region. Measures, such as construction of regulating reservoirs, diversion pivots, canal seepage controls, and development of shaft irrigation and drainage, can be implemented to reduce the impacts of drought on the agricultural ecosystem (Jin and Wang 2016).

2. For the Alpine Ecological Region, first, the number of livestock should be controlled to maintain the balance of livestock and grass (Yang et al. 2004). Excessive grazing has led to extensive degradation of natural grasslands in Qaidam Basin (Liu et al. 2006). Second, construction of farmland shelterbelts, windbreak, and sand stabilization forests should be conducted to improve the condition of the regional eco-environment. Third, the organization and management of nature preserves should be strengthened to curb the deterioration of the Three River Source Region.

3. For the Humid and Semi-humid Region, first, the population size should be controlled, particularly where the ecological load-carrying capacity of the population is small, such as the Loess Plateau. Typical belief states that the population density in the Loess Plateau, which has reached 65 persons/km², should not exceed 20 persons/km² (Hou et al. 2015); this must be regulated. Second, the reconversion of farmland to forests and grasslands should be implemented in sloping lands to ensure effective vegetation restoration and reconstruction (Li et al. 2009). Third, improved water conservation and water use efficiency should be adopted to ease the ecological pressures caused by insufficient water resources.

6. Conclusions

For a comprehensive consideration of the diversity of ecosystems in the Silk Road Economic Belt of China, the partition–integration concept has been introduced herein to assess the ecological vulnerability of the study region. The main conclusions are as follows.
1. The dominant eco-environmental problems differ greatly over the whole study region, and the relative importance of each factor in three sub-regions is also different. The new assessment model of ecological vulnerability based on the partition–integration concept has strong operational and practical value.

2. NPP was introduced to help determine the thresholds of ecological vulnerability, which can better ensure accurate comparison and analysis of ecological vulnerability across the three sub-regions.

3. The spatial patterns of zones at different vulnerability levels differ greatly. The mild vulnerability zone (accounting for 25.9% of total area) was the most widely distributed whereas the zone of slight vulnerability (accounting for 7.3% of total area) covered the smallest area.

4. Specific environmental protection and treatment measures should be conducted to remedy each of the three sub-region’s different dominant ecological problems.

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ORCID
Bing Guo http://orcid.org/0000-0003-0042-9643
Yewen Fan http://orcid.org/0000-0003-2606-1621
Fei Yang http://orcid.org/0000-0002-5095-7703
Lin Jiang http://orcid.org/0000-0003-0237-9547
Wenna Yang http://orcid.org/0000-0001-5113-7849
Shuting Chen http://orcid.org/0000-0001-6138-7905
Rui Gong http://orcid.org/0000-0002-8122-8589
Tian Liang http://orcid.org/0000-0001-8884-7246

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