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Comment

RSEI or MRSEI? Comment on Jia et al. Evaluation of Eco-Environmental Quality in Qaidam Basin Based on the Ecological Index (MRSEI) and GEE. *Remote Sens.* 2021, *13*, 4543

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Abstract: Recently, Jia et al. employed the index, modified remote sensing ecological index (MRSEI), to evaluate the ecological quality of the Qaidam Basin, China. The MRSEI made a modification to the previous remote sensing-based ecological index (RSEI), which is a frequently used remote sensing technique for evaluating regional ecological status. Based on the investigation of the ecological implications of the three principal components (PCs) derived from the principal component analysis (PCA) and the case study of the Qaidam Basin, this comment analyzed the rationality of the modification made to RSEI by MRSEI and compared MRSEI with RSEI. The analysis of the three PCs shows that the first principal component (PC1) has clear ecological implications, whereas the second principal component (PC2) and the third principal component (PC3) have not. Therefore, RSEI can only be constructed with PC1. However, MRSEI unreasonably added PC2 and PC3 into PC1 to construct the index. This resulted in the interference of each principal component. The addition also significantly reduced the weight of PC1 in the computation of MRSEI. The comparison results show that MRSEI does not improve RSEI, but causes the overestimation of the ecological quality of the Qaidam Basin. Therefore, the modification made by MRSEI is questionable and MRSEI is not recommended to be used for regional ecological quality evaluation.

Keywords: RSEI; MRSEI; principal components analysis (PCA)

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1. Introduction

In their recent study, Jia et al. [1] employed an ecological index, the modified remote sensing ecological index (MRSEI), as a key technique for the evaluation of the ecological quality of the Qaidam Basin in northwestern China. However, they did not detail the rationality and feasibility of the application of the index to the basin, but simply listed some cases [2–6] to support their use of the index. However, these cases did not use MRSEI to evaluate ecological quality, but employed another index named the remote sensing-based ecological index (RSEI) [7]. Therefore, the cases that they erroneously cited cannot support the success of MRSEI. Because Jia et al. [1] did not acknowledge that the basic ideas of MRSEI originated from those of RSEI at all, it is necessary to introduce RSEI, clarify the difference between RSEI and MRSEI, and discuss whether the modification made to RSEI by MRSEI is necessary and reasonable; and whether MRSEI is suitable for the evaluation of regional ecological quality.

2. Comparison of RSEI with MRSEI

2.1. RSEI

The RSEI was developed by Xu [7] and Xu et al. [8] and has become a commonly-used remote sensing-based technique to evaluate ecological status in different geographical

areas at various scales. The index integrates four indicators (greenness, wetness, dryness, and heat) that are often used to evaluate ecological conditions because the four indicators are closely related to ecological quality and can be directly perceived by people [9–11]. Accordingly, RSEI is a function of the four indicators:

$$RSEI = f\ (Greenness, Wetness, Heat, Dryness)$$

The four indicators can be computed using related thematic remote sensing indices/algorithms. Greenness is represented by the normalized difference vegetation index (NDVI) [12], wetness by the wet component of the tasseled cap transformation (TCT) [13,14], heat by land surface temperature (LST), and dryness by the normalized difference soil index (NDSI) [15], as these indices/algorithms have been frequently used for the evaluation of the ecological quality of various regions such as [16–18].

The four indicators are integrated to formulate RSEI via a principal component analysis (PCA) rather than a traditional weighted sum method. RSEI is represented by the first principal component (PC1) of PCA. As such, RSEI can be expressed as:

$$RSEI = f\ (NDVI, Wet, LST, NDSI) = \mathrm{PC1}(NDVI, Wet, LST, NDSI)$$

The contribution of each indicator to RSEI is weighted by its eigenvector loading to PC1. This avoids a subjective assignment of a fixed weight to the indicator used in the weighted sum method. Therefore, RSEI has robustness and has been applied to different geographical regions, such as urban [4,19–21], rural [3,7], forest [22,23], wetland [24,25], island [26,27], desert [5,28], loess plateau [29,30], and mining areas [31]. The advantages of RSEI were summarized as (1) visualizable, (2) scalable, (3) comparable, and (4) customizable to minimize the error caused by other properties in weight definitions [26].

2.2. MRSEI

MRSEI also used the four indicators identical to those of RSEI; i.e., NDVI, Wet, LST, and NDSI. These four indicators were also integrated with the PCA technique similar to RSEI. The only difference is that MRSEI took the first three principal components (PCs 1–3) to integrate MRSEI and assigned a weight to each of the components. The difference between the two indices can be expressed as follows:

$$\begin{cases} RSEI = \mathrm{PC1} \\ MRSEI = w_1\mathrm{PC1} + w_2\mathrm{PC2} + w_3\mathrm{PC3} \end{cases}$$

where w_i is the weight assigned to the ith PC determined by its proportional eigenvalue. w_i can be different for each year as a different year can have different proportional eigenvalues and thus, weights for each of PCs. In this way, MRSEI can be generalized for any specific year.

Obviously, the difference between RSEI and MRSEI lies in whether the index should be integrated with three PCs (PCs 1–3) or just one PC (PC1). To discuss this matter, it is necessary to recall the principle of PCA.

2.3. Principal Component Transformation

PCA is a data-dimension compression technique. In a multidimensional data set, PCA compresses the information of the data set to several perpendicular principal components by rotating the coordinate axes to reduce the data dimension and redundancy. Figure 1 illustrates the basic principle of principal component transformation by taking 2-dimension and 3-dimension normal data as examples.

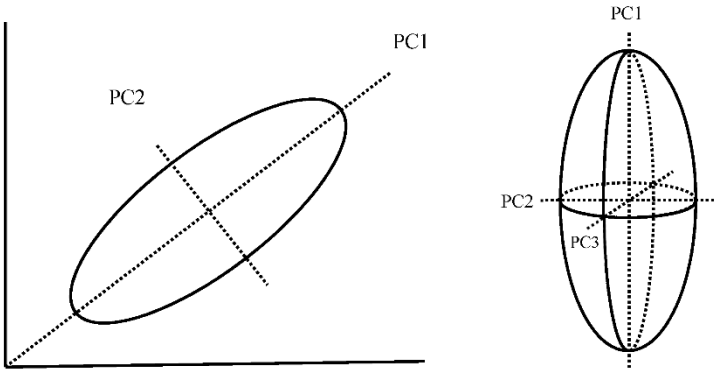


Figure 1. Transects of an ellipse (**left**) and an ellipsoid (**right**) to graphically show the three principal components (PCs 1–3) after principal component transformation (PC 4 is not presented as Jia et al. [1] did not use it).

As seen in Figure 1, the three principal components (PCs 1–3) have the following important characteristics: PC1 is the transect that corresponds to the major (longest) axis of the ellipse/ellipsoid after coordinate rotation; thus, it measures the highest variation within the data set and has the largest eigenvalue; PC2 is the second-longest axis that defines the second-largest amount of variation and is orthogonal to PC1; and PC3 is the shortest axis of the ellipsoid perpendicular to PC2. Accordingly, for the eigenvalue, PC1 > PC2 > PC3. It should be emphasized that the three PCs are not correlated to each other as the PCs are perpendicular to each other and thus, are independent.

Each PC usually contains specific information related to certain kinds of physical features; therefore, it needs to be explored and scientifically interpreted. This is sometimes difficult because the interpretation of physical features in the derived PCs presents considerable problems [32,33]. In the change detection of multitemporal images, PC1 usually collects the common features of all images, whereas the succeeding PCs are independent (orthogonal) of the preceding PC; therefore, they often contain the different information of the images. The change information can often be found in PC3 or PC4 [32,33]. In addition, in remote sensing-based mineral mapping, the information of a target mineral is often related to specific PCs, such as PCs 3, 4, or 6 [34–36]. Therefore, an important task of PCA application is to determine the PC that can reasonably reveal particular information of interest.

Since the pieces of information represented by each PC after principal component transformation are uncorrelated to each other, it is incorrect to add several unrelated PCs together without careful analysis, which will inevitably result in mutual interference and confusion of different information represented by different PCs. For a time-series change detection, if PC1, which represents the common information of multi-temporal images, and PC3, which denotes the change information among the multi-temporal images, are added together, the result can neither represent the common features of the images nor the change of information among them. Therefore, the PCs are mostly used independently rather than accumulatively because each of them contains specific information that is independent of the other.

Among the four indicators selected by RSEI, greenness and wetness have positive effects on ecosystems and thus, are the ecologically favorable indicators, whereas dryness and heat have negative effects on ecosystems and hence, are ecologically unfavorable ones. Accordingly, the ecologically favorable indicators (greenness and wetness) should be positively correlated with each other, but negatively correlated with the two ecologically unfavorable indicators (dryness and heat). Similarly, the two ecologically unfavorable indicators should be positively correlated with each other, but negatively correlated with the ecologically favorable indicators. Accordingly, it is important to identify which PC has the same signs for greenness and wetness, but has the opposite signs for dryness and heat.

Xu [7] and Xu et al. [8] have found that the four indicators were divided into two groups in PC1 according to their signs. The two ecologically favorable indicators (greenness and wetness) have the same sign; in addition, the two ecologically-unfavorable indicators (dryness and heat) also have the same sign, but are opposite to those of ecologically favorable indicators. Existing research has proved that there had been no exception to this rule elsewhere [2,3,19,20,22–31]. This rule, however, cannot be found in succeeding PC2 and PC3. The loading signs of the four indicators in PC2 and PC3 are not fixed. The ecologically favorable and unfavorable indicators can have the same sign and thus, are often mixed in the same group (see Section 3.1). This suggests that PC1 has clear ecological meanings, whereas PC2 and PC3 have not. In addition, PC1 has the largest eigenvector value among the PCs. Therefore, PC1 has been selected to construct RSEI for the evaluation of regional ecological status [7]. On the other hand, if PC2 and PC3 are added together with PC1, as what has been done by Jia et al. [1] for MRSEI, it will disturb the ecological information in PC1 rather than improve it, since PC2 and PC3 have no ecological implications.

3. Case of the Qaidam Basin

3.1. Characteristics of PCs 1, 2, and 3

Jia et al. [1] used MRSEI to retrieve the ecological quality of the Qaidam Basin, the highest desert on Earth. Unfortunately, they simply added PCs 1, 2, and 3 together, and did not analyze the sign and loading of each indicator in each PC to identify which PC has ecological significance; moreover, they did they provide any relevant PCA data. Therefore, we conduct this analysis to examine the ecological implications of PCs 1, 2, and 3.

To be comparable with the results of Jia et al. [1], we downloaded the Landsat 8 imagery of the basin from the Google Earth Engine (GEE) platform and removed snow and water pixels following their methods. Jia et al. [1] used Landsat surface reflectance (Landsat_SR) products for their study. Each image of a study year in their work was combined with the image of the target year and two other images; one before and one after the target year (three years' images in total). The period for GEE to select images was confined between 1 July and 31 August.

Accordingly, we downloaded the 2019, 2020, and 2021 images of the Landsat 8 surface reflectance (Landsat_SR) product and land surface temperature (Landsat_ST) product between 1 July and 31 August from GEE to compose the 2020 Landsat 8 basin image using the median of the involved images. No further atmospheric correction was performed as this has already been conducted for the Landsat_SR product [1]. As suggested by Jia et al. [1], the snow pixels in the composite basin image were removed based on the snow attribute field in the quality evaluation band "pixel_qa", and the water pixels were removed using the modified normalized difference water index (MNDWI) [37].

The processed basin image was used to calculate the four indicators: Wet, NDVI, NDSI, and LST, respectively. PCA was then performed on these four indicators to obtain the images of PCs 1, 2, and 3 of the indicators, respectively (Figure 2). Table 1 provides the eigenvector loading values and signs of the four indicators to each PC.

Table 1. Eigenvector statistics for four indicators.

	PC1	PC2	PC3	PC4
Wet (wetness)	0.3852	–0.4742	0.1806	0.7708
NDVI (greenness)	0.1958	0.6937	0.6716	0.1716
NDSI (dryness)	–0.4714	0.4329	–0.4659	0.6110
LST (heat)	–0.7688	–0.3263	0.5472	0.0553
Eigenvalue	0.0180	0.0068	0.0044	0.0004
Proportional eigenvalue	0.61	0.23	0.15	0.01

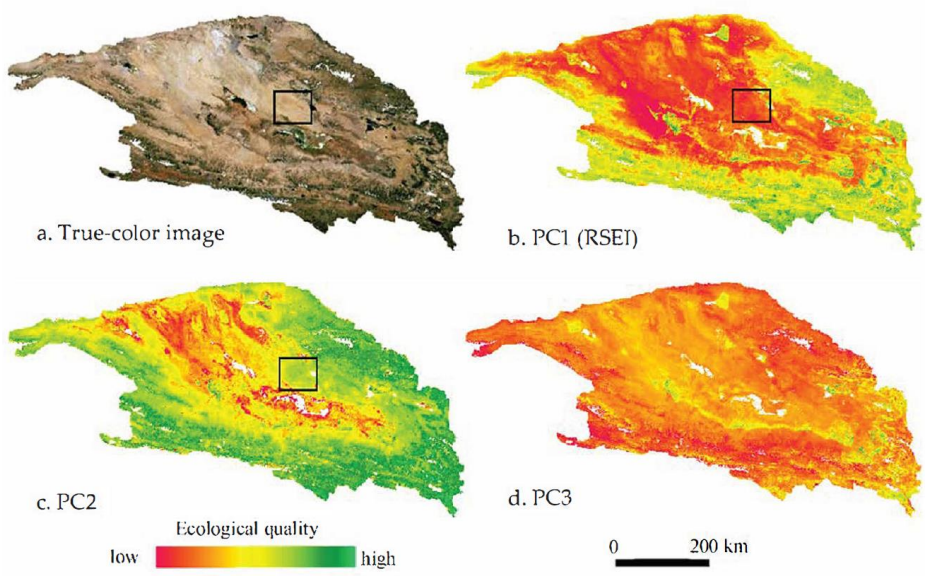


Figure 2. The true-color image (**a**) of the Caidam Basin, and the PC1, PC2, and PC3 images (**b**–**d**) derived from four indicators. The box area shows that a bare desert area in the true color image appears as a low ecological quality (red) area in the PC1 image, but presents mistakenly as a high ecological quality (green) area in the PC2 image.

As revealed in Table 1, the three PCs have the following characteristics (PC 4 is not discussed as Jia et al. [1] did not use it):

(1) In PC1, the loading values of NDVI (greenness) and Wet (wetness) have the same positive sign, while those of NDSI (dryness) and LST (heat) have the same negative sign. Wet and NDVI are positively correlated with each other and negatively correlated with NDSI and LST (Figure 3). The four indicators are thus divided into two groups with clear ecological significance: ecologically favorable NDVI and Wet in one group; and ecologically unfavorable NDSI and LST in the other group. In addition, the absolute loadings of LST ($|-0.7688|$) and NDSI ($|-0.4714|$) are much greater than those of Wet (0.3852) and NDVI (0.1958) in PC1, indicating that heat and dryness have much greater impacts on the basin's ecological quality than greenness and wetness since the basin is a hot, exposed desert area. Accordingly, PC1 has clear ecological implications. In addition, PC1 has the greatest eigenvalue, indicating it integrates most characteristics of all the indicators. Therefore, PC1 is suitable for mapping the ecological conditions of the basin.

	Wet	NDVI	NDSI	LST
Wet	1.000	0.381	–0.765	–0.410
NDVI	0.381	1.000	–0.754	–0.556
NDSI	–0.765	–0.754	1.000	0.415
LST	–0.410	–0.556	0.415	1.000

Figure 3. Correlations matrix of the four indicators.

(2) In PC2, NDSI (dryness) and NDVI (greenness) are in the same group as they both have positive signs. This is unusual because bare land represented by NDSI is the main negative factor for ecological quality in desert areas and therefore, cannot appear as a positive factor in the same group as ecologically favorable NDVI. Similarly, the ecologically favorable Wet (wetness) and the ecologically unfavorable LST (heat) are in the same group

in PC2, which is also abnormal. Therefore, interpreting ecological conditions with PC2 will produce confusing results.

(3) In PC3, LST (heat) has a positive sign and thus, is in the same group with greenness and wetness. However, heat is a major negative ecological factor for hot deserts and therefore, cannot be a positive factor as with wetness and greenness. Obviously, PC3 is also not suitable for interpreting ecological status.

Figure 2 shows the images of each PC as well as the original true-color image of the Qaidam Basin. In the PC1 image (Figure 2b), vegetation has a green tone, indicating good ecological quality, whereas bare land has yellow to red colors, suggesting poor to very poor ecological quality. This indicates that the PC1 image well represents the ecological status of the original image. However, an exaggerated green tone appears in the PC2 image because NDSI representing bare soil presents in the image as a positive, ecologically favorable indicator; thus, it has a green color. A typical example is given in the box area in the PC2 image (Figure 2c). This indicates that the information represented by PC2 is against the actual ecological status of the basin. The PC3 image is dominated by noise and is mainly in red and orange colors (Figure 2d), which also cannot denote the real ecological status of the basin.

The above analysis shows that only PC1 can reasonably interpret the regional ecological status; hence, it can be used directly as the ecological index, RSEI. On the other hand, the signs of loadings of the four indicators in PC2 and PC3 are contradictory. The indicators that have a positive impact on ecological quality can be interpreted as negative factors and vice versa. Existing papers also showed that the signs of the four indicators' loadings in PC2 and PC3 in different regions/years are not fixed and can be either positive or negative [2,3,19,24,25,27–29]. Therefore, it is unreasonable to add them into PC1 to evaluate ecological quality.

3.2. Quantitative Comparison between RSEI and MRSEI

The RSEI image is directly represented by PC1 (Figure 2b), whereas MRSEI was computed using the following equation:

$$MRSEI = 0.61 * PC1 + 0.23 * PC2 + 0.15 * PC3$$

where the weights for PCs 1, 2, and 3 (0.61, 0.23, and 0.15) were derived from the proportions of eigenvalues (Table 1).

Figure 4 is the basin's MRSEI image that has higher values in minimum, maximum, mean, and standard deviation (SD) than those of RSEI (Figure 5); thus, it is greener than RSEI (Figure 2b). This is due largely to the presence of NDSI (bare soil) as a positive factor in PC2 after PC2 was added and the proportion (weight) of PC1 was reduced to 0.61 in the calculation of MRSEI. Consequently, the green tone was exaggerated in the MRSEI image, suggesting an overestimation of the basin's ecological quality.

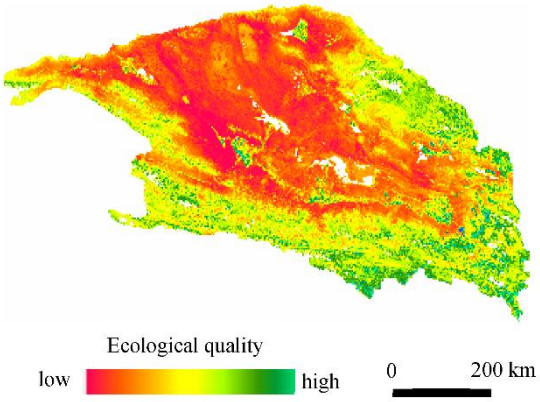


Figure 4. MRSEI image of the Qaidam Basin.

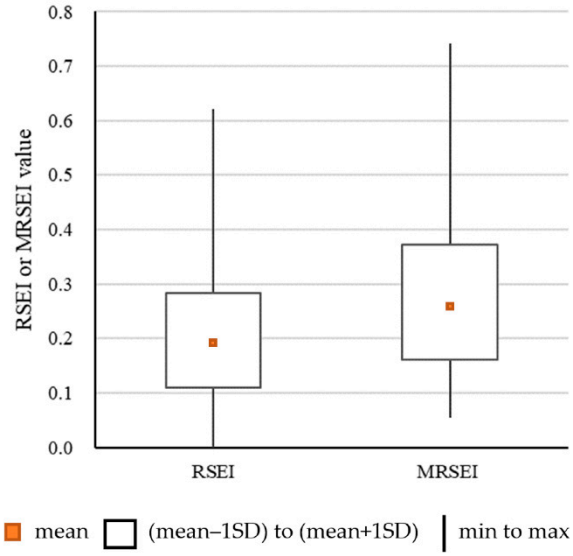


Figure 5. Box plot depicting the data distributions of RSEI and MRSEI.

4. Conclusions

Based on the principle of PCA and the characteristics of three PCs, this comment compared RSEI and MRSEI and analyzed the rationality of the modification to RSEI made by MRSEI. Detailed analysis of the three PCs indicates that only PC1 has clear ecological significance, and PC2 and PC3 have not. The simple addition of PC2 and PC3 into PC1 in constructing MRSEI in the work of Jia et al. has caused the distortion of the PC1's result of the Qaidam Basin due to their erroneous understanding of PCA principles. The addition of PC2 and PC3, and the reduction of the proportion of PC1 resulted in the overestimation of the ecological quality of the basin; therefore, the use of MRSEI to evaluate regional ecological quality is inadvisable.

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Conflicts of Interest: The authors declare no conflict of interest.

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