Research Article

Influence of Fractional Differential on Correlation Coefficient between $EC_{1.5}$ and Reflectance Spectra of Saline Soil

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Soil salinization is one of the most serious environmental issues in arid and semiarid area with severe social, economic, and ecological problems. At present, most inversion models are based on raw reflectance spectra or integer differential transform. In this study, we measured the hyperspectral reflectance and $EC_{1.5}$ of soil samples collected from Ebinur Lake to analyze the influence of fractional differential on correlation coefficient between $EC_{1.5}$ and reflectance spectra. The results showed that the fractional differential increased sensibly the accuracy for the analysis of the reflectance spectra. The study might provide a new insight for monitoring soil salinity using hyperspectral data, and further researches should be concentrated on physical meaning of fractional differential in hyperspectral data to provide theoretical basis to building, describing, and spreading inversion models.

1. Introduction

1.1. Hyperspectral Data for Estimation of Soil Salinity. Soil salinization is occurring at a progressively rapid rate in the world [1], which brings severe social, economic, and ecological consequences in fragile arid and semiarid area. Thus, identifying, monitoring, and mapping soil salinity are badly needed for sustainable agricultural management in the areas which are facing the salinization problem [2].

Due to limits of time, labor, and funds, the conventional method of intensive field sampling combined with physical and chemical analyses in the laboratory is not suitable for large-scale analysis [3, 4]. With technology development, hyperspectral remote sensing and spectroradiometer, a wide-spectral range from 350 nm to 2500 nm with a spectral resolution of 1 nm~10 nm per spectral band, have been shown as good alternatives to traditional field work and become a promising tool for estimating soil salinity [5–7]. The target in hyperspectral data could be identified by spectral features deposited in the spectral libraries when the data has a wide-spectral range and a high-spectral resolution [8].

The slope and the change in slope of spectral curve at every band could be showed clearly by the first and second derivative algorithms [9]. Using derivative algorithms could remove the baseline effects and locate the corresponding bands of inflection point, maximum and minimum reflectance [10]. The spectral derivative is one of most valuable algorithms for the preprocessing and analyses of hyperspectral data [11].

Spectral derivative is one of most valuable algorithms for preprocessing and analyzing the hyperspectral data. Using derivative algorithms could remove the baseline effects and locate the corresponding bands of inflection point, maximum and minimum reflectance. The slope and the change in slope of spectral curve at every band could be showed clearly by the first and second derivative algorithms.

To date, a number of studies on soil salinization pay much attention to quantify the relationship between integer differential transforms of hyperspectral data and the salt content or electrical conductivity of soil to water extract.

Mashimbye et al. [12] set South Africa as the study area, used reflectance spectral and bagging partial least square regression to build a quantitative model basing on reflectance

FIGURE 1: Study area and distribution of sampling sites.

to predict electrical conductivity (validation $R^2 = 0.85$). Zhang et al. [13] used the first derivative to locate salt-sensitive bands and built-vegetation indices as a proxy for monitoring soil salinity in the Yellow River Delta. Shi et al. [14] employed first-order derivative to identify six sensitive spectral bands and then used derived-discriminant functions to assess reclamation levels of coastal saline lands in Zhejiang Province, China. Nawar et al. [15] used partial least square regression and multivariate adaptive regression splines to compare the models based on raw spectra, first-derivative spectra and continuum-removed reflectance, and found that the MARS model based on continuum-removed reflectance had better performance to estimate the EC_e ($R^2 = 0.81$).

For the cases introduced above, the inversion models are usually built on the raw reflectance and integer order derivative. Due to huge differences among the curves of raw reflectance, the first and second order derivative spectra, these methods ignore the differences and potential messages of fractional order, which might cause information loss and decrease in accuracy.

1.2. Fractional Differential. The fractional calculus has a long history of more than 300 years since 1695. However, the fractional calculus had been stayed in the pure theories of

mathematics during almost 300 years [16]. After holding the First Conference on Fractional Calculus and its Applications on June 1974 [17], the fractional calculus has been widely applied in various fields [18–26], because the fractional models are more accurate than the integer ones. In the field of remote sensing, fractional calculus is mainly used for image enhancement and feature extraction [27–30].

Fractional calculus extends integer calculus to an arbitrary (noninteger) order, and there are several definitions of fractional calculus that could be found in the literature, such as Riemann-Liouville, Grünwald-Letnikov, and Caputo [31]. In this study, we employed Grünwald-Letnikov fractional differential to calculate the fractional derivative spectra of hyperspectral data.

The definition of Grünwald-Letnikov differential is shown below.

$$d^\nu f(x) = \lim_{h \rightarrow 0} \frac{1}{h^\nu} \sum_{m=0}^{(t-\nu)/h} (-1)^m \frac{\Gamma(\nu+1)}{m! \Gamma(\nu-m+1)} f(x-mh), \quad (1)$$

and here, ν is the order of fractional differential (Loverro, 2004) and the gamma function is defined as

$$\Gamma(z) = \int_0^\infty e^{-u} u^{z-1} du = (z-1)!. \quad (2)$$

Because the spectroradiometer we used has a resampling spectral resolution of 1 nm per spectral band, so set $h = 1$, and definition (1) could be simplified as

$$\begin{aligned} \frac{d^v f(x)}{dx^v} \approx & f(x) + (-v)f(x-1) + \frac{(-v)(-v+1)}{2}f(x-2) \\ & + \cdots + \frac{\Gamma(-v+1)}{n!\Gamma(-v+n+1)}f(x-n) \end{aligned} \quad (3)$$

and v means the order (Liu [32]). If $v = 1$ and 2, formula (3) is equivalent to the first and second order derivative formulas of hyperspectral data where differential window equals 1.

1.3. Objectives. In this study, the Ebinur Lake in Xinjiang, China, with research foundation of salinization, was chosen as the study area to research the application of fractional differential to study the distribution of saline soil. Using the hyperspectral data combined with the $EC_{1:5}$ of saline soil samples, we aimed to discuss the influence of fractional differential on correlation coefficient between $EC_{1:5}$ and reflectance spectra of saline soil and to provide a basis reference for building inversion model of soil salinity by using hyperspectral data.

2. Materials and Methods

2.1. Study Area and Soil Sampling. The Ebinur Lake (81.65°~83.27°E and 44.73°~45.13°N) situates in the north-west border of Xinjiang, China, with 50,321 km² drainage area (Figure 1) [32]. The lake is surrounded by Maili Mountain, Alatau Mountain, and Borokhoro Mountain to the north, west, and south, respectively. Because of the particular terrain, Ebinur Lake is the lowest collection point of salt water and is the largest salt water lake with an average depth of 1.4 m in Xinjiang [33].

This region locates in the midtemperate zone with a typical continental climate, which characterized by little precipitation, strong evaporation, and much wind [34]. Around the lake, the mean annual precipitation is about 95 mm, and by contrast, mean annual evaporation is 1315 mm. An average wind velocity above 20 m·s⁻¹ blows more than half a year [35]. Due to the high volume of total dissolved solids (85~124 g·L⁻¹), high-water table, and the climate, soil salinization is very severe with about 500 km² of the saline playa around the lake.

2.2. Soil Sampling and Laboratory Experiment. 43 soil samples from the 0~20 cm depth that collected around the Ebinur Lake on the 13rd to 20th of May, 2014, were used in this study (Figure 1). Before sampling, the handheld global positioning system (GPS) equipment was applied to record the coordinates of each sampling site. Five subsamples in every sampling site were collected in a 30 × 30 m square and combined together as one sample to reduce the errors. Each sample (about 1 kg) was put into a sealed plastic bag, labeled and brought to the laboratory. After completely air drying, all soil samples were passed through a 1 mm sieve in order to remove impurities, such as stones and weed roots. Each sample was divided into two parts for further analyses (one for

FIGURE 2: Spectral reflectance of soil samples after smoothing.

TABLE 1: Statistical result of $EC_{1:5}$ and pH of soil samples.

	Unit	Min	Max	Mean	Standard deviation	Coefficient of variation
$EC_{1:5}$	dSm ⁻¹	2.1	118.5	24.05	22.359	92.972%
pH	—	7.443	9.252	8.442	0.406	4.811%

measuring soil properties determination and the other for laboratory spectroscopy measurement).

The ratios of 1 : 1, 1 : 2, 1 : 2.5, 1 : 5, and 1 : 10 soil to water extract have been used to determine the EC of soil samples. In China, many studies prefer to use the 1 : 5 (soil to distilled water) extract to determine the EC value of soil. Compared to saturation paste extracts, the ratio of 1 : 5 is simple, time saving, inexpensive, and able to dissolve larger quantity of solutes [36]. In this study, the ratio of 1 : 5 was chosen to determine the EC values of soil samples. The 1 : 5 soil to distilled water extracts used in this study were made by adding 100 mL of distilled water to 20 g of each sample and used to measure $EC_{1:5}$ of soil samples. The $EC_{1:5}$ and pH values of 43 soil samples were measured by a WTW inoLab® Cond 7310 Laboratory Conductivity Meter and a pH 7310 Benchtop Meter at 25°C.

2.3. Spectral Measurements. ASD FieldSpec®3 portable spectroradiometer (Analytical Spectral Device, Inc.) was used for measuring spectra. The instrument could measure reflectance of samples in 3~10 nm bandwidths over the range 350~2500 nm covering the Vis-NIR-SWIR wavelength range and resample to a 1 nm output value [37, 38].

In order to control the light condition, the experiment was conducted in dark room. The processed samples were fully filled a petri dish (height 2 cm and diameter 15 cm) and scraped with a ruler to ensure a flat sample surface. Two 90 W tungsten halogen light sources with aluminum reflectors were used for illumination. They were put on each

FIGURE 3: The correlation coefficient between $EC_{1.5}$ and each order differential of original spectra. Note: $**P_{0.01}$ represents 0.01 level of significance test of correlation coefficient.

side of the sample. The illumination angle was set to 30° from vertical, and the distance between the lamps and the sample was 1 m. The sensor of the spectroradiometer was a fixed

distance of 10 cm perpendicular to the surface of the soil sample to collect the reflected light. All the configurations could ensure that all the spectral data were acquired in the

same condition. The spectrometer was calibrated every 5 min using measurements of dark current and a white Spectralon reflectance panel ($0.3 \times 0.3 \text{ m}^2$ Labsphere, North Sutton, USA).

2.4. Data Processing. ViewSpecPro software (version 6.0.11) was used to average the 20 spectral curves of each soil sample for minimizing the instrument noise after splice correction. Due to the low signal-to-noise ratios, the ranges from 350 to 399 nm and from 2451 to 2500 nm were removed. The Savitzky-Golay filter was employed to smooth the spectral data of 43 samples ranging from 400 to 2450 nm (Figure 2).

After preprocessing the spectral data, the spectral reflectance data (R) were calculated by 5 different ways: root mean square, inversion, logarithm, inversion-logarithm, and logarithm-inversion ($\sqrt{R}$, $1/R$, $\log(R)$, $\log(1/R)$, and $1/\log(R)$, resp.). Then we calculated their 0~2nd-order (interval 0.2-order) derivative by using Grünwald-Letnikov fractional differential formula (Equation 3) and computed the correlation coefficient between the $EC_{1.5}$ and the data of each mathematical transform and each order differential. All calculations were computed by using the Java programming language under the open-source platform of Eclipse Kepler Service Release 1 with JDK 1.7.0_45.

3. Results

3.1. Statistics of Soil Properties. Statistical analysis results of the $EC_{1.5}$ and pH of the 43 saline soil samples collected around the Ebinur Lake are shown in Table 1. The chemical analytic results of $EC_{1.5}$ values for the samples show that the soil salinity is high and exhibits a wide range from 2.1 to 118.5 dSm^{-1} . Coefficient of variation (CV) for $EC_{1.5}$ is relatively high (>60%), but CV for pH is very low (<10%) [39]. Among the samples, one sample is neutral ($6.5 < \text{pH} < 7.5$), 22 samples are alkaline ($7.5 < \text{pH} < 8.5$) and 20 samples are strong alkaline ($\text{pH} > 8.5$).

3.2. Influence of Fractional Differential on Correlation Coefficient: Full-Spectrum. The curves of correlation coefficient between $EC_{1.5}$ and each order differential of spectral reflectance data (R) are plotted in Figure 3. It is clearly showed that the curves of 0-order, 0.2-order, and 0.4-order which have no band passed the significant test ($p < 0.01$) and there are bands passed the significant test ($p < 0.01$) from 0.6-order to 2nd order. It is also showed that the correlation coefficient curves of 0-order, 1st order, and 2nd order are quite different, but the curves of fractional order detail these differences.

However, the numbers of bands that passed the significant test ($p < 0.01$) could not be seen directly from Figure 3 and Table 2 presents the numbers of bands treated by each mathematical transform and each order differential which passed the significant test ($p < 0.01$). For spectral reflectance and of the five mathematical transforms, the differential could evidently increase the number of the bands, and the numbers do not increase with the increase of differential order but follow the nearly increasing-decreasing trend, reaching the

TABLE 2: The number of the bands through 0.01 level of significance test of correlation coefficient.

Order	R	$\sqrt{R}$	$1/R$	$\log(1/R)$	$\log(R)$	$1/\log(R)$
0	0	0	0	0	0	0
0.2	0	0	0	0	0	0
0.4	0	0	0	0	0	8
0.6	25	23	18	22	22	54
0.8	34	33	20	26	26	56
1	28	26	16	29	29	56
1.2	70	56	29	51	51	73
1.4	79	80	40	66	66	80
1.6	75	67	40	58	58	93
1.8	65	53	35	46	46	84
2	59	54	29	46	46	81

maximum at fractional order (1.4-order > 2nd order > 1st order > 0-order for R , $\sqrt{R}$, $1/R$, $\log(1/R)$, $\log(R)$ and 1.6-order > 2nd order > 1st order > 0-order for $1/\log(R)$).

Table 3 shows the bands corresponding to the maximal absolute value of the correlation coefficient of each transform and each order differential. $\sqrt{R}$, $1/R$, $\log(1/R)$, $\log(R)$, and $1/\log(R)$ all decrease the correlation coefficient between $EC_{1.5}$ and R in band 490 nm at 0-order. Meantime, at the 1st, 1.2, and 2nd orders, $\sqrt{R}$, $1/R$, $\log(1/R)$, and $\log(R)$ decrease the correlation coefficient but $1/\log(R)$ increases that in bands 1770 nm, 2249 nm, and 824 nm, respectively.

3.3. Influence of Fractional Differential on Correlation Coefficient: Single Band. In Table 3, the bands of which correlation coefficient passed the significant test ($p < 0.01$, i.e., $|r| > 0.389$) is chosen to examine the influence of fractional differential on correlation coefficient of single band and 14 bands that were eligible to this condition: 505 nm, 824 nm, 1056 nm, 1770 nm, 1867 nm, 2150 nm, 2151 nm, 2232 nm, 2239 nm, 2245 nm, 2249 nm, 2370 nm, 2442 nm, and 2443 nm.

Figure 4 provides the correlation coefficient varying trend of 14 bands of spectral reflectance and the five types of mathematical transforms. Table 4 presents the absolute value of correlation coefficient of each mathematic conversion and the maximal absolute value of correlation coefficient after differential with corresponding order. According to Figure 4 and Table 4, it is clearly showed that spectral derivative algorithms could evidently increase the correlation coefficient between $EC_{1.5}$ and spectral reflectance (R) and other mathematical transforms ($\sqrt{R}$, $1/R$, $\log(R)$, $\log(1/R)$, and $1/\log(R)$).

For 824 nm and 2150 nm, the absolute value of correlation coefficients of R , $\sqrt{R}$, $1/R$, $\log(R)$, $\log(1/R)$, and $1/\log(R)$ all reach the maximum at integer order. For 505 nm, 1056 nm, 2151 nm, 2232 nm, 2239 nm, 2245 nm, 2249 nm, and 2443 nm, they all reach the maximum at fractional order.

TABLE 3: The bands corresponding to the maximum of the absolute value of the correlation coefficient of each transform.

Order	R		$\sqrt{R}$		$1/R$		$\log(1/R)$		$\log(R)$		$1/\log(R)$	
	Band	$ r $	Band	$ r $	Band	$ r $	Band	$ r $	Band	$ r $	Band	$ r $
0	490	0.350	490	0.349	490	0.339	490	0.347	490	0.347	490	0.346
0.2	489	0.351	478	0.352	478	0.343	478	0.350	478	0.350	489	0.349
0.4	472	0.360	472	0.359	2239	0.357	472	0.358	472	0.358	2443	0.413
0.6	2239	0.568	2239	0.569	2239	0.543	2239	0.565	2239	0.565	2232	0.511
0.8	2442	0.492	1770	0.481	2245	0.518	2245	0.499	2245	0.499	2370	0.468
1	1770	0.505	1770	0.496	1770	0.461	1770	0.486	1770	0.486	1770	0.517
1.2	2249	0.541	2249	0.525	1056	0.467	2249	0.507	2249	0.507	2249	0.578
1.4	505	0.598	505	0.594	505	0.532	505	0.578	505	0.578	2249	0.578
1.6	2151	0.600	2151	0.605	2151	0.591	2151	0.605	2151	0.605	824	0.572
1.8	1867	0.610	1867	0.595	2151	0.575	2151	0.588	2151	0.588	824	0.612
2	824	0.608	824	0.594	2150	0.529	824	0.576	824	0.576	824	0.621

Note: $|r|$ represents the absolute value of correlation coefficient.

4. Discussion

According to the results found in this study, spectral derivative algorithm could evidently increase the number of bands to pass the significant test ($p < 0.01$) with increase of the order; the numbers followed nearly increasing-decreasing trend, and all reached the maximum at fractional order. Also, to some extent, the curves of fractional order detailed the differences among 0-order, 1st order, and 2nd order. Meanwhile, for some bands, spectral derivative algorithms were able to increase the correlation coefficient between $EC_{1:5}$ and spectral reflectance (R) and other mathematical transforms. Some bands (824 nm and 2150 nm) reached the peak at integer order while some more (505 nm, 1056 nm, 2151 nm, 2232 nm, 2239 nm, 2245 nm, 2249 nm, and 2443 nm) at fractional order.

The main reason for these results is that fractional differential extends the concept of integer order differential. The integer order differential is just a special case of fractional differential. As we have known, the first derivative means the slope while the second expresses the curvature of spectral curves, but fractional derivative lacks the physical meaning definitely in spectroscopy. Zhang et al. [40] agreed with Schmitt [41] that fractional derivative was interpreted as the sensibility to the slope and the curvature of the spectral curves. When the order increases from 0 to 1, the derivative value becomes more sensitive to the slope and less sensitive to reflectance, and while the order increases from 1 to 2, the derivative value turns out more sensitive to the curvature and less sensitive to the slope.

For spectral reflectance and the mathematical transforms, integer order differential value of a band only associates with the reflectance data of bands in the differential window. However, it is clear to see from Equation 3 that fractional differential value of a band not only correlates with the reflectance, but also has relationships with the reflectance data of bands. By assigning different weight values to the bands according to the order of differential, we found that the more closer to the band, the greater weight value is, and the influence of the fractional

differential on this band is greater. The advantages of fractional differential: memory and nonlocality, and these are the main differences between fractional and integer order differential. Besides, the order of fractional differential is not confined to the integer and is extended to an arbitrary (noninteger) order, and this brings more options and liberal of choosing order; although it would be hard to implement, but with the development of computing software, this problem will be easily solved.

Furthermore, some studies [42–48] show that many systems in reality are belonged to fractional order, and the models based on integer differential which used to describe these systems may cause large deviation between models and the actual results; it could not only be well for system simulation and prediction but also neglects the authenticity of systems to some extent. Before using fractional differential to build models to quantify the relationship between hyperspectral data and soil salinity, the physical meaning of fractional differential should better explain and describe the model, improve the inversion precision, and spread model application.

During the course of building the hyperspectral inversion models of soil salinity, characteristic bands usually chose based on the correlation coefficient between reflectance data and soil salt content or EC; the higher the correlation coefficient, the more sensitive the band is. According to the results of this study, fractional differential has a wider selection of choosing orders and details the varying trend of the correlation coefficient curves of 0-order, 1st order, and 2nd order, and it is able to increase the correlation coefficient; these features provide much more flexibility to the characteristic bands selection.

Fractional differential focuses on the qualities of memory and nonlocality of spectral curves, but integer differential pays attention to the local property of spectral curves. Moreover, spectral characteristics of soil are the comprehensive representation of the physicochemical properties of soil. Thus, future researches should not only study the local spectral features from the integer differential angle but also comprehensively explore spectral characteristics

FIGURE 4: Continued.

FIGURE 4: The correlation coefficient between $EC_{1.5}$ and each order differential of original spectra.

by using fractional differential combined with physico-chemical properties of soil which in order to deeply mine potential information of spectral dimension and fast accurately the use of hyperspectral data to estimate soil salinity.

5. Conclusion

In this paper, we took the Ebinur Lake in the northwest border of Xinjiang, China, as the study area, used the

hyperspectral reflectance data and $EC_{1.5}$ values of 43 saline soil samples that were collected around the Ebinur Lake, and studied the influence of fractional differential on correlation coefficient between $EC_{1.5}$ and reflectance spectra of saline soil. The conclusions are as follows:

- (i) For the range of full-spectrum, differential could evidently increase the number of the bands that passed the significant test ($p < 0.01$), and with the increase of differential order, the numbers followed

TABLE 4: The absolute value of correlation coefficient of each mathematic conversion and the maximal absolute value of correlation coefficient after differential with corresponding order.

Band	$ r _0$	$ r _{\max}$	Order	$ r _0$	$ r _{\max}$	Order	$ r _0$	$ r _{\max}$	Order
		R			$\sqrt{R}$			$1/R$	
505	0.347	0.598	1.4	0.346	0.602	1.6	0.337	0.567	1.6
824	0.274	0.608	2	0.271	0.594	2	0.257	0.529	2
1056	0.271	0.473	1.2	0.269	0.478	1.2	0.256	0.476	1.4
1770	0.235	0.505	1	0.237	0.496	1	0.236	0.503	0.8
1867	0.229	0.610	1.8	0.230	0.595	1.8	0.227	0.504	1.8
2150	0.160	0.555	2	0.161	0.555	2	0.163	0.539	2
2151	0.159	0.6	1.6	0.161	0.605	1.6	0.163	0.591	1.6
2232	0.195	0.511	0.6	0.198	0.502	0.6	0.203	0.45	0.6
2239	0.199	0.568	0.6	0.202	0.569	0.6	0.206	0.543	0.6
2245	0.202	0.506	0.6	0.204	0.51	0.6	0.208	0.518	0.8
2249	0.201	0.577	1.6	0.204	0.572	1.6	0.208	0.540	1.6
2370	0.141	0.39	1	0.141	0.365	1	0.136	0.286	1
2442	0.004	0.492	0.8	0.005	0.457	0.8	0.008	0.327	1
2443	0.002	0.452	0.8	0.003	0.418	0.8	0.006	0.273	0.8
		$\log(1/R)$			$\log(R)$			$1/\log(R)$	
505	0.344	0.598	1.6	0.344	0.598	1.6	0.342	0.496	1.6
824	0.267	0.576	2	0.267	0.576	2	0.277	0.621	2
1056	0.265	0.480	1.4	0.265	0.480	1.4	0.275	0.423	1.4
1770	0.237	0.488	0.8	0.237	0.488	0.8	0.212	0.517	1
1867	0.229	0.572	1.8	0.229	0.572	1.8	0.209	0.570	1.8
2150	0.163	0.552	2	0.163	0.552	2	0.131	0.493	2
2151	0.163	0.605	1.6	0.163	0.605	1.6	0.131	0.504	1.8
2232	0.200	0.490	0.6	0.200	0.490	0.6	0.170	0.511	0.6
2239	0.204	0.565	0.6	0.204	0.565	0.6	0.176	0.472	0.6
2245	0.206	0.508	0.6	0.206	0.508	0.6	0.180	0.371	0.6
2249	0.206	0.564	1.6	0.206	0.564	1.6	0.180	0.578	1.2
2370	0.140	0.338	1	0.140	0.338	1	0.132	0.468	0.8
2442	0.007	0.408	0.8	0.007	0.408	0.8	0.002	0.399	0.8
2443	0.004	0.371	0.8	0.005	0.371	0.8	0.004	0.446	0.6

Note: $|r|_0$ represents the absolute value of correlation coefficient of each mathematic conversion without differential treatment; $|r|_{\max}$ represents the maximal absolute value of correlation coefficient after differential.

increasing-decreasing trend reaching the maximum at fractional order.

- (ii) For some bands (505 nm, 1056 nm, 2151 nm, 2232 nm, 2239 nm, 2245 nm, 2249 nm, and 2443 nm), spectral derivative algorithm could evidently raise the correlation coefficient between $EC_{1.5}$ and reflectance spectral data, but fractional differential had better capacity than that of integer differential.

- (iii) Fractional differential detailed the varying trends among 0-order, 1st order, and 2nd order, and to some extent, it might avoid the problems of information loss and decrease in accuracy.

Fractional differential enriches the methods of preprocessing hyperspectral data and deeply digs the potential information hiding behind the spectral demission from

fractional differential angle. It may provide a new insight for monitoring soil salinity by using the hyperspectral technology.

Conflicts of Interest

The authors declare that there are no competing interests regarding the publication of this paper.

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