APPLYING NDVI FROM DIFFERENT NUMBER OF SPECTRAL SENSORS IN DELIMITING SOYBEAN FERTILIZATION MANAGEMENT ZONES

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Abstract. The normalized difference vegetation index (NDVI) obtained by GreenSeeker sensors can be used to delimit fertilization management zones and realize variable fertilization. We used six GreenSeeker sensors to build a soybean NDVI data acquisition system, studied the effect of different number of GreenSeeker sensors on the delimitation of fertilization management zones. The NDVI data collected by the different number of GreenSeeker sensors were used to delimit the management zones by the fuzzy c-means algorithm. Silhouette coefficient and adjusted Rand index were used to evaluate the effect. The results show that using different number of GreenSeeker sensors has a particular effect on the delimitation of fertilization management zones. In the case of delimiting fertilization management zones through 10,000 NDVI data collected by three GreenSeeker sensors, silhouette coefficient is 0.563, and adjusted Rand index is 0.76. In the case of 20,000 NDVI data collected by three GreenSeeker sensors, silhouette coefficient is 0.559, and adjusted Rand index is 0.698. It indicates that the effect of using three GreenSeeker sensors on the delimitation of fertilization management zones is not different from that of using six GreenSeeker sensors.
Keywords: *soybean, fuzzy c-means, scikit-fuzzy, silhouette coefficient, adjusted Rand index*

Introduction

As more and more chemical fertilizers are used to increase crop yield and income, adverse effects on crops environmental pollution increases (Chen et al., 2018). With the continuous development of precision agriculture, the use of management zones to guide variable fertilization is becoming more and more widespread (Rogovska et al., 2019). Variable fertilization technology can effectively reduce chemical fertilizers, protect the ecological environment, and achieve sustainable agricultural development (Verma et al., 2018). The delineation of fertilization management zones is an important part of the application of variable fertilization techniques, and there are many related research works. The delineation of fertilization management zones based on soil fertility and topography is currently the most commonly used and highly accurate division method. However, this method has an extended measurement period and poor timeliness. It is difficult to grasp the measurement distance during the measurement process, and the workload is enormous. It cannot solve the problem of dividing a large area of management zones, and it is easy to cause mechanical losses to crops during the measurement process. The Normalized Vegetation Difference Index (NDVI) (Rouse et al., 1974) is one of the commonly used indicators to detect and indicate the status and dynamics of vegetation coverage. Different phenology metrics from the NDVI data can support several decisions to improve the efficiency of several farming practices (Duarte et al., 2018). The delineation of fertilization management zones based on NDVI data collected in real-time can avoid the need to detect soil nutrients first and then process

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nutrient differences offline in the past. Efficient variable fertilizer management can be carried out by obtaining the NDVI data of crops in real-time and establishing management partitions online. Yuchun et al. (2006) used GIS to simulate different soil nitrate levels and spatial variability and studied variable fertilization based on management zones. Fu et al. (2010) analyzed the spatial variation characteristics and structure of six soil nutrients, defined the soil nutrient management zones as a variable, and used the fuzzy clustering algorithm optimized by particle swarm optimization to delimit the management zones. Their study showed that the fuzzy clustering optimized by particle swarm optimization had a good effect in delimiting the management area. Schwalbert et al. (2019) considered the combination of crop spectral sensors and management zoning as an alternative technical solution to improve nitrogen use efficiency, delimiting management zones with different responses to nitrogen input, and using simulations to compare different wheat fertilization strategies (Schwalbert et al., 2019; Meriame et al., 2017).

GreenSeeker is a widely used spectral sensor for collecting NDVI of crops (Matese and Di, 2015). GreenSeeker sensor does not depend on the external light source, can work day and night, acquire data quickly, and has good timeliness, which can reflect the growth status of crops (Billa et al., 2020; Fabbri et al., 2020). GreenSeeker is an active optical sensor that generates red light (650 nm) and near-infrared light (770 nm) through light-emitting diodes (LED) and measures the amount of light reflected by the plant with a photodiode. The measurement range of NDVI values is 0 to 0.99 with an accuracy of 0.01. Variable fertilizer application based on crop canopy spectral information and targeted fertilizer application to farmland can improve the fertilizer utilization rate and reduce environmental pollution. Van Eerd et al. (2021) used a handheld GreenSeeker sensor to obtain NDVI data from sugar beets to guide nitrogen fertilizer use (Van Eerd et al., 2021). Reznick et al. (2021) used the GreenSeeker sensor to obtain NDVI data of the whole wheat growth stage to estimate nitrogen fertilizer use (Reznick et al., 2021). Shah et al. (2021) managed nitrogen fertilizer application in oats based on the GreenSeeker sensor to obtain more yield. Kaur (2021) used the GreenSeeker sensor to collect NDVI of different varieties of Basmati rice to establish a prediction model of grain yield and nitrogen uptake.

In our previous research (Chen et al., 2021), we found that the general arrangement of GreenSeeker spectral sensors is to arrange one above each ridge, but due to the continuity of crop growth, there is little difference in crop growth in a small range. Arranging sensors in this way increases the complexity of installation and increases the economic burden. In this study, we innovatively used the Soybean NDVI data acquisition system applying by different number of GreenSeeker spectral sensors to delimit the fertilization management zones. The aim was to study the effect of different number of GreenSeeker on the delineation of soybean fertilization management zones and to evaluate the effect of delimiting fertilization management zones using the silhouette coefficient and adjusted Rand index to determine the most reasonable number of GreenSeeker spectral sensors layout.

Materials and methods

Study area

Our Study area is a soybean field in Zhaoguang Farm (*Fig. 1*). Zhaoguang Farm is located in Heilongjiang Province of China, east of the Daxingan Mountain range and the

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north of the Xiaoxingan Mountain range. The elevation range of the study area is 240-330 m. It belongs to the cold temperate zone and continental monsoon climate, with an annual average temperature of 0.5°C and a frost-free period of 120 days (He et al., 2016). In summer, Zhaoguang Farm has more rainfall, and the air is warm and humid, which is conducive to the growth of crops. In winter, Zhaoguang Farm has less rainfall, and the air is cold and dry, which is not conducive to the growth of crops. The mean precipitation is 356.4 mm in the summer and 12.3 mm in the winter. The specific study area is the No. 12-2 of the 17th station in the fourth management area of Zhaoguang Farm. This plot covers an area of 34 ha, the surrounding area is open, and there is no building block. The soil type in this area is black soil, which is a good trait, highly trophic and very suitable for plant growth, and has superior physical and chemical properties compared to other soils (Qiang et al., 2007). The soybean variety planted is Heihe 43 produced in China. Heihe 43 is a new hybrid soybean seed suitable for planting in the fourth accumulated temperate zone of Heilongjiang Province. This variety has the advantages of strong resistance and stable yield, with an average yield of 3,000 kg/ha.

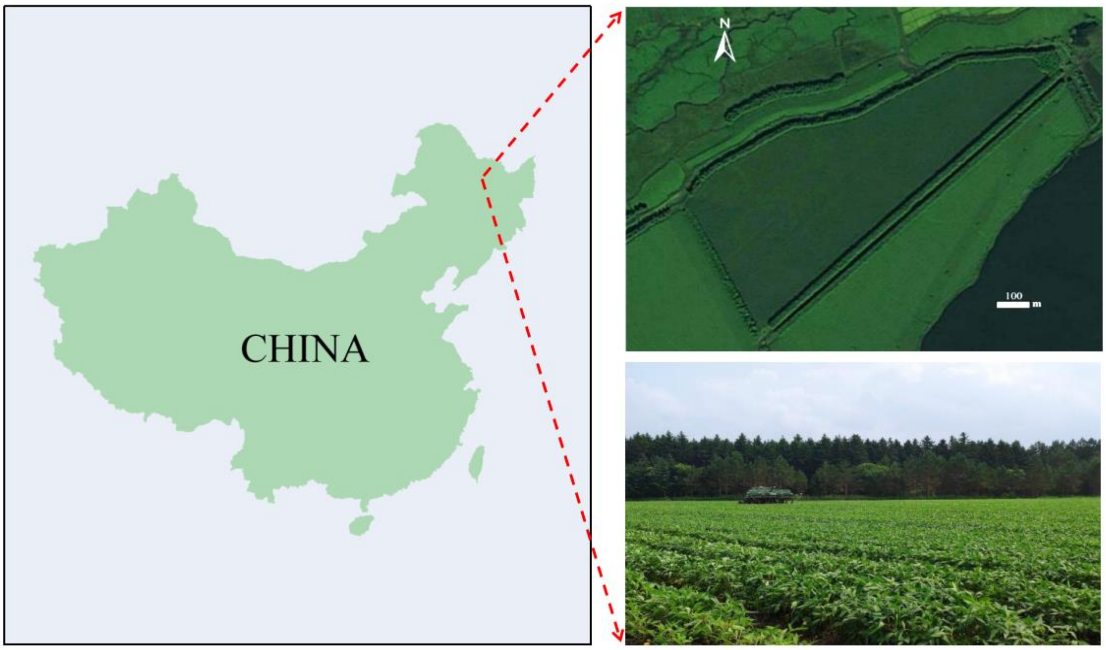

Figure 1. *Study area of Zhaoguang Farm (34 ha)*

Data collection

The soybean NDVI data used in this study was obtained by the soybean NDVI data acquisition system mounted on the tractor cultivator and fertilizer applicator, and shown in *Figure 2*. The data was collected during the flower bud differentiation period of soybeans. The soybean NDVI data acquisition system consists of 6 GreenSeeker spectral sensors produced by Trimble company, a set of AG332 satellite positioning systems produced by Trimble company, and an NDVI data recorder. The spacing of GreenSeeker spectral sensors is 1.1 m, and the working width is 6.6 m. In the process of soybean NDVI data collection, the GreenSeeker spectral sensors are located 80 cm above the soybean, emits red light (660 nm) and near-infrared light (770 nm) and

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capture the light reflected by the crop canopy and the internal processor analyzes the captured light to obtain the NDVI of the crop, with a measurement area of 61 cm ± 10 cm (width) × 1.5 cm ± 0.5 cm (length). The data is recorded in the data logger. The data in the logger can be downloaded to the computer in Excel format for further processing.

Figure 2. *Soybean NDVI data acquisition system (the number in the figure represents the position of the sensor)*

Delimitation of fertilization management zones

Fuzzy c-means algorithm

Ruspini (1972) proposed a concept of fuzzy partition based on fuzzy set theory, and Dunn (1973) extended the hard c-means algorithm to the direction of fuzzy partition according to the concept of fuzzy partition, forming a preliminary fuzzy c-means algorithm. Bezdek extended the objective function in Dunn’s fuzzy c-means algorithm to a more general form, forming a more general description of fuzzy partition based on the objective function (Kanzawa and Miyamoto, 2021; Bezdek et al., 1984). The fuzzy c-means algorithm is a flexible data partition algorithm at the forefront of all fuzzy partition algorithms. Based on optimizing the objective function, the fuzzy c-means algorithm can obtain the membership degree of each data in all categories to determine the attribution of data (Liu and Xu, 2008; Wu, 2012). For the data set $X = [x_1,...,x_n]$, the objective function of the fuzzy c-means algorithm is given as *Equation 1*.

$$\mathrm{J}_{FCM}(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-v_i\right\|^2 \qquad \text{(Eq.1)}$$

where U is the fuzzy membership matrix, V is the center of the division, c is the number of partitions, n is the number of data, m is the fuzzy weight index, u_{ij} is the membership ($0 \le u_{ij} \le 1$;i = 1,2,...,c;j = 1,2,...,n), $\left\|x_j-v_i\right\|^2$ is the Euclidean distance from the jth data to the ith division center v_i.

The condition for the objective function of the fuzzy c-means algorithm to reach the minimum value is given as *Equations 2* and *3*.

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$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \quad \text{(Eq.2)}$$

$$u_{ij} = \left(\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{2/(m-1)} \right)^{-1} \quad \text{(Eq.3)}$$

The calculation process of the fuzzy c-means algorithm is constantly seeking the minimum value of objective function *Equation 1*. The calculation process of the fuzzy c-means algorithm is as follows: First, set the number of partitions *c*, the stop threshold $\mathcal{E}$, the fuzzy weight index *m*, and randomly select the initial partition centers. Then, the fuzzy membership matrix U is updated according to Euclidean distance, update the partition center *V*; Finally, determine whether the change of partition center is less than the stop threshold $\mathcal{E}$. If it is less than the stop threshold $\mathcal{E}$, stop the calculation process and output *U* and *V*. Otherwise, update the fuzzy membership matrix *U* again. Moral et al. (2010) used the fuzzy c-means algorithm to delimit management zones according to soil properties to realize regional precision agriculture and guide variable fertilization. Schenatto et al. (2017) used the fuzzy c-means algorithm to delimit management zones and evaluated the impact of data normalization methods on delineation of management zones. Ohana-Levi et al. (2021) used the fuzzy c-means algorithm to delimit the management zones of precise nitrogen fertilizer application in citrus orchards according to the normalized vegetation index, crop water stress index, digital surface model, slope and other factors.

Evaluation of delimiting fertilization management zones

The silhouette coefficient (SC) proposed by Rousseeuw (1987) is an internal evaluation indicator for unsupervised clustering based on two factors: cohesion and separation. This variable can be used to evaluate different clustering algorithms based on a given data set and the effects of different methods of operation of the same clustering algorithm on the partitioning result. The function of the silhouette coefficient is given as *Equations 4* and *5*.

$$SC(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}} \quad \text{(Eq.4)}$$

$$SC(i) = \begin{cases} 1 - \dfrac{a(i)}{b(i)}, a(i) < b(i) \\ 0 \quad , a(i) = b(i) \\ \dfrac{b(i)}{a(i)} \quad , a(i) > b(i) \end{cases} \quad \text{(Eq.5)}$$

In the equation, $-1 \leq SC(i) \leq 1$, a(i) represents the compactness of the cluster to which (i) belongs, and the lower the a(i) value is, the more compact the points are in the

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cluster; and b(i) represents the degree of separation of (i) and the other clusters, and the higher the b(i) value is, the more separated (i) is from the other clusters (Han et al., 2011). However, when SC (i) < 0, (i) is closer to the samples in other clusters than to those in the same cluster. This situation is not ideal in actual clustering and should be avoided. Zhou and Gao (2014) used silhouette coefficient and SSE to determine the number of divisions, and experiments show that this method can usually find the optimal number of divisions and effectively divide data divisions. Triayudi and Fitri (2018) proposed a new delimiting algorithm called ALG (Average Linkage Dissimilarity Increment Distribution-Global Cumulative Score Standard) and used silhouette coefficients to evaluate the delimiting results of this new algorithm.

The clustering process can be viewed as a series of decision-making processes to decide whether to assign each pair of data points in the dataset to the same cluster, and the Rand index is used to measure the accuracy of this decision (Hubert and Arabie, 1985; Vinh et al., 2010). Assuming that U is the ideal cluster set and that V is the clustering result. Rand index is defined according to *Equation 6*.

$$RI = \frac{a+d}{a+b+c+d} \tag{Eq.6}$$

where *RI* is Rand index, *a* is the number of data pairs that fall in the same cluster in both U and V, *b* is the number of data pairs that fall in the same cluster in U but not in V, *c* is the number of data pairs that fall in the same cluster in V but not in U, *d* is the number of data pairs that do not fall in the same cluster in U and V.

The RI values are in the range of [0,1]. When the clustering result perfectly matches the ideal clustering result, RI is 1. However, the RI value cannot guarantee a value of 0 in the case of random clustering, so the adjusted Rand index (ARI) (Yeung and Ruzzo, 2001; Steinley, 2004; Chacón, 2021) is introduced to address this issue and is defined in *Equation 7*.

$$ARI = \frac{RI - E[RI]}{\max(RI) - E[RI]} \tag{Eq.7}$$

where *ARI* is the adjusted Rand index, *RI* is the Rand index, *E*[*RI*] is the expected value of the *RI*, and max(*RI*) is the maximum value of the *RI*. Rayala and Kalli designed and developed a simple fuzzy c-means (IFCM) algorithm and used ARI to evaluate the algorithm results to prove the superiority of the IFCM algorithm (Rayala and Kalli, 2020).

Results and discussion

The soybean NDVI data acquisition system used has six GreenSeeker spectral sensors with an interval of 1.1 m. The installation positions and numbers of the sensors are shown in *Figure 2*. The corresponding relationship of the soybean NDVI data collected by the different number of sensors is as follows: the NDVI data of the two sensors is position 1 and position 6; the NDVI data of the three sensors is position 1, position 3 and position 6; the NDVI data of the four sensors is position 1, position 3, position 4 and position 6.

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We compiled the fuzzy c-means algorithm program through the scikit-fuzzy toolbox for Python and obtained the delineation of management zones from the algorithm. The soybean NDVI data obtained by different number of GreenSeeker spectral sensors are taken as the program’s input data. The number of zones is set to 4, and the membership index is set to 2. When the change of membership degree is less than 0.005, the iteration is terminated in advance, and the maximum iteration number is set to 1000. The soybean NDVI data obtained by the different number of GreenSeeker spectral sensors were finally divided into four zones by the fuzzy c-means program. We used ArcGIS10.2 software to draw the map of fertilization management zones. Farid et al. (2016) used the spatial analysis tool in ArcGIS software to delimit the management zones and generalized the point data by using the ordinary Kriging spatial interpolation technique. Peralta et al. (2015) used ArcGIS software to delimit management zones according to soil conductivity, topographic elevation, and soil depth. They also used ArcGIS software to calculate the average wheat yield and nitrogen application rate of each test unit to guide nitrogen fertilizer application. We imported the soybean NDVI data and their latitude and longitude coordinates obtained by different number of GreenSeeker spectral sensors into ArcGIS software. Then, the built-in spatial analysis module in ArcGIS software was used for interpolation analysis. Finally, the fertilization management zones map of soybean NDVI data obtained by the different number of GreenSeeker spectral sensors was obtained, as shown in *Figures 3* and *4*.

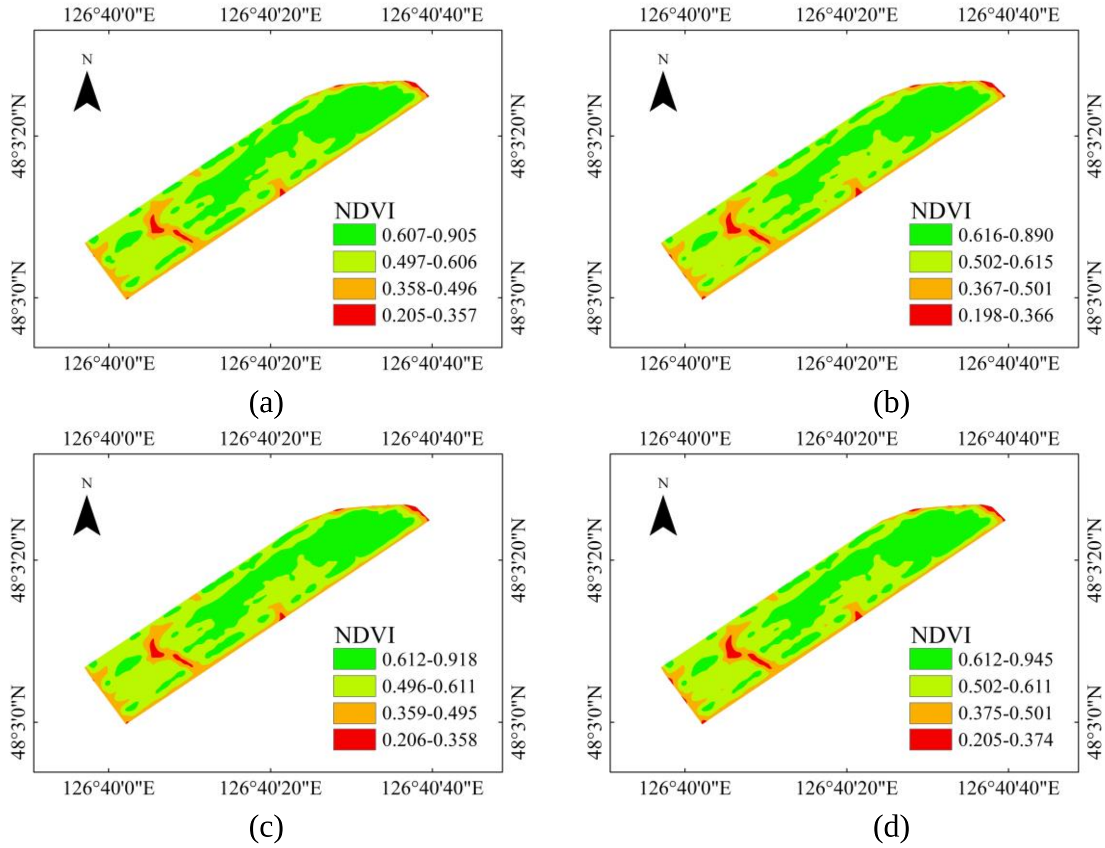

Figure 3. *Map of fertilization management zones based on soybean NDVI data collected by different number of GreenSeeker spectral sensors. (a) 2 GreenSeeker spectral sensors; (b) 3 GreenSeeker spectral sensors; (c) 4 GreenSeeker spectral sensors; (d) 6 GreenSeeker spectral sensors*

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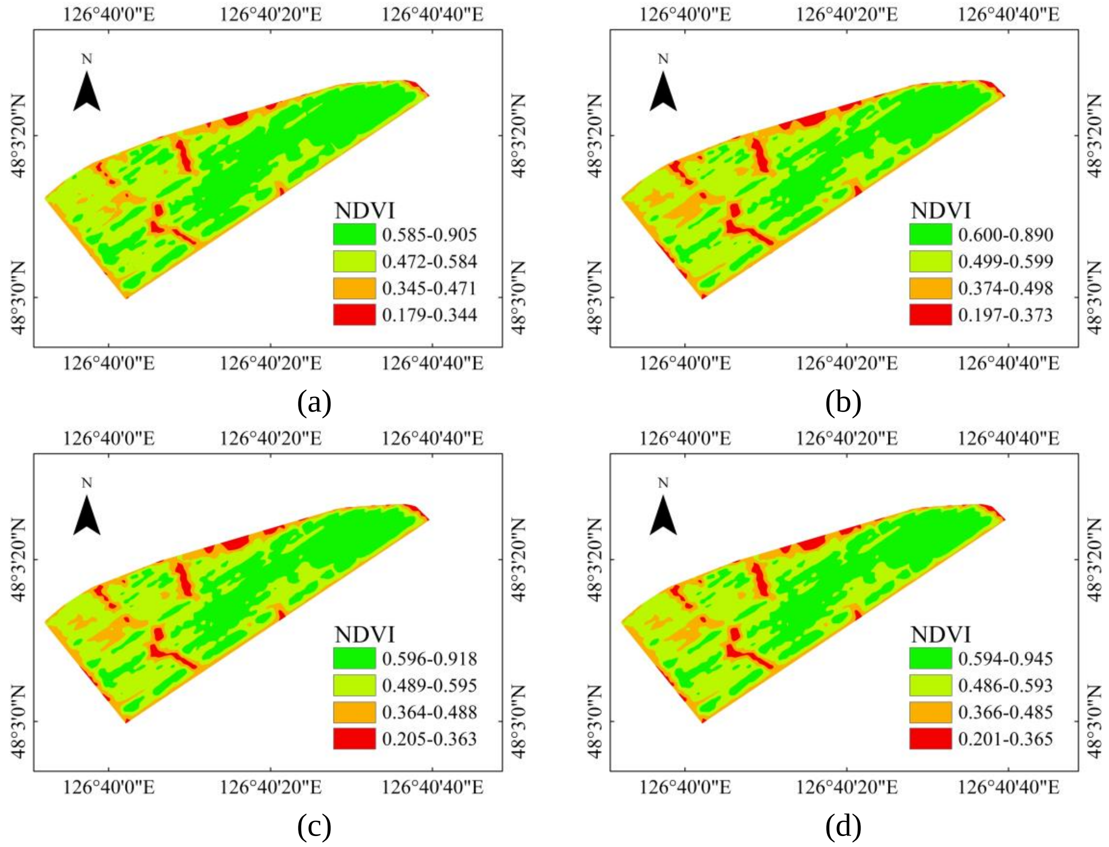

Figure 4. *Map of fertilization management zones based on soybean NDVI data collected by different number of GreenSeeker spectral sensors. (a) 2 GreenSeeker spectral sensors; (b) 3 GreenSeeker spectral sensors; (c) 4 GreenSeeker spectral sensors; (d) 6 GreenSeeker spectral sensors*

Processing of 10,000 NDVI data

As shown in *Figure 3*, the four fertilization management zone maps are relatively close in the case of 10,000 NDVI data. The NDVI data range of the green zones is 0.393, 0.274, 0.306, and 0.333. In the case of green zones, the maximum difference between two sensors and three sensors is 0.119, and the difference between the other cases is less than 0.1. The NDVI data range of the yellow zone is 0.109, 0.113, 0.11, and 0.109. In the case of yellow zones, the difference in NDVI data range of the zones corresponding to the different number of GreenSeeker spectral sensors is less than 0.01. The NDVI data range of the orange zone is 0.138, 0.134, 0.136, and 0.126. In the case of orange zones, the maximum difference between two sensors and six sensors is 0.012, and the difference between the other cases is less than 0.01. The NDVI data range of the red zone is 0.152, 0.168, 0.152, and 0.169. In the case of red zones, the NDVI data range of two sensors and four sensors is basically the same, and the NDVI data range of three sensors and six sensors is basically the same. The maximum difference between other cases is 0.017. In conclusion, in the case of 10,000 groups of soybean NDVI data, the management zones corresponding to different numbers of sensors are different. The difference of green zones is the largest. In conclusion, the different number of GreenSeeker spectral sensors have a particular impact on the delineation of green management zones but have little impact on the delineation of other management zones.

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Processing of 20,000 NDVI data

As shown in *Figure 4*, the four fertilization management zone maps are relatively close in the case of 20,000 NDVI data. The NDVI data range of the green zone is 0.415, 0.29, 0.322, and 0.351. In the case of green zones, the maximum difference between two sensors and three sensors is 0.125, and the difference between the other cases is less than 0.1. The NDVI data range of the yellow zone is 0.112, 0.1, 0.106, and 0.107. In the case of yellow zones, the maximum difference between two sensors and three sensors is 0.012, and the difference between the other cases is less than 0.01. The NDVI data range of the orange zone is 0.126, 0.124, 0.124, and 0.119. In the case of orange zones, the difference in NDVI data range of the zones corresponding to the different number of GreenSeeker spectral sensors is less than 0.01. The NDVI data range of the red zone is 0.165, 0.176, 0.158, and 0.164. In the case of red zones, the difference in the NDVI data range of the zones corresponding to the different number of GreenSeeker spectral sensors is less than 0.02. In conclusion, the different number of GreenSeeker spectral sensors have a particular impact on the delineation of green management zones but have little impact on the delineation of other management zones; with the increase of NDVI number, this effect has little change.

Analysis of evaluation indexes for fertilization management zones

We compiled the silhouette coefficient calculation program through the sklearn toolbox in Python software. The divided NDVI data was input to the silhouette_score function, and the parameter metric was set to Euclidean distance. The silhouette coefficients were obtained from the silhouette coefficient calculation program and shown in *Figure 5*. When 10,000 soybean NDVI data were processed, the silhouette coefficient varied in the range of 0.553-0.565. When four GreenSeeker spectral sensors were used, the maximum silhouette coefficient was 0.565, and the zoning effect was the best. The difference of the silhouette coefficient of the different number of sensors was at most 0.012. When 20,000 soybean NDVI data were processed, the silhouette coefficient varied in the range of 0.545-0.559. When two GreenSeeker spectral sensors were used, the maximum silhouette coefficient was 0.559, and the zoning effect was the best. The difference of the silhouette coefficient of the different number of sensors was at most 0.014. Overall, the number of soybean NDVI collections and the number of GreenSeeker spectral sensors have influence on the silhouette coefficient, but the influence is small (0.014).

We calculated the adjusted Rand index using Python software, and used the adjusted_rand_score function in the sklearn library. The zoning results of six sensors were set as ideal results, and the other conditions were compared with ideal results. The higher the adjusted Rand index value, the better the zoning effect. The adjusted Rand index of delineation of management zones by the different number of GreenSeeker spectral sensors were obtained through the calculation program, and the specific values are shown in *Figure 6*. When 10,000 soybean NDVI data were processed, the adjusted Rand index varied in the range of 0.675-0.823. When four GreenSeeker spectral sensors were used, the maximum adjusted Rand index was 0.823, and the zoning effect was the best. The difference of the silhouette coefficient of the different number of sensors was at most 0.148. When 20,000 soybean NDVI data were processed, the adjusted Rand index varied in the range of 0.651-0.824. When four GreenSeeker spectral sensors were used, the maximum adjusted Rand index was 0.824, and the zoning effect was the best.

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The difference of the silhouette coefficient of the different number of sensors was at most 0.173. Overall, the number of soybean NDVI collections and the number of GreenSeeker spectral sensors have influence on the silhouette coefficient, but the influence is small (0.173).

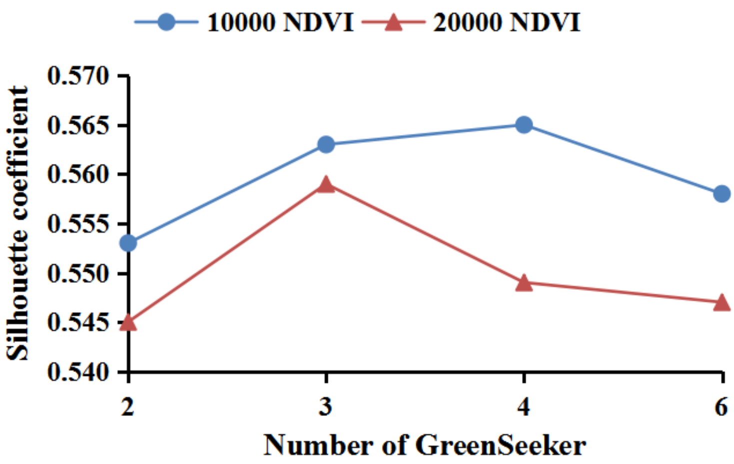

Figure 5. *Silhouette coefficient of fertilization management zones based on soybean NDVI data collected by different number of GreenSeeker spectral sensors*

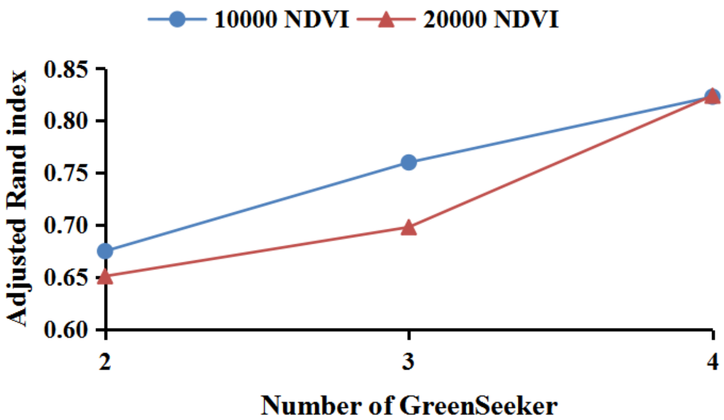

Figure 6. *Adjusted Rand index of fertilization management zones based on soybean NDVI data collected by different number of GreenSeeker spectral sensors*

Conclusions

In this study, we obtained soybean NDVI data of the different number of GreenSeeker spectral sensors through the soybean NDVI data acquisition system, delimited management zones using fuzzy c-means algorithm, and studied the influence of the number of GreenSeeker spectral sensors on delimiting soybean fertilization management zones. From our results, it is best to collect NDVI data according to setting one GreenSeeker sensor on each ridge, and the delineation of fertilization management zones in this way is the most accurate. However, the way in which Greenseeker sensors are installed on each ridge will cause unnecessary economic losses. Due to the continuous influence of soil fertility on crops, although the dense arrangement of

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GreenSeeker spectral sensors can improve the accuracy of delimiting fertilization management zones, the effect is not significant. Considering the economic impact, the number of GreenSeeker spectral sensors used can be reduced. When we reduced the number of GreenSeeker spectral sensors to 3, compared with the situation of 6 sensors, the change of silhouette coefficient was tiny, and the adjusted Rand index was about 0.7. Therefore, we believe that appropriately reducing the number of sensors has little impact on the division of fertilization management zones. When the tractor's operating width is 6.6 m, setting three GreenSeeker spectral sensors can meet the accuracy requirements and save the number of sensors used. Subsequent research will further increase the number of NDVI data collection, optimize the fuzzy c-mean algorithm, and conduct more experiments to verify the impact of the different number of GreenSeeker spectral sensors on the delineation of management zones.

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REFERENCES

[1] Bezdek, J. C., Ehrlich, R., Full, W. (1984): FCM: Fuzzy C-Means algorithm. – Computers & Geoscience 10: 191-203.

[2] Billa, S. K., Murthy, K. R., Ramana, A., Jagannadham, J. (2020): The potential of green seeker in nitrogen management of transplanted rice crop under north coastal environment of Andhra Pradesh, India. – Int. J. Agricult. Stat. Sci. Vol 16: 1925-1929.

[3] Chacón, J. E. (2021): A close-up comparison of the misclassification error distance and the adjusted Rand index for external clustering evaluation. – British Journal of Mathematical and Statistical Psychology 74: 203-231.

[4] Chen, H., Wang, X., Zhang, W., Wang, X. Z., Di, X. D., Qi, L. Q. (2021): A new soybean NDVI data-based partitioning algorithm for fertilization management zoning. – Applied Ecology and Environmental Research 19(2):1391-1405.

[5] Chen, J., Lü, S., Zhang, Z., Zhao, X., Li, X., Ning, P., Liu, M. (2018): Environmentally friendly fertilizers: a review of materials used and their effects on the environment. – Science Of the Total Environment 613: 829-839.

[6] Duarte, L., Teodoro, A. C., Monteiro, A. T., Cunha, M., Gonalves, H. (2018): QPhenoMetrics: an open source software application to assess vegetation phenology metrics. – Computers and Electronics in Agriculture 148: 82-94.

[7] Dunn, J. C. (1973): A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. – Journal of Cybernetics 3: 32-57.

[8] Fabbri, C., Napoli, M., Verdi, L., Mancini, M., Orlandini, S., Dalla Marta, A. (2020): A sustainability assessment of the Greenseeker N management tool: a lysimetric experiment on barley. – Sustainability 12: 7303.

[9] Farid, H., Bakhsh, A., Ahmad, N., Ahmad, A., Mahmood-Khan, Z. (2016): Delineating site-specific management zones for precision agriculture. – The Journal of Agricultural Science 154: 273-286.

[10] Fu, Q., Wang, Z., Jiang, Q. (2010): Delineating soil nutrient management zones based on fuzzy clustering optimized by PSO. – Mathematical and Computer Modelling 51: 1299-1305.

[11] Han, J., Pei, J., Kamber, M. (2011): Data Mining: Concepts and Techniques. – Elsevier, Amsterdam.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_51755187

[12] He, P., Xu, X., Zhang, B., Li, Z., Jin, X., Zhang, Q., Zhang, Y. (2016): Crop classification extraction based on multitemporal GF-1 remote sensing image. – Journal of Henan Agricultural Sciences 45: 152-159.
[13] Hubert, L., Arabie, P. (1985): Comparing partitions. – Journal of Classification 2: 193-218.
[14] Kanzawa, Y., Miyamoto, S. (2021): Generalized fuzzy c-means clustering and its property of fuzzy classification function. – Journal of Advanced Computational Intelligence and Intelligent Informatics 25: 73-82.
[15] Kaur, R. (2021): Prediction of grain yield and nitrogen uptake by basmati rice through in-season proximal sensing with a canopy reflectance sensor. – Precision Agriculture 1-15.
[16] Liu, J., Xu, M. (2008): Kernelized fuzzy attribute C-means clustering algorithm. – Fuzzy Sets and Systems 159: 2428-2445.
[17] Matese, A., Di, G. S. (2015): Technology in precision viticulture: a state of the art review. – International Journal of Wine Research 7: 69-81.
[18] Meriame, M., Ali, E., Fatiha, O., Mohammed, E. H., Ana, C. T. (2017): Mapping forest species in the Central Middle Atlas of Morocco (Azrou Forest) through remote sensing techniques. – ISPRS International Journal of Geo-Information 6: 275.
[19] Moral, F., Terrón, J., Da Silva, J. M. (2010): Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. – Soil and Tillage Research 106: 335-343.
[20] Ohana-Levi, N., Ben-Gal, A., Peeters, A., Termin, D., Linker, R., Baram, S., Raveh, E., Paz-Kagan, T. (2021): A comparison between spatial clustering models for determining N-fertilization management zones in orchards. – Precision Agriculture 22: 99-123.
[21] Peralta, N. R., Costa, J. L., Balzarini, M., Franco, M. C., Córdoba, M., Bullock, D. (2015): Delineation of management zones to improve nitrogen management of wheat. – Computers and Electronics in Agriculture 110: 103-113.
[22] Qiang, M., Wan-Tai, Y., Shao-Hua, Z., Zhang, L. (2007): Relationship between water-stable aggregates and nutrients in black soils after reclamation. – Pedosphere 17: 538-544.
[23] Rayala, V., Kalli, S. R. (2020): Big data clustering using improvised fuzzy c-means clustering. – Rev. d'Intelligence Artif. 34: 701-708.
[24] Reznick, J. P., Pauletti, V., Barth, G. (2021): Field estimate with NDVI of grain yield and quality of wheat flour. – Revista Brasileira de Engenharia Agrícola e Ambiental 25: 801-806.
[25] Rogovska, N., Laird, D. A., Chiou, C.-P., Bond, L. J. (2019): Development of field mobile soil nitrate sensor technology to facilitate precision fertilizer management. – Precision Agriculture 20: 40-55.
[26] Rouse, J. W., Haas, R. H., Scheel, J. A., Deering, D. W. (1974): Monitoring vegetation systems in the great plains with ERTS. – Proceedings, 3rd Earth Resource Technology Satellite (ERTS) Symposium, pp. 48-62.
[27] Rousseeuw, P. J. (1987): Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. – Journal of Computational and Applied Mathematics 20: 53-65.
[28] Ruspini, E. (1972): Optimization in sample descriptions: data reduction and pattern recognition using fuzzy clustering. – IEEE Transactions on Systems, Man and Cybernetics 2: 541.
[29] Schenatto, K., De Souza, E. G., Bazzi, C. L., Gavioli, A., Betzek, N. M., Beneduzzi, H. M. (2017): Normalization of data for delineating management zones. – Computers and Electronics in Agriculture 143: 238-248.
[30] Schwalbert, R., Amado, T., Reimche, G., Gebert, F. (2019): Fine-tuning of wheat (Triticum aestivum, L.) variable nitrogen rate by combining crop sensing and management zones approaches in southern Brazil. – Precision Agriculture 20: 56-77.

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[31] Shah, J., Wang, X., Khan, S. U., Khan, S., Gurmani, Z. A., Fiaz, S., Qayyum, A. (2021): Optical-sensor-based nitrogen management in oat for yield enhancement. – Sustainability 13: 6955.
[32] Steinley, D. (2004): Properties of the Hubert-Arable Adjusted Rand Index. – Psychological Methods 9: 386.
[33] Triayudi, A., Fitri, I. (2018): Comparison of parameter-free agglomerative hierarchical clustering methods. – ICIC Express Letters 12: 973-980.
[34] Van Eerd, L. L., Macfarlane, J. M., Chahal, I. (2021): Optical sensors to predict sugarbeet yield, quality, and fertilizer nitrogen application rate. – Canadian Journal of Plant Science 101: 984-998.
[35] Verma, R. R., Manjunath, B. L., Singh, N. P., Kumar, A., Asolkar, T., Chavan, V., Srivastava, T. K., Singh, P. (2018): Soil mapping and delineation of management zones in the Western Ghats of coastal India. – Land Degradation & Development 29: 4313-4322.
[36] Vinh, N. X., Epps, J., Bailey, J. (2010): Information theoretic measures for clusterings comparison: variants, properties, normalization and correction for chance. – The Journal of Machine Learning Research 11: 2837-2854.
[37] Wu, K.-L. (2012): Analysis of parameter selections for fuzzy c-means. – Pattern Recognition 45: 407-415.
[38] Yeung, K. Y., Ruzzo, W. L. (2001): Details of the adjusted rand index and clustering algorithms, supplement to the paper an empirical study on principal component analysis for clustering gene expression data. – Bioinformatics 17: 763-774.
[39] Yuchun, P., Xuzhang, X., Liping, C., Chunjiang, Z., Xiu, W. (2006): Using GIS to study relationship between fertilization amount and management zone size on variable--rate fertilization. – Journal of Biomathematics 21: 412-418.
[40] Zhou, H. B., Gao, J. T. (2014): Automatic method for determining cluster number based on silhouette coefficient. – Advanced Materials Research 951: 227-230.

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DOI: http://dx.doi.org/10.15666/aeer/2106_51755187