Optimization of sample points for monitoring arable land quality by simulated annealing while considering spatial variations

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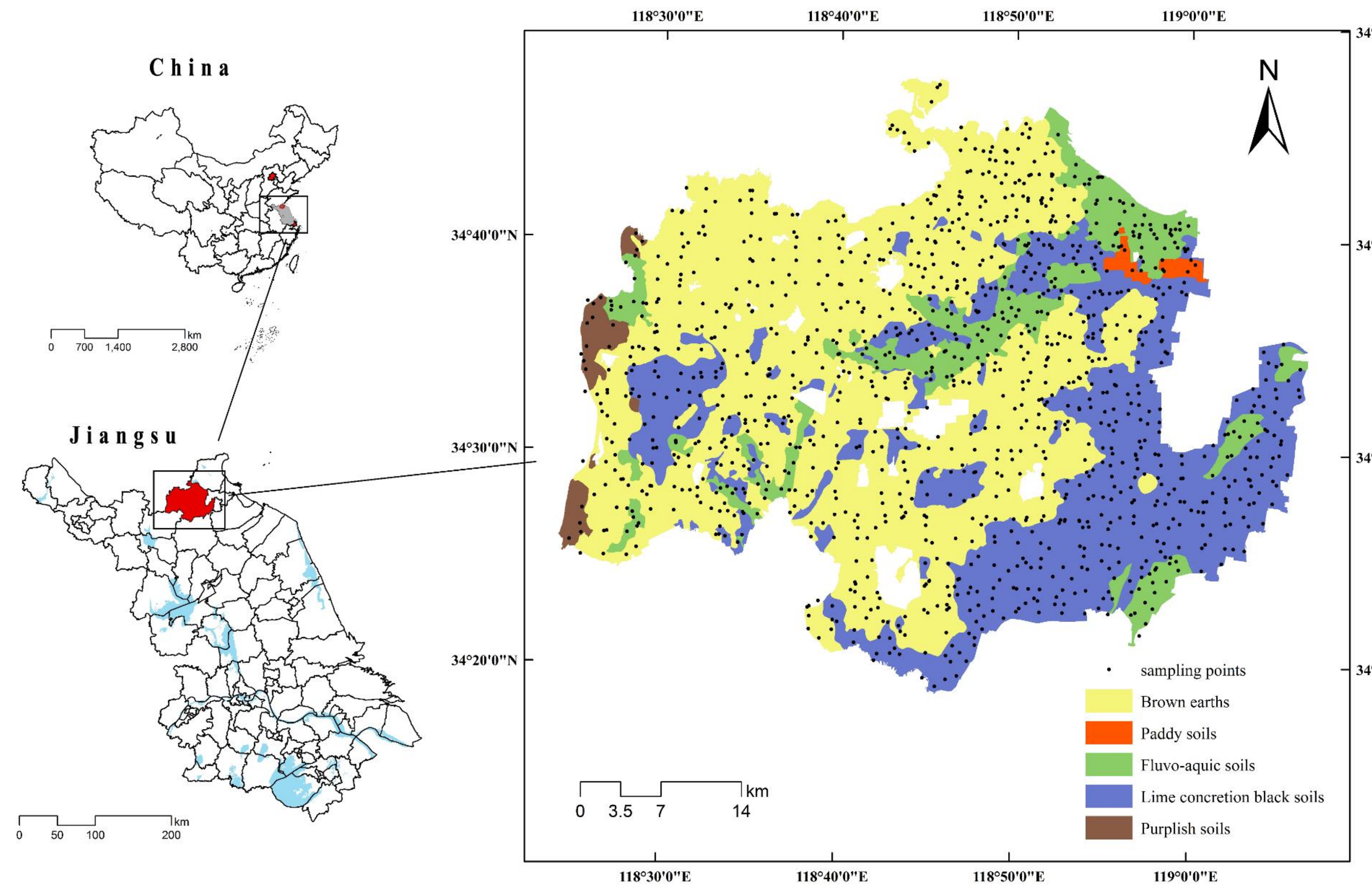
Introduction

Arable land is the basis of food production, the most valuable input in agricultural production, and an important factor in sustainable agricultural development and national food security. In China, the reduction and degradation of arable land due to industrialization and urbanization has gradually emerged as one of the most prominent challenges. In this context, the long-term dynamic monitoring of arable land quality becomes important for protecting arable land resources. However, little consideration has been given to optimizing sample points number and layout in previous monitoring studies on arable land quality. When considering the optimization of sample points, various strategies are needed, depending on the indicators. In addition, the distribution of soil properties displays spatial variations. However, existing sampling studies have paid little attention to spatial variations during scenarios with multiple indicators. Therefore, it is necessary to further investigate how to improve the efficiency and accuracy of arable land quality monitoring and evaluation by optimizing the number and layout of sample points when there are spatial variations in multiple indicators.

Goals

- optimize the sampling strategy using SA while maintaining a certain level of accuracy and to monitor and evaluate the arable land quality accurately using fewer sample points.
- optimize the sample points with regards to multiple indicators of arable land quality and to analyze the characteristics and differences in sample layouts with regards to various indicators.
- improve the SA algorithm by considering the spatial variations in soil properties and then optimizing the number and layout of soil sample points.
- investigate a method that reduces the number of sample points for characterizing the spatial distribution of soil properties while ensuring its accuracy, and to determine the optimal layout of sample points to achieve the highest accuracy. The minimum number and optimal locations for soil sample points are obtained by comparing the number and layout of sample points before and after optimization.

Study area

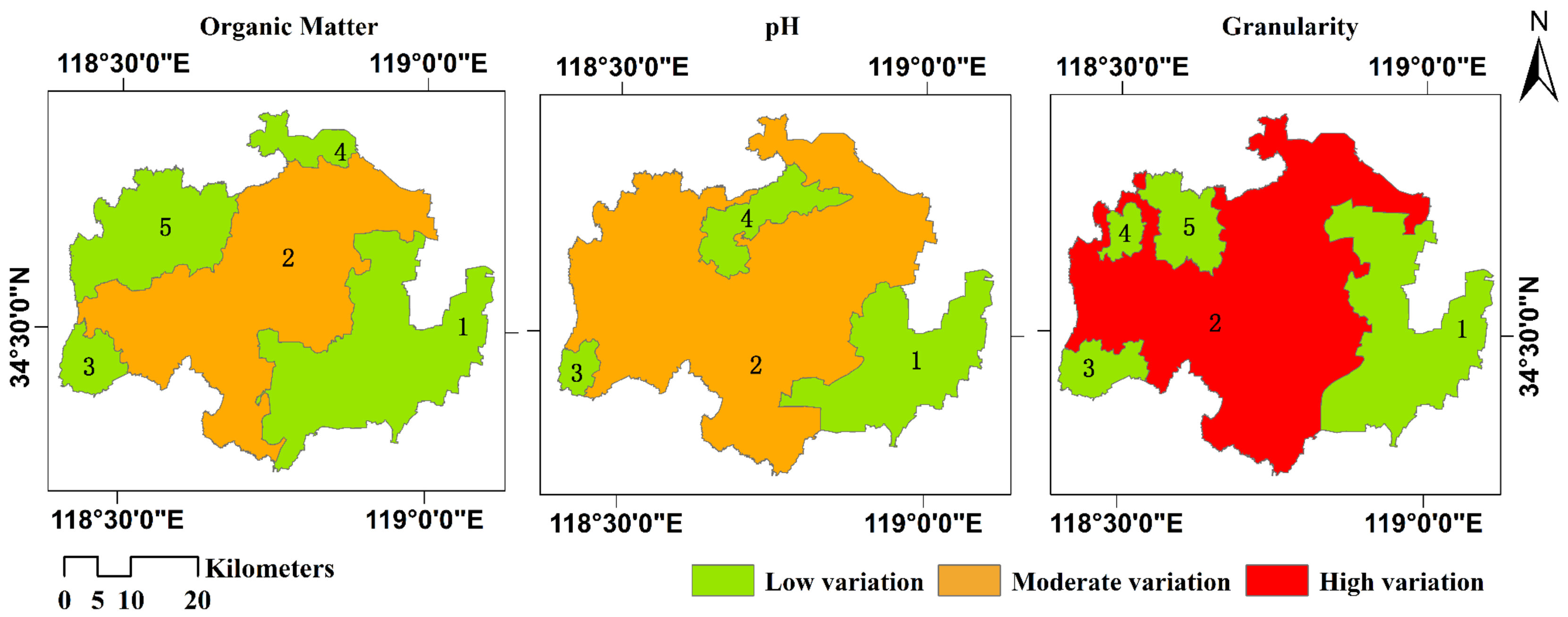


A total of 1440 sample points were randomly selected throughout the study area after the rice harvests in November 2007, November 2008, and November 2009. Among them, 140 sample points were randomly selected as a validation set; the remaining 1300 sample points were included in the optimization by SA.

Method

- The SA algorithm is commonly used to optimize a sampling layout. The use of conventional SA has been described by Chimi-Chiadjeu and other researchers .Generally, the improved SA algorithm is still made up of four steps. The change is in step 2.
  - In common SA, we randomly select one point from the complementary set. In improved SA, we select the point for which spatial variation is the maximum from the complementary set and replace a point from the initial solution with it to generate a new solution. The other parts remain unchanged.
- Moran's I Index
- ANOVA
- RMSE

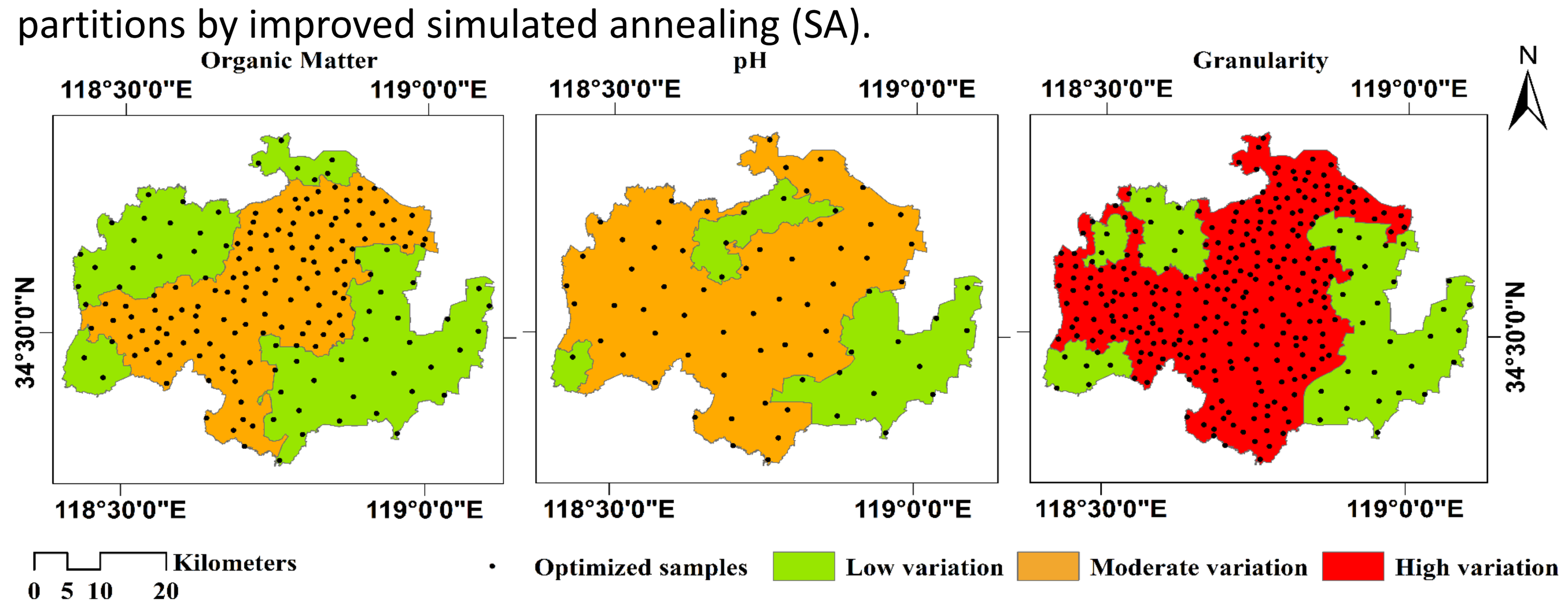
Results



Spatial variation partitions of the three soil properties

Soil Property	Low-Variation Partitions			Moderate- and High-Variation Partitions		
	Raw sample points	Optimal sample points	Percentage of optimal sample points	Raw sample points	Optimal sample points	Percentage of optimal sample points
Organic matter	631	58	9.19%	669	120	17.94%
pH	388	19	4.90%	912	53	5.81%
Granularity	486	46	9.47%	814	269	33.05%

Comparison of the optimization results for soil properties in different spatial variation partitions by improved simulated annealing (SA).



Spatial distribution of sample points for the three soil properties after optimization with the improved simulated annealing (SA)

Soil Property	Spatial Variation		
	Raw sample points	Optimal sample points from conventional SA	Optimal sample points from improved SA
Organic matter	0.3458	0.3412	0.4288
pH	0.4700	0.4553	0.4859
Granularity	0.4898	0.5001	0.6423

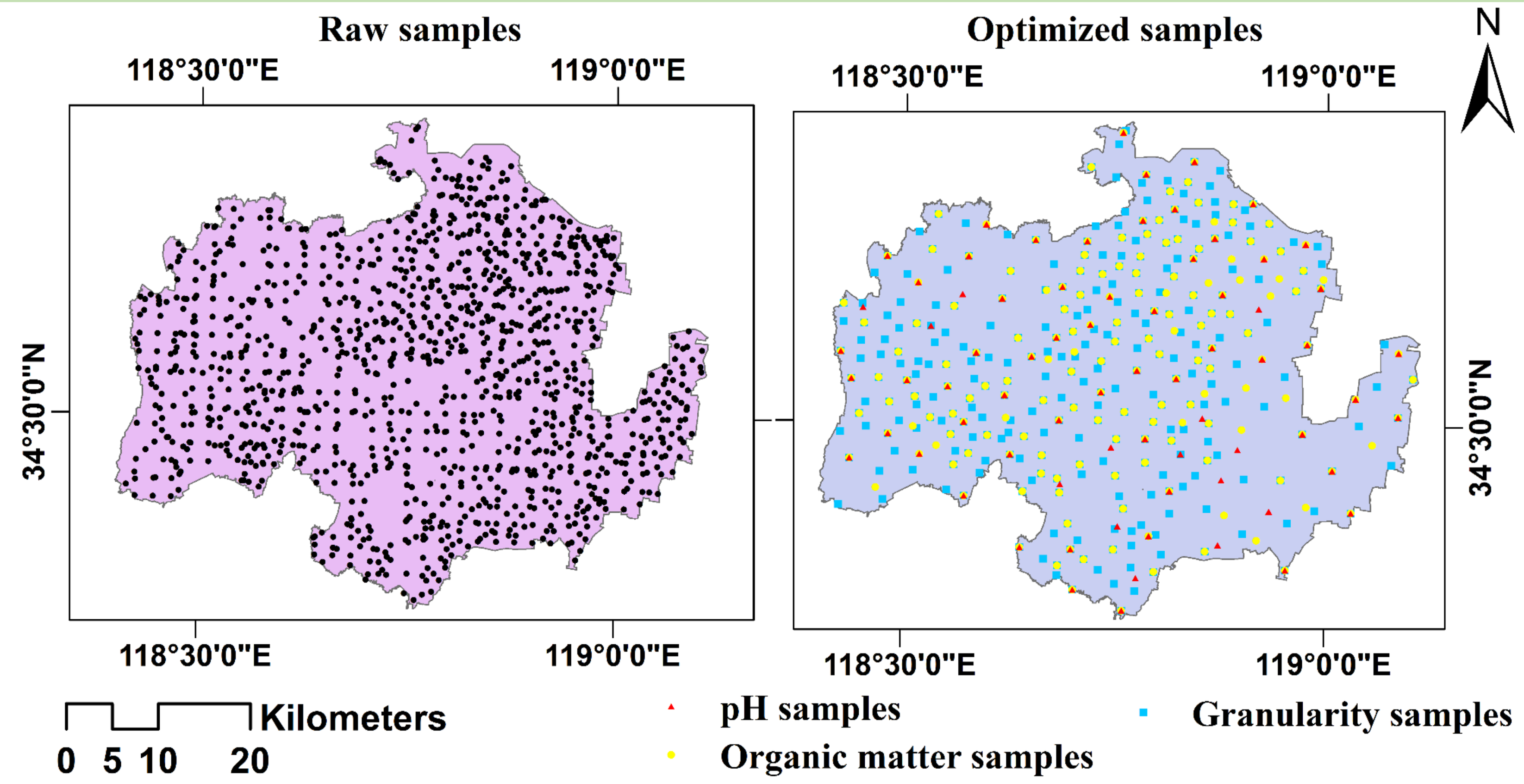
Comparison of optimization results for different soil properties obtained using two simulated annealing (SA) algorithms.

Soil Property	Low-Variation Partitions			Moderate- and High-Variation Partitions		
	Raw sample points	Optimal sample points	Percentage of optimal sample points	Raw sample points	Optimal sample points	Percentage of optimal sample points
Organic matter	631	58	9.19%	669	120	17.94%
pH	388	19	4.90%	912	53	5.81%
Granularity	486	46	9.47%	814	269	33.05%

Comparison of the optimization results for soil properties in different spatial variation partitions by improved simulated annealing (SA).

Soil Property	Raw Sample Points		Optimal Sample Points from Conventional SA		Optimal Sample Points from Improved SA	
	Number	Prediction accuracy (R^2)	Number	Prediction accuracy (R^2)	Number	Prediction accuracy (R^2)
Organic matter	1300	0.8823	226	0.8331	178	0.8926
pH	1300	0.7363	78	0.7108	72	0.7488
Granularity	1300	0.8527	418	0.8116	315	0.8693

Accuracy of predicted soil properties based on sample points that were optimized using the two simulated annealing (SA) algorithms



Spatial distribution of optimal sample points for the three soil properties in the study area

Source	Number	Percentage
Optimal sample points for organic matter only	25	7.16%
Optimal sample points for pH only	12	3.44%
Optimal sample points for granularity only	158	45.27%
Optimal sample points for organic matter and pH	12	3.44%
Optimal sample points for organic matter and granularity	94	26.93%
Optimal sample points for pH and granularity	2	0.57%
Optimal sample points for organic matter, pH, and granularity	46	13.18%

Numbers of optimal sample points.

Conclusion

- Despite a large reduction in the number of sample points, all three predicted soil properties retain the statistical characteristics of the raw data, and the optimal sample points are uniformly distributed in space. Compared with the conventional SA algorithm, the improved SA algorithm further reduces and optimizes the number of sample points, while all three properties retain the statistical characteristics of the raw data. During the optimization procedure, more sample points are retained in the moderate- and high-variation partitions, whereas fewer sample points are retained in the low-variation partitions. Higher CVs for soil properties lead to greater differences in the optimization of sample points between the high-variation and low-variation partitions. To ensure high monitoring accuracy, more sample points are needed in regions with relatively high spatial variations in soil properties.
- The improved SA achieves higher prediction accuracy for soil properties through the selection of fewer (optimal) sample points. The number of optimal sample points obtained from the improved SA is markedly reduced, while the accuracy of the predictions is improved by approximately 5% compared with the raw data. It is therefore reasonable to optimize the number and layout of soil sampling points using SA, and the modified SA developed in this study is useful.
- A total of 349 sample points are obtained by combining the optimization of sample points for the various soil properties. To monitor the arable land quality, a dense set of sample points is required for monitoring the soil granularity, whereas monitoring the pH requires the lowest number of sample points in the study area. For the long-term dynamic monitoring of arable land quality, it is most important to monitor the soil granularity, followed by the soil organic matter; the soil pH is the least important parameter to monitor in this area.

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