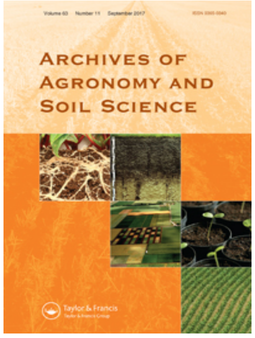

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Characterizing spatial variability of soil properties in alluvial soils of India using geostatistics and geographical information system

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ABSTRACT

Alluvial soils constitute significant portion of cultivated land in India and it contributes towards food grain production predominantly. The objectives of this study were to assess the spatial variability of soil pH, organic carbon (OC), available (mineralizable) nitrogen (N), available phosphorus (P), available potassium (K) and available zinc (Zn) of alluvial floodplain soils of Kadwa block, Katihar district, Bihar, India. A total of 85 soil samples, representative of the plough layer (0–25 cm depth from surface) were randomly collected from the study area. The values of soil pH, OC, N, P, K and Zn varied from4.4 to 8.4, 0.20% to 1.20%, 141 to 474, 2.2 to 68.2, 107 to 903 kg ha^{-1} and 0.22 to 1.10 mg kg^{-1}, respectively. The coefficient of variation value was highest for available P (94.3%) and lowest for soil pH (11.3%). Spherical model was found to be the best fit for N, P and Zn contents, while exponential model was the best fit for OC, and Gaussian model was the best-fit model for pH and K. The nugget/sill ratio indicates that except pH and available K all other soil properties were moderately spatially dependent (25–57%). Soil properties exhibited different distribution pattern. It was observed that the use of geostatistical method could accurately generate the spatial variability maps of soil nutrients in alluvial soils.

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Soil nutrients; kriging; semivariogram; accuracy assessment

Introduction

Alluvial soils are one of the major soil groups in India as well as in Bihar state, which are mainly found along the river plains of Ganges, Kosi, Mahananda and their tributaries, and they largely contribute to the national food basket. These alluvial soils in Bihar are intensively cultivated with blanket recommendations of N, P and K for individual crops resulting in under- or over-fertilization. These nutrient imbalances may also cause nutrient antagonism (viz. Zn–P interactions) and waste of costly inputs like K fertilizer, which is fully imported by India (Chatterjee et al. 2015).

Site-specific soil management has received considerable attention due to potential benefits of increasing input use efficiency, improving the economic margins of crop production and reducing environmental risks (Yasrebi et al. 2008). Hence, a comprehensive understanding of spatial variability of soil properties is becoming increasingly essential. Variability in soil properties results mainly from the complex interactions between geology, topography and climate, as well as soil use and management (Shi et al. 2009; Liu et al. 2015). As a consequence, soils exhibit marked spatial variability at the macro-scale and micro-scale (Amirinejad et al. 2011; Shukla et al. 2016).

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Spatial distribution maps of soil properties, obtained from soil surveys, help in correct management of soil nutrients (Brevik et al. 2015). These maps are required to understand the patterns and processes of soil spatial variability, which is the combined effect of soil physical, chemical and biological processes operating at different spatiotemporal scales combined with anthropogenic activities (Goovaerts 1998). Geostatistical tools are useful in preparation of the maps based on limited number of samples collected from agricultural landscapes. Kriging interpolation technique predicts the values at unsampled locations by spatial correlation and reduces variance of estimation error and investigation costs (Saito et al. 2005; Pereira et al. 2015). Spatial variability of soil properties is assessed effectively by geostatistical methods (Moosavi Sepaskhah 2012; Nourzadeh et al. 2012; Reza et al. 2013, 2015; Emadi et al. 2016; Shahabi et al. 2016) for site-specific management of nutrients. In recent years, many researchers have studied the spatial variability of soil chemical (Reza et al. 2010, 2012a, 2012b, 2016a, 2016b; Behera et al. 2011, 2016; Behera Shukla 2015; Tripathi et al. 2015) and physical properties (Santra et al. 2008; Reza et al. 2016c) in different soils of India. However, the information regarding spatial variability of soil properties in alluvial soils of India is limited.

Keeping above things in view, a systematic study was carried out to explore the spatial variability of pH, organic carbon (OC), available nitrogen (N), available phosphorus (P), available potassium (K) and available zinc (Zn) in intensively cultivated soils of Kadwa block of Katihar district, Bihar, India, for site-specific soil management. A better understanding of the spatial variability of soil properties would enable for refined agricultural and environmental management practices by identification of proper sites for management.

Material and methods

Site description

The study was carried out in Kadwa block of Katihar district (25°30′–25°47′ N latitude and 87°35′–87°55′ E longitude) covering an area 340.47 km^2 (Figure 1) situated in north-eastern part of Bihar, India. The maximum temperature is 43°C during July and August; a minimum temperature falls up to 8°C in the month of January. The difference between the mean summer and mean winter soil temperature is more than 5°C. Mean annual rainfall is 2100–2500 mm and about 85% of rainfall is from south-west monsoon. Geomorphologically, the study area represents flat topography (1–2% slope) with regional slope towards south. The regional slope takes a tilt from west to east and shifting of channels and courses of rivers over a period of times. Based on regional slope, the block is divided into four major physiographic units, viz. old alluvial plain, recent alluvial plain, meander plain and flood plain. The elevation varied from 11 to 53 m above the mean sea level. The soils under investigation have been generally formed on unconsolidated sediments of Quaternary period. There are six soil types in the study area according to WRB (2014) soil classification, viz. Haplic Fluvisols, Stagnic Cambisols, Fluvic Cambisols, Haplic Cambisols, Endogleyic Cambisols and Haplic Arenosols.

Soil sampling and analysis

A total of 85 georeferenced composite soil samples were collected from surface (0–25 cm depth) layers which included 10 from old alluvial plain, 27 from recent alluvial plain, 43 from meander plain and 5 from flood plain sites using stainless steel soil augers and handheld global positioning system (Figure 1). Two to three subsamples were collected for making a composite sample. Soil samples were air-dried and ground to pass through a 2-mm sieve. Soil pH was determined by pH meter in a 1:2.5 soil:water suspension, available N by Subbiah and Asija (1956) method, OC by Walkley and Black (1934) method. Available P content was measured by Olsen method by extracting 2.5 g of soil with 50 ml of 0.5 M $NaHCO_3$ (pH 8.5) for 30 min and determining the phosphorus in

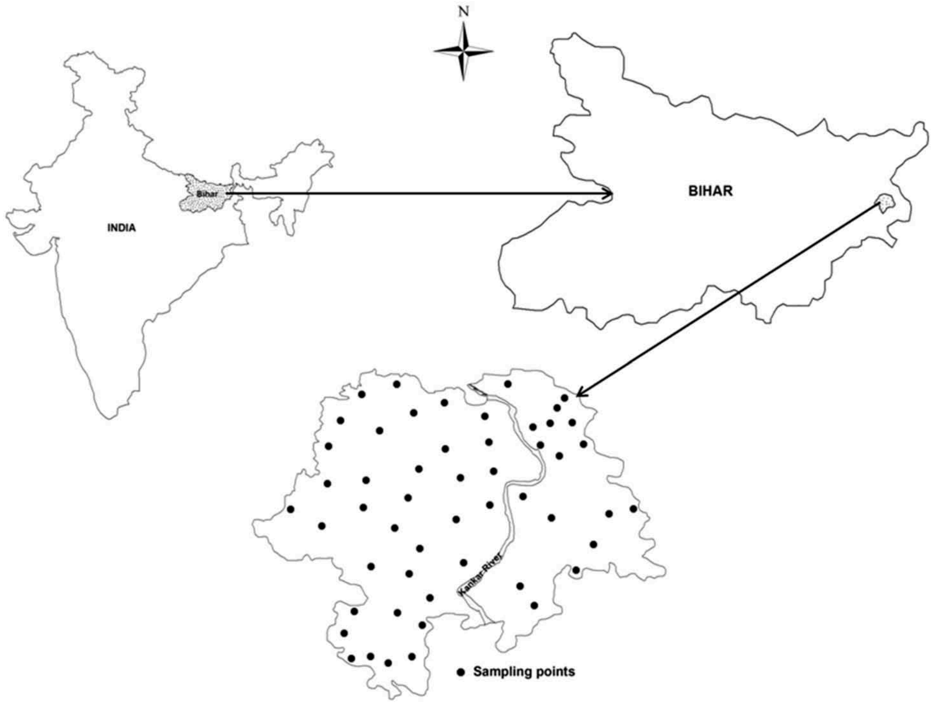

Figure 1. Location and sampling points map of the study area.

the extract by the L-ascorbic acid method (Murphy & Riley 1962). Available K was extracted with 1 M NH_4OAc and then estimated by flame photometry (Hanway & Heidel 1952). Available Zn was determined by Lindsay and Norvell (1978) method.

Statistical analysis

The statistical parameters like minimum, maximum, mean, standard deviation, coefficient of variation (CV), skewness and kurtosis were obtained. The Pearson correlation coefficients were estimated for all possible paired combinations of the response variables to generate a correlation coefficient matrix. The normal frequency distribution of data was verified by the Kolmogorov–Smirnov (K–S) test. The results indicated that the available P, available K and Zn data passed the K–S normality test at a significance level of 0.05 after logarithmic transformation. These statistical parameters were calculated with EXCEL® 2007 and SPSS 15.0® (SPSS Inc., Chicago, IL, USA).

Geostatistical analysis

Spatial interpolation and GIS mapping techniques were employed to produce spatial distribution maps for the investigated soil properties, and the software used for this purpose was ArcGIS v.10.1 (ESRI Co, Redlands, CA, USA). In ArcGIS, kriging can express the spatial variation and allow a variety of map outputs, and at the same time minimize the errors of predicted values (González et al. 2014). The semivariogram analyses were carried out before application of ordinary kriging interpolation as the semivariogram model determines the interpolation function (Goovaerts 1997) as given below.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \quad (1)$$

where $z(x_i)$ is the value of the variable z at location ofx_i, $h$the lag and $N(h)$ the number of pairs of sample points separated by h. For irregular sampling, it is rare for the distance between the sample pairs to be exactly equal to h. That is, h is often represented by a distance band.

Different semivariogram models were evaluated to select the best fit with the data. Best-fit models with minimum root-mean-square error (RMSE) were selected for each soil property:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2} \tag{2}$$

The spherical, exponential and Gaussian models were best fitted to all the soil properties. Expressions for different semivariogram models used in this study are given below:

Spherical model:

$$\gamma(h) = C + C_0\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] \text{for } 0 \le h \le a \text{ otherwise } C + C_o \tag{3}$$

Exponential model:

$$\gamma(h) = C_o + C\left[1 - \exp\left\{-\frac{h}{A}\right\}\right] \text{for } h \ge 0 \tag{4}$$

Gaussian model:

$$\gamma(h) = C_o + C\left[1 - \exp\left\{\frac{-h^2}{A^2}\right\}\right] \text{for } h \ge 0 \tag{5}$$

where h is the lag interval, $C_o$is the nugget variance ≥ 0, C is the structure variance $\ge C_o$ and A is the range parameter.

Using the model semivariogram, basic spatial parameters such as nugget(C_0), sill $(C + C_0)$ and range (A) were calculated which provide information about the structure as well as the input parameters for the kriging interpolation. The nugget/sill ratio, i.e. $(C_0)/(C + C_0)$ and the range are the parameters which characterize the spatial structure of a soil property. The range defines the distance over which the soil property values are correlated with each other. A low value of $(C_0)/(C + C_0)$ and a high range generally indicates that high precision of the property can be obtained by kriging (Cambardella et al. 1994). The nugget/sill ratio was used as the criterion to classify the spatial dependence of variables. Ratio values lower than or equal to 0.25 were considered to have strong spatial dependence, whereas values between 0.25 and 0.75 indicate moderate dependence and those greater than 0.75 show weak spatial dependence (Cambardella et al. 1994).

Accuracy of the soil maps was evaluated through cross-validation approach (Davis 1987). Among three evaluation indices used in this study, mean absolute error (MAE) and mean squared error (MSE) measure the accuracy of prediction, whereas goodness of prediction (G) measures the effectiveness of prediction (Utset et al. 2000). MAE is a measure of the sum of the residuals (e.g. predicted minus observed) (Voltz & Webster 1990).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} z(x_i) - \hat{z}(x_i) \tag{6}$$

where$\hat{z}(x_i)$ is the predicted value at location i. Small MAE values indicate less error. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE will be calculated.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2 \tag{7}$$

Squaring the difference at any point gives an indication of the magnitude; for example, small MSE values indicate more accurate estimation, point-by-point. The *G* measure gives an indication of how effective a prediction might be relative to that which could have been derived from using the sample mean alone (Schloeder et al. 2001).

$$G = \left[1 - \frac{\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right]^2}{\sum_{i=1}^{N}\left[z(x_i) - \bar{z}\right]^2}\right] \times 100 \tag{8}$$

where *z* is the sample mean. *G* is one of the methods used for accuracies of interpolated maps (Tesfahunegn et al. 2011). Accuracies of interpolated maps of studied soil properties were checked by *G* values. According to Parfitt et al. (2009), positive *G* values indicate that the map obtained by interpolating data from the samples is more accurate than a catchment average. Negative and close to zero *G* values indicate that the catchment-scale average predicts the values at unsampled locations as accurately as or even better than the sampling estimates.

Results and discussion

Descriptive statistics of soil properties

The descriptive statistics revealed considerable variability of soil properties (Table 1). The mean values of pH, OC, N, P, K and Zn were 6.0, 0.67%, 315 kg ha^{-1}, 16.0 kg ha^{-1}, 324 kg ha^{-1} and 0.44 mg kg^{-1}, respectively. The values of CV for soil properties ranged from 11.3% to 94.3%. The value of CV for pH revealed their low variability (CV <25%). Other researchers also documented a smaller variation of soil pH compared to other soil properties (Reza et al. 2012b, 2016a; Shukla et al. 2016). Low variability of pH may be attributed to the fact that pH values are log scale of proton concentration in soil solution; there would be much greater variability if soil acidity is expressed in terms of proton concentration directly. Generally, soil buffering capacity resists the abrupt change of soil pH or its high variability under different cropping systems and its management in the study area. The rest of the soil properties exhibited moderate (CV 25–75%) variability except available P. Skewness values of 0.01–2.10 for different soil proprieties revealed that some soil properties were not normally distributed. This variation and non-normal distribution of soil properties in the studied areas may be due to adoption of different soil management practices including variation in fertilizer application and other crop management practices (Srinivasarao et al. 2014; Behera et al. 2016).

The Pearson linear correlation analysis results (Table 2) showed highly significant positive relationship of soil pH with available P ($r = 0.44$, $p < 0.01$). There have been reports on a positive relationship between OC and the capacity of the soil to supply essential plant nutrients including N and P (Rezaei & Gilkes 2005; Reza et al. 2011). Pearson linear correlation analysis indicated significant positive relationships of OC with available N ($r = 0.28$, $p < 0.05$) and available P ($r = 0.23$, $p < 0.05$).

Table 1. Summary statistics for soil properties.

Soil property	Mean	Minimum	Maximum	SD	CV (%)	Skewness	Kurtosis	Distribution pattern
pH	6.0	4.4	8.4	0.68	11.3	0.68	2.53	Normal
Organic carbon (%)	0.67	0.20	1.20	0.21	31.3	0.29	0.45	Normal
Available N (kg ha^{-1})	315	141	474	74.5	23.6	0.01	0.13	Normal
Available P (kg P_2O_5 ha^{-1})	16.0	2.2	68.2	15.1	94.3	1.49	1.91	Log
Available K (kg K_2O ha^{-1})	324	107	903	164	50.6	1.71	3.42	Log
Available Zn (mg kg^{-1})	0.44	0.22	1.10	0.14	31.8	2.10	8.15	Log

SD: standard deviation; CV: coefficient of variation.

Table 2. Correlation coefficients among soil properties and their level of significance.

	pH	Organic carbon	Available N	Available P	Available K	Available Zn
pH	1.00					
Organic carbon	−0.09	1.00				
Available N	0.03	0.28*	1.00			
Available P	0.44**	0.23*	0.07	1.00		
Available K	0.07	0.08	−0.08	0.01	1.00	
Available Zn	0.02	0.10	0.22	0.21	0.30*	1.00

*Correlation is significant at $p < 0.05$ level (two-tailed); **correlation is significant at $p < 0.01$ level (two-tailed).

Spatial variability of soil properties

Four models, viz. circular, exponential, spherical and Gaussian were identified as best-fit models for the studied soil properties based on minimum RMSE. Based on a best-fit model criterion, only one model was selected for kriging. Other researchers also used the similar methodology for selecting the best model for interpolation using kriging (Santra et al. 2008; Foroughifar et al. 2013; Tripathi et al. 2015; Reza et al. 2016a, 2016c). Analysis of the isotropic variograms indicated that, semivariograms for soil pH and available K were well described by Gaussian model with distance of spatial dependence being 3315 and 2345 m, respectively. Available N, available P, and Zn semivariograms were well described by spherical model, with the distance of spatial dependence being 1958, 2420 and 2247 m, respectively, while the OC was well described by exponential model, with the distance of spatial dependence being 3101 m (Table 3).

The nugget (an indication of micro-variability) was highest for K, which is ascribed to the fact that the selected sampling distance could not capture the spatial dependence well. The nugget/sill ratio values were 17%, 57%, 50%, 38%, 82% and 43% for pH, OC, N, P, K and Zn, respectively, indicating moderate spatial dependence for N, P and Zn, and strong spatial dependence for pH. This is attributed to inherent soil properties as well as management factors including fertilization and cropping sequences practiced. Reza et al. (2016a) reported similar results.

Surface maps of soil properties were prepared by ordinary kriging (Figure 2). The surface map of soil pH showed that pH value in the north-east portion, central and extreme north-west portion was in acidic range and the value in the south-east and south-west portion was neutral to alkaline range of the study area. The greater distribution of acid soils in the study area was due to Mahananda river carrying high load of acid sediments and deposited in the block (Kumari 2014) as well as application of high dose of N fertilizer in rice–wheat cropping system (Yadav et al. 1998). The surface map of OC content showed that the north-west and extreme north-east corner of the study area had low OC content.

The surface map of available N showed that the N content in south-east portion was high may be due to the high OC content in south-east portion of the study area since these parameters are interlinked via the microbial mineralization processes. The available P content of the study area was scattered in their distribution. The surface map of available K content was found low in western portion of the study area, where the rate of K fertilizer application is low, while available Zn was low in north-west and south-east portion of the study area.

Table 3. Geostatistical parameters of the fitted semivariogram models for soil properties.

Soil properties	Fitted model	Nugget (C_0)	Sill ($C + C_0$)	Range(A)(m)	Nugget/Sill (%)	RMSE
pH	Gaussian	0.117	0.688	3315	17	0.679
Organic carbon (%)	Exponential	15.11	26.15	3101	57	0.215
Available N (kg ha^{-1})	Spherical	443.2	885.1	1958	50	73.99
Available P (kg P_2O_5 ha^{-1})	Spherical	81.57	210.7	2420	38	16.12
Available K (kg K_2O ha^{-1})	Gaussian	3518	4253	2345	82	152.4
Available Zn (mg kg^{-1})	Spherical	0.414	0.948	2247	43	0.152

RMSE: root mean square error.

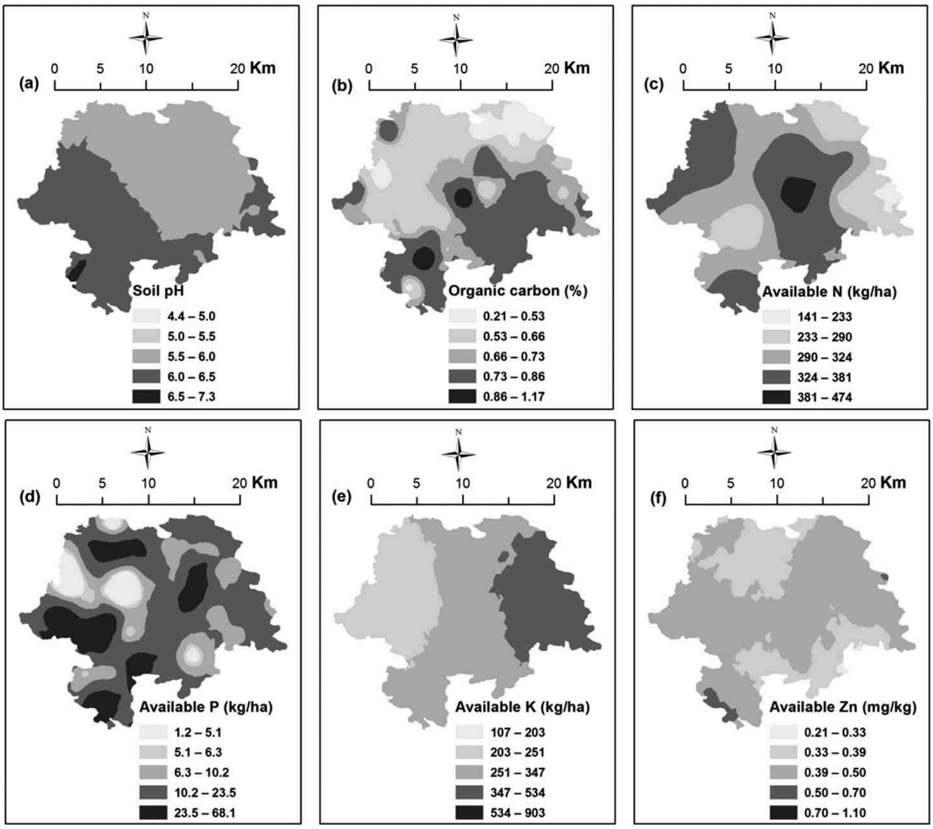

Figure 2. Surface maps of (a) soil pH, (b) organic carbon, (c) available N, (d) available P, (e) available K and (f) available Zn content.

Table 4 shows the evaluation indices resulting from cross-validation of surface maps of soil properties. It was observed that pH, OC and Zn had low MAE than other soil properties. For all the soil properties, the *G* value was greater than 0, which indicates that spatial prediction using semivariogram parameters is better than assuming mean of observed value as the property value for any unsampled location. This also shows that semivariogram parameters obtained from fitting of experimental semivariogram values were reasonable to describe the spatial variation of all the studied soil properties.

Conclusions

The classical and geostatistical method on a large scale could be accurately used to evaluate spatial variability of soil physical properties. The summary statistics for soil properties were shown that CV

Table 4. Evaluation performance of kriged map of soil properties through cross-validation.

Soil properties	Mean absolute error	Mean square error	Goodness of prediction
pH	0.009	0.461	14.2
Organic carbon (%)	0.007	0.046	16.5
Available N (kg ha^{-1})	0.251	5475	24.8
Available P (kg P_2O_5 ha^{-1})	0.279	261.3	13.3
Available K (kg K_2O ha^{-1})	2.361	9879	12.6
Available Zn (mg kg^{-1})	0.005	0.023	14.7

for soil properties ranged from 11.3% to 94.3%. The raw data sets of P, K and Zn strongly positively skewed and the application of log transformation was effective in normalizing the data. Geostatistical analysis revealed Gaussian, exponential and spherical best-fit semivariogram models for studied soil properties. The nugget/sill ratio values indicate moderate spatial dependence for N, P and Zn, and strong spatial dependence for pH. The kriged surface maps of soil properties exhibited different distribution pattern. The spatial distribution maps developed for soil properties could be the primary guide for region-specific nutrient management and designing future soil sampling strategies in the intensively cultivated alluvial soils of India.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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