Plant Cover as Predictor Variable of Salinity and Alkalinity in Abandoned Saline Soils of the Huang-Huai-Hai Plain, China

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The capacity of vegetation to indicate soil properties is widely used in the mapping of salt-affected lands (BALLENEGGER, 1929). In areas covered by semi-natural vegetation this practice is considered to be standard.

In the abandoned saline plots of the Huang-Huai-Hai Plain of China, owing to the economic and demographic pressure the farmers have a keen interest in judging the suitability of the lands for cropping. The stabilized vegetation of the land looked promising for using it as a covariable in the prediction of soil properties.

Based on the long history of the study of soil-vegetation correlations in salt-affected soils (SHANTZ, 1911, KEARNEY, 1913; SHANTZ & PIEMEISEL, 1924; 'SIGMOND, 1927; MAGYAR, 1928; CHAPMAN, 1960; BODROGKÖZY, 1965) and also our previous experience (TÓTH & RAJKAI, 1994; TÓTH et al., 1994), an attempt was made to utilize the information provided by the vegetation of the abandoned soil to predict the values of soil properties quantitatively. The idea was to use "easily available" field measured variables in the prediction of soil properties either in spatial interpolation or in regression analysis and to compare the precision of the two methods in two different block sizes.

The results showed the advantage of spatial interpolation over multiple regression analyses, but, especially in the case of a highly variable property in smaller blocks, multiple regression analysis with easily available field properties provides very similar precision.

Materials and Methods

The research area - The study was carried out in the Luosibowadi plot, Wangsu, Hebei Province, China (Figure 1). The plot and the surrounding 5,000 hectare area, called Qi Wan Mu, is used by local authorities as a flood water reservoir area to keep some of the river flood that arises during the heavy rains of June and July or November and December. This use began in the late seventies. Recent records of the area show that since 1949 it has been ploughed about 5 times. Inside the plot there are abandoned channels, dams and pieces of cropland. According to two years of observation, farmers tend to crop the same patches.

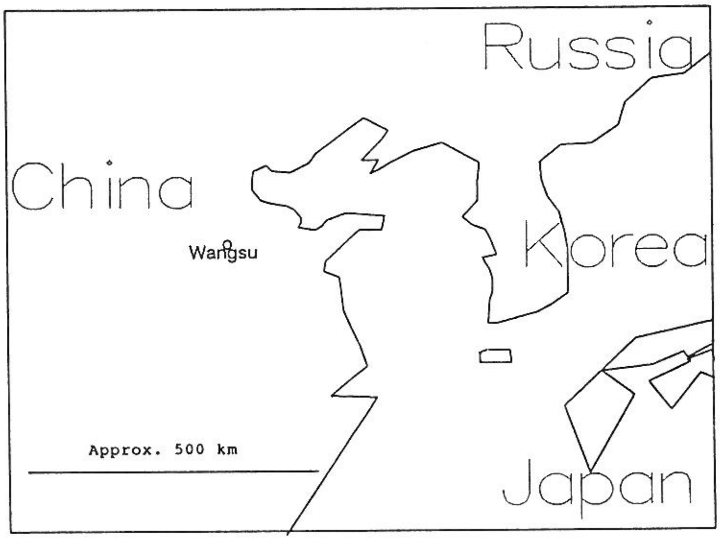

Figure 1
The location of the study area, Wangsu

The study area lies at about 7 m above sea level. The groundwater table is located 0.6 m below the surface in November and at a depth of 3 m in April.

The parent material of the soil is strongly stratified transported loess. The soil is "pale meadow soil" according to the Chinese genetic classification.

Plant cover . - In the abandoned salt-affected plots covered by the semi-natural vegetation studied the plants are the same as on the nearby coast. The most common plant, *Phragmites communis*, lives in areas covered by the sea at high tide.

The capacity of the plants to indicate salinity and therefore the suitability of the land for wheat production, is also known by the farmers. They prefer places covered by *Agropyron (Clynelinus) dahuricus* and *Imperata cylindrica* and do not like to sow wheat in areas covered mostly by *Aeluropus littoralis, Scorzonera albicaulis* or *Suaeda salsa*. Farmers make use of leaching provided by the old canals, and the wheat that now occupies the place of the usual *Imperata cylindrica* grows better than on the nearby higher-lying plot.

Experimental layout. - The sampling scheme was designed to meet the requirements of spatial interpolation and multiple regression analysis at two block sizes, and sampling was carried out in a 100 x 220 m rectangule (Figure 2). There were three scales, or size classes, of blocks/quadrats used for observation, including large blocks (55) of 20 x 20 m size which were located in a

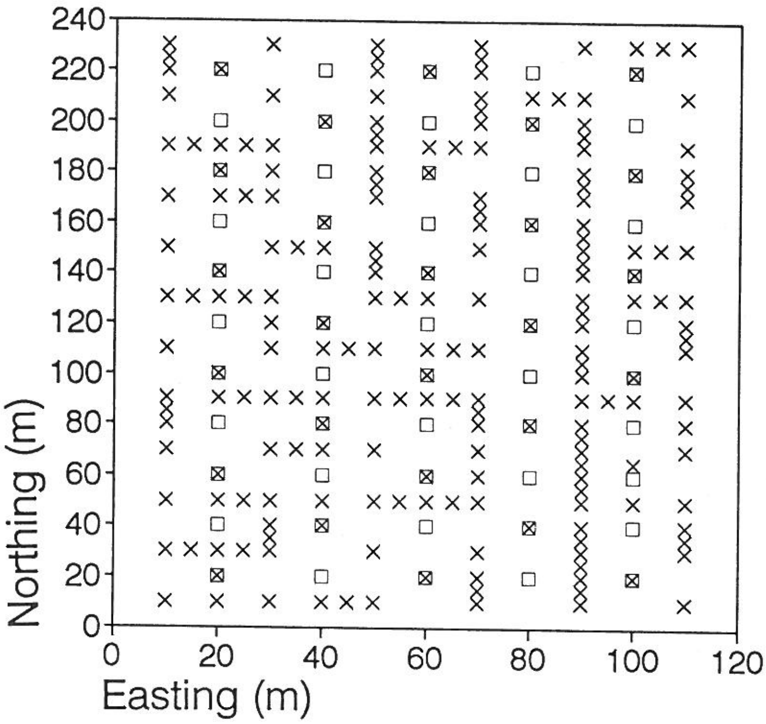

Figure 2
The arrangement of the sampling blocks.
□ Large block (20x20 m); x Medium block (5x5 m)

completely regular manner to cover all the territory; the medium blocks of 5 x 5 m size (n = 206) were arranged on a grid but did not fill all the possible grid points (880), only 206 randomly; four small blocks of 0.25 x 0.25 m size were arranged regularly inside each medium block.

During the survey a general map was drawn first of the land use, and of the semi-natural and weed vegetation of the plot. On all scales the estimated percentage cover of each plant species noticed was recorded. The relative ground height was measured in each small block. Penetrometric resistance was measured at 16 points in each medium block, i.e. four points were measured around each small block.

Soil samples were collected from each small block and then bulked up for the medium block. Samples were taken from 0-5 cm, 20-25 cm and 40-45 cm.

From the soil samples 1: 5 soil:water extracts were prepared, and from these the pH (only in the top layer) and the carbonate and bicarbonate contents were measured by titration with 0.01 *N* H_2SO_4 using phenolpthalein and methyl orange indicators. Cl was measured by argentometry, sulphate was measured with iodometry, calcium and magnesium with EDTA and sodium was calculated as the difference between the hypothetical cation content (assumed to be the same as the sum of the anions measured) and the measured calcium and magnesium. Consequently potassium was included in the sodium content, but was considered to be constant. The salt content of the soil was calculated by summing these ions and was expressed as percentage salt.

Penetration resistance was measured with a pocket penetrometer and expressed as penetration of the cone in mm.

The preparation of the variables from the data of smaller blocks is shown in Table 1.

The variables and the abbreviations used in the paper were the following: *tota* is the total plant cover (%); Phra is the percentage cover of *Phragmites communis;* Scor is the percentage cover of *Scorzonera albicaulis*; Aelu is the percentage cover of *Aeluropus littoralis*; Impe is the percentage cover of *Imperata cylindrica*, Suae is the percentage cover of *Suaeda salsa*, fsc1 and fsc2 are factor scores obtained by principal component analysis from plant cover, height and penetration resistance; heig is relative ground height (mm); *pene* is soil penetration resistance (mm), pH_0-5 is the pH of the 1:5 soil:water extract at the 0-5 cm depth, HCO_3-0-5 is the HCO_3 content of the 1:5 soil:water extract (meq/100 g soil), Cl_0-5 is the Cl content of the 1:5 soil:water extract (meq/100 g soil), SO_4-0-5 is the SO_4 content of the 1:5 soil:water extract (meq/100 g soil), Ca_0-5 is the Ca content of the 1:5 soil:water extract

Table 1

The preparation of the variables for different block sizes

Variables n	**Small block** 824	**Medium block** 206	**Large block** 55
Penetration	4 points measured	Average	Kriging from medium blocks
Ground height	1 point measured	Average	Kriging from medium blocks
Plant cover	Observed	Observed	Observed
Soil data		Sample bulked from small blocks	Kriging from medium blocks
Factor scores		Calculated from medium block	

(meq/100 g soil), Mg_0-5 is the Mg content of the 1:5 soil:water extract (meq/100 g soil), Na_0-5 is the Na content of the 1:5 soil:water extract (meq/100 g soil), salt_0-5 is the salt content of the 1:5 soil:water extract (g/100 g soil), HCO_3_20-25 is the HCO_3 content of the 1:5 soil:water extract (meq/100 g soil) of the 20-25 cm layer.

Statistical procedures . - For the estimation of soil properties two techniques were used, geostatistics and multiple regression analysis (MRA). The selected methods have different backgrounds:

Estimation method	**Basis of the estimation technique used**	
	Linear relation between variables	**Spatial dependence of variables**
Multiple regression analysis	+	-
Autokriging	-	+
Cokriging	+	+

One third of the examined blocks were left out randomly from the calculation of the predictor function and then used as a check (Table 2).

Table 2
The separation of available data into predicting and checking sets in the block sizes and vegetation categories studied

Data set	**Number of blocks**				
	Large blocks (20x20m)	**Medium blocks (5x5 m)**			
		Phragmites	**Imperata**	**Cropland**	**Total**
Predictor	37	47	35	43	125
Check	18	27	19	16	62

The goodness of estimation was calculated on the basis of the standard error of the estimate (SEE) (DAVIS, 1986).

$$SEE = \sqrt{\frac{\Sigma\left(z_m - z_e\right)^2}{n}} \qquad \text{(Eq.1)}$$

z_m = measured value;
z_e = estimated value;
n = number of estimations checked

which was normalized by the standard deviation to give the "estimation efficiency" (E%) (TÓTH & RAJKAI, 1994)

$$E\% = \left(1 - \frac{SEE}{sd}\right) \cdot 100 \qquad \text{(Eq.2)}$$

sd = standard deviation

in order to enable us to compare the estimations made for different soil properties. YATES and WARRICK (1987) used similar statistics then normalized with the SEE of autokriging to compare the performance of estimations made by cokriging.

Geostatistical calculations (WARRICK et al., 1986; OLIVER, 1987) were carried out with the help of standard software packages, GEOEAS from US-EPA (ENGLUND & SPARKS, 1988) and GEOPACK (YATES & YATES, 1989) from the US Salinity Laboratory.

Besides the estimated plant cover, an artificial variable was also used: in Principal Component Analysis two factor scores were calculated from the following variables: tota, cover percentages of 25 plant species, heig and pene.

The effect of a shower during sampling on the salt concentration and pH of the surface soil layer was evident. Due to the fact that the omission of samples affected by leaching would have an unfavourable effect on the number of samples, we kept these data for further calculations. It is obvious that without this bias the precision of predicting soil variables would be higher.

Results and Discussion

Selection of promising variables for the quantitative prediction of soil properties in the medium blocks

First the basic statistics of the variables were calculated, and then correlations among predicted (soil) variables and predictor (easily available) variables (relative ground height, penetration resistance, plant cover) were calculated, after which the sensible and important ones were checked using scatterplots and through the use of histograms for outliers. The typical situation for false correlations was when the plant cover data were overwhelmingly 0, but there was some cover accidentally giving some oblique arrangement of the data seen on the scatter plot, resulting in strong correlations. The basic statistics of the important variables are shown in Table 3.

Table 3

Basic statistics of the most important variables in the medium blocks

A. Relative ground height, penetration resistance and plant cover percentages

Variable	Height	Pene	Tota	Phra	Scor	Aelu	Impe	Suae
Mean	258.88	18.94	10.20	4.17	0.09	0.76	2.49	0.78
Std. dev.	140.41	3.78	6.00	3.62	0.38	1.81	2.98	3.14
Skewness	0.36	-1.33	1.49	0.85	5.55	3.92	0.96	7.94
Kurtosis	2.62	5.31	8.72	3.22	38.64	24.86	3.03	79.87
Minimum	23.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	680.00	25.00	45.00	15.00	3.00	15.00	13.00	35.00

B. Chemical properties of the surface (0-5 cm) soil layer measured in 1:5 soil:water extract

Variable	pH	HCO_3	Cl	SO_4	Ca	Mg	Na	Salt
Mean	8.10	0.31	9.59	8.95	3.26	6.24	9.53	1.15
Std. dev.	0.37	0.12	11.92	7.43	2.40	7.18	10.42	1.11
Skewness	-0.36	2.48	1.66	1.07	0.73	2.02	1.37	1.36
Kurtosis	3.47	12.71	5.04	3.44	2.86	7.03	3.97	4.07
Minimum	7.09	0.15	0.15	0.30	0.15	0.20	0.20	0.07
Maximum	9.14	1.05	55.60	30.90	10.80	38.90	44.15	5.00

On the basis of the above table it was possible to distinguish between plant variables with a promising number of non-zero observations for further analyses; for example total cover, or *Phragmites communis* cover as variables with more than 3/4 of non-zero observations, *Imperata cylindrica, Aeluropus littoralis* and *Lactuca tatarica* as cover percentages with about 1/2 of all values with non-zero data.

Some soil chemical variables were found to have low variance, therefore, these are possibly good subjects for interpolation, such as pH, HCO_3 and penetration resistance values. These chemical parameters showed less variance in the deeper layers than in the surface one.

Plant coalitions

Among the plants various plant coalitions, groups of plants often occurring jointly, were found, such as *Phragmites communis* with *Aeluropus littoralis, Suaeda salsa* with *Lactuca tatarica* and wheat with *Setaria v.*

The only important plant without a significant tendency to build up a coalition was *Imperata cylindrica*, the notorious weed of many continents. Often this species is the dominant grass in derived or man-made savannas of previous forest-lands in South-Eastern Asia, West Africa and South America. *Imperata cylindrica* also grows quickly after bush fires and has a high propagating capacity, since it is not grazed when fully grown (GIRARD & ISARWA, 1990).

Correlation between plant coverage, plant dry weight and soil properties in medium blocks (5x5m)

Salinity itself, and all the ion contents, with the exception of bicarbonate, seemed to promote the settling of *Phragmites communis* (and *Aeluropus littoralis*), but salinity restricted a high cover of *Imperata cylindrica*. pH and the bicarbonate content showed positive correlations with the cover of *Imperata cylindrica*.

The mean (n=4) relative ground height showed a strong positive correlation with the cover and dry matter of *Phragmites communis* and the cover of *Aeluropus littoralis*, and showed a negative correlation with the cover of *Setaria viridis*.

The mean (n=16) penetration resistance showed a positive correlation with the cover of *Imperata cylindrica*, and a negative one with the total dry matter of the plants growing in the small blocks and the cover of wheat.

Consequently, there seemed to be two large categories in the stabilized vegetation of the abandoned plots, one with at least higher salinity, and a more neutral pH, higher-lying and covered with *Phragmites communis* and *Aeluropus littoralis* and another with less salinity but slightly more alkalinity and higher penetration resistance, covered with *Imperata cylindrica*. The separability of these vegetation categories and their use in the prediction of soil properties is described by TÓTH et al. (1994). The reason for the lower salinity and penetration resistance of the wheat is irrigation, and therefore the leaching of the salts, and cultivation which loosened the surface.

As previous experience showed, a transformation of the plant cover percentages may improve their correlation: therefore, some plant covers were transformed using a logit transformation (ln (x/(100-x)). The correlation of logit-transformed cover percentages of the most promising three plant species (as predictor variables of soil variables) with soil properties is shown in Table 4, where the stronger correlations are underlined.

The logit transformation may be effective in improving the correlation, but may also be unfavourable, such as in the case of *Phragmites communis*. In the case of *Aeluropus littoralis* the original distribution of the variable was very peaked (Table 3) and skewed, and here the logit transformation improved the correlation.

Table 4

Correlation coefficients (R) between selected plant covers and surface soil properties with and without the use of logit transformation (n = 187)

Predictor cover percentages	Predicted soil properties in the 0-5 cm layer					
	Cl	SO_4	Ca	Mg	Na	Salts
Phragmites communis	0.55	0.57	0.48	0.55	0.55	0.57
Phragmites logit	0.41	0.47	0.45	0.42	0.42	0.44
Aeluropus littoralis	0.42	0.44	0.42	0.36	0.44	0.44
Aeluropus logit	0.48	0.49	0.44	0.44	0.48	0.49
Imperata cylindrica	-0.25	-0.33	-0.31	-0.28	-0.27	-0.29
Imperata logit	-0.27	-0.34	-0.29	-0.30	-0.28	-0.31

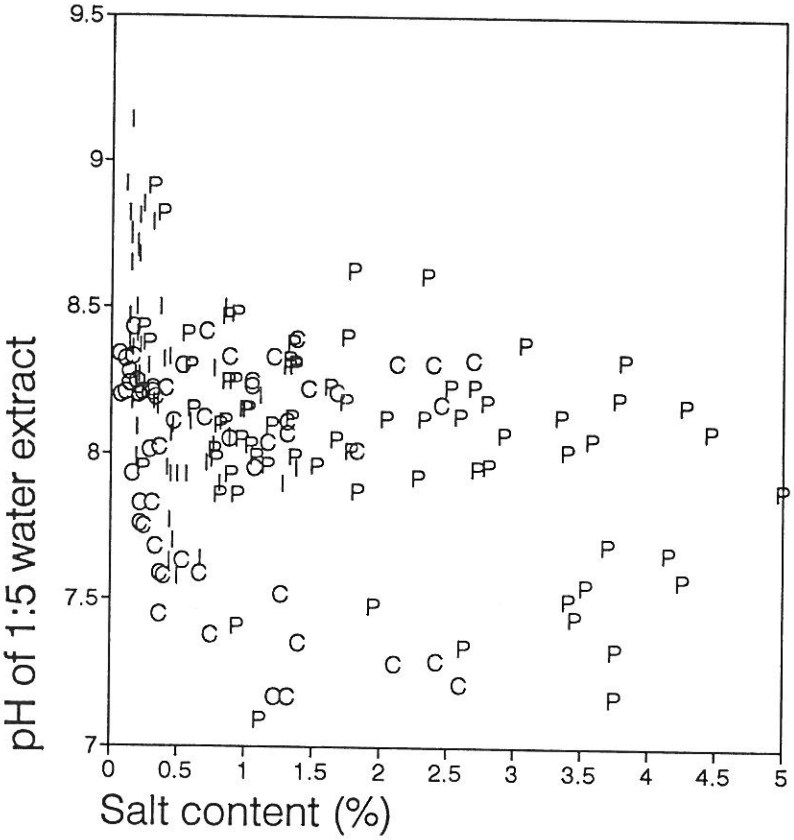

Figure 3

Scatterplot of surface pH and salinity in the PHRAGMITES (P), IMPERATA (I) and CROPLAND (C) categories

Correlation among soil properties

The strongest positive correlation was found between the bicarbonate content of the 1:5 extract and the pH. Among the ions found (no carbonate was found in the extracts) it was the only one that promotes alkalinity. The surface salt content showed a strong negative correlation with surface pH and indicated the differences between the vegetation categories (Figure 3).

The IMPERATA category does not have a high salt content, and the salts are predominantly bicarbonate and give rise to a high pH. The salts in the CROPLAND category are a mixture of bicarbonate and other salts, with an increasing ratio of neutral salts as the salt content increases. The PHRAGMITES category is composed mainly of neutral salts, such as chlorides and sulphates, and has varying salinity. The differences between the categories are shown in Table 5. The PHRAGMITES category and the IMPERATA category showed significant differences, but the means of some properties in the CROPLAND category were similar either to the IMPERATA or to the PHRAGMITES category.

In lower-lying spots, where the salts are usually more leached out bicarbonates sometimes remain and these cause a higher penetration resistance of the soil. The accumulation of bicarbonates at a low salinity level is a possible indicator of alkalinization. Bicarbonates are the dominant, and seemingly only factors in the development of high pH, as was reflected by the percentage of bicarbonate to the sum of ions. When the ratio of bicarbonate to salt was lower than 0.01% the pH was very close to 7; when this ratio was about 0.5 the pH reached 9. On the other hand, where the salt content was high the penetration resistance was lower, and the soil was neutral.

The ion contents showed a strong correlation with salinity; the strongest correlations among the anions and cations were given by chloride and sodium, respectively.

Table 5

Mean values of some soil properties in the medium blocks (5x5m) for the 3 categories distinguished*

Category	N	Elevation, mm	Penetration mm	pH_0-5 cm	Salt_0-5 cm %
PHRAGMITES	74	337	19	8.1a	1.92
IMPERATA	54	185a	21	8.3	0.40
CROPLAND	59	228a	16	8.0a	0.84

*Means within a column followed by the same letter are not significantly different at P=0.05. N is the number of blocks in the category

The mean relative ground height showed a strong negative correlation with the bicarbonate content of the topsoil and a strong positive correlation with the salt content. This indicates that the alkaline plots are located in the deeper or intermediate spots, and that the higher lying spots have not been leached out. The occurrence of bicarbonate in lower lying spots is a usual sign of alkalinization. The penetration resistance showed a correlation with the bicarbonate content of the second depth (20-25 cm) and with the sodium percentage of each layer. This indicates that the relative accumulation of salts with alkaline hydrolysis may promote the formation of a dense top layer or crust (RENPEI, 1988).

Possibilities of predicting soil properties from plant data

Based on some basic statistics the chance of precise estimation of some of the soil properties with kriging and cokriging was considered (Table 6). Besides the parameters listed, there is one more factor required for precise cokriging: a well-structured cross-variogram.

The judgement of the chance of interpolation was based on the parameters of Table 6. A high sill-nugget/nugget ratio and a low coefficient of variance are the conditions that suggest successful (precise) kriging. If there are easily available variables which, besides meeting the requirements for kriging, have a strong correlation with the main variable, and also show a structured cross-variogram, the chances for successful cokriging are great. The chances of multiple regression analysis are improved when easily available variables show a strong correlation with the main variable.

Table 6

Chance of precise estimation with kriging and cokriging using plant cover and other easily measured data in the medium blocks (n=187)

Main variable			Covariable				Good chance for		
	CV	S/N		CV	S/N	R	Kriging	Cokriging	MRA
pH_0-5	5	40	*Imperata*	120	3.5	0.28	*		
HCO_3_0-5	38	5	*Imperata*	120	3.5	0.41	*		*
Salt_0-5	100	7	*Phragmites*	87	2.2	0.57			*
HCO_3_20-25	22	0.7	pene	20	6.0	0.20		*	
Salt_20-25	51	3	*Phragmites*	87	2.2	0.47	*		*

CV is the percentage coefficient of variation; S/N is the ratio of sill-nugget to nugget in the variogram of the variable; R is the correlation coefficient; MRA is multiple regression analysis

In Table 6 the only variable with a good chance for multiple regression analysis was the surface salt content. In the 20-25 cm layer spatial interpolation showed better chances than regression analysis in the prediction of soil properties.

Results of the estimations carried out for large blocks (number of check blocks was 18)

After calculating the appropriate predicting algorithms (semivariograms, cross-semivariograms and multiple regression equations) with two-thirds of the available blocks, the value of several soil properties was predicted for the remaining one third of the blocks, and the predicted values were compared with the measured ones. The precision of the prediction was expressed by the standard error of estimate (SEE) (Eq. 1) and the E% (Eq. 2) (Table 7).

Comparing Table 7 with Table 6, which prognosticated the precision of the interpolation techniques, it can be stated that basic statistics can be helpful when choosing an estimation method. As factor scores were not included in Table 6 the results obtained did not fully match the prognoses. The best covariable, for its low variance and well-structured semivariogram, was the penetration resistance and this improved kriging best. The variable with the strongest correlations was the surface salt content and this had the most precise estimation with regression. Other covariables did not improve the precision of the estimations. With kriging the most precise estimations were made for bicarbonate content because it had a smooth variation. The least precise estimations were made for the pH, because it had a very small original dispersion and the

Table 7

Precision of the most precise estimations obtained with cokriging and regressions in the large blocks (n=18)

Predicted variable	Autokriging		Cokriging			Regression		Trans-forma-tion
	SEE	E%	SEE	E%		SEE	E%	
pH_0-5	0.277	28	0.279	29	factorsc2	0.221	-2	-
HCO_3_0-5	0.025	49	0.025	49	factorsc2	0.040	17	-
Salt_0-5	0.599	37	0.589	38	*Phragmites*	0.701	26	logit
HCO_3_20-25	0.016	44	0.014	50	penetration	0.032	-13	logit
Salt_20-25	0.050	42	0.052	39	factorsc2	0.097	-12	-

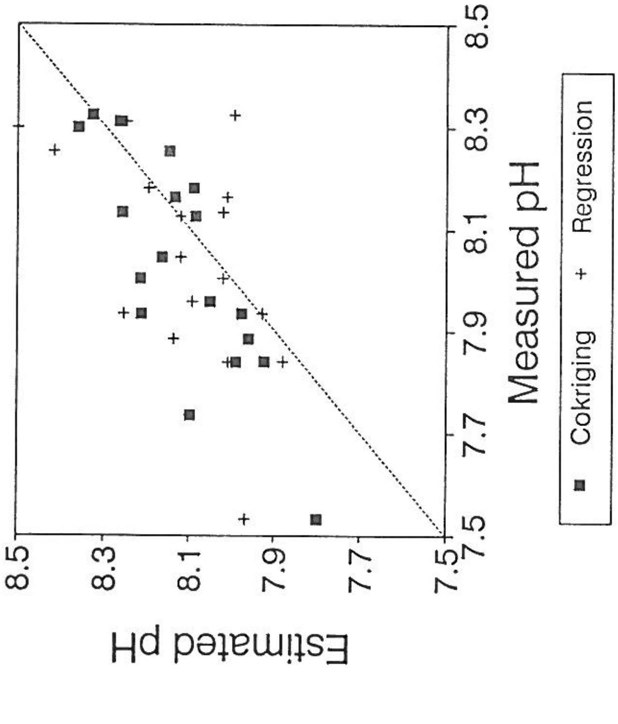

Figure 4
Precision of estimating surface pH in large blocks (20x20 m)

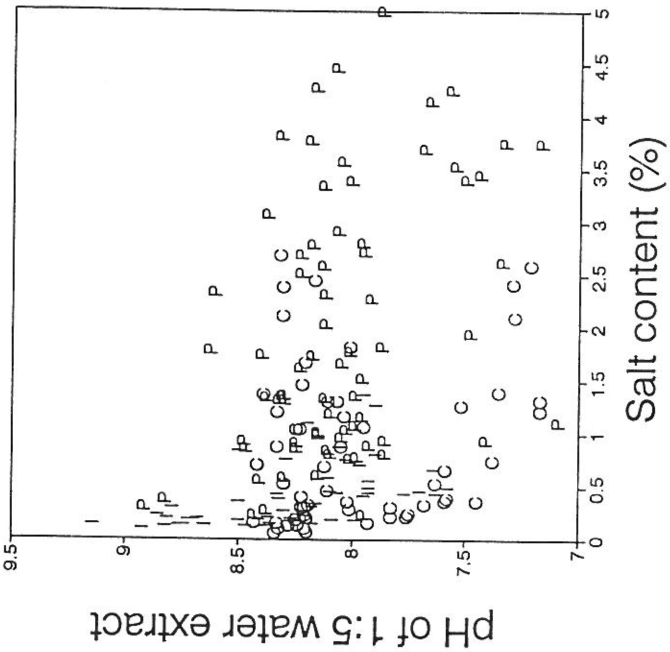

Figure 5
Precision of estimating bicarbonate content in the 20-25 cm layer in large blocks (20x20 m)

estimation could not improve on it very much since E% measures the precision of estimation compared to the original standard deviation (Eq. 2). Kriging was more precise in the deeper layer where the changes of the surface are not perceptible so much. Regression was more precise in the surface layer where much of the survival of the plants (predictor variables) is decided during emergence, and where height and penetration resistance (other predictor variables) were also measured.

The estimations are considered to be good, and as examples Figure 4 shows the least precise estimation (in terms of E%), obtained with surface pH, and Figure 5 shows the most precise estimation obtained with the bicarbonate content of the 20-25 cm layer. The estimates given by regression equations fell in a shorter range.

Estimation of soil properties with the help of plant data in the medium blocks (number of check blocks was 62)

The estimation was studied in two ways, first leaving all plant categories joined, and second separating the major categories (PHRAGMITES category, IMPERATA category and CROPLAND category) according to Table 2.

The predictor variables in the regression equations were two factor scores, total plant cover, cover of *Phragmites communis*, *Aeluropus littoralis*, *Imperata cylindrica, Suaeda salsa*, *Lactuca t.* and *Limonium b.*, relative ground height and penetration resistance. The regression equations fitted to the 2/3 of the sample used as the predictor showed the following R values (Table 8).

As the correlation coefficient of the regression equation is a good indicator of the goodness of the estimation, which is provided by its use, it was expected that the regression equations of the united sample would give a lower precision than the equations of the separate categories.

Table 8

Table of the multiple correlation coefficients (R) received with the predictor regression equations in the medium blocks

Predicted variable	PHRAGMITES category	IMPERATA category	CROPLAND category	United
No. of blocks	47	35	43	125
pH_0-5	0.49	0.68	0.53	0.36
HCO_3_0-5	0.67	0.62	0.68	0.61
Salt_0-5	0.79	0.70	0.71	0.75
HCO_3_20-25	0.53	0.65	0.60	0.36
Salt_20-25	0.66	0.77	0.77	0.64

Owing to the ecological importance of the surface layer the surface soil properties were chosen for further calculations. Among the properties of the surface layer the pH and salt content were chosen, because these properties are traditionally thought to be strongly influencing factors on soil and plant conditions and because different precisions of prediction were prognosticated for the two variables. The surface pH showed low, but different correlation coefficients in the three vegetation categories, but the surface salt content showed similar high values throughout.

Table 9

Precision of the estimations obtained with multiple regression equations in medium blocks (5x5m)

Category	No. of check blocks	pH, 0-5 cm		Salt, 0-5 cm	
		SEE	E%	SEE	E%
PHRAGMITES	27	0.355	-6	0.939	12
IMPERATA	19	0.323	12	0.285	3
CROPLAND	16	0.378	-6	0.594	30
Combined	62	0.352	6	0.707	35
United	62	0.348	7	0.732	33

In Table 9 the results of the estimation using a regression equation are shown for the medium blocks. The combined estimation here is the summed precision of the estimations performed for individual categories (obtained by the summation of the standard errors of the estimates received in the groups) with the separate regression equations. The united estimation is the estimation performed with only one regression equation calculated for the whole sample.

The separation of the area into categories during estimation did not improve the precision expressed by the E%, because now it was calculated with the smaller standard deviations of the separate categories (Eq 2), but the SEE showed an improvement in the precision of the estimation. The dominant factors that influence the categories, such as the pH in the IMPERATA category, the salt content in the PHRAGMITES category and in the CROPLAND category were easier to estimate precisely.

A comparison was made of improvements in the precision of estimation provided by the covariables in the cokriging of surface pH and salt content (Table 10).

Table 10 showed that the greatest improvement in the precision of estimation was given in the PHRAGMITES category by the use of the cover of *Imperata cylindrica* as covariable and in the IMPERATA category by the use of the cover of *Phragmites communis*. The plants inside a category dominated by the other important species are most capable of indicating changes in soil salt content and pH.

Table 10

Precision of the estimations made by kriging and cokriging in the medium blocks performed separately for categories, expressed as E%

Predicted variable	Category		
	PHRAGMITES	IMPERATA	CROPLAND
No. of check blocks	27	19	16
St. dev.	0.334	0.369	0.358
pH_0-5 cm	17 auto	28 auto	3 auto
pH_0-5 cm	25 x Impe	33 x fsc2	3 x tota
pH_0-5 cm	21 x Phra		
pH_0-5 cm	21 x fsc1		
pH_0-5 cm	20 x Aelu		
St. dev.	1.072	0.294	0.854
Salt_0-5 cm	13 auto	7 auto	36 auto
Salt_0-5 cm	16 x Phra	20 x Phra	37 x Phra
Salt_0-5 cm		18 x fsc2	37 x tota
Salt_0-5 cm		11 x fsc1	
Salt_0-5 cm			

st. dev.: standard deviation; auto: autokriging; for other abbreviations: see Experimental layout part.

Table 11 shows the precisions achieved when the predictions were carried out in the distinct vegetation categories separately or together.

Table 11

The precision of the estimations received in the kriging and cokriging in the medium blocks (5x5m) combined and united (n=62)

Predicted variable	Combined kriging				Covariable
	Autokriging		Cokriging		
	SEE	E%	SEE	E%	
pH_0-5	0.293	22	0.278	26	x tota/fsc2/Impe
Salt_0-5	0.693	36	0.666	39	xtota/Phra/Phra

Predicted variable	United kriging				Covariable
	Autokriging		Cokriging		
	SEE	E%	SEE	E%	
pH_0-5	0.285	24	0.286	24	x Impe
Salt_0-5	0.709	35	0.675	38	x Phra

There were no substantial differences between the precisions provided by the separate semivariograms. The increase in precision provided by cokriging also seemed to be small.

Table 12 compares the precision of prediction achieved with multiple regression analysis and spatial interpolation.

Table 12

Comparison of regression and geostatistics in terms of best estimations provided in medium blocks (5x5m), expressed as E%

Category	No. of check blocks	pH_0-5 cm		Salt_0-5 cm	
		Kriging	MRA	Kriging	MRA
PHRAGMITES	27	25	-6	16	12
IMPERATA	19	33	12	20	3
CROPLAND	16	3	-6	37	30
Combined	62	26	6	39	35

The values of surface pH (Figure 6) showed only a small variation (5% coefficient of variance), and there was no significant difference between the mean pH values in the PHRAGMITES and CROPLAND categories; the variances inside the groups were also similar. The correlations with the easily measurable properties (Table 8) were not strong; therefore kriging, was much more precise than regression.

The values of the surface salt content (Figure 7) showed high variation (97% coefficient of variance) and there were significant differences between the categories in terms of means and variation. On the other hand, the correlations shown with the vegetation were strong (Table 8): therefore, the two types of estimations performed similarly. The good performance of regression in estimating surface salt inside the cropland was a consequence of the strong correlations with total plant coverage, made up mostly by *Imperata cylindrica* (negative) and *Phragmites communis* (positive). The high precision, expressed as E%, achieved in the combined estimation (both kriging and regression) is the reason for the high standard deviation of the salt content that promotes its high value (Eq.2).

Finally, the precision obtained with different block sizes was compared (Table 13).

The precision achieved in the medium blocks was similar to that obtained in the large blocks for kriging, but the precision of regression increased with a decrease in the size of the block (Table 13), since regression equations for the large block covered shorter ranges of properties. On the other hand, the precision of kriging decreased somewhat with a decrease in block size, because the

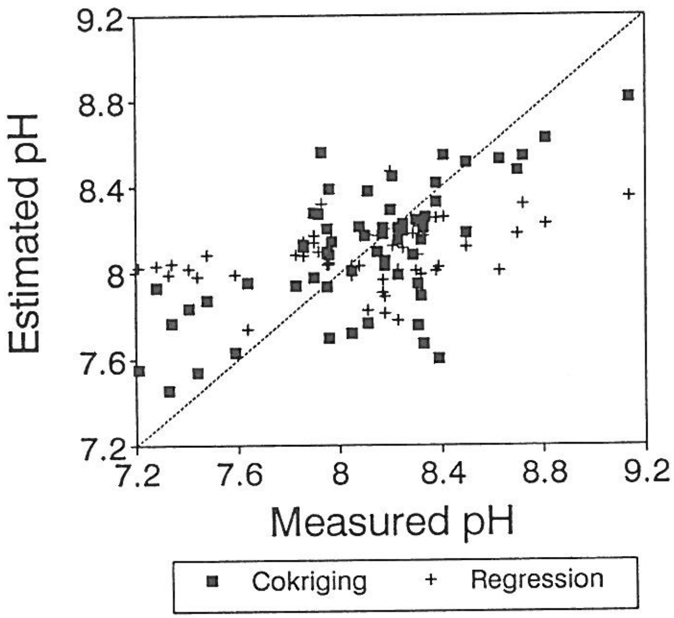

Figure 6
Precision of estimating surface pH in medium blocks (5x5 m)

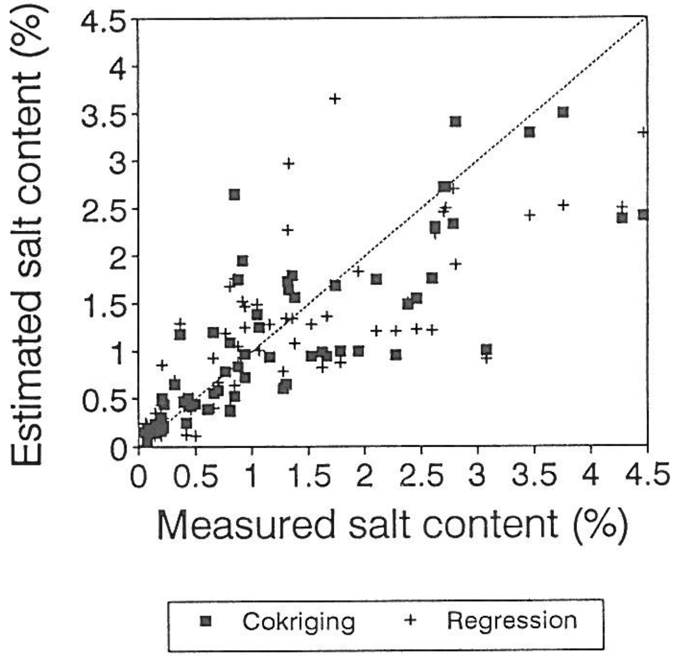

Figure 7
Precision of estimating surface salt content in medium blocks (5x5 m)

Table 13
Comparison of the precision, expressed as E%, of the estimations obtained at different block sizes

Predicted variable	Large block (20x20 m)		Medium block (5x5 m)	
	Cokriging	MRA	Cokriging	MRA
No. of check blocks	18		62	
pH_0-5	29	-2	26	6
Salt_0-5	42	26	39	35

large blocks were created by kriging; therefore, the variation between the large blocks was much less.

Conclusions

The correlations existing between soil properties and easily measurable variables (plant cover, ground height and penetration resistance) showed that the main plants of the abandoned saline plot, *Phragmites communis* and *Imperata cylindrica* showed distinctive preferences for soil properties. The two categories distinguished for established vegetation cover, the PHRAGMITES category and the IMPERATA category showed different means for surface soil pH, salinity, penetration resistance and relative ground height.

The relative precision of the estimation of surface salt content, expressed as E%, was better than that of surface pH, because the original scatter of the salt content was high and because the salt content showed a strong correlation with the plant properties.

The best predictor properties, i.e. the variables which most improve the precision of soil property prediction in cokriging and multiple regression analysis, were artificial variables, factor scores derived from the measured plant cover, the cover percentage of the two most important plants, *Phragmites communis* and *Imperata cylindrica*, and soil penetration resistance.

The two block sizes showed comparable precision in the estimation of soil properties, and the size of the large block is reasonable for the mapping of the fertility of abandoned plots. There seemed to be a difference in that kriging was more precise in the larger, averaged block and regression was more precise in the medium block. Kriging and cokriging with plant factor scores, plant cover and penetration resistance were more precise and should always be used for estimating the soil properties when there is a large enough uniform plot to do it. When the plots to be mapped are too small and not contiguous, multiple regression with easily measurable properties can be used with similar precision.

Summary

The correlation between the semi-natural vegetation cover and soil properties is useful for predicting soil properties in the abandoned saline soils of the Huang-Huai-Hai Plain of China. For the mapping of soil properties a basic study of the correlation and spatial distribution of important soil properties and plant cover is proposed. Based on this, it is possible to select variables of plant cover and other easily available field measured properties as predictor variables for soil properties. These predictor variables can be used in regression equations and cokriging to improve the prediction of soil properties.

In an area of 100x220m, large blocks of 20x20m size and medium blocks of 5x5m size were used for the prediction of soil pH and soil salt content.

The correlations existing between soil properties and easily measurable plant cover, surface elevation and penetration resistance showed that the main plants of the abandoned land, *Phragmites communis* and *Imperata cylindrica,* have distinct preferences for soil properties.

The best predictor variables of soil properties were artificial variables, factor scores derived from the measured plant cover, the cover percentage of the two most important plants, *Phragmites communis* and *Imperata cylindrica* and soil penetration resistance.

The two block sizes showed comparable precision in the estimation of soil properties, and the size of the large block was reasonable for the mapping of the fertility of abandoned plots. Kriging was more precise in the larger, averaged blocks and regression was more precise in the medium blocks. Kriging and cokriging with plant factor scores, plant cover and penetration were more precise than regression analysis for the estimation of soil pH and salinity and should always be used for estimating soil properties when there is a large enough uniform plot to do it. When the blocks to be mapped are small and not contiguous, multiple regression with easily measurable properties can be used with similar precision.

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