INT. J. BIOL. BIOTECH., 16 (2): 363-373, 2019.

SPATIAL PATTERN ANALYSIS OF SOME COASTAL AND INLAND PLANTS AND CORRESPONDING SOILS USING GEOSTATISTICS

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ABSTRACT

Spatial association between plant densities of inland and coastal plots and selected soil variables such as pH, OC (organic carbon), exchangeable cations Na, K, Ca, Mg; and NO_3–N (nitrate nitrogen) as well as available phosphorus were examined using a geostatistical technique, namely, semivariogram analysis. The selected plant species were the dominant halophytes of Karachi. At both sites, one square plot of 16m × 16m in size was deterministically selected and subdivided into 64 (2×2 m) square sub-plots (quadrats). Soil and plant density data from each sub-plot was obtained. Spherical model was best fitted for all soil characteristics and the parameters of the model such as nugget (C_o), sill (C_1+C_o) and range (a), were used to explain the spatial structure of different soil properties and the halophytes. All inland and coastal soil attributes (except OC of the coastal site) as well as the plant densities showed zero nugget effect which specified spatial continuity to be very even between adjacent points. Ca showed highest sill variance for both inland and coastal soil attributes. Coastal halophyte *Suaeda fruticosa* showed highest sill variance compared to other plant populations. The density of all inland plant populations showed autocorrelation range close to unity. All inland and coastal soil properties (except OC of the coastal site) and plant densities showed strong spatial dependence.

Keywords: Semivariogram, geostatistics, density, autocorrelation, soils, halophytes.

INTRODUCTION

Conventional sampling utilizes a technique of random selection of the samples (in our case; for plants and soils) in which the association between the samples is not considered. Every sample that is taken away from the field is independent showing no variability between that sample and the neighboring samples. Variables of the samples are generally averaged out which represent the mean value of the variable for the whole area under investigation or the field. This value for average does not satisfactorily portray the variable's behaviour across the area of interest.

On the other hand, geostatistical methods explain spatial association between the samples and inspect the changes in the values of the samples over distance and direction (Guertal and Westerman, 1992).The variables examined are called regionalized variables. Spatial methods employ the hidden spatial variations to produce better estimates of differences among treatments or field sites. As stated by Burrough (1993), and Wilding *et al.,* (1994), spatial continuity as a function of space and time for different soil attributes is important to develop the logical, empirical, and physical models of soil and landscape processes. Geostatistics, is a commonly used approach to discover the spatial structure in the variability of soil characteristics (Carvalho *et al.,* 2002; Vieira *et al.,* 2002). More simply, geostatistics can be defined as the study of attributes that change in space or time (Deutsch, 2002). It deals with the data that is spatially autocorrelated. As stated by Olea (1999), geostatistics includes all numerical techniques which are focused on the categorization of spatial characteristics. Mainly it uses random models in a similar way as time series analysis categorizes temporal data.

The interest in the study of spatial variation in soil characteristics has been increased with the successful development of geostatistical methods since 1970's. Various scientists have worked in this field such as Steiger *et al.* (1996); White *et al.* (1997); Yu *et al.* (2001) and Romic and Romic (2003) who discussed the spatial variation of soil heavy metal concentrations. Webster and Oliver (2001) and Liu *et al.* (2004, 2008) showed interest on spatial distribution of micronutrients in soils. Nevertheless, a great stack of study exists on spatial variability of other soil properties by Yost *et al.* (1982); Yanai *et al.* (2001); Corwin *et al.* (2003); Gilbert and Wayne (2008) and Liu *et al.* (2008).

Variogram construction is a commonly used geostatistical technique for the assessment of spatial variability of various soil characteristics, though it can also be utilized to unravel the plant species patterns. The method, in general, employs regionalized variables. Matheron (1963) first defined the semivariograms function $\gamma(h)$ as half the average squared difference between points separated by a distance h. It is expressed by the following formula:

$$\gamma(h) = \frac{1}{2|N(h)|}\sum_{N(h)}\left(z_i - z_j\right)^2$$

Where *N(h)* is the set of all pairwise Euclidean distances $i-j=h$, $|N(h)|$ is the number of distinct pairs in *N(h)*, and z_i and z_j are data values at spatial locations *i* and *j*, respectively.

The semivariance function characterizes the spatial continuity / variability between points. Semivariogram is a plot obtained when semivariance is plotted against the lag distance (McBratney and Webster, 1986). More details and information about the theories and methodologies involved in the construction of semivariograms can be found in the work of Journel and Huijbregts (1978); Burgess and Webster (1980); Hamlett *et al.* (1986); Warrick and Myers (1987); and Isaaks and Srivastava (1989).

The structure of a semivariogram is described by its three components, namely, the nugget, the sill and the range. The nugget is the non-zero value for γ when lag distance (h) = 0. It is produced by various errors such as measurement error or when the data is not collected from sufficiently smaller spacing to expose continuous spatial behavior. The sill is that value of semivariance when the variogram levels off. Sill should be equal to the dataset variance. Range is the value of lag distance (h) at which the semivariogram reaches the value of the sill. These spatial components (nuggets, sill and range) help identifying autocorrelation and replicating samples and exposing a dominant pattern in the data series (Si *et al.,* 2007). The semivariogram components also quantify the spatial dependence between observations (Goovaerts, 1997, 1999).

MATERIALS AND METHODS

SITE DESCRIPTION

The study area comprised of inland and coastal sites. One square plot of 16m × 16m in size was selected from the coastal site (lat. 24° 51.317'N; long. 66° 52.684'E) and another was chosen from the inland site (lat. 24° 56.365'N; long. 67° 7.523'E) within the University of Karachi campus. Each plot was subdivided into 64 (2×2m) square quadrats keeping in view that the plots were topographically uniform parts of the study area. The plots were permanently marked using steel nails to avoid erroneous measurements.

SAMPLE COLLECTIONAND ESTIMATIONS

Soil samples were collected from all 64 square quadrats from the depth of 30cm (from centre) using a soil auger from both inland and coastal fields. The collected soil samples were dried at room temperature in an airy place for a few days for the estimations of pH, OC (organic carbon), exchangeable Na, K, Ca and Mg, NO_3–N, and available phosphorus (Available P). Coning and quartering were performed in the laboratory to obtain representative samples. The soil pH was determined by a digital pH meter (Jenway, England) in the saturation extract of the soil. Organic carbon (OC) was estimated by the loss-on- ignition method (at 450°C) in a muffle furnace. Exchangeable Na, K, Ca and Mg were determined by extracting in neutral normal ammonium acetate (*N* CH_3COONH_4) solution (Schollenberger and Simon, 1945). For NO_3–N, nitrate extracting $CuSO_4$ (0.5M) and Ag_2SO_4 (0.6%) solutions were utilized as suggested by Jackson (1958). However, plant available phosphorus (Available P) was determined by Olsen's method using alkaline sodium bicarbonate solution as an extractant for plant available P in soil. All soil analyses were performed in the Department of Geography, University of Karachi.

Plant density was determined in each of the sub plots (quadrats). The density for selected halophytes including *Atriplex griffithii*, *Cyperus conglomeratus*, *Haloxylon recurvum*, *Salsola imbricata* and *Suaeda fruticosa,* was recorded. The criteria for selection of halophytic species was their occurrence and abundance at study sites. Rare halophytic species were excluded from the study as the excessive zero entries would have marred the data analysis.

STATISTICAL AND GEOSTATISTICAL ANALYSIS

The descriptive statistics (i.e., mean, minima, maxima, standard deviation, variance, standard error, coefficient of variation and skewness) of measured soil characteristics were computed using MS-Excel (Ver. 2007)..

The semivariograms for soil variables and plant densities of inland and coastal plots were made through MATLAB software. The parameters for models fitted to the semivariograms (nugget, sill and range) were calculated so as to analyse the nature of semivariograms.

RESULTS

DESCRIPTIVE STATISTICS OF INLAND SOIL SAMPLES

The pH of inland soil samples ranged from 7.12 to 7.97 (Table 1). The amount of organic carbon (OC) varied between 0.609 to 1.064% of the inland samples with a mean value of 0.789%. The percent coefficient of variation (CV%) for OC in inland samples was found to be 13.36% (Table 1). The mean values for exchangeable cations followed Ca > Na > Mg > K trend. The amount of NO_3–N and Available P ranged from 1.218 to 8.897µg/g and

0.024 to 1.4µg/g (Table 1). The coefficient of variation was found to be maximum (54.56%) for available P and minimum for pH (2.532%) of the inland soil samples. Skewness measures the symmetry or asymmetry of the data set. All parameters for inland soils showed positive values for skewness except Mg and available P. Positively skewed soil variables indicate that data for these soil variables was skewed towards right, whereas negatively skewed variables showed that their data was skewed towards left side (Table 1).

DESCRIPTIVE STATISTICS OF COASTAL SOIL SAMPLES

The coastal samples showed average pH range from 6.987 to 8.946 with a mean of pH 8 (Table 2). The coefficient of variation (CV%) for coastal soil pH was 6.41%. Soil OC content showed the average amount of 0.745% with a CV value 14.67%. The mean concentrations of exchangeable cations followed Ca (23.98me/100g) > Na (11.22) > Mg (3.75) > K (0.654) for coastal soils (Table 2). Mean values for NO_3–N and available P for coastal soils were 3.73 and 0.392 µg/g respectively. The coefficient of variation (CV%) was found to be highest for available P (79.14%). All coastal soil samples were found to be positively skewed except OC (Table 2).

For inland site, *Atriplex griffithii* was found significantly correlated with Mg ($p < 0.05$) (Table 3). On the other hand, *Cyperus conglomeratus* showed significant positive correlation with Ca ($p < 0.05$) (Table 4). In addition some soil factors showed significant correlation (p at the most 0.05) with each other (Table 3 and 4).

Table 1. Descriptive statistics for inland soil variables (N=64).

Inland samples								
Soil attributes	**pH**	**OC (%)**	**Na**	**K**	**Ca**	**Mg**	**NO_3–N**	**AP**
Min.	7.128	0.609	6.4	0.11	20.01	1.01	1.218	0.024
Max.	7.972	1.064	18.99	1.2	49.28	8.91	8.897	1.4
Mean	7.561	0.789	10.996	0.596	33.566	5.347	4.211	0.592
SD	0.191	0.105	3.144	0.314	7.637	2.202	1.546	0.323
Var.	0.037	0.012	9.885	0.099	58.318	4.851	2.39	0.105
SE	0.024	0.013	0.393	0.039	0.955	0.275	0.193	0.04
CV (%)	2.532	13.366	28.594	52.655	22.751	41.191	36.708	54.56
Sk.	0.066	0.506	0.662	0.36	0.161	−0.322	0.606	−0.15

Note: The exchangeable cations, Na, K, Ca and Mg are in me/100g of soil, whereas NO_3–N and Available Phoshorus (AP) are in µg/g. SD means standard deviation, *Var.* variance, *SE* standard error, *CV.* coefficient of variation and *sk*, skewness.

Table 2. Descriptive statistics for coastal soil variables (N=64).

Coastal samples								
Soil attributes	**pH**	**OC (%)**	**Na**	**K**	**Ca**	**Mg**	**NO_3–N**	**AP**
Min.	6.987	0.435	6.9	0.11	18.8	0.8	1.088	0.017
Max.	8.946	0.899	18.44	1.3	29.33	8.1	6.885	1.15
Mean	8.009	0.745	11.222	0.654	23.984	3.753	3.726	0.392
SD	0.514	0.109	2.66	0.314	3.069	1.89	1.662	0.31
Var.	0.264	0.011	7.077	0.099	9.419	3.572	2.764	0.096
SE	0.064	0.014	0.333	0.039	0.384	0.236	0.208	0.039
CV (%)	6.413	14.673	23.705	47.977	12.796	50.361	44.621	79.14
Sk.	0.175	−0.810	0.598	0.105	0.09	0.363	0.278	0.613

The meaning of abbreviations are given at the bottom of Table 1.

Table 3 Correlation matrix between three inland halophytes and associated soil variables.

	Inland Halophytes			Inland Soil Variables							
	Suaeda fruticosa	*Salsola imbricata*	*Atriplex griffithii*	Nitrate nitrogen	Available PO_4	pH	OC	Na	K	Ca	Mg
Suaeda fruticosa	1	0.025	-0.11	0.044	0.157	-0.023	0.107	-0.06	-0.1	0.227	-0.02
Salsola imbricata		1	-0.115	0.028	0.102	-0.022	0.022	-0.13	0.02	0.033	0.035
Atriplex griffithii			1	0.025	-0.004	0.055	0.009	-0.09	-0.053	-0.04	.307*
Nitrate nitrogen				1	-0.222	-.362**	0.234	-0.09	.333**	.264*	0.005
Available PO_4					1	0.112	0.039	.321**	-0.05	-0.03	-0.16
pH						1	-.410**	.329**	-0.087	0.056	0.025
OC							1	-0.1	-0.094	0.009	-0.2
Na								1	0.035	0.089	-.262*
K									1	0.13	0.164
Ca										1	0.044
Mg											1
* p<0.05; ** p< 0.01											

Table 4 Correlation matrix between three coastal halophytes and associated soil variables.

	Coastal Halophytes			Coastal Soil Variables							
	Suaeda fruticosa	*Haloxylon recurvum*	*Cyperus conglomeratus*	Nitrate nitrogen	Available PO_4	pH	OC	Na	K	Ca	Mg
Suaeda fruticosa	1	.037	-.208	-.015	-.061	-.188	-.110	.014	.032	-.133	.044
Haloxylon recurvum		1	.058	-.042	-.155	.221	-.182	.075	-.179	.019	-.095
Cyperus conglomeratus			1	-.180	-.054	-.035	.060	.097	-.151	.256*	.068
Nitrate nitrogen				1	.021	-.021	-.227	.105	-.151	-.080	.015
Available PO_4					1	-.109	-.038	-.104	-.118	.153	-.102
pH						1	-.258*	.096	.021	-.030	-.078
OC							1	-.033	.255*	.027	.028
Na								1	-.043	-.015	-.212
K									1	-.022	.055
Ca										1	.158
Mg											1
* p<0.05; ** p< 0.01											

SEMIVARIOGRAM ANALYSIS

The spatial behavior of the selected variables of soils for inland and coastal sites and the densities of plants within these plots were assessed with the help of their semivariograms (Fig. 1 and Fig. 2). The spherical model was fitted for all soil properties for both sites, i.e., inland and coastal sites, as this model was found most appropriate to the observed data. The parameters for the best fitted model such as nugget (C_o), sill (C_1+C_o) and range (a) are presented in Table 5 and Table 6. The nugget variance was found to be nil for all inland and coastal soil samples, however, only one coastal sample showed some nugget effect for OC content (Table 5). Soil parameters such as organic carbon content (OC), Na, Ca, and Mg showed higher total semivariance estimates (i.e., Sill variance) for inland soils than coastal samples. However, the remaining parameters (pH, K and NO_3–N) represented higher values of total semivariance for coastal soils than inland samples (Table 5).

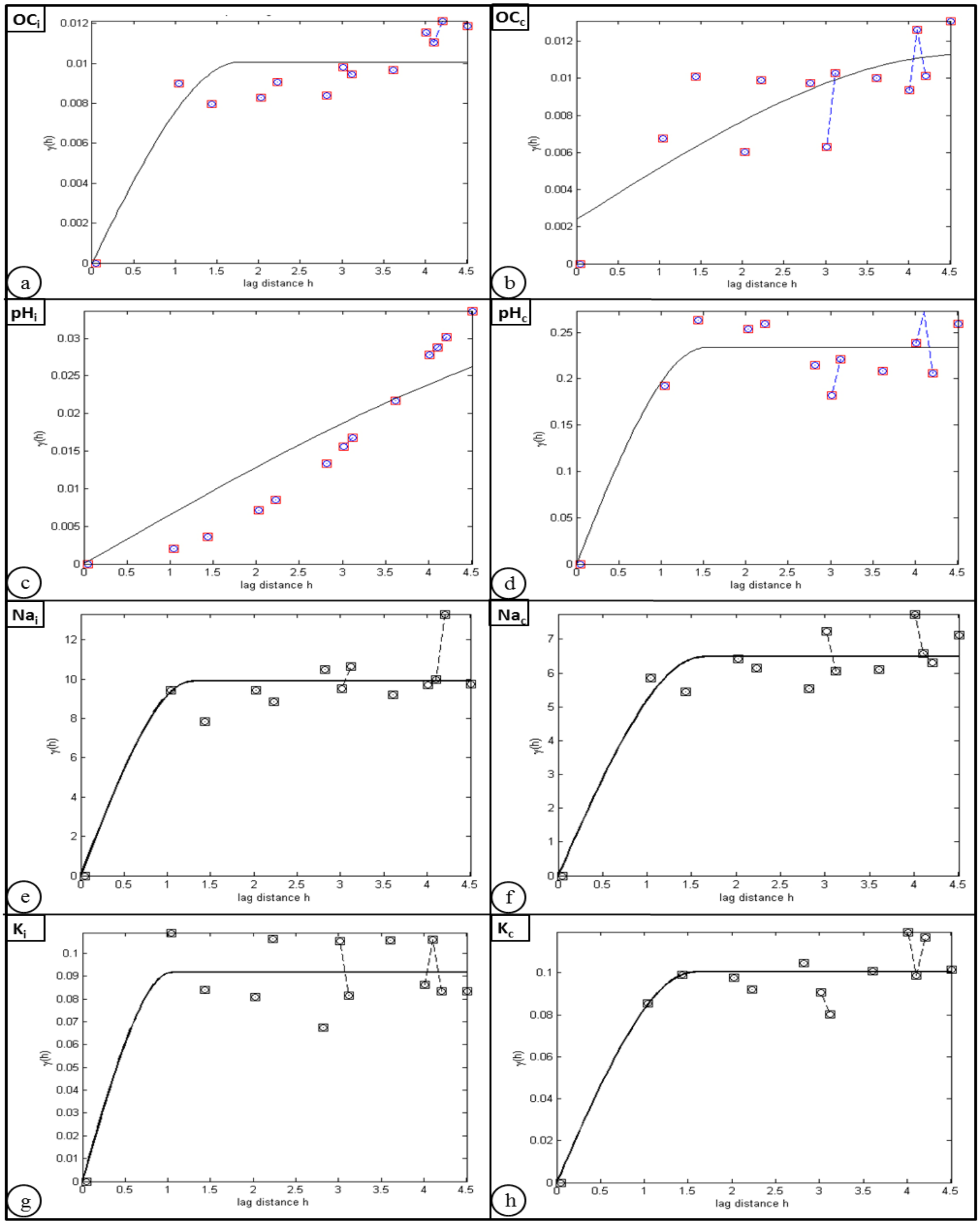

Fig. 1 Semivariograms of soil variables of inland (left column) and coastal plots (right column). The soil variables are shown on the upper left side whereas, the figure numbers are mentioned on the bottom left corner of every figure.

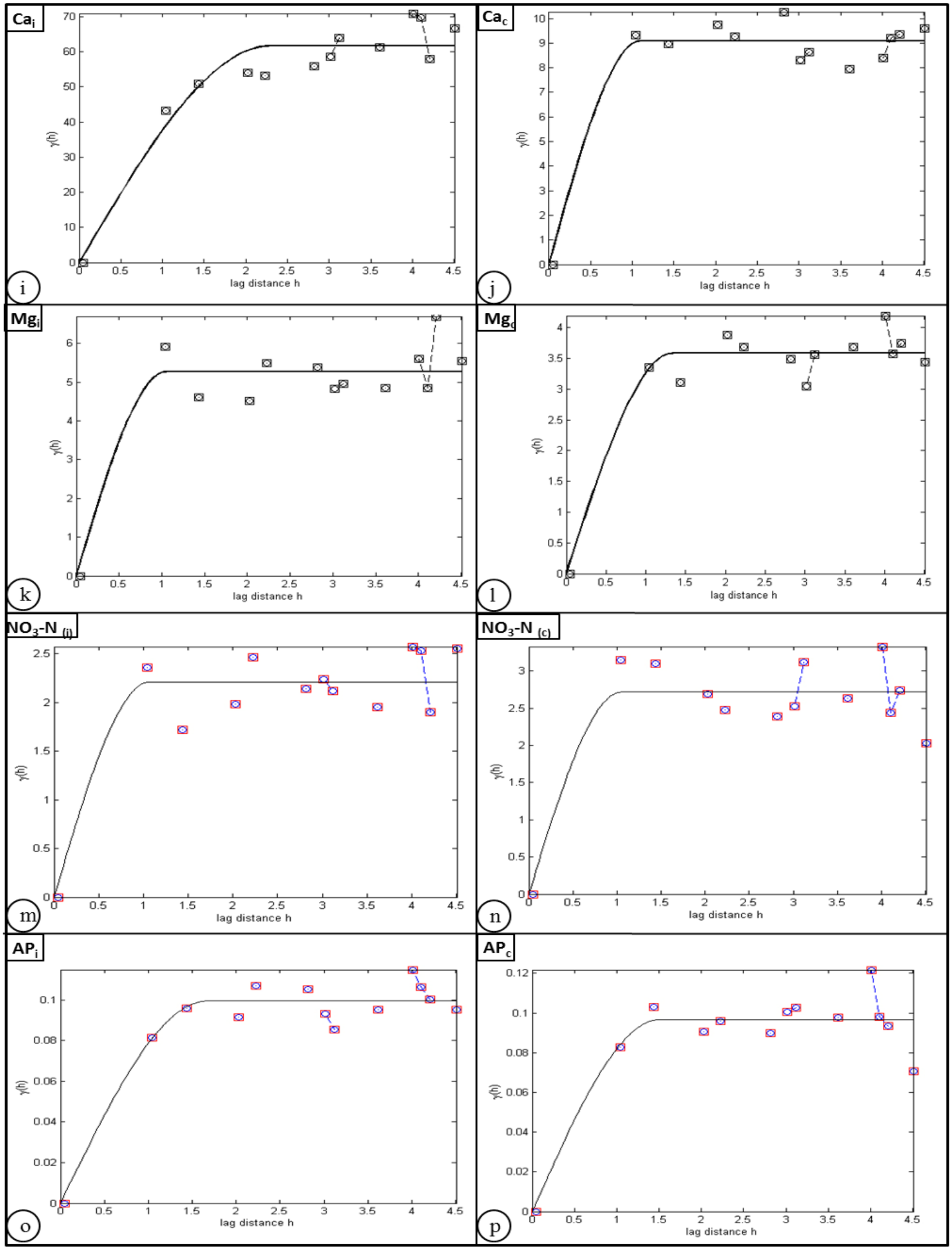

Fig. 1 Semivariograms of soil variables of inland (left column) and coastal plots (right column). The soil variables are shown on the upper left side whereas, the figure numbers are mentioned on the bottom left corner of every figure.

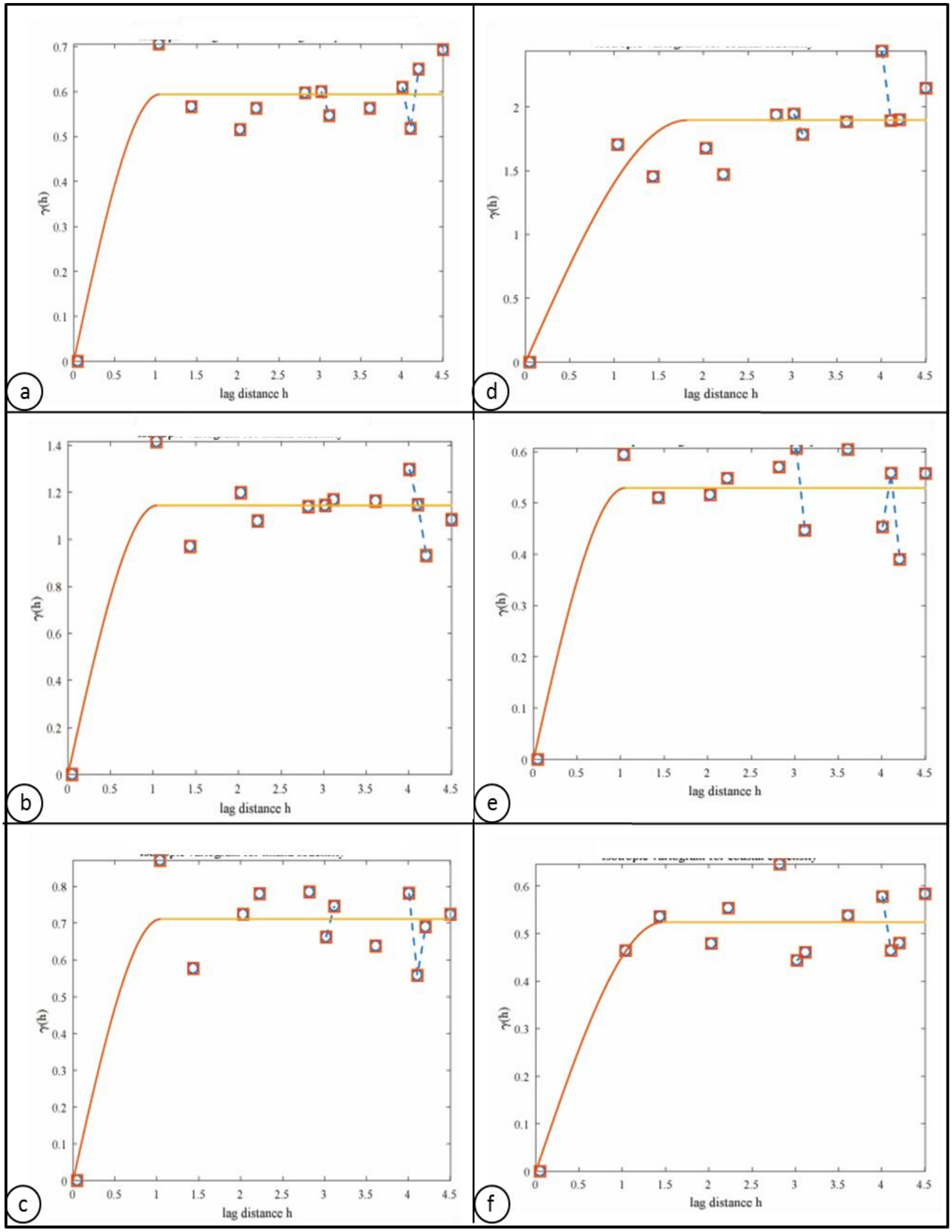

Fig. 2 Semivariograms of plant densities of (a) *Atriplex griffithii* (b) *Suaeda fruticosa* and (c) *Salsola imbricata* of inland plot, whereas (d) *Suaeda fruticosa* (e) *Haloxylon recurvum* and (f) *Cyperus conglomeratus* of coastal plot.

Table 5. Geostatistical parameters for spherical semivariogram model for inland and coastal soil properties.

Stations	Parameters	Nugget	Sill	Range*	Nugget/Sill percent	Spatial class
		C_O	C_1	a	$C_o/C_1\times 100$	
Inland	pH	0	0.034	7.694	0	Strong
	OC	0	0.010	1.781	0	Strong
	Na	0	9.896	1.295	0	Strong
	K	0	0.092	1.049	0	Strong
	Ca	0	61.761	2.311	0	Strong
	Mg	0	5.268	1.054	0	Strong
	NO_3–N	0	2.210	1.066	0	Strong
	Available P	0	0.099	1.670	0	Strong
Coastal	pH	0	0.234	1.534	0	Strong
	OC	0.0024	0.009	4.749	26.66	Moderate
	Na	0	6.479	1.638	0	Strong
	K	0	0.100	1.577	0	Strong
	Ca	0	9.089	1.101	0	Strong
	Mg	0	3.582	1.343	0	Strong
	NO_3–N	0	2.719	1.051	0	Strong
	Avialable P	0	0.097	1.512	0	Strong

Table 6. Geostatistical parameters for spherical semivariogram model for inland and coastal plant densities.

Stations	Plants	Nugget	Sill	Range*	Nugget/Sill percent	Spatial class
		C_O	C_1	a	$C_o/C_1\times 100$	
Inland	*Atriplex griffithii*	0	0.595	1.048	0	Strong
	Suaeda fruticosa	0	1.144	1.047	0	Strong
	Salsola imbricata	0	0.711	1.047	0	Strong
Coastal	*Suaeda fruticosa*	0	1.896	1.182	0	Strong
	Haloxylon recurvum	0	0.524	1.054	0	Strong
	Cyperus conglomeratus	0	0.524	1.468	0	Strong

Among selected inland soil attributes, K, Mg and NO_3–N showed nearly similar autocorrelation ranges (~1m), whereas Na, Ca and available P possessed slightly higher ranges (1.295m, 2.311m and 1.67m, respectively) (Table 5). The inland soil pH showed a much larger spatial autocorrelation range (7.694m). The coastal soil grid samples represented the highest spatial range for organic carbon content (4.749m), whereas nearly similar autocorrelation ranges for pH (1.534m), K (1.577m) and available P (1.512m) were examined for coastal samples (Table 5).

The ratio of C_o / C_1 (nugget semivariance / total semivariance) expressed in percentage was used to identify the levels of spatial dependence for soil attributes. A strong spatial dependence for the variable is predicted if the ratio is found to be less than 25%, the ratio value between 25–75% showed moderate spatial dependence, whereas more than 75% ratio value represented weak spatial dependence for soil variables. The percent nugget / sill ratio categorized all inland and coastal soil attributes (except OC of coastal site) in strongly dependent class (Table 5) whereas OC (organic carbon) of coastal site showed moderate spatial dependence.

The nugget effect was found to be nil for all inland and coastal plant densities (Table 6). The sill variance was found to be highest for coastal *Suaeda fruticosa* (1.896). However, coastal species of *Haloxylon recurvum* and *Cyperus conglomeratus* showed similar sill variance (Table 6). The autocorrelation ranges for all inland populations (i.e., *Atriplex griffithii, Suaeda fruticosa* and *Salsola imbricata* were similar and nearly unity (~1). Among coastal populations, *Cyperus conglomeratus* showed high autocorrelation range of 1.468m (Table 6). The percent nugget / sill ratio of all inland and coastal populations represented strongly dependent spatial class (Table 6).

DISCUSSION

More alkaline pH (avg. 8) was observed for coastal samples compared to inland soil samples (avg. 7.56) as shown in the descriptive statistics in Table 1. Organic carbon content was nearly found to be similar for inland and coastal soils; however the mean values for NO_3–N and available P were slightly higher for inland samples than for coastal soils (Table 2). The average amount of exchangeable cations followed a similar sequence of Ca > Na > Mg > K for both inland and coastal sites (Table 1 and 2). The percent coefficient of variation (CV%) showed difference with respect to soil parameters. It was found maximum for available P for both inland and coastal samples (54.56% and 79.14%, respectively) (Table 1 and 2). Minimum values for CV were noticed for pH of both inland and coastal samples (2.53 and 6.41%, respectively). Reza *et al*. (2016) and Sun *et al*. (2003) also documented minimum variation for pH compared to other soil properties. The inland population of *Atriplex griffithii* was positively correlated with Mg content in the soil whereas coastal *C. conglomeratus* showed significant correlation with Ca. However, the density of halophytes, in general, was not correlated with other soil characteristics. Some of the soil characteristic exhibited correlation, e.g. inland nitrate nitrogen (NO_3-N) correlated significantly with soil pH, K and Ca. However, available P and pH represented excellent correlations with Na in inland soils.

Semivariograms were constructed for eight soil properties such as soil pH, OC, Na, K, Ca, Mg, NO_3–N and Available P. Spherical model was best fitted for all soil attributes and the parameters of the model such as nugget (C_o), sill (C_1+C_o) and range (a), were used to explain the spatial structure of different soil properties and plant densities (Table 5 and Table 6). The spherical model is a most commonly used model which represents gradual decrease in spatial autocorrelation till a distance (range) is reached, further than that autocorrelation becomes zero.According to Bhatti *et al.,* (1991), semivariogram construction is used to depict the spatial structure of attributes of soil and plants. All inland and coastal soil attributes (except OC of the coastal site) showed zero nugget effect (Table 5).

According to Webster and Nortcliff (1984) and Webster (1985) nugget effect is the semivariance when h=0. The semivariograms showing zeros nugget variance specified spatial continuity to be very even between adjacent points (Vieira and Gonzalez, 2003). The total variance (i.e., sill variance) was found to be more for OC, Na, Ca, Mg and available P of inland plot compared to coastal plot's soil attributes. However, coastal plot possessed more sill variance for pH, K and NO_3–N as compared with inland plot's corresponding soil attributes (Table 5). Similar results were obtained for inland and coastal soil parameters for variance obtained through conventional statistics (Table 1). Pawar (2003) stated that sill should be equal to the variance of the dataset.

The autocorrelation ranges varied among different soil attributes for both inland and coastal soils. Generally K, Mg and NO_3–N showed nearly similar autocorrelation ranges (~1m), whereas Na, Ca and available P showed slightly higher ranges. However, pH of inland soils represented highest autocorrelation range (Table 5). The smaller autocorrelation ranges indicated that the spatial continuity vanishes very quickly. Among the coastal site, the highest autocorrelation range was observed for OC (4.749m), however, pH, K and available P showed nearly similar ranges of around 1.5m. `

The ratio of nugget to sill was utilized to examine levels of spatial dependence of soil properties. The spatial dependence was found to be strong if the nugget / sill ratio (expressed as a percentage) was less than 25%, moderate if it existed between 25 to 75%, and weak for more than 75% ratio. As stated by Trangmar *et al*. (1985), nugget semivariance (C_o) calculated as a percentage of sill semivariance (C_1) is used for comparison of relative amount of the nugget effect for soil variables. Cambardella *et al*. (1994), also used the ratio of C_o/C_1 (nugget semivariance/total semivariance) expressed in percentage to identify the levels of spatial dependence for soil attributes. All inland and coastal site's soil properties (except OC of the coastal site) showed strong dependence for soil properties based on percent nugget / sill ratio stated above (Table 5). Moderate dependence (26.58%) was detected in coastal organic carbon content. Reza (2016) noticed strong spatial dependence for soil pH and a weak dependence for organic carbon content (OC).

For plant densities the autocorrelation ranges were found to be similar for nearly all species found in inland and coastal sampling grids except *Cyperus conglomeratus* which showed slightly higher autocorrelation ranges of 1.468m. All inland and coastal populations exhibited strongly dependent spatial class.

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(*Accepted for publication March 2019*)