Spatial / Time Variability of Soil Physical Properties

3rd Brazilian Soil Physics Meeting
May 04 to May 08,2015

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OUTLINE

- **State-space approach: basic theoretical aspects;**
- **Some applications of the State-space approach;**
- **New research topics: present and future.**

Classical Statistics...

- **INDEPENDENCE** of observations among themselves;

- **SAMPLING LOCATIONS** in the field are **IGNORED**, **DISREGARDING** the potential **SPATIAL DEPENDENCE of observations** within a field;

- **INADEQUATE** experimental design as a result.

Taking account the spatial dependence of observations.....

-**Geostatistics Analysis**: semivariograms, kriging, cross-semivariograms, co-kriging, etc

-**Time/Spatial Series Analysis**

Time/Spatial Series

Series definition:

-Physical phenomena that, when observed and numerically quantified, result in a sequence of data distributed along time (or space).

<u>“Time”</u> Series (time data sequences) examples:

a) ***<u>weekly</u>*** **average values of soil water storage at a given location;**

b) ***<u>yearly</u>*** **sugarcane crop yield data for a given field; etc.**

Spatial series (space data sequences) examples:

a) soil organic carbon content measured across a field;

b) soil water content values measured across a coffee field on the same day; etc.

"<u>Basic</u> objectives" to analyze a Time/Space Series (Tukey,1980):

-<u>modeling</u> of the process under consideration;

-obtaining <u>conclusions</u> in <u>statistical</u> terms; and

-evaluating <u>model´s ability</u> in terms of <u>forecast</u>.

"Two" ways to analyze a temporal (spatial) series:

1st) **"frequency"** domain: presence of a **periodic** phenomenum.

Examples are:

-**Spectral** and **Cospectral** analyses: many applications in the soil-plant-atmosphere system.

2**^{nd}*) **"time (space)"** ***domain**: to identify the** **<u>stationary</u> components (aleatory or random variables) and the <u>nonstationary</u> components which define the mean function of the process.**

<u>Examples</u> are:

AR model; ARIMA model;

"*<u>STATE-SPACE</u>*" model

Analysis of a series in the "time (or space)" domain:

<u>Frequent assumption</u>:

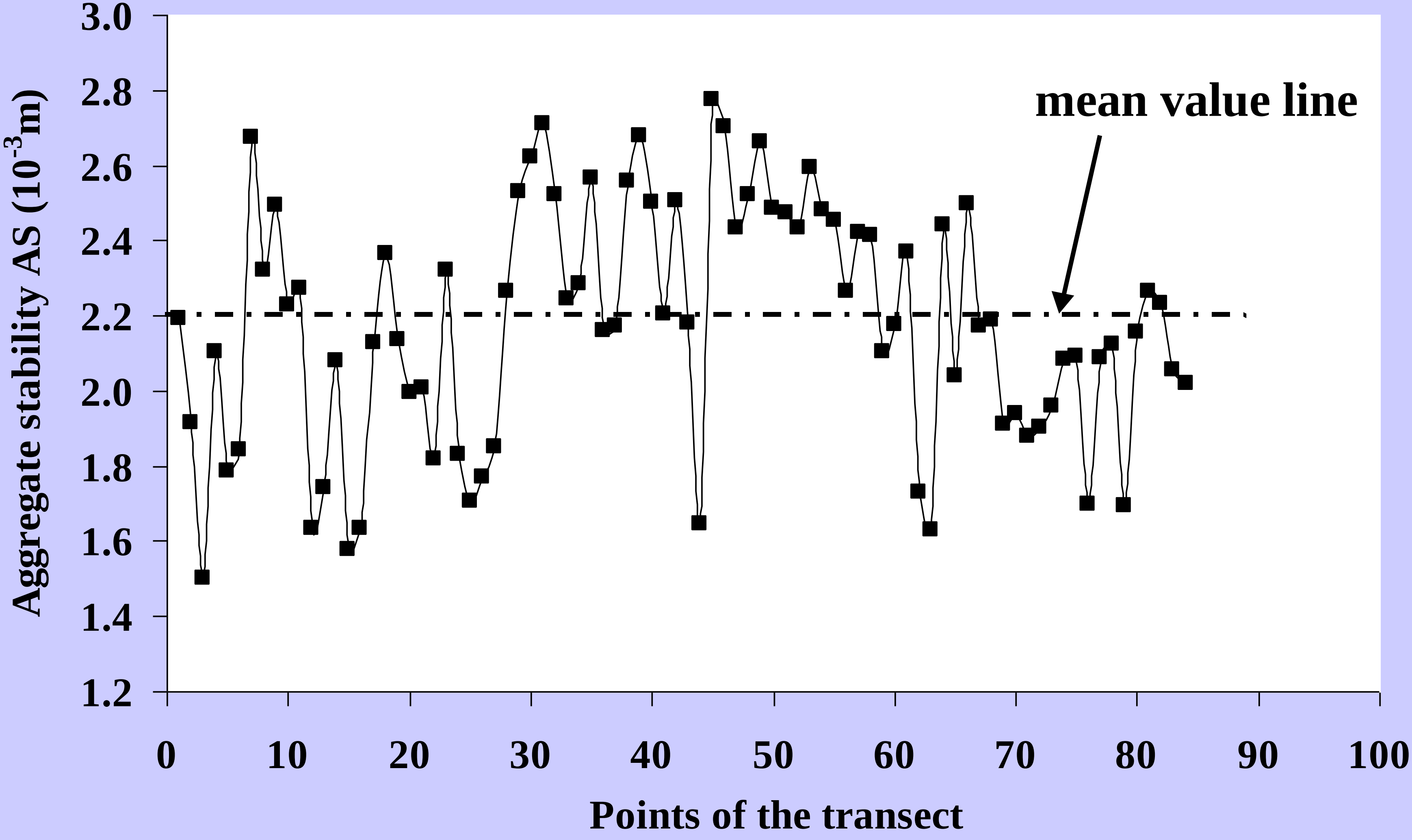
***series is* "stationary"**

Stationarity ….

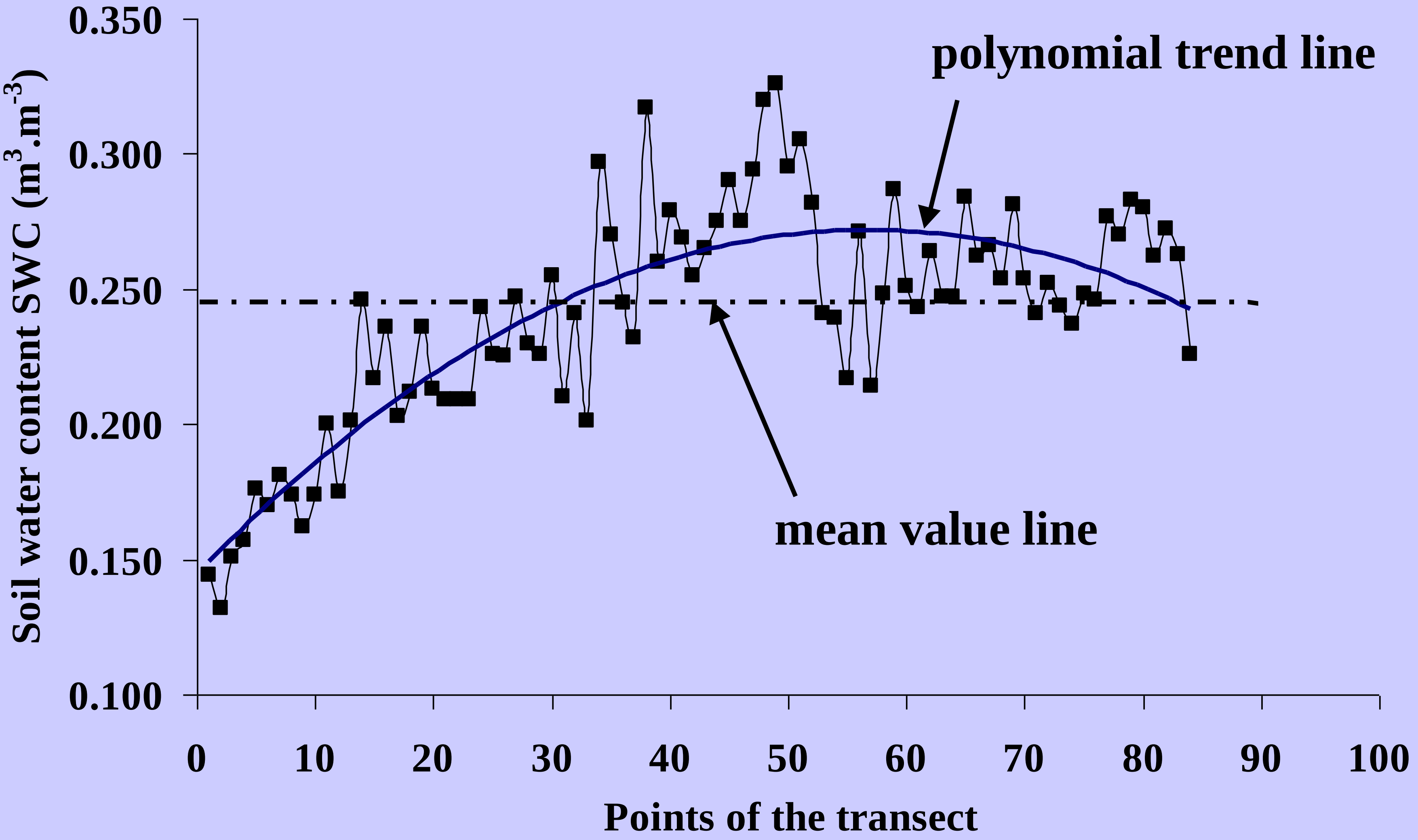
What does it mean ?

-series develops in a “random way” in time (or space) reflecting some sort of a “stable equilibrium” (no trend line).

“*Stationary*” series: example



“*Nonstationary*” series:example



Statistical tools for

analyzing and characterizing

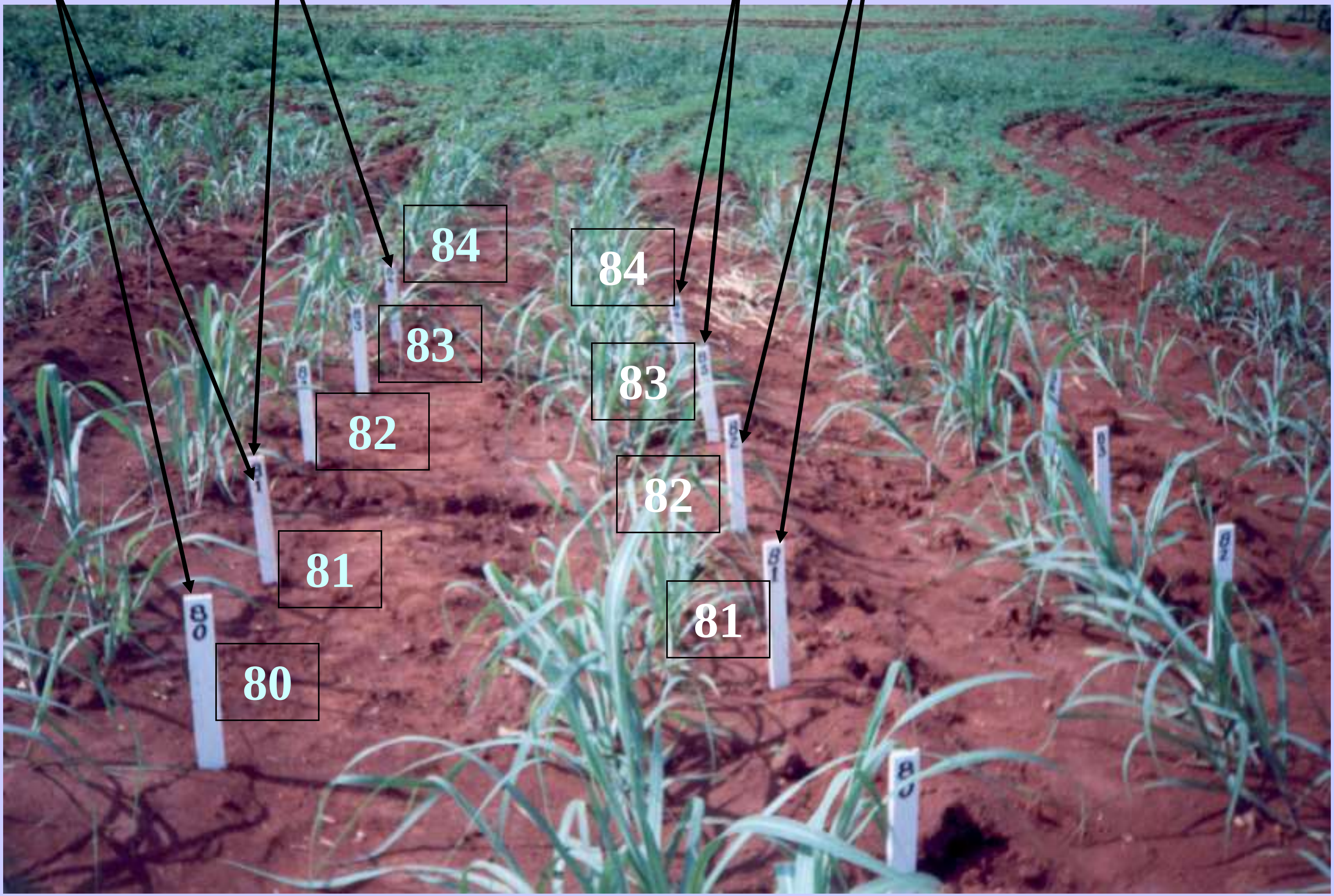
“time (or spatial)”

variability of data sets

a) ***<u>Autocorrelation</u>*** **function: to indicate the distance of "auto-dependence" between "adjacent observations" of a variable.**

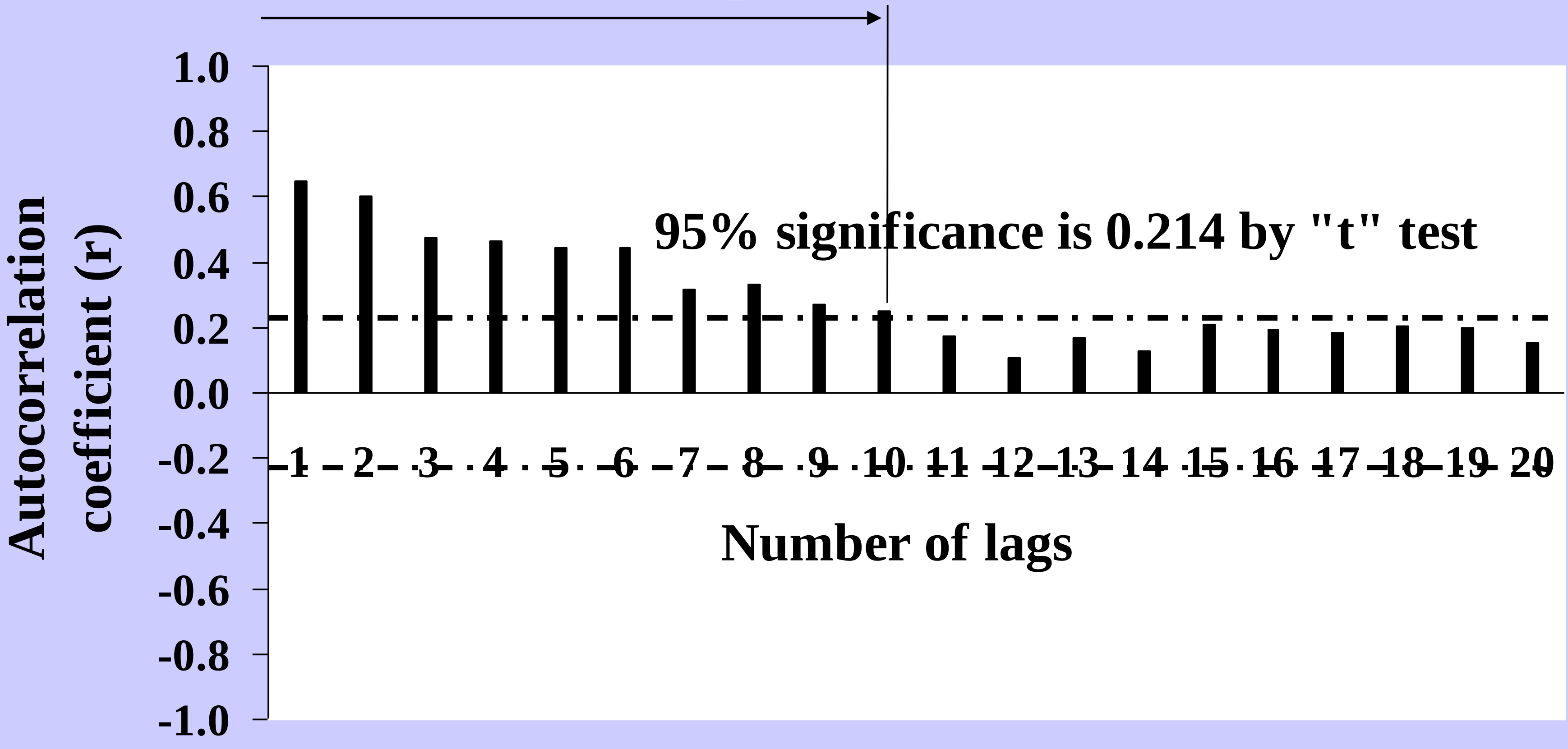
"Space series" are collected along <u>transects</u> at spacings of "<u>α</u>" in cm, m, km, etc.

h = 1 lag h = 3 lags α = 1 m



Autocorrelogram *plot: an example*

range of spatial auto-dependence
10 lags



b) Crosscorrelation function (CCF):

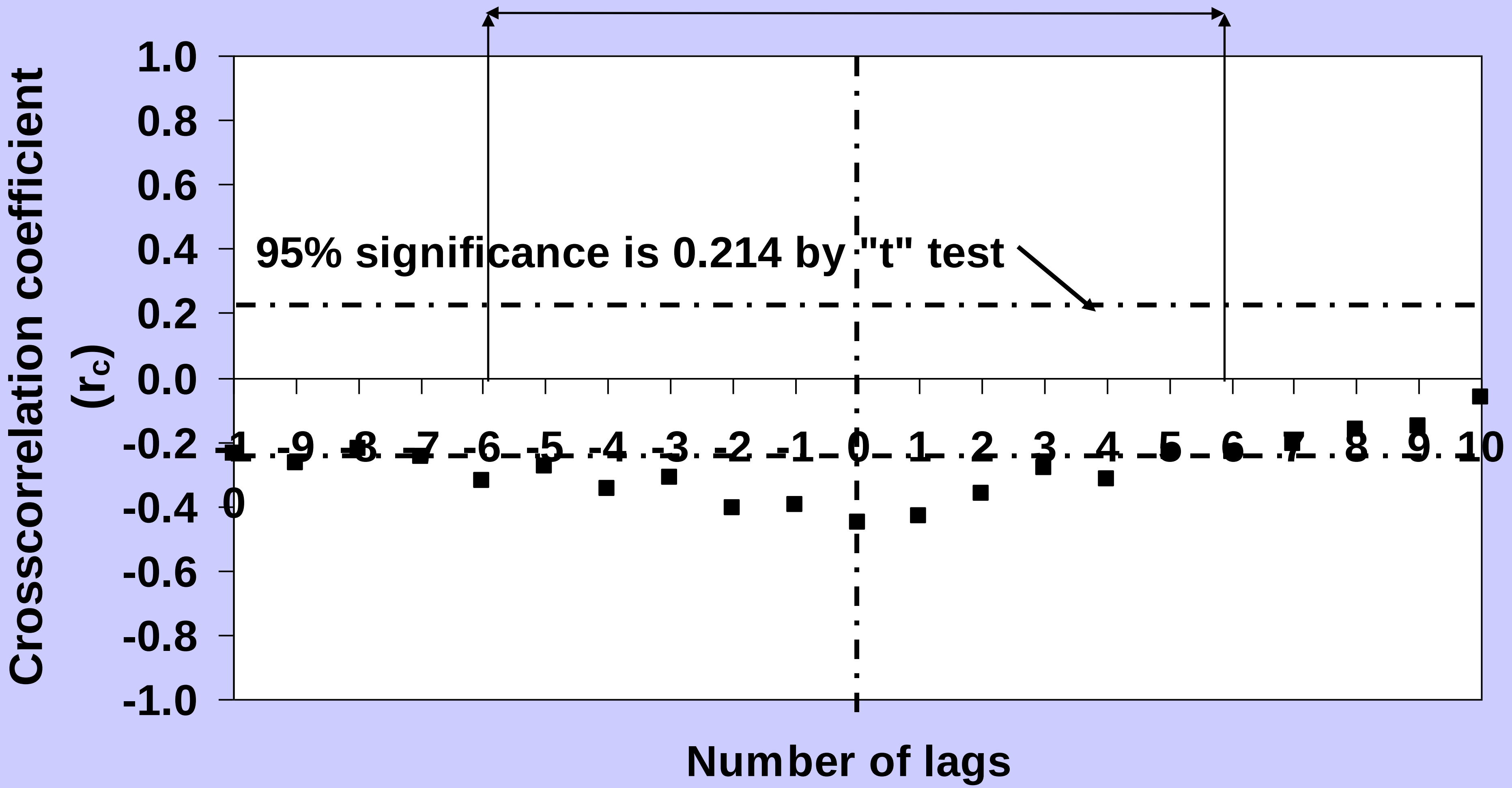
-to indicate the spatial correlation between two sets of variables: $Y(x_i)$ and $W(x_i)$ observed at the <u>same locations</u> x_i.

<u>Example:</u>

Y = soil temperature; W = soil water content

Spatial dependence: two variables

6 lags in both directions



"State-Space" approach:

-the "**State-Space**" model of a stochastic process involving j data sets Y_j, all collected at the same locations x_i, is based on the property of Markovian systems, i.e., the independence of the future of the process in relation to its past, once given the present state;

-It is a combination of **two** systems of equations:

1st: "Observation" equation

$$\mathbf{Y_j}(\mathbf{x_i}) = \mathbf{M_{jj}}(\mathbf{x_i})\,\mathbf{Z_j}(\mathbf{x_i}) + \mathbf{v_{Y_j}}(\mathbf{x_i}) \qquad (1)$$

Y_j = **observation vector** of the process at **location** x_i;

M_{jj} = **observation matrix** at **position** x_i;

Z_j = **non observed state vector** of the process at **location** x_i;

$\mathbf{v_{Yj}}$ = **observation error vector** at position $\mathbf{x_i}$.

The "matrix M_{jj}" comes from a set of j linear observation equations (all at position i):

$$
\begin{aligned}
Y_1(x_i) &= m_{11}Z_1(x_i) + m_{12}Z_2(x_i) + \dots\dots\dots + m_{1j}Z_j(x_i) + v_{Y_1}(x_i) \\
Y_2(x_i) &= m_{21}Z_1(x_i) + m_{22}Z_2(x_i) + \dots\dots\dots + m_{2j}Z_j(x_i) + v_{Y_2}(x_i) \\
&\vdots \\
Y_j(x_i) &= m_{j1}Z_1(x_i) + m_{j2}Z_2(x_i) + \dots\dots\dots + m_{jj}Z_j(x_i) + v_{Y_j}(x_i)
\end{aligned}
$$

Which can be written in the **matrix form:**

$$\begin{bmatrix} Y_1(x_i) \\ Y_2(x_i) \\ \vdots \\ Y_j(x_i) \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} \,\ldots\ldots\ldots\, m_{1j} \\ m_{21} & m_{22} \,\ldots\ldots\ldots\, m_{2j} \\ \vdots & \vdots \qquad\qquad \vdots \\ m_{j1} & m_{j2} \,\ldots\ldots\ldots\, m_{jj} \end{bmatrix} \times \begin{bmatrix} Z_1(x_i) \\ Z_2(x_i) \\ \vdots \\ Z_j(x_i) \end{bmatrix} + \begin{bmatrix} v_{Y_1}(x_i) \\ v_{Y_2}(x_i) \\ \vdots \\ v_{Y_j}(x_i) \end{bmatrix}$$

observation vector	**observation matrix**	**non observed state vector**	**observation error vector**

2^{nd}: "State" equation

$$Z_j(x_i) = \phi_{jj}(x_i) Z_j(x_{i-1}) + u_{Z_j}(x_i) \qquad (2)$$

ϕ_{jj}= <u>state coefficient matrix</u> (<u>transition matrix</u>) at <u>location</u> x_i;

$Z_j(x_{i-1})$ = <u>non observed state vector</u> of the process at <u>location</u> x_{i-1};

u_{Zj} = is an error vector associated to the state at <u>position</u> x_i;

The <u>matrix</u> ϕ_{jj} comes from a set of j linear state equations (relating position i to position i-1):

$$
\begin{array}{l}
Z_1(x_i) = \phi_{11} Z_1(x_{i-1}) + \phi_{12} Z_2(x_{i-1}) + \ldots\ldots\ldots\ldots + \phi_{1j} Z_j(x_{i-1}) + u_{Z_1}(x_i) \\
Z_2(x_i) = \phi_{21} Z_1(x_{i-1}) + \phi_{22} Z_2(x_{i-1}) + \ldots\ldots\ldots\ldots + \phi_{2j} Z_j(x_{i-1}) + u_{Z_2}(x_i) \\
\quad \vdots \qquad\qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\
Z_j(x_i) = \phi_{j1} Z_1(x_{i-1}) + \phi_{j2} Z_2(x_{i-1}) + \ldots\ldots\ldots\ldots + \phi_{jj} Z_j(x_{i-1}) + u_{Z_j}(x_i)
\end{array}
$$

Or in the <u>matrix</u> form:

$$\begin{bmatrix} Z_1(x_i) \\ Z_2(x_i) \\ \vdots \\ Z_j(x_i) \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots\cdots\cdots\phi_{1j} \\ \phi_{21} & \phi_{22} & \cdots\cdots\cdots\phi_{2j} \\ \vdots & \vdots & \vdots \\ \phi_{j1} & \phi_{j2} & \cdots\cdots\cdots\phi_{jj} \end{bmatrix} \times \begin{bmatrix} Z_1(x_{i-1}) \\ Z_2(x_{i-1}) \\ \vdots \\ Z_j(x_{i-1}) \end{bmatrix} + \begin{bmatrix} u_{Z_1}(x_i) \\ u_{Z_2}(x_i) \\ \vdots \\ u_{Z_j}(x_i) \end{bmatrix}$$

non observed state vector at position x_i

state coefficient matrix

non observed state vector at position x_{i-1}

state error vector

<u>Applications of the "State-Space" approach:</u>

Spatial and **time** series

NEURAL NETWORK AND STATE-SPACE MODELS FOR STUDYING RELATIONSHIPS AMONG SOIL PROPERTIES

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ABSTRACT: The study of soil property relationships is of great importance in agronomy aiming for a rational management of environmental resources and an improvement of agricultural productivity. Studies of this kind are traditionally performed using static regression models, which do not take into account the involved spatial structure. This work has the objective of evaluating the relation between a time-consuming and "expensive" variable (like soil total nitrogen) and other simple, easier to measure variables (as for instance, soil organic carbon, pH, etc.). Two important classes of models (linear state-space and neural networks) are used for prediction and compared with standard uni- and multivariate regression models, used as reference. For an oat crop cultivated area, situated in Jaguariuna, SP, Brazil (22°41' S, 47°00' W) soil samples of a Typic Haplustox were collected from the plow layer at points spaced 2 m apart along a 194 m spatial transect. Recurrent neural networks and standard state-space models had a better predictive performance of soil total nitrogen as compared to the standard regression

Model performances

The models were adjusted in two versions. For the first version, the last 10 transect points of STN were omitted in order to make their prediction (Table 1). For the second, the first 10 points of STN were omitted with the same objective (Table 2). As already mentioned, the statistical measures considered for comparisons between models were the MSE (equation 8a) and the MAPE (equation 8b).

It can be seen that among the models without latent variables, i.e., among the true regression models, the original VAR model gives the worst results (independent of the statistical measure considered, MSE = 0.00713 and MAPE = 0.0639) since, in this case, unlike other models it uses the lagged SOC as a regressor variable and not the SOC value at the same point, which has a stronger linear relation with STN as shown in Figures 4A and 5D. The corrected VAR shows the best results among the regression models,

for which the minimum values of M
MAPE (=0.0395) were found. This
as a more appropriate predictor m
point in space, which is consistent
although being a global model (i.e.
equations 2a and 2b are fixed and
space), is presented as a bi-dimen
posed of two equations which tre
the relation between STN and SOC
adequate way, i.e., there is no a hier
ables, both being treated in the sa
as random variables. The standar
model (scalar model) is, also, a glo
ever, is presented as a unidimensi
hierarchical treatment between STN
(only the variable STN is conside
able). Therefore, both statistical pe
(MSE = 0.00388 and MAPE = 0.0
values as compared to the correct

Table 1 - Predictive performance (10 last transect points) of standard regression, of state-space and of neural network models, for soil total nitrogen STN.

Prediction models			Statistical measures	
			MSE	MAPE
without latent variable	Scalar Regression	Standard linear	0.00388	0.04301
		AR (1) error	0.00389	0.04279
	Vector Auto-regression	Standard VAR	0.00713	0.06390
		Corrected VAR	0.00350	0.03905
	No-parametric regression	GAM/splines	0.00435	0.04359
		GAM/lowess	0.00361	0.04084
with latent variable	Artificial neural networks	Feedforward	0.00313	0.03727
		Recurrent	0.00279	0.03599
	State-space models	Standard	0.00096	0.02302
		Dynamic	0.00288	0.03960

Table 2 - Predictive performance (10 first transect points) of standard regression, of state-space and of neural network models, for soil total nitrogen STN.

Prediction models			Statistical measures	
			MSE	MAPE
without latent	Scalar Regression	Standard linear	0.00483	0.04665
		AR (1) error	0.00475	0.04601
		Standard VAR	0.00713	0.06390

Soil & Tillage Research 145 (2015) 135–147

Contents lists available at ScienceDirect

Soil & Tillage Research

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State-space approach to evaluate effects of land levelling on the spatial relationships of soil properties of a lowland area

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ARTICLE INFO

ABSTRACT

CSIRO PUBLISHING
www.publish.csiro.au/journals/sr
Soil Research, 2011, **49**, 77–86

Temporal variability of soil water storage evaluated for a coffee field

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Abstract. Sampling field soils to estimate soil water content and soil water storage (*S*) is difficult due to the spatial variability of these variables, which demands a large number of sampling points. Also, the methodology employed in most cases is invasive and destructive, so that sampling in the same positions at different times is impossible. However, neutron moderation, time domain reflectrometry, and, more recently, frequency domain reflectrometry methodologies allow measurements at the same points over long time intervals. This study evaluates a set of neutron probe data, collected at

Plant Soil (2015) 387:395–411
DOI 10.1007/s11104-014-2304-5

REGULAR ARTICLE

Temporal processes of soil water status in a sugarcane field under residue management

G. O. Awe · J. M. Reichert · L. C. Timm · O. O. Wendroth

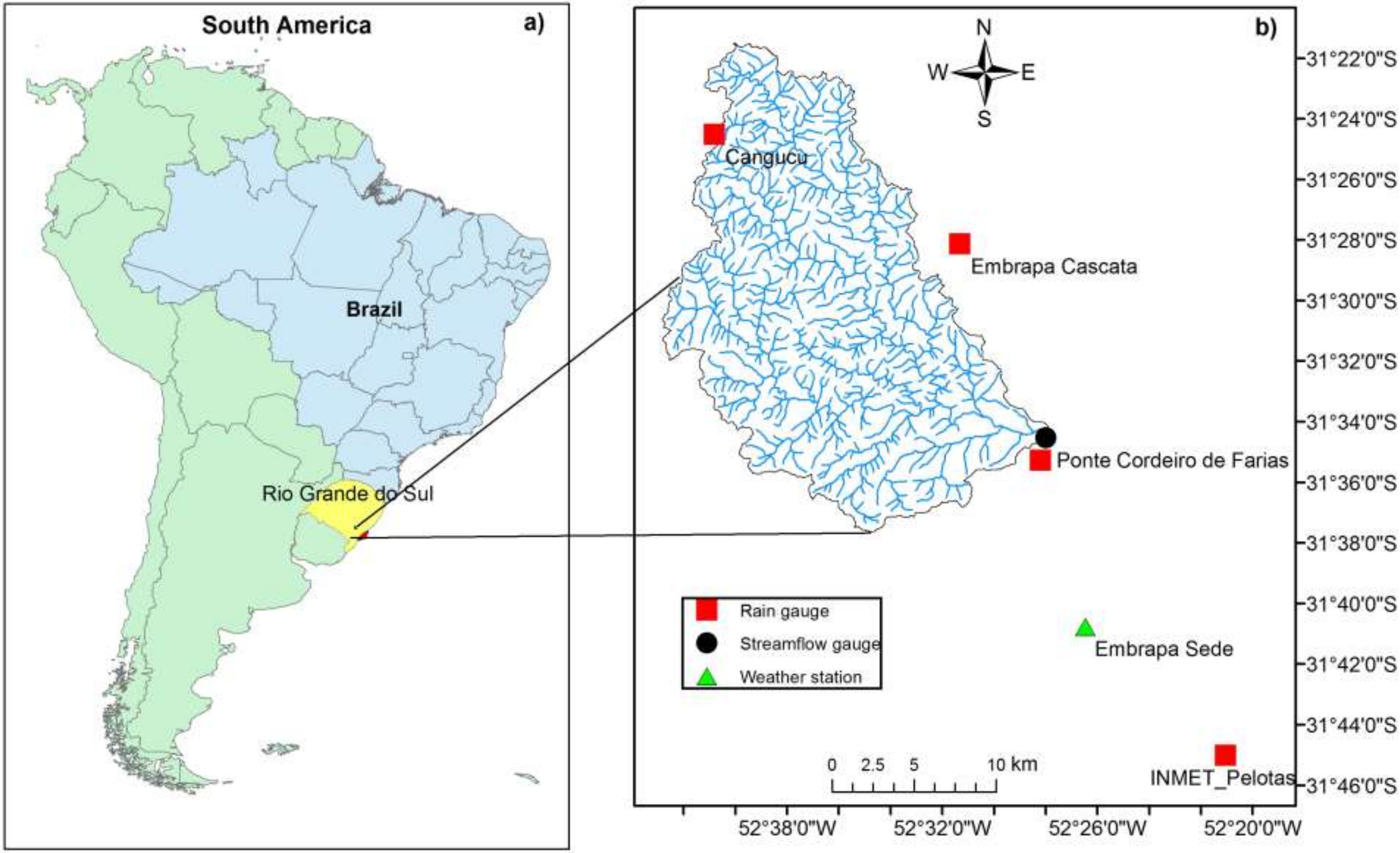
Received: 1 August 2014 / Accepted: 12 October 2014 / Published online: 25 October 2014

Abstract
Background and aims The knowledge of soil water storage is vital for rational agricultural management, and in soil-plant-water relations. This study was conducted to evaluate the temporal processes of soil water

cross-correlated with other variables, however, results were not the same for the different soil depths and treatments. Classical regression of SWS from combinations of log (Ψ), ET and P gave satisfactory results, however state-time analysis was better with higher R^2

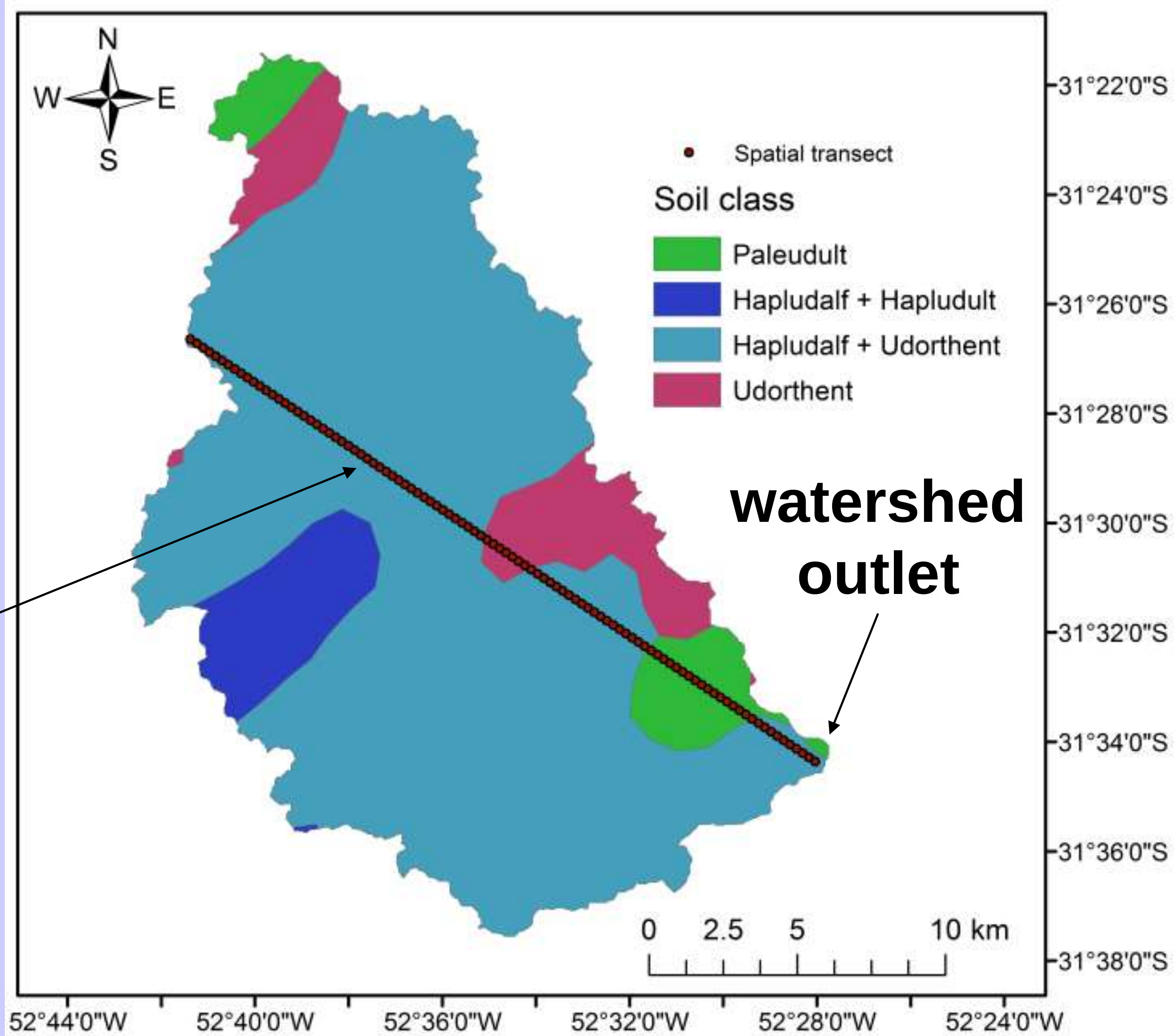
Applications of the "State-Space" approach:

"<u>watershed</u>" scale



Location of the Arroio Pelotas watershed – Southern of Rio Grande do Sul state (Brazil).

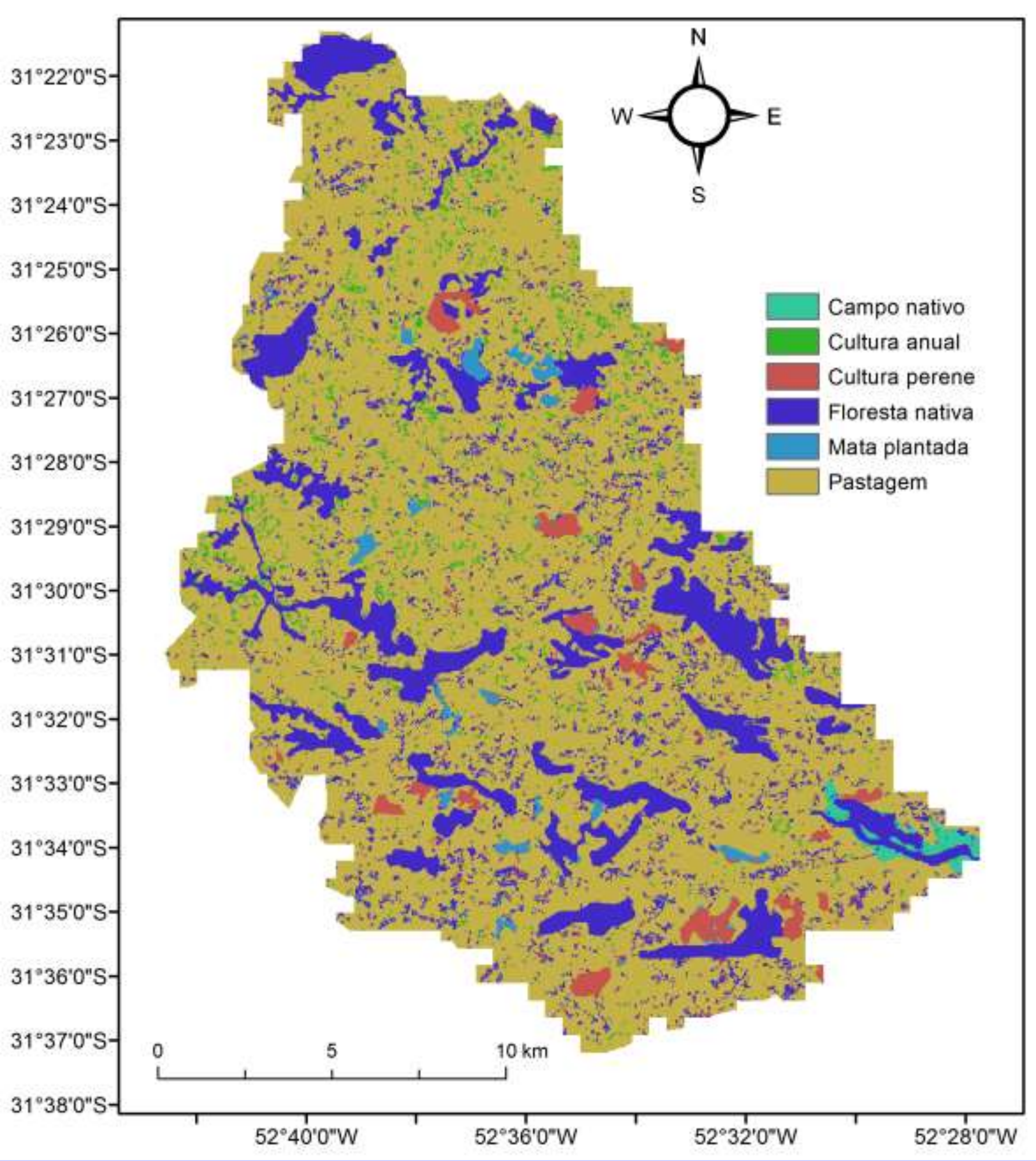
drainage area: 362 km^2



25 km spatial transect

Map of the main soil types (Brasil, 1973)

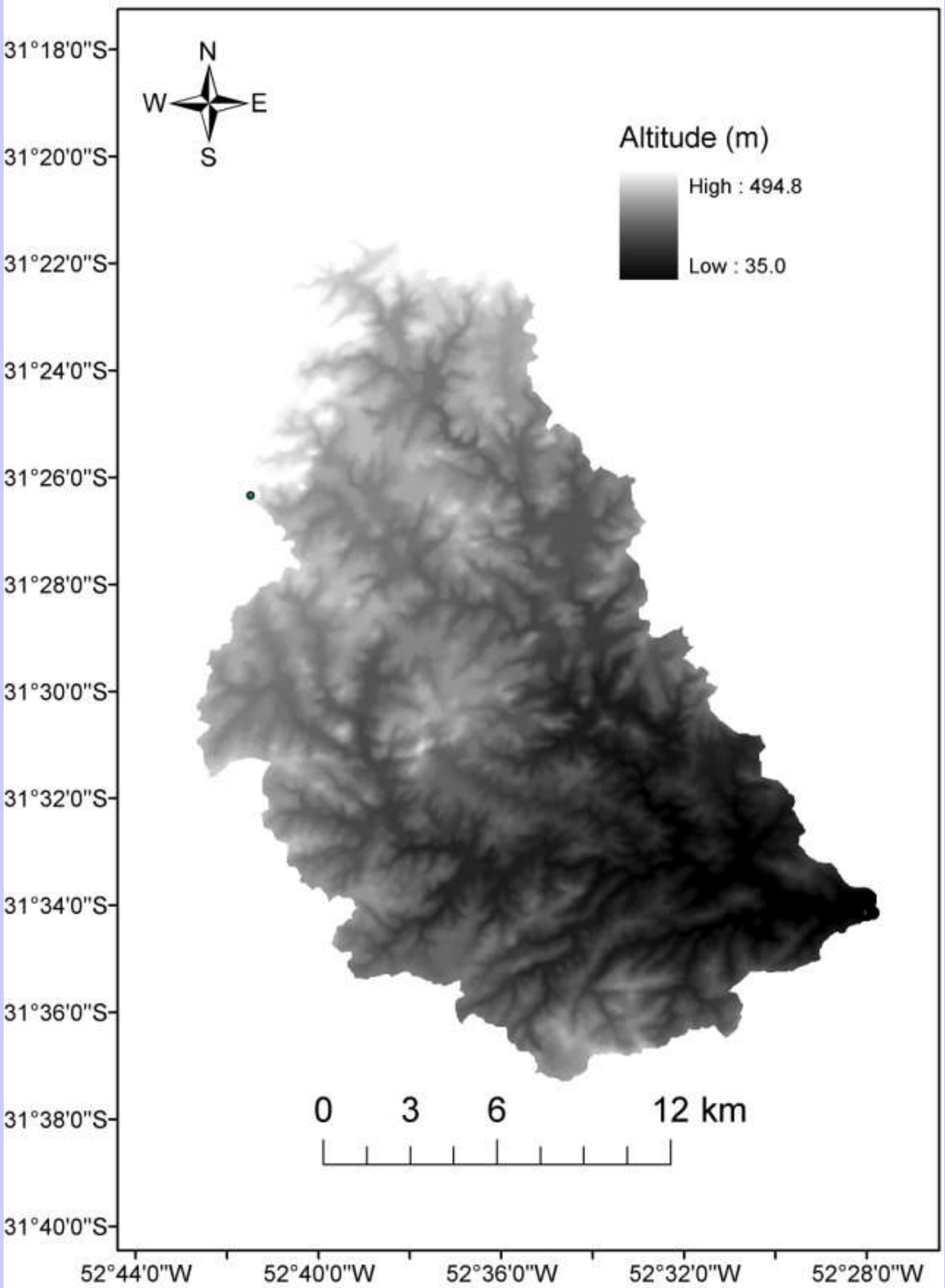
-Native grassland;
-Annual cropping;
-Permanent cropping;
-Native forest;
-Silviculture; and
-Cultivated pasture.



Arroio Pelotas watershed land uses.

Arroio Pelotas watershed:

Digital Elevation Model



Primary and secondary topographic attributes: DEM

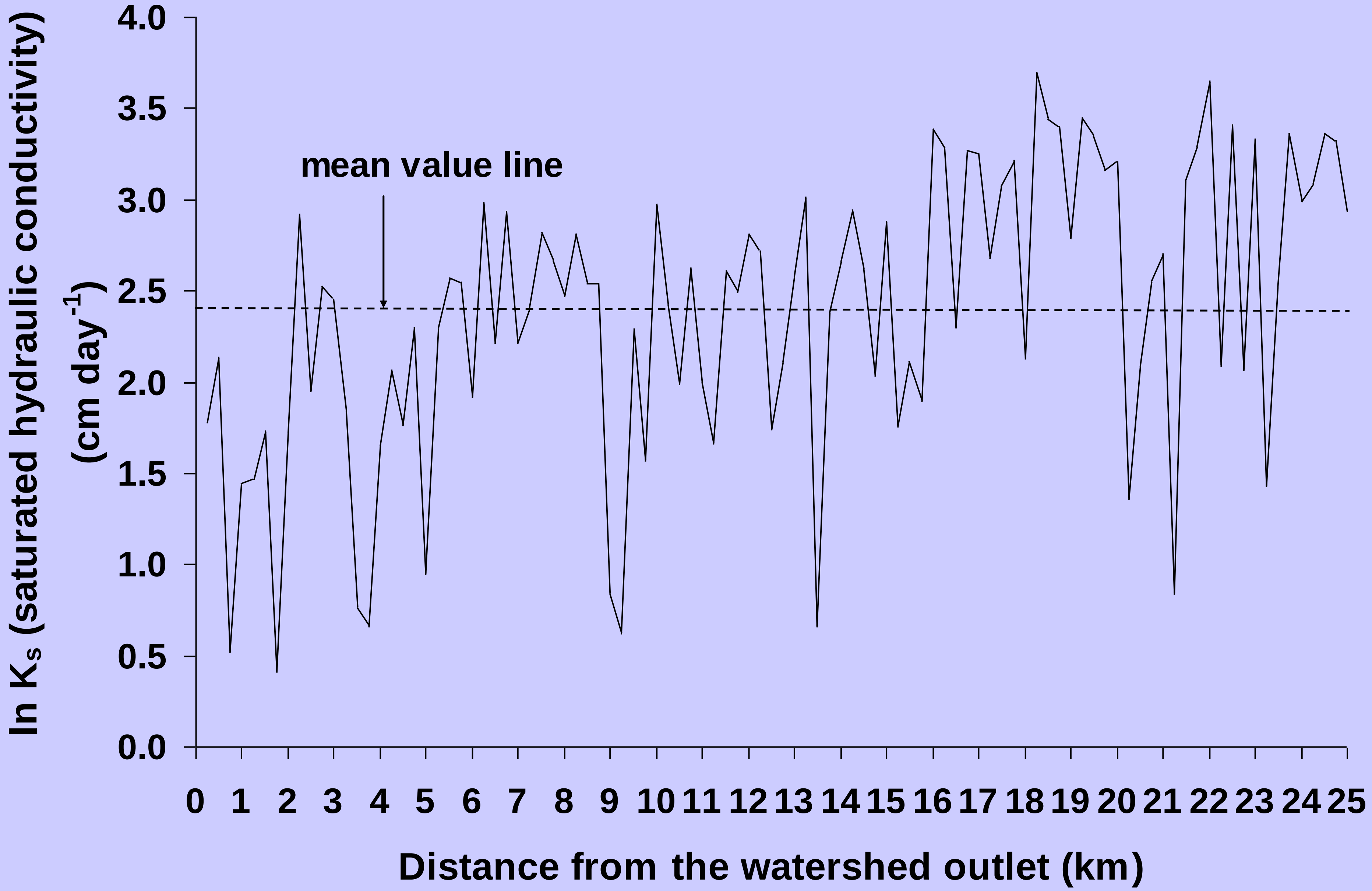
- -Elevation;
- -Slope;
- -Aspect;
- -Curvature;
- -Upslope contributing area;
- -Soil surface roughness;
- -Soil wetness index;
- -etc.

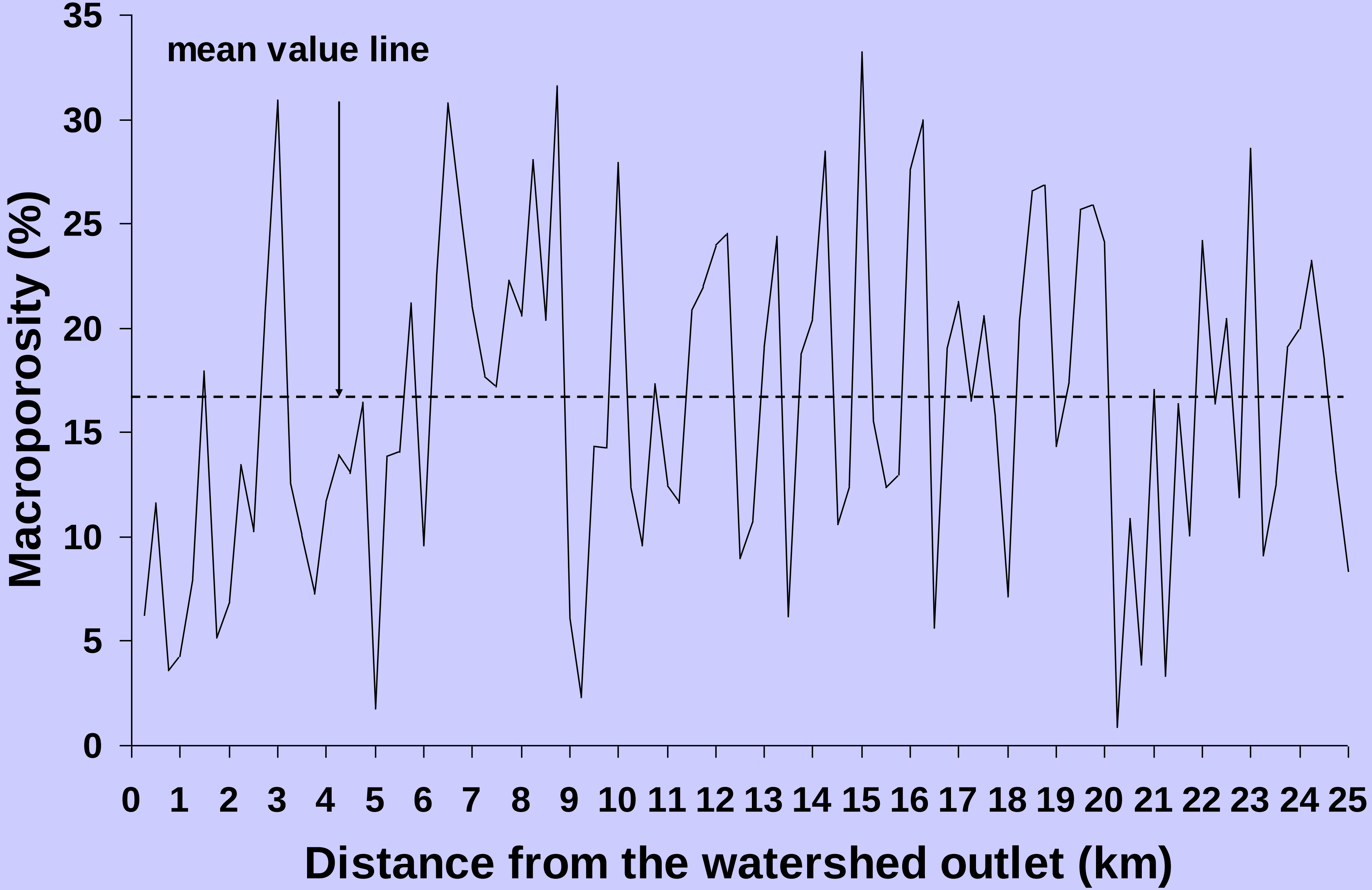
-**Soil samples**: spaced 250 m from each other totalizing 100 samples;

- Evaluated soil layer: 0- 0.20 m depth

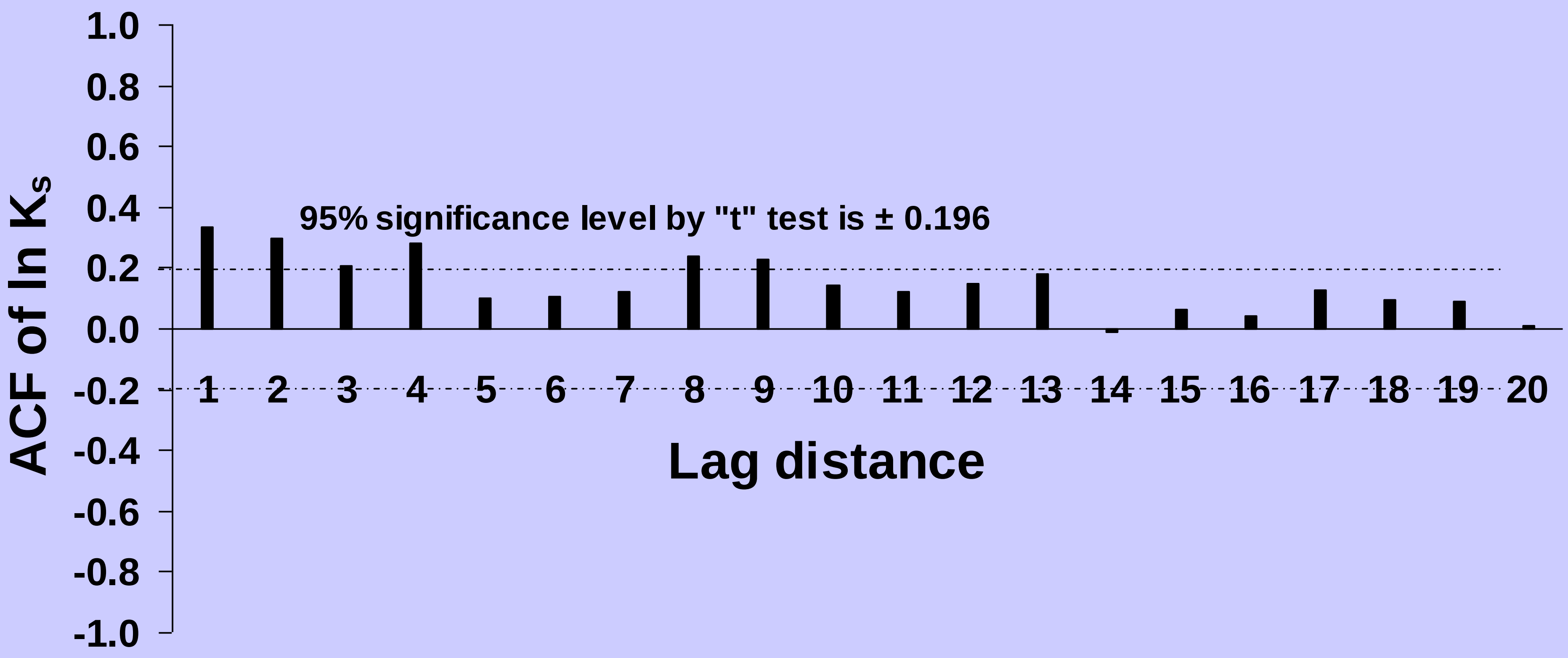
-**Measured soil physical and hydraulic properties**: soil texture, soil bulk density, SWRC, saturated hydraulic conductivity, soil total porosity, soil organic carbon, etc.

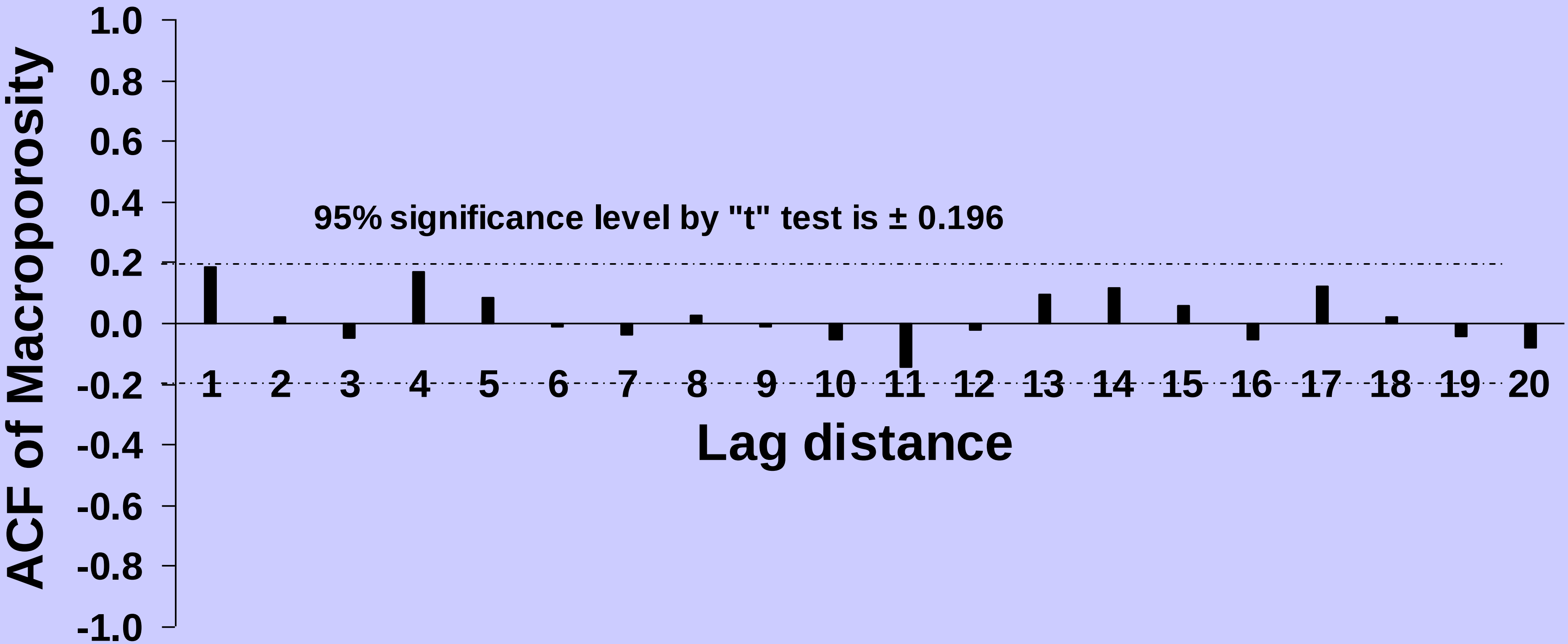
Preliminary Results

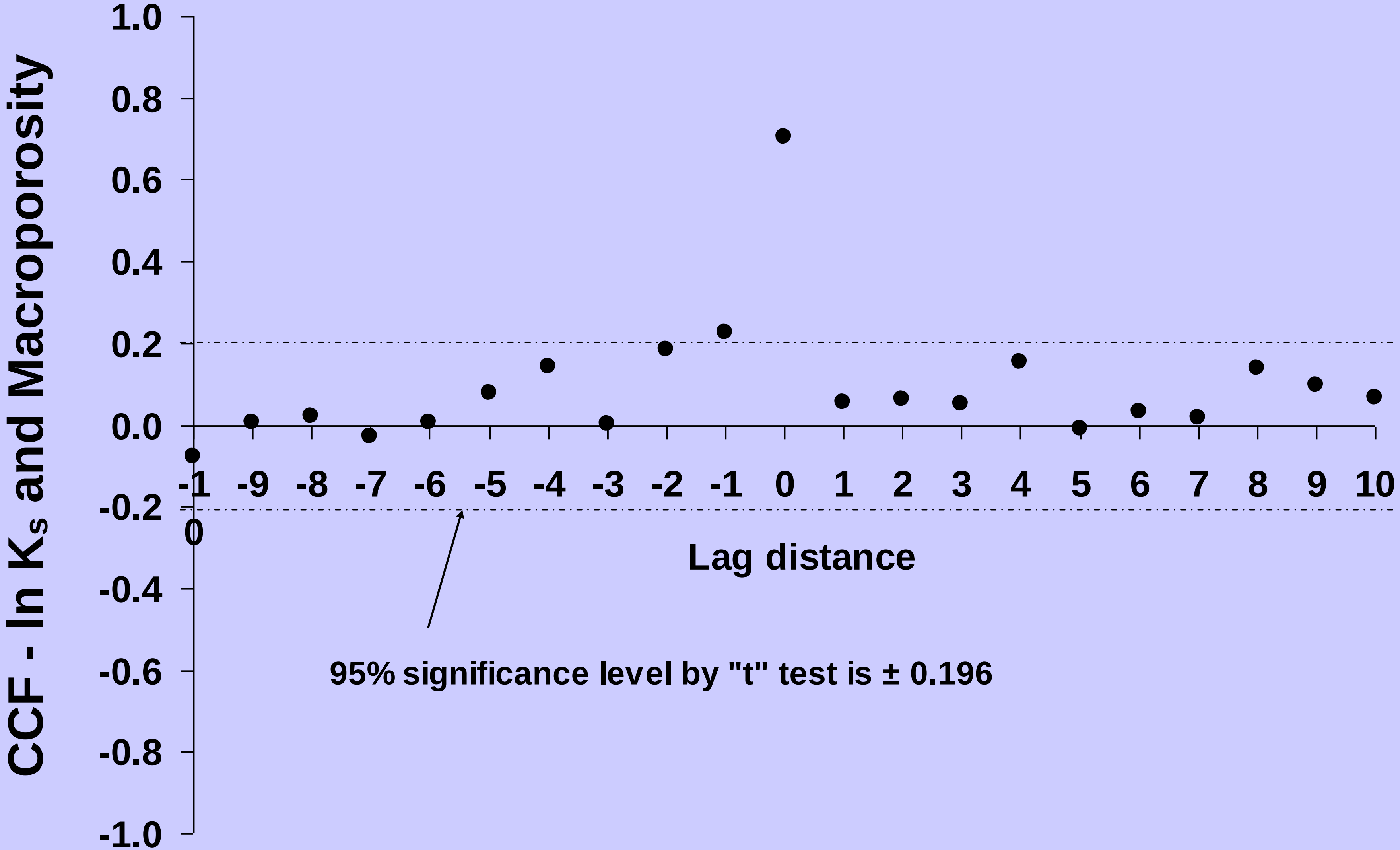

mean value line
ln K_s (saturated hydraulic conductivity) (cm day^{-1})
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Distance from the watershed outlet (km)



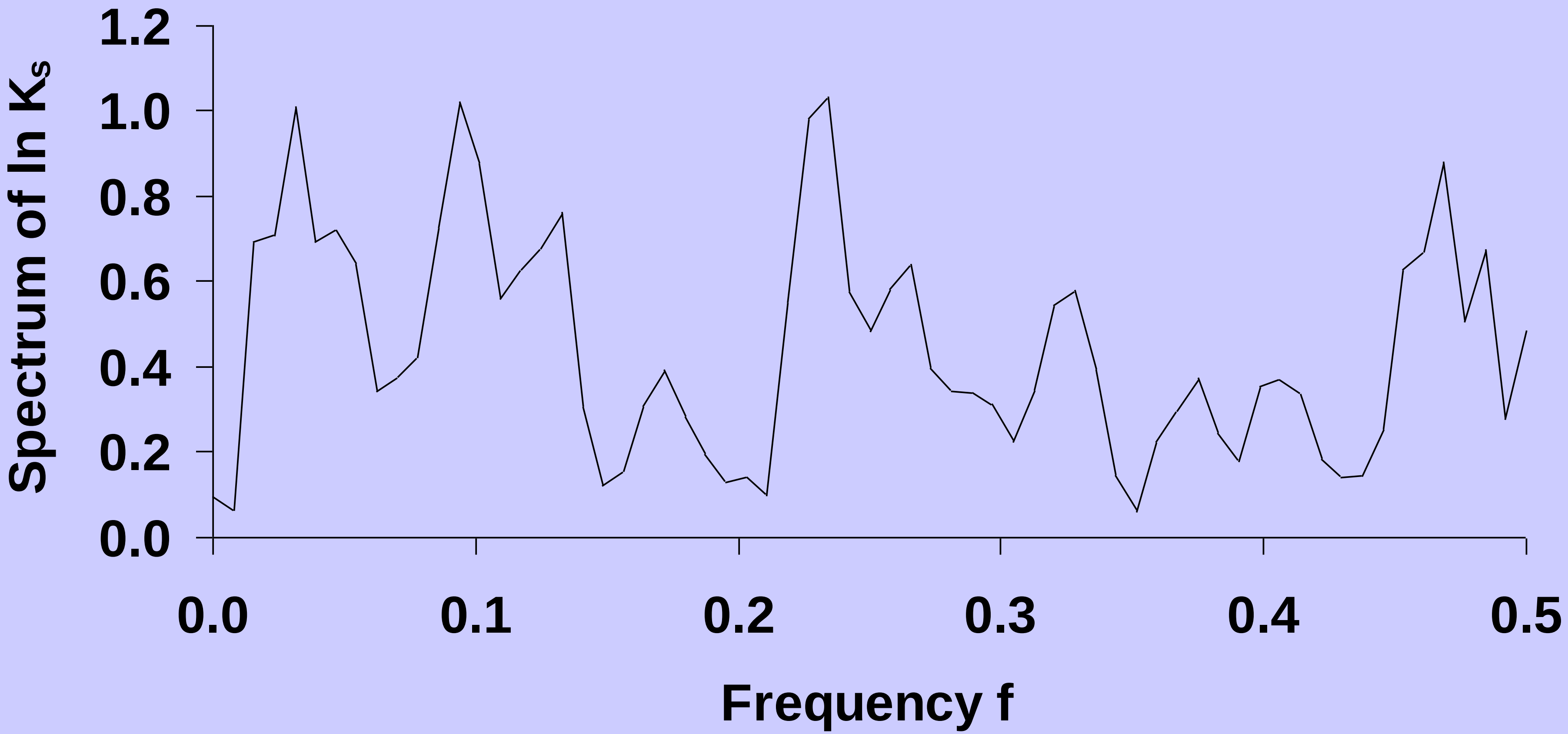
mean value line
Macroporosity (%)
0
5
10
15
20
25
30
35
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Distance from the watershed outlet (km)


ACF of ln K_s
95% significance level by "t" test is ± 0.196
Lag distance
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

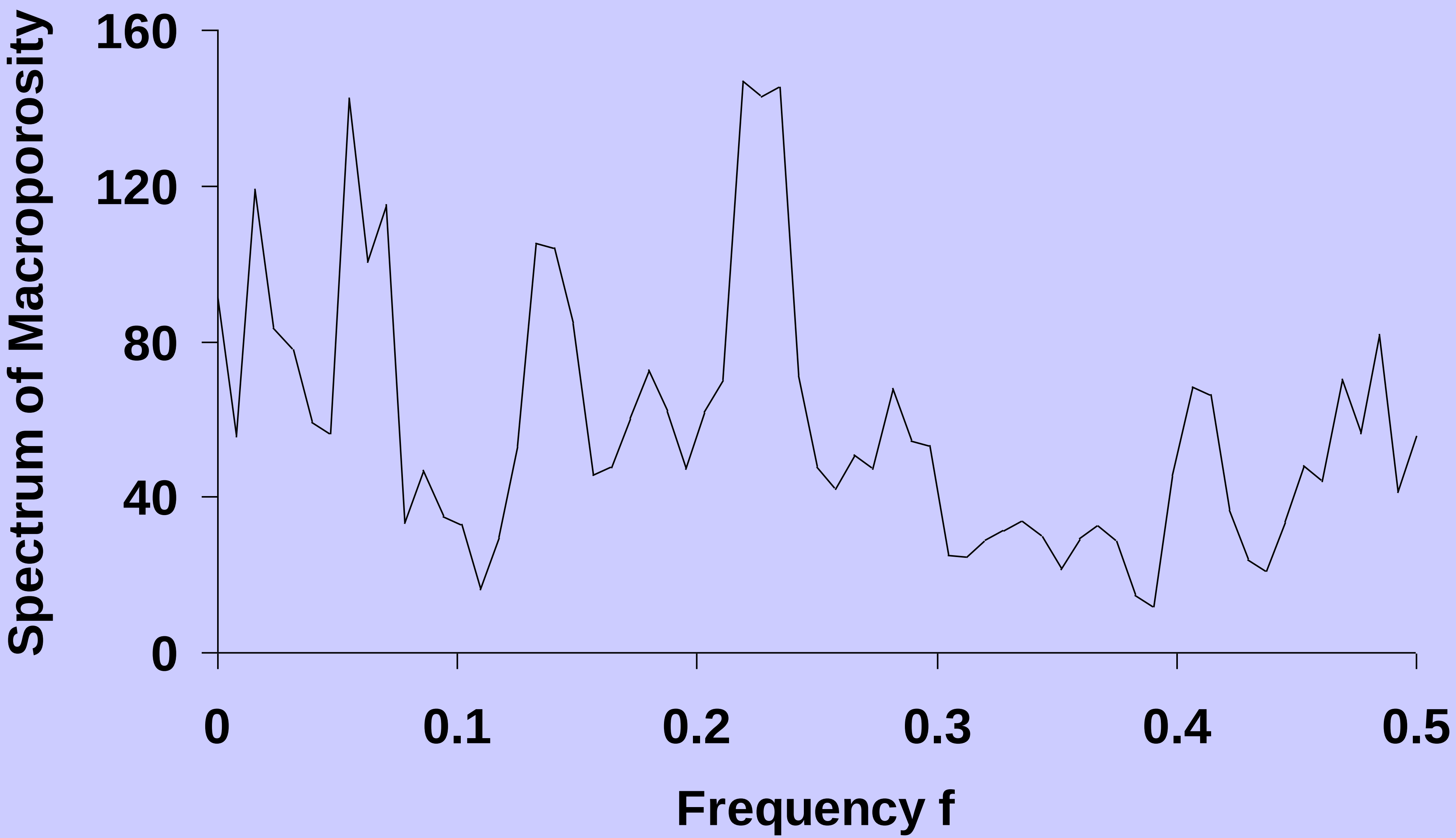

ACF of Macroporosity
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
95% significance level by "t" test is ± 0.196
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Lag distance

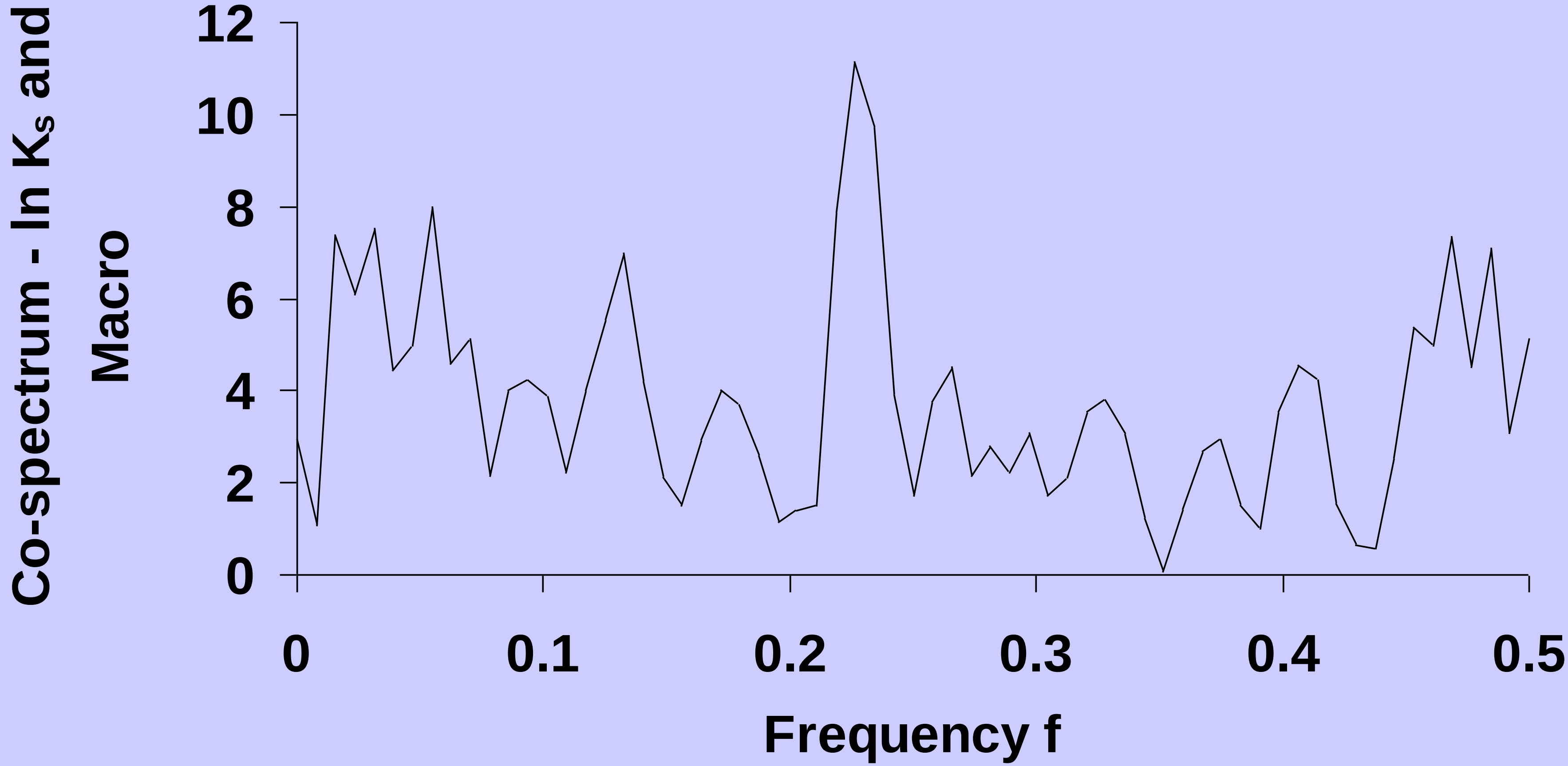


CCF - ln K_s and Macroporosity
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10
Lag distance
95% significance level by "t" test is ± 0.196

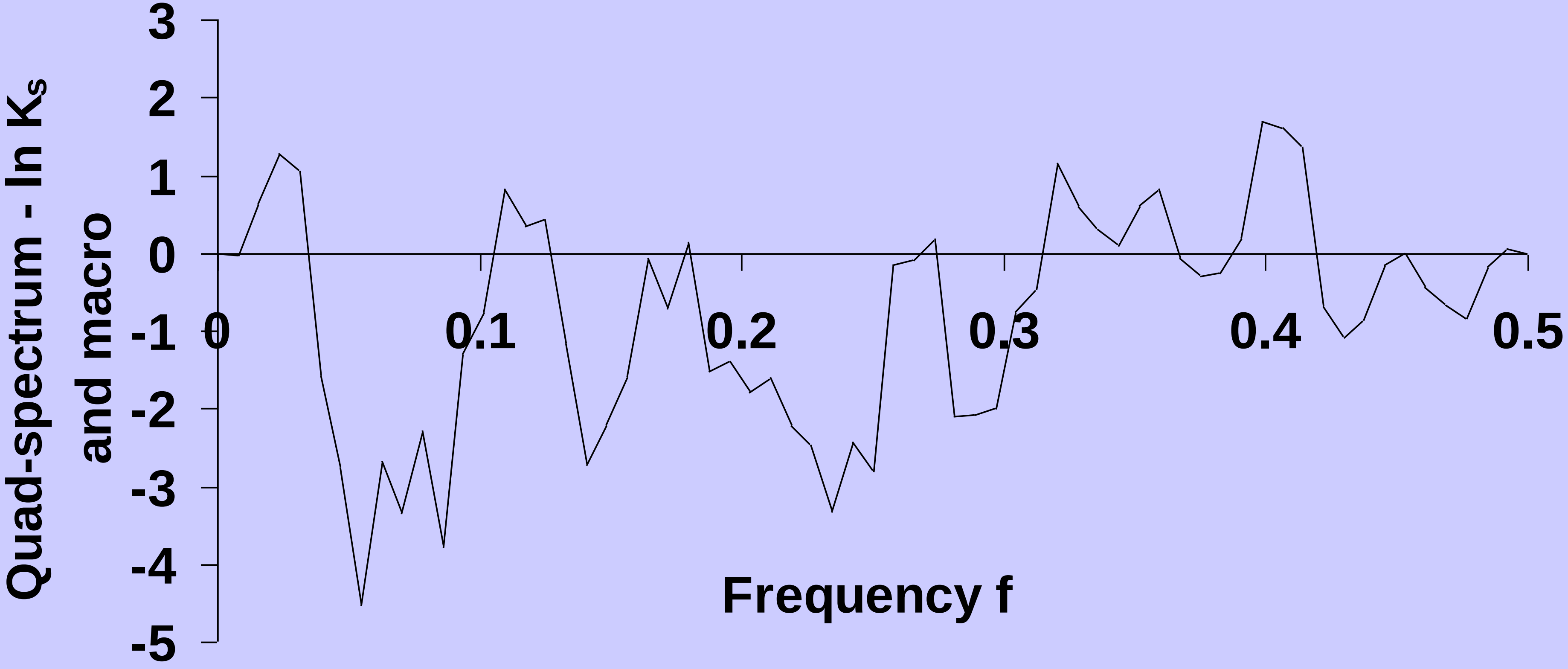


Spectrum of ln K_S
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.1
0.2
0.3
0.4
0.5
Frequency f

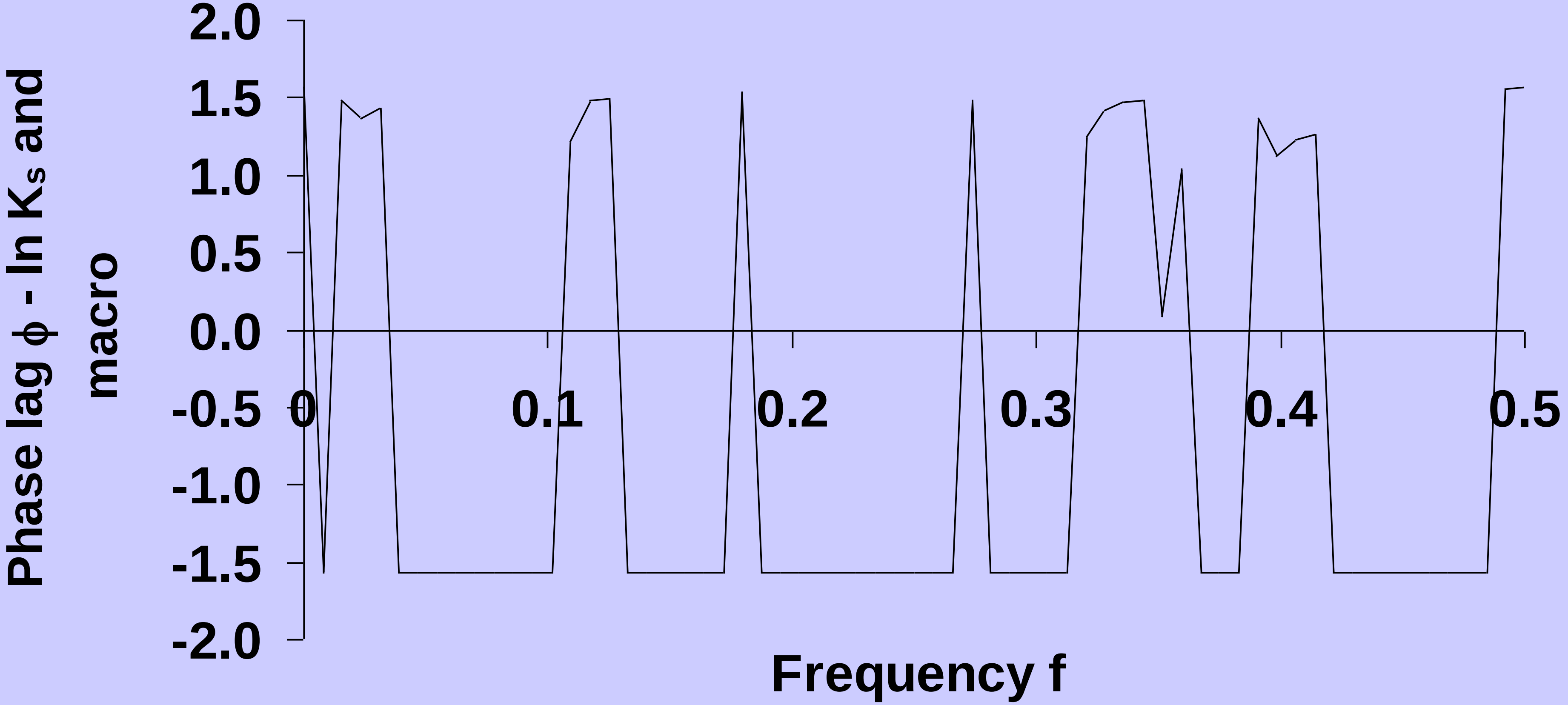

Spectrum of Macroporosity
160
120
80
40
0
0
0.1
0.2
0.3
0.4
0.5
Frequency f



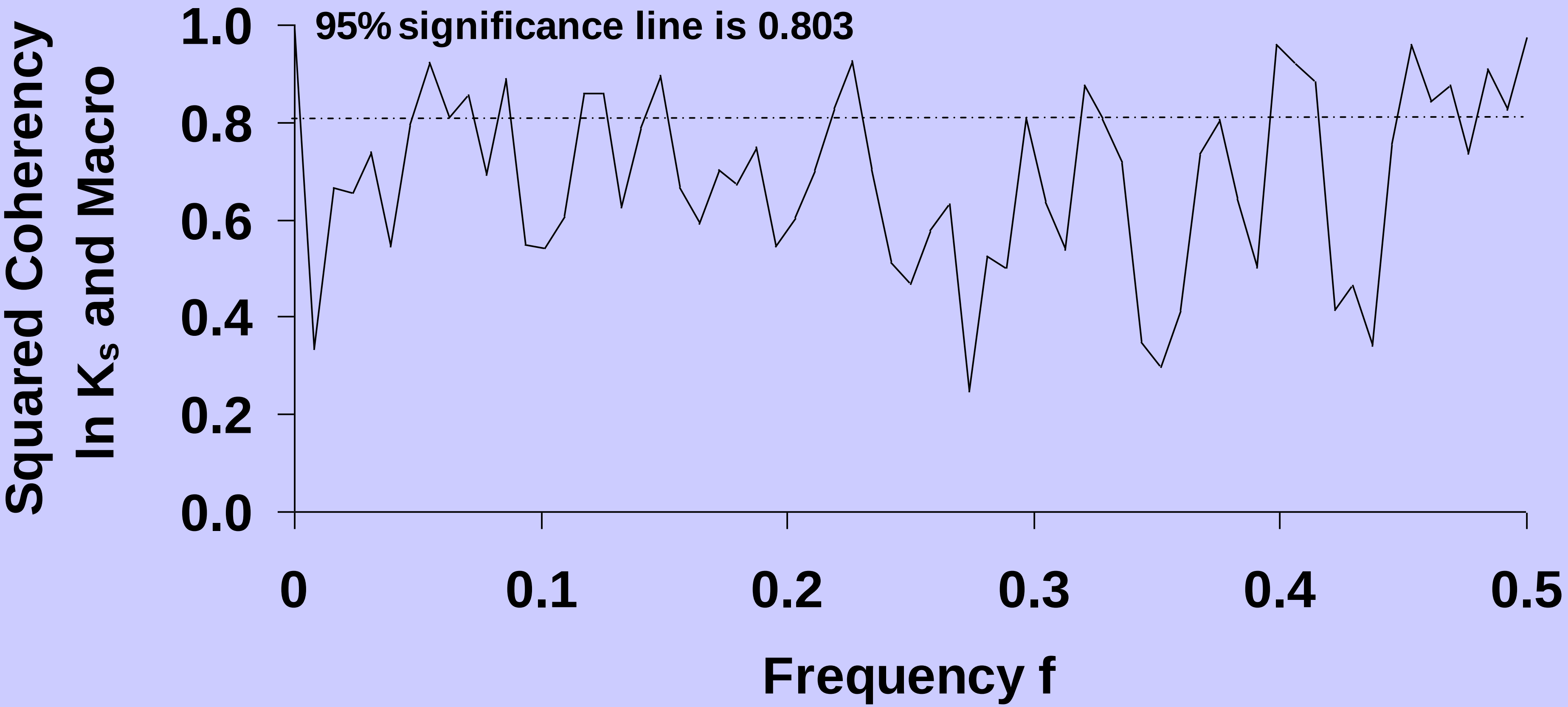
The <u>Co-spectrum</u> identifies those spatial frequencies for which two sets of observations are correlated with each other regardless of their relative location (Nielsen & Wendroth, 2003).



The Quadrature spectrum measures the contribution of the different frequencies to the total covariance of the two sets of observations when all of the cyclic variations of one set of observations are delayed by a quarter period (Nielsen & Wendroth, 2003).



The <u>Phase lag ϕ</u> (or <u>phase angle ϕ</u>) is the phase lag between oscillations of a given frequency f (Nielsen & Wendroth, 2003)



The <u>Coherency</u> is a quantitative measure of the goodness of the correlation between the two sets of observations for various frequencies f (Nielsen & Wendroth, 2003).

Wenceslau Geraldes Teixeira
Marcos Bacis Ceddia
Marta Vasconcelos Ottoni
Guilheme Kangussu Donnagema
Editors

Application of Soil Physics in Environmental Analyses

Measuring, Modelling and Data Integration

Chapter 3
State-Space Analysis in Soil Physics

Ole Wendroth, Yang Yang, and Luís Carlos Timm

Abstract Over the past three decades, state-space models have been used in soil physics mostly to describe spatial processes of transport- or biomass-related state variables. The objective of this contribution on behalf of the second Brazilian Soil Physics Meeting is to provide an introduction into the opportunities of state-space models and to explain their conceptual differences and advantages compared to current widely used analytical approaches that do not account for space/time covariance behavior, measurement or model uncertainty. An overview on the diversity of state-space model applications is provided. The opportunities of state-space models for designing and analyzing experiments with and without treatments especially

Chapter 5
State-Space Approach to Understand Soil-Plant-Atmosphere Relationships

Luís Carlos Timm, Klaus Reichardt, Cláudia Liane Rodrigues de Lima, Leandro Sanzi Aquino, Letiane Helwig Penning, and Durval Dourado-Neto

Abstract This chapter presents two different state-space approaches to evaluate the relation between soil and plant properties using examples of sugarcane, coffee and forage. These state-space approaches take into account sampling positions and allow a better interpretation of the data in relation to the field. Concepts of auto-correlation and crosscorrelation functions are first introduced, followed by theoretical aspects of both state-space approaches. More emphasis is given to the last one based on the Bayesian formulation, which gives more attention to the evolution of the estimated observations. It is concluded that the use of these dynamic regression models improve data analyses, being therefore recommended for several studies involving time and space data series, related to the performance of a given soil-plant-atmosphere system.

Research project cooperations

Soil organic carbon estimation with topographic properties in artificial grassland using a state-space modeling approach

Dongli She[1], Gao Xuemei[1], Song Jingru[2], Luis Carlos Timm[3], and Wei Hu[4,5]

[1]Key Laboratory of Efficient Irrigation-Drainage and Agricultural Soil-Water Environment in Southern China, Ministry of Education, College of Water Conservancy and Hydropower Engineering, Hohai University, Nanjing 210098, China; [2]Water Diversion and Irrigation Engineering-technology Center, Yellow River Institute of Hydraulic Research, Xinxiang 453003, China; [3]Faculty of Agronomy, Federal University of Pelotas, Department of Rural Engineering, P.O. Box 354, 96001-970, Pelotas, RS, Brazil; and [4]University of Saskatchewan, Department of Soil Science, Saskatoon, Saskatchewan, Canada S7N 5A8.
Received 27 June 2013, accepted 9 January 2014. Published on the web 17 January 2014.

She, D., Xuemei, G., Jingru, S., Timm, L. C. and Hu, W. 2014. **Soil organic carbon estimation with topographic properties in artificial grassland using a state-space modeling approach**. Can. J. Soil Sci. **94**: 503–514. Knowledge of the distribution of soil organic carbon (SOC) in artificial grasslands in semiarid areas is helpful in optimizing management for soil fertility recovery and carbon sequestration. Accurate estimation of SOC with easy-to-obtain topographic properties can save considerable labor and cost as well as protect the grassland from being disturbed by intensive soil sampling. In our study, a total of 113 sampling points were setup within a patch of artificial grassland in a small catchment located in the north Loess Plateau of China. State-space modeling and traditional linear regression were used to estimate the localized variation of SOC in the 0- to 20-cm surface soil layer using five selected topographic properties (elevation, slope, aspect, plan curvature, and surface soil roughness). Soil surface roughness and plan curvature were identified as the most effective variables for SOC estimation in state-space models. Soil surface roughness and plan curvature explained 92.5% and 84.5% of the total variation of SOC, respectively. The best state-space model was the one using both plan curvature and surface soil roughness, explaining 94.5% of the total variation of SOC, whereas the best linear regression model could only explain 15.9% of the total variation of SOC. The results indicate that all the derived state-space models performed better than the equivalent linear regression models. Our study provides an insight into the possibility of accurate estimation of SOC only using one or two easy-to-obtain topographic properties with state-space modeling approach.

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Int. Agrophys., 2014, 28, 185-194
doi: 10.2478/intag-2014-0007

State-space estimation of soil organic carbon stock

Joshua O. Ogunwole[1]*, *Luis C. Timm*[2], *Evelyn O. Obidike-Ugwu*[3], *and Donald M. Gabriels*[4]

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Received March 25, 2013; accepted January 20, 2014

A b s t r a c t. Understanding soil spatial variability and identifying soil parameters most determinant to soil organic carbon stock is pivotal to precision in ecological modelling, prediction, estimation and management of soil within a landscape. This study investigates and describes field soil variability and its structural pattern for agricultural management decisions. The main aim was

a landscape will, therefore, provide information needed to understand the structure and distribution pattern of SOC and to identify soil determinants for its prediction for informed decisions on soil management. Forests represent one of the largest carbon pools on earth (van de Walle *et al*., 2001), and

Communications in Soil Science and Plant Analysis, 00:1–19, 2014

ISSN: 0010-3624 print / 1532-2416 online
DOI: 10.1080/00103624.2014.912288

Assessment of Spatial Distribution of Selected Soil Properties using Geospatial Statistical Tools

JOSHUA O. OGUNWOLE,[1] EVELYN O. OBIDIKE,[1,2]
LUIS C. TIMM,[3] AZUBUIKE C. ODUNZE,[1]
AND DONALD M. GABRIELS[4]

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To gain additional knowledge and better understand forest soil management on a small scale, geostatistical analytical tools were employed to examine the spatial distribution in dry aggregate mean weight diameter (MWD) and other selected soil properties and to assess the possible relationships between MWD and other soil properties. Selected properties of forest soils collected along a 300-m transact in the Nimbia Forest Reserve of Nigeria exhibited moderate to high variability in distribution with sodium ion displaying the greatest variability [coefficient of variation (CV, 91.2%)] and principal component analysis revealed the exchange complex cluster as influencing total vari-

New research topics:

present

Multivariate Empirical Mode Decomposition method (MEMD)

Objective:

- to characterize scale-dependent spatial relationships between soil properties of non-stationary and nonlinear systems, into different intrinsic mode functions (IMFs) and residue representing different scales.

Huang, N.E. et al. The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc Roy Soc London A , 1998, 454:903-995.

Research Paper

Multivariate empirical mode decomposition derived multi-scale spatial relationships between saturated hydraulic conductivity and basic soil properties†

Dongli She[1,2], Jiaxing Zheng[1], Ming'an Shao[3], Luis Carlos Timm[4] and Yongqiu Xia[2,*]

DOI: 10.1002/clen.201400143

Issue

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Saturated hydraulic conductivity (K_s) is affected by various factors operating at different scales. This study identified the multi-scale spatial relationships between K_s and selected basic soil properties (soil organic matter (SOM), clay, silt, and sand contents, and bulk density) along two landscape transects (with various soil textures and land use covers) on the Loess Plateau. Multivariate empirical mode decomposition (MEMD) yielded four different intrinsic mode functions (IMFs) for the multivariate data series of each transect according to the scale of occurrence. The dominant scales in terms of explained variance of K_s were IMF1 (scale: 403 m) for transect 1, and IMF1 and IMF2 (scale: 407 and 775 m) for transect 2. The multi-scale correlation between K_s and soil properties was more complex for transect 1

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Wavelet analysis:

-to study nonstarionary spatial series locally with detail matched to their scale, i.e., broad features at a large scale and fine features at small scales (Si, B.C. - 2003 – Vadose Zone J.)

Acknowledgments:

Special thanks:

Prof. D.R. Nielsen (UCDavis)
Prof. O. Wendroth (Kentucky Univ.)