Geoderma 317 (2018) 23–31

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

Detecting nonlinearity in the spatial series of nitrous oxide emission by delay vector variance

Wenxiu Zou[a,1], Wenjun Ji[b,1], Bing Cheng Si[c], Asim Biswas[d,*]

[a] Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, No.138 Haping Road, Harbin, 150081 China
[b] Department of Bioresource Engineering, McGill University, 21111 Lakeshore Road, Ste-Anne-de-Bellevue, QC H9X 2V9, Canada
[c] Department of Soil Science, University of Saskatchewan, 51 Campus Drive, Saskatoon, SK S7N 5A8, Canada
[d] School of Environmental Sciences, University of Guelph, 50 Stone Road East, Guelph, ON N1G 2W1, Canada

ARTICLE INFO

Handling Editor: A.B. McBratney

Keywords:
Nonlinearity
Data analysis
Spatial and temporal variability
Greenhouse gas
Climate change

ABSTRACT

Soil spatial variability may exhibit nonlinearity and this has been assumed in studies without proper quantification. Owing to the complexity of underlying biogeochemical processes, greenhouse gas emission, in particular, nitrous oxide (N_2O) flux from soil, is highly variable over space and time. The goal of this work was to examine the nonlinearity associated with the spatial series of N_2O flux from soil using the delay vector variance (DVV) method. DVV uses the predictability of a spatial series in a phase-space to identify linearity/nonlinearity within a data series using a surrogate data methodology to derive a test statistic. A two-piece closed vented chamber was used to measure N_2O fluxes along a transect of 128 points located within the hummocky landscape of central Saskatchewan, Canada. There was nonlinearity associated with the spatial series of early spring and spring measurements. The uneven distribution of snowmelt water facilitated the favourable situations for denitrifying bacterial activity creating hotspots for denitrification processes. The flux measured during the fall season exhibited a nonlinear pattern, whereas the flux measured during the time of plant growth exhibited a linear pattern over space. Strong evapotranspiration demand during the growing season in the semi-arid climate of the study area controlled the hydrological processes and thus, the spatial N_2O flux measurements giving rise to a linear spatial pattern. The DVV detected nonlinearity in a spatial series will improve the understanding of the complexity of underlying soil processes.

1. Introduction

Soil spatial variability is inescapable and influences the precision of any statement that can be made about soil properties at any location (Trangmar et al., 1985). Information about soil spatial variability is necessary for enhanced agricultural and environmental management (Trangmar et al., 1985), soil quality assessment (Heuvelink and Pebesma, 1999), soil-landscape process modelling (Corwin et al., 2006), and natural resource management. Systematic studies have identified various aspects of soil spatial variability including spatial autocorrelations or dependence (Trangmar et al., 1985), periodic or cyclical patterns (Kachanoski et al., 1985), and nonstationarity (Biswas and Si, 2011; Biswas and Si, 2013; Lark et al., 2004b). Additionally, the variability of a soil property cannot be quantified by observing the effect from each factor individually and adding them subsequently. For example, soil water storage that can directly regulate the gas flux from soil may be controlled by a series of environmental factors and processes such as topography, vegetation, and rainfall. The combined influences of these factors may not be the same as the sum of the individual influences. Therefore, the processes determining variation in a soil spatial series cannot be represented using a linear function or equation (Biswas et al., 2013; Pai and Palazotto, 2008). In this situation, the spatial series may exhibit nonlinearity because of the nonlinear responses from underlying soil processes. While other fields of science may define nonlinearity differently (Emanuel, 1997; Jaksic et al., 2016; Mandic et al., 2008; Schreiber, 1999), in this manuscript, we refer to the outcome of nonlinear responses from underlying soil processes on the spatial series of soil measurements.

Geostatistical, spectral and wavelet analyses have been used for characterizing, simulating and interpolating spatial series in soils. However, all these methods assume the data series of soil properties created by the underlying soil processes that can be represented by a linear function. The variability of soil properties is controlled by numerous environmental factors and processes that may affect soil

* Corresponding author.
E-mail addresses: wxzou_540@163.com (W. Zou), wenjun.ji@mail.mcgill.ca (W. Ji), bing.si@usask.ca (B.C. Si), biswas@uoguelph.ca (A. Biswas).
[1] Contribution equally shared between two first authors.

https://doi.org/10.1016/j.geoderma.2017.12.023
Received 17 September 2017; Received in revised form 8 November 2017; Accepted 20 December 2017
Available online 30 December 2017
0016-7061/ © 2017 Elsevier B.V. All rights reserved.

individually, or in combination. Therefore, the spatial series of soil properties resulting from these complex interactions and their variability may cause a spatial series, that may not be represented by a linear function (Biswas et al., 2013). Even though the soil system is fundamentally deterministic (variations in soil properties are caused by the underlying processes and they are not random), it may exhibit some degree of randomness. The randomness may arise from the underlying strong variability of environmental factors and processes and may not show any predictable behaviour over space. Therefore, nonlinearity is one of the important aspects associated with a spatial series and needs to be examined for quantifying soil spatial variation.

Nonlinear Dynamical System Theory (Fuchs, 2013) has been used to explain the long-term quantitative behaviour of dynamical systems such as physical and biological. It studies the nature and workable solutions of phenomena that is variable over time and often mechanical and physical in nature. It concentrates more on understanding the system's behaviour over time than determining the actual solutions of the causes that have been used to explain and/or predict nonlinear evolution of soil formation (Phillips, 1998), ecological data (Turchin and Taylor, 1992) or complex soil systems (Culling, 1988). Similar to others methods, such as the spectral analysis, this time series based method (Nonlinear Dynamical System Theory) can be extended to study complex spatial soil systems (Millan et al., 2009). The variability of a spatial series where soil properties are measured as a function of spatial positions along a given direction, could be associated with a nonlinear response of many interacting variables and expressed as a stochastic or a deterministic function of measurement locations (Millan et al., 2009; Phillips, 1998; Phillips, 2008). However, unlike temporal measurements, there will be fewer variables that can be measured within a narrow range of spatial scales to analyze soil as a complex physical system. Therefore, alternative methods are required to quantify the spatial variability of soil properties with limited length of a spatial series.

Comparing several established nonlinearity analysis methods including deterministic versus stochastic plots (DVS) (Casdagli, 1992) and traditional nonlinearity matrices (Schreiber and Schmitz, 1997), such as third order autocovariance, time reversibility-based measure of deviation and δ-ε method (Kaplan, 1994), Gautama et al. (2004) introduced the delay vector variance (DVV) in detecting determinism and nonlinearity. The DVV assesses a series than a system as nonlinear and can be connected as the variations of a soil spatial series is the representation of underlying soil and environmental processes (Si, 2008). It characterizes a series based on its predictability and compares those obtained from linearized version of the series, i.e. surrogate data. The surrogate series are generated from the original series after destroying the underlying pattern. Thus, a comparison of DVVs between the unknown original series and the linearized version of the original series or surrogates may reveal the presence or absence of nonlinearity. Basically, it verifies if the series was generated by a linear stochastic system (Jaksic et al., 2016) or in the context of this manuscript, if the soil spatial series are generated by the linear response of underlying soil processes. It tests a series' deterministic-stochastic and linear-nonlinear behaviour simultaneously (Mandic et al., 2008). It is robust even in the presence of noise, straight forward to interpret and visualize, and does not require any prior knowledge of the series yet shows superior performance over other available methods (Gautama et al., 2004). It has been successfully used in many fields, including biomedical and health sciences (Mandic et al., 2008), mechanical engineering (Schreiber, 1999), construction engineering (Jaksic et al., 2015) and others mainly as time series analysis methods but shows strong promise to characterize nonlinear soil spatial variability.

Nitrous oxide (N_2O) is an important greenhouse gas contributing about 5% of the increased greenhouse effect (IPCC, 2007). Agriculture is one of the major sources of N_2O emissions contributing up to 84% of the global anthropogenic N_2O emissions (IPCC, 2007) and up to 70% of Canadian anthropogenic N_2O emissions (Environment Canada, 2008). N_2O emissions from agricultural soils are typically intermittent across the landscape and exhibit strong spatio-temporal variability in a complex way (Lark et al., 2004a; Lark et al., 2004b; Nieder and Benbi, 2008; Yates et al., 2006) and the emission rate is scale dependent (Milne et al., 2011; Milne et al., 2013; Yates et al., 2007). The processes that make the emission transient includes both denitrification and nitrification, although the former is generally more important. As the supply of the substrate to the denitrifying bacteria is limited to the micro sites, the control of denitrification is marked by nonlinear processes (Lark et al., 2004a; Lark et al., 2004b; Webster and Goulding, 1989). The water filled pore space (WFPS), as controlled by soil water content, is often determined in part by topography (Groffman and Tiedje, 1989), and is considered as the primary environmental factor controlling N_2O emissions from soil (Tian et al., 2015). Another key physical factor is soil temperature that determines the activity of soil microorganisms and controls N_2O emission (Creze, 2015).

The spatial variability of N_2O emissions from soil has been studied using advanced analysis techniques including wavelets (Lark et al., 2004a; Lark et al., 2004b; Milne et al., 2011; Milne et al., 2013; Yates et al., 2006; Yates et al., 2007). These studies used wavelet analysis to examine the spatial variability of N_2O emission that exhibited nonstationarity in the spatial series. Similarly, a spatial series can also exhibit nonlinear behaviour due to the nature of underlying soil processes (Anthony et al., 1995; Kroon et al., 2008; McSwiney and Robertson, 2005; Shcherbak et al., 2014) and thus, needs to be analyzed or examined. Therefore, the objective of this manuscript was to examine if the spatial series of N_2O emissions from soil exhibit nonlinearity using the delay vector variance. This will provide a framework for examining the presence or absence of nonlinearity in a spatial series of soil properties and can be used elsewhere.

2. Theory

The Delay Vector Variance (DVV) method characterizes a spatial series based upon its predictability and compares the results to those obtained for linearized versions of the series that are known as surrogates. The success of this method depends on two steps; 1) generation of the surrogate series, and 2) the test of nonlinearity.

2.1. Surrogate series generation

The nonlinearity analysis was performed by computing a test statistic for the original series based on 99 surrogates (this allowed for a one tailed statistical rank test at the level of 0.01). Surrogates are the realization of a composite null hypothesis and are generated from the linear and stationary processes driven by a Gaussian white noise input. The output of surrogates is the amplitude transformed by a zero-memory observation function (Gautama et al., 2004). Among the available methods for generating surrogate series (Schreiber and Schmitz, 2000), a well known is Iterative Amplitude Adjusted Fourier Transform (IAAFT), which is derived from the Amplitude Adjusted Fourier Transform (AAFT) (Theiler et al., 1992). The surrogates generated using IAAFT maintains the probability density functions and the power spectrum of the original series was used in this study. The surrogates were generated following the steps outlined below (Schreiber and Schmitz, 1996).

i. The spatial series$\{s_n\}$, $n = 1, \ldots, N$ was rank ordered according to a set of Gaussian random numbers. The sorted series $s_n{}' = g(s_n)$, followed the same spatial distribution as the original series, $\{s_n\}$ but Gaussian.
ii. The surrogates of $\{s_n{}'\}$ were phase randomized and marked them $\{\tilde{s}_n'\}$.
iii. The rescaling g was inverted by rank ordering $\{\tilde{s}_n'\}$ according to the distribution of the original series, $\{\tilde{s}_n = \overline{g}(\tilde{s}_n')\}$.
iv. Amplitudes of the Fourier transform of the sorted series $\{S_n\}$, were

Download English Version:

https://daneshyari.com/en/article/8894204

Download Persian Version:

https://daneshyari.com/article/8894204

Daneshyari.com