ASSESSMENT OF NITRATE-NITROGEN LEACHING IN A PADDY FIELD USING MULTIVARIATE STATISTICAL TECHNIQUES

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Introduction

The detrimental impacts of nitrogen losses from agricultural lands on environmental quality have long been recognized. Nitrate-Nitrogen (NO3-N) leached from agricultural fields elevates nitrogen concentrations in groundwater and surface water bodies which contaminates drinking water supplies and enhances eutrophication of surface waters causing hypoxia problems (Gilliam et al., 1999). Nitrogen is an essential plant nutrient, which is taken up by the crops throughout the growing season. From a public health standpoint, the protection of groundwater quality has become an important concern for many communities. Nitrate is the most common nutrient in groundwater (Nolan and Stoner, 2000) and is the most ubiquitous groundwater contaminant in the world (Spalding and Exner, 1993). Human consumption of water with elevated levels of nitrate has been linked to the infant disorder methemoglobinemia (Fewtrell, 2004, Fan and Steinberg, 1996) and to non-Hodgkin's disease lymphoma in adults (Freedman et al, 2000).

Leaching is often the most important pathway for loss of mineral nitrogen from arable soils. Leaching is a direct loss of nitrogen resources, both agronomically and economically. Nitrate leaching potential depends on soil properties, crops and crop rotation, irrigation methods, management practices and climatic parameters. In the rooting zone nitrogen is important for satisfactory plant growth and yield, but once it has moved below this layer it will no longer contribute to crop production but now represents a contaminant species to both surface and subsurface water resources.

Objectives

The general objective of using multivariate statistical techniques is to delineate the principle components and temporal variations of nitrate leaching. The specific objectives are:

1. To explain the variance of intercorrelated data whilst identifying contributory factors to nitrate leaching using PCA.
2. To determine the temporal variations of nitrate leaching by discriminant analysis.

Methodology

Study area

The study site is known as Ladang Merdeka Ismail Mulong. It is situated in Kampung Mulong Lating, about 10 km from Kota Bharu and 12 km from Ketereh, Kelantan. The approximate location is 06^0 02.005N-102^0 15.62E.

Field measurements

Lysimeter installation

Three lysimeter each of $1m^2$ in size (1m x 1m) was installed to a depth of 1 m in two adjacent plots in the study area. Lysimeters were used to avoid any movement of substances or water whether from or into the lysimeters.

Soil water sampling

Soil water solution was collected using soil water samplers (porous ceramic cups or suction cups). Soil water existing in the soil pores were collected by soil water samplers having diameter of 4.8 cm (model 1900, Soil moisture Equipment Co.). Vertical holes were dug at each of the drainage lysimeter on the paddy plot with a hand auger at depth of 10, 20, 30 and 40 cm. A total of 12 soil water samplers were used each time. Vacuum pressure of 80 cb was applied to each sampler before sampling. The soil water was sampled before cultivation, after fertilization and after harvest. Sampling was carried out approximately every 3 weeks according to the existing management practices. The soil water was collected for two seasons. The water samples were analyzed for nitrate-nitrogen concentration using the standard method (APHA, 1998). At the end of the season when no irrigation water supply was required, soil samples were collected instead from each lysimeter at the same depth increments using a soil core sampler. The water from soil was extracted with potassium chloride and analyzed for nitrate by cadmium reduction method (Bremner et al, 1965).

Determination of pressure and hydraulic head using tensiometers

Tensiometers are used in measuring the energy status of water in soil (Cassel and Klute 1986). The vertical gradients measured with the tensiometers and the hydraulic conductivity of the soil material can be used to calculate a flux of water moving within the profile (Cooper, 1980; Sophocleous and Perry, 1985; Moutonnet and Fardeau, 1977). Two tensiometers were installed in each lysimeter at a depth of 15 and 45 cm to measure the soil pressure. Data gathered with the tensiometers were used in the calculations of the pressure head, and hydraulic head, hydraulic gradient and the downward water flux.

Determination of water flux

In this study, Darcy's law was used for estimation of water flux (Odhiambo and Murthy, 1996; Singh et al., 2001 and Yu H-M et al 2006) and is given as:

$q= -Ks \ dH/dz$

Where q= water flux (mm/day) , Ks the saturated hydraulic conductivity (mm per day) and dH/dz is the head gradient.

Multivariate statistical methods

PCA is a powerful pattern recognition technique to explain the variance of a large set of intercorrelated variables with a smaller set of independent variables (principal components). Therefore, it is basically for classification and data reduction. The eigenvalues of the PCs are a measure of their associated variance, the participation of the original variables in the PCs is given by the loadings, and the individual transformed observations are called scores. A varimax rotation allows to `clean up' the PCs by increasing the participation of the variables with higher contribution, and by simultaneously reducing that of the variables with lesser contribution (Aruga et al, 1993, Helena et al, 2000 and Mandal et al, 2007).

DA was used to determine the variables, which discriminate between two or more naturally occurring groups. It operates on raw data and the technique constructs a discriminant function for each. It can confirm the group found by PCA. In this case, two groups for temporal (wet and dry seasons) evaluation was selected. DA was performed on each raw data matrix using standard, forward stepwise and backward stepwise modes in constructing discriminant functions to evaluate the temporal variations for leaching activity (Hussain et al 2008 and Shrestha et al 2007). The seasons (wet and dry) were the grouping dependent variables, whereas all the measured and calculated parameters constituted the independent variables.

Results and Discussion

1. Principal Component Analysis, PCA

Table 1 :
Principal component loadings.

Variables	PC1	PC2	PC3	PC4
nitrate	-0.270	-0.042	***1.010***	0.052
h2	0.312	***0.907***	-0.111	-0.093
h1	***0.937***	0.288	-0.146	0.149
H1	***0.938***	0.298	-0.153	0.101
H2	0.312	***0.907***	-0.111	-0.093
ΔH	***-0.964***	-0.001	0.134	-0.152
Δz	0.258	-0.101	0.088	***0.926***
dx	-0.388	***0.741***	-0.113	-0.363
dH/dz	***0.955***	-0.008	-0.122	0.227
q=cm/hr	***0.824***	-0.007	-0.077	0.213
rainfall	***0.511***	***-0.648***	0.033	-0.341
ET	***0.796***	-0.391	0.010	-0.003
Temp	0.491	-0.168	-0.201	0.256
Eigenvalues	6.636	3.836	2.315	1.608
% variance	35.274	17.868	18.440	13.091
%cumulative	35.274	53.142	71.585	84.676

* Figures in italics and bold indicate absolute greater than 0.5

Principal component analysis was applied to the data sets containing 13 variables. The input data matrices were 140 X 13 for the PCA analysis. PCA evolved three PC’s with eigenvalue >1, explaining 83.71% of the total variance with respective to leaching activity at the study area. Same numbers of PC’s were also obtained after varimax rotation. The corresponding PC’s, variables loadings and variance explained are presented in Table 1.

The PCA was carried out by diagonalization of the correlation matrix, so the problem of different numerical ranges of the original variables was avoided, since all variables were scaled to variance unit and contributed equally. Table 1 summarized the PCA results including the loadings and the eigenvalues of each PC after varimax rotation. There were several criteria to identify the number of PC’s to be retained in order to understand the underlying data structure (Jackson, 1991).

Factors with eigenvalues greater than 1 were taken into account and fine tune by varimax rotation. Four independent factors were extracted which explained 84.7% of the total variance. The first one was responsible for 35.3% of the total variance and was represented by h1(pressure head), H1(hydraulic head), ΔH (hydraulic head gradient), dH/dz (hydraulic gradient), q (flux), rainfall and evapotranspiration. PC2 explained 17.87% of the total variance and was mainly participated by h2 (pressure potential), H2 (hydraulic head), dx(distance) and rainfall. In PC3 it gave 18.4% of the total variance and was contributed by nitrate concentration. Additional 13.09% was explained in PC4 and contributed by Δz (change in gravitational head).

2. Temporal variations in leaching activity- Disriminant Analysis, DA

Table 2: Classification matrix for discriminant analysis of temporal variation in leaching activity.

Monitoring seasons	% correct	Season assign by DA	
1.Standard mode		Dry	Wet
Dry	100.0	35	0
Wet	0.00	15	0
2. Forward stepwise DA			
Dry	100.0	35	0
Wet	100.0	0	15
3. Backward stepwise			
Dry	100.0	35	0
Wet	0.00	15	0

Both the standard and backward stepwise mode yielded the corresponding CM's assigning none is correct for the wet season but 100.0 % correct for dry season. However, with forward stepwise mode DA gave CM's with 100.0% of the cases correctly using only seven discriminant parameters. Thus the temporal DA results suggest that pressure head (h), hydraulic gradient (ΔH), flux (q), rainfall and temperature are the most significant parameters to discriminate between the two seasons which means that these seven parameters are affected by change in season.

Significance of study

1. Principle component analysis was able to extract four independent factors which explained 84.7% of the total variance. Data reduction is obtained because only four PC's are required to describe more than 80% of the entire dataset variability without loss of information. PC loadings also showed that greatest positive PC1 loadings. Soil physical properties namely pressure potential of the soil and hydraulic gradient influences nitrate leaching of the study area rather than nitrate concentration in the soil and climatic factors.

2. Discriminant analysis was able to determine the data that best discriminate between wet and dry season. Results suggested that pressure head (h), hydraulic gradient (ΔH), flux (q), rainfall and temperature are the most significant parameters to discriminate between the two seasons. It confirms the result

obtained from PCA for pressure head and hydraulic gradient as important parameters for studying nitrate leaching in this area.

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