Computers & Geosciences 37 (2011) 1642–1652

Contents lists available at ScienceDirect

Computers & Geosciences

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

Integrating spectral indices with environmental parameters for estimating heavy metal concentrations in rice using a dynamic fuzzy neural-network model

Meiling Liu [a], Xiangnan Liu [a,*], Menxin Wu [b], Lufeng Li [a], Lina Xiu [a]

[a] School of Information Engineering, China University of Geosciences, Beijing 100083, China
[b] National Meteorological Center/CMA, Beijing 100081, China

ARTICLE INFO

Article history:
Received 31 October 2010
Received in revised form
7 March 2011
Accepted 12 March 2011
Available online 1 April 2011

Keywords:
Dynamic fuzzy neural-network model
Environmental parameters
Spectral indices
Heavy metal concentrations

ABSTRACT

A generalized dynamic fuzzy neural network (GDFNN) was created to estimate heavy metal concentrations in rice by integrating spectral indices and environmental parameters. Hyperspectral data, environmental parameters, and heavy metal content were collected from field experiments with different levels of heavy metal pollution (Cu and Cd). Input variables used in the GDFNN model were derived from 10 variables acquired by gray relational analysis. The assessment models for Cd and Cu concentration employed five and six input variables, respectively. The results showed that the GDFNN for estimating Cu and Cd concentrations in rice performed well at prediction with a compact network structure using the training, validation, and testing sets (for Cu, fuzzy rules = 9, R^2 greater than 0.75, and RMSE less than 2.5; for Cd, fuzzy rules = 9, R^2 greater than 0.75, and RMSE less than 1.0). The final GDFNN model was then compared with a back-propagation (BP) neural network model, adaptive-network-based fuzzy interference systems (ANFIS), and a regression model. The accuracies of GDFNN model prediction were usually slightly better than those of the other three models. This demonstrates that the GDFNN model is more suitable for predicting heavy metal concentrations in rice.

1. Introduction

Crop contamination by heavy metals from agricultural sources has affected food security and threatened human health in many developed and developing countries in recent years (Rodriguez et al., 2007). However, accurate and fast detection of heavy metal concentrations for crops growing in agricultural soil over large areas is difficult and challenging. Traditionally, the assessment of heavy metal contamination in crops has been carried out through soil testing, crop tissue analysis, and long-term field trials in sequential steps with increasing complexity and cost. With the arrival of hyperspectral data, quick monitoring of crop stress under heavy metal pollution over large areas has become feasible (Collins et al., 1983; Liu et al., 2010a). This is because hyperspectral remote sensing has many advantages over other methods, such as the ability to detect variations in biochemical composition, in situ sampling, lower cost, faster data acquisition, and better spatial and temporal continuity. Great progress has been made in identifying crops with heavy metal stress using hyperspectral remote sensing (Chen et al., 2007; Ren et al., 2008; Chi et al., 2009), but the existing work recognizes that spectral parameters lack the sensitivity needed for estimating heavy metal concentration in plants directly (Kooistra et al., 2001, 2004). To improve the sensitivity in obtaining macrolevel data about the precise levels of heavy metal pollution applicable to agroecosystems, environmental parameters, including those relating to soil and weather that serve as important factors determining heavy metal diffusion in crops, should be taken into account as potential parameters for assessing heavy metal concentrations in crops (Jung and Thornton, 1997; Zeng et al., 2011). By combining hyperspectral data with environmental factors, which can be as readily available as spectral indices, accurate and fast detection of heavy metal concentrations in crops over large areas can be achieved. Therefore, the development of a method for effectively integrating spectral and environmental parameters is of great interest for evaluating heavy metal concentrations in crops. It is well known that fuzzy neural-network (FNN) models can serve as a powerful tool for dealing efficiently with imprecision and nonlinearity, as well as for determining input–output relationships for complex systems, based on the strength of their interconnections presented in a set of sample data. Since FNN combines a neural network and a fuzzy logic system by carrying out fuzzy reasoning within the structure of a neural network (Lin and Lin, 1997), it not only is able to express fuzzy knowledge and carry out fuzzy reasoning, but it also is strong in learning ability, nonlinear mapping, and data processing ability within the neural network. Moreover, this FNN was selected because it allowed consideration of the neural network not as a black box model,

* Corresponding author. Tel.: +86 10 82321796; fax: +86 10 82322095.
E-mail addresses: liumeiling427@126.com (M. Liu), liuxncugb@163.com (X. Liu).

0098-3004/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.cageo.2011.03.009

but as a model able obtain rules with a physical meaning from experimental data.

Research on FNN has recently become an important issue, and some progress has been made (Buckley and Hayashi, 1994; Ouenes, 2000; Liao and Tsao, 2004). A few researchers have developed different fuzzy neural network models, such as the adaptive-network-based fuzzy inference system (ANFIS) (Jang, 1993; Ertunc and Hosoz, 2008; Moghaddamnia et al., 2009), the self-organizing fuzzy neural network (SOFNN) (Leng et al., 2005), the dynamic fuzzy neural network (DFNN) (Wu and Er, 2000), and generalized dynamic fuzzy neural networks (GDFNN) (Er et al., 2004; Wen and Zhu, 2004; Zhu et al., 2007). They have developed a number of applications for solving a range of real world problems. Compared with other fuzzy neural networks, GDFNN is highly accurate and has a compact structure based on new adding and pruning techniques, with an ellipsoidal basis function (EBF) in hidden layers of the network. Thus, GDFNN was adopted in this study. The objective of this research was to apply the GDFNN model to estimate heavy metal concentrations in rice samples using a combination of spectral indices and environmental parameters.

2. Materials and methods

2.1. Study area

To develop a model for estimating the heavy metal concentration in rice, the three experimental fields with different heavy metal contamination levels were selected. The fields (43°52.2′N–44°06.3′N, 125°10.2′E–125°10.4′) are located in Changchun city, Jilin province, China. The site is within the temperate continental climate zone, with a mean annual rainfall of 522–615 mm; soils are dominated by black soils. The plant selected in this site is rice, which is one of the most important crops in China. The rice growing in the field was cultivated scientifically and supplied with abundant fertilizers, manures, and irrigation water to avoid other environmental factors causing unwanted stress. The main physicochemical characteristics of the soil are displayed in Table 1. As seen in Table 1, the average values of total carbon (C), total nitrogen (N), total potassium (K), and total phosphorus in the soil were 0.19%,1.92%, 1.12% and 0.65 g kg^{-1}, respectively. The field experiment has soils with Cu and Cd concentrations above the background level; other heavy metal elements were lower than the background level. Since the rice is not affected by nutrient deficiency, water stress, etc., it could be hypothesized that rice was mainly influenced and stressed by Cu and Cd.

2.2. Data collection

The data sets collected included hyperspectral data, meteorological data, soil data, and concentration data for heavy metals in rice.The spectral data collection was carried out during four days during a typical rice growth season: 8 July, 4 August, 29 August, and 18 September 2008, which corresponded to the seeding, tillering, booting, and mature growth stages of rice. All spectral measurements were taken under cloudless or near-cloudless conditions between 10:00 and 14:00, using an ASD FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, Co., USA). This spectrometer was fitted with fiber optics having a 10° field of view, and was operated in the spectral region 350–2500 nm with sampling interval 2 nm. Reflectance spectra were measured through calibration with a standardized white Spectralon panel. A panel radiance measurement was taken before and after the crop measurement with two scans each time. The measurements were carried out from 1.0 m above the rice canopy. Each site was scanned 10 times and these measurements were then averaged for the particular sites.

Crop and soil sampling were done almost synchronously with canopy spectral reflectance measurements. The leaves from rice plants and soil from sample sites were collected and placed into respective sealed plastic bags to obtain biochemical compositions, such as nutrient elements and heavy metal concentrations. The 120–160 samples from heavy metal of crop leaves were collected at each growth stage of rice. Heavy metal concentrations in soil and rice were determined by an atomic absorption spectrophotometer (AAS) (Spectr AA 110/220, Varian, USA). Total C, total N, and total K were measured by an elemental analyzer (Leco, USA), and total phosphorus in the soil were determined by a spectrophotometer analyzer (751GD, Shanghai Metash Instrument Co. Ltd.) at the Chinese Academy of Agricultural Sciences (Bao, 2005). Spectral indices were derived from original reflectance. A number of studies have demonstrated that the spectral shift of plants induced by heavy metal pollution occurred in both the visible and the near-infrared (NIR) parts of the spectrum (Kooistra et al., 2004). To improve the accuracy in estimating heavy metal concentrations in rice, spectral indices sensitive to

Table 1
The physical and chemical properties of the soils in the experimental fields (mean+S.D.).

Heavy metal concentrations	Cu (mg/kg)	Zn (mg/kg)	Pb (mg/kg)	Cr (mg/kg)	As (mg/kg)	Cd (mg/kg)
Background value[a]	20.8	63.2	26.7	60.1	10.2	0.078
Measured value	54.78+2.58	58.06+6.03	19.51+4.05	15.79+6.56	9.39+0.88	0.35+0.01
Measured other soil property	Total carbon (%)	Total nitrogen (%)	Total phosphorus (g/kg)	Total potassium	pH	Organic matter (%)
	0.19+0.03	1.92+0.41	0.65+0.09	1.12+0.32	6.8+0.1	2.8+0.15

[a] Soil quality standard according to the Environment Monitoring Centre of China.

Table 2
Five spectral indices used as input variables of the GDFNN model.

Spectral indices	Wavebands (nm)	Formula	Reference
REP	680–760	$D_{\lambda_i}=\frac{R(\lambda_{i+1})-R(\lambda_{i-1})}{\lambda_{i+1}-\lambda_{i-1}}$, when D_{λ_i} is maximum value spectra between the red and NIR	Chang and Coll1ins (1983)
OSAVI[670,800]	670, 800	$\mathrm{OSAVI}=(1+0.5)(R_{800}-R_{670})/(R_{800}+R_{670}+0.5)$	Huete (1988)
RVI[700,750]	700, 750	$\mathrm{RVI}=R_{750}/R_{700}$	Schuerger et al. (2003)
NDVI[695,760]	695, 760	$\mathrm{NDVI}=\frac{R_{760}-R_{695}}{R_{760}+R_{695}}$	Schuerger et al. 2003
DVI[682,734]	682, 734	$\mathrm{DVI}=R_{734}-R_{682}$	Kooistra et al. (2004)

Note: R_i is the reflectance of band *i*.