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Linking hydro-meteorological factors to the assessment of nutrient loadings to streams from large-plotted paddy rice fields

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ABSTRACT

Excessive nutrient loadings from rice paddy fields has been a great concern in Korea as rice paddy area spans over 1,153,000 ha, which covers approximately 60% of the total agricultural land area in Korea. The principal tasks of this study included undertaking work to better identifying the scope of the nutrient loadings from paddy fields to assess their adverse effects. Hydro-meteorological factors, rainfall and surface discharge, were considered as the major driving forces of nutrients into the water. A Generalized Regression Neural Network (GRNN) model was applied and its capability evaluated to predict the nutrient loading into the neighboring water. The 15 ha paddy fields surrounded by drainage and irrigation channels were chosen as a study area. Field data, such as rainfall, quantities of irrigation and discharge water, and nutrient contents (total nitrogen (T-N) and total phosphorus (T-P)) from two different water sources, were obtained throughout the study period. Simulation results showed that surface discharge had a positive correlation with rainfall (R = 0.84). In addition, the resulting predictions for nutrient concentrations corresponding to surface discharge were varied (R = 0.72 and 0.40 in total nitrogen and total phosphorus, respectively). This study found that both natural and artificial variations of nutrient contents in irrigation streams were significantly influenced the model results of nutrient predictions. Therefore, the nutrient loadings into the neighboring water can be accurately described with a more comprehensive and sufficient representation of both environmental inputs and hydrological processes.

1. Introduction

The production of proteins, chlorophyll, stimulation of root development, flowering, and the prevention of disease and stress are all dependent upon the presence of nitrogen and phosphorus (Cho et al., 2002). Thus, total nitrogen (T-N) and total phosphorus (T-P) have been known as essential nutrients in crop or plant growth. In spite of their important roles in plant growth, excessive concentration of nitrogen and phosphorus in water can cause eutrophication. This results in over-nourishment, reduction of light penetration, depletion of dissolved oxygen in surface water, and production of toxins that are potentially poisonous to fish, cattle, and humans by causing changes in their biological structure (Karul et al., 2000). To properly manage watershed water quality in Korea, total maximum daily loads (TMDLs) for T-N and T-P have been adopted, particularly to control excessive fertilization, leading to eutrophication of surface water (Lee et al., 2005). Nitrogen

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and phosphorus stem from various point and non-point sources such as domestic and industrial wastewater discharge, runoff from forestry and agriculture, and atmospheric deposits. A considerable proportion of the nutrients that endanger inland waters originate from agricultural land (Kim et al., 2004).

Despite the evidence of agricultural non-point pollution sources, there exists little data in regards to the extent to which they participate in the deterioration of water quality. The capability of streams to export nutrients is controlled by many factors, such as runoff, geomorphologic properties (topology, vegetation, soil type, etc.), and other climatic factors (rainfall, temperature, etc.) of the watershed. Particularly, the dynamic interactions between nutrients and surface discharge water have been a worldwide concern for many years because draining directly involves the transfer of dissolved and fixed forms of total nitrogen and phosphorus into water bodies (Werner and Wodsak, 1995; Steinheimer et al., 1998). However, it has been a challenge to define the interactive process of surface water discharge–nutrient transport due to the extreme non-linearity of the hydrologic process and watershed-dependence on geological conditions (Sarle, 1994). The full understanding of this process is difficult, causing the limited capability of the process-oriented models because all underlying physical processes need to be known in order to use these models (Bhattacharya and Solomatine, 2000). Although such models exist and have become more elaborate, their application is impeded by the large amount of specific data required, which are not readily available (Arnell, 1996). In addition, agricultural circumstances in Korea, such as limited farmland, small-scale farming, and complex land-uses, brought more complicated dynamics to apply these physical-based modeling tools. Therefore, researchers have been devoted to seek alternatives which are based on a limited knowledge of the modeling process and rely on data to describe input and output characteristics (Solomatine, 2002). During the last decade, such models became popular due to the availability of data of which artificial neural networks (ANNs) appear to be the most popular modeling method.

In this study, GRNN, one of the well-known algorithms in ANNs, was applied to evaluate the quantitative assessment of nutrients from agricultural watersheds. This method was introduced by Specht in 1991 and estimates the most probable value for continuous dependent values of a given dataset. It computes the probability density functions of the given patterns and finally attributes them to the values to which they most likely belong (Specht, 1991). During the past decade, the application of the GRNN model has made incredible progress in the simulation for extremely non-linear processes. Owing to the fact that it does not require much knowledge on watershed characteristics and hydrological processes, it has been successfully used in many applications (Zaghloul and Kiefa, 2001).

The specific objectives of this study include: (1) monitoring the water quantity and quality of neighboring streams which receive surface discharge water from agricultural paddy fields and (2) assessing the feasibility of the use of GRNN to predict surface discharge and nutrient concentrations corresponding to time-dependent rainfall and surface discharge data.

2. Model description

2.1. Generalized Regression Neural Network

Generalized Regression Neural Network (GRNN) is a one-pass learning algorithm that can be used for the estimation of continuous variables, and converges to the underlying regression surface. It is a feed-forward neural network based on the non-linear regression theory consisting of four layers: the input layer, the pattern layer, the summation layer, and the output layer.

The number of normalized input units in the first layer is equal to the total number of experimental parameters. The first layer is fully connected to the second, the pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. An exponential activation function is applied and the corresponding activation level is forwarded to the summation layer (S-summation and D-summation neurons, where the density estimate on each pattern of each group or possible value is summarized). The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value to an unknown input vector x as

$$\hat{y}_i(x) = \frac{\sum_{i=1}^{n} y_i \exp[-D(x, x_i)]}{\sum_{i=1}^{n} \exp[-D(x, x_i)]} \quad (1)$$

where n indicates the number of training patterns and y_i is the target output value corresponding to the ith input pattern. The Gaussian kernel function in (1) is defined as

$$D(x, x_i) = \sum_{j=1}^{p} \left(\frac{x_j - x_{ji}}{\sigma} \right)^2 \quad (2)$$

where p indicates the number of elements of an input vector. The x_j and x_{ji} represent the jth element of x and x_i, respectively. The σ is generally referred to as the spread factor, whose optimal value is often determined experimentally (Chtioui et al., 1999).

3. Materials and methods

3.1. Site description

The city of Icheon located in Gyunggi province, Korea (37°18′20.34″N, 127°30′40.46″E), is famous for its rice with its excellent taste and production rate. Therefore, one of the intensive paddy fields in the Icheon area, which covers about 15 ha, was chosen as the study area shown in Fig. 1. The enclosing bank sectionalizes areas between streams and paddy fields. Necessary water during the growing season was irrigated from two irrigation canals (732 and 544 m long, respectively) pumped from Bok-ha stream. In addition, excessive water from paddy fields is drained to Jook-Dang stream through a drainage canal (668 m long).

The background soil had T-N contents of 1.0 and 1.2 g kg^{-1} and available P_2O_5 content of 68.0 and 67.1 mg kg^{-1} before