Understanding nitrogen transport in the unsaturated zone with fluctuations in groundwater depth

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ABSTRACT

Fluctuations in groundwater depth play an important role and are often overlooked when considering the transport of nitrogen in the unsaturated zone. To evaluate directly the variation of nitrogen transport due to fluctuations in groundwater depth, the prediction model of groundwater depth and nitrogen transport were combined and applied by least squares support vector machine and Hydrus-1D in the western irrigation area of Jilin in China. The calibration and testing results showed the prediction models were reliable. Considering different groundwater depth, the concentration of nitrogen was affected significantly with a groundwater depth of 3.42–1.71 m, while it was not affected with groundwater depth of 5.48–6.47 m. The total leaching loss of nitrogen gradually increased with the continuous decrease of groundwater depth. Furthermore, the limited groundwater depth of 1.7 m was found to reduce the risk of nitrogen pollution. This paper systematically analyzes the relationship between groundwater depth and nitrogen transport to form appropriate agriculture strategies.

Key words | ecological critical groundwater depth, fluctuations in groundwater depth, LS-SVM

HIGHLIGHTS

- The total leaching loss of nitrogen increases with the decrease of groundwater depth.
- The limited groundwater depth is proposed for determining appropriate agriculture strategies.

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INTRODUCTION

Nitrogen fertilizer is widely used on farmland to increase crop productivity. However, the utilization rate of nitrogen fertilizer for crops (wheat, rice, and corn) is only 28–41% (Zhu & Chen 2002; China 2016). Excessive nitrogen on the soil surface infiltrates into groundwater through the unsaturated zone with precipitation or irrigation, and becomes one of the main sources of groundwater pollution (Zhang et al. 2012a, 2012b). Fluctuations in groundwater depth are a significant factor in changing the physical, chemical, and biological properties of the underground environment, thus leading to variations in the transport of nitrogen by leaching (Li et al. 2015; Akbariyeh et al. 2019).

In recent decades, many studies have been conducted on fluctuations in groundwater depth, mainly focusing on water and salt content (Seeboonruang 2012; Talebnejad & Sepaskhah 2015; Chen et al. 2018; Yang et al. 2019), crop growth processes (Fu & Burgher 2015; Han et al. 2015; Xia et al. 2016; Qiu et al. 2019), and organic matter transport and redistribution (Teramoto & Chang 2017; Gatsios et al. 2018; Yimsiri et al. 2018; Atteia et al. 2019).

Additionally, the correlation between groundwater depth and nitrogen content is of interest. For example, Zhiye et al. (2013) compared the conditions between stable and changing groundwater depth and indicated that elevated groundwater depth increased the content of nitrate nitrogen and decreased the content of ammonium nitrogen in the soil column. Li et al. (2015) showed that the content of nitrate nitrogen was closely related to groundwater depth through field monitoring data. Kawagoshi et al. (2019) and Akbariyeh et al. (2019) indicated that fluctuations in groundwater depth due to rainfall had an effect on the concentration of nitrogen.

The western irrigation area of Jilin is a severely saline region in China. The Chinese government launched a project to divert the Nen River to Baicheng City and developed approximately 2,000 hectares of farmland. The groundwater depth at a local location in this area changed with environmental factors (irrigation and meteorology) (Qi 2019) and had an effect on the transport of nitrogen. Considering this change, it is essential to establish an
effective model to predict the groundwater depth. Empirical models, such as artificial neural network (ANN), support vector machine (SVM) and the least squares support vector machine (LS-SVM) (Ghose et al. 2010; Mohanty et al. 2015), were widely applied because they are more cost-effective at obtaining useful results with less data. LS-SVM uses different loss functions where inequality constraints are replaced by equality constraints and overcomes a huge computing burden (Wang & Hu 2005). So far, LS-SVM has been applied to estimate evapotranspiration and precipitation (Kundu et al. 2017), predict groundwater depth (Tang et al. 2018), and analytical chemistry (Balabin & Lomakina 2014). Therefore, LS-SVM was adopted to predict the groundwater depth.

However, the above literature rarely discussed the transport of nitrogen quantitatively for different groundwater levels or proposed a reliable groundwater depth limit for groundwater-ecological risk assessments. In this study, based on the field-measured and collected data, LS-SVM and Hydrus-1D were applied to evaluate the groundwater depth and nitrogen transport, respectively. Additionally, the transport of nitrogen in the unsaturated zone at varying groundwater depths was simulated. Finally, the ecological threshold for groundwater depth was determined to provide a sustainable limit for contaminated sites.

MATERIALS AND METHODS

Field site

The study area is located at Liangjiazi Town, Da’an City, west of Jilin (123°52′48″E–45°18′45″N). The annual average temperature is 5.02°C and the annual average precipitation is 422 mm. The annual average evaporation is 1,749 mm, which is 4.14 times the precipitation. The location is shown in Figure 1 and the area is approximately 600 m². In the field site, the fertilizer points are distributed in an ‘S’ type (see the right panel in Figure 1) to avoid farming errors.

The research area is a paddy field modified by saline soil and the planted rice is Jijing 88. Shallow and deep irrigation are used in the farmland during different periods of crop growth. From regreening to tillering, shallow irrigation was applied; from booting to heading and flowering, deep irrigation was applied; and then shallow irrigation was applied during the ripening period. The irrigation was stopped until

Figure 1 | The location and diagram of the field site.
the rice was harvested. According to the usual application mass of nitrogen fertilizer for paddy fields in the research area (150 kg/hm²-250 kg/hm²), the trial plot was fertilized in two patterns: A (180 kg/hm²) and B (220 kg/hm²), which were used for calibration and testing, respectively. The proportion of base fertilizer, tillering fertilizer, booting fertilizer, and granule fertilizer was 3:4:2:1. Potassium and phosphate fertilizers of 90 kg/hm² and 70 kg/hm² were applied once in the base fertilizer. The field experiments were conducted for 150 days. The rice was raised on May 15, transplanted on June 19, harvested on October 11.

During the period of regreening, tillering, booting, ripening, and harvesting, the soil samples were collected at a depth of 0-20 cm, 20-50 cm, 50-80 cm, and 80-100 cm. The soil samples were taken to the laboratory and tested for concentration of nitrate nitrogen, ammonium nitrogen, and moisture content.

**Groundwater depth modeling**

Groundwater depth data in the study area are estimated by LS-SVM (Levenberg 1944; Marquardt 1963). In the modeling process, the groundwater depth is simulated by mapping the input space to the high-dimensional space nonlinearly. Linear regression is then performed and the regression function by a vector form is represented as \( f(\mathbf{x}) = \mathbf{w}^T \Phi(\mathbf{x}) + b \), where \( \mathbf{w} \) is the plane weight vector, \( b \) is the threshold value, \( \Phi(\mathbf{x}) \) is the nonlinear transfer function which maps the input vectors to the high-dimensional space. In the LS-SVM algorithm, the corresponding optimized problem is shown in Equation (1):

\[
\min \, f(\mathbf{w}, \xi) = \frac{1}{2} ||\mathbf{w}||^2 + \frac{c}{2} \sum_{i=1}^{l} \xi_i^2
\]

s.t \[
y_i [\Phi(\mathbf{x}_i)^T \mathbf{w} + b] = 1 - \xi_i
\]

where \( f(\mathbf{w}, \xi) \) is the objective function; \( c \) is the equilibrium constant; and \( \xi_i \) is the relaxation variable. The Lagrange function is shown as follows:

\[
L(\mathbf{w}, b, \xi, \delta) = \frac{1}{2} ||\mathbf{w}||^2 + \frac{c}{2} \sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} \delta_i [y_i [\Phi(\mathbf{x}_i)^T \mathbf{w} + b] - 1 + \xi_i]
\]

where \( \delta_i \) is the Lagrangian operator, and the differentiation of \( w, b, \xi, \delta \) with the Lagrange function is described as follows:

\[
\begin{align*}
\frac{\partial L}{\partial \mathbf{w}} &= 0 \rightarrow \mathbf{w} = \sum_{i=1}^{l} \delta_i \Phi(\mathbf{x}_i) \\
\frac{\partial L}{\partial b} &= 0 \rightarrow \mathbf{b} = \sum_{i=1}^{l} \delta_i = 0 \\
\frac{\partial L}{\partial \xi_i} &= 0 \rightarrow \delta_i = c \xi_i, \; i = 1, 2, \ldots, l \\
\frac{\partial L}{\partial \delta_i} &= 0 \rightarrow y_i [\Phi(\mathbf{x}_i)^T \mathbf{w} + b] = 1 - \xi_i
\end{align*}
\]

The kernel function is defined as \( K(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i)^T \Phi(\mathbf{x}_j) \) and the regression function is described in Equation (5):

\[
f(\mathbf{x}) = \text{sgn} \left[ \sum_{i=1}^{l} \delta_i K(\mathbf{x}_i, \mathbf{x}) + b \right]
\]

In the LS-SVM algorithm, the radial basis function (RBF) is taken as the kernel function, which is pivotal for determining the mapping function and feature space.

\[
K(\mathbf{x}_i, \mathbf{x}_j) = \exp \left( -\frac{||\mathbf{x}_i - \mathbf{x}_j||^2}{2\sigma^2} \right)
\]

Groundwater depth data from 2003 to 2014 in the field site was collected by Da’an Water Resources Office. The distribution of groundwater wells is shown in Figure 1. In addition, monthly meteorological data for temperature, precipitation, and evaporation from 2003 to 2015 were downloaded and collated from, the China Meteorological Science Data Sharing Service Website (http://www.cma.gov.cn/2011qxfw/2011qsjgx/). For the reliability and integrity of the groundwater depth data, as well as the correlation between groundwater depth and the meteorological data, the current month’s meteorological data of temperature, precipitation, and evaporation, and last month’s groundwater depth, were input into the LS-SVM algorithm. The current month’s groundwater depth was the output result. During the simulation process, data for 2003–2012 was set as training samples and data for 2013–2014 was set as testing samples. Finally, meteorological data for 2015 was input and the groundwater depth in 2015 was predicted by the LS-SVM algorithm.
Hydrus-1D model

Hydrus-1D can be used to simulate the transport of flow, solute, heat, and other processes in saturated and unsaturated porous media under various conditions (Dagois et al. 2017; Iha et al. 2017; Shahrokinia & Sepaskhah 2018). More complex situations can also be modeled by Hydrus-1D, with additional modules such as UnsatChem, HP1, and Wetland (Mallants et al. 2017; Simunek et al. 2018). Hydrus-1D is widely used for research on actual problems in agriculture and groundwater pollution (Li 2020; Li et al. 2020), and it can be downloaded for free from www.hydrus2d.com (or www.pc-progress.cz). This paper established a nitrogen transport model with the modules of flow, solute, and root uptake in Hydrus-1D. The simulated depth was 0–100 cm from the soil surface. The observation points (10, 40, 70, and 100 cm) in the modeling domain were the same as the sampling points in the field experiments. The simulated period was 144 days from May 5 to October 5, 2015 (the period from transplanting to harvesting of the rice). A variable time step was used and the initial time step was 1 day. The time step was adjusted with the number of iterations and ranged from 0.01 days to 7 days. The iteration accuracy of moisture content and pressure head was 0.0001 and 0.01, respectively.

First, data for 180 kg/hm² were used to calibrate the parameters in the transport model of nitrogen. Then, data for 220 kg/hm² were applied to test the calibrated transport model. Finally, consistency between modeling and observation values was assessed using the evaluation indexes in calibration and testing processes.

Flow transport

The process of flow in the unsaturated zone is described by the modified Richard equation, which varies with soil matrix potential, as shown in Equation (7) (Simunek et al. 2013):

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x_i} \left[ k_n \left( k^A_\theta \frac{\partial h}{\partial x_i} + k^S_\theta \right) \right] - S
\]

where \( \theta \) is the volume moisture content; \( t \) is time; \( h \) is the pressure head; \( k \) is the unsaturated hydraulic conductivity; \( k^A_\theta \) is the dimensionless expression of anisotropic tensor; \( x_i \) is the space coordinate; and \( S \) is the sources and sinks of root uptake. The soil moisture characteristics parameters are obtained using the van Genuchten model. The expressions are as follows:

\[
\theta(h) =\begin{cases} 
\theta_s + \frac{\theta_s - \theta_r}{\left(1 + |h|m\right)^n}, & h < 0 \\
\theta_s, & h \geq 0 
\end{cases}
\]

\[
k(h) = k_s S_h \left[1 - \left(1 - S_h^n\right)^{n} \right]^2
\]

\[
S_h = \frac{\theta - \theta_r}{\theta_s - \theta_r}
\]

where \( \theta_s \) and \( \theta_r \) are the saturated and residual water content; \( n, m, \) and \( l \) are the empirical fitting parameters, \( m = 1 - 1/n \); \( \alpha \) is the reciprocal of intake pressure, \( \alpha = 1/h_b; \) and \( k_s \) is the saturated hydraulic conductivity.

Soil hydraulic parameters are identified by the size of soil particles. The soil moisture characteristic curves in this study are obtained using the soil conversion function in RETC Software (Genuchten et al. 1992) based on physical and chemical characteristics of collected soil samples in 2015. The simulated soil moisture data were compared with measured moisture data and fitted parameters were obtained. The related parameters including the saturated water content (\( \theta_s \)), the residual water content (\( \theta_r \)), the empirical fitting parameters (\( \alpha, n, l \)) and the saturated hydraulic conductivity (\( k_s \)) are shown in Table 1.

### Table 1

| Soil depth (cm) | \( \theta_s \) (cm³/cm³) | \( \theta_r \) (cm³/cm³) | \( \alpha \) (cm) | \( n \) | \( l \) | \( k_s \) (cm/d) |
|-----------------|-------------------------|-------------------------|-----------------|-----|-----|-----------------|
| 0–20            | 0.4051                  | 0.0726                  | 0.0181          | 1.3174 | 0.5 | 12.160          |
| 20–50           | 0.4373                  | 0.0789                  | 0.0214          | 1.3482 | 0.5 | 21.468          |
| 50–80           | 0.4248                  | 0.0673                  | 0.0225          | 1.3837 | 0.5 | 31.016          |
| 80–100          | 0.39                    | 0.0641                  | 0.031           | 1.4166 | 0.5 | 14.368          |

Solute transport

During the leaching process of nitrogen in the unsaturated zone, excessive organic nitrogen undergoes biological transformation processes of mineralization, biological
immobilization, nitrification, and denitrification, and produces inorganic nitrogen of ammonium nitrogen and nitrate nitrogen. In addition, chemical processes covering volatilization, adsorption–desorption, fixation and release of nitrogen occur in leaching (Tillotson et al. 1980). The transformation process is described by zero-order and first-order dynamic equations in Hydrus-1D and is shown as follows:

\[
\frac{\partial c_1}{\partial t} = \frac{\partial}{\partial x_i} \left( D_{ij} \frac{\partial c_1}{\partial x_i} \right) - \frac{\partial q_i c_1}{\partial x_i} - k_1 c_1 \tag{11}
\]

\[
\frac{\partial c_2}{\partial t} + \frac{\partial s}{\partial t} = \frac{\partial}{\partial x_i} \left( D_{ij} \frac{\partial c_2}{\partial x_i} \right) - \frac{\partial q_i c_2}{\partial x_i} + k_3 c_N - k_1 c_1 - k_2 c_2 - k_3 \rho s - Sc_2 \tag{12}
\]

\[
\frac{\partial c_3}{\partial t} = \frac{\partial}{\partial x_i} \left( D_{ij} \frac{\partial c_3}{\partial x_i} \right) - \frac{\partial q_i c_3}{\partial x_i} + k_2 c_2 + k_3 \rho s - (k_3 + k_4) \theta c_3 - Sc_3 \tag{13}
\]

where \(c_1, c_2,\) and \(c_3\) are the concentration of urea, ammonium nitrogen, and nitrate nitrogen, respectively; \(q_i\) is the soil moisture flux in \(i\) direction; \(s\) is the mass concentration of ammonium nitrogen in soils (adsorption mass), \(s = k_d c_2; k_d\) is the adsorption coefficient of ammonium nitrogen; \(c_N\) is the organic matter content of soils; \(k_0, k_1, k_2, k_3,\) and \(k_4\) are the mineralization rate of organic matter, hydrolysis rate of urea, nitrification rate \((k_{2W}\) and \(k_{2S}\) are the nitrification rates in solid and liquid phases), denitrification rate, and fixation rate of biology, respectively; \(\rho\) is the bulk density of soils; \(S\) is the term of root water uptake; and \(D_{ij}\) is hydrodynamic dispersion tensor in all directions.

Considering the concentration of nitrate nitrogen is much greater than that of ammonium nitrogen in the unsaturated zone (Li et al. 2007), nitrate nitrogen was regarded as the only product in the mineralization process. With the increase of soil depth, the content of soil organic matter, breathability of soil and mineralization of nitrogen decreases. Therefore, the mineralization and fixation were ignored in the deep soil and assumed to occur in the shallow soil. The denitrification was assumed to occur in the integrative domain. The volatilization of nitrogen was also ignored due to the irrigation of the paddy field (Tafteh & Sepaskhah 2012). Organic nitrogen fertilizer and nitrate nitrogen are non-adsorptive, and ammonium nitrogen is adsorbed easily (Ravikumar et al. 2011). The adsorption coefficients \((k_d)\) of ammonium nitrogen are determined by batch adsorption experiments. It was difficult to obtain the remaining parameters of the nitrogen transport model so they were identified by calibration based on actual measured data. The calibrated parameters of solute transport are described in Table 2.

### Root uptake

The driving force of root uptake is mainly derived from crop transpiration. The mass of root uptake is closely related to the distribution of crop root. In this research, the root uptake model (Feddes model) (Reicosky & Ritchie 1976) and the root growth model (Simunek et al. 2013), which are calculated in Hydrus-1D, are used and shown as follows:

\[
S(x, h) = a(x, h) b(x_1) L_r TP
\]

where \(a(x, h)\) refers to the function of soil matrix potential or suction head; \(b(x_1)\) refers to the distribution of the function of relative root density; \(L_r\) refers to the root depth; and \(TP\) refers to the potential transpiration rate.

The function of \(a(x, h)\) is determined by the negative pressure head in crop root. The rice root parameters in the Feddes model used the values in Tan et al. (2015) and are shown in Table 3. The corresponding function of \(b(x_1)\) was provided by the database in Hydrus-1D as follows:

\[
b(x_1) = \begin{cases} 
\left( \frac{1}{x_1} \right) \left( 0.5 \frac{x_1}{x_{1m}} \right) e^{-\left(0.5 \frac{x_1}{x_{1m}}\right)^2} & 0 \leq x_1 \leq 70 \\
0 & 70 \leq x_1 \leq 150 
\end{cases}
\]

### Table 2 | The related parameters of solute transport

| Soil depth (cm) | \(a_i\) | \(k_d\) | \(k_0\) | \(k_1\) | \(k_2\) | \(k_3\) | \(k_4\) |
|----------------|--------|--------|--------|--------|--------|--------|--------|
| 0–20           | 0.3    | 0.08   | 0.070  | 0.002  | 0.0045 |
| 20–50          | 0.3    | 0.08   | 0.037  | 0.002  | 0.0045 |
| 50–80          | 0.3    | 0.15   | 0.001  | 0.002  | 0.0045 |
| 80–100         | 0.3    | 0.15   | 0.001  | 0.002  | 0.0045 |

### Table 3 | The simulated parameters of the Feddes model

| Pressure head | \(h_1\) | \(h_2\) | \(h_{10g}\) | \(h_{10l}\) | \(h_e\) |
|---------------|--------|--------|------------|------------|--------|
| cm            | – 10  | – 55  | – 160      | – 250      | – 15,000 |
where \( x_{1m} \) refers to the vertical maximum distance of the root distribution; \( x_1 \) represents the horizontal coordinate of the vertical maximum root density; \( P_x \) refers to the empirical parameter indicating the asymmetry of the root in the longitudinal direction. The root nitrogen uptake is the product of the water uptake mass and nitrogen concentration of the calculation point.

In addition, the parameter \( L_r \) in the calculation process of root uptake was determined by the root growth module in Hydrus-1D, which considered the actual growth situation. The model assumes that the root depth is the function of the maximum root depth and the root growth coefficient (Simunek et al. 2013) as follows:

\[
L_r(t) = L_m \times f_r(t)
\]

\[
f_r(t) = \frac{L_0}{L_0 + (L_m - L_0)e^{-rt}}
\]

where \( L_r(t) \) represents the root depth which changes with time; \( L_m \) refers to the maximum root depth; \( f_r(t) \) is the root growth coefficient; and \( L_0 \) and \( r \) are the initial root depth and the root growth rate, respectively. The rice crop in this study had a certain depth of root in transplanting. The initial root depth was 15 cm and the maximum root growth depth was 50 cm.

**Boundary and initial conditions**

In the simulation process, the initial moisture content and the concentration of nitrate nitrogen and ammonium nitrogen were evenly distributed in the horizontal direction. In the field site, basin irrigation was used and the depth of irrigation was 10 cm. The moisture content of soil surface was saturated after the rice transplanting and the moisture content at other points was defined by linear interpolation. The variable upper boundary condition was set up with the atmospheric boundary and the depth of surface water layer changed with rice growth (the maximal depth of the surface water layer was 20 cm). The bottom of the soil profile was set up with the free drainage boundary. The left and right positions were no-flux boundaries.

**Model evaluation**

Four statistical criteria – the correlation coefficient \( R \), the root mean square error \( \text{RMSE} \), the mean absolute error \( \text{MAE} \), and the Nash–Sutcliffe efficiency coefficient \( \text{NS} \) – were used to evaluate the model performance. \( R \) measures the correlation degree linearly between two variables. \( \text{RMSE} \) and \( \text{MAE} \) provide different types of information about the model prediction capabilities. \( \text{NS} \) evaluates the reliability of the model results.

\[
R = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2}
\]

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |P_i - O_i|
\]

\[
\text{NS} = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]

where \( n \) represents the number of input parameters; \( O_i \) and \( P_i \) refer to the observation and simulated values of groundwater depth at time \( t \), respectively; and \( \bar{O} \) and \( \bar{P} \) are the average observation and simulated values of groundwater depth.

**RESULT AND DISCUSSION**

**Groundwater depth evaluation**

A model for predicting groundwater depth was established using the LS-SVM algorithm with MATLAB. The calibration and testing results are shown in Figure 2, and the evaluation results of the four statistical criteria are shown in Table 4. The values of \( R \) and \( \text{NS} \) reach 0.8 or higher and the values of \( \text{RMSE} \) and \( \text{MAE} \) are closer to 0. These results indicate
that the LS-SVM method is suitable for predicting the groundwater depth.

Based on the successfully calibrated and tested LS-SVM model, the monthly mean average values of groundwater depth in 2015 were obtained by inputting the corresponding meteorological data. The results are presented in Figure 3 and Table 5. It is observed that the groundwater depth ranges from 5.48 to 6.47 m. The modeled groundwater depth manifests the actual seasonal fluctuation observed in 2015.

| The evaluation results of the calibration and testing periods of groundwater depth |
|-------------------------------|---------------------|---------------------|
| **LS-SVM**                   | **Calibration period** | **Testing period** |
| \( R \)             | 0.964               | 0.919               |
| \( NS \)           | 0.928               | 0.849               |
| \( RMSE \) (cm)    | 0.148               | 0.297               |
| \( MAE \)          | 0.082               | 0.208               |
Calibration and testing in Hydrus-1D

According to the defined parameters, the model of flow and solute were calibrated with a fertilization rate of 180 kg/ha and tested with a load of 220 kg/ha. The transport results of moisture content and nitrogen are shown in Figures 5-10 and the distribution of precipitation and evaporation in the simulation period.

Table 5 | The monthly mean data of groundwater depth in 2015

| Month | Jan | Feb | Mar | Apr | May | Jun |
|-------|-----|-----|-----|-----|-----|-----|
| Groundwater depth (m) | 6.31 | 6.32 | 6.36 | 6.42 | 6.47 | 6.35 |
| Month | Jul | Aug | Sept | Oct | Nov | Dec |
| Groundwater depth (m) | 5.99 | 5.59 | 5.84 | 5.63 | 5.54 | 5.48 |

Figure 4 | The distribution of precipitation and evaporation in the simulation period.

Figure 5 | The calibrated results of moisture content of 180 kg/hm² (O and M represent the observed and simulated data).
evaporation during the simulation period are shown in Figure 4.

It can be seen in Figures 5–10 that moisture content, ammonium nitrogen, and nitrate nitrogen exhibit similar trends in variation at different layers. The moisture content decreases with time due to crop uptake, and fluctuates locally due to precipitation and irrigation. As the topsoil is easily recharged by precipitation and irrigation, moisture content is higher in the shallower layers than in the deeper layers.

Due to the effects of precipitation, evaporation (Figure 4), and fertilization, the concentration of ammonium nitrogen at different layers fluctuates with time, and its maximum value appears during June and July (the period of tillering and booting of crops). In general, the fluctuation range of ammonium nitrogen concentration, which first increases and then decreases, is related to the amount of fertilization, precipitation and irrigation. In addition, the concentration of ammonium nitrogen is greater in shallower layers than in deeper layers because of the adsorption behavior.

For nitrate nitrogen, the concentration in soil reduces rapidly and it fluctuates slightly until it reaches a stable state in September. Initially, nitrogen fertilizer on the soil moves downward with the flow of precipitation and

![Figure 6](http://iwaponline.com/ws/article-pdf/21/6/2691/932323/ws021062691.pdf)

**Figure 6** | The calibrated results of ammonium nitrogen of 180 kg/hm² (O and M represent the observed and simulated data).

![Figure 7](http://iwaponline.com/ws/article-pdf/21/6/2691/932323/ws021062691.pdf)

**Figure 7** | The calibrated results of nitrate nitrogen of 180 kg/hm² (O and M represent the observed and simulated data).
irrigation, and the concentration of nitrate nitrogen in the unsaturated zone reaches the maximum value. During the crop growing season, nitrate nitrogen is absorbed by the crop and is affected by precipitation and irrigation, resulting in the concentration of nitrate nitrogen decreasing with time. At harvest time, the concentration of nitrate nitrogen reaches a minimum after this long-term decrease. Nitrate nitrogen also leaches into groundwater more easily and the concentration in shallower layers is lower than in deeper layers.

The values of RMSE are lower than 1.5 mg/kg and the values of R are greater than 0.8, as shown in Table 6. These results indicate that the Hydrus-1D model is viable for exploring the migration and transformation of nitrogen. In different layers, the structure of soil pores, connectivity, and physicochemical properties of salinity, pH, and moisture affect the transport and transformation of nitrogen. These related parameters change with crop growth and could not be modified in Hydrus-1D. The fitting accuracies therefore vary with different layers, as shown in Table 6.
Transport of nitrogen at 100 cm of soil under groundwater fluctuation

Considering the uncertainty of the data and parameters, the prediction interval of \(t\)-distribution is applied to improve the accuracies of the simulation results. The calculation result of 95% confidence interval is obtained as in Nie et al. (2017) and is shown in Table 7.

Based on the dynamic range of groundwater depth shown in Table 7, Plan 1 (the upper limit of the predictive interval) and Plan 2 (the lower limit of the predictive

### Table 7

| Month | Jan | Feb | Mar | Apr | May | Jun |
|-------|-----|-----|-----|-----|-----|-----|
| Upper limit (m) | 6.39 | 6.49 | 6.69 | 6.71 | 6.75 | 6.81 |
| Groundwater depth (m) | 6.31 | 6.32 | 6.36 | 6.42 | 6.47 | 6.35 |
| Lower limit (m) | 5.16 | 5.21 | 5.92 | 5.94 | 5.97 | 6.03 |

### Table 6

| Fertilizing amount | Depth (cm) | Moisture content | RMSE (mg/kg) | R | Nitrate nitrogen | RMSE (mg/kg) | R | Ammonium nitrogen | RMSE (mg/kg) | R |
|--------------------|------------|------------------|--------------|---|-----------------|--------------|---|-------------------|--------------|---|
| 180 kg/hm²         | 10         | 0.009            | 0.97         |   | 0.47            | 0.91         |   | 0.42              | 0.83         |   |
|                    | 40         | 0.013            | 0.96         |   | 1.29            | 0.81         |   | 0.26              | 0.91         |   |
|                    | 70         | 0.014            | 0.95         |   | 0.64            | 0.83         |   | 0.68              | 0.84         |   |
|                    | 100        | 0.015            | 0.92         |   | 0.70            | 0.80         |   | 0.48              | 0.86         |   |
| 220 kg/hm²         | 10         | 0.023            | 0.97         |   | 0.87            | 0.85         |   | 0.72              | 0.85         |   |
|                    | 40         | 0.021            | 0.96         |   | 1.18            | 0.94         |   | 1.20              | 0.94         |   |
|                    | 70         | 0.017            | 0.97         |   | 0.43            | 0.96         |   | 1.09              | 0.96         |   |
|                    | 100        | 0.016            | 0.94         |   | 0.81            | 0.88         |   | 1.90              | 0.86         |   |
interval) were designated as the lower boundary (100 cm from the surface soil) in Hydru-1D model. The results of the concentration of ammonium nitrogen and nitrate nitrogen for Plans 1 and 2 were then compared with those of the initial data (180 kg/hm²).

The comparative results of the concentration of ammonium nitrogen for the two plans are shown in Figure 11. A similar trend is observed for both plans, except that the value and time of peak ammonium nitrogen are different. Furthermore, the concentration ranges of ammonium nitrogen for Plans 1 and 2 are 1.96–7.32 and 2.03–6.80 mg/kg, respectively. The difference between Plans 1 and 2 is small. Thus, the concentration of ammonium nitrogen at 100 cm is slightly affected by the groundwater depth of 5.48–6.47 m.

The comparative results of the concentration of nitrate nitrogen for different plans are shown in Figure 12. A similar trend, which shows a significant decrease with time and a different amplitude of variation in the short term, was observed for both plans. The concentration ranges of nitrate nitrogen for Plans 1 and 2 are 1.96–7.32 and 2.03–6.80 mg/kg, respectively. The difference between Plans 1 and 2 is small. Thus, the concentration of ammonium nitrogen at 100 cm is slightly affected by the groundwater depth of 5.48–6.47 m.

The comparative results of the concentration of nitrate nitrogen for different plans are shown in Figure 12. A similar trend, which shows a significant decrease with time and a different amplitude of variation in the short term, was observed for both plans. The concentration ranges of nitrate nitrogen for Plans 1 and 2 are 1.96–7.32 and 2.03–6.80 mg/kg, respectively. The difference between Plans 1 and 2 is small. Thus, the concentration of ammonium nitrogen at 100 cm is slightly affected by the groundwater depth of 5.48–6.47 m.
The cumulative leaching loss of nitrogen was calculated from the modeling results in Table 8. For ammonium nitrogen, the cumulative leaching loss in the initial data is 24.63 kg/ha and increased to 24.86 and 24.76 kg/ha for Plans 1 and 2, with an increase in amplitude of 0.9% and 0.5%, respectively. For nitrate nitrogen, the cumulative leaching loss in the initial data is 12.41 kg/ha, which increased to 12.46 and 12.52 kg/ha for Plans 1 and 2 with an increase in amplitude of 0.4% and 0.8%, respectively. The average increase in amplitude of nitrogen is approximately 0.6%, indicating that the mass of ammonium nitrogen and nitrate nitrogen varies little when the groundwater depth ranges from 5.48 to 6.47 m. The result was affected by the physicochemical properties of silty clay in saline areas (such as poor permeability).

### Ecological regulation of groundwater depth

Enhanced loss of nitrogen through leaching poses a threat to the ecological environment of groundwater. Nitrogen pollution in some parts of the study area has exceeded the Level III standard of groundwater quality in China. According to the result that the loss of nitrogen by leaching is affected by fluctuations in groundwater depth, it is necessary to quantitively evaluate the ecological threshold of groundwater depth in the vadose zone in combination with crop cultivation and solute transport. In this section, the 2015 groundwater depth was continuously decreased by 50%. Two scenarios are defined: B1 (groundwater depth of 2.99–3.42 m) and B2 (groundwater depth of 1.49–1.71 m). To compare these scenarios with groundwater depth in 2015, the transport and leaching loss of nitrogen was analyzed under different conditions, as shown in Figures 13 and 14.

Figure 13 shows that the trend lines of the three situations vary similarly for ammonium nitrogen. However, there are significant differences in the concentration of ammonium nitrogen in soil in the three scenarios. In

| Index                        | Cumulative leaching loss | Increase amplitude (%) |
|------------------------------|--------------------------|------------------------|
|                              | Initial data Plan 1 Plan 2 | Plan 1 Plan 2 |
| Ammonium nitrogen (kg/ha)    | 24.63 24.86 24.76 0.9 0.5 |
| Nitrate nitrogen (kg/ha)     | 12.41 12.46 12.52 0.4 0.8 |

Figure 13 | The dynamic range of ammonium nitrogen in 100 cm from the surface soil.
scenario B1, the concentration of ammonium nitrogen in soil is 0.09–6.84 mg/kg and changes significantly after 72 days of crop planting compared to the initial data. In scenario B2, the concentration of ammonium nitrogen in soil is 0.007–6.91 mg/kg and changes more significantly compared with scenario B1 during the period of crop growth. Therefore, the comparative results indicate that the concentration of ammonium nitrogen in soil decreases with the decrease of groundwater depth. When groundwater depth decreases, the moisture content and root uptake of nitrogen in soil increase, which leads to a decrease in the concentration of ammonium nitrogen.

The concentration of nitrate nitrogen in soil for both scenario B1 and B2 decreases sharply with time, and the rate of reduction is different, as shown in Figure 14. In scenario B1, the initial concentration of nitrate nitrogen in soil is 7.221 mg/kg and reduces rapidly to zero on the 24th day after crop planting (the early stage of tillering). In scenario B2, the initial concentration of nitrate nitrogen in soil is 7.543 mg/kg and reduces rapidly to zero on the 14th day after crop planting (the early stage of regreening). The results indicate that the reduction rate of nitrate nitrogen in scenario B1 is faster than that in scenario B2. The concentration of nitrate nitrogen in the initial data also varies more than in scenario B1 and B2. The reason for this is related to the lower groundwater depth, which can cause capillary moisture to be closer to the lower boundary, allowing nitrate nitrogen to migrate down more easily. Therefore, the concentration of nitrate nitrogen in soil decreases with a decrease in groundwater depth.

As shown in Table 9, for ammonium nitrogen, the cumulative leaching loss in the initial data is 24.63 kg/hm². This increases to 25.28 and 27.65 kg/hm² in scenario B1 and B2, respectively, with an increase in amplitude of 2.64% and 12.26%. For nitrate nitrogen, the cumulative leaching loss in the initial data is 12.41 kg/ha, and this increases to 15.11 and 20.01 kg/hm² in scenario B1 and B2, respectively, with an increase in amplitude of 21.75% and 61.24%. Combined with Figures 13 and 14, these results indicate that

![Figure 14](https://example.com/figure14.png)

**Figure 14** The dynamic range of nitrate nitrogen in 100 cm from the surface soil.

| Index                  | Cumulative leaching loss (kg/hm²) | Increase amplitude (%) |
|------------------------|-----------------------------------|------------------------|
| Initial data           | 24.63                             | 25.28                  |
| Scenario B1            | 27.65                             | 12.26                  |
| Scenario B2            | 26.45                             | 12.26                  |
| Scenario B1            | 15.11                             | 20.01                  |
| Scenario B2            | 20.01                             | 61.24                  |

As shown in Table 9, for ammonium nitrogen, the cumulative leaching loss in the initial data is 24.63 kg/hm². This increases to 25.28 and 27.65 kg/hm² in scenario B1 and B2, respectively, with an increase in amplitude of 2.64% and 12.26%. For nitrate nitrogen, the cumulative leaching loss in the initial data is 12.41 kg/ha, and this increases to 15.11 and 20.01 kg/hm² in scenario B1 and B2, respectively, with an increase in amplitude of 21.75% and 61.24%. Combined with Figures 13 and 14, these results indicate that...
cumulative leaching losses of nitrate increase with the gradual decrease in groundwater depth. In particular, for nitrate nitrogen in scenario B2, the cumulative leaching loss is 20.01 kg/hm² and the increase in amplitude exceeds 50% compared to the initial data. There are significant differences among the three scenarios, and the leaching risk indicators for nitrate nitrogen can be classified into six levels (Table 10) according to the study of Hasegawa & Denison (2005).

When the groundwater depth decreases to 1.37–1.62 m, the leaching risk indicator of nitrate nitrogen rises to Level II and the risk to the ecological environment of groundwater is under threat. Therefore, the groundwater depth should be limited to 1.7 m or more in the study area, and the irrigation and fertilization should remain unchanged to reduce the risk of nitrate nitrogen pollution.

### CONCLUSION

This study used the LS-SVM algorithm and Hydrus-1D software to analyze the transport process of nitrogen at different groundwater depths. The groundwater depth in the western irrigation area of Jilin in China ranged from 5.48 to 6.47 m, as predicted by LS-SVM. Hydrus-1D was then used to explore the movement of nitrogen in this region. Modeling results reveal that the concentration at different layers fluctuates with time. The fluctuation range first increases and then decreases for ammonium nitrogen, while for nitrate nitrogen, the concentration in soil decreases rapidly and fluctuates slightly until reaching a stable state. In relation to predicting the effects of different groundwater depth on nitrogen transport, a groundwater depth of 5.48–6.47 m has little effect on the mass of nitrogen in the study area, but a depth of 3.42–1.71 m changes the concentration of nitrogen significantly. The cumulative leaching loss of nitrogen increases with a decrease in groundwater depth. When the groundwater depth decreases to 1.49–1.71 m, the leaching loss risk of nitrate nitrogen reaches Level II. The groundwater depth should therefore be limited to 1.7 m or more in the study area to reduce the risk of nitrate nitrogen pollution.

This work highlighted the quantitative relationship between fluctuations in groundwater depth and nitrogen mass in a case study and tried to provide a guide for the nitrate accumulation in a similar agricultural area. However, the relationship is affected by a number of key conditions, such as climate change, fertilizer application, irrigation, growth process of crops, and so on. Further efforts on developing modeling coupled with complex conditions should be considered.

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### DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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