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# Three-dimensional Sensitivity Analysis of Dynamic Agricultural Nonpoint Source Assessment Tool (DANSAT)

# 동적 농업비점오염 평가모델 (DANSAT)의 3차원 민감도 분석

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**ABSTRACT**

새로 개발된 모형에 대한 민감도 분석은 입력변수의 선정 및 보정을 위한 필요한 지침을 제공하기위해 수행되어야 할 필수적인 과정이다. 동적 농업비점오염 평가모델 (dynamic agricultural nonpoint source assessment tool, DANSAT)은 농업 최적관리기법 (BMP)의 지표 및 지하수에 대한 영향을 평가하기위해 개발된 3차원 모델이다. 본 연구의 목적은 서로 다른 토층 및 유역내 위치에서 입력변수의 변화에 따른 지표 및 지하관련 출력들의 반응을 토대로 DANSAT의 일반적인 민감도 분석을 수행하는 것이다. 선정된 입력변수들의 변화에 따른 세가지의 지표관련 출력 (유출량, 유사량, 유출수중 농약 부하량) 및 두가지의 지하관련 출력 (지하수로의 유입 유량 및 지하수로의 농약 유입량)의 반응이 고려되었다. 민감한 입력변수들은 하나의 격자만을 이용한 예비 민감도 분석을 통하여 선정되었는데, 대체로 토양 관련 인자들이 지표 및 지하에서 양적/질적으로 민감하게 작용하는 것으로 나타났다. 예비민감도 분석을 통해 선정된 토양입력변수들의 서로 다른 토층에서의 변화에 따른 모형 출력들의 반응을 고려한 수직적 민감도 분석결과, 지표관련 출력들의 경우 지표 부근의 상층 토양의 인자가, 지하관련 출력들의 경우 하부 토층의 인자가 각각 민감하게 작용하는 것으로 평가되었다. 유역내에서 입력변수들의 공간적 위치의 변화에 따른 반응을 고려하는 수평적 민감도 분석결과, 유역 경계의 주변보다 하천 주변에서의 입력변수 변화가 모형의 지표 및 지하관련 출력들에 민감한 것으로 나타났다. 본 연구 결과는BMP 의 지표 및 지하의 수문/수질에 미치는 영향을 평가하기 위해 개발된DANSAT 모형의 입력변수 선정 및 보정에 유용한 자료로 활용될 것으로 기대된다.

***Keywords:*** Sensitivity analysis; DANSAT; three-dimensional modeling; runoff; sediment; pesticide

## I. Introduction

Sensitivity analysis is used for identifying critical model parameters and as guidelines for future data collection and experimental design (Ma et al., 1998). Both deterministic and stochastic approaches have been used for the sensitivity analysis of NPS models. The stochastic approach, which usually varies multiple parameters simultaneously based on predefined parameter ranges and underlying probability distribution, requires large number of simulation runs (Haan and Zhang, 1996). However, the sensitivity analysis of watershed-scale, distributed, physically-based model is difficult because there are too many parameters, which usually impact a local area of watershed. Physically-based and distributed models such as MIKE-SHE (Refsgaard and Storm, 1995) and ANSWERS-2000 (Bouraoui and Dillaha, 1996) require intensive input parameters and computational time. Even though over-parameterization problem in applications of distributed models can be avoided by minimizing the number of free

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parameters that are subject to adjustments during subsequent calibration (Refsgaard, 1997), sensitivity analysis for three-dimensional and distributed parameter models is very complex (Christiaens and Feyen, 2002). As models become more complex, data and parameter requirements and uncertainty in model prediction may increase (Anderton et al., 2002). As a result, deterministic approach has been used with further simplification for sensitivity analysis of physically-based and distributed models (Bouraoui, 1994; Byne, 2000; Niu et al., 2001; Xevi et al., 1997). This approach is commonly based on independent parameter changes in which one parameter is varied individually with the other parameter fixed at base values. Difficulties exist in performing deterministic sensitivity analysis because of complex interactions between parameters. Deterministic sensitivity of individual parameter can be changed according to the values taken by other parameters and the state of the system because of complex interactions between parameters (Anderton et al., 2002; Beven, 1989; Refsgaard et al., 2007). As a result, deterministic sensitivity analysis is not appropriate for dealing with the model's uncertainties caused by errors in parameter estimation.

Within the distributed models, spatially-distributed parameters including soil and land use related parameters influence changes in characteristics of local area where the parameter value is assigned while watershed-scale parameters influence changes in the characteristics of the overall watershed. Reduced number of soil, crop, and channel types have been used in order to simplify the sensitivity analysis of ANSWERS-2000 (Byne, 2000; Niu et al., 2001) and MIKE-SHE (Christiaens and Feyen, 2002; Xevi et al., 1997) without considering spatial distribution of input parameters. However, few efforts have been made to evaluate the sensitivity of the three-dimensional watershed models by considering the horizontal- and vertical-distribution of parameter values.

The Dynamic Agricultural Nonpoint Source Assessment Tool (DANSAT) is a newly developed three-dimensional model to evaluate the impacts of agricultural best management practices (BMPs) on both surface and ground water (Cho, 2007; Cho and Mostaghimi, 2009b, 2009c). Frequently-used watershed-scale hydrology and water quality models include AnnAGNPS (Bingner and Theurer, 2001), SWAT (Arnold et al., 1998), ANSWERS-2000, MIKE SHE, and HSPF (Bicknell et al., 1993; Borah and Bera, 2003). Compared to the SWAT, AnnAGNPS, and HSPF, DANSAT has advantages in evaluating impacts of BMPs on hydrology and water quality mainly due to selected Green-Ampt infiltration method and physically-based sediment component. HSPF requires intensive model calibration because of conceptual equations and parameters which are not directly linked to the physical conditions of a watershed. AnnAGNPS and SWAT models also have difficulties in evaluating BMPs because of major limitations of curve number (CN) and universal soil loss equation (USLE) methods (Bouraoui, 1994; Bouraoui and Dillaha, 2000; Byne, 2000). These conceptual and empirically derived methods restrict the capability of the model to evaluate the impacts of BMPs on hydrology and water quality because there are difficulties in selecting appropriate parameters for different BMP scenarios. In addition, semi-distributed models such as HSPF and SWAT have difficulties in simulating the impacts of different locations of BMPs. The selected approach and equations for hydrology and sediment components of DANSAT are described in detail by Cho and Mostaghimi (Cho and Mostaghimi, 2009b). DANSAT was applied to two agricultural watersheds in Virginia to evaluate the capability of model for considering impacts of temporal variations and spatial distribution of agricultural land management on hydrology and sediment (Cho and Mostaghimi, 2009a). Information on development of pesticide component and field-scale model evaluation by simulating water, sediment, and pesticide movement both in surface and through the soil profile are described in another paper (Cho and Mostaghimi, 2009c). DANSAT was in reasonable agreement with field results considering both the temporal and spatial variations in stream flow and water quality, even though several limitations were suggested.

DANSAT has three-dimensional model structure for evaluating both spatial distribution of weather, topographic, soil, and land use and vertical movement of water and pollutant in soil profile which are considered by rectangular grids and multiple soil layers, respectively. DANSAT requires intensive input parameters and computational time because of its physically-based and distributed model characteristics. Structural sensitivity analysis was conducted to select the appropriate grid size and time step for reducing computational time by considering the scale effects on hydrology and water quality (Cho and Mostaghimi, Submitted). The objective of this study was to analyze functional parameter sensitivity of DANSAT by considering the responses of surface and subsurface output variables to the changes in parameters at different soil layers and locations.

## II. Methods and Materials

### 1. DANSAT

DANSAT was developed to evaluate the impacts of temporally and spatially changing agricultural BMPs on both surface and ground water by considering their dynamic interactions at the watershed scale (Cho, 2007). Three-dimensional model structure is useful for predicting water and pollutant transport within the entire system by considering vertical movement in a representative soil profile using cell-scale components and horizontal movement between cells using watershed-scale routing components. Cell-scale components are used to simulate water and pollutant movement within one cell while watershed-scale components route the water and pollutants to down-slope cells until it reaches the watershed outlet. Multiple soil layers is defined based on physical soil layer depth and rotation-based depths to simulate water and pesticide movement through the intermediate zone to groundwater by considering different application methods at various crop growth stages. In DANSAT, daily variable infiltration and soil detachment related parameters can be internally predicted based on agricultural management practices (dynamic approach) or user-defined constant parameters can be used throughout the entire simulation period (constant approach). The parameters, including effective hydraulic conductivity for Green-Ampt infiltration (Keff) and rill/interrill erodibility factors (Krill and Kinter), are predicted by dynamic soil components on a daily basis for considering the impacts of temporal changes of BMPs on hydrology and water quality. The dynamic approach is incorporated based on the processes utilized by the WEPP (Flanagan and Nearing, 1995).

### 2. Study Plot and Watershed

The Nomini Creek (NC) watershed is located in Westmoreland County within the Coastal Plain region of Virginia. A QNB plot and QN2 subwatershed within the NC watershed were selected for the sensitivity analysis (Fig. 1). A plot-scale monitoring study was conducted to characterize the fate and transport of pesticide using two filed plots (Heatwole et al., 1992). Previous DANSAT application to a tilled plot (QNB) by Cho and Mostaghimi (2009c) was used for cell-scale sensitivity analysis. The soil in the plot is a Suffolk sandy loam characterized as deep and well-drained. QN2 in the Nomini Creek (NC) watershed (Mostaghimi et al., 1989) was selected for watershed-scale sensitivity analysis. Suffolk and Rumford series, characterized by a sandy loam texture, are the major soils in NC watershed. Suffolk and Rumford series cover approximately 58% and 33% of the watershed, respectively. Both soils are deep and well drained.

### 3. Procedures

In this study, sensitivity analysis was conducted at two different scales: cell-scale and watershed-scale. Cell-scale sensitivity analysis involved two steps without considering routing processes: 1) preliminary cell-scale sensitivity

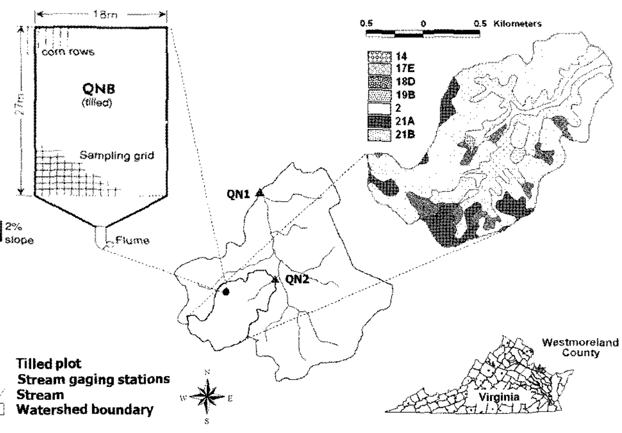


**Fig. 1 Location of the selected plot (QNB) and watershed (QN2) with spatial distribution of soil types**

**Table 1 List of cell-scale, watershed-scale, and channel-related parameters used in sensitivity analysis**

| Parameters | Parameter Description analysis. |
|---|---|
| **Spatial parameters (Cell-scale parameters)** | |
| TPor | Total porosity |
| FCap | Field capacity |
| PClay | Percent clay |
| PSand | Percent sand |
| PSilt | Percent silt |
| POM | Percent of organic matter |
| Ksat | Saturated hydraulic conductivity for soil layers |
| Keff* | Effective hydraulic conductivity for Green-Ampt infiltration equation |
| Kinter* | Constant interrill erodibility |
| MRtDep | Maximum root depth (m) |
| D2GWT | Depth to the groundwater table from surface (m) |
| RR2nd | Random roughness of secondary tillage immediately after tillage (m) |
| HLsoil | Half-life on soil |
| Koc | Partitioning coefficient |
| AppDep | Pesticide application depth |
| **General parameters (Watershed-scale parameters)** | |
| InfilDep | Effective soil depth for infiltration calculation |
| coeffrain | Rainfall adjustment factor for Keff |
| RSpace** | Rill space |
| ManRill | Manning's n in the rill |
| FDRoff** | Fraction of dissolved chemical available for runoff |
| InterDep | Interflow depth |
| AnioFac | Anisotropic factor for interflow (ratio of horizontal to vertical hydraulic conductivities) |
| LenRill | Length for rill detachment calculation (m) |
| LenChan | Length for channel detachment calculation(m) |
| GwCoeff | Baseflow coefficient |
| GwPow | Power coefficient for baseflow equation |
| GwSlope | Slope coefficient for baseflow equation |
| GwInter | Intercept for the baseflow equation |
| GwThr | Threshold value for the baseflow equation |
| GwBD | Average bulk-density in groundwater zone |
| GwTPor | Average total porosity in groundwater zone |
| Disp | Dispersivity |
| AHGrad | Average hydraulic gradient |
| **Channel related parameters** | |
| ChaWid | Channel width |
| FUES | Fraction of Unerodible channel soil, or erosion resistant |
| CClay | Percent clay in channel |
| CSand | Percent sand in channel |
| CSilt | Percent silt in channel |
| COM | Percent organic matter in channel |

* only for constant approach

** treated as cell-scale parameters in the preliminary cell-scale sensitivity analysis

analysis to assort sensitive cell-scale parameters based on homogeneous soil layers and 2) vertical sensitivity analysis to determine the model response to the changes in soil-related parameters at different soil layers. Watershed-scale sensitivity analysis was performed by considering routing processes to understand how the model responses to changes in soil parameters at different locations (horizontal sensitivity analysis). The cell-scale, watershed-scale, and channel-related parameters are shown in Table 1. Three surface output variables (total runoff, sediment yields, and total pesticide load at a watershed outlet) and two subsurface output variables (recharge and pesticide flux to groundwater) were selected for both plot-scale and watershed-scale sensitivity analysis. Among simulated pesticides, only atrazine result was used for sensitivity analysis of pesticide components.

### 3.1. Preliminary cell-scale sensitivity analysis

Preliminary cell-scale sensitivity analysis was conducted on the QNB plot with the assumption of homogeneous soil layers. A homogeneous soil profile was assumed to exclude impact of different soil layers on selected output variables. Effective hydraulic conductivity (Keff) and interrill erodibility factor (Kinter) are important parameters used to distribute excess rainfall into surface and subsurface related processes and to estimate soil detachment on soil surface, respectively. Preliminary sensitivity of cell-scale parameters was conducted based on both dynamic approach and constant approach for the Keff and Kinter parameters. Simultaneous change in two or more parameters was occasionally necessary to adequately reflect the physical meaning. Sum of clay, sand, and silt percent should be 100% and increase in clay percent should cause decrease in silt or sand percent. In this study, increase or decrease in percent of a soil particle class such as clay, silt, or sand was considered by equally distributing the changes to the remaining soil particle classes. Rill space (RSpace) and fraction of dissolved chemical for runoff (FDRoff) parameters were treated as cell-scale parameters in the analysis even though they are watershed-scale parameters.

### 3.2. Soil layer sensitivity analysis

Among selected sensitive cell-scale parameters based on the preliminary sensitivity analysis, only the soil-related parameters were changed in different locations of soil layers to determine the sensitivity to water quantity and quality in both surface and ground water (vertical sensitivity analysis). Soil layer sensitivity was also analyzed based on the dynamic approach for the effective hydraulic conductivity (Keff) and interrill erodibility factor (Kinter). Soil related parameters were changed at three different zones of soil layers: top (0-1.52 m), middle (1.52-5.26 m), and bottom (5.26-9.0 m). Top, middle, and bottom zones of soil layers represent root zone soil layers, upper half of intermediate zone soil layers, and the bottom half of intermediate zone soil layers, respectively. Weighted change in input parameters for each zone was used to consider different depth of soil layers within each zone. The weighted change in soil parameters for each soil layer zone was calculated based on total depth of soil profile by:

$$\frac{\triangle P}{P}=\frac{D_1 \cdot \triangle P_1/P_1+D_2 \cdot \triangle P_2/P_2+\cdots \cdots+D_n \cdot \triangle P_n/P_n}{D_1+D_2+\cdots\cdots+D_n} \tag{1}$$

Where $D_n$ is thickness of the soil layer using parameter value $P_n$ and n is total number of soil layers.

### 3.3. Soil location sensitivity analysis

Sensitivity to the changes in soil-related parameters at different locations was analyzed using the QN2 subwatershed with the assumption of homogeneous soil layers (horizontal sensitivity analysis). Two different groups of soil were assigned for considering the changes in soil-related parameters at different locations: (1) soil groups near the watershed boundary (near-boundary) and (2) soil group near streams (near-stream). Flow path from a boundary cell to a stream cell is an important factor to be considered for simulating fate and transport of pollutants. As a result, soil type was assigned to each cell by considering the flow routing path rather than the straight distance from a cell to a nearest stream segment. In DANSAT, simulated outflow in a cell is added to the down-stream cell according to the order of routing calculation which is defined by the cell number. Among 265 cells, near-boundary soil group was assigned to the cells where cell numbers from 1 to 132 were assigned while near-stream soil group was assigned to the remaining cells from 133 to 256 of cell number. Sensitivity according to the changes in soil-related parameters at different locations was analyzed based on weighted changes in soil parameters using the equation:

$$\frac{\triangle P}{P}=\frac{NC_1 \cdot \triangle P_1/P_1+NC_2 \cdot \triangle P_2/P_2+\cdots \cdots+NC_n \cdot \triangle P_n/P_n}{NC_1+NC_2+\cdots\cdots NC_n} \tag{2}$$

Where $NC_n$ is the number of cells using parameter value $P_n$ which is distributed horizontally within a watershed and n is total number of parameter types (soil types) in a watershed.

## 4. Statistics

Deterministic approach was selected considering intensive computation time requirement as a result of the physically-based and distributed model characteristics of DANSAT. Relative sensitivity (Sr), which describes how model output varies over changes of input parameters, was selected as measure for sensitivity. Sensitivity parameter was calculated using specific percentage of base value at six different levels (+50%, +25%, +10%, -10%, -25%, and -50% changes from base value) to consider non-linear response of the model to input parameters. The specific percentage was adjusted if the parameter value exceeds the default boundary of the selected input parameter. A sensitivity index (SI), providing a method to compare overall relative sensitivities (Sr) of output variables, was then calculated. The relative sensitivity (Sr) and sensitivity index (SI) are expressed by:

$$S_r = \frac{\Delta O/O_b}{\Delta P/P_b} = \frac{(O-O_b)/O_b}{(P-P_b)/P_b} \tag{3}$$

$$SI = \frac{1}{N} \cdot \sum_{i=1}^{N} |S_r(i)| \tag{4}$$

Where $S_r$ is relative sensitivity, $\Delta O$ is change in the output, $O_b$ is base output, O is output according to the new input parameter, $\Delta P$ is the change in the parameter value, $P_b$ is the base parameter value, P is new input parameter, SI is sensitivity index for each output variable, and N is total number of levels of parameter changes for $S_r$.

# III. Results and Discussions

## 1. Preliminary cell-scale sensitivity analysis

The sensitivity index (SI) for five different output variables based on changes in each selected parameter value are shown in Fig. 2. Selected parameters can be classified into several groups including: 1) parameters

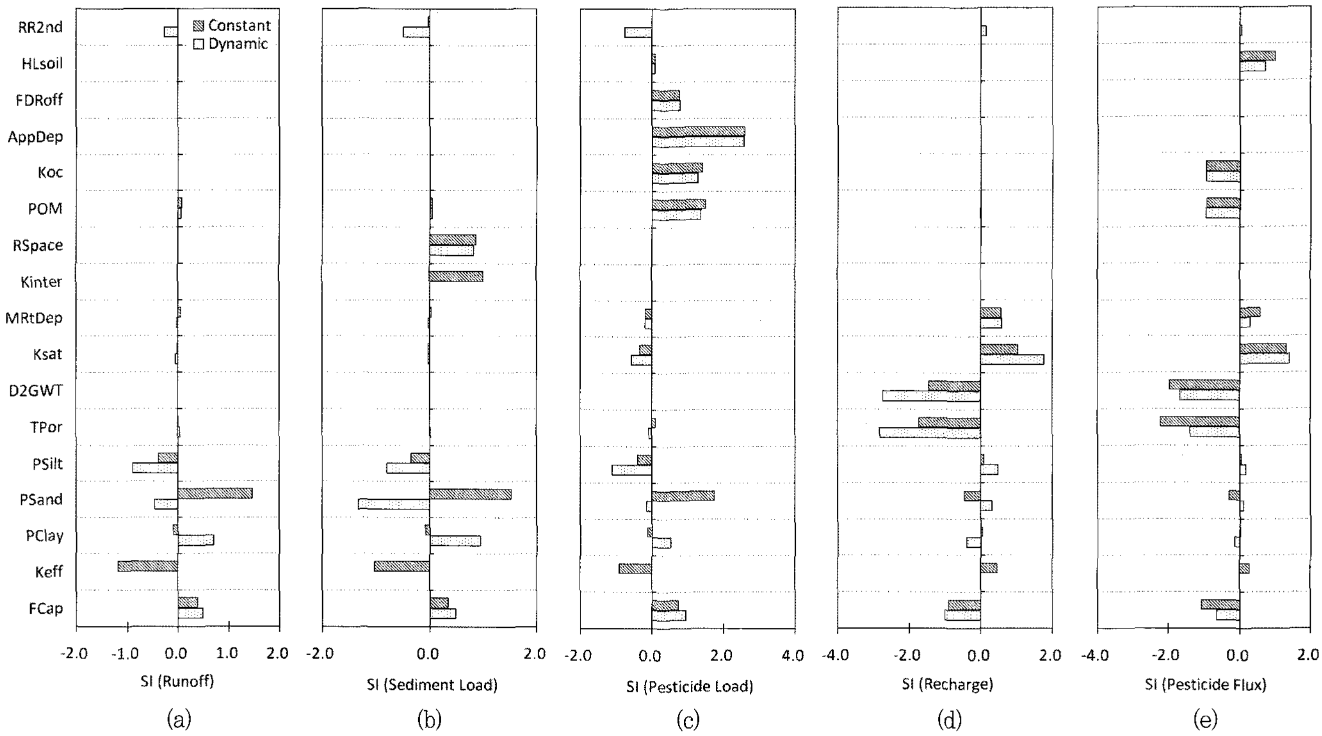


**Fig. 2 Sensitivity to changes in plot-scale parameters: (a) runoff, (b) sediment load, (c) pesticide load, (d) recharges, and (e) pesticide flux to groundwater**

sensitive to both surface and subsurface output variables (FCap); 2) parameters more sensitive to surface output variables (Keff, PClay, PSand, and PSilt); 3) parameters more sensitive to subsurface output variables (TPor, D2GWT, Ksat, and MRtDep); 4) parameters only sensitive to sediment output variable (Kinter and RSpace); 5) parameters only sensitive to pesticide output variables (POM, Koc, AppDep, FDRoff, and HLsoil).

The model was sensitive to variations in the field capacity of the soil (FCap). Surface runoff increased and groundwater recharge decreased as the FCap increased. Increases in FCap within a capacity-based percolation approach reduce the volume of available water for percolation which results in a decrease in recharge. With increase in FCap, more water can be stored in soil layers and effective matrix potential for Green-Ampt infiltration can be decreased, which may result in decrease in infiltration and increase in surface runoff. Increases in sediment and pesticide loads at a watershed outlet were expected due to increases in total runoff. Subsurface pesticide flux to groundwater also showed similar trend to the recharges to groundwater.

Soil particle contents (PClay, PSand, PSilt) and effective hydraulic conductivity for Green-Ampt infiltration (Keff) were more sensitive to surface output variables compared to subsurface outputs. Keff was only sensitive at the constant approach by showing reduction in surface runoff volume due to the increase in Keff value. Changes in clay content of the soil (PClay) were more sensitive with the dynamic approach because PClay is used in estimation of Keff for Green-Ampt infiltration. An increase in PClay resulted in a decrease in Keff value which increases runoff volume. Neither surface nor subsurface output was impacted by changes in PClay within the constant approach in which the Keff value is fixed as user-input. Both the dynamic and constant approaches sensitively responded to changes in sand content of the soil (PSand). Howerver, dynamic and constant approaches also showed the opposite responses to each other: surface output variables decreased in the dynamic approach while surface output variables increased in the constant approach when PSand increased. PSand is connected with infiltration process in two different ways. PSand is related to the estimation of both the effective hydraulic conductivity (Keff) and wetting front capillary potential (Sf) for Green-Ampt infiltration method. The Keff increases and Sf decrease as PSand increases. As a result, within the constant approach, runoff volume increases as PSand increases because the Keff value is fixed as user-input and only Sf is influenced by changes in PSand. However, increases in PSand influence both Keff and Sf in opposite direction within the dynamic variable approach and its impacts on hydrology can be cancelled by each other. In addition, PSand is related to soil erodibility parameters. An increase in sand content makes the soil more sensitive to erosion process. An increase in the silt content of the soil (PSilt) resulted in a decrease in surface output variables and an increase in the subsurface output variables even though PSilt is only involved in estimating the sealing and crusting adjustment factor for rill erodibility. The responses of PSilt to all five output variables can be attributed to the changes in both PClay and PSand due to the changes in PSilt.

Subsurface outputs such as recharges and pesticide flux to groundwater were sensitive to changes in total porosity (TPor), depth to groundwater table (D2GWT), saturated hydraulic conductivity of soil layer (Ksat), and maximum root depth (MRtDep). Increases in TPor and D2GWT decreased recharge and pesticide flux to groundwater while increases in Ksat and MRtDep increased the subsurface output variables. An increase in TPor decreased subsurface outputs in both the dynamic and constant approaches. An increase in TPor resulted in an increase of soil space in which more infiltrated water can be stored and extracted through evapotranspiration process. If the same amount of water is infiltrated and more water is extracted through evapotranspiration, less water will be percolated through soil profile. Similar trend to the hydrology was expected in pesticide flux to groundwater because atrazine has moderately soluble characteristics in water. Increases in D2GWT decreased the recharges and pesticide flux to groundwater. D2GWT can be considered in conjunction with the initial condition of soil water content. If the initial soil water content is less than the field capacity, more infiltrated water can be stored in the increased depth of soil profile which causes decreases in recharges. The Ksat value is related to the percolation process by controlling the leaching velocity of soil water. An increase in Ksat value increases the percolation and results in an increase of groundwater recharge. An increase in MRtDep also increased the recharge and pesticide flux to the groundwater.

Sediment yield decreased as rill space (RSpace) values decreased. A decrease in RSpace decreased the sediment detachment within rills because contributing flow rate per rill, which is calculated by dividing total flow rate by number of rills, decreases as rill space decreases. An increase in Kinter increased the sediment load only at the constant approach. Increases in Kinter value, which is used in the soil detachment process for estimating interrill erosion, increase sediment load from the cell without considering routing process in this cell-scale sensitivity analysis.

Pesticide outputs were sensitive to pesticide related parameters including organic matter content (POM), pesticide partitioning coefficient (Koc), pesticide application depth (AppDep), fraction of dissolved chemical available for runoff (FDRoff), and pesticide half-life in soil (HLsoil). POM and Koc were sensitive to both surface and subsurface pesticide outputs. AppDep and FDRoff were sensitive to pesticide in runoff while HLsoil was more sensitive to subsurface pesticide flux to groundwater. Higher Koc value increases pesticide persistence in a soil profile and enhances the possibility that more pesticide attaches to soil particles. As a result, pesticide load in surface runoff increases with an increase in sediment-bound pesticide in runoff and pesticide flux to groundwater decreases with decrease in dissolved pesticides in soil water. Responses of both surface and subsurface pesticide outputs due to changes in POM value showed similar trend to the results of Koc because Koc is a function of POM. An increases in AppDep and FDRoff increased surface pesticide loads in both the dynamic and constant approaches. An increase in HLsoil increases the pesticides persistence in the soil profiles. More pesticide movements in both surface and soil water are expected because of the increased possibility of interaction among water, soil, and pesticide during the increased residence time. An increase in random roughness of secondary tillage (RR2nd) increased infiltration rates and decreased the surface runoff because RR2nd is used for adjusting effective hydraulic conductivity (Keff) of fallow soil.

## 2. Soil layer sensitivity analysis

Fig. 3 show the calculated sensitivity index of DANSAT for surface and subsurface output variables for changes in parameters at different zones in the soil layers. Soil parameters can be classified into three groups: 1) surface process parameters related to infiltration and soil detachment processes (PClay, PSand, and PVFSand); 2) subsurface process parameters related to percolation process (TPor, FCap, and Ksat); and 3) combined parameters involving both surface and subsurface processes (POM).

Surface process parameters are used in estimating

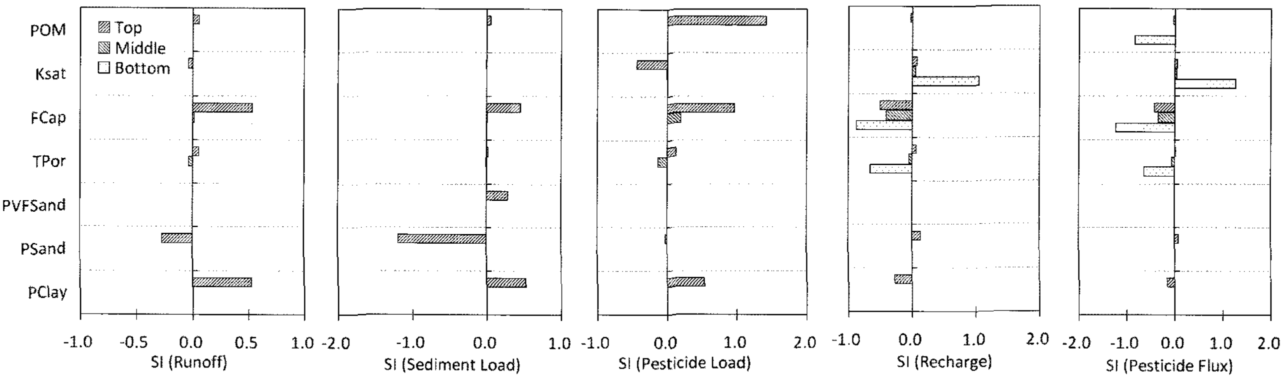


**Fig. 3 Sensitivity to changes in soil parameters at different soil layers: (a) runoff, (b) sediment load, (c) pesticide load, (d) recharges, and (e) pesticide flux to groundwater**

infiltration and soil detachment rates which are influenced by the characteristics of top soil layers. As a result, changes in the surface process parameters including clay content (PClay), sand content (PSand), and very fine sand content (PVFSand) within middle or bottom zone of soil layers had no impacts on the output variables (Fig. 3). Changes in PClay and PSand within the top zone of soil layers showed similar responses in output variables to the preliminary cell-scale sensitivity analysis. Increases in PClay increased the values of the surface output variables and decreased the subsurface output variables values while changes in PSand caused decrease and increase for surface and subsurface output variables values, respectively. VFSand is used in the soil detachment process for estimating soil erodibility and critical shear stress without any influence on hydrologic process. As a result, only sediment yield in surface runoff was sensitive to the changes in VFSand within the top soil zone.

Subsurface-process parameters including total porosity (TPor), field capacity (FCap), and saturated hydraulic conductivity (Ksat) are used to calculate the percolation and pesticide leaching rates within each soil profile. In general, changes in the subsurface process parameters in bottom zone of soil layers had a greater impact on the values of subsurface output variables such as recharge and pesticide flux to the groundwater (Fig. 3d and 3e). Changes in FCap in all soil zones showed higher impacts on subsurface output variables while changes in TPor and Ksat within top and middle zones of soil layers were not sensitive to subsurface output variables. An increase in TPor value in bottom zone of soil layers decreased the recharge and pesticide flux to the groundwater while an increase in Ksat in bottom zone of soil layers increased subsurface output variables. Both surface and subsurface output variables were sensitive to the changes in the FCap within top zone of soil layers by showing increase in surface runoff and decrease in groundwater recharge due to the increase in FCap. It can be explained by the indirect impacts of subsurface process parameters on infiltration process. Higher soil water content in the top zone of soil layers may decrease effective matrix potential in Green-Ampt equation and it may cause changes in total runoff. However, the impacts of subsurface-process parameters on the infiltration process are generally negligible below a certain soil depth. As a result, impacts of changes in subsurface-process parameters within middle or bottom zone of soil layers on the surface output variables were negligible (Fig. 3a through 3c).

Organic matter content (POM) was only sensitive to pesticide-related output variables. Similar to the surface-process parameters, changes in POM only within the top soil zone, had impact on surface outputs. POM is indirectly used in estimating infiltration-related parameters in DANSAT. As a result, changes in POM value within middle or bottom layers of soil profile did not impact surface runoff and subsurface recharge to groundwater (Fig. 3a and 3d) while changes in POM in top soil layers had an impact on total runoff, sediment load, and pesticide in runoff (Fig. 3a through 3c). Only pesticide loss in runoff was sensitive to the POM changes in top soil layers while runoff and sediment load were not sensitive to the changes in POM. Similar to the subsurface-process parameters, pesticide flux to groundwater was sensitive to the changes in POM within bottom soil zone only. Pesticide partitioning coefficient (Koc) is determined as a function of the POM in DANSAT and Koc is used in pesticides persistence within a soil profile.

### 3. Soil location sensitivity analysis

Fig. 4 show the estimated sensitivity index values for selected surface and subsurface output variables for changes in soil parameters at different locations within the watershed. Most of output variables were sensitive to changes in Total porosity (TPor) and field capacity (FCap). Pesticide in runoff was very sensitive to the changes in TPor and FCap at near-stream cells with -17.1 and 12.8 of sensitivity index, respectively. Pesticide flux to groundwater was sensitive to the change in total porosity (TPor), field capacity (FCap), and organic matter content (POM) and showed more sensitivity to the changes in POM value at near-stream cells. Groundwater recharge was also sensitive to the changes in TPor and FCap. Parameter changes in TPor and FCap at near-stream cells had greater impacts on the groundwater recharges than changes at near-boundary cells. Total runoff and

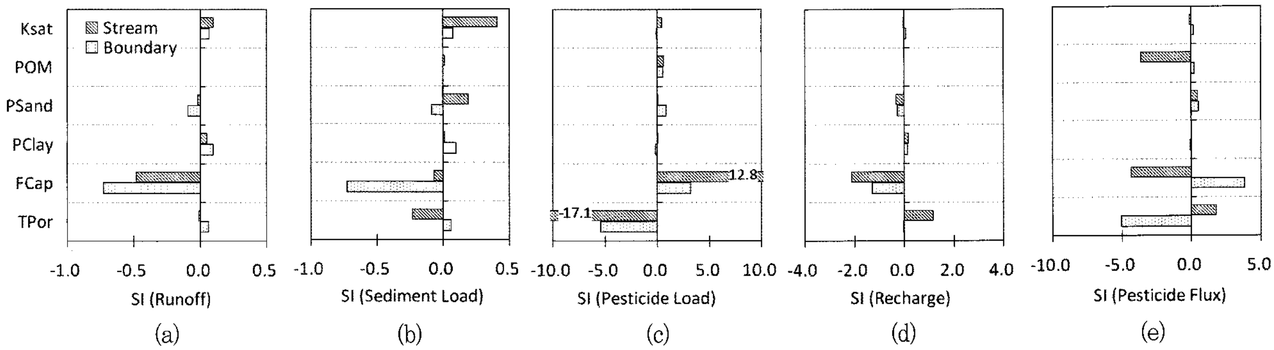


**Fig. 4 Sensitivity to changes in soil parameters at different location of watershed: (a) runoff, (b) sediment load, (c) pesticide load, (d) recharges, and (e) pesticide flux to groundwater**

sediment load were also sensitive to the changes in FCap. However, changes in FCap at near-boundary cells had greater impacts on the runoff and sediment loads than changes at near-stream cells. Overall, the selected output variables were more sensitive to the parameter changes in cells located near the stream.

In some cases, changes in the same parameter at different locations showed opposite responses in the same output variable. For example, an increase in TPor and FCap at near-boundary cells decreased spatially averaged pesticide flux to groundwater while an increase in TPor and FCap at near-stream cells increased the value of the same output variable. The opposite response of the same output variable due to changes in the same parameter at different locations can be explained by considering the possible paths of water and pollutants from overland areas to a stream segment. Parameter changes near the watershed boundary may influence the downward routing process within the path from the overland cells to the stream cells. For example, increased infiltration near the watershed boundary may increase the groundwater recharges in that area. However, decreased overland flow to the downstream cells may decrease the groundwater recharges near stream cells. As a result, it is possible that the overall spatially averaged recharge can be reduced after compensation between increase in recharges at near-boundary cells and decrease in recharges near-stream cells. If the same application is considered without considering the routing processes, increases in infiltration rates at any location within the watershed would decreased the total surface runoff and increase the watershed averaged recharge to the groundwater.

## Ⅳ. Summary and Conclusion

Responses of five output variables to the changes in the selected functional parameters of DANSAT were examined on both cell-scale and watershed-scale. In a cell-scale sensitivity analysis, soil related parameters such as field capacity and soil particle sizes were sensitive to majority of the five output variables.

In preliminary cell-scale sensitivity analysis, considered parameters were classified into several groups including: 1) parameters sensitive to both surface and subsurface output variables (FCap), 2) parameters more sensitive to surface output variables (Keff, PClay, PSand, and PSilt), 3) parameters more sensitive to subsurface output variables (TPor, D2GWT, Ksat, and MRtDep), 4) parameters only sensitive to sediment output variable (Kinter and RSpace), and 5) parameters only sensitive to pesticide output variables (POM, Koc, AppDep, FDRoff, and HLsoil). In vertical sensitivity analysis, parameters were grouped into surface process and subsurface process parameters which are related to infiltration and soil detachment processes and percolation and pesticide leaching processes, respectively. Changes in surface-process parameters (PClay, PSand, and VFSand) within middle or bottom zone of soil layers had no impact on output variables while changes in subsurface process parameters (TPor, FCap, and Ksat) within bottom zone of soil layers had significant impact on subsurface output variables. In horizontal sensitivity analysis at watershed-scale, both surface and subsurface output variables were more sensitive to the parameter changes in near-stream cells compared to the parameter changes in near-boundary cells. Overall, total porosity and field capacity were sensitive to most output variables.

The methodology and results of this sensitivity analysis based on changes in soil parameters at different layers and locations will be helpful in understanding the impacts of spatially distributed agricultural BMPs, which are applied at different locations within a watershed, on hydrology and water quality of both surface water and ground water.

Even though the results in this study can be used as a guideline for a calibration of the model, it should be noted that the sensitivity index for each output variable could be different in other watersheds with different hydrologic characteristics. Ferreira et al. (1995) discussed the site- and condition-specific nature of sensitivity analysis and demonstrated that user-side sensitivity analysis is an essential step in model application even though general sensitivity analysis are provided by model developers.

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