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Groundwater vulnerability mapping: A GIS and fuzzy rule based integrated tool

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Abstract

Contamination of groundwater has become a major concern in recent years. Since testing of water quality of all domestic and irrigation wells within large watersheds is not economically feasible, one frequently used monitoring strategy is to develop contamination potential maps of groundwater, and then prioritize those wells located in the potentially highly contaminated areas for testing of contaminants. However, generation of contamination potential maps based on groundwater sensitivity and vulnerability is not an easy task due inherent uncertainty. Therefore, the overall goal of this research is to improve the methodology for the generation of contamination potential maps by using detailed landuse/pesticide and soil structure information in conjunction with selected parameters from the DRASTIC model. The specific objectives of this study are (i) to incorporate GIS, GPS, remote sensing and the fuzzy rule-based model to generate groundwater sensitivity maps, and (ii) compare the results of our new methodologies with the modified DRASTIC Index (DI) and field water quality data. In this study, three different models were developed (viz. DI_{fuzz}, VI_{fuzz} and VI_{fuzz_ped}) and were compared to the DI. Once the preliminary fuzzy logic-based (DI_{fuzz}) was generated using selected parameters from DI, the methodology was further refined through VI_{fuzz} and VI_{fuzz_ped} models that incorporated landuse/pesticide application and soil structure information, respectively. This study was conducted in Woodruff County of the Mississippi Delta region of Arkansas. Water quality data for 55 wells were used to evaluate the contamination potential maps. The sensitivity map generated by VI_{fuzz_ped} with soil structure showed significantly better coincidence results when compared with the field data.

Keywords: GIS; Remote sensing; Fuzzy logic; Groundwater sensitivity; Pesticides

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1. Introduction

Contamination of groundwater with agricultural chemicals is a major concern for citizens as well as local, state, and federal agencies involved with the management, quality and quantity of water and human health. One monitoring strategy used by local, state and federal agencies is to develop contamination potential maps of groundwater and prioritize those wells located in potentially highly contaminated areas for testing of agricultural contaminants such as animal waste components, fertilizers, and pesticides.

Mapping contamination potential of groundwater is comprised of sensitivity mapping and vulnerability mapping. Ground-water sensitivity to agricultural chemicals is determined by assessing natural factors favorable or unfavorable to the transport of chemicals to the groundwater. Sensitivity is the ease with which chemicals can move from surface to the groundwater through underlying soils and geological formation to pollute groundwater. Aquifer sensitivity is assessed from hydrogeologic setting (depth to groundwater, presence or absence of confining layers or clay caps), recharge of groundwater, soil hydraulic conductivity soil retardation, and attenuation factors (Hamerlinck & Arneson, 1998; Lowe & Butler, 2003). Ground-water vulnerability to chemicals is determined by assessing how ground-water sensitivity is modified by the activities of humans such as potential for contaminants to be present. Ground-water vulnerability to chemicals is determined by combining groundwater sensitivity maps with the presence of crop type, landuse practices, pesticide use and applied water (irrigation) (Aller, Bennett, Lehr, Petty, & Hackett, 1987; Connell & Daele, 2003; Hamerlinck & Arneson, 1998; Lowe & Butler, 2003).

Although, it is easy to see the benefits of a map to guide environmental monitoring strategy, the generation of maps showing delineated contamination potential zones for monitoring purposes are difficult since groundwater contamination depends upon numerous, complex interacting parameters with inherent spatial and temporal uncertainty.

Therefore, there is a need to develop an affordable but reliable mapping methodology that is capable of dealing with uncertainty to generate groundwater contamination potential maps at the watershed or county scale. This will be a useful groundwater management tool. Environmental managers could use this tool to prioritize and guide sampling strategies.

Advent of Geographic Information System (GIS) has facilitated assessment of groundwater vulnerability through mapping. Burrough (1996) mentioned that integration of GIS and solute transport modeling has the potential to facilitate sensitivity analyses interactively and the results can be seen in a spatial context. An integrated system of advanced information technologies such as GIS, Global positioning System (GPS), remote sensing and fuzzy logic could provide a framework from which real-time or simulated assessment of non-point source (NPS) pollution can be made (Corwin, Loague, & Ellsworth, 1996). Loague & Corwin (1998) have shown that integrated process-based computer simulations with GIS could be a useful tool in regional scale assessment of NPS contamination of groundwater. Integration of GIS and vulnerability indices that allows generation of contamination potential maps could improve management of water resources and landuse (Connell & Daele, 2003). Research has shown that fuzzy rule-based models are capable of producing comparable results using about 40% fewer variables (Bardossy & Disse, 1993). The fuzzy rule-based approach has been used in solute transport studies (Dou, Wolt & Bogardi, 1999) and assessing an aquifer's pollution potential (Cameron & Peloso, 2001; Dixon, Scott, Dixon & Steele, 2002). Coupling between GIS and fuzzy rule-based techniques are particularly useful when modeling fuzzy inputs common to hydrogeologic parameters because they tolerate imprecision and uncertainty and show marked reduction in information loss when used with simple GIS techniques (Burrough & McDonnell, 1998; Burrough Macmillan, & Van Deursen, 1992; Sui, 1992; Wang, Hall & Subaryono, 1990).

The theory of fuzzy logic based on fuzzy sets was proposed by Zadeh (1965), which states that a complex system will be better represented by descriptive variable of linguistic types than by the traditional representation of differential equations (Cox, 1994). For more detailed discussion on fuzzy logic please refer to Cameron & Peloso (2001); Dixon & Scott (2001); Dixon et al. (2002); Mitra, Scott, Dixon and McKimmey (1998), and Yen & Langarria (1998).

Therefore, overall goal of this research is to improve the methodology for the generation of groundwater sensitivity as well as vulnerability maps by using detailed landuse/pesticides and soil structure information in conjunction with selected parameters from the DRASTIC model (Aller et al., 1987). The specific objectives of this study are (i) to incorporate GIS, GPS, remote sensing and the fuzzy rule-based model to generate groundwater sensitivity maps through enhanced environmental modeling capability, and (ii) compare the results of our new methodologies with the DRASTIC Index.

DRASTIC, an overlay and index method developed for the Environmental Protection Agency (EPA) by the American Water Well Association (Aller et al., 1987) is a widely used model. This model assesses contamination potential of an area to pollution by bringing together key factors believed to influence the solute transport. The original DRASTIC Index ($\mathrm{DI}_{\mathrm{org}}$) was calculated using the most important hydrogeologic factors that affect the potential for groundwater pollution.

$$\mathrm{DI}_{\mathrm{org}} = DwDr + RwRr + AwAr + SwSr + TwTr + IwIr + CwCr \tag{1}$$

where

$\mathrm{DI}_{\mathrm{org}}$ DRASTIC Index
R net recharge
A aquifer media
S soil media
w weight
D depth to water table
T topography
I impact of vadose-zone media
C hydraulic conductivity (aquifer)
r rate

The DRASTIC Index does not provide absolute answers; it only differentiates highly vulnerable areas from less vulnerable areas. The nature of the DRASTIC model is additive. Every parameter in the model has a fixed weight indicating the relative influence of the parameter in transporting contaminants and water to groundwater. The parameter rates are variable, which allow the user to calibrate the model to suit a given region.

The approach discussed in the paper is unique because it attempts to improve sampling strategies by improving sensitivity mapping tools that incorporates soil structure as one of the key physical factors that controls water and contaminant transport processes through the soils. Although the DRASTIC model maps sensitivity of groundwater based on hydrogeologic parameters, it does not include soil structure in the model. The parameter *S* (soil media) of the DRASTIC Index was developed using soil textural information. It has been recognized that textural properties of soil are far less dynamic than soil hydraulic properties. Therefore, relatively dynamic soil properties such as soil water or macro pores should be incorporated in a model that attempts to predict groundwater contamination potential. Studies have shown the importance of soil structure in determining water and contaminant transport through preferential flow (Lin & McInnes, 1995; Lin, McInnes, Wilding & Hallmark, 1999; Quisenberry, Smith, Phillips, Scott & Nortcliff, 1993). Soil structure, viz. pedality of a soil, indicates a soil's ability to transport water and contaminant through the soil profile as it alters a soil's pore size distribution, continuity and connectivity (Scott, 2000). Therefore, in this study the preliminary sensitivity map generated by incorporating selected parameters from DRASTIC was modified using soil structure (pedality).

This study also incorporates landuse data from Landsat TM5 to create a vulnerability map from pesticide loading index (PI). Landuse is an extremely important parameter for groundwater vulnerability mapping as it controls the potential presence or absence of contaminants. It also affects the nature of the pesticides. For example in an agricultural watershed, a particular pesticide is used for a particular crop with unique properties including sorption, solubility in water and half life. Several studies have shown that landuse parameters have to be considered when studying the impact of agricultural diffuse pollution on the environment (Bolstad & Swank, 1997; Hong-Il & Hyo-Taek, 1999; Kanchanakool, 1999; Reijnders, van Drecht, Prins & Boumans, 1998; Tonmanee and Kanchanakool, 1999; Zhang, Beavis & Gray, 1999).

1.1. Location of the study

The study area, Woodruff County, is located in the Mississippi River Valley region of Arkansas. This county was selected to conduct the pilot project for the entire Mississippi Delta region of Arkansas because it represented two of the major land resources areas (MLRAs); MLRA 131 and MLRA 134 of the region (Fig. 1). MLRAs are similar physiographic provinces based upon aggregations of geographically associated land resource units containing nearly homogeneous land use, elevation, topography, climate, water resources, potential natural vegetation, and soils. MLRAs are contiguously numbered for the entire country and provide useful basis for making decisions about natural/environmental and agricultural resource management. MLRA 131 represents Southern Mississippi Valley Alluvium region while MLRA 134 represents Southern Mississippi Valley Silty Uplands. About 80% of the study area is drained by the Cache-Lower White-Big River. The upper most aquifer system lying underneath the study area is

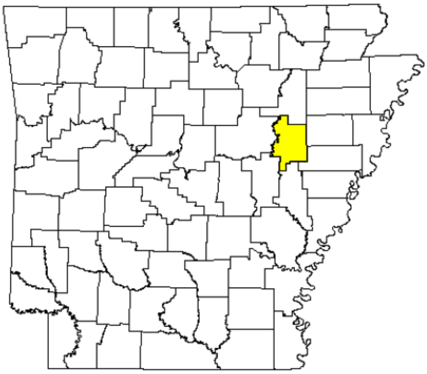

Fig. 1. Location of the study area.

part of a much larger sedimentary system known as the Mississippian Embayment Alluvial Aquifer System.

2. Methodology

2.1. Digital database

The primary data layers used in this study are soils, elevation, potentiometric surface, recharge, clay confining units, geology and landuse (Table 1). Detailed description of the generation of data layers for the parameters *D*, *R*, *A*, *S*, *T*, *I* and *C* can be found from (Dixon et al., 2002). Fig. 2 shows GIS preprocessing and manipulation techniques used to create seven input data layers for the DRASTIC Index. The DRASTIC Index was generated by using seven raster layers in GRASS GIS (Westervelt, Shipiro & Goran, 1989). A map calculation script was written using Eq. (1) where each raster layer was multiplied by their

Table 1
Primary data layers used in the study

Attributes	Scale/resolution	Source[a]
Soils	1:24,000	NRCS
Elevation	30 m	USGS
Potentiometric surface	20 ft contour interval	USGS
Recharge	Point data	USGS
Clay confining unit	Point data	USGS
Geology	1:24,000	AGC
Landuse	30 m	USGS
Pesticide application rate	Tabular	UAEX
Well water quality	Tabular	ADEQ
Well location	GPS	ADEQ

[a] [a]NRCS, Natural Soil Conservation Services; USGS, US Geological Survey; AGC, Arkansas Geological Commission; UAEX, University of Arkansas, Extension Services; ADEQ, AR Department of Environmental Quality.

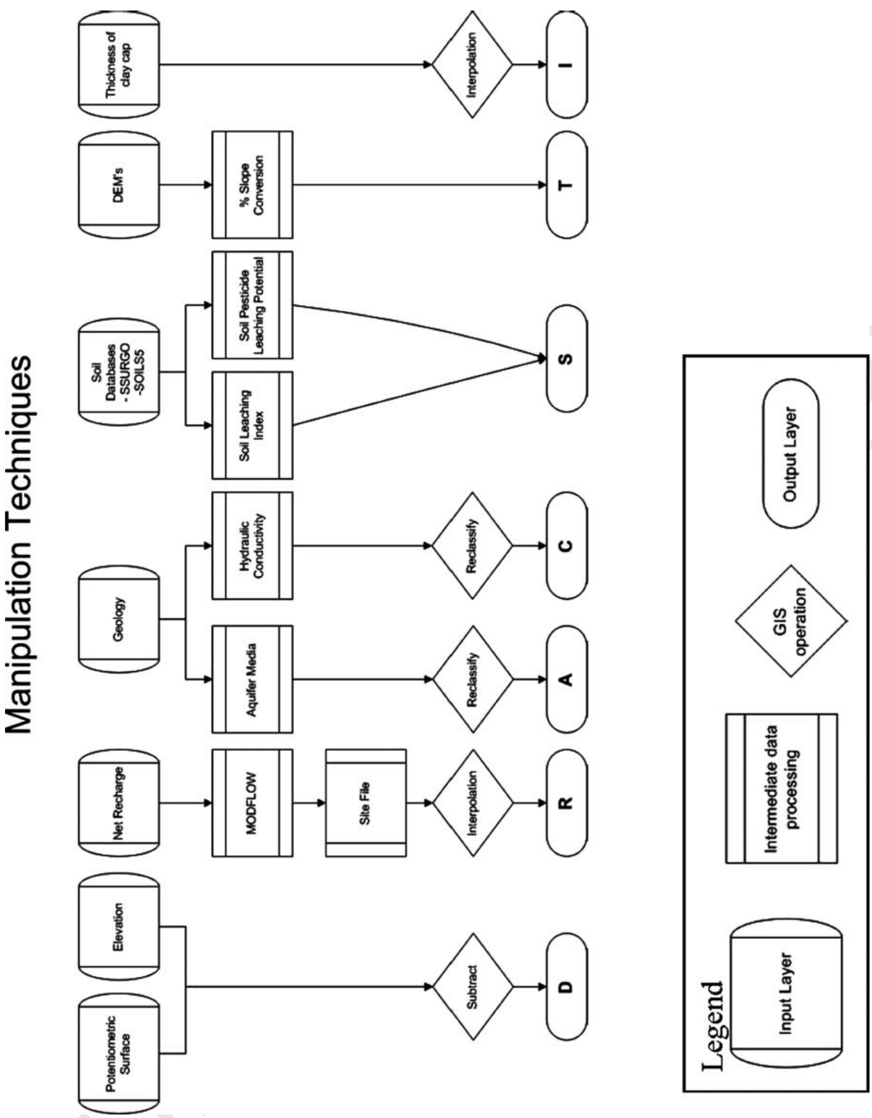

Fig. 2. Flowchart showing manipulation techniques used to create GIS data layers.

weight and ratings and then added to create the DRASTIC Index. The fuzzy rule-based model was developed using selected parameters from the DRASTIC Index. The fuzzy rule-based model used parameters such as *D*, *R*, *S*, and *I*. The parameters *A*, *T*, and *C* varied little within the county; therefore, they were not included in the fuzzy rule-based approach.

The generalized soil map and soil permeability values, estimated from the soil textural information, were obtained from the SOILS5 database to create the *S* layer. Once the preliminary fuzzy rule-based map was developed, it was modified by using soil structural data. Soil structural information for each soil series found in the study area was obtained from Official Soil Series Description (OSSD), an on-line tabular database of Iowa State (http://www.statlab.iastate.edu/soils/nsdaf/; viewed 1/16/02). The base map for the soil was county level SSURGO data that include vector polygons and ID for the soil map units. In order to bring the series level tabular data from the OSSD to our GIS, the county level SSURGO map for soil map units was reclassified into a series level soil map. This allowed direct integration of tabular data from OSSD to the GIS. The soil series map then was reclassified according to the soil structural information viz. pedality points outlined in Lin et al. (1999) to indicate water and contaminant transport properties of the soils based on soil structure. Pedality points are calculated based on the soil structure information viz. ped shape + ped size + ped grade.

All of the reclassification routines were performed using the r.reclass command in GRASS, a GIS software. The command r.reclass assigns new values to old values in the raster domain. In this study, pedality of the top horizon was included in the development of the sensitivity map, with the assumption that water and contaminant transport properties of the A horizon ultimately control the amount of contaminant and water available for transmission through the profile.

The landuse data used in this study was obtained from Landsat 5 Thematic Mapper (TM) 1992. TM images from two seasons, spring and summer, were used in this study. The image was classified into 4 level I classifications, such as urban, forests, water and agriculture. Then the images were further classified for agricultural crops. The major crops identified in the study area are rice, soybeans, corn, wheat, and cotton. The average pesticide application rates by crop, surveyed by University of Arkansas Extension Services (UAEX), for 1992, were used with landuse data layers to create the data layer for the PI. Summation of application rates of all pesticides applied to a given crop was used in PI. In a double cropped field, e.g. soybean and wheat, the PI was adjusted by summation of pesticide rates applied to both crops. While generating the data layer for PI, pesticide application rates were set to 0 for the landuse categories pasture, forests, water, and urban areas. Irrigation was not used as one of the factors that control vulnerability because the study area is intensely irrigated and irrigation can be held as constant.

2.2. Models

The original DRASTIC (Aller et al., 1987) was modified to agricultural DRASTIC by Scott, Smith and Spradley (1992) to reflect the hydrogeologic conditions of the intensely cultivated Mississippi Valley Alluvial Aquifer region of Arkansas. This modified DRASTIC Index (here on referred to as DI) was used in our study. Example of weights and ratings used for the DI in this study are given in Table 3. Each input parameter was

Table 2
Examples of actual fuzzy rules used in di fuzz

Input fuzzy sets				Output fuzzy set
If D = high and	R = low and	S = low and	I = thick then,	DI fuzz = low
If D = low and	R = high and	S = high and	I = thin and then,	DI fuzz = high

assigned a relative weight (w) ranging from 2 to 5 and a rating (r) that varied between 1 and 10. The weights indicate the relative importance of each factor with respect to the other factors. The higher the value of DI, the greater the aquifer contamination potential or sensitivity. In this study, sensitivity maps were generated using three different methods viz. DI_{fuzz}, VI_{fuzz} and VI_{fuzz_ped} then compared with DI. First, the preliminary fuzzy rule-based model DI_{fuzz} was developed using four parameters from the DI. The Fuzzy Inference Engine (Numata, 1991) was modified and loosely coupled with the GIS software GRASS. A fuzzy model is comprised of fuzzy sets and fuzzy rules. The input parameters for the model DI_{fuzz}, were D, R, S and I. The output parameter DI_{fuzz} indicated the contamination potential. Four fuzzy sets were defined for each of the input parameters except I. Three fuzzy sets were created for the input parameter I. The output parameter, DI_{fuzz}, also had four fuzzy sets. The rules were of the form 'if D (depth to groundwater) is H (high) then DI_{fuzz} (sensitivity) is L (low)', where D and DI_{fuzz} are linguistic variables while H and L are their linguistic values. Examples of fuzzy rules used in the model are presented in Table 2. In the fuzzy rule-based model the concepts of rates and weights used in DI were reflected through the number of fuzzy sets and rule bases. A slight change in a highly influential parameter had more effect on the output parameter of the rule base than a less influential parameter.

Once the preliminary fuzzy-rule based DI_{fuzz} was developed, the fuzzy rule-based model was refined by adopting/modifying methods proposed by Lin, Scott, and McKimmey (1996). This includes calculations of the model parameters for aquifer sensitivity index (SI) and PI. PI was calculated from Landsat TM images by multiplying average application rate of pesticides to the major crops of the region. Eqs. (2) and (3) show methodologies proposed by Lin et al. (1996), whereas Eqs. (4)–(6) show methodologies used in this study with GIS data layers. Map calculation scripts were written to perform these operations (Table 3).

Table 3
Weights and ratings used in modefied drastic index (DI)

DI parameters	Weight	Range	Rate
D (m)	5	0–22	10–3
R (cm/yr)	4	0–53	1–9
A (dimensionless)	3	Sand and gravel	8
S (dimensionless)	5	Soil series	1–10
T (% slope)	3	0–6	9–10
I (m)	4	0–12	8–1
C (gpm)	2	2000	10

$$\frac{VI = (SI \times PI) \times 100}{VI_{max}} \tag{2}$$

where

VI	relative groundwater vulnerability index
SI	aquifer sensitivity index
PI	pesticide loading index
VI_{max}	maximum value of VI calculated from DRASTIC

$$SI = (DI/DI_{max}) \times 100 \tag{3}$$

where

DID	RASTIC Index calculated by methodology proposed by (1)
DI_{max}	the maximum DRASTIC Index

$$\frac{VI_{fuzz} = (SI_{fuzz} \times PI) \times 100}{VI_{fuzz\_max}} \tag{4}$$

where

SI_{fuzz}	aquifer sensitivity index
PI	pesticide loading Index
VI_{fuzz_max}	maximum value of the fuzzy rule-based vulnerability (255)

$$SI_{fuzz} = (DI_{fuzz}/DI_{fuzz\_max}) \times 100 \tag{5}$$

where

DI_{fuzz}	fuzzy rule-based sensitivity model
DI_{fuzz_max}	maximum value of fuzzy rule-based sensitivity (255)

$$VI_{fuzz\_ped} = DI_{fuzz} \times Pedality_{top} \tag{6}$$

where

VI_{fuzz_ped}	sensitivity from the fuzzy rule-based model and soil structural information
DI_{fuzz}	fuzzy rule-based sensitivity model
$Pedality_{top}$	soil structural information (Ped shape + Ped size + Ped grade)

2.3. Coincidence reports

Once the contamination potential maps were generated using the DI_{fuzz}, VI_{fuzz} and VI_{fuzz_ped} methodologies, field data were used to generate coincidence reports to evaluate the performance of these models. Arkansas soil and water (ASW) provided well data for 723 wells for Woodruff County. These data include location, depth of the well, maximum allowable pumping rate, screen and casing information. Out of these large data set, 56 wells contained identical well depth, pumping and casing information. Water quality data for the 55 wells were used in this study. The Arkansas Department of Environmental Quality (ADEQ) sampled and analyzed the wells for 61 pesticides and degradation products. The ADEQ provided an Excel workbook with GPS locations as well as water quality data for the 55 wells. Seven out of 55 wells were contaminated with at least one type of pesticide. Out of 55 wells, 11 wells were sampled more than once. Therefore in our final analysis, only the 44 wells with single visits were used. The command r.coin was used in GRASS to generate the coincidence reports. This command shows mutual occurrence of categories between two raster images. Raster maps of well contamination data and model prediction (DI, DI_{fuzz}, VI_{fuzz}, and VI_{fuzz_ped}) were used with the command r.coin.

3. Results and discussion

In this study, three models: DI_{fuzz}, VI_{fuzz} and VI_{fuzz_ped} were developed and resultant contamination potential maps were compared with the field data. The initial fuzzy rule-based model, DI_{fuzz}, was created in a GIS by incorporating the four parameters *D*, *R*, *S* and *I* from the DI. Fig. 3 shows the spatial distribution of these input parameters in Woodruff County. Fig. 4 shows relationship among models. Locations of contaminated wells are shown in Fig. 5. Table 4 shows the pesticides detected in contaminated wells. Seven (well # 7, 9, 11, 25, 26, 29 and 34) wells out of 44 wells were contaminated by pesticides. Bentazon was the most common pesticide found in the contaminated wells. Four out of seven contaminated wells had Bentazon, a highly soluble pesticide. One well out of seven contaminated wells had more than one pesticide.

The spatial distribution of sensitivity categories generated by the DI model is shown in Fig. 6 and summarized in Table 5. About 38% of the study area shows low vulnerability category and occur mainly in the eastern part of the county. The central and western part of the Woodruff County shows moderately vulnerable areas and accounts for about 50% of the study area. Small patches of moderately high and highly vulnerable areas occur in the central and western part of the county.

The spatial distribution of sensitivity categories generated by fuzzy rule-based model DI_{fuzz} is shown in Fig. 7 and summarized in Table 6. Fig. 7 shows the spatial distribution of sensitivity categories generated by fuzzy rule-based model DI_{fuzz}. The western part of Woodruff County has more areas classified as highly vulnerable than the eastern part of the county. About 13% of the total area was classified as highly vulnerable (Table 6). The low sensitivity category also covers about 13% of the study area. The eastern part of the Woodruff County shows relatively higher proportion of low vulnerable areas. About 44 and 30% of the county is classified as moderately vulnerable and moderately high vulnerable, respectively.

The sensitivity map from the model VI_{fuzz} was created from PI and SI_{fuzz}. The spatial distribution of VI_{fuzz} is shown in Fig. 8 and summarized in Table 7. The primary data layer for the PI are landuse maps of summer and spring shown in Fig. 9 and summarized in

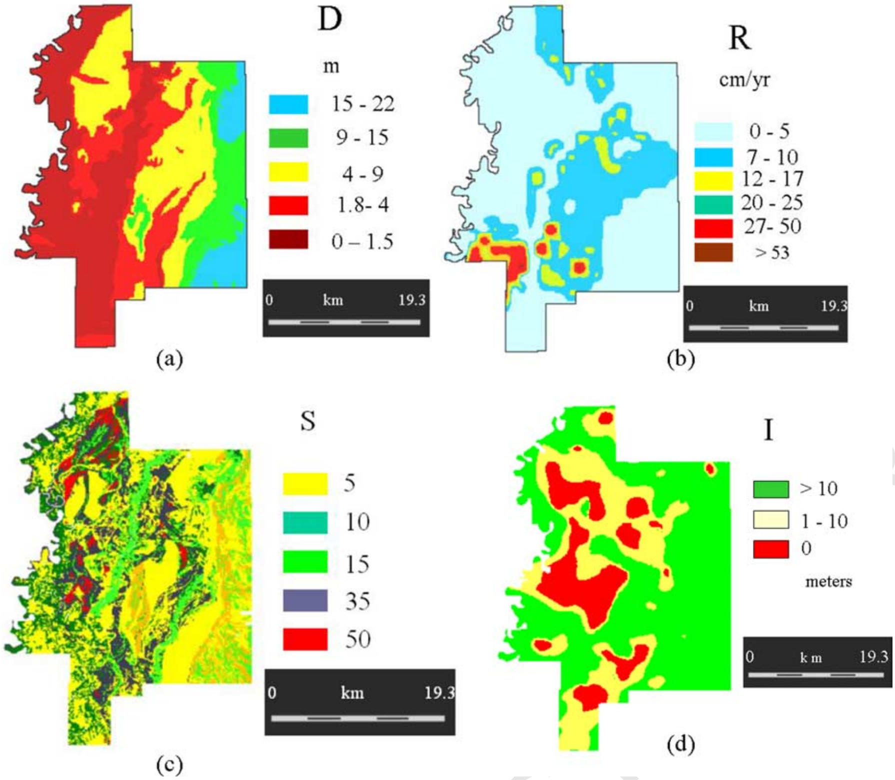

Fig. 3. Spatial distribution of input data layers: (a) *D*, (b) *R*, (c) *S* and (d) *I*.

Table 8. Fig. 10 shows the spatial distribution of the PI. About 23% of the study area shows 0 application rate which adds to approximately the total area covered by forest, water and urban areas. About 21 and 32% of the study area has pesticide application rate of 6 and 8 lbs/acre, respectively. A pesticide application rate of 10 lbs/acre covers 12% of the study area. Average application rates for the pesticides surveyed by the UAEX are presented in Table 9. The parameter SI_{fuzz} was created from the DI_{fuzz} model. Spatial distribution of SI_{fuzz} is shown in the Fig. 11 and summarized in Table 10. The spatial distribution of SI_{fuzz} closely follows the spatial pattern of DI_{fuzz}.

Incorporation of landuse data did not improve the model prediction markedly. Poor correlation was noted between landuse data and well contamination data. This could be attributed to the preferential flow paths as well as lateral flow of the ground water. Well number 25 and 9 coincided with soybeans, whereas well number 6 and 29 coincided with rice and cotton, respectively. Wells 26 and 34 coincided with bare soils during summer while well 11 coincided with forests. This could be attributed to the point source nature of the contamination such as presence of the mixing activity/spills (forest landuse in particular) or due to horizontal preferential flow (bare soils). Surrounding landuse for well number 34 was pasture during spring. Farmers do not waste their money to fertilize forests.

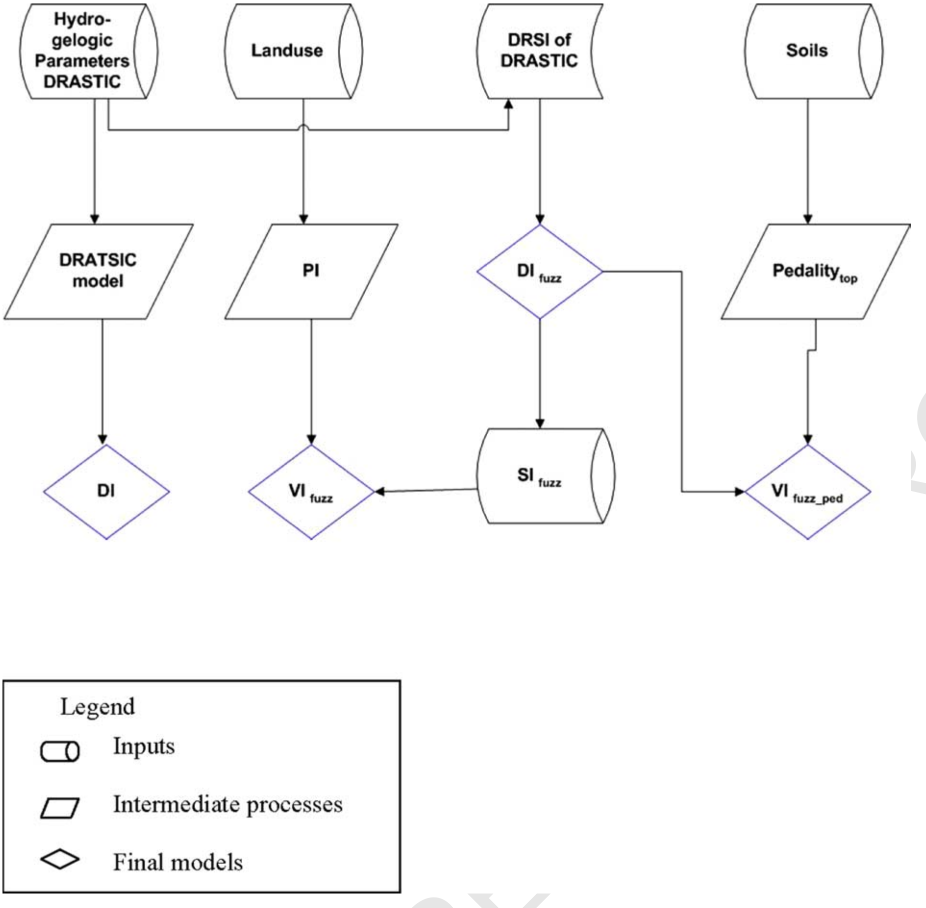

Fig. 4. Schematics showing relations among the models.

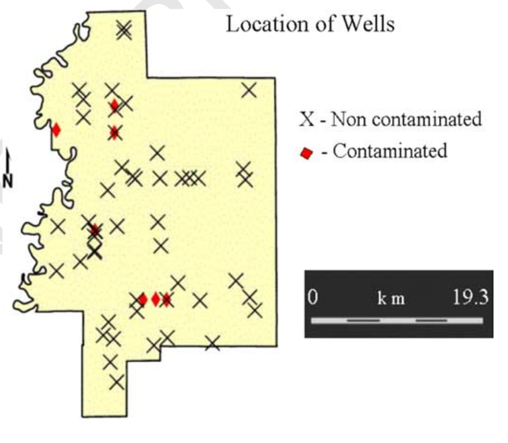

Fig. 5. Locations of wells in Woodruff County.

Table 4
Name and occurrence of pesticides

Pesticide	Occurrence	Well #
Bentazon	4	7, 9, 25, 26
Metalochlor	2	11
Fluometron	1	9
Acifluorfen	1	9
Metribuzin	1	29
Alachlor	1	34

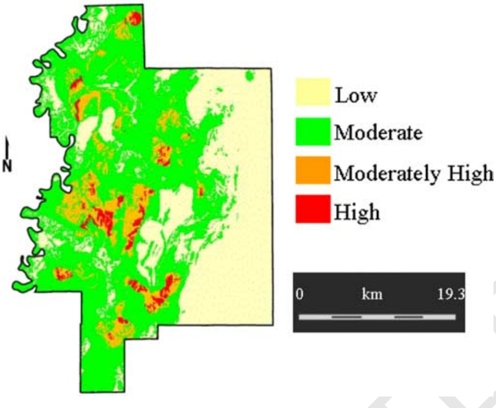

Fig. 6. DI: spatila distribution of vulnerability categories.

These highly contaminated seven wells were revisited and consistently showed higher concentration of contaminants. A buffer analysis of 90 and 120 m was performed around these wells to determine any unique hydrogeologic condition. Coincidence analysis did not provide any conclusive results. Preferential flow paths created by soil structure (pedality) or roots from the forest could be attributed to the relatively higher concentrations. Areas identified as bare soils during all three seasons (fall, spring and summer) could be a fallow field. Dead roots from the past landuse could create preferential flow paths that causes horizontal movements of soil and water and hence the wells 34 and 26 are found to be contaminated.

Table 5
DI: distribution of vulnerability categories

DI	Hectares	Percent cover
Low	59,047	38.4
Moderate	77,653	50.2
Moderately high	13,687	8.9
High	3383	2.2
Total	153,770	100

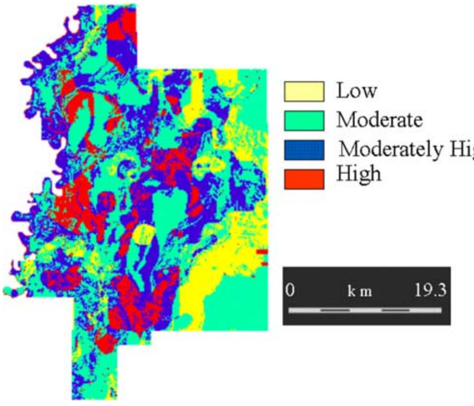

Fig. 7. DI_{fuzz}: spatial distribution of vulnerability categories.

Table 6
DI_{fuzz}: distibution of vulnerability categories

DI_{fuzz}	Hectares	Percent cover
Low	20,467	13.3
Moderate	67,866	44.2
Moderately high	45,523	29.6
High	19,914	12.9
Total	153,770	100

Finally, a sensitivity map VI_{fuzz_ped} was created by incorporating pedality data for the top soil horizon with the preliminary fuzzy rule-based model DI_{fuzz}. The spatial distribution of the VI_{fuzz_ped} is shown in Fig. 12 and summarized in Table 11. The majority of highly vulnerable areas occurs in the western part of the county. Comparison among the

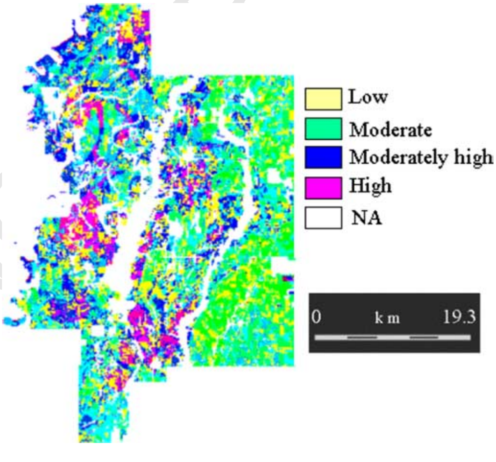

Fig. 8. VI_{fuzz}: spatial distribution of vulnerability categories.

Table 7
VI_{fuzz}: distribution of vulnerability categories

VI_{fuzz}	Hectares	Percent cover
No pesticides	35,531	23.1
Low	31,895	20.7
Moderate	43,493	28.3
Moderately high	35,611	23.2
High	7237	4.7
Total	153,770	100

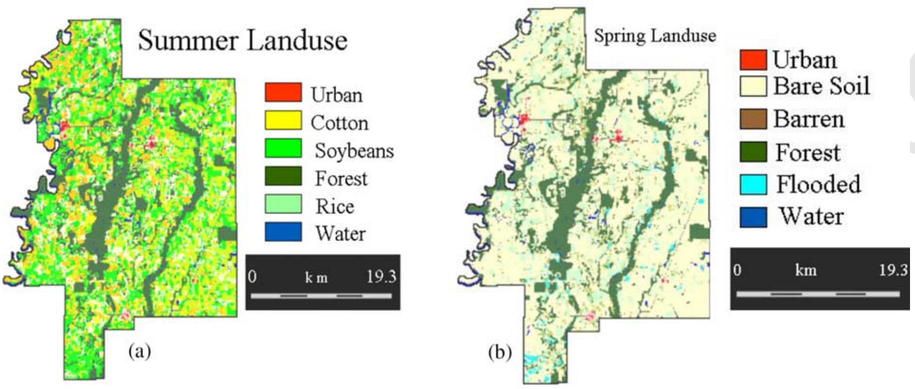

Fig. 9. Spatial distribution of landuse (a) summer and (b) spring.

three sensitivity maps showed that DI_{fuzz}, and VI_{fuzz_ped} resulted in similar spatial trends, whereas VI_{fuzz} showed considerable spatial variation. The model VI_{fuzz} was generated using pesticide loading information, and did not improve the prediction, mainly due to the presence of ‘0 values’ in the PI layer.

Table 8
Distibution of landuse used for PI

Landuse	Hectares	Percent cover
Urban	2101	1.4
Water	1797	1.1
Forests	31,505	20.5
Soybeans	42,681	27.8
Rice	25,969	16.9
Cotton	4517	2.9
Sorghum/corn	19,094	12.4
Pasture	1322	0.9
Bare Soil	24,784	16.1
Total	153,770	100

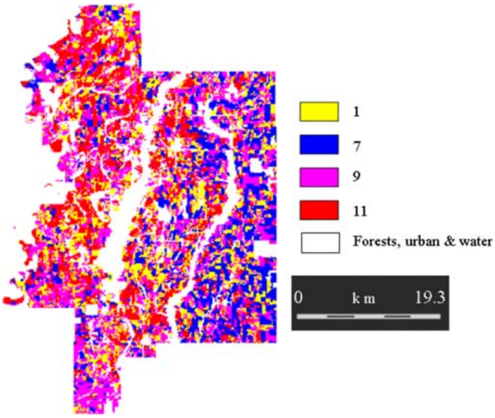

Fig. 10. Spatial distribution of pesticide loading index (PI).

Table 9
Average application rate of pesticide application for major crops in 1992

Crops	Application (kg/ha)
Soybean	9
Rice	7
Cotton	9
Wheat	1
Grain Sorghum	11
Corn	11

3.1. Coincidence analyses

This coincidence analysis provided the answer to our question 'Can groundwater sampling or monitoring strategies be improved by using the new sensitivity mapping

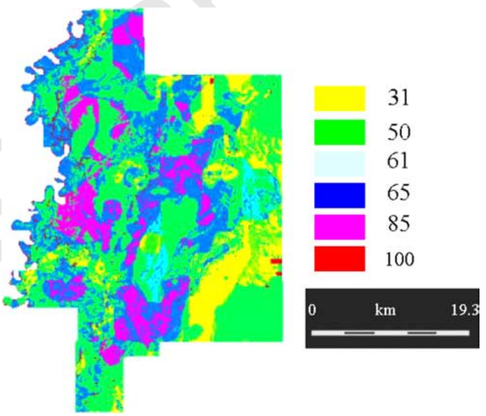

Fig. 11. SI_{fuzz}: spatial distribution of aquifer sensitivity categories.

Table 10
SI_{fuzz}: distribution of aquifer sensitivity

SI_{fuzz}	Hectares	Percent cover
31	17,170	11.0
38	2484	1.6
41	814	0.5
50	67,864	44.2
58	2	0
61	2885	1.9
65	42,637	27.8
85	17,475	11.4
100	2439	1.6
Total	153,770	100

tool?' A good model should not only be able to predict contaminated wells with elevated sensitivity, but also show most of the non-contaminated wells classified in the low sensitivity category.

The first set of coincidence analysis was performed between DI and well water quality data (Figs. 13 and 14). The DI predicted two of the contaminated wells in low sensitivity category, whereas none of the contaminated wells were predicted in highly vulnerable category. When non-contaminated wells were compared, over 20 wells that were not contaminated were predicted in moderately high contamination category. Also, about three wells coincided with highly vulnerable areas that were not contaminated. If environmental managers were to use this map to select and prioritize the well sampling strategy—they would have been greatly disappointed with the results.

The model DI_{fuzz} predicted three out of seven contaminated wells as highly vulnerable. The same model predicted two of the contaminated wells in moderately high sensitivity

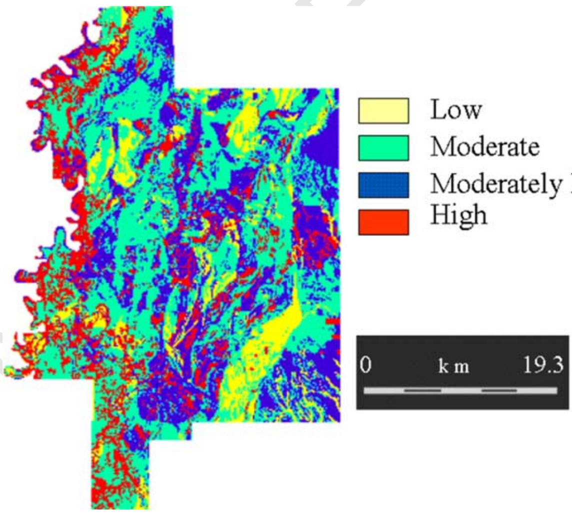

Fig. 12. VI_{fuzz_ped} spatial distribution of vulnerability categories.

Table 11
VI_{fuz_ped}: spatial distribution of vulnerability categories

VI_{fuzz_ped}	Hectares	Percent cover
Low	16,053	10.3
Moderate	68,265	44.5
Moderately high	42,584	27.7
High	26,868	17.5
Total	153,770	100

category and one in moderately vulnerable category. This prediction is better than that found with the DI model. When the DI_{fuzz} model was compared with the non-contaminated wells, the result was not promising. Thirteen of the non-contaminated wells were classified in the highly vulnerable category, whereas 14 non-contaminated wells were classified as moderately vulnerable. Only two wells that were not contaminated coincided with the low sensitivity category.

From this result it also becomes obvious that sensitivity predicted by the VI_{fuzz} model was not adequate. Five out of seven contaminated wells were classified in the moderately high sensitivity category (Fig. 13). When the same model was compared to the non-contaminated wells (Fig. 13), 13 of the non-contaminated wells coincided with highly vulnerable category. If a watershed manager were to sample the groundwater based on the map generated by this model, the result may not have been very useful. The model DI_{fuzz} showed higher coincidence with contaminated wells, however, both the models (DI_{fuzz} and VI_{fuzz}) showed similar performance when coincided with non-contaminated wells.

The sensitivity map VI_{fuzz_ped} generated by incorporating pedality information resulted in a relatively useful map. Coincidence reports between contaminated wells and the sensitivity map indicated that five out of seven wells coincided with moderately high vulnerable categories and two coincided with highly vulnerable area. None of the contaminated wells coincided with moderately vulnerable areas. When the non-contaminated wells were coincided with the sensitivity map generated by the model VI_{fuzz_ped}, 16 wells coincided with the low sensitivity category, and 14 wells with the moderate category. Only three and four wells that were not contaminated coincided with

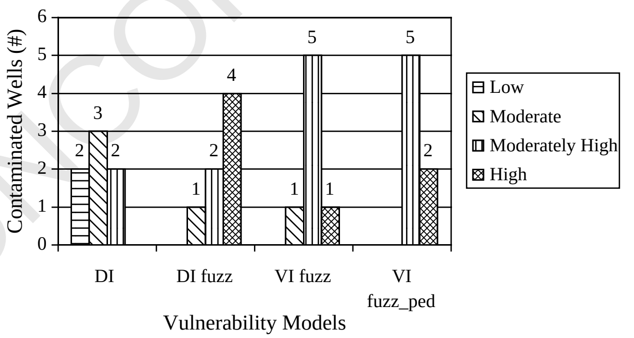

Fig. 13. Model mutual occurrence of contaminated wells and vulnerability categories in different models.

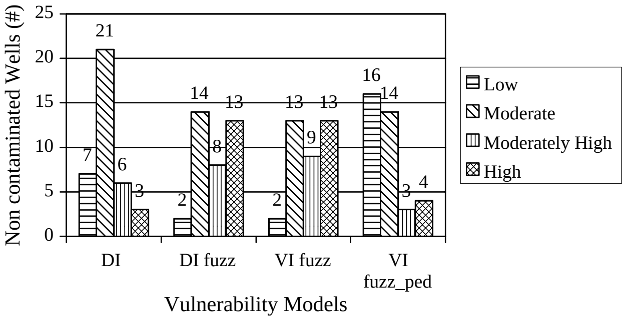

Fig. 14. Mutual occurrence of non-contaminated wells and vulnerability categories in different models.

the moderately high and high sensitivity categories, respectively (Fig. 14). If a watershed manager use this map to guide the groundwater sampling strategy for potential agricultural contaminant in the county, this map will be far more useful, compared to maps generated by DI, DI_{fuzz} and VI_{fuzz}. This result also indicates that soil structure information or pedality should be incorporated in groundwater sensitivity modeling. Pedality indicates preferential contaminant transport potential of a soil horizon based on cumulative effects of soil structure particularly shape, size and grade of soil peds. Impacts of the shape of peds on soils' hydraulic properties are mainly related to the continuity/connectivity and amount of interpedal pores (Lin, 1995). Conceptually, the potential for transmission of water and contaminant vertically among different shapes of peds are: massive < platy < blocky, prismatic < granular.

4. Concluding remarks

The sensitivity maps for Woodruff County were generated in three different ways (VI_{fuzz_ped}, DI_{fuzz}, and VI_{fuzz}). The resultant sensitivity maps were compared with the DI and field water quality data. The sensitivity map from the model VI_{fuzz_ped} was better correlated with the field water quality data. This map was generated using a fuzzy rule-based model and soil structure information. Environmental managers in Woodruff County may use the model VI_{fuzz_ped} to prioritize sampling of the wells. Coincidence analysis with contaminated and non-contaminated wells showed that incorporation of soil structure or pedality information with the fuzzy rule-based model improved groundwater sensitivity mapping. This result also indicates that soil structure information or pedality should be incorporated in groundwater sensitivity modeling.

The preliminary sensitivity map DI was not adequate. This study shows that incorporation of a fuzzy rules (DI_{fuzz}) with the preliminary sensitivity map (DI) showed better coincidence results when compared with the well water quality data. The model DI_{fuzz} was generated using 40% less data than the DI. DI_{fuzz} showed better coincidence results when compared with contaminated wells, but it was not adequate for non-contaminated wells. The model VI_{fuzz} was generated using PI information, which did not improve the prediction markedly. Incorporation of landuse and pesticide use information in these groundwater sensitivity models needs further exploration.

Integration of these models with a GIS enhanced visualization of sensitivity zoned from different models. From this study it is evident that integrated approach with GIS offers great opportunities for groundwater sensitivity mapping and simulations, however, rendered or simulated results should never supplant field observations. Appropriate field data should be used to evaluate the predicted maps. In the future, the model VI_{fuzz_ped} will be used for other counties in the Mississippi Delta of Arkansas to assess its performance.

5. Uncited reference

Soil Survey Division, (2001).

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References

L.T. Aller, H. J, R. Bennett, J. Lehr. Petty, and G, Hackett. DRASTIC: A Standardized System for Evaluating Ground Water Pollution Potential Using Geo-Hydrogeologic Settings. U.S. Environmental Protection Agency Report., (1987) EPA600/2–EP87/036

Bardossy, A., & Disse, M. (1993). Fuzzy rule-based models for infiltration. *Water Resources Research*, *29*(2), 373–382.

Bolstad, P. V., & Swank, W. T. (1997). Cumulative impacts of landuse on water quality in a southern appalachian watershed. *Journal of the American Water Resources Association*, *33*, 519–534.

Burrough, P. A. (1996). Opportunities and limitations of GIS-based modeling of solute transport at the regional scale. In application of GIS to the non-point source pollutants in the vadose zone, SSSA, Special Publication # 48, D. Corning and K. Loague eds., Madison, WI.

Burrough, P. A., & McDonnell, R. (1998). *Principles of geographical information systems*. New York: Oxford University Press p. 346.

Burrough, P. A., Macmillan, R. A., & Van Deursen, W. (1992). Fuzzy classification methods for determining land suitability from soil profile observations and topography. *Jounal of Soil Science*, *43*(2), 193–210.

Cameron, E., & Peloso, G. F. (2001). An application of fuzzy logic to the assessment of aquifers' pollution potential. *Environmental Geology*, *40*, 1305–1315.

Connell, L. D., & Daele, G. V. D. (2003). A quantitative approach to aquifer vulnerability mapping. *Journal of hydrology*, *276*(71), 88.

Corwin, D. L., Loague, K., & Ellsworth, T. R. (1996). Introduction to non-point source pollution in the Vadose zone with advanced information technologies. In D. L. Corwin, K. Loague, & T. R. Eliisworth, *Assessment of non-point source pollution in the Vadose zone*. *Geophysical monograph* (vol. 108). Washington, DC: AGS.

Cox, E. (1994). *The fuzzy systems handbook*. London: Academic Press.

Dixon, B., Scott, D. H. (20010. Application of Fuzzy Logic to Predict Ground Water Vulnerability in Northwest Arkansas. AWRC-USGS Report. MSC, 240.

Dixon, B., Scott, H. D., Dixon, J. C., & Steele, K. F. (2002). Prediction of aquifer vulnerability to pesticides using fuzzy rule-based models at the regional scale. Physical Geography, 23, in press.

Dou, C., Wolt, W., & Bogardi, I. (1999). Fuzzy rule-based approach to describe solute transport in the unsaturated zone. *Journal of Hydrology*, *220*(1-2), 74–85.

Wyoming ground water vulnerability assessment handbook: volume 2. Asssessing ground water vulnerability to pesticides. In J. D. Hamerlinck, & C. S. Arbeson (Eds.). (1998). *Spatial data and visualization center publication SDVC 98-01-2*. Laramie, Wyoming: University of Wyoming.

Hong-Il, A., & Hyo-Taek, C. (1999). Assessment of groundwater contamination using geographic information systems. *Environmental Geochemistry and Health*, *21*, 273–289.

Lin, H. S., & McInnes, K. J. (1995). Water flow in clay soil beneath a tension infiltrometer. *Soil Science*, *159*, 375–382.

Lin, H. S., Scott, H. D., & McKimmey, J.M. (1996). Identification of optimal locations for sampling ground water for pesticides in the mississippi delta region of Eastern Arkansas. University of Arkansas: Arkansas Water Resources Center. MSC-185.

Lin, H. S., McInnes, K. J., Wilding, L. P., & Hallmark, C. T. (1999). Effects of soil morphology on hydraulic properties: I. quantification of soil morphology. *Soil Science Society of America Journal*, *63*(948), 953.

Loague, K., & Corwin, D. (1998). Regional scale assessment of non-point source ground water contamination. *Hydrological Processes*, *12*, 957–965.

Lowe, M., & Butler, M. (2003). Ground water sensitivity and vulnerability to pesticides, Heber and Round Vallyes, Wasatch County, Utah. Miscellaneous Publication 03-5, Utah Geological Survey.

Mitra, B., Scott, H. D., Dixon, J. C., & McKimmey, J. M. (1998). Application of fuzzy logic to the prediction of soils erosion in a large watershed. *Geoderma*, *86*, 183–209.

Numata, K. (1991). *General purpose fuzzy reasoning library*. Japan: Tokyo University (Version 3.0).

Quisenberry, V. L., Smith, B. R., Phillips, R. E., Scott, H. D., & Nortcliff, S. (1993). A soils classification system for describing water and chemical transport. *Soil Science*, *156*, 306–315.

Reijnders, H. F. R., van Drecht, G., Prins, H. F., & Boumans, L. J. M. (1998). The quality of the groundwater in the Netherlands. *Journal of Hydrology*, *207*, 179–188.

Scott, H. D., Smith, P. A., & Spradley, P. (1992). *Using DRASTIC and pesticide usage to determine potential locations of pesticides in ground water in Arkansas*. Fayetteville, AR: Arkansas Association of Pesticide Applicators.

Scott, H. D. (2000). *Soil physics: Agricultural and environmental applications*. Ames, Iowa: Iowa State University Press.

Sui, D. Z. (1992). A fuzzy GIS modeling approach for urban land evaluation. *Computers, Environment, and Urban Systems*, *16*(2), 101–115.

Tonmanee, N., & Kanchanakool, N. (1999). Agricultural diffuse pollution in Thailand. *Water Science and Technology*, *39*, 61–66.

Wang, F., Hall, B., & Subaryono, G. (1990). Fuzzy information representation and processing in conventional GIS software: Database design and application. *International Journal of Geographical Information Systems*, *4*(3), 261–283.

Westervelt, J., Shipiro, M., & Goran, W. (1989). *GRASS: Geographical resources analysis support system*. Champaign, IL: US Army Corps of Engineers, Construction Engineering Research Laboratories.

Yen, J., & Langaria, R. (1998). *Fuzzy Logic: Intelligence, control and information*. New Jersey: Prentice Hall.

Zadeh, A. L. (1965). Fuzzy sets. *Information and Control*, *8*, 338–353.

Zhang, L., Beavis, S. G., & Gray, S. D. (1999). Development of a spatial database for large-scale catchments management: Geology, soils, and landuse in the Namoi Basin, Australia. *Environment International*, *25*, 853–860.

Soil Survey Division, Natural Resources Conservation Service, United States Department of Agriculture. Official Soil Series Descriptions [Online WWW]. Available URL: ' http://ortho.ftw.nrcs.usda.gov/osd/' [Accessed 23 Mar 2001].