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VULNERABILITY AND USE OF GROUND AND SURFACE WATERS IN THE SOUTHERN MISSISSIPPI VALLEY REGION

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INTRODUCTION

There is a concern in the Southern Mississippi River Valley of the United States over non-point source pollution of ground and surface waters resulting from activities associated with agricultural production. This agriculturally intensive region consists of two major land resource areas (MLRAs): Southern Mississippi Valley Silty Uplands (MLRA 134) and the Southern Mississippi Valley Alluvium (MLRA 131). Both MLRAs have level to undulating and rolling topography, relatively fertile soils and a climate particularly conducive for row crop production.

The mid south region is a major agricultural production area in the US with agronomic crops such as rice, soybean, cotton, and grain sorghum and reservoir fish production all of which use extensive amounts of water. In 1994, Arkansas ranked first in the US in the production of rice, fourth in cotton, fifth in grain sorghum, eight in soybeans and third in fish production. During the same year, Mississippi ranked third in cotton, fifth in rice, eleventh in soybeans, twelfth in grain sorghum and first in fish production. Irrigation is a major management input to crop production in the region with well over 4 million acres of cropland irrigated annually in these two states. In addition, to the extensive amounts of water, used in crop production extensive use of pesticides for control of weeds, insects and diseases coupled with nitrogen fertilizers applied as plant nutrients are potential sources of non-point pollution in the region. Essentially all crops receive pesticides and fertilizers sometime during the growing season. These organic and inorganic compounds are susceptible to vertical movement through the soil profile and to surface runoff in both the aqueous and sediment phases.

Contamination of ground and surface waters involves transport from the sites of application. This movement is caused by water percolating through the soil profile and vadose zone, over the land surface to drainage ditches, bayous and small ponds. Prominent features of the landscape also include wooded areas that often have been designated as wetlands. There is strong interest in examining the factors involved in quantifying the movement and fate of contaminants such as pesticides and fertilizers to surface and ground waters in the Southern Mississippi River Valley region.

Protection and enhancement of the region's surface and ground water resources, while sustaining agricultural production has been the general goal of all federal and state agencies concerned with water resource protection and especially the Water Resources Research Centers of Arkansas and Mississippi. The proposed project addresses the research priorities of the Southeastern and Island Region and the Water Resources Centers of Arkansas and Mississippi related to water quality, water management and water quantity. Specifically, we concentrated our research on contaminant transport of herbicides in selected dominant soils of the mid south region as well as on water quality and use of surface and ground waters in rice production.

OVERALL OBJECTIVES

This regional research study was sectioned into two groups, each containing three projects. Projects in Group A were centered around the theme: Transport of contaminants to ground and surface waters of the mid-south region. The overall objectives of this group of research studies were:

This document includes the summary report for each research project and the final overall conclusions of the research. Emphases are placed on the impact of the findings on water resources in the mid south region.

1. To test and evaluate existing methods for assessing ground water vulnerability to pesticide contamination in a representative area of the Mississippi River Valley alluvial aquifer region, and to select the most suitable approaches for use in the region in order to achieve a more quantitative and justifiable assessment on a regional basis, and
2. To evaluate varying widths of tall fescue filter strips and their effects on metolachlor and metribuzin losses in surface runoff from conventionally tilled soybean fields.

Projects in Group B were centered around the theme: Evaluation of factors important in the quality and use of water in rice production in the mid-south region. The overall objectives of the research studies in group B were

1. To determine the rates of movement and persistence of pesticides in flooded rice fields, and to compare the rates and persistence levels with those obtained under rice production conditions in California,
2. To demonstrate simultaneous benefits in water quality, soil conservation, non-point source pollution, agronomic and waterbird habitats by winter flooding of rice fields, and
3. To assess the suitability of existing computer models for ground water use in estimating the conjunctive use of surface and ground waters for irrigation, and to develop and add economic components to the hydrologic model in order to evaluate the economic utilization of surface and ground waters for irrigation.

PROJECT GROUP A

Title: TRANSPORT OF CONTAMINANTS TO GROUND AND SURFACE WATERS OF THE MID-SOUTH REGION.

Specific Subtitles:

1. MODELING HERBICIDE MOVEMENT IN A MEMPHIS SOIL
2. USE OF FUZZY LOGIC WITH MODIFIED DRASTIC PARAMETERS TO PREDICT GROUND WATER CONTAMINATION
3. UTILIZING VEGETATIVE FILTER STRIPS OF VARYING WIDTHS TO REDUCE HERBICIDES IN RUNOFF WATER

MODELING HERBICIDE MOVEMENT IN A MEMPHIS SOIL

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INTRODUCTION

Pesticide contamination of ground water has become a major concern in recent years. Farm communities in the United States actively involved in row crop production use pesticides to sustain yields. High crop production requires management programs that include timely application of pesticides. As a result, there are many opportunities for misuse or over application of these pesticides which, may lead to ground water contamination. The protection and enhancement of the nation's surface and ground water resources, while sustaining agricultural activities, has been the general goal of the United States Department of Agriculture research plan for water quality. The U.S. Environmental Protection Agency, in recent years, has become concerned with pesticide contamination of groundwater (USEPA, 1989). Most aquifers, which are sources of drinking water, are recharged by the downward movement of surface water through the soil profile. Pesticides were assumed not to leach to the groundwater over a decade ago. However, a survey of groundwater quality indicated considerable contamination of the nation's aquifers with agrichemicals (Whetje et al., 1984). The occurrence of pesticides in groundwater progressed from 12 in 18 states to 40 in 26 states as a result of normal agricultural practices (Cohen et al., 1984).

Two of the most commonly used herbicides for soybean [*Glycine max* (L) Merr.] production in the Southern Mississippi Valley are metolachlor [2-chloro-N-(2ethyl-6-methylphenyl)-N-(2-methyl)acetamide] and metribuzin [4-amino-6-(1,1-dimethylehyl)-3-(methythio)-1,2,4-triazin-5(4H)-one]. These herbicides are usually mixed and applied at planting for weed control. For regulatory agencies, assessment of potential groundwater contamination begins with considering those areas where pesticides are used. Evaluation of pesticide mobility in those areas, to determine the trends in the potential for groundwater loading, has not been fully investigated.

Practical management options for pesticide transport to groundwater have traditionally been identified on the basis of site-specific experimental results. It might not be possible in all cases to extend results from a small number of research situations to all conceivable scenarios. Furthermore, large-scale field sampling programs designed to determine pesticide fate in the environment are often considered to be too expensive. Since the number of variables and/or combinations of variables impacting pesticide movement to ground water are large, an indirect method such as modeling can be employed as a surrogate for experimental observations. Further, reduction in the need for a labor-intensive experimentation can be obtained through modeling (Hutson et al., 1988).

Previous studies have assessed pesticide movement through soil columns (Wilson et al., 1998; Romero et al., 1997; Xue et al., 1997). Results from these studies can be used to compare the mobility of different pesticides, however, assessing the mobility of a mixture of different pesticides is needed. This will enhance the understanding of how one pesticide behaves in the presence of another.

Much of the drinking water in MLRA 134, the Southern Mississippi Valley and Silty Uplands, a major land resource area of Arkansas and Mississippi comes from wells that may be affected by loading of pesticides from agricultural practices. Assessing the transport of commonly used pesticides in a dominant soil in the major land resource area provides insight on the potential for groundwater contamination. Little or no information exists on the transport of metolachlor and metribuzin to the ground water in this region.

SPECIFIC OBJECTIVE

The objective of this study was to assess the movement of metolachlor and metribuzin under saturated conditions in a dominant soil in the Southern Mississippi Valley and Silty Uplands.

MATERIALS AND METHODS

Materials. The soil used in this study was a loessial Memphis silt loam (Typic Hapludalf) collected from a field near the main campus of Alcorn State University in Lorman, Mississippi. The soil consisted of 0.54% organic carbon (OC), 3% sand, 76% silt, 21% clay, and had a pH of 5.3. Soil was collected in bulk from the 0 - 15 cm depth, air-dried, and passed through a 2-mm sieve prior to use. The pulse solution for miscible displacement experiments contained 10 g mL^{-1} of metolachlor and metribuzin in 100 g mL^{-1} Br^{-} and 50 M $CaCl_2$.

Batch Sorption Experiment. Equilibrium distribution coefficients (K_d) of the two herbicides were determined in triplicate. Herbicides solutions for the batch experiments had initial concentrations of 0, 2, 4, 6, 10, and 20 g m L^{-1}, and were prepared in 50 M $CaCl_2$. Five g of soil and 15 mL of herbicide solution at the different concentrations were added to 25-mL glass centrifuge vials sealed with Teflon-lined screw caps. The soil-solution mixtures were shaken on a reciprocating shaker for 24 hrs at room temperature (~23 ^{0}C). The vials were centrifuged at 3500 rpm for 30 minutes. This protocol was carried out separately for each herbicide. The supernatant was then filtered through a disposable 0.45- m nylon filter and the filtrates injected into a High Performance Liquid Chromatography (HPLC) column for metolachlor and metribuzin analyses. The sorbed concentration of the hericides was calculated as the difference between the initial concentration in solution and the concentration in solution at equilibrium.

Miscible Displacement Experiments. Air-dry Memphis silt loam was packed into three polyvinyl chloride (PVC) columns at room temperature (23 ^{o}C) and allowed to establish steady-state upward flow condition. Experimental conditions of the miscible displacement study are given in Table 1. An acid-washed gravel (3 mm dia.) was placed over screens in PVC funnels and each column placed on a funnel to collect leachate at specified times. To prevent surface smearing, acid-washed gravel was also placed on the soil surface prior to introduction of solution. A pulse of 1 pore volume of a mixture of metolachlor and metribuzin as described above was applied to each column. The herbicides were then displaced by tracer-free 50 M C aCl_2 solution. The effluent from each column was collected in beakers and the samples were either analyzed immediately or stored under 4 ^{o}C until analyzed.

Table 1. Miscible displacement experimental conditions.

Column transport properties†	Units	Column number 1	2	3
ρ_b	g cm^{-3}	1.38	1.34	1.36
PV	mL	564.0	582.0	574.0
v	cm hr^{1}	1.63	1.57	0.90
θ	cm^3 cm^{-3}	0.479	0.494	.487
D	cm^2 hr^{-1}	1.63	0.55	33.18
L	cm	15.0	15.0	15.0

†ρ_b = bulk density, PV = pore volume ,v = pore water velocity, θ = soil water content, D = dispersion coefficient, L = soil length

Chemical Analysis. Effluent samples were analyzed for metolachlor and metribuzin with a Dionex 500 HPLC and bromide was analyzed with a Dionex 500 Ion Chromatography (IC) system with a ED40 electrochemical detector. The HPLC system was a Dionex 500 with an AD20 UV/Visible detector at a wavelength of 220 nm. A Zorbax HPLC C-18 column (4.6 mm i.d. x 25 cm) was used with 80:20 acetonitrile/water ratio as the mobile phase at the flow rate of 1 mL min^{-1}. The lower detection limit of these herbicides was 5 g L^{-1}. Bromide was injected in an IonPac AS4A-SC analytical column at a flow rate of 2 mL min^{-1}. The breakthrough curve (BTCs) for each column was expressed in relative concentration (C/C_o) vs. number of pore volumes (PV).

Theory

The one-dimensional transport of Br^- through soil under saturated flow condition was modeled by the one-region convective-dispersion equation (CDE):

$$\theta_s \partial C/\partial t = D\partial^2 C/\partial z^2 - v\partial C/\partial z \qquad [1]$$

where C is the solution concentration (g mL^{-1}), v is the average pore water velocity, D is the dispersion coefficient that lumps the effects of mechanical dispersion and solute diffusion ($cm^2 hr^{-1}$), θ_s is the saturated water content ($cm^3 cm^{-3}$), z is the distance (cm), and t is time (hr). Breakthrough curves for Br^- were fitted to the solution of the nonequilibrium CDE. The dispersion coefficient for each soil column was computed using the program CXTFIT (Parker and van Genuchten, 1984). This computer program uses the nonlinear least-square inversion technique to optimize parameters for several theoretical one-dimensional solute transport models. The initial and boundary conditions used were:

$$C = 0 \qquad 0 < z < L, t = 0 \qquad [2]$$

$$vC = -D\partial C/\partial z \qquad z = 0, t < t_p \qquad [3]$$

$$0 = -D\, \partial C/\partial z + vC \qquad z = 0, t > t_p \qquad [4]$$

$$\partial C/\partial z = 0 \qquad z = L, t > 0 \qquad [5]$$

where t_p is the pulse duration time.

The transport of the herbicides metolachlor and metribuzin was described by the one-dimensional single-region convective dispersion equation:

$$\theta_s\partial C/\partial t + p_b\partial S/\partial t = \theta_s D\partial^2 C/\partial z^2 - \theta_s v\partial C/\partial z \qquad [6]$$

where S is the amount of pesticides retained ($g\ g^{-1}$), and p_b is the soil bulk density ($g\ cm^{-3}$). In this study, the parameters p_b and v were measured directly and θ_s calculated from p_b values.

The dispersion coefficient (D) and distribution coefficient (K_d) were transport and sorption parameters of metolachlor and metribuzin. The K_d for each herbicide was determined independently from the equilibrium batch experiments using the nonlinear form of the Freundlich equation

$$S = K_d C_e^{\ N} \qquad [7]$$

where C_e is the concentration at equilibrium (mg L^{-1}) and N is the Freundlich constant. The K_d values were fitted using JMP statistical software (SAS Institute, 1995). Both of the K_d values for the two herbicides were used for retardation factor (R) calculation and used as inputs in the modeling process. The retardation factor is expressed as

$$R = 1 + (p_b K_d)/\theta \qquad [8]$$

where p_b is the soil bulk density and θ is the volumetric soil water content.

RESULTS AND DISCUSSION

Distribution Coefficient. The K_d values for metolachlor and metribuzin were 1.76 $cm^3\ g^{-1}$ (N = 0.86; r^2 = 0.97) and 0.18 $cm^3\ g^{-1}$ (N = 1.03; r^2 = 0.90), respectively. The lower distribution coefficient for metribuzin than for metolachlor indicates lower sorption by the surfaces of the Memphis soil. This trend was consistent with those reported by Wauchope et al. (1991).

Herbicide Transport. As shown in Figure 1, the peak concentrations for metribuzin were consistently higher (average C/C_o = 0.51) than metolachlor (average C/C_o = 0.31) in all columns. The higher peaks for metribuzin can be attributed to its lower sorption than metolachlor. Average maximum peak concentration was reached at approximately 2.4 PV for metribuzin and 3.5 PV for metolachlor. The metolachlor BTCs showed slightly more tailing than the metribuzin BTCs. In the field, these two herbicides are usually mixed and broadcast applied for weed control. However, the degree to which one may have impact on groundwater quality than the other is not known.

This study indicates that under saturated conditions metribuzin will leach faster than metolachlor when both herbicides were applied together to a Memphis silt loam. Since the K_d for metribuzin was lower than for metolachlor, sorption of metribuzin in the presence of metolachlor may decrease in that competition for sorption sites between the two herbicides would occur. As reported by Wauchope (1991), the half-life of metribuzin also is much shorter than metolachlor. While metribuzin had higher mobility than metolachlor in our study, the concentrations of these herbicides under field conditions in the ground water may be far below the health advisory and maximum contamination levels.

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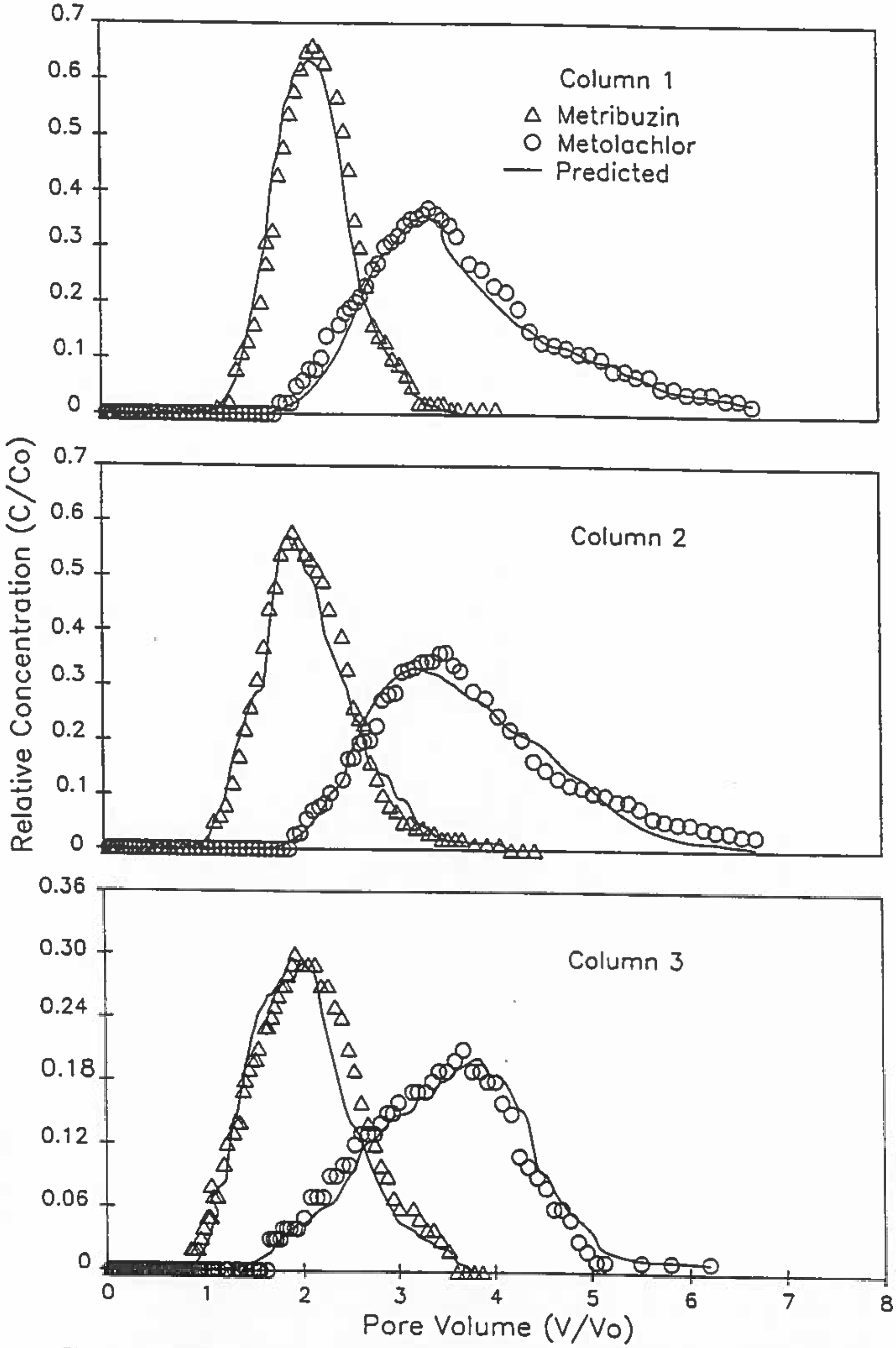

Fig. 1. Breakthrough curves for metolachlor and metribuzin in soil columns.

USE OF FUZZY LOGIC WITH MODIFIED DRASTIC PARAMETERS TO PREDICT GROUND WATER CONTAMINATION

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INTRODUCTION

The potential for ground water contamination depends upon a wide range of hydrologic parameters. Although sophisticated computer models are available for assessing potential ground water contamination on a site by site basis, most deterministic simulation models are far too complex to use for impact assessment on a regional or state basis and require input data that are quite variable in the landscape (Walton, 1984; Journel, 1996). Most, if not all, agricultural systems are complex or ill-defined causing problems related to parameter estimation and parameter uncertainty to allow precise mathematical analysis (Fang, 1997). Therefore, prediction of ground water vulnerability is an imprecise exercise (NRC, 1993).

Stochastic approaches and uncertainty analyses could help to identify which hydrologic attribute requires more accurate measurements in order to reduce overall uncertainty, identify those attributes for which less precise information is required, and thereby reduce efforts in data collection and determine whether a simpler approach would suffice or if a more sophisticated approach is needed for better reliability (Heuvelink et al., 1989).

Applying seven hydrologic parameters, the modified DRASTIC model has been extensively used to locate areas with greater likelihood of susceptibility to ground water contamination (Scott et al., 1992). In general, the hydrologic parameters are not crisp in the landscape but have fuzzy boundaries. The DRASTIC model contains three significant parts: weights, ranges and ratings for the seven hydrologic parameters, which are based upon "expert" opinion, not an outcome of ab initio calculation or determination. Fuzzy logic-based models help in quantifying conceptual and qualitative models because they emulate the flexibility of human reasoning in drawing conclusions from imprecise and incomplete information (Fang, 1997). They are particularly useful when evaluating fuzzy inputs because they tolerate imprecision and uncertainty and show marked reduction in information loss (Burrough et al., 1992).

Fuzzy logic-based models could provide output from alternative approaches to the modified DRASTIC model by using the same parameters as the DRASTIC model incorporated in fuzzy rulebases. Unlike the GIS-based modified DRASTIC model, fuzzy logic-based models accommodate fuzziness of the input parameters. Therefore, a comparative study between the results based on fuzzy-logic models and the GIS-based modified DRASTIC model along with field data can be useful in assessing the performance of fuzzy logic-based models. Moreover, development of different fuzzy logic-based models with different fuzzy rulebases and a comparison of these models with GIS-based modified DRASTIC model and field data can help in identifying the relative importance of the input parameters.

OBJECTIVES

The objectives of this study were to incorporate fuzzy logic techniques into a modified DRASTIC model, to use the fuzzy models to determine the potential vulnerability of ground water due to pesticide contamination, and to compare fuzzy logic-based models with the modified DRASTIC model. The project aimed to (1) form rulebases for fuzzy logic-based models using similar weights as the modified DRASTIC,

(2) to develop different rulebases reflecting various weight combinations of the input parameters in order to determine the effects of change in the weights on the model predictions, and (3) to compare the results of six fuzzy logic-based models and the GIS-based modified DRASTIC models with results of well water analyses.

METHODOLOGY

Six fuzzy logic-based models were developed to describe the vulnerability of ground water to pesticide contamination. All models were created from digital data layers originally developed for Woodruff County, Arkansas (Smith et al., 1994; Nichols et al., 1997). Woodruff County lies within the Mississippi Delta region of eastern Arkansas where landuse is agriculturally intensive. It is bounded on the west by the White River, which drains northwest and north central Arkansas and Southern Missouri, and is dissected by the Cache River and Bayou De View, two large drainage basins.The geographic information system (GIS) software used in this work is The Geographical Resources Analysis Support System or GRASS (Westervelt et al., 1989).

Development of the GIS based Modified DRASTIC Model

The modified DRASTIC model for pesticides used seven hydrologic parameters that affect the vulnerability of ground water to contamination (Smith et al. 1994). The model assumes that surface water is the only source to contaminate ground water from surface-applied pesticides. Mathematically, the modified DRASTIC index (DI) was computed from

$$\mathbf{DI = DrDw + RrRw + ArAw + SrSw + TrTw + IrIw + CrCw} \qquad [1]$$

where D is the depth to ground water, R is the net recharge, A is the aquifer media, S is the soil media, T is the topography (slope), I is the impact of vadose zone media, and C is the hydraulic conductivity of the aquifer. Each parameter was assigned a relative weight (w) ranging from 3 to 7 and a rating (r) varying between 1 and 10 according to expert opinion. Of the seven parameters in the modified DRASTIC model, only four parameters were used as inputs in the fuzzy logic-based model to obtain one output parameter.

Development of the Fuzzy logic-based Models

Mathematically, the fuzzy logic-based models were represented as

$$\text{Output} = f(D,R,S,I) \qquad [2]$$

where f is a non-linear function, which was difficult to express in closed form. The parameters along with their corresponding weights and ratings used in the modified DRASTIC model are presented in Table 1. Parameters "A", "T", and "C" in equation [1] were not used because they were considered to be spatially constant with no fuzziness in Woodruff County.

The input maps for the models, obtained from a GIS environment, were manipulated from the base layers in GRASS (Smith et al., 1994). The parameter "D" required manipulation of the surface elevation and potentiometric elevation of the aquifer. The parameter "R" was created from site files furnished by US Geological Survey (USGS) using the GRASS module s.surf.tps. By way of the reclass module of GRASS, the parameter "S" was reclassed and normalized according to leaching index ratings for the dominant soil series in each soil mapping unit furnished by Natural Resource Conservation Service (NRCS) in Arkansas. The parameter "I" was created by interpolation from clay confining unit data provided by USGS with 3-m (10 ft) contour intervals (Smith et al., 1994).

The general purpose fuzzy inference engine of Numata (1991) was used with a modified "main function" to suit the specific application of the fuzzy logic-based models to ground water vulnerability. This inference engine required four input files and one rulebase file to give a fuzzy output. All four parameters plus the output were divided into several fuzzy sets. The range of data associated with each parameter and their relative importance played an important role in the determining the number of fuzzy sets for the individual parameters.

The functional relationship for the fuzzy sets was expressed by the composition of the rulebase. An example of a fuzzy-logic-rulebase used is

Rule X: If (D = high) & (R = M) & ...., Then (output = MOH) [3]

where "high" is a fuzzy set to the universe "D", "M" or "moderate" is a fuzzy set to the universe of "R", and "MOH" "moderately high" is a fuzzy set to the universe "output".

The six fuzzy logic rulebases involved different combinations of the four parameters to determine the effects of change in the weights on the model prediction. This application enabled us to determine the relative importance of the DRASTIC parameters in a way somewhat different from the "Delphi technique" used in the original formulation of the DRASTIC model. The relative influence of the parameters used in the models was reflected in the number of fuzzy sets (Table 2) and output columns in the rulebases are presented in Table 3.

Trapezoidal membership functions were used to define fuzzy sets for fuzzy logic-based models and are presented in Tables 4 and 5. While forming the fuzzy-logic rulebases, relative weights of the parameters played important roles; i.e., slight changes in the parameter with a higher weight affected the output more than the parameters with less weight. Rulebase I was created for objective one, which reflects similar weights as used in the modified DRASTIC. Rulebases II to VI were developed for objective two to determine the effects of changes in the weights on the fuzzy logic model predictions.

Comparison of GIS-Based Modified DRASTIC and Fuzzy logic-based Models

In order to assess the performance of the fuzzy logic-based models, the fuzzy logic-based outputs were compared with GIS-based modified DRASTIC model. Two sets of coincidence reports were created from the GRASS command r.coin between modified DRASTIC and fuzzy logic-based model outputs. Coincidence reports tabulate the mutual occurrence of categories for two map layers with respect to one another. First, coincidence reports were run for the modified DRASTIC model with five reclassed output categories and five fuzzy logic-based models (Rulebases I through V) with five output categories. Second, the modified DRASTIC output with four reclassed categories were compared to the fuzzy logic-based model with four output categories (Rulebase VI). The output from the modified DRASTIC was reclassed into five categories: < 50 = low (L), 51 to 59 = moderately low (ML), 60 to 69 = moderate (M), 70 to 79 = moderately high (MOH), > 80 = high. Since Rulebase VI had only four output fuzzy sets, the modified DRASTIC output also was reclassed into the same four categories: < 50 = L; 51 to 69 = M; 70 to 79 = MOH; and > 80 = high. The fuzzy-logic model outputs were reclassed according to the fuzzy sets.

Comparison of the Model Predictions with Field Data

To assess performance of the predictions of the six models, model outputs were compared with field data. In Woodruff County, 55 wells were surveyed by the Arkansas Water Resources Institute for pesticide contamination (Nichols et al., 1997). The locations of the wells were georeferenced and ground water was analyzed for 13 pesticides commonly applied to agronomic crops grown in the area. Seven wells were found to be contaminated. A set of coincidence analyses was performed between the well data taken in the field and all of the six model predictions to compare the performance of the models in representing the real world. Since wells are represented as point data and the source of contamination might not be point-based, nine neighboring cells were also examined for soils, geology, slopes and landuse (LULC). Nine neighboring cells around the wells were created using the GRASS command s.menu. The command r.buffer in GRASS was also used to create buffer zones of 160, 240 and 560 m around the seven contaminated wells, in order to facilitate a greater understanding for the surroundings of contaminated wells. Another set of coincidence reports was run to examine the relationships between contaminated wells and their surroundings, which include geology, soils, slopes and landuse.

RESULTS AND DISCUSSION

Fuzzy logic-based Models

The fuzzy logic techniques for prediction of ground water vulnerability to pesticides in Woodruff County involved four parameters (D, R, S, and I) from the modified DRASTIC model. The fuzzy logic-based approach included application of four rulebases having either 3, 4 or 5 input fuzzy sets and resulting in either 4 or 5 output fuzzy sets (Table 2).

Distribution of Fuzzy Output Categories By Rulebase

The number of rules in the output within a fuzzy category varied by rulebase (Table 6). These rulebases were independent of each other with the majority of the rules written in the moderate and moderately high fuzzy categories. For Rulebase I (R-I), 36%

of the total number of rules were in the fuzzy category moderate and 35% in the moderately high vulnerability category. For Rulebase II (R –II), 32.1 and 44.4% of the total number of rules were in fuzzy categories moderate and moderately high, respectively, and for Rulebase III (R- III) 29.1 and 34.5%, for Rulebase IV (R-IV) 36.2 and 40.3%, and for Rulebase V (R-V) 33% and 30% were in these same two categories, respectively. For Rulebase VI (R–VI), 50% of the total number of rules were in the fuzzy category moderate and 34.4% were in the moderately high vulnerability category.

Areal Distribution

Areal distributions for each fuzzy category varied by model and rulebase. The spatial distribution of the reclassed version of the modified DRASTIC indices for Woodruff County is shown in Figure 1a. The areal proportion of the land area in the five fuzzy categories is summarized in Table 7. For the 5-class modified DRASTIC (D-5), the highest percentage of land area was in the low fuzzy category (almost 38%) and the percentage decreased as the vulnerability category increased. For the 4-class modified DRASTIC model (D-4) the moderate category contained slightly over 50% of the land area. For both models only about 2.2% of the area was in the high fuzzy category. The area in the category highly vulnerable to pesticides tended to occur between the Cache and White Rivers where the soils tend to be coarse textured and the ground water shallower.

The spatial distributions of the fuzzy-logic categories of potential vulnerability of the ground water to pesticides for six rulebases are summarized in Table 7. With Rulebase I (Figure 1b), the highest proportion (36%) of the land area in Woodruff County was classed in the moderate fuzzy set with about 30% in the moderately high fuzzy set.

Only about 10% and less than 1% of the land area was classed in the low and high categories, respectively. In comparison with the 5-class modified DRASTIC model, this rulebase predicted less land area in the lower and the higher vulnerability categories.

For Rulebase II with five fuzzy sets about 52% of the land area in Woodruff County was in the moderately high fuzzy set (Figure 2a). As compared to Rulebase I, a greater proportion of the land area was in the moderately high vulnerability category and a lower proportion was in the moderate and high fuzzy categories. Rulebase II also showed greater areal coverage than the 5-class modified DRASTIC for the high category; this result was attributed to the defensive nature of fuzzy logic. In comparison with the 5-class modified DRASTIC model, less land area was placed in the lower vulnerability classes with this rulebase. The lower potential vulnerability areas were mainly found in the eastern part of the Woodruff County while higher potentially vulnerable areas were found mainly in the north central part of the county.

For Rulebase III with five fuzzy sets, about 32% of the land area in Woodruff County was in the moderately high fuzzy set (Figure 2b). As compared to Rulebase I and II, less land area was in the low category and a lower proportion was in the high fuzzy categories. For the fuzzy category moderate, Rulebase III showed greater areal coverage than Rulebase II, IV and V, but lower than Rulebase I. Rulebase III also showed greater areal coverage than the 5-class modified DRASTIC for the high category, and this result was attributed to the defensive nature of fuzzy logic. In comparison with the 5-class modified DRASTIC model, less land area was found in the lower vulnerability classes with this rulebase. The lower potential vulnerability areas were mainly found in the eastern part of the county while higher potential areas were found mainly in the central part of the county.

For Rulebase IV (Figure 3a), the highest proportion of land area in Woodruff County was in the moderately high fuzzy category (41%). The land area in the low and high fuzzy categories was about 9 and 8%, respectively. In comparison with the 5-class modified DRASTIC model, this rulebase had more land area in the higher vulnerability classes. Lower potential vulnerability areas were found in eastern part of the county while moderately high and high areas were found in the central and western part of the county.

For Rulebase V (Figure 3b), the highest proportion of land area (35%) of Woodruff County was in the moderately low fuzzy category. The land area in the moderately high fuzzy category occupies about 27% of the county. About 15% of the land area is considered as low fuzzy category. In comparison with the 5-class modified DRASTIC model, this rulebase also had more land area in the higher vulnerability classes. Lower potential vulnerability areas were found in eastern part of the county while moderately high and high areas were found in the central part of the county.

With Rulebase VI, the highest proportion of the land area (45%) in Woodruff County was classed in the moderate fuzzy set with about 30% in the moderately high fuzzy set. About 14 and 12% of the land area was classed in the low and high categories, respectively. In comparison with the 4-class modified DRASTIC model (Figure 4a), Rulebase VI predicted less land area in the lower vulnerability and more in the higher categories (Figure 4b). Areal distributions of different fuzzy categories are presented in Figure 5.

Comparison of GIS-Based Modified DRASTIC and Fuzzy logic-based Model Outputs

Coincidence analyses were performed to compare GIS-based modified DRASTIC and the fuzzy logic-based model using Rulebase I. The Rulebase I has similar weights as the modified DRASTIC for pesticides which were reflected in the number of fuzzy sets and rules of the rulebase. About 8,124 ha of the low fuzzy category from Rulebase I coincided with low category of GIS-based modified DRASTIC (Table 8). The majority of the moderately low category of GIS-based modified DRASTIC model coincided with moderately low category of Rulebase I. About 5,409 ha of the moderate category of GIS-based modified DRASTIC model coincided with the moderate category of Rulebase I. A majority of the moderate category of GIS-based modified DRASTIC model coincided with the low followed by the moderately low category of Rulebase I. About 2113 ha of the high category of GIS-based modified DRASTIC coincided with moderate category of Rulebase I (Table 8). The model with Rulebase I with GIS-based modified DRASTIC weights showed minimum resemblance of spatial distribution for low and high categories with GIS-based modified DRASTIC model.

Determination of the Effects of Changing Weights of the Input Parameters on the Model Predictions

Rulebases II to VI were developed reflecting various weight combinations of input parameters to determine their relative sensitivity. Coincidence analyses were performed to compare GIS-based modified DRASTIC and fuzzy logic-based models. Two coincidence reports were performed between outputs from: (i) GIS-based modified

DRASTIC with five categories and Rulebases II, III, IV, V (Tables 9-12) and (ii) GIS-based modified DRASTIC with four categories and model outputs from Rulebase VI (Tables 13). Map outputs are given in hectares.

Coincidence between GIS-based modified DRASTIC with five categories and Rulebases III and V were better than those for Rulebase II and IV. However, none of the fuzzy-logic output exactly matched the output from GIS-based modified DRASTIC i.e. none of the occurrence was restricted to only one category. For example, the low category of GIS-based modified DRASTIC coincided with low, moderately low, moderate and moderately high categories of Rulebase II (Table 9). Rulebase VI appears to be the best in predicting contaminated wells and coincidence with GIS-based modified DRASTIC in general. The Rulebase VI has S as an important parameter, D has almost similar weight but has little less influence on the rulebase followed by R, and the parameter I has minimum influence.

Comparison of Model Output with Well Data

The relationship between the fuzzy categories for each rulebase and the seven contaminated wells is presented in Table 14. The distribution of contaminated wells and total wells for each rulebase are shown in Figures 6 and 7, respectively. Relatively higher numbers of contaminated wells were found in the moderately high category of all the fuzzy models except Rulebase VI. Rulebase VI had four contaminated wells in high vulnerability category. The modified DRASTIC model with four categories showed the highest number of wells for the moderate category. The modified DRASTIC model with five categories showed equal number of contaminated wells in low, moderate and moderately high categories. The results show that for these wells there was no relation between fuzzy categories and pesticide contamination of wells. For the six rulebases, all of the contaminated wells were found in other fuzzy categories except the low category while, for the modified DRASTIC, contaminated wells were found in low vulnerability area and not in high vulnerability areas. In general, the categories of the fuzzy logic models tended toward the higher vulnerability categories. So far as the total wells were concerned, fuzzy logic-based models as well as modified DRASTIC models show a tendency to overestimate the potential for contamination (Figure 7). Most of the wells that were not found contaminated after laboratory testing were considered to have moderately high potential for vulnerability.

Relationships between contaminated wells and input parameters such as D, R, S and I are presented in Table 15. So far as the occurrence of contaminated wells in different fuzzy categories for different rulebases are concerned, wells numbers 9 and 26 showed maximum variability across fuzzy logic-based models. The input parameter I was similar for both wells, but all other parameters such as D, R, S, LULC, soil series and geology were different for wells number 9 and 26. For wells 7 and 9 all the parameters were similar except S and I. Since similar values of I for wells number 9 and 26 did not result in similar pattern for those two wells, the S parameter seemed to be the most sensitive parameter. This result showed the complexity of the field situation and justified the use of fuzzy logic-based models.

Figure 8 shows occurrence of wells with different agronomic crops. Out of seven contaminated wells, three wells were associated with grass, two were associated with soybean production, one each with rice and forest. Most of the wells sampled occurred with soybean followed by forests. The results show that for these seven wells there was no definite relation between landuse and pesticide contamination. Levels of contamination for each well are shown on Figure 9 and the pesticides detected for each contaminated well are shown in Figure 10.

In order to understand the distribution of contaminated wells and predicted potential for ground water contamination in different models, analyses of the surroundings of contaminated wells were performed with the use of (i) neighboring cell analyses and (ii) buffer analysis. Relationships between landuse, soil series, geology and contaminated wells with nine neighboring cells are presented in Table 16. Distribution of landuse patterns with nine neighboring-cell analysis showed more diversity than single cell analysis. With the exception of wells number 11 and 26, at least two soil series with different surface textures were found in the vicinity of the contaminated wells when nine neighboring-cell analyses were performed. All of the wells, except well number 26, have the same geology for single cell and nine neighboring-cell analyses.

Buffers were created for each contaminated well at 160, 240 and 560 m. Coincidence reports were run between the buffer zones and soils, geology, and slope along with landuse for each contaminated wells. So far as the slopes are concerned, all of the contaminated wells have similar surroundings for all buffer zones. Landuse pattern differed at each buffer zone around the contaminated wells. Landuse pattern around wells numbered 11, 25, 26, 29 and 34 were similar for each buffer zone. However, compared to other wells, wells number 7 and 9 had different landuse pattern (Table 17). Similar distribution patterns were found for soils (Table 18). Soils differed at each buffer zone around the contaminated wells. Soil series for wells numbered 11, 25, 26, 29 and 34 were similar for each buffer zone. Soil series found around well number 7 and well 9 were different from others. Landuse and soils became more diversified with increasing thickness of the buffer zone. Secondary attributes of the dominating soil series from nine neighboring-cell and buffer analyses are presented in Table 19. This pattern was not found for geology, which did not change across the buffer zones. Unlike the pattern observed in case of landuse and soils, geology for wells numbered 7 and 9 were the same.

CONCLUSIONS

The objectives of this study were to develop fuzzy logic-based models using parameters from the modified DRASTIC model and to compare fuzzy logic-based model outputs with GIS-based modified DRASTIC model output. Among six different fuzzy logic-based models, Rulebase VI with four fuzzy output categories was best in predicting contaminated wells. The rulebase for this model had S as the dominating parameter. This model also showed reasonably good coincidence with GIS-based modified DRASTIC. Rulebase III also showed reasonably good coincidence with GIS-based modified DRASTIC. However, the Rulebase III overestimated the prediction of contaminated wells.

For the six rulebases of the fuzzy logic-based prediction models, all of the contaminated wells were in fuzzy categories except the low vulnerability cagegory, but for the modified DRASTIC model, contaminated wells were found in the low vulnerability areas but not in areas with high vulnerability. Therefore, use of the modified DRASTIC model for screening potential areas for vulnerability has an inherent risk of underestimation. Fuzzy logic-based models did not underestimate the vulnerability and, thereby, eliminate the risk of neglecting a potential vulnerable area. Fuzzy logic-based models may have a tendency to overestimate, however, from an environmental management point of view, it is often better to have overestimated risk than to neglect a potential source of problems. Moreover, fuzzy logic-based models with their flexibility of defining rulebases and fuzzy sets provide scope for custom designing a model to suit a particular geo-hydrological situation and vulnerability mapping for specific purposes. In the future, a fuzzy logic-based model may be designed with additional information such as landuse and chemical properties of pesticides.

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Table 1. Ratings and weights for four of the parameters used in the modified DRASTIC model.

DRASTIC Parameters	Weight	Range	Rate
D	5	0 - 75	10 - 3
R	4	0 - 9	1 - 9
S	5	Different soil series	0 - 10
I	4	0 - 10	8 - 1

Table 2. Number of fuzzy sets developed for the six fuzzy logic-based models.

Rulebase	Number of Fuzzy sets				
	Inputs				Output
	D	R	S	I	Vulnerability
I	5 [1.]	4	5	4	5
II	4	4	4 [1.]	3	5
III	4	4 [1.]	3	3	5
IV	4	3	4	4 [1.]	5
V	4 [1.]	4	4	3	5
VI	4	4	4 [1.]	3	4

[1.] Important parameters, therefore has more influence in the rulebases.

Table 3. Example of different output rules in the six fuzzy logic rulebases. The symbols are as follows: [1.] H: High, [2.] L: Low, [3.] M: Moderate, [4.] ML: Moderately low, and [5.] MOH: Moderately high.

Rulebase	Input D	Input R	Input S	Input I	Output
I	H [1.]	L [2.]	L	H	L
II	H	L	L	H	L
III	H	L	L	H	L
IV	H	L	H	H	M
V	H	L	H	H	ML [4.]
V I	H	L	L	H	L
I	H	L	L	L	L
II	H	L	L	L	L
III	H	L	L	L	L
IV	H	L	H	L	MOH [5.]
V	H	L	H	L	M
V I	H	L	L	L	ML
I	L	L	L	H	M
II	L	L	L	H	ML
III	L	L	L	H	ML
IV	L	L	L	H	M
V	L	L	L	H	MOH
V I	L	L	L	H	ML

Table 4. Membership functions for each fuzzy set for Rulebase I, where the fuzzy logic-based model used similar weights as the modified DRASTIC model.

		Trapezoidal membership functions for Rulebase I			
Parameters	Fuzzy sets	I			
		0	**1**	**1**	**0**
D	Low	0	10	15	20
	Moderately low	16	21	25	30
	Moderate	26	30	35	40
	Moderately high	36	41	45	48
	High	46	49	50	50
R	Low	0	0	1	5
	Moderate	4	7	10	12
	Moderately high	11	13	16	21
	High	18	25	36	36
S	Low	0	4	5	12
	Moderately low	7	10	15	20
	Moderate	17	21	22	25
	Moderately high	23	26	30	35
	High	31	36	50	50
I	Low	0	0	10	13
	Moderate	11	14	23	26
	Moderately high	24	27	30	36
	High	34	38	56	56
Vulnerability (output)	Low	0	71	100	110
	Moderately low	101	125	130	140
	Moderate	131	141	161	165
	Moderately High	162	166	184	191
	High	185	192	246	246

Table 5. Membership functions for each fuzzy set in five fuzzy logic-based rulebases.

Parameters	Fuzzy sets	Trapezoidal membership functions for different rulebases																			
		II				III				IV				V				VI			
		0	**1**	**1**	**0**	**0**	**1**	**1**	**0**	**0**	**1**	**1**	**0**	**0**	**1**	**1**	**0**	**0**	**1**	**1**	**0**
D	L	0	0	5	10	0	0	5	10	0	0	5	10	0	0	5	10	0	0	5	10
	M	5	10	15	20	5	10	15	25	5	10	15	20	5	10	15	20	5	10	15	20
	MOH	15	20	25	30	20	25	30	45	15	20	25	30	15	20	25	30	15	20	25	30
	H	25	30	50	50	38	40	75	75	25	30	50	50	25	30	50	50	25	30	50	50
R	L	0	0	1	7	0	0	1	7	0	0	1	11	0	0	1	5	0	0	1	5
	M	5	5	10	11	5	5	10	11	10	12	16	21	5	7	10	11	5	7	10	11
	MOH	10	12	16	21	10	12	16	21	-	-	-	-	10	12	16	21	10	12	16	21
	H	18	25	36	36	18	25	36	36	18	25	36	36	18	25	36	36	18	25	36	36
S	L	0	4	5	12	0	4	5	15	0	4	5	12	0	4	5	12	0	4	5	12
	M	7	12	18	22	8	15	25	33	7	12	18	22	7	12	18	20	7	12	18	20
	MOH	18	22	30	35	-	-	-	-	18	22	30	35	18	22	30	38	18	22	30	38
	H	30	35	60	60	30	33	60	60	30	35	60	60	36	40	60	60	36	40	60	60
I	L	0	0	14	18	0	0	14	21	0	0	10	13	0	0	14	20	0	0	14	20
	M	18	26	30	36	18	26	30	36	10	13	23	26	18	26	30	36	18	26	30	36
	MOH	-	-	-	-	-	-	-	-	23	26	30	36	-	-	-	-	-	-	-	-
	H	34	38	56	56	32	38	56	56	34	38	56	56	32	38	56	56	32	38	56	56
Output	L	1	71	90	95	1	71	100	110	1	71	100	110	1	60	95	100	1	60	100	115
	ML	93	101	115	121	100	125	130	140	100	125	130	140	93	101	115	121	-	-	-	-
	M	117	124	130	138	130	140	161	165	130	140	161	165	117	124	130	138	110	115	130	155
	MOH	132	140	148	155	161	165	184	191	161	165	184	191	132	140	148	155	150	155	175	191
	H	150	159	246	246	184	191	246	246	184	191	246	246	150	159	246	246	185	191	246	246

Table 6. Distribution of the number of rules written for the output of the fuzzy rulebases by fuzzy category.

	Rulebases					
Fuzzy category	I	II	III	IV	V	VI
High	22	18	19	16	12	14
Moderately high	140	83	51	79	64	73
Moderate	143	12	43	67	57	86
Moderately low	78	63	24	19	40	-
Low	17	16	11	11	19	19
Total	400	192	148	192	192	192

Table 7. Percentage of the total areal distribution of the different models by fuzzy category.

Fuzzy categories	Modified DRATSIC		Fuzzy models					
	5 class	4 class	I	II	III	IV	V	VI
Low (L)	38.47	38.47	9.92	13.53	8.11	9.07	14.89	13.51
Moderately low (ML)	29.99		31.96	14.44	17.98	21.43	34.92	
Moderate (M)	20.26	50.25	35.78	12.0	34.22	20.06	15.77	44.87
Moderately high (MOH)	8.93	8.93	22.32	52.02	32.21	41.2	26.73	30.06
High (H)	2.19	2.19	0.02	8.04	7.48	8.04	7.7	11.55

Table 8. Coincidence report in hectares between GIS-based 5-class modified DRASTIC and fuzzy model using Rulebase I.

Rulebase I	5-class modified DRASTIC					
	Low	Moderately low	Moderate	Moderately high	High	W/o 0
Low	8,124	3,868	3,034	13	0	15,039
Moderately low	15,492	19,967	8,585	5,205	0	49,249
Moderate	27,469	16,813	5,409	3,110	2,113	54,914
Moderately High	8,076	5,455	14,133	5,413	1,249	34,326
High	0	28	0	0	0	28
W/o 0	59,161	46,131	31,161	13,741	3,362	153,556

Table 9. Coincidence report in hectares between GIS-based 5-class modified DRASTIC and fuzzy model using Rulebase II.

Rulabse II	5-class modified DRASTIC					
	Low	Moderately low	Moderate	Moderately high	High	W/o 0
Low	21,975	665	227	13	0	22,880
Moderately low	13,805	7,976	0	0	0	21,781
Moderate	9,846	8,285	0	0	0	18,131
Moderately high	13,535	29,205	30,058	5,816	0	78,614
High	0	0	876	7,912	3,362	12,150
W/o 0	59,161	46,131	31,161	13,741	3,362	153,556

Table 10. Coincidence report in hectares between GIS-based 5-class modified DRASTIC and Fuzzy model using Rulebase III.

Rulabse III	5-class modified DRASTIC					
	Low	Moderately Low	Moderate	Moderately high	High	W/o 0
Low	13,798	665	227	13	0	14,703
Moderately low	23,572	3,592	0	0	0	27,164
Moderate	20,849	24,787	6,034	40	0	51,710
Moderately high	943	17,088	22,750	7,177	718	48,676
High	0	0	2,149	6,511	2,643	11,303
With 0	59,162	46,132	31,160	13,741	3,361	153,556

Table 11. Coincidence report in hectares between GIS-based 5-class modified DRASTIC and fuzzy model using Rulebase IV.

Rulebase IV	5-class modified DRASTIC					
	Low	Moderately low	Moderate	Moderately high	High	With/o 0
Low	15,237	665	227	13	0	16,142
Moderately low	24,209	8,172	0	0	0	32,381
Moderate	15,902	14,720	0	0	0	30,622
Moderately High	3,813	22,574	30,058	5,816	0	62,261
High	0	0	876	7,912	3,362	12,150
W/o 0	59,161	46,131	31,161	13,741	3,362	153,556

Table 12. Coincidence report in hectares between GIS-based 5-class modified DRASTIC and fuzzy model using Rulebase V.

Rulebase V	5-class modified DRASTIC					
	Low	Moderately low	Moderate	Moderately High	High	With/o 0
Low	21,747	664	227	13	0	22,651
Moderately Low	31,378	16,691	5,636	0	0	53,705
Moderate	5,692	10,812	6,803	943	0	24,250
Moderately High	344	17,964	12,862	9,937	0	41,107
High	0	0	5,633	2,848	3,362	11,843
W/o 0	59,161	46,131	31,161	13,741	3,362	153,556

Table 13 . Coincidence report in hectares between GIS-based 4-class modified DRASTIC and fuzzy model using Rulebase VI.

	4-class modified DRASTIC				
Rulebase VI	Low	Moderate	Moderately high	High	W/o 0
Low	21,747	892	13	0	22,652
Moderate	33,830	33,145	943	0	67,918
Moderately high	3,584	36,826	5,093	0	45,503
High	0	6,429	7,692	3,362	17,483
W/o 0	59,161	77,292	13,741	3,362	153,556

Table 14. Relationship between fuzzy categories and rulebases at the contaminated well sites.

Contaminated wells	5-class modified DRASTIC (D-5)	Rulebases					4-class modified DRASTIC (D-4)	Rulebase VI
		I	II	III	IV	V		
7	Moderately high (MOH)	MOH	High	High	High	MOH	MOH	High
9	Low (L)	ML	Moderate	ML	ML	ML	Low	Moderate
11	Moderately high	Moderate	High	MOH	High	MOH	MOH	High
25	Moderately low (ML)	Moderate	MOH	Moderate	MOH	MOH	Moderate	MOH
26	Low (L)	MOH	MOH	Moderate	MOH	ML	Low	MOH
29	Moderate (M)	Moderate	MOH	MOH	MOH	High	Moderate	High
34	Moderate (M)	Moderate	MOH	MOH	MOH	High	Moderate	High

Ml: Moderately low, Mh: moderately high.

Table 15. Relationship between contaminated wells and parameters such as D, R, S and I.

Well Number	D in meters [1]	R m^3./yr *	S indice	I in meters [1]
7	4.88 – 9.14	0 – 65,839	35	0
9	4.88 – 9.14	0 – 65,839	5	> 3
11	1.83 – 4.57	0 – 65,839	35	0
25	0 – 1.52	0 – 65,839	20	> 3
26	9.44 – 15.24	263,357 – 396,036	10	> 3
29	1.83 – 4.57	263,357 – 396,036	20	0.3 – 3
34	1.83 – 4.57	263,357 – 396,036	20	0.3 – 3

[1] Original source data were in feet, * Original source data were in mi^2 in/yr

Table 16. Relationship between landuse, soil series and geology with seven contaminated wells.

Well numbers	LULC	LULC with 9 neighboring cells	Soils	Soils with 9 neighboring cells	Gelogy	Geology with 9 neighboring cells
7	Soybean	Soybean (56%), Wheat-DC-Soybean (33%), Forest (11%)	Bosket	Overcup(33%), Bosket (66%)	Terrace deposit	Terrace deposit (100%)
9	Soybean	Soybean (56%), Rice (22%), Forest (11%), Milo/sorghum (11%)	Kobel	Askew (33%), Kobel (67%)	Terrace deposit	Terrace deposit (100%)
11	Rice	Rice (56%), Soybean (22%), Milo/sorghum (11%)	Willlville	Willville (100%)	Terrace deposit	Terrace deposit (100%)
25	Grass	Grass (33%), Soybean (22%), Milo/sorghum (22%), Forest (11%), Wheat-DC-Soybean (11%)	Commerce	Commerce (55%), Arrigton (44%)	Alluvium	Alluvium (100%)
26	Grass	Layout (56%), Grass (11%), Soybean (11%), Wheat-DC-Soybean (22%)	Greneda	Greneda (100%)	Dune sand	Dune sand (67%) Terrace deposit (33%)
29	Grass	Grass (44%), Layout (22%), Rice (22%), Soybean (11%)	Askew	Askew (33%), Tuckerman (22%), Amagon (22%), Bosket (11%)	Terrace deposit	Terrace deposit (100%)
34	Forest	Layout (33%), Soybean (22%), Forest (22%),Grass (11%)	Dundee	Dundee (22%), Tuckerman (44%), Foley-Bonn (22%), Dubbs (11%)	Terrace deposit	Terrace deposit (100%)

Table 17. Distribution of landuse (TM '92) within different buffer zones for contaminated wells.

Well number(s)	Buffer zones in meters 160	240	560
7	Soybean (50%) Wheat/Soybean (33.33%) Forest (16.67%)	Soybean (50%) Forest (12.50%) Layout (12.50%) Rice (6.25%) Grass (6.25%) Wheat /Soybean (6.25%) Corn/Milo (6.25%)	Layout (35.83%) Soybean (25.83%) Corn/Milo (19.17%) Forest (7.50%) Rice (6.67%) Milo/Sorghum (3.33%) Wheat/Soybean (0.83%) Grass (0.83%)
9	Soybean (50%) Rice (25%) Milo/Sorghum (16.67%) Forest (8.33%)	Rice (43.75%) Milo/Sorghum (25%) Soybean (12.5%) Forest (12.5%) Wheat /Soybean (6.25%)	Rice (42.5%) Soybean (35.83%) Forest (8.33%) Milo/Sorghum (7.5%) Wheat /Soybean (5.83%)
11, 25, 26, 29 and 34	Soybean (30.95%) Layout (19.05) Rice (16.67%) Grass (9.52%) Wheat /Soybean (9.52) Milo/Sorghum (7.14%) Forest (5.95%) Water (1.19%)	Soybean (25%) Layout (23.21%) Forest (14.29%) Rice (13.39%) Milo/Sorghum (6.25%) Grass (5.36%) Wheat/Soybean (5.36%) Corn/Milo (1.79) Soybean/Cotton (0.89%) Water (4.46%)	Soybean (27.74%) Layout (20.71%) Rice (17.98%) Wheat/Soybean (9.64%) Forest (7.74%) Grass (6.9%) Milo/Sorghum (3.21%) Corn/Milo (2.86%) Soybean/cotton (0.95%) Water (2.26%)

Table 18. Distribution of soil series and geology within different buffer zones for contaminated wells.

Well number	Buffer zones in meter for soils			Buffer zones in meter for geology		
	160	240	560	160	240	560
7	Overcup (33.33%) Amagon (16.67%) Bosket (50%)	Overcup (31.25%) Amagon (18.75%) Bosket (43.75%)	Askew (6.67%) Dundee (1.67) Overcup (34.17%) Jackport (0.83%) Amagon (4.17%) Bosket (47.5%) Grubbs (5%)	Terrace Deposit	Terrace Deposit	Terrace Deposit
9	Kobel (58.33%) Askew (33.33%) Dundee (8.33%)	Kobel (50%) Dundee (25%) Askew (12.5%) Grubbs (12.50%)	Kobel (26.67%) Dundee (12.50%) Askew (7.5%) Grubbs (28.3) Patterson (8.33%) Wiville (9.17%) Bulltown (0.83%) Folley-Bonn (2.5%)	Terrace Deposit	Terrace Deposit	Terrace Deposit
11, 25, 26, 29,34	Askew (9.52%) Dundee (3.57%) Greneda (14.28%) Overcup (5.95%) Tuckerman (9.52%) Amagon (4.76%) Bosket (9.52) Foley-Bonn (3.57%) Commerce (7.14) Wiville (14.29) Arrington (5.95%) Kobel (8.33)	Askew (1.79%) Dundee (4.46%) Greneda (14.29%) Overcup (6.25%) Tuckerman (11.61%) Amagon (7.14%) Bosket (10.72) Dubbs (2.68%) Foley-Bonn (2.68%) Grubbs (0.89%) Commerce (4.46%) Wiville (12.5) Arrington (5.36%) Kobel (7.14)	Askew (2.74%) Dundee (4.76%) Greneda (11.07%) Overcup (8.21%) Jackport (0.12%) Tuckerman (4.05%) Amagon (2.98%) Patterson (1.19%) Bosket (15.47%) Foley-Bonn (3.69%) Grubbs (6.19%) McCrory (1.07%) Oaklimeter (1.31%) Forestdale (0.24%) Bulltown (2.50%) Commerce (6.07%) Kobel (4.17%) Wiville (12.62%) Arrington (6.19%)	Terrace Deposit (76.19%) Alluvium (14.29%) Dune sand (9.52%)	Terrace Deposit (76.19%) Alluvium (14.29%) Dune sand (9.52%)	Terrace Deposit (78.10%) Alluvium (14.29%) Dune sand (7.62%)

Table 19. Secondary attributes for dominating soils (>= 10% areal coverage) found around contaminated wells from nine-neighboring cell analysis and buffer zones.

Soil Series	Texture	pH	Shrink-swell	OM (%)by weight	Permeability cm/hr	Drainage	Runoff
Amagon	SIL	4.5 – 6.5	Low	1 – 2	1.34 – 5.08	Poorly drained	Negligible to medium
Askew	FSL	5.1 – 7.3	Low	1 – 3	5.08 – 15.24	Moderately well drained	Slow to rapid
Bosket	FSL	5.1 – 6.5	Low	0.5 – 2	5.08 – 15.24	Well drained	Negligible to medium
Dundee	SIL	4.5 - 6	Low	0.5 – 2	1.34 – 5.08	Somewhat poorly drained	Negligible to high
Grenada	SIL	4.5 – 6	Low	0.5 – 2	1.34 – 5.08	Moderately well drained	Medium to slow
Grubbs	SIL	5.1 – 6.5	Low	1 – 2	1.34 – 5.08	Moderately well drained	Negligible to very high
Kobel	SICL	5.1 – 7.3	Moderate	1 – 3	0.508 – 1.34	Poorly drained	Slow to very slow
Overcup	SIL	5.1 – 7.8	Low	1 – 2	1.34 – 5.08	Poorly drained	Slow
Tuckerman	L	4.5 – 6	Low	0.5 – 2	1.34 – 5.08	Poorly drained	Negligible to low
Wiville	FSL	5.1 – 7.3	Low	0.5 – 2	1.34 – 5.08	Well drained	Slow to rapid
Dubbs	SIL	4.5 – 6	Low	0.5 – 2	2.54 – 5.08	Well drained	Slow
Arrington	SIL	6.1 – 7.8	Low	2 – 4	2.54 – 5.08	Well drained	Medium – Slow
Folly-Bonn	SIL	4.5 – 7.3	Low	0.5 – 2	2.54 – 5.08/0-2.54	Poorly drained	Negligible – Medium / Slow

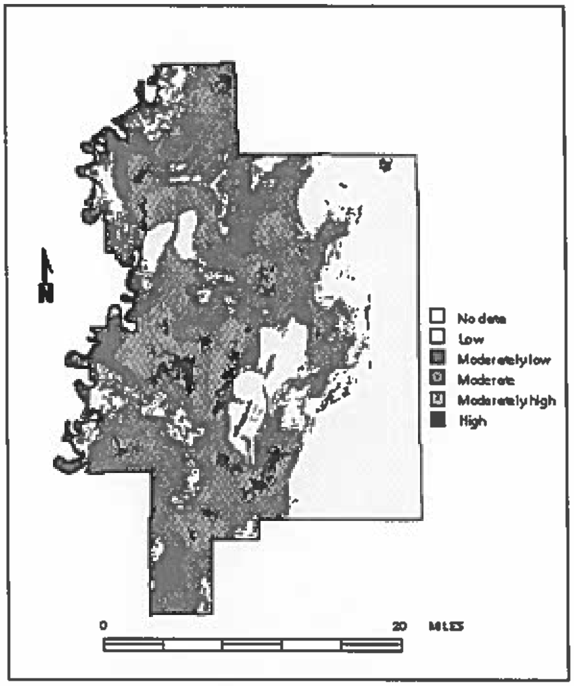

Figure 1a. Spatial distribution of vulnerability from 5-class modified DRASTIC model.

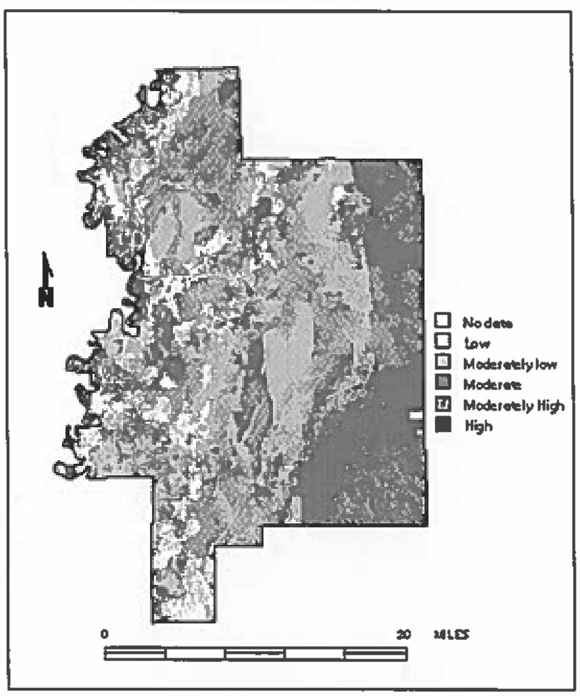

Figure 1b. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase I.

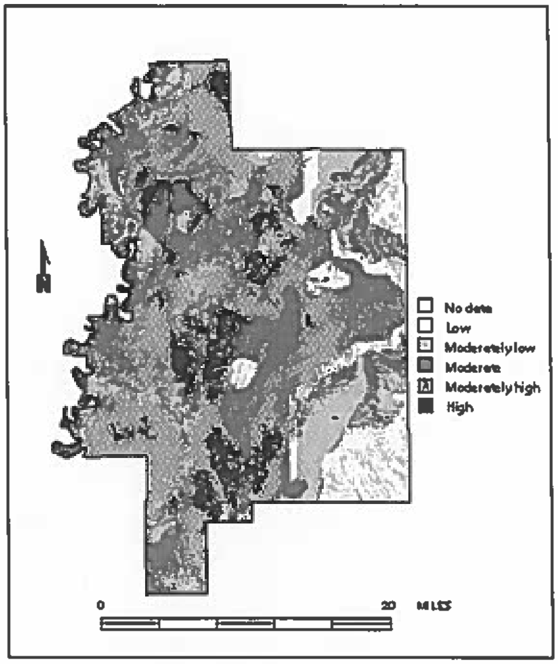

Figure 2a. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase II.

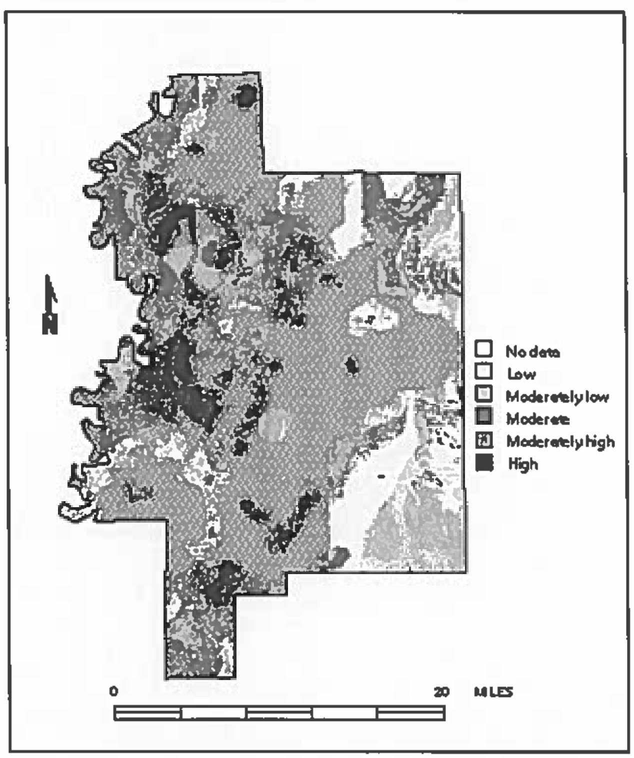

Figure 2b. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase III.

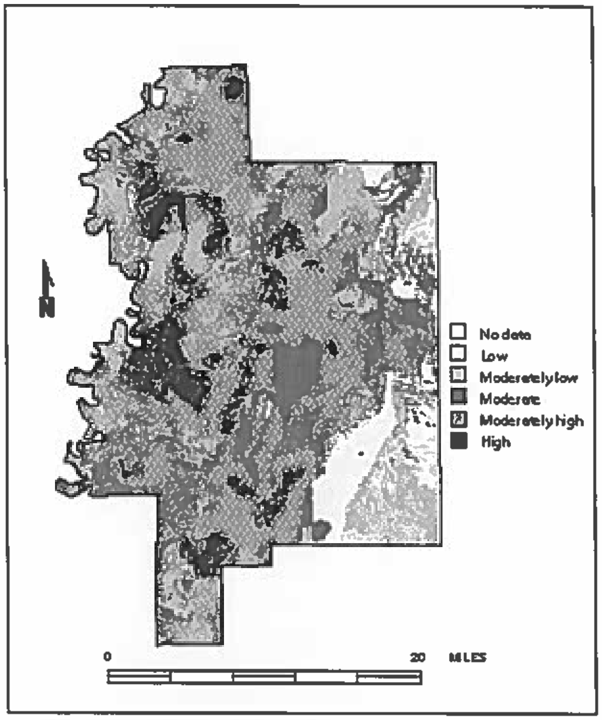

Figure 3a. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase IV.

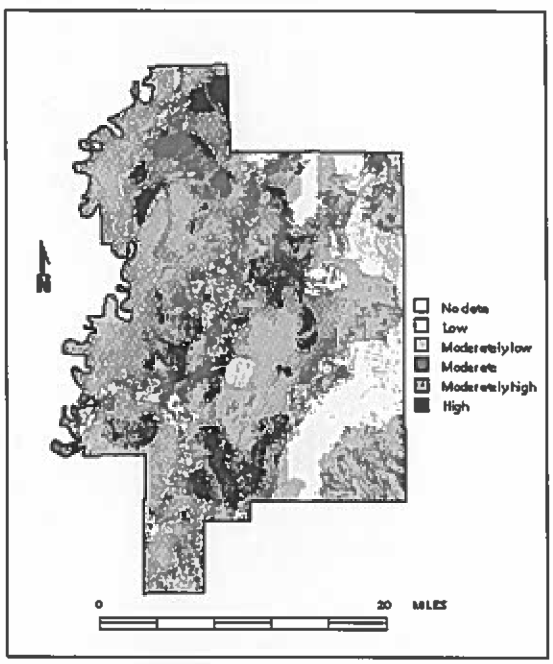

Figure 3b. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase V.

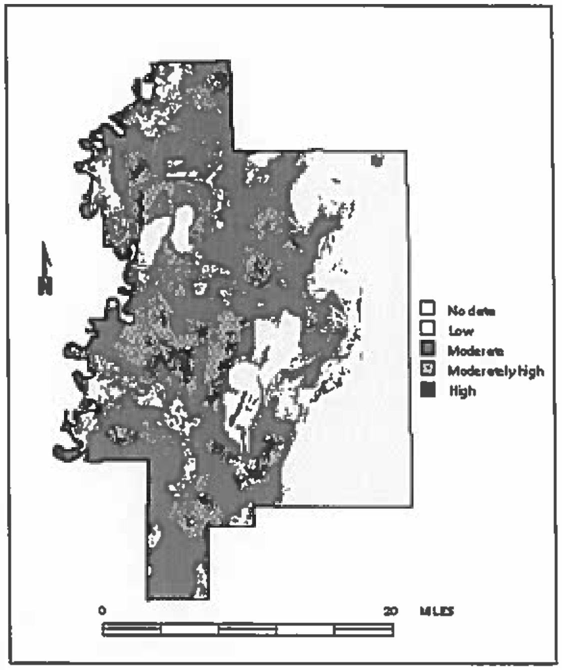

Figure 4a. Spatial distribution of vulnerability from 4-class modified DRASTIC model.

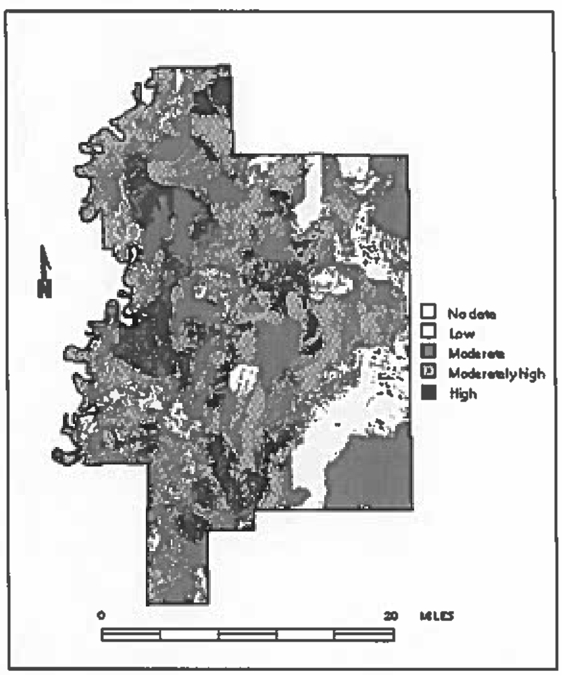

Figure 4b. Spatial distribution of vulnerability from fuzzy logic-based model output using Rulebase VI.

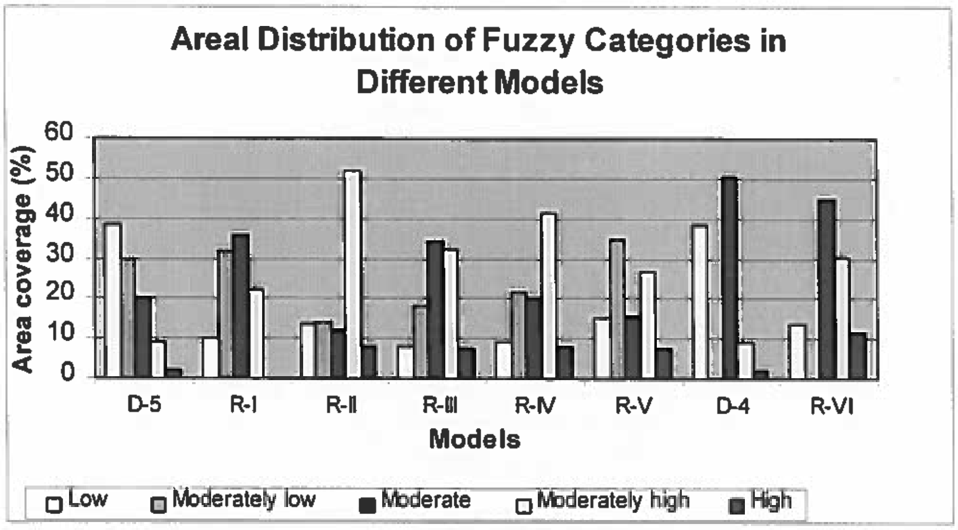

Figure 5. Areal distribution of fuzzy categories in different models. Where D-5 : DRASTIC model With 5 categories, R-I: Rulebase I, R-II: Rulebase II, R-III: Rulebase III, R-IV: Rulebase IV, R-V: Rulebase V, D-4: DRASTIC with four categories, R-VI: Rulebase VI.

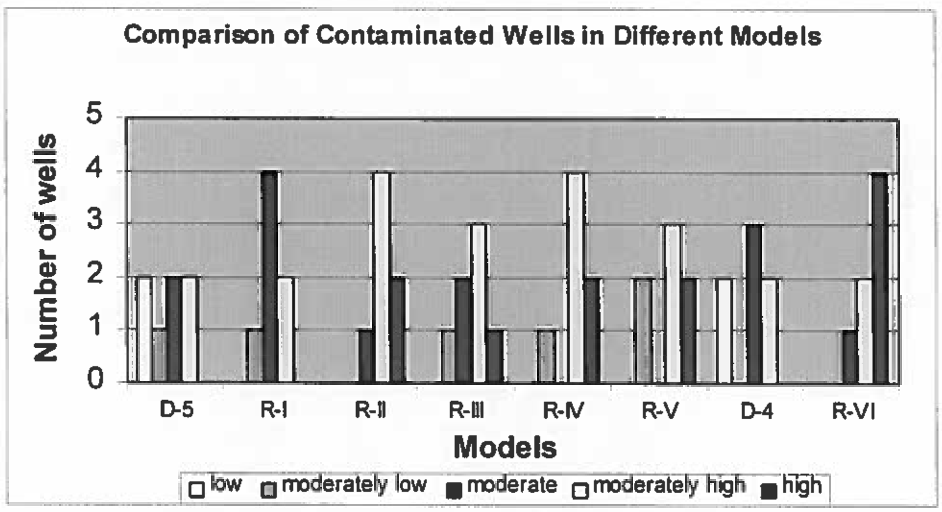

Figure 6. Comparison of contaminated wells in different models. Where D-5 : DRASTIC model With 5 categories, R-I: Rulebase I, R-II: Rulebase II, R-III: Rulebase III, R-IV: Rulebase IV, R-V: Rulebase V, D-4: DRASTIC with four categories, R-VI: Rulebase VI.

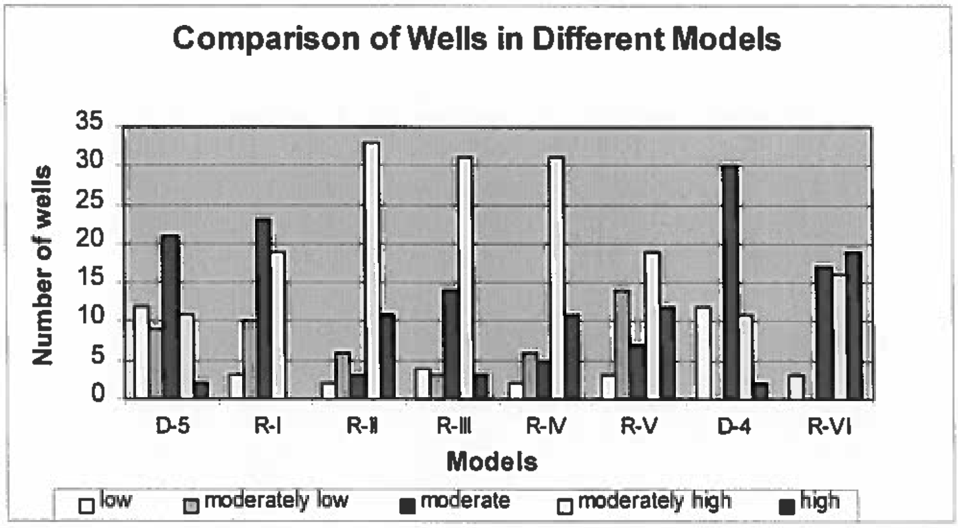

Figure 7. Comparison of wells in different models. Where D-5 : DRASTIC model With 5 categories, R-I: Rulebase I, R-II: Rulebase II, R-III: Rulebase III, R-IV: Rulebase IV, R-V: Rulebase V, D-4: DRASTIC with four categories, R-VI: Rulebase VI.

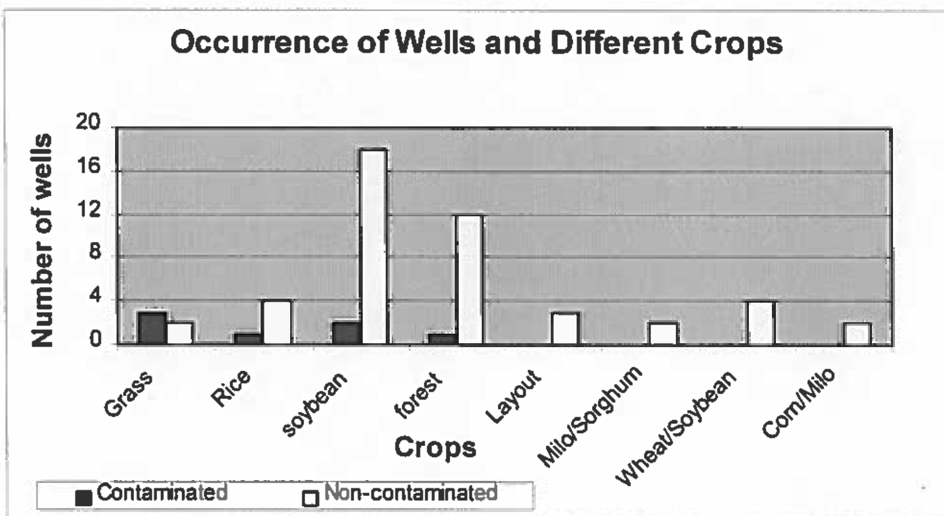

Figure 8. Relationship between crops with contaminated wells and non-contaminated wells.

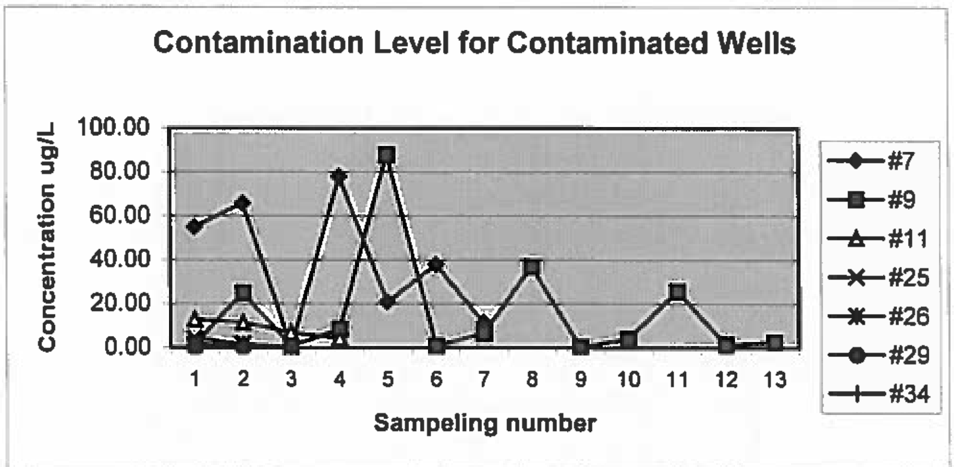

Figure 9. Contamination level for contaminated wells.

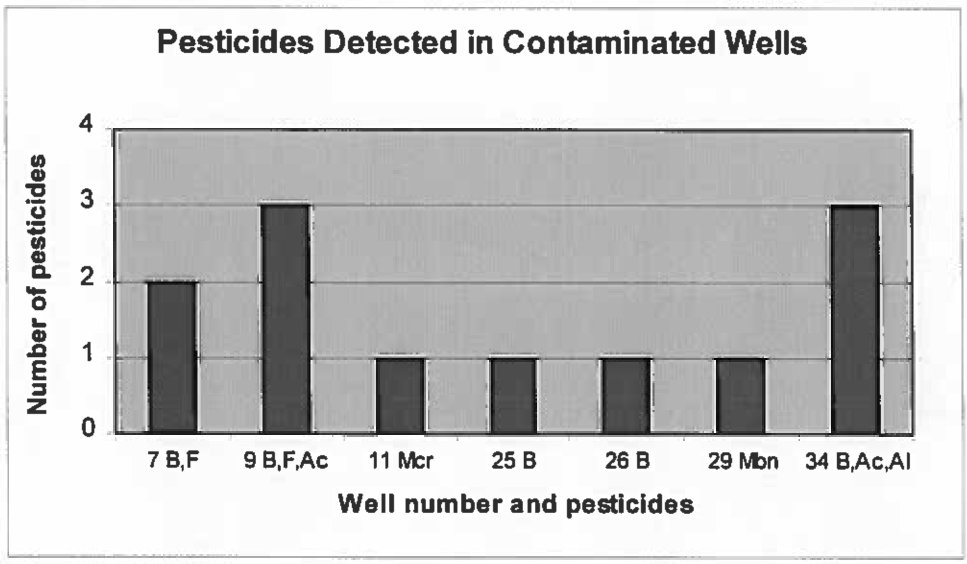

Figure 10. Pesticides detected in contaminated wells. B:Bentazon, F: Fluometuron, Ac: Acifluorfen, Mcr: Metolachlor, Mbn: Metribuzin, Al: Alachlor.

UTILIZING VEGETATIVE FILTER STRIPS OF VARYING WIDTHS TO REDUCE HERBICIDES IN RUNOFF WATER

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INTRODUCTION

This field study was designed to ascertain the influence of tall fescue (*Festuca arundinacea* Schreb.) filter strip width on the off-site movement of metolachlor and metribuzin in surface water.

METHODOLOGY

The research was conducted at the Black Belt Experiment Station near Brooksville, MS. On July 9, 1996, soybean [*Glycine max* (L.) Merr.] was planted into standard soil erosion plots (22.1 m long by 4.1 m wide) and the herbicides metolachlor and metribuzin were applied preemergence at 2.8 and 0.42 kg ai /ha, respectively. Treatments consisted of tall fescue filter strips (0, 0.5, 1, 2, 3, and 4 m in length) established across the entire width of the plot just prior to entry into the flume.

A simulated rainfall event was initiated within 2 days after treatment (DAT) all years using an irrigation system patterned after that described by Sumner et al. (1992). This system applied water through individual cycling irrigation sprinkler heads mounted on 3 m risers spaced 3 m apart. All plots received simulated rainfall at an intensity of 25 mm h^{-1} simultaneously. Other rainfall simulations were employed later in the growing season each year to provide adequate runoff events at timely intervals. Rainfall simulation for a given event was continued until runoff had occurred on all plots for 10 min. Each year runoff was monitored for at least 84 d following herbicide application. Metolachlor and metribuzin have high water solubilities, at 530 ppm and 1,220 ppm, respectively. Half-lives in soil range from 15-25 days for metolachlor, and 7-60 days for metribuzin. The relatively short half-lives combined with high solubilities favored increased losses early in the growing season and, by 84 DAT, no detectable levels were present in runoff.

Automated flow meters[1] and water samplers[2] were installed. The flow meters were programmed to determine flow rates and total runoff at the outlet of the flume. The automated water samplers were programmed to collect a 0.64-L sample from runoff passing through the flume at 200-L intervals during runoff events occurring from natural and simulated rainfall events. Samples were recovered within 24 h of the runoff event and stored at 2 C until analysis.

Water samples were filtered under vacuum through a Buchner funnel containing a 9 cm diameter filter paper. Filtered sediment was oven-dried at 66 C for 24 h and quantified. These values were combined with total runoff to establish sediment loss on a per ha basis, and subsequently cumulative sediment loss. Only the runoff water was subjected to herbicide analysis, since the high solubility and low adsorption of these compounds result in minimal amounts on sediment. A 500 ml aliquot of the runoff water was placed in liquid-liquid extractor with 250 ml of methylene chloride. The extractor was then placed on a 500 ml flat-bottom flask containing 300 ml methylene chloride, and

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[1]Isco Model 4230 Flow Meter, Isco, Inc., 531 Westgate Blvd., Lincoln, NE 68528.

[2]Isco Model 3700 Portable Sampler, Isco, Inc., 531 Westgate Blvd., Lincoln, NE 68528.

heated at 215 C for 16 h. Samples were subjected to rotary evaporation to just dryness, and brought to a volume of 10 ml with hexane. The samples were analyzed by gas chromatography. The gas chromatograph was equipped with a ^{63}Ni electron capture detector, a 30 m long by 0.53 mm i.d. capillary column with a (5%-phenyl)-methylpolysiloxane stationary phase, and an integrator to compare sample peaks against standard peaks to quantify metolachlor and metribuzin. Residues were determined with a lower detection limit of 250 and 100 ng L^{-1} for metolachlor and metribuzin, respectively.

Herbicide solution concentrations were multiplied by the total runoff to determine total loss of each herbicide per runoff event on a per ha basis, and subsequently cumulative off-site movement in runoff. Attempts were made to regress herbicide losses, runoff amounts, and sediment amounts, both within events and cumulative, in linear, quadratic, and exponential form against filter strip width. However, these regression forms were unable to accurately predict actual values for the unfiltered, because of the dramatic difference compared to all filter strip widths; therefore, regression results are not reported. Total runoff, sediment loss, and metolachlor losses and metribuzin losses, along with cumulative losses, were subjected to analysis of variance. Total runoff, sediment and herbicide loss were separated using Fisher's protected LSD at $P \leq 0.05$.

RESULTS AND DISCUSSION

Total rainfall amounts during the sampling period for 1994 through 1996 were 1411, 726, and 744 mm, respectively. The first runoff event was a simulated event and occurred 2 DAT in all years. Through the 2 and 48 DAT sampling dates, total rainfall averaged 152 and 100 mm, respectively. Simulated events occurred on 2 and 48 DAT each year, while other events were supplied by natural rainfall.

Surface runoff. At 2 DAT, the highest runoff came from the unfiltered treatment, at 137000 L ha^{-1} (Figure 1). Runoff from filter strips was 10000-23000 L ha^{-1}. The addition of a filter strip reduced surface runoff by 83-93%, with no differences in filter strip widths. The same trends were observed through 48 DAT, where cumulative runoff was highest from the unfiltered treatment, at 657000 L ha^{-1} (Figure 2). Filter strips reduced the cumulative runoff to 206,000-349,000 L ha^{-1}. Again, the same trends were observed with the addition of a filter strip, resulting in the reduction of cumulative runoff from 47-69%, and no differences between filter strip widths. Total runoff losses at the end of season were again highest from the unfiltered, at 658,000 L ha^{-1} (Figure 3), and the addition of a filter strip reduced cumulative runoff to 350,000-207,000 L ha^{-1}, or a 47-68% reduction. The presence of a filter strip substantially reduced runoff velocity, allowing increased infiltration and reducing the total amount of off-site movement.

Herbicide loss. At 2 DAT, metribuzin concentration in solution from the unfiltered treatment was 231 ng ml^{-1} (Figure 4). Filter strips reduced metribuzin concentrations to 74-119 ng ml^{-1}, or a reduction of 48-68%, regardless of width. Metolachlor concentrations were higher, but the same trends were observed (Figure 5). The highest concentration was from the unfiltered, at 1009 ng ml^{-1}. The addition of a filter strip reduced metolachlor concentration to 313-523 ng ml^{-1}, or a reduction of 48-69%.

When total runoff was combined with herbicide concentrations, losses per ha were calculated. At 2 DAT the unfiltered treatment resulted in a metribuzin loss of 32 g ha^{-1} (Figure 6). This loss is equivalent to 7% of the applied metribuzin. Filter strips reduced metribuzin concentrations to 0.8-2.7 g ha^{-1}, regardless of width. The presence of a filter strip reduced metribuzin loss 91-98% on this date, with no differences between widths. The highest metolachlor loss 2 DAT was from the unfiltered, at 141 g ha^{-1}, or 5% of the amount applied (Figure 7). Filter strips reduced metolachlor losses to 3.5-13 g ha^{-1}. The presence of a filter strip of any width effectively reduced metolachlor concentrations by 91-98%. When considering total herbicide loss for the unfiltered treatment, 78% of the total metribuzin loss was accounted for in the first runoff event, and 77% for metolachlor.

At 48 DAT, the trends continued with respect to cumulative metribuzin and metolachlor losses. Metribuzin loss was 41 g ha^{-1} from the unfiltered treatment (Figure 8). Again, all filter strips reduced metribuzin loss to 1.7-11 g ha^{-1}. Similarly, the highest cumulative metolachlor loss was from the unfiltered, at 183 g ha^{-1}, or 6.5% of the amount applied (Figure 9). Filter strips effectively reduced cumulative metolachlor losses to 19-60 g ha^{-1}.

Cumulative metribuzin and metolachlor losses through the growing season followed previous trends. The highest cumulative metribuzin loss was again observed from the unfiltered (Figure 10). Cumulative metribuzin loss was 41.5 g ha^{-1}, or 9.8% of the applied metribuzin. Filter strips reduced cumulative metribuzin losses to 1.7-11 g ha^{-1}, or 0.4-2.6% of the applied. Cumulative metolachlor losses were higher for the unfiltered treatment, resulting in 183 g ha^{-1} or 6.5% of the amount applied (Figure 11). The addition of a filter strip also reduced cumulative metolachlor losses to only 19-60 g ha^{-1}, or 0.7-2.1% of the applied. Since herbicide loss patterns were the focus of this study, each year the experiment was terminated 84 DAT. By this time, metribuzin and metolachlor concentrations in the runoff were below the detection limit of 100 and 250 ng L^{-1}, respectively. By doing this, cumulative loss patterns accurately reflect annual loss patterns for both compounds. Increasing filter strip width did not affect reductions of cumulative metribuzin or cumulative metolachlor loss, and all filter strips reduced herbicide losses compared to the unfiltered treatment. The higher metribuzin and metolachlor loss from the unfiltered treatment is related to a combination of higher runoff amounts and higher concentrations in the early events. The presence of a filter strip reduced total runoff and consequently reduced cumulative metribuzin and metolachlor loss. This research indicates that filter strip widths from 0.5 to 4.0 m can effectively reduce metribuzin and metolachlor losses when compared to the unfiltered, and provide a viable management tool for the reduction of herbicide losses.

Sediment loss. At 2 DAT, sediment loss was highest from the unfiltered area, at 90 kg ha^{-1} (Figure 12). By providing a filter strip, sediment losses were reduced to 2-11 kg ha^{-1}, or a 99-98% reduction. The same trends were observed at 48 DAT. Cumulative sediment from the unfiltered treatment was 182 kg ha^{-1}, compared to only 19-60 kg ha^{-1} from plots which contained filter strips (Figure 13). Due to less precipitation resulting in fewer runoff events later in the year (as is normal), cumulative sediment at the end of the growing season was similar to that of previous sampling dates. The highest amount of sediment loss was from the unfiltered treatment, at 442 kg ha^{-1} (Figure 14). Filter strips continued to reduce cumulative sediment loss, with losses of only 25-78 kg ha^{-1}. Filter strips reduced runoff amounts, and consequently sediment losses, by increasing backwater depths prior to entry of the filter strips thus increasing deposition of suspended solids. Although there were no differences in filter strip widths in reducing sediment losses, all widths reduced the off-site movement of sediment.

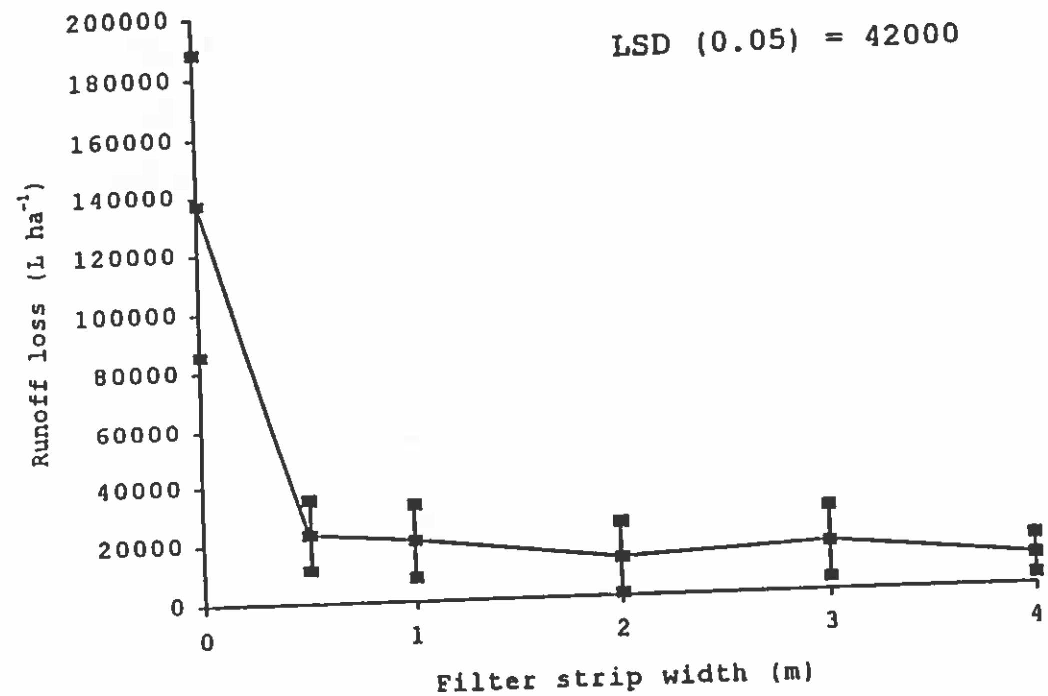


Figure 1. The effect of filter strip width on runoff loss 2 days after initiation of study. Means are shown with standard deviations.

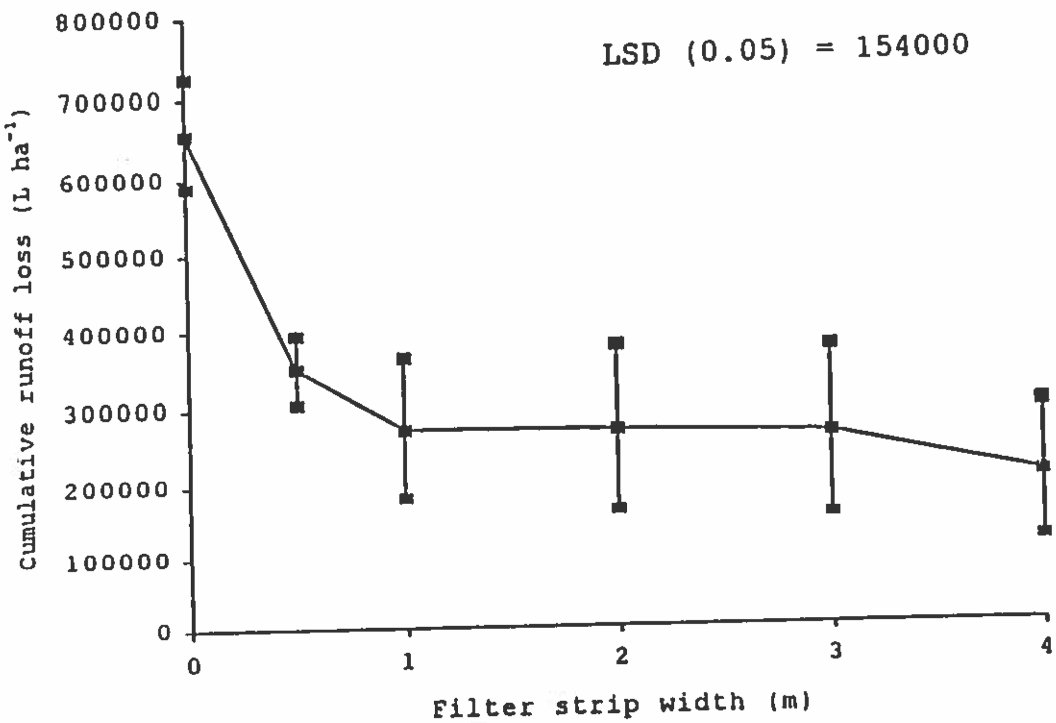


Figure 2. The effect of filter strip width of cumulative runoff loss through 48 days after initiation of study. Means are shown with standard deviations.

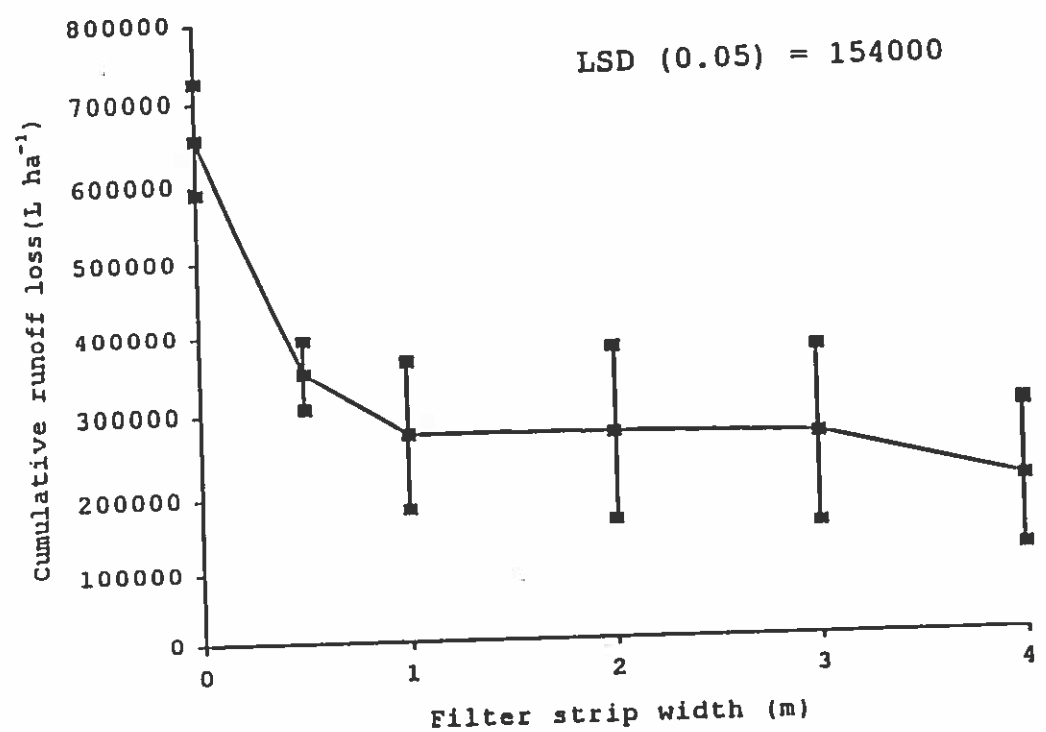


Figure 3. The effect of filter strip width on cumulative runoff loss through 84 days after initiation of the study. Means are shown with standard deviations.

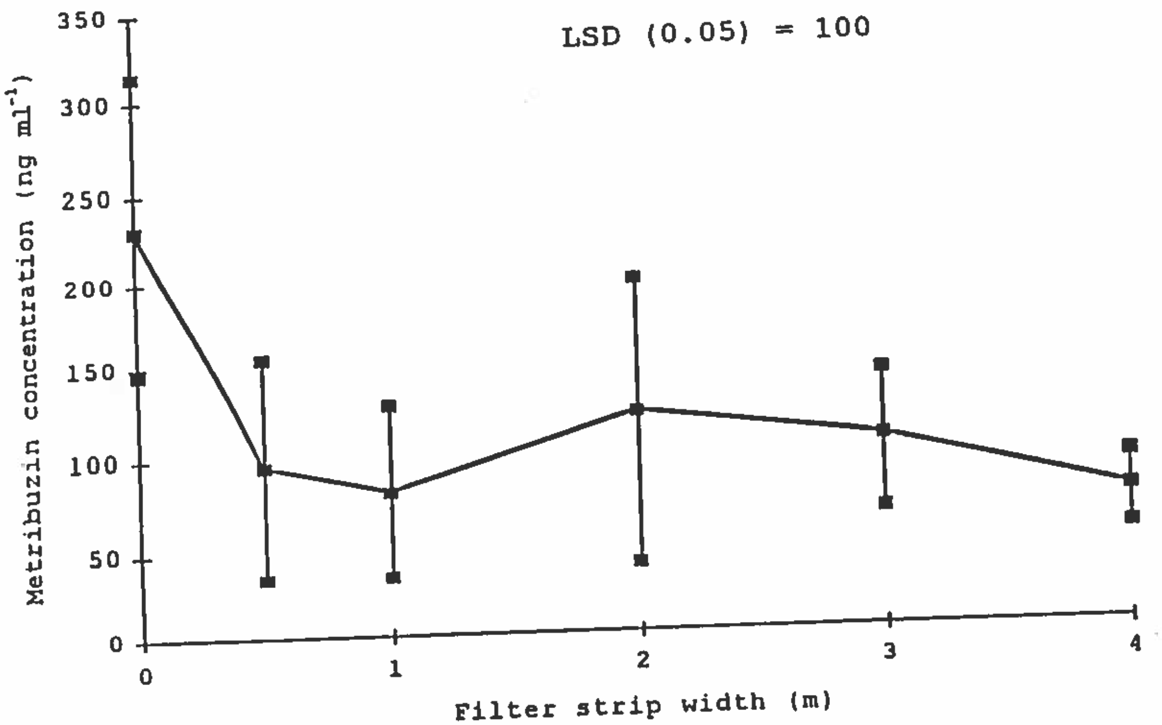


__Figure 4.__ The effect of filter strip width on metribuzin concentration 2 days after initiation of study. Means are shown with standard deviations.

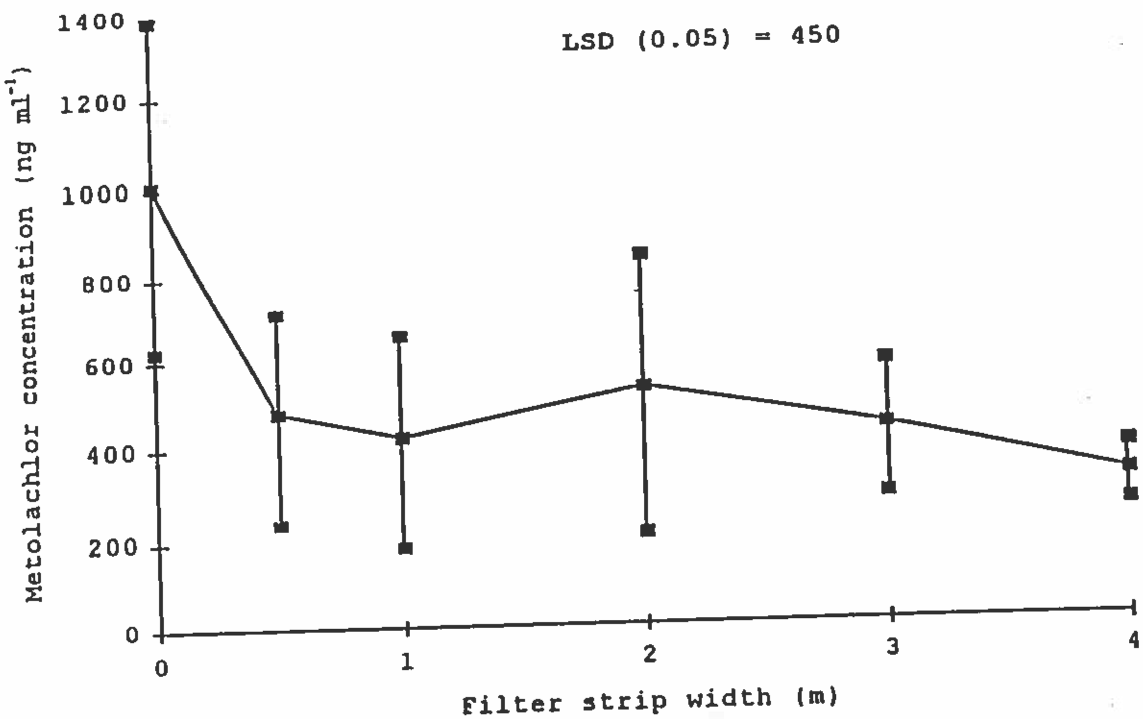


__Figure 5.__ The effect of filter strip width on metolachlor concentration 2 days after initiation of study. Means are shown with standard deviations.

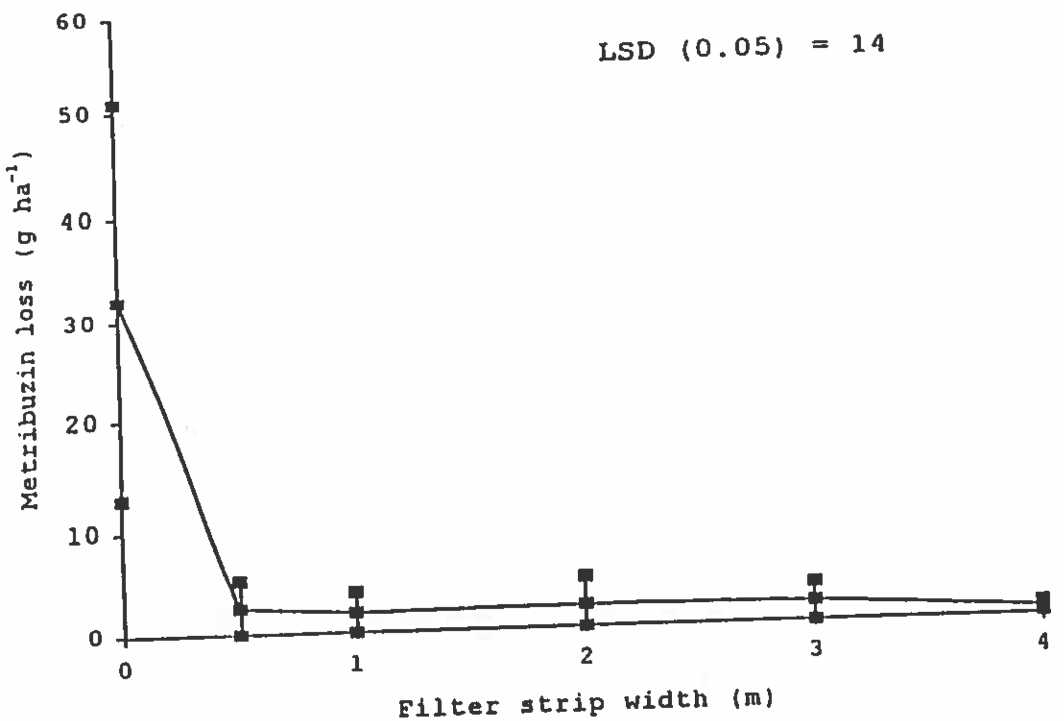
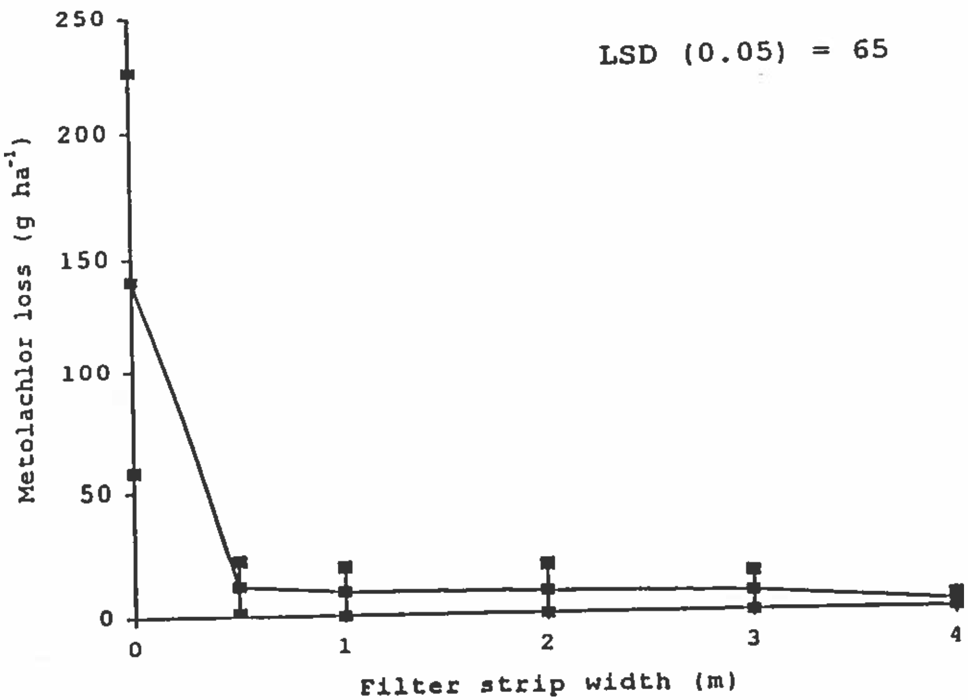


Figure 6. The effect of filter strip width on metribuzin loss 2 days after initiation of study. Means are shown with standard deviations.



<u>Figure 7.</u> The effect of filter strip width on metolachlor loss 2 days after initiation of study. Means are shown with standard deviations.

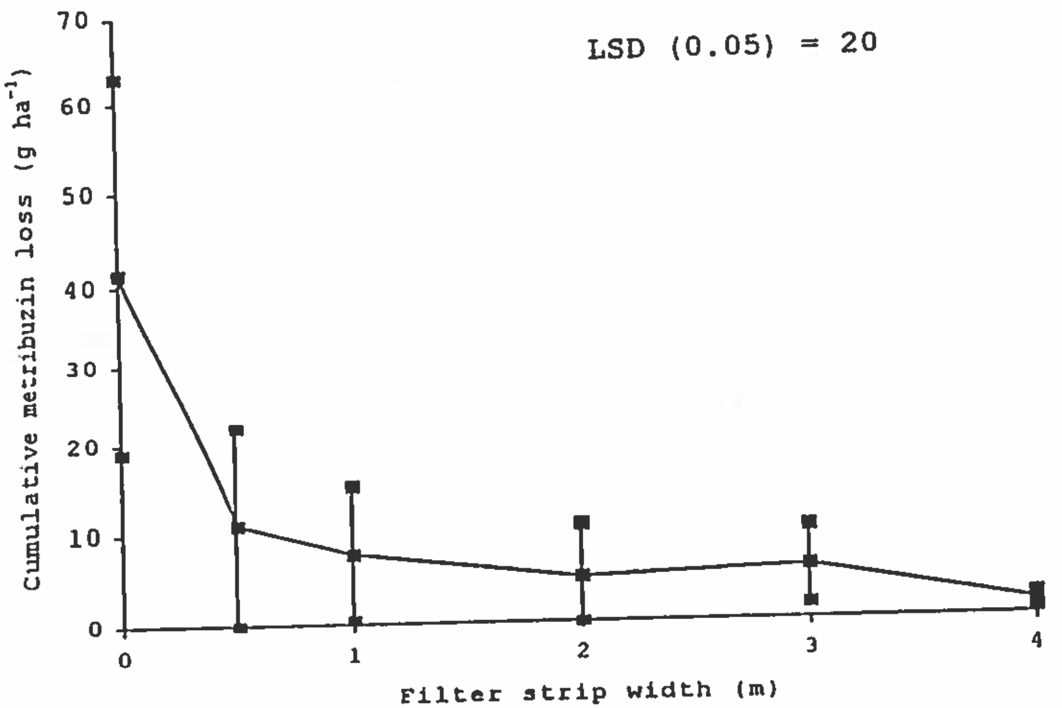


Figure 8. The effect of filter strip width on cumulative metribuzin loss through 48 days after initiation of study. Means are shown with standard deviations.

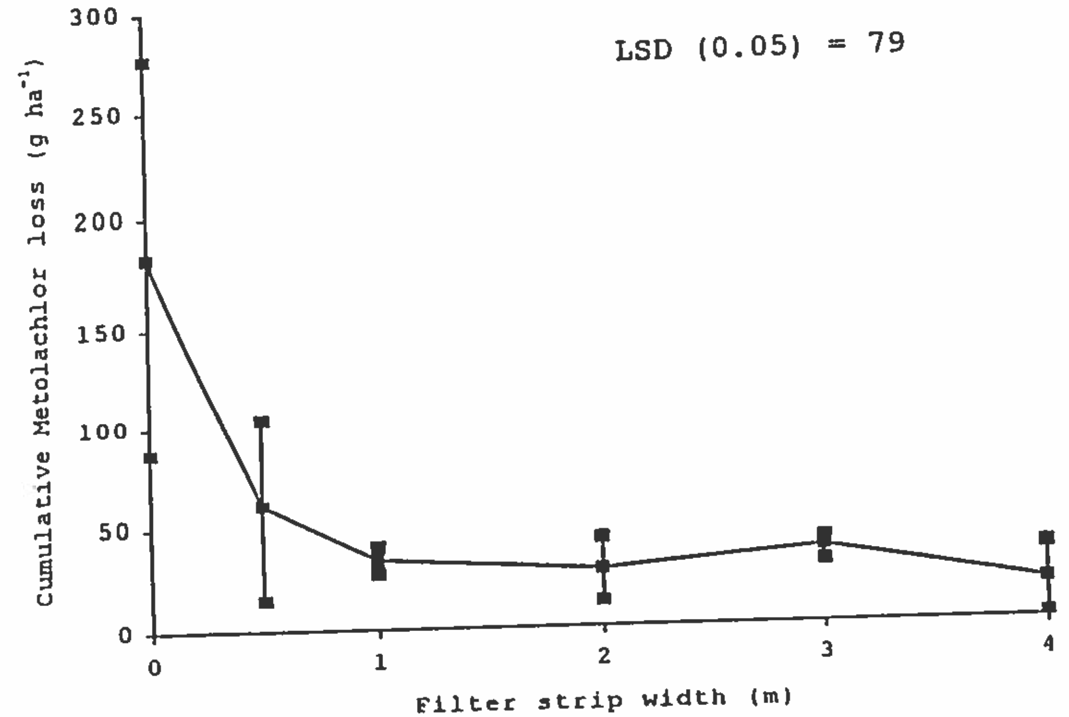


Figure 9. The effect of filter strip width on cumulative metolachlor loss through 48 days after initiation of study. Means are shown with standard deviations.

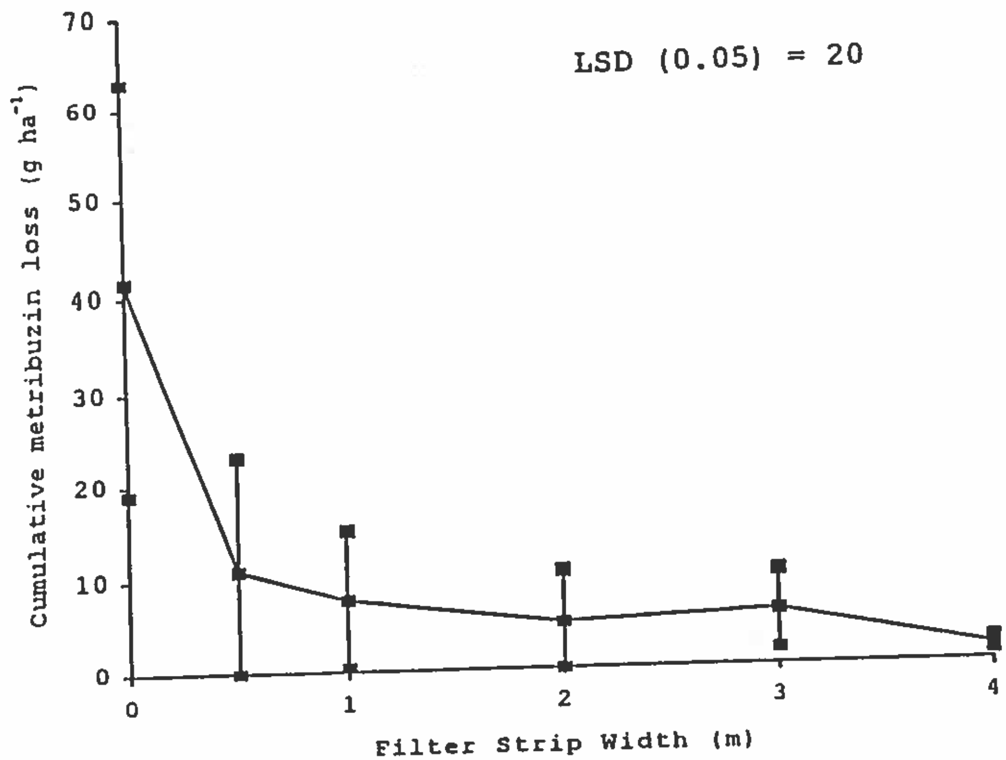
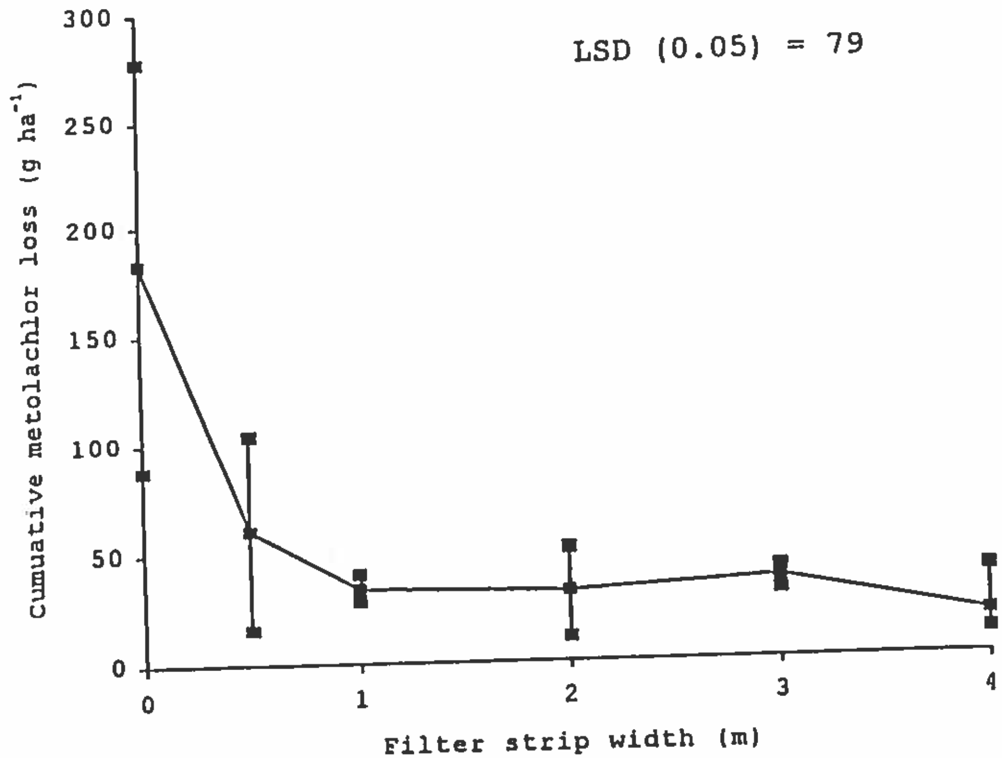
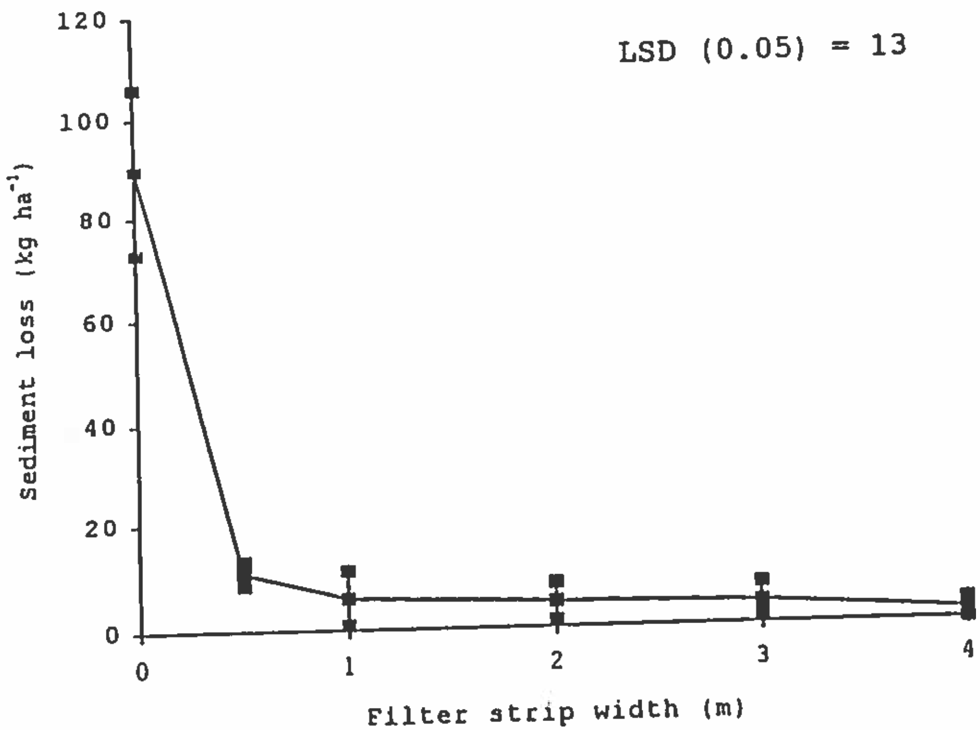


Figure 10. The effect of filter strip width on the reduction of cumulative metribuzin loss through 84 days after initiation of the study. Means are shown with standard deviations.



<u>Figure 11.</u> The effect of filter strip width on cumulative metolachlor loss through 84 days after initiation of the study. Means are shown with standard deviations.



<u>Figure 12.</u> The effect of filter strip width on sediment loss 2 days after initiation of study. Means are shown with standard deviations.

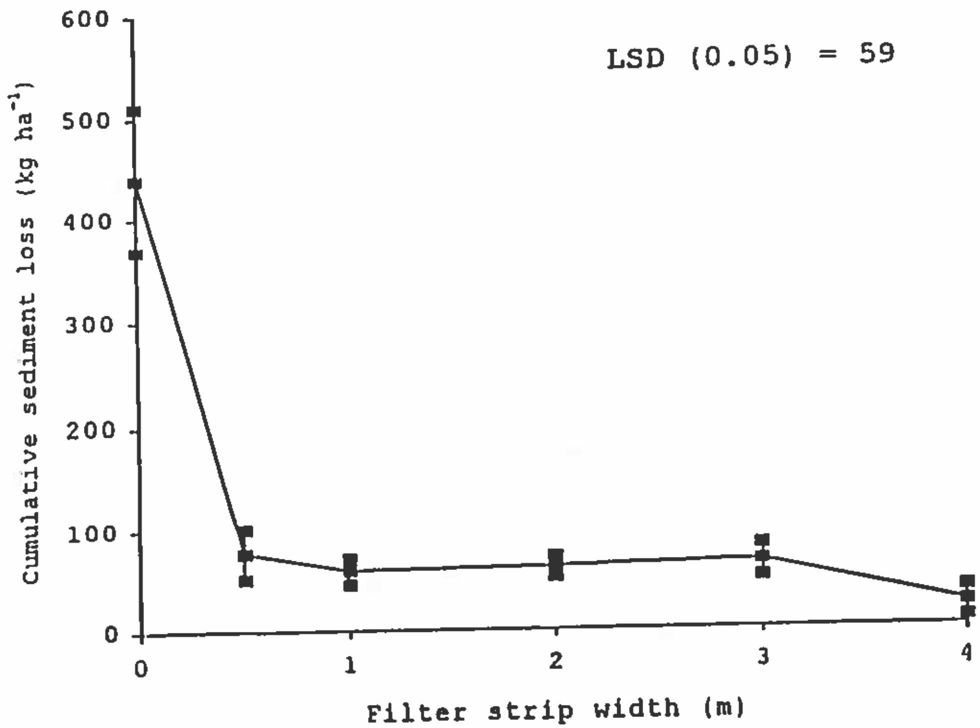
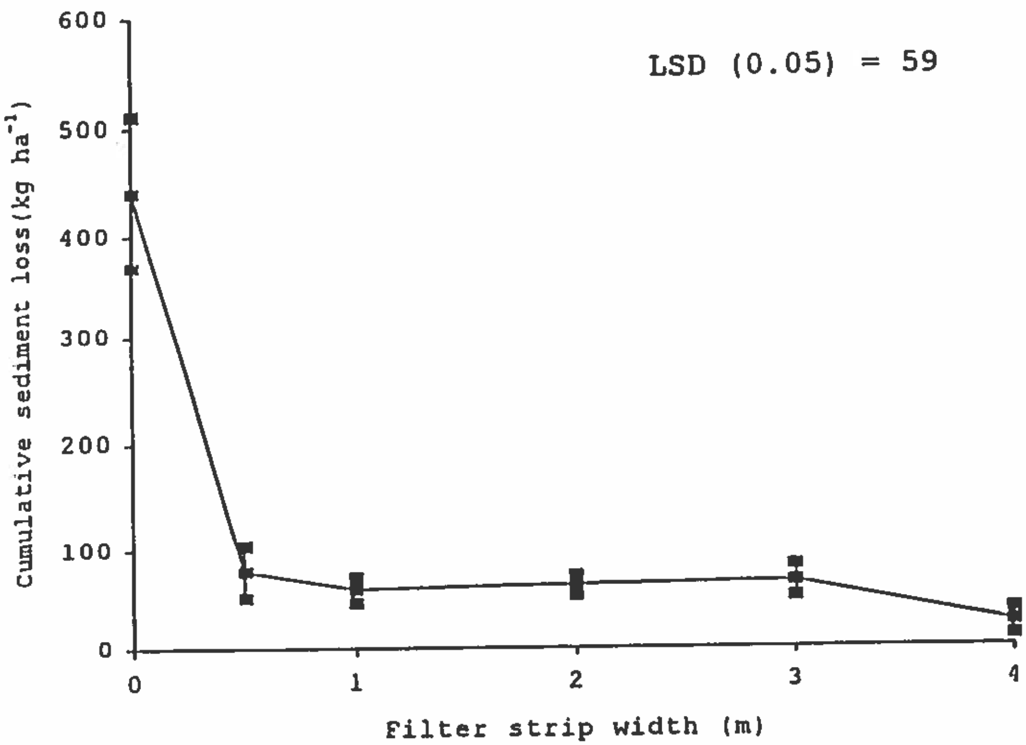


Figure 13. The effect of filter strip width on cumulative sediment loss through 48 days after initiation of study. Means are shown with standard deviations.



<u>Figure 14.</u> The effect of filter strip width on cumulative sediment loss through 84 days after initiation of the study. Means are shown with standard deviations.

PROJECT GROUP B

Title: EVALUATION OF FACTORS IMPORTANT IN THE QUALITY AND USE OF WATER IN RICE PRODUCTION IN THE MID-SOUTH REGION.

Specific Subtitles:

1. IDENTIFYING FACTORS WHICH INFLUENCE THE FATE OF PESTICIDES IN WATER USED FOR RICE PRODUCTION.
2. ECOLOGICAL AND AGRICULTURAL VALUES OF WINTER-FLOODED RICE FIELDS IN MISSISSIPPI
3. ANALYZING CONJUNCTIVE USE OF ON-FARM RESERVOIRS AND IRRIGATION WELLS IN THE ARKANSAS DELTA

IDENTIFYING FACTORS WHICH INFLUENCE THE FATE OF PESTICIDES IN WATER USED FOR RICE PRODUCTION

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INTRODUCTION

The detection of pesticides in agricultural runoff and water supplies have resulted in concern from both the general public and numerous environmental groups. Typically, pesticide residues in surface water supplies have been associated with the commonly used corn and soybean herbicides like atrazine, metolachlor and alachlor. However, in recent years, low levels of several rice pesticides have also been detected in various water supplies.

Water quality issues revolving around Ordram and Bolero residues began to attract attention in the early 1980's in California. As a result, regulations were implemented that required specified water holding periods before release back into the Sacramento River (Ross and Sava, 1986). In the early 1990's, similar compounds were also reported in the Mississippi River and its tributaries (Pereira and Hostettler, 1993). Recent reports from California suggest decreasing concentrations of Ordram and Bolero at downstream locations of the Sacramento River result primarily from dilution and not from aquatic degradation (Crepeau et al., 1995).

OBJECTIVES

Specific objectives of this research were: 1) to monitor tailwaters and confined surface water irrigation sources for pesticide residues and assess dissipation trends, and 2) to determine the dissipation mechanisms involved with the pesticides frequently detected in collected water samples.

PROCEDURES

Four to seven sampling locations were established, between 1994 and 1996, to observe water management systems which had the potential to collect and recycle rice tailwater drainage from the field into confined reservoirs for reuse as irrigation water. Tailwaters, pond, and irrigation water samples were collected on a bimonthly schedule which began with the permanent flood establishment. Water samples (900 mL) were transported, on ice, from the sampling locations to the Altheimer Laboratory for extraction and analysis. At the time of sample collection, additional pesticide fortified samples were also prepared from each location to monitor the stability of the selected pesticides in water during transport. Based on state recommendations for rice production and our analytical capabilities, the following 17 pesticides were selected for analysis: Benlate (benomyl), Bolero (thiobencarb), 2,4-D, Facet (quinclorac), Furadan (carbofuran), Grandstand (triclopyr), Londax (bensulfuron methyl), malathion, MCPA, methyl parathion, Ordram (molinate), Prowl (pendimethalin), Rovral (iprodione), Sevin (carbaryl), Stam (propanil), Tilt (propiconazole), and Whip (fenoxaprop ethyl). All samples were prefiltered through Whatman GF/F filter paper (0.7 m particle retention) to remove any suspended sediment. Filtered water (250 mL) was extracted using a 47-mm vacuum extraction manifold equipped with Empore C-18 extraction disks. Analytes were eluted with methanol and analyzed using high performance liquid chromatography (HPLC). Samples resulting in a positive HPLC detection were then subjected to gas chromatography/mass spectrometer (GC-MS) analysis for final confirmation.

In a greenhouse study, 16 water systems were used to investigate the effects of various environmental factors on the dissipation trends of commonly detected rice pesticides under aquatic conditions. The 16 systems included all combinations of the following factors: deionized or pond water, sediment or no sediment, light or dark conditions, and static or dynamic (bubbling air) systems. Individual water systems were prepared in 1 gallon, clear glass fish bowls and contained 3 L of either deionized or pond water. The systems containing sediment were prepared by adding actual pond sediment from Arkansas County to the bowls (sediment volume = 600 mL). Aquarium pumps were used to provide a continuous supply of air to half of the systems. Two replications of each treatment were randomly arranged on benches in the greenhouse with one bench having a black plastic cover over it to eliminate sunlight. Quinclorac, 2,4-D, benomyl, carbofuran, propanil, molinate, thiobencarb, and pendimethalin were added to each system to obtain an initial concentration of 50 g L^{-1}. Water samples (250 mL) were collected 1 h, 3, 7, 14, 28, and 56 d after treatment and analyzed to determine the concentrations of pesticide remaining over time. Three separate runs of this experiment were conducted over a one year period (May-June 1995, October-December 1995, and May-June 1996).

RESULTS AND DISCUSSION

Field Study

Since each location was independently managed, individual results were site specific. In general, applied pesticides were detected in tailwaters shortly following flood establishment or application of postemergent materials. Residues detected in these tailwaters did not lead to a pesticide buildup in adjacent reservoirs used for water collection.

Quinclorac residues in tailwaters were more persistent (6 to 8 weeks after flood establishment) than the other detected compounds which tend to persist less than two weeks in water. In some instances, quinclorac residues were detected in irrigation water coming from nearby water sources (sloughs or bayous). Residues in these waters were probably the result of runoff water coming from neighboring rice fields. Similarly, the low pendimethalin concentrations may have resulted from applications to nearby soybean fields.

Greenhouse Study

Ranges of slope estimates obtained for all eight compounds in the greenhouse study are shown in Table 1. These values are based on the following regression equation:

$$\text{natural log of concentration (ppb)} = k\ (\text{time}) \qquad [1]$$

Negative values for these estimates indicate that pesticide dissipation occurred from all water systems. The amount or rate of pesticide loss is indicated by the magnitude of each slope estimate. Overall, quinclorac was the most persistent pesticide in these water systems while pendimethalin, propanil, and thiobencarb dissipated most readily from these aquatic conditions

Table 1. **Range of regression slope estimates obtained for the aquatic dissipation of eight rice pesticides from sixteen model water systems under greenhouse conditions.[1]**

Pesticide	Slope Estimates (k)[day^{-1}]
Benomyl	-0.012 to -0.139
Carbofuran	-0.002 to -0.302
2,4-D	-0.010 to -0.131
Molinate	-0.047 to -0.195
Pendimethalin	-0.150 to -0.940
Propanil	-0.094 to -0.882
Quinclorac	-0.001 to -0.034
Thiobencarb	-0.047 to -0.837

[1] Regression Equation: natural logarithm of concentration (ppb) = k (time).

[2] Negative values indicate pesticide dissipation from individual water systems. Magnitude of slope estimates signify overall rate and amount of dissipation which occurred (i.e., values near zero indicate persistence and limited dissipation while values near -1.0 suggest rapid dissipation from water).

Due to this experiment being conducted inside the greenhouse, the effects of photodegradation could not be accurately evaluated since the greenhouse covering filters out most of the ultraviolet rays (< 385 nm). Both quinclorac and 2,4-D are known to undergo indirect photodegradation in environmental water systems. Therefore, the limited dissipation of these compounds is not surprising. Although exposure to ultraviolet radiation could not be addressed, differences in temperature were observed between the light and dark treatments. In general, the daily high temperatures observed from the covered bench were about 10 to 15 C lower than those measured from benches exposed to ambient greenhouse light (Figure 1).

Aeration resulted in significant dissipation of molinate, pendimethalin, propanil, and thiobencarb. This is due to the higher vapor pressures associated with these compounds which result in volatile losses. For all four compounds, bubbling air through the system resulted in enhanced dissipation, indicating losses through volatilization were occurring.

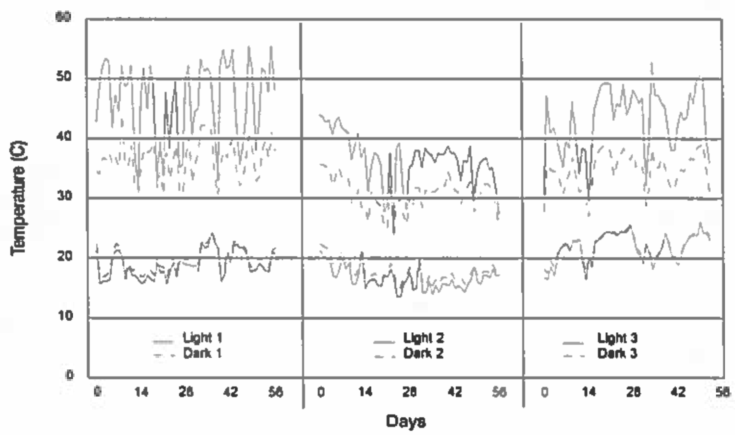

Figure 1. Minimum and maximum daily temperatures © measured during three greenhouse experiments.

This suggests that dissipation of these compounds under environmental conditions should be greater from turbulent water systems (i.e. streams, rivers, etc.) than from static systems such as reservoirs. It also suggests that, if needed, one should be able to stimulate the dissipation of these four compounds from static water bodies by applying an external source of agitation, such as an aerator.

The air component was the only significant factor involved in pendimethalin dissipation. However, molinate, propanil, and thiobencarb dissipation was also influenced by other factors in addition to the air component. The solar component influenced molinate losses probably due to increased temperatures further stimulating volatilization.

Thiobencarb was influenced by the difference between water-type which suggests that some microbial activity was occurring in the pond water systems that was not present in the deionized water treatments. Dissipation of propanil also indicated a water*sediment interaction in which the addition of sediment to deionized water increased the dissipation rate and amount but there was no enhanced dissipation when sediment was added to pond water. This suggests that the addition of sediment provided microbial activity necessary for propanil dissipation. Another explanation may be that adsorption onto the sediment was enhanced in the deionized water system, but not in the pond-water system due to pH differences.

Similar to the dissipation of propanil, quinclorac and 2,4-D dissipation resulted in a water*sediment interaction indicating enhanced dissipation when sediment was added to deionized water, but not when sediment was added to the pond water. The same interaction (marginally significant: $p = 0.0496$) was present with benomyl dissipation also. With benomyl, sediment addition to both water-types resulted in enhanced dissipation, but the magnitude of enhancement was less dramatic in pond water. A sediment*air interaction was also found with the analysis of 2,4-D dissipation. In this situation, the increased dissipation was more significant following addition of sediment to bubbling systems than to static systems. This was probably due to greater interaction between the 2,4-D molecules and the microbes added by the sediment in the well-mixed bubbling systems. The increased interaction, along with an abundant supply of oxygen for the microbes in the bubbling systems, probably enhanced the microbial degradation of this compound.

Results from the carbofuran analysis were complex and resulted in a four-way interaction among all factors. The primary effect appears to be pH related as the pond water systems without sediment resulted in the greatest losses. The measured pH values in these systems were between 7.5 and 8.5, compared to the remaining systems which ranged between 4.8 and 6.5. Carbofuran is rapidly hydrolyzed under high pH conditions and that is what appears to have occurred. The addition of sediment may have influenced dissipation in two different ways. One is due to lowering the pH of the pond water and the second could be due to a stabilization effect resulting from adsorption to the sediment particles.

SIGNIFICANCE OF FINDINGS

Even though some pesticides were detected in the tailwaters shortly after application, we see no evidence to show a pesticide buildup in the reservoirs. Overall, the dissipation of rice pesticides from water is rapid; this is evident from observing residues at one sampling time and not detecting the pesticide two weeks later. As expected, the period of highest pesticide concentration in water occurs shortly following pesticide application. Therefore, containment of water on the field should be emphasized immediately following postemergence applications to flooded rice. Flushing early in the season is most likely to cause loss of pesticides from preflood applications. Depending on application timing and flushing, the potential exists for rice pesticides to be present in surface waters used to irrigate other crops.

The greenhouse studies suggest that the aquatic dissipation of many pesticides are not easily explained by a single environmental factor. Frequently, interactions were detected during the analyses which confirm the complexity of environmental waters and warrants further research in the area of evaluating the fate of pesticides in aquatic environments.

ACKNOWLEDGMENTS

The authors would like to acknowledge the cooperation of all our cooperators for allowing us to collect water samples from their production systems. The financial support of the USGS, Arkansas Water Resources and the Rice Research and Promotion Board is also appreciated.

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ECOLOGICAL AND AGRICULTURAL VALUES OF WINTER-FLOODED RICE FIELDS IN MISSISSIPPI

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INTRODUCTION

Winter-flooded croplands in the Mississippi Alluvial Valley (MAV) provide habitat for migrating and wintering waterfowl, shorebirds and other wetland birds. Rice is especially important because: (1) the grain is nutritious and resists decomposition; (2) rice fields provide other foods, such as weed seeds, plant tubers, and aquatic invertebrates; and (3) the grain is grown in aquatic environments using water-management systems, which readily convert to wetland habitat for waterfowl and other waterbirds.

Abundant wetland habitat for waterfowl and other waterbirds exists in MAV rice fields. In 1993-95, an average 526,000 and 114,000 ha of rice were harvested in Arkansas and Mississippi, respectively. In winters 1993-96, approximately 60,000 (11%) and 6,000 (5%) ha of harvested rice were managed to promote winter flooding in Arkansas and Mississippi, respectively (W.B. Uihlein, U.S. Fish & Wildlife Service, pers. commun.). These statistics illustrate the excellent opportunity to manage additional rice acreage as winter wetland habitat. Additionally, results from mail surveys indicated that MAV farmers maintain a significant interest in waterfowl management and did not perceive problems with winter flooding practices. Finally, private lands programs initiated by public and private organizations have demonstrated success in restoring substantial acreage of MAV wetlands by providing technical assistance on wetland management.

Potential agriculture and conservation benefits associated with winter-flooded rice fields include, but are not limited to, decreased soil erosion, nutrient loss, winter weeds, red rice, and rice stubble. Consensus exists among farmers and wildlife professionals that additional flooding of rice fields would be best motivated by demonstrating positive effects on agricultural practices, soil conservation, water quality and wildlife habitat. Therefore, we designed and implemented research to assess values of winter flooding rice fields in Mississippi during winters 1995-97.

OBJECTIVES

i) Test effects of winter rice field management on soil conservation and water quality in Mississippi Alluvial Valley.

ii) Test effects of winter rice field treatments on straw and winter weeds (Agronomic benefits).

iii) Test effects of rice field management on biomass of potentially available waterfowl and shorebird foods.

STUDY AREA AND EXPERIMENTAL TREATMENTS

We conducted this research on rice/soybean farms in Bolivar, Leflore, Sunflower and Washington counties, where 65% of Mississippi's rice crop was harvested during 1993-96. We combined post-harvest rice field and winter flooding treatments because these occur together in practice. Post-harvest rice field treatments included leaving stubble stand following harvest and fall disking. Flooding treatments included leaving fields open to drain naturally following winter rains and closing water control structures to impound water until early March. Therefore, we established the following experimental combinations: (1) stubble/open, (2) disk/open, (3) stubble/ long flood, and (4) disk/long flood. An additional flooding treatment; i.e., blocking water control structures to impound water through the waterfowl hunting season (e.g., 20 January) was added to all agricultural and wildlife-food aspects of the study to better assess effects of flood duration. This relatively short duration flood added two treatments to the previous four for a total of six treatment combinations: (5) stubble/short flood, and (6) disk/short flood. Treatments were applied to one field at each of six farms in winters 1995-96 and 1996-97 to generate either 48 experimental units for water-quality and soil-conservation aspects (4 treatments X 6 farms X 2 winters) or 72 experimental units (6 treatments X 6 farms X 2 winters) for agricultural and wildlife-food aspects.

STATISTICAL ANALYSES AND REPORTING

August 1, 1998 marked the end of our 4 year evaluation of the environmental, agricultural, and wildlife benefits of winter-flooded ricefields. Following is a synopsis of results and analyses completed to date.

Water and Soil Conservation

Erosion from agricultural lands and consequent nonpoint source (NPS) pollution downstream has been a primary concern for agriculturalists and conservationists for decades. Costs are incurred at both origination and destination sites. Origination costs include: (1) decreased crop production, (2) decreased infiltration and water-holding capacity, (3) increased tillage costs of compacted subsoils and (4) increased fertilizer costs. Costs at destination site include: (1) decreased water quality, (2) decreased transport and storage capacities of streams, canals, lakes, and reservoirs and (3) degradation of aquatic habitat. An estimated 3.6 billion metric tons of topsoil is lost from U.S. land each year. Losses from agricultural lands in the MAV range from 5-18 metric tons/ha annually. Conservation tillage is a potentially effective means of reducing NPS pollution. Impoundment of agricultural field runoff is another means of NPS pollution reduction. Harvested rice fields lend themselves well to both strategies. Impoundment of agricultural fields reduces overland flow energies of runoff carrying sediments and nutrients. Moreover, impounded surface waters reduce rainfall impact and allow time for sediments and nutrients to settle-out of suspension. Therefore, we tested the effects winter rice field management on soil conservation and water quality in the MAV.

Measurement of Ricefield Runoff Water

We developed flow-rate equations for 48 flash-board riser drain pipes available for use in experimental rice fields. A total of 354 runoff events (113 during 1995-96, 241 in 1996-97) were measured from experimental rice fields using flow meters and water samplers programmed with these equations. Regression analyses predicted flow rates with excellent precision ($R^2 = 0.86\text{-}0.99$). Seven of 48 pipes (>15%) were calibrated a second time to assess accuracy of our predictions. Paired flow-rate equations differed ($0.001 <= P <= 0.037$) in 5 of 7 calibrations

(Table 1); however, the resulting differences in winter runoff volumes averaged only 6%.

Water Quality

Runoff volumes and concentrations of sediment/nutrients were combined to estimate exports (kg/ha) from rice fields in relation to post-harvest/flood treatments. We used mixed model analysis of variance in a randomized complete block design followed by all pairwise comparisons of differences in least square means to test the following null hypothesis (α =0.05):

Ho: *Exports of sediment/nutrients from rice fields do not differ among post-harvest/winter flooding treatments.*

Results indicated a combination of flooding fields and retaining stubble after harvest resulted in runoff water with fewest suspended solids, dissolved solids, and sulfate (Table 2). Flooded fields that were fall disked exported the least soluble phosphate (Table 2). Fall disking rice fields and leaving drain pipes open throughout winter yielded the greatest export of suspended solids. Soluble phosphate exports were greatest from open fields left in stubble. Whereas most export variables are affected by actual concentrations (mg/L) in the water (e.g., sediment [Fig. 1]), others including dissolved solids (i.e, sum of calcium, chlorides, magnesium, potassium, sodium, organic colloids, etc.) are affected more by differences in runoff volume (Fig. 2). Nitrite/nitrate export was at or below the minimal detectable limit of 0.10 kg/ha in 27 of 43 fields (63%) used in water quality research and thus was removed from further analyses. Other variables, such as pH, conductivity, and dissolved oxygen, did not differ ($0.159 <= P <= 0.084$) among ricefield treatments.

Soil Nutrient Dynamics

Bulk density and laboratory results from soil samples (mg/kg) were combined to estimate soil nutrients (kg/ha) in ricefields after exposure to post-harvest/flood treatments. We used the mixed model analysis of covariance, with nutrients present in fall as covariates, in a randomized complete block design followed by all pairwise comparisons of differences in least-square means to test the following null hypothesis (α =0.05):

Ho: *Spring soil nutrients in ricefields do not differ after post-harvest/winter flooding treatments.*

Of eight soil nutrients only ammonium differed among experimental ricefield categories

(Table 3). Ammonium is likely conserved in the less aerobic soils of both stubble- or disked-flooded fields, however, the modest 0.8-1.3 kg/ha savings is negligible compared to the 190 kg/ha of inorganic nitrogen applied annually as fertilizer. Nitrite/nitrate was at or below the minimal detectable limit of 1.5 kg/ha in 26 of 47 fields (55%) used in soil nutrient research and thus was removed from further analyses. The remaining six variables were positively related ($P < 0.001$) to fall nutrient levels, and these relationships were sensitive to treatment by covariate interactions (e.g. total sulfur and pH).

Agronomic Benefits

Rice Straw and Winter Weed Reductions

If present in spring, residual rice straw inhibits seed bed preparation and continues microbial decomposition, which may compete with crops for available nitrogen. Additionally, the MAV typically has wet winters with mild temperatures, enabling weeds (e.g. dock [*Rumex* spp.], buttercup [*Ranunculus* spp.]) to germinate and grow on agricultural lands. Weeds increase farming costs as they must be eliminated by herbicides and/or tillage prior to spring planting. Farmers are interested in mechanisms which reduce straw and retard growth of winter weeds. Therefore, we tested effects of winter ricefield treatments on straw and winter weed biomass.

Core samples were collected to estimate over-winter changes in straw and winter weeds (kg/ha). We used a repeated measures mixed model analysis of variance in a randomized complete block design followed by all pairwise comparisons of differences in least-square means to test the following null hypothesis ($\alpha = 0.05$):

Ho: *Winter biomass of rice straw and weeds in ricefields do not differ among post-harvest/winter flooding treatments.*

Results indicated that fall disking was highly effective ($P < 0.001$) in reducing straw while flooding was moderately effective ($P = 0.074$ [Table 4]). While straw biomass decreased throughout winter in all post-harvest and flooding combinations, the combination of disking and flooding until 1 March reduced straw 68% from the initial fall level of 10,000 to 3210 kg/ha (Fig. 3). In contrast, winter weeds decreased in response to flooding ($P < 0.001$); however, no post-harvest treatment effect was detected (Table 4). In general, weeds increased throughout winter, with flooding until 1 March having the greatest effect on inhibiting growth (Fig. 4).

Red Rice Viability

Red rice has become increasingly problematic to rice growers in the MAV. Compared to white rice, red rice exhibits profuse tillering with greater height and vegetative production. Red rice grains separate from panicles during harvest and lie dormant in soils for up to 7 years. Red rice reduces yield and quality of rice by an estimated $50 million annually. Therefore, we placed retrievable nylon-mesh bags of red rice in experimental fields to test effects of winter management on subsequent viability of red rice stocks. Additionally, we tested potential mechanisms which may affect spring red rice viability such as over-winter decomposition and premature germination.

Results indicate very different trends in spring viability between the 2 winters of research. In winter 1995-96, a winter with cold temperatures and below average rainfall, disking moderately reduced ($P = 0.059$) red rice viability but flooding had no effect (Table 5). Flooding until 1 March did however promote greater decomposition of red rice. In winter 1996-97, a warm wet winter, not disking stubble and leaving red rice on the surface of the ground decreased spring viability to about 9%. This decrease was likely driven by winter germination and subsequent decomposition in stubble and open fields (Table 5).

Wildlife Food Benefits

Rice lands are thought to provide quality feeding habitat for waterfowl and shorebirds by providing waste grain, moist-soil plant seeds, invertebrates, and browse. In winter, wildlife managers recommend shallow flooding of ricefields, making rice, moist-soil plant seeds, and invertebrates available to waterbirds. As fields gradually fill with impounded rain water, a continuum of water depths provide diverse of foraging areas.

Core samples were collected to estimate winter food densities (kg/ha) in relation to post-harvest/flood treatments. We used a repeated measures mixed model analysis of variance in a randomized complete block design followed by all pairwise comparisons of differences in least-square means to test the following null hypothesis ($\alpha = 0.05$):

Ho: *Winter biomass of waterbird foods do not differ among post-harvest/winter flooding treatments.*

In general, waterbird foods did not differ among experimental categories, however, there were differences between years (Table 6-7). Winter 1995-96 had more residual "growing season produced" foods such as rice and weed seeds ($0.002 <= P <= 0.058$) while winter 1996-97 had more invertebrates ($P = 0.016$). There was no detectable difference in winter weeds between years ($P = 0.257$). These trends may be affected by weather conditions mentioned previously; winter 1995-96 was cold and dry, winter 1996-97 was warm and wet. Most noticeable was the significant decline of available rice in all treatments between fall harvest and early winter when floods are established and waterbirds arrive (Fig. 5). Although 500 kg/ha of rice was available in experimental fields after harvest, less than 80 kg/ha was remaining by 10 December. This result has significant implications regarding forage carrying capacity of ricefields and habitat needs for wintering waterfowl.

SUMMARY

Ricefield management during the winter months offers different strategies to address conservation challenges. Winter flooding conserved soil while increasing quality of runoff waters, especially when ricefields were not disked in the fall. Winter flooding also retarded growth of winter weeds. Residual rice straw was reduced by flooding, especially when combined with fall disking. Together, these attributes alone make winter flooding a beneficial agricultural and environmental practice. In fields with red rice infestation, viability can be reduced to below 10% during normal winters of sufficient rainfall and high temperatures by not disking (i.e., leave seeds on ground surface). Flooding these infested fields may deter premature germination and decomposition of red rice during such years. Waterbird food resources are similar among experimental ricefield categories, but availability of these resources is likely less in areas void of water. The significant decrease of waste rice grain between harvest and early winter has significant implications regarding forage carrying capacity of ricefields and subsequent habitat needs for wintering waterfowl. In conclusion, no single ricefield management option is right for all management concerns. Nonetheless, winter flooding in combination with specific post-harvest management strategies, is effective for addressing an array of ecological and agriculture issues such as soil conservation, water quality, spring field preparation, and waterfowl and shorebird habitat.

Table 1. Pipe and equation characteristics for validation of partial-pipe flow measurement techniques used in winter ricefield research, 1 November to 10 March, 1995-97, Mississippi Alluvial Valley, Mississippi.

Pipe Characteristics				Equation Characteristics							
Pipe	Length (m)	Inside Diameter (cm)	Slope (%)	Calibration	N	Y-Intercept (m^3/minute)	X-Coefficient (cm)	R^2	Runoff Volume (m^3/hectare)	%RSD[a] Runoff Volume	P-Value[b]
1	6.00	33.0	5.6	1	20	-1.20	0.51	0.96	1946	7.2	0.037
				2	24	-1.67	0.54	0.97	1684		
2	6.10	30.5	1.5	1	23	-0.87	0.34	0.86	1930	7.3	0.022
				2	20	-1.70	0.39	0.97	1667		
3	9.14	55.9	6.7	1	20	-2.72	1.08	0.97	1309	10.4	<0.001
				2	20	-2.12	1.05	0.97	1612		
4	10.97	43.2	1.4	1	20	-3.17	0.65	0.99	2290	3.2	0.005
				2	20	-3.03	0.62	0.98	2149		
5	7.62	43.2	7.0	1	20	-1.20	0.76	0.94	1290	12.7	<0.001
				2	20	-1.25	0.88	0.96	1665		
6	10.36	43.2	3.5	1	20	-3.02	0.78	0.96	788	1.0	0.584
				2	20	-2.73	0.75	0.99	772		
7	9.14	43.2	3.3	1	18	-2.47	0.79	0.96	273	0.4	0.665
				2	20	-2.64	0.80	0.98	270		

[a] Percent residual standard deviation: $\left\{\sqrt{\frac{(x^{(1)}-\bar{x})^2+(x^{(2)}-\bar{x})^2}{N}} \Big/ x \right\} \cdot 100$

[b] Equations compared using Chow's Method (1960) for simultaneous test of y-intercept and slope differences.

Table 2. Mean values and comparisons[a] of water quality export variables among ricefields (*n*) in the Mississippi Alluvial Valley, Mississippi, winters 1995-97.

	Stubble/Flooded			Stubble/Open			Disked/Flooded			Disked/Open			
Export[b] (kg/ha)	$\bar{x}$	SE	*n*	$\bar{x}$	SE	n	$\bar{x}$	SE	*n*	$\bar{x}$	SE	*n*	*P*
Water[b] volume (m^3/ha)	1971 A	195	10	3126 B	324	12	2427 AB	430	9	3070 B	262	12	0.004
Suspended solids	35.2 A	7.9	10	221.6 B	43.8	12	335.5 AB	170.0	9	1120.9 C	252.1	12	<0.001
Dissolved solids	262.6 A	25.2	10	423.9 B	53.7	12	327.5 AB	73.2	9	472.2 B	72.2	12	0.010
Sulfate ($S\text{-}SO_4^{2-}$)	3.99 A	0.70	10	19.38 B	6.39	12	10.85 AB	5.21	9	35.66 B	14.13	12	0.014
Phosphate ($P\text{-}PO_4^{2-}$)	0.15 AB	0.07	10	0.54 C	0.12	12	0.03 A	0.01	9	0.15 B	0.04	12	<0.001
Ammonium ($N\text{-}NH_4^+$)	0.20	0.03	10	0.24	0.07	12	0.30	0.07	9	0.27	0.06	12	0.453

[a] Means within rows with unlike letters differ ($P \leq 0.05$) by linear contrasts of least square means.

[b] All exports expressed as kilograms per hectare (kg/ha) except for water volume which is cubic meters per hectare (m^3/ha).

Table 3. Both fall and spring mean values with comparisons[a] of spring soil nutrient variables among ricefields in the Mississippi Alluvial Valley, Mississippi, following winters 1995-97.

	Stubble/Flooded			Stubble/Open			Disked/Flooded			Disked/Open			
Soil nutrients (kg/ha)[b]	Fall $\bar{x}$	Spring $\bar{x}$	Spring SE	Fall $\bar{x}$	Spring $\bar{x}$	Spring SE	Fall $\bar{x}$	Spring $\bar{x}$	Spring SE	Fall $\bar{x}$	Spring $\bar{x}$	Spring SE	P^{a}
Organic carbon	15902.9	16376.0	529.8	14411.3	15648.0	532.2	15698.7	15826.2	554.6	15338.8	15970.1	527.5	0.788
Total nitrogen	1525.7	1516.3	46.0	1395.9	1469.1	46.0	1491.5	1460.8	47.2	1452.6	1486.8	44.8	0.799
Total sulfur	302.1	280.8	17.7	272.6	265.5	17.7	304.4	286.7	18.9	344.6	220.7	17.7	c
Sulfate ($S\text{-}SO_4^{2-}$)	32.4	9.6	1.7	34.8	10.3	1.7	22.9	11.8	1.7	33.2	10.4	1.7	0.357
Extractable phosphorus	31.4	27.4	1.5	32.8	29.6	1.5	31.6	27.4	1.5	32.3	31.8	1.5	0.224
Ammonium ($N\text{-}NH_4^{+}$)	7.9	7.1 A	0.6	7.0	4.9 B	0.6	8.2	6.9 A	0.6	7.0	5.5 AB	0.6	0.025
pH	6.4	6.4	0.2	6.5	6.5	0.2	6.2	6.3	0.2	6.1	6.8	0.2	c

[a] Means within rows with unlike letters differ ($P \leq 0.05$) by linear contrasts of least square mean, adjusted for significant fall amounts revealed by ANCOVA. All probabilities associated with pair-wise comparisons available in Appendix A.3.

[b] Soil nutrient expressed as kilograms per hectare using bulk density = 1180 Mg/ha, 10 cm depth, 27% moisture.

[c] Year*treatment*fall amount (covariate) interaction ($P \leq 0.001$); hence main-effects were not tested.

Table 4. Least-square means and comparisons[a] of rice straw (*Oryzae sativa*) and winter weed reductions among ricefields (*n*) in the Mississippi Alluvial Valley, Mississippi, winters 1995-97.

	Post-harvest treatment							Winter-flooding treatment[b]									
	Stubble			Disk				Open			Early Drain			Late Drain			
Variable (kg/ha)	$\bar{x}$	SE	n	$\bar{x}$	SE	n	*P*	$\bar{x}$	SE	n	$\bar{x}$	SE	n	$\bar{x}$	SE	n	*P*
Rice straw	6196	406	35	4456	408	35	<0.001	5596	432	24	5578	436	23	4804	439	23	0.074
Winter[c] weeds	29.7	6.6	35	19.0	6.6	35	0.148	44.2A	7.4	24	19.1B	7.5	23	9.7B	7.6	23	<0.001

[a] Where necessary, means within rows with unlike letters differ ($P \leq 0.05$) by linear contrasts of least square means.

[b] Open refers to fields left to drain after rain events, early drain equals 20 January after waterfowl hunting season, late drain equals March 1.

[c] Common winter weeds include bittercress (*Sibara virgica*), bluegrass (*Poa annua*), buttercup (*Ranunculus sardous*), chickweed (*Cerastium glomeratum*), fiddledock (*Rumex crispus*), mousetail (*Myosurus minimus*), neckweed (*Veronica peregrina*), peppergrass (*Lepidium virginicum*), yellowtop (*Senecio glabellus*), and others.

Table 5. Least-square means and comparisons[a] of red rice (*Oryzae sativa* var.) variables among ricefields (*n*) in the Mississippi Alluvial Valley, Mississippi, winters 1995-97.

Variable (percent)	Post-harvest treatment							Winter-flooding treatment[b]									
	Stubble			Disk				Open			Early Drain			Late Drain			
	$\bar{x}$	SE	n	$\bar{x}$	SE	n	*P*	$\bar{x}$	SE	n	$\bar{x}$	SE	n	$\bar{x}$	SE	n	*P*
1995-96																	
Viable red rice remaining	33.9	4.9	15	20.2	4.7	15	0.059	23.9	5.5	11	34.5	6.6	8	22.8	5.5	11	0.367
Winter biomass remaining	85.9	1.6	14	84.7	1.4	16	0.556	87.4A	1.6	12	88.5A	2.0	8	80.2B	1.8	10	0.005
Winter germination	50.8	5.4	15	44.4	5.3	15	0.298	54.4	5.8	11	48.0	6.7	8	40.4	5.8	11	0.143
1996-97																	
Red rice viability	8.8	6.6	17	31.4	6.8	16	0.004	15.7	7.5	11	17.5	7.2	12	27.0	7.8	10	0.397
Winter biomass remaining	60.4	4.4	16	72.0	4.4	16	<0.001	61.5	4.6	11	68.5	4.6	11	68.6	4.7	10	0.062
Winter germination	68.8	10.3	17	47.6	10.4	16	0.005	72.1A	10.9	11	54.7B	10.7	12	47.8B	11.1	10	0.024

[a] Where necessary, means within rows with unlike letters differ ($P \leq 0.05$) by linear contrasts of least square means.

[b] Open refers to fields left to drain after rain events, early drain equals 20 January after waterfowl hunting season, late drain equals March 1.

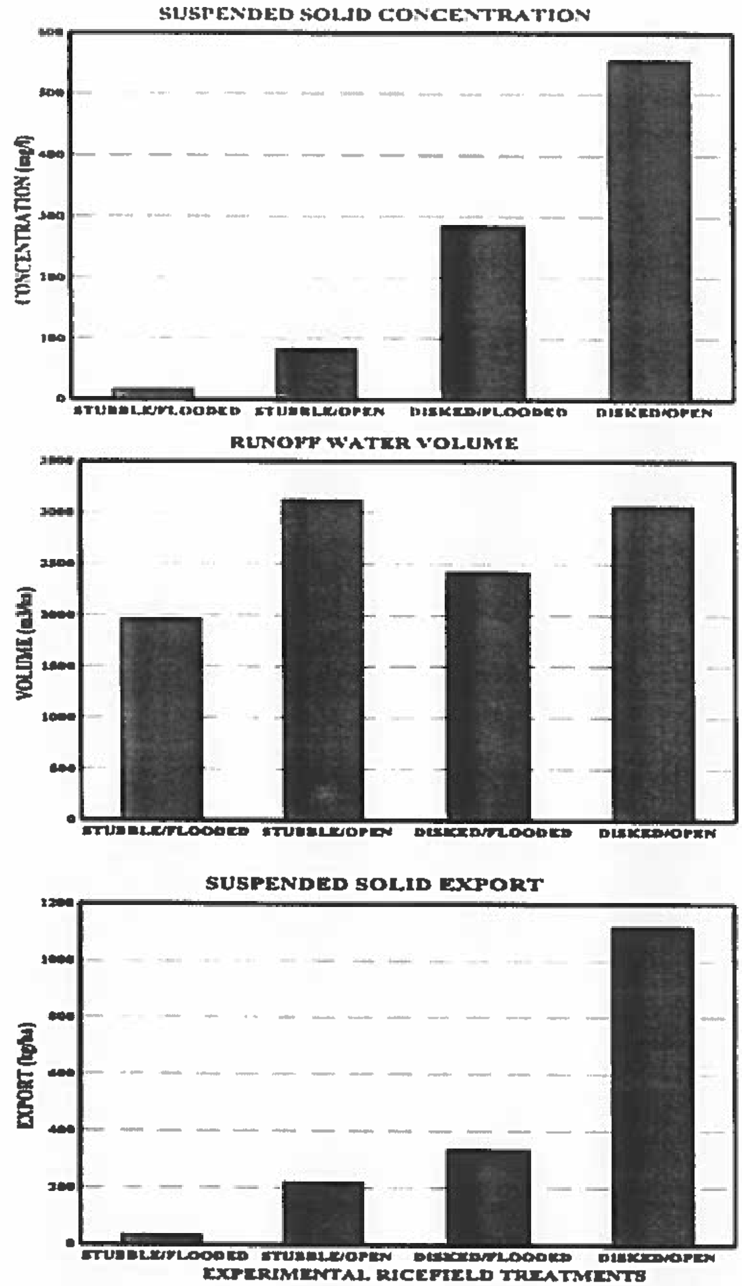

Figure 1. Relationships between suspended solid (sediment) export, concentration, and runoff volume from experimental ricefields in the Mississippi Alluvial Valley, Mississippi, winters 1995-97. Note sediment export closely follows pattern of water quality (concentration).

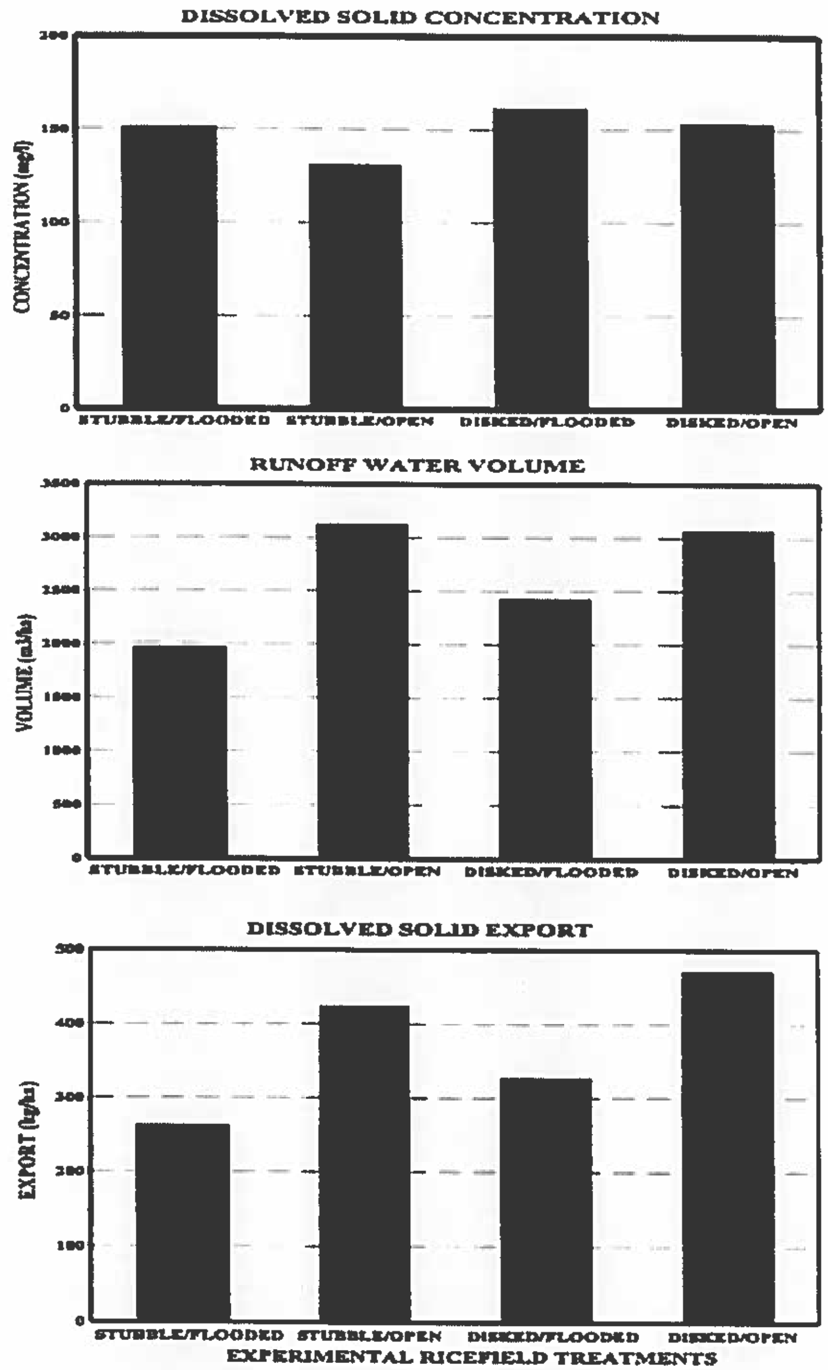

Figure 2. Relationships between dissolved solid export, concentration, and runoff volume from experimental ricefields in the Mississippi Alluvial Valley, Mississippi, winters 1995-97. Note dissolved solid export closely follows pattern of water quantity (volume).

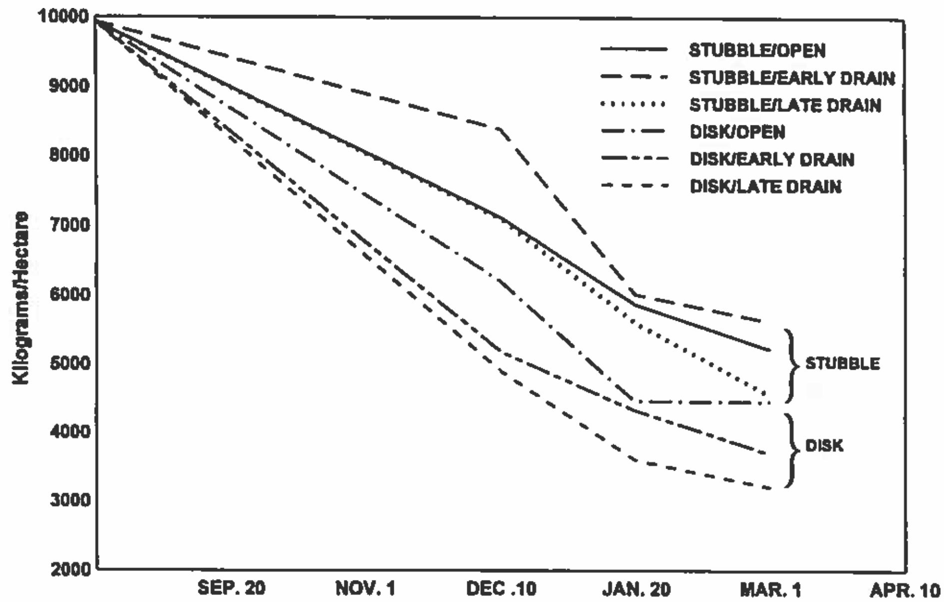

Figure 3. Straw reductions in experimental ricefields, Mississippi Alluvial Valley, Mississippi, winters 1995-97.

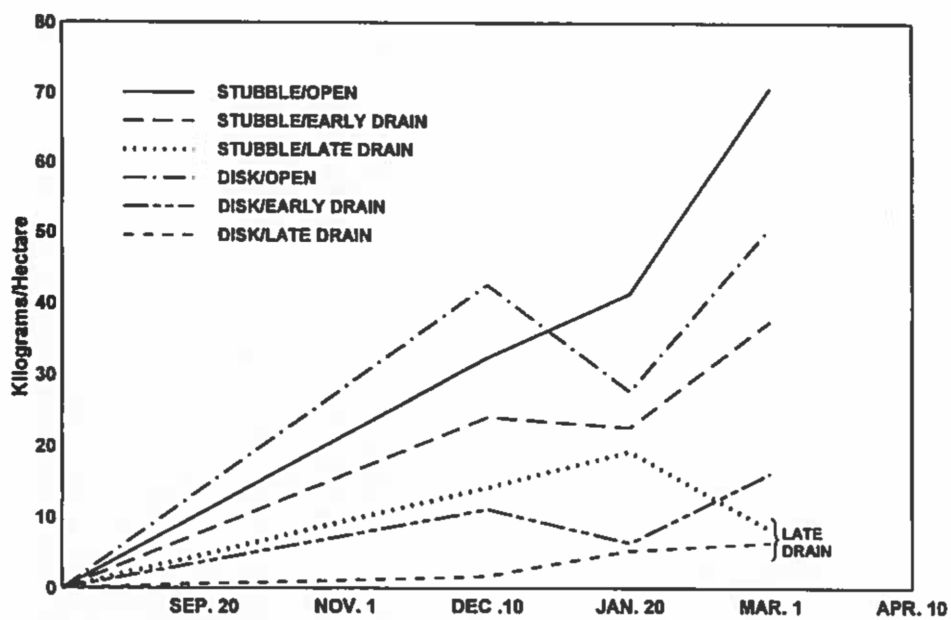

Figure 4. Winter weeds in experimental ricefields, Mississippi Alluvial Valley, Mississippi, winters 1995-97.

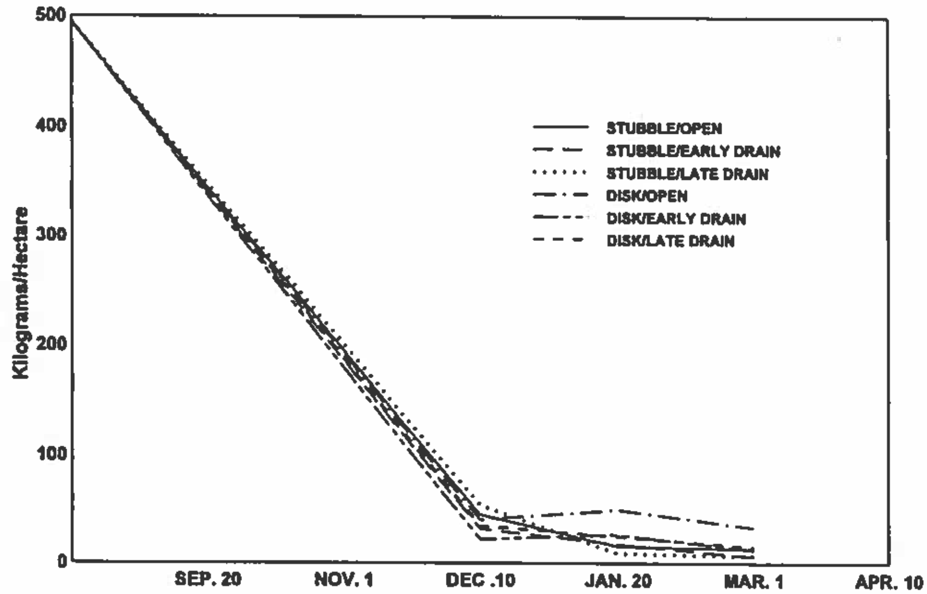

Figure 5. Residual rice in experimental ricefields, Mississippi Alluvial Valley, Mississippi, winters 1995-97.

ANALYZING CONJUNCTIVE USE OF ON-FARM RESERVOIRS AND IRRIGATION
WELLS IN THE ARKANSAS DELTA

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INTRODUCTION

Ground water is the dominant water source used for crop irrigation as well as for flooding over 45,000 acres of fish farms in eastern Arkansas. With increased exploitation of the Mississippi Alluvial Aquifer, the principal aquifer of the region, numerous wells have failed, forcing owners to lower their pumps and/or drill additional wells[1]. Only about 20 feet of saturated thickness currently remains in the older, more developed irrigated areas such as the Grand Prairie (Arkansas Soil and Water Conservation Commission, 1988). Excessive pumping is also causing salt water encroachment in parts of the aquifer. Artificial recharge is not feasible (Smith and Griffis, 1972) and natural recharge averages only 0.4 inches per year (ASWCC, 1988). Six counties in Eastern Arkansas have aquifer areas defined as critical by the Arkansas Soil and Water Conservation Commission (ASWCC, 1997).

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[1]The Sparta deep water aquifer is generally not feasible for irrigation use because of the high cost. Estimates exceeding $80,000 for drilling an irrigation well requiring at least 300 ft. depth. This aquifer is also declining.

About 3.5 million acres are currently irrigated annually in eastern Arkansas, comprising over half of the total 6 million acres of cropland (Scott, et al., 1998). Although the climate is subhumid, with average annual rainfall approaching 50 inches, irrigation is essential for rice production, valued at over one billion dollars per year. Irrigation is also needed to assure high yields of cotton and soybeans due to frequent droughts during the crop growing season. Rainfall only contributes about 46 percent of the average water requirement for rice and 58 percent for irrigated soybeans (National Resource Conservation Commission, 1987).

In contrast to the irrigation problem in most western states, rainfall is an under-utilized water source available to supplement ground water use in the mid south region. Nearly half of the annual rainfall is lost to runoff that may be at least partially captured with on-farm reservoirs (NRCS, 1987). The major constraint to increased surface water utilization by individual farmers is the high cost of reservoir construction including loss of crop land with a longer term and less certain payback on the investment compared to drilling additional wells.

The objective of our research was to develop an improved and more complete system analysis model to evaluate the multiple-purpose benefits of using on-farm reservoirs in the Arkansas delta. Our model is designed to evaluate the economic benefits and costs of conjunctive use of surface water and ground water for alternative resource situations on representative Arkansas farms. A system analysis model is needed because cost-benefit analysis of investment in on-farm reservoirs for irrigation is a complicated decision. The complexity is a result of the dynamic interactions among crop production, weather, resource management options including multiple uses for reservoirs, input and crop prices and government policies. A systems model is also useful if its parameters can accommodate the varying resource management situations found on different farms. Reservoir management and multi-purpose uses of economic importance include recycling intra-seasonal tailwater and rainfall runoff during the crop growing season, capturing periodic runoff from particular cropping practices, eg., from flushing rice fields for germination and draining rice fields prior to harvest, improving the chemical quality of irrigation water, facilitating water management and recreational uses as well as the primary purpose of capturing rainfall runoff for irrigation. To evaluate the economic feasibility of an on-farm reservoir investment, the farmer also needs assistance in determining the appropriate size of reservoir to construct after taking account of expected input and product prices, the variable annual runoff, the expected irrigation requirements of all crops and the field application efficiency.

Current economic analysis of proposed on-farm irrigation reservoirs by agencies such as the Natural Resource Conservation Service (NRCS) is typically based on general guidelines or rules of thumb rather than actual simulation modeling of the individual farm for which the investment is being considered.. For example, the reported NRCS recommendation for Kentucky on irrigation reservoir sizing for corn without any ground water supplement is to store adequate water to survive a 60-day drought (Palmer et al, 1982).

Palmer was among the first to develop a simulation model to enable users to make more informed decisions regarding the selection and design of irrigation water supply reservoirs. Palmer's simulation model for Kentucky combined a watershed runoff model and a corn growth model to determine the reservoir size necessary to ensure water availability on a probability basis for irrigation (Palmer, et al, 1982). As in other reported economic models of on-farm reservoirs, Palmer only evaluated the returns from one off-season filling of the reservoir and excluded intra-seasonal benefits such as tailwater recovery. A subsequent study by Shulstad in Arkansas determined in a present worth analysis of projected annual costs and returns that an on-farm reservoir of 120 to 180 acre feet (ac. ft.) capacity may be an economic alternative to drilling a new irrigation well at rice and soybean prices in the 1980's (Shulstad et al, 1985). Reservoir costs including the income loss of idled cropland were compared with well investment and operating costs in their study. Following Shulstad's study, a computer simulation model for Arkansas was developed by Edwards and Ferguson to estimate the present worth of annual net income over a 30-year period under alternative ground water supply conditions with and without a reservoir (Edwards and Ferguson, 1990, Edwards, et al., 1991, 1992). The simulation model only evaluated irrigated soybeans and utilized the reservoir for only one annual fill of surface runoff in the winter season. Additional information on their model is provided below in section 2.

In section 2, this report describes the major parameters and the structure of the model. The third section describes the application of the model and the alternative resource situations addressed in the application. In the fourth section we show the results of the model application.

DESCRIPTION OF MODEL COMPONENTS AND STRUCTURE

The model used in our study is an expanded and improved version of the Arkansas Offstream Reservoir Analysis (ARORA) simulation model developed by Edwards and Ferguson (1990). Major algorithms of ARORA include: a) soil water balance, b) ground water hydraulics, c) crop yield estimation (for soybeans), d) reservoir water balance, and e) direct search optimization to identify the optimum reservoir capacity as a function of the net annual income discounted over a 30-year period. These components allow ARORA to simulate soybean yield and daily water balance for situations in which a) only surface water is used to irrigate, b) both surface and groundwater are used to irrigate and c) no irrigation is practiced. The ARORA model computes reservoir construction and annual maintenance costs, pumping costs, soybean production costs, and annual soybean income under variable daily weather conditions. The water source is assumed to be surface runoff captured on the farm to fill the reservoir one time per year during the winter period.

The daily soil water balance is calculated as:

$$SMD_t = SMD_{t-1} - RAINEFF_t + ET_t - NIR_t \qquad (1)$$

where SMD_t is the soil moisture deficit, $RAINEFF_t$ is effective rainfall, ET_t is soil evaporation plus crop transpiration, and NIR_t is the net irrigation application. Excess daily rain and irrigation tailwater loss are assumed to be not recovered or recycled in the ARORA model as developed by Edwards and Ferguson (1990).

The daily reservoir water balance is calculated as:

$$EL_t = EL_{t-1} + RAIN_t + FILL - EVAP_t - SEEP_t - GIR_t \qquad (2)$$

where EL_t is the reservoir water elevation, $RAIN_t$ is rainfall on the reservoir, FILL is the water added to the reservoir by the relift pump. $EVAP_t$ is reservoir evaporation loss, $SEEP_t$ is reservoir seepage loss and GIR_t is the gross irrigation discharge from the reservoir.

Water table decline is specified exogenously to the model based on local average annual decline rates. However, the daily well draw down is calculated in the model in relation to the volume pumped. A waiting period is specified for well recovery when the point of maximum draw down is reached (see Edwards and Ferguson, 1990). Annual water table decline for the individual farm model application is assumed to be determined by total pumping by all irrigators in the local region. (ASWCC, 1997).

Crop yield estimation for soybeans in ARORA is defined as:

$$Y/YP = AT/PT \qquad (3)$$

where Y is yield, YP is potential yield, AT is crop transpiration over the growing season, and PT is potential crop transpiration over the growing season.

Economic computations in ARORA to select an optimal size reservoir for use at the outset of the 30-year period and an irrigation plan for use of the reservoir include annual computation of depreciation and interest for the well, connecting underground pipe and reservoir investment over the expected useful life, using the straight-line method. The criterion for decision-making involves calculation of the present worth of annual net income over a 30-year period. The optimal solution is based on the maximum present worth of discounted annual net crop income.

For the present study, the ARORA model was substantially modified and will be referred as MARORA (Modified ARORA) in the remainder of the report. The significant modifications included, 1) the addition of rice production, 2) adjustability to shift between rice and soybean production and 3) capture of surface water runoff. Rice was added to evaluate the typical Grand Prairie farm cropping system in Arkansas with area planted to one third rice and two-thirds soybeans. The rice to soybean ratio can be easily modified to accommodate different farm and market situations. A crop yield equation was introduced for rice to impose a yield penalty for interrupted irrigation during critical growth stages. Rice yield is currently assumed in the model to fall by 10 percent per day when the flood is not maintained. With a severe water shortage, the revised model permitted rice to decline and shift to soybeans. The model was further modified to evaluate other reservoir management benefits including capturing all types of available runoff during the growing season whenever the reservoir was not full so as to make more effective use of the reservoir. A flow diagram of MARORA for this study is shown in Figure 1 to depict the major daily decision processes on the use of reservoir and well water for crop irrigation. A complete description of various processes and organization of the modified ARORA model is shown in the appendix to this report.

APPLICATION OF THE MODEL

The MARORA model described above and in the appendix is used to determine whether a reservoir is economically justified, the optimal size of reservoir if the reservoir is economically justified and the use of the reservoir on a daily basis for irrigation on representative Arkansas delta farms with a rice-soybean crop rotation. Validation of the model is based on evaluation of reservoir investment for a 160-acre contiguous cultivated area with one irrigation well, with a capacity of up to 2200 GPM depending on the saturated thickness operating along with the irrigation reservoir. Both the well and reservoir are assumed to be connected by pipeline to crop fields. The reservoir system includes a fill pump to lift water into the reservoir from drainage ditches and a discharge pump to irrigate from the reservoir, both with 2200 GPM capacity.

Model results are based on varying ground water supply situations: (1) 50 feet (ft.) initial saturated thickness with water table declines rates of one, 0.75 and 0.5 ft. per year; and (2) 25 ft. initial saturated thickness with annual declines of one, 0.75 and 0.5 ft. Baseline crop prices used are the Arkansas January 1998 prices of $6.75 per bu. for soybeans and $5.00 per bu. for rice. Sensitivity of model results to crop prices is evaluated by varying prices 20 percent above and below the baseline prices. The baseline interest rate used to calculate the annual amortization cost of the well and reservoir investment cost is 8 percent. Alternative discount rates of 8 percent and 4 percent are used to calculate present worth of annual net returns. Crop production costs, other than water supply costs, are based on 1997 Arkansas Cooperative Extension Service budgets for irrigated soybeans and rice. Reservoir construction cost was based on a range of \$0.75 -0.90 per cubic yard of excavation. Other well and pump cost data are retained from the ARORA model (Edwards and Ferguson, 1990).

The results are based on 160 acres of cultivated silt loam soil typical of in the Grand Prairie region of Arkansas. Daily rainfall and other weather data over the 30-year projection period are generated from data including rain, air temperature variation, solar radiation and wind. The weather data are computed with a modified Weather Generator Model developed by Edwards and Ferguson (1990) from historical weather data at Stuttgart, Arkansas. Irrigation efficiency is assumed to be 95 percent for rice, except in the initial flush for germination when only 50 percent efficiency is assumed, and 65 percent for soybeans. A 2-inch flush for rice germination is assumed with 50 percent runoff. The recovery rate for all tailwater and other field runoff is assumed to be 80 percent of the total available when the reservoir is not full.

Some preliminary analysis was also conducted on the optimal construction time of a reservoir over the 30-year period. The effect of increasing reservoir size on unit cost of storage is also evaluated.

RESULTS OF THE MODEL APPLICATION

The MARORA model was used to determine the optimal reservoir size under two initial saturated thickness conditions, three rates of annual water table decline, three levels of crop prices and two discount rates, to compute the present worth of projected annual net returns to 160 acres of irrigated cropland. Results for the 50-ft and 25-ft initial saturated thickness levels and one irrigation well are shown in Tables 1 and 2.

Construction of a reservior in year 1 was determined by the MARORA program to be not economically justified with 50-ft. initial saturated thickness under any of the scenarios reported in Table 1. However, at the 25-ft. initial saturated thickness level, typical of the critical water areas in Arkansas, the MARORA program selected an optimal reservoir size of 250 acre-feet capacity at both discount rates, with the medium and high crop price levels, and 170 acre-feet capacity with low crop prices with all three rates of annual water table decline. As depicted in Table 2 for the 25 ft. initial saturated thickness, the availability of a reservoir results in similar present worth of net incomes when only the rate of annual water decline is varied.[2] It is noted in Table 2 that the present worth value declined by a fractional amount with lower decline rates which permitted ground water pumping to continue. This result occurred because of the

[2]It is noted in Table 2 that the present worth value declined by a fractional amount with lower decline rates which permitted ground water pumping to continue. This result occurred because of the tolerance level set for crop damage to occur when crop water use was reduced below the level required for maximum crop yield in the water response equations of the model. The difference in present worth value is considered neligible.

tolerance level set for crop damage to occur when crop water use was reduced below the level required for maximum crop yield in the water response equations of the model. The difference in present worth value is considered negligible. The present worth results, however, are very sensitive to changes in crop prices and discount rates. Differences in crop prices, ranging from actual January 1998 levels, plus or minus 20 percent changed the choice of reservoir size from 250 ac. ft. with high and medium crop prices to 170 ac. ft. for the case of low crop prices (Table 2). Starting with 50 ft. thickness in Table 1 the present worth value ranged from $21,150-$33,270 with low crop prices up to $336,240-$361,320 with high crop prices. With 25 ft. initial water table thickness in Table 2, the present worth value ranged from only about $16,000 for the low crop price level to $262,000 for the high crop price level.

Detailed information on the water use and water cost for average crop prices and 25 ft. thickness is shown in Table 3. The results indicate that water use and irrigation cost do not vary with the ground water decline rate for the optimal reservoir size, which, for this situation, is large enough to meet all irrigation requirements. Ground water was not needed because annual reservoir fill plus tailwater recovery provided sufficient water supply.

Average annual irrigation water use over the 30-year with 25 ft. initial saturated thickness period was estimated at 16.8-16.9 inches per acre for soybeans and 20.5 inches per acre for rice with the three cases of varying ground water decline rates reported in table 3. The computer model had the option of reducing water use for soybeans with a corresponding reduction in yield. There was also some flexibility to vary the rice irrigation application as well as discontinuing rice if a severe water shortage was encountered.

The reservoir with 250 acre-feet capacity displaced 34 acres of cropland allowing production of 84 acres of soybeans and 41.9 acres of rice on 160 acres. The cost of cropland displaced by the reservoir is included in the present worth calculation with the model. Reservoir costs, totaling $65,071 include $41,604 for excavation, $7,467 for seeding and $16,000 for pumps (Table 3).

Estimated average annual tailwater and other runoff recovery during the crop growing season from the 160-acre area containing the 250 ac. ft. reservoir was 14.8 acre feet. The estimated total water collected from recovery plus the required annual fill during the winter period is estimated to be greater than the reservoir supply available for the annual discharge for irrigation use due to evaporation and seepage losses. Estimated average annual reservoir water use with one complete winter fill was only 189 ac. ft. from the 250 ac. ft. reservoir (Table 3).

Annual fixed cost for a 250 ac. ft. capacity reservoir was $5,304 for depreciation and interest. Annual average operating cost of the reservoir over the 30-year period was $4,191. The well was not used for irrigation with a 250 ac. ft. reservoir (Table 3). Average total reservoir cost per acre-foot of water was $50.23.

It was noted in the analysis for the 50-ft initial saturated thickness that even though the model determined that it was not profitable to construct a reservoir in year 1 the water table declined to a critical level before the end of the 30-year period with the 1.0 and 0.75 ft. decline rates. At these rates, rice production was eventually discontinued and soybeans received only partial irrigation.

One of the possible uses of the model is for policy analysis. Depending on the size of public benefits derived from stemming the decline in the water table, the public may be willing to provide incentives (i.e. incur costs) to stimulate investment in on-farm reservoirs. For the farmer with 50 ft. saturated thickness, for whom the model found the optimal solution based on private costs and benefits to be no reservoir, what would be the monetary incentive needed to induce this farmer to construct a reservoir before the water table becomes severely depleted and be as well off as his present worth based on the optimum solution of no reservoir? We have addressed this question and presented some preliminary results in Table 4.[3] For this analysis, we studied three options. Option 1 required the farmer to invest in any size reservoir of his choice but only in year 1 of the 30-year horizon. Option 2 allowed the farmer to invest in the optimal size reservoir at anytime when it is needed to replace the short fall in ground water supply to continue rice production during the 30-year horizon. Finally, Option 3 mandates that the farmer must construct in year 1 the optimal size reservoir selected in Option 2. The farmer should be indifferent to Option 1 and 3 if his annual present worth of income can be made to be equal. Therefore, the difference in present worth between Options 1 and 3 suggest the amount of public expenditures needed to stimulate the reservoir construction. At the more rapid rate of decline of 1 ft per year, $41,600 is needed whereas at the slower rates of decline in saturated thickness, 0.75 and 0.5 ft per year, the farmer would have maintained full irrigation for 30 years without needing a reservoir. The size of the incentive is even larger if we compare Options 2 and 3, where Option 2 allows the farmer to construct the reservoir when he sees fit versus building it in the first year. At the decline rate of 1.0 , 0.75, and 0.5 ft per year, the difference in present worth of income is $44,500. It is noted that only ground water was used in Option 1 and in Option 2 until the reservoir was built. Only surface water was used in Option 2 after the reservoir was built. Option 3 involved conjunctive use of both surface and ground water over the 30-year period.

Preliminary analysis of scale effects of on-farm reservoir investment indicates that unit reservoir supply costs are lower as the farm scale increases. The scale of farm operations was studied with land area under cultivation at three levels, 160, 240, and 320 acres. Cost per ac. ft. was estimated at $55.15 for a 250 ac. ft. reservoir, declining $48.89 for a 400 ac. ft. reservoir, and to $43.68 34 for a 520 ac. ft. reservoir (Table 5).

The results of this study are preliminary estimates of the value of on-farm reservoirs as the MARORA model and input data are being modified over time. A current input data file is attached to this report that contains the general simulation parameters, crop and field data, operating and ownership data, groundwater data, other pump data and optimization data. All of these data input values can be easily changed in application of the model.

CONCLUSION AND IMPLICATIONS

Results of this study indicate that on-farm reservoirs are economically feasible in the Arkansas delta when the ground water supply is restricted. The investment decision is found to be sensitive to the initial saturated thickness of the water table, its rate of decline, and expected crop prices. The MARORA model provides useful guidelines on selecting the optimal size of on-farm reservoir and projects how the reservoir would be used under varying weather conditions. The ARORA model has been modified to address the typical Arkansas rice-soybean crop farm production situation. This initial development provides a framework to assess individual farm investment decision-making. It also has the potential to contribute to a broader framework to assess the regional impacts and policies to address the water supply and use issues confronting the Mississippi Delta. Further refinement and analysis of the MARORA model and data input are needed for different farm resource situations in Arkansas and to address relevant policy questions.

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Table 1. Effect of varying decline rates, crop prices, and discount rate on optimal reservoir size with 50-ft. initial saturated thickness for 160-acres with one well.[1]

Annual Water Decline (ft.)	Discount Rate %	Soybean Price $/ bu.	Rice Price $/ bu.	Optimal Reservoir Capacity (acre-ft.)	Present Worth of Net Income
1.00	8	6.75	5.00	0.00	$178,680
0.75	8	6.75	5.00	0.00	$193,500
0.50	8	6.75	5.00	0.00	$197,310
1.00	8	8.10	6.00	0.00	$336,240
0.75	8	8.10	6.00	0.00	$357,510
0.50	8	8.10	6.00	0.00	$361,320
1.00	8	5.40	4.00	0.00	$ 21,150
0.75	8	5.40	4.00	0.00	$ 29,460
0.50	8	5.40	4.00	0.00	$ 33,270
1.00	4	6.75	5.00	0.00	$255,600
0.75	4	6.75	5.00	0.00	$292,140
0.50	4	6.75	5.00	0.00	$299,610

[1]Average draw down per well in eastern Arkansas is 1.77 ft. per 100 gpm (USDA, NRCS, 1987).

Table 2. Effect of varying decline rates, crop prices, and discount rate on optimal reservoir size with 25-ft. initial saturated thickness for 160-acres with one well.[1]

Annual Water Decline (ft.)	Discount Rate %	Soybean Price $/ bu.	Rice Price $/ bu.	Optimal Reservoir Capacity (acre-ft.)	Present Worth of Net Income
1.00	8	6.75	5.00	250	$134,940
0.75	8	6.75	5.00	250	$134,550
0.50	8	6.75	5.00	250	$134,430
1.00	8	8.10	6.00	250	$262,260
0.75	8	8.10	6.00	250	$261,960
0.50	8	8.10	6.00	250	$261,840
1.00	8	5.40	4.00	170	$ 16,920
0.75	8	5.40	4.00	170	$ 16,530
0.50	8	5.40	4.00	170	$ 16,290
1.00	4	6.75	5.00	250	$207,900
0.75	4	6.75	5.00	250	$206,970
0.50	4	6.75	5.00	250	$206,790

[1]Average draw down per well in eastern Arkansas is 1.77 ft. per 100 gpm (USDA,NRCS, 1987).

Table 3. Average annual water cost, 25-ft. saturated thickness, three decline rates, average crop prices, 8 % discount rate.

Factor Evaluated	Case 1	Case 2	Case 3
Discount rate	8%	8%	8%
Soybean price	$6.75/bu.	$6.75/bu.	$6.75/bu.
Rice price	$11.11/cwt.	$11.11/cwt.	$11.11/cwt.
Annual decline	1.00 ft.	0.75 ft.	0.50 ft.
Average soybean irrigation (in./ac)	16.8.(in./ac)	16.9 (in./ac)	16.9 (in./ac)
Average rice irrigation (in./ac)	20.5 (in./ac)	20.5 (in./ac)	20.5 (in./ac)
Reservoir capacity	250ac. ft.	250ac. ft.	250ac. ft.
Idled cropland	34.1 acres	34.1 acres	34.1acres
Soybean area	84.0 acres	84.0 acres	84.0 acres
Rice area	41.9 acres	41.9 acres	41.9 acres
Reservoir excavation cost	$41,604	$41,604	$41,604
Levee seeding cost	$7,467	$7,467	$7,467
Lift/discharge pumps (2)	$16,000	$16,000	$16,000
Average tailwater runoff recovery[1]	14.8 ac. ft.	14.8 ac. ft.	14.8 ac. ft.
Average reservoir water use[1]	189 ac. ft.	189 ac. ft.	189 ac. ft.
Average well use	0 ac. ft.	0 ac. ft.	0 ac. ft.
Avge. annual reservoir op. cost	$4,191	$4,191	$4,191
Annual reservoir fixed cost	$5,304	$5,304	$5,304
Distribution fixed cost[2]	$2,810	$2,810	$2,810
Average reservoir cost/ ac. ft.	$50.23	$50.23	$50.23

[1]The annual reservoir fill plus other water recovered during the growing season is greater than reservoir use due to surface evaporation and seepage losses from the reservoir that exceed rainfall additions during the growing season.

[2]Includes overhead cost of underground pipe system, risers and one well connected to system.

Table 4. Effect of requiring farmers to construct a reservoir in year 1 versus waiting for groundwater to become critical before choosing to construct a reservoir with 50-ft initial saturated thickness, average crop prices and 8 percent discount rate on 160 acres over 30 years.

Effect on Irrigation and Present Worth of Annual Net Income	Annual Water Table Decline								
	1.00 ft.			0.75 ft.			0.50 ft.		
	Option 1[1]	Option 2[2]	Option 3[3]	Option 1[1]	Option 2[2]	Option 3[3]	Option 1[1]	Option 2[2]	Option 3[3]
Average Annual Water Use per Acre (Inches):									
Groundwater per acre -Rice	21.2	21.2[5]	0.6[5]	20.9	20.9	n.a.	20.9	20.9	n.a.
-Soybeans	17.6	17.6[5]	1.7[5]	18.0	18.0	n.a	18.0	18.0	n.a.
Surface Water per acre -Rice	0	20.5[5]	20.5[5]	0	0	n.a	0	0	n.a.
-Soybeans	0	16.5[5]	16.8[5]	0	0[5]	n.a	0	0	n.a.
Years of Full Irrigation[4]									
-Rice	24	30	30	30	30	n.a	30	30	n.a.
-Soybeans	24	30	30	19	30	n.a	30	30	n.a.
Opt. reservoir size ac.ft.	0	250	250	0	240	0	0	0	0
Present Worth of Income ($1,000)	178.7	181.6	137.1	193.5	193.5	n.a.	197.3	197.3	n.a.

[1]Option 1 requires farmers to choose in year 1 whether or not to construct a reservoir to operate with over the next 30 years.
[2]Option 2 allows farmers to choose an optimal size reservoir to construct whenever they need it in the 30- year period, i.e. in year 24 with 1.00 ft decline.
[3]Option 3 mandates that an optimum size on-farm reservoir be constructed in year 1 to conserve on ground water use.
[4]Full irrigation is defined as at least 75% of the average level when water is not restricted.
[5]Irrigated with groundwater before reservoir is built, then only surface water was used except when Option 3 was followed when both were used conjunctively.
n.a = not applicable

Table 5: Estimated cost economies of increasing reservoir size, 25-ft saturated thickness, average crop prices, 8 percent discount rate.

Cost Item	160 Acres	240 Acres	320 Acres
Present worth of income	$134,550	$266,250	$409,380
Reservoir size (ac.ft.)	250	400	520
Idled cropland (ac)	34	54	69
Soybean area (ac)	84	124	167
Rice area (ac)	42	62	84
Reservoir excavation cost	$41,604	$54,333	$63,066
Levee seeding cost	$7,467	$9,499	$10,866
Lift/discharge pumps (2)	$16,000	$16,000	$16,000
Average tailwater recovery (ac.ft.)	15	19	25
Annual reservoir water use (ac.ft.)	190	284	385
Distribution fixed cost	$2,810	$2,810	$2,810
Annual reservoir fixed cost	$5,304	$6,386	$7,127
Annual reservoir op. cost	$5,174	$7,499	$9,690
Reservoir cost per acre foot	$55.15	$48.89	$43.68

MODIFIED ARORA MODEL DESCRIPTION

The modified ARORA model uses weather, farm, and field data, along with economic data related to soybean and rice production in order to simulate the income and expenses associated with off stream reservoirs of various capacities. When executed in optimization mode, the program will operate in a manner which will identify the reservoir size which will result in the maximum present worth of simulated net income for the number of years specified. When executed in non- optimization mode, the model will identify yearly costs and returns for a reservoir of a specified capacity. The modified ARORA model incorporates algorithms to simulate reservoir and soil water balances, water dispersion and recapture, rice and soybean production costs , crop yields and profits, and other processes related to reservoir performance. It is written in the FORTRAN programming language and is intended for use on PCs (personal computers) with at least a 386 processor. Input data for the program are read from two separate files. The first contains weather data for 30 years for a particular geographic area. (Weather files for the major agricultural areas of eastern Arkansas are available) The second file contains a large number of agricultural and economic variables which allow the simulation to be fine tuned for a particular area and adjusted to investigate the impact of numerous factors on optimal reservoir size and performance.

The basic structure of the model remains unchanged from the original ARORA model as presented by Edwards and Ferguson (1990). Some minor changes to the order in which events unfold were required in order to support the program enhancements. These enhancements include the simultaneous simulation of water use by both soybeans and rice, the dynamic reallocation of rice acreage to soybeans when insufficient water for rice production is detected, the recovery of excess runoff and tail water, the ability to specify multiple wells, lift pumps and irrigation pumps, and the ability to calculate the cost and returns for flooding the harvested rice fields for duck hunting.

The following numbered text describes the basic processes and organization of the modified ARORA water resource model.

1. Weather and other input data are read into memory and appropriate unit conversions are performed.

2. If ground water is available, then the associated costs of the well and pump(s) are computed.

3. If a reservoir is indicated then the ownership costs for the reservoir and pump(s) are calculated. Dimensions are calculated based on capacity. Depreciation, interest, maintenance, and tax costs are calculated.

4. Rice and soybean field sizes are determined based on input data minus the area occupied by the reservoir if a reservoir is indicated.

5. Depreciation and interest cost associated with the irrigation system are calculated. If no reservoir is indicated and no ground water is available, then these costs are set to zero.

6. Ownership and operating costs which are not associated with irrigation or dependent on crop yield are computed.

7. Reservoir fill begins on the date specified and continues until the reservoir capacity has been met. Costs are computed.

8. Recharge of the aquifer surrounding the well is allowed providing that ground water is available and the well is not currently being used for irrigation, and ground water has been used during the current year. If recharge is allowed then the new potentiometric surface elevation is computed.

9. Rainfall for the day is checked and any runoff from the soybean fields and from any rice fields (if they are not presently flooded), is specified as recoverable runoff. Runoff from a flooded rice field is calculated if the rainfall amount when added to the flood level brings the flood level above six inches. Any amount over the six inch level is assumed to be drained off to protect the levees and is marked as recoverable runoff.

10. If the day of the year is the specified initial rice flush date then the rice soil moisture deficit is set to trigger a two inch flush of the rice field. One inch of the flush is specified as recoverable as tail water.

11. If the day of the year is the specified rice flood date then the rice soil moisture deficit is set to trigger a four inch flood of the rice fields (four inches at the deep end within each levee).

12. If the day of the year is the specified rice "drain for harvest" date then the rice fields are drained and the drainage marked as recoverable tail water.

13. If the day of the year is the "flood for ducks" date (optional) then the soil moisture deficit is set to trigger a 2 inch flood for duck habitat.

14. Check for any available runoff or tail water and return this water to the reservoir. Any amount exceeding the reservoir capacity is lost. The recovery cost is computed.

15. Determine whether to irrigate. Irrigation is allowed if (a) no rain occurred on the current day, (b) surface or ground water is available, (c) the soil moisture deficit is greater than the triggering value, (d) the date is within the growing season of the crop to be irrigated. Irrigation is provided from the reservoir if available. Otherwise it is provided from ground water if available. Irrigation is supplied based on irrigation pump(s) capacity and system efficiency and constrained by the amount needed to negate the soil moisture deficit.

16. If any irrigation was supplied by ground water then a new potentiometric surface depth is calculated. If the saturated depth surrounding the well is drawn down to zero then ground water irrigation is decreased and restricted until one day of recharge takes place.

17. Irrigation costs are calculated.

18. Evapotranspiration is computed for rice and soybeans, and reservoir evaporation is calculated.

19. Soil moisture deficit values for both rice and soybeans are calculated based on rainfall, irrigation, and evapotranspiration.

20. Reservoir water level is calculated based on changes due to seepage, percolation, evaporation, irrigation, rainfall, and tail water/runoff recovery. (Steps 7 thru 17 are repeated for each day of the year)

21. Crop yield and value for soybeans are computed based on plant transpiration over the growing season and the current price of soybeans. Rice yield is assumed to be the maximum specified provided the water requirements are met, but is reduced by 10 percent each day the rice flood level drops to zero inches. If the rice yield drops to zero for a year it is assumed that the ground water and reservoir water combination is no longer sufficient to support rice so the rice field acreage is converted to soybeans for the remaining years of the simulation. Rice crop value is calculated based on yield and the current rice price. Net income is computed. (This step is repeated for each year of the simulation)

22. Yearly net incomes are converted to present worth.

23. When operating in optimizing mode, the program seeks the reservoir size that maximizes the total of net yearly incomes converted to present worth. The program does this by running through the 30- year simulation for a series of reservoir sizes. The user specifies the maximum reservoir size to be examined and an increment size (normally 5 or 10 acre ft.). The program calculates the present worth of income for the series beginning with no reservoir and continuing for reservoir sizes up to the maximum. It then writes detailed data to file for the reservoir size that resulted in the greatest present worth value.

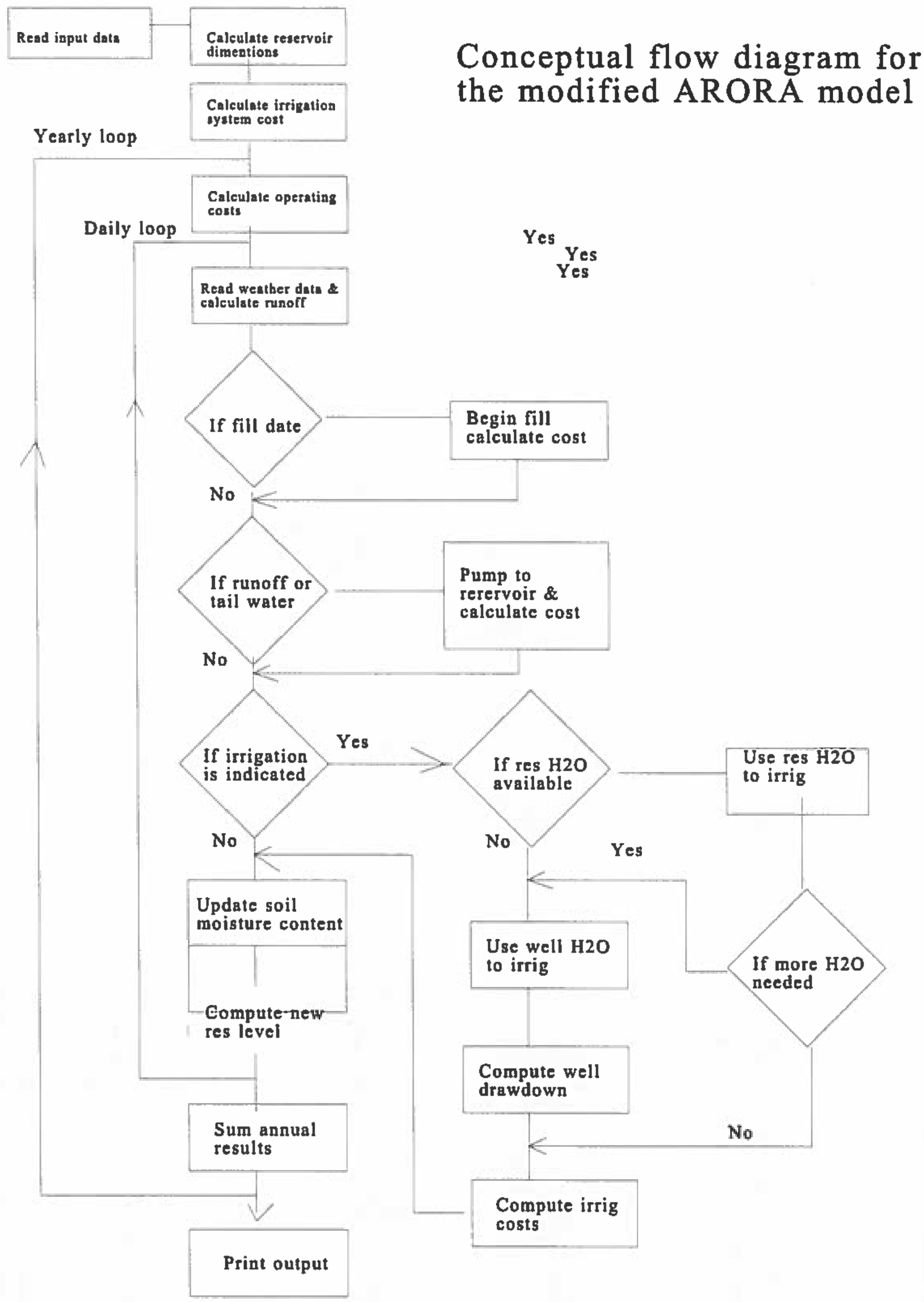
MODIFIED ARORA PROGRAM INPUT PARAMETERS

The modified ARORA program requires two data files for execution. The first file contains 30 years ' daily weather data to include precipitation, temperature minimum, temperature maximum, solar radiation and wind run. A modified version of the WGEN weather generator program was used to produce weather data for the major agricultural areas of eastern Arkansas. The second data file contains the general simulation parameters, crop and field data, operating and ownership data, ground water data, irrigation system data, reservoir data, well, lift, and irrigation pump data, economic, and optimization data. In order to facilitate modifications to this data, a template file (arsd2.tmp) has been created which contains an explanation or description of each parameter followed by an asterisk and an example value. This values in this file can be modified using any editor found on your computer system. The user then executes a data transformation program (datatran) which takes this data and creates the data file (arsd2.dat) which is used by the modified ARORA program. A printout of this template file follows:

```
Number years to simulate                                        * 30
option (0 = non-optimizing  1 = optimizing)               * 1
insufficient water option (1=more wells 0=stop rice)    * 0
tailwater recovery option (1=all year 0=growing season)                * 0
total farm acres (decimal)                                                                      * 160.0
SCS curve number for average moisture (integer)                        * 75
average elevation of fields in feet (integer)                                      * 220
mean of solar radiation sine wave (decimal)                                        * 570.46
amplitude of solar radiation sine wave (decimal)                       * 234.50
phase shift of solar radiation sine wave (decimal)                     * 1.22
soil evaporation parm  (alphasoil) (mm)                                   * 4.04
soil evaporation parm  (usoil) (mm)                                       * 9
depth of soybean root zone                                     (inches)                 * 18.00
available water in root zone  (in/in)                                     * 0.22
albedo (soil)                                                                      * 0.17
day of year for planting soybeans (julian date)                        * 140
days past plant day until maturity for soybeans                        * 145
maximum expected soybean crop yield  (bu/ac)                           * 52.6
maximum expected rice crop yield     (bu/ac)                           * 135.0
rice plant day                                                                     * 140
days until rice maturity                                               * 120
percent of acreage planted in rice                                                         * .333
tailwater recovery rate                                                            * .80
day of year to flood rice stubble for ducks (999 = never)              * 999
duck lease rate (dollars per acre)                                        * 30.00
interest rate                                                                      * 0.08
discount rate                                                                                                * 0.08
insurance rate                                                                     * 0.025
tax rate as fraction of initial cost                                      * 0.01
soybean price                                                  ($/bu)                                 * 6.75
rice price                                                     ($/bu)                                 * 5.00
soybean seed cost ($/ac)                                                                        * 10.80
soybean fertilizer cost  ($/ac)                                           * 14.00
soybean lime & application cost  ($/ac)                                   * 7.91
soybean herbicide cost  ($/ac)                                            * 15.03
soybean fungicide cost          ($/ac)                          * 1.53
soybean insecticide cost  ($/ac)                                          * 0.00
soybean defoliant cost  ($/ac)                                            * 0.00
soybean aerial application cost  ($/ac)                                   * 0.00
soybean machinery fuel, oil, and lubricants cost ($/ac)                * 10.69
soybean annual machine repair cost  ($/ac)                             * 20.82
soybean labor cost  ($/ac)                                                * 8.65
soybean custom spread cost  ($/ac)                                                         * 3.00
soybean custom haul cost    ($/bu)                                        * 0.15
soybean custom drying costs  ($/bu)                                       * 0.00
soybean misc cost  ($/ac)                                                 * 0.00
soybean crop insurance costs  ($/ac)                                                       * 0.00
soybean other costs  ($/ac)                                               * 0.00
rice seed costs   ($/ac)                                                           * 14.81
```

rice fertilizer costs ($/ac)	* 42.90
rice lime cost ($/ac)	* 0.00
rice herbicide costs ($/ac)	* 39.39
rice fungicide costs ($/ac)	* 16.67
rice insecticide costs ($/ac)	* 4.72
rice defoliant costs ($/ac)	* 0.00
rice aerial application cost ($/ac)	* 30.73
rice machinery fuel, oil, & lubricants cost ($/ac)	* 11.10
rice annual machine repair costs ($/ac)	* 24.59
rice labor costs ($/ac)	* 12.00
rice custom spread costs ($/ac)	* 3.50
rice custom haul costs ($/bu)	* 0.11
rice custom dry or ginning costs ($/bu)	* 0.24
rice misc costs ($/ac)	* 4.70
rice crop insurance costs ($/ac)	* 0.00
rice other costs ($/ac)	* 0.00
tractor depreciation ($/ac)	* 8.49
tractor interest ($/ac)	* 7.01
equipment depreciation ($/ac)	* 7.30
equipment interest ($/ac)	* 4.00
special equipment depreciation ($/ac)	* 10.98
special equipment interest ($/ac)	* 4.02
misc equipment depreciation ($/ac)	* 0.00
misc equipment interest ($/ac)	* 0.00
taxes and insurance ($/ac)	* 3.42
interest ($/ac)	* 0.37
overhead labor ($/ac)	* 0.00
other overhead ($/ac)	* 0.00
land and property tax ($/ac)	* 0.00
management cost ($/ac)	* 0.00
initial groundwater depth (ft)	* 120
ground water decline rate (ft/yr)	* 1.0
storage coefficient (decimal)	* 0.30
saturated hydraulic conductivity of aquifer (ft/day)	* 270.00
initial saturated thickness of aquifer (ft)	* 50.0
number of wells in operation (decimal)	* 1.0
well diameter (ft)	* 1.33
well cost ($)	* 4320.00
expected life of well (yrs)	* 30
annual well repair cost as % initial cost (dec)	* 0.01
well flow (gal/min)	* 1100.00
well pumping plant efficiency (decimal)	* 0.18
cost of pump and gearhead ($/well)	* 6060.00
expected life of pump and gearhead (yr)	* 15.00
pump & gearhead repair as % of initial cost (decimal)	* 0.025
discharge diameter of well pump (ft)	* 0.75
cost of power unit ($)	* 5600.00
expected life of power unit (yr)	* 15.00
annual repair cost of power unit as % of initial cost ($)	* 0.025
energy cost ($/KW-hr)	* 0.075
lubrication cost as % of initial cost ($)	* 0.03
soybean application efficiency (decimal)	* 0.65
rice application efficiency (decimal)	* 0.80
cost of irrigation system ($)	* 11715.00
expected life of irrigation system (yr)	* 15.00
annual irrig system repair cost as % of initial cost (dec)	* 0.005
irrigation labor (hr/acre-inch)	* 0.18
irrigation labor cost ($/hr)	* 4.15
irrigation system operating pressure (psi)	* 15.00
soil moisture deficit to begin soybean irrigation (mm)	* 50.80
drop in flood level to begin rice irrigation (mm)	* 50.80
reservoir freeboard (ft)	* 1.50
top width of reservoir levees (ft)	* 12.00
outside slope (hor to vert) of reservoir levee	* 3.00
inside slope of reservoir levee	* 3.00
excavation cost ($/cu-yd)	* 0.75
levee seeding cost ($)	* 1000.00
expected life of the reservoir (yr)	* 30.00
annual res maintenance cst as % of construction cst (dec)	* 0.02
saturated hydraulic conductivity of levee bottom (ft/day)	* 0.009

average lbedo of water (decimal)	* .36
day of year to begin reservoir fill	* 110
number of relift pumps	* 1.0
operating head for relift pump(s) (ft)	* 20.00
capacity of relift pumps (gal/min)	* 2200.00
efficiency of relift pumps (decimal)	* 0.18
cost of relift pump(s) ($/pump)	* 8000.00
expected life of relift pumps (yr)	* 15.00
cost of relift pump repairs as % of initial cost	* 0.025
relift pump lubrication cost as % of fuel costs	* 0.03
number of irrigation pumps	* 1.0
operating head for irrigation (ft)	* 10.00
capacity of irrigation pump(s) (gal/min)	* 2200.00
irrigation pump efficiency (decimal)	* 0.18
cost of irrigation pump(s) ($/pump)	* 10500.00
expected life of irrigation pump(s) (yr)	* 15.00
irrigation pump(s) repair cost as % of initial cost	* 0.025
irrig pump lubrication cost as % of fuel cost	* 0.03
maximum value of reservoir capacity (ac-ft)(decimal)	* 260.0
reservoir size increment (for optimization) (ac-ft)	* 10.0


Conceptual flow diagram for the modified ARORA model
Read input data
Calculate reservoir dimentions
Calculate irrigation system cost
Yearly loop
Calculate operating costs
Daily loop
Yes
Yes
Yes
Read weather data & calculate runoff
If fill date
Begin fill calculate cost
No
If runoff or tail water
Pump to rerervoir & calculate cost
No
If irrigation is indicated
Yes
If res H2O available
Use res H2O to irrig
No
No
Yes
Update soil moisture content
Use well H2O to irrig
If more H2O needed
Compute new res level
Compute well drawdown
No
Sum annual results
Compute irrig costs
Print output

OVERALL SUMMARY

This research project was subdivided into two groups of three projects each. Group A projects were centered around the transport of herbicides to ground and surface waters in the mid south-region.

Johnson concluded that the simultaneous transport in soil columns of two herbicides commonly applied to soybeans in the mid south region varied in their sorption and transport characteristics through the A horizon of a Memphis silt loam. Under saturated soil conditions metribuzin moved faster than metolachlor as shown by the lower peak relative concentrations at 2.4 and 3.5 pore volumes for metribuzin and metolachlor, respectively. The retardation factors were 5.9 and 1.5 for metolachlor and metribuzin, respectively. This work showed that the higher the retardation the lower the transport of the herbicide through the Memphis soil.

Dixon and Scott developed six fuzzy logic models and compared the predictions with the modified DRASTIC model in predicting the potential contamination by pesticides of the ground water in Woodruff County, Arkansas. They concluded that the fuzzy logic models had a higher incidence of detecting the most vulnerable wells to pesticide contamination than the frequently used DRASTIC model.. The use of the modified DRASTIC model for screening potential areas for vulnerability has an inherent risk of underestimation. The fuzzy logic-based model did not underestimate the vulnerability, and thereby, eliminate the risk of neglecting a potential vulnerable area. The model containing four fuzzy parameters was best in predicting the locations of the contaminated wells. This rulebase had the soil physical characteristics related to leaching of contaminants as the dominant parameter.

Shaw found that vegetative filter strips significantly reduced off site losses of surface water runoff, sediment and herbicide. At 2 days after treatment surface runoff was reduced by 83-93% with no difference due to filter strip width. At the end of the soybean growing season the addition of a filter strip reduced cumulative runoff between 47 and 68%. Herbicide concentrations in the runoff and cumulative losses were lower in the treatments containing filter strips. Both the highest herbicide concentration and cumulative loss due to runoff were in the first runoff event. The presence of filter strips of widths ranging from 0.5 to 4.0 m effectively reduced herbicide losses as compared to unfiltered conditions. The addition of filter strips at the edges of soybean production fields provide a viable management tool for the reduction of herbicide losses.

Group B projects were centered around the evaluation of factors important in the quality and use of water in rice production.

Dewell and Lavy sampled the water in the tailwater, flood and reservoirs in flooded rice production fields for pesticides commonly applied during the growing season. They concluded that although some pesticides were detected in the tailwater shortly after application to flooded rice fields, no increase in concentration in the reservoirs was found. The dissipation of pesticides in the tailwater was rapid. The highest concentrations in the water on the field was highest shortly after application. In order to minimize contamination of surface waters, they recommended that containment of water on the field should be emphasized immediately following post-emergence applications of pesticides to flooded rice. The greenhouse studies suggested that the aquatic dissipation of many pesticides are not easily explained by a single environmental factor.

Manley and Kaminiski examined several conservation management alternatives for flooding of rice fields during the winter. Winter flooding conserved soil while increasing quality of runoff, especially when the fields were not disked in the fall. It also retarded growth of winter weeds, residual rice straw, red rice infestation and increased water bird food resources. They concluded that there was no single rice field management option that is best for all management concerns. Nevertheless, winter flooding in combination with specific post harvest management strategies, is effective for addressing an array of ecological and agricultural issues such as soil conservation, water quality, spring field preparation and waterfowl and shorebird habitat.

Young, Wailes and Smartt modified an existing model to estimate the value of on-farm reservoirs for irrigation. Their model, which incorporated aquifer saturated thickness and rice production economics into sizing of on-farm reservoirs, provided the appropriate size of reservoir to construct after taking into account surface runoff, the expected irrigation requirements of all crops and the field application efficiency. They concluded that the reservoirs are economically feasible when the ground water to be used for irrigation is restricted. The model could be used for examination of economic incentives for farmers to construct surface water reservoirs, which may reduce the rate of depletion of ground water.