Economic Impact of Water Allocation on Agriculture in the Lower Chattahoochee River Basin

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Abstract

The relative value of irrigation water was assessed for three important crops (corn, cotton, and peanuts) grown in the southeastern United States. A decision tool was developed with the objective of allocating limited available water among competing crops in a manner that would maximize the economic returns to the producers. The methodology was developed and tested for a hypothetical farm located in Henry County, Alabama in the Chattahoochee river basin. Crop yield – soil moisture response functions were developed using Monte Carlo simulated data for cotton, corn, and peanuts. A hydrologic model was employed to simulate runoff over the period of observed rainfall in the county to provide inflows to storage facilities that could be used as constraints for the optimal allocation of the available water in the face of the uncertainty of future rainfall and runoff. Irrigation decisions were made on a weekly basis during the critical water deficit period in the region. An economic optimization model was employed with the crop responses, and soil moisture functions to determine the optimum amount of water to place on each crop subject to the amount of irrigation water availability and climatic uncertainty. The results indicated even small amounts of irrigation could significantly benefit farmers in the region if applied judiciously. A weekly irrigation sequence was developed that maintained the available water on the crops that exhibited the most significant combination of water sensitivity and cash value.

Key Words: irrigation, hydrologic modeling, optimization, agricultural economics

1. Introduction

Agriculture is an important sector of the economy of the southeastern United States and produces many high-value crops. For example, the Southeast region currently accounts for over half of the US timber harvest and a quarter of US crop value. In 1997, agriculture accounted for over $33 billion in revenue for eight states in this region

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(USDA, 1997). However, agricultural production in the southeast is highly vulnerable to natural climate variability in terms of both rainfall and temperature extremes (Burket et al. 2001). For example, unexpected Florida freezes in both 1983 and 1985 resulted in crop damages in excess of $1 billion, and the summer drought in 1998 is estimated to have caused from $6-$9 billion in damages in the region (Burket et al., 2001). In fact, agriculture is considered one of the most weather dependent of all human activities (Oram 1989). The vulnerability of agriculture to weather and climate variability is expected to increase as population increases and marginal lands are brought into production (Glantz 1994), and as other sectors (urban, industry, and recreation) grow and compete for land, water, and other natural resources. This situation, combined with the fact that the average size of farms in the southeast is much smaller than other places, makes farming in the region a financially hazardous occupation for the individual farmer.

Although the Southeast receives a significant amount of precipitation and has an extensive system of water supply projects, water demand is beginning to exceed the available supply because of increases in population, urbanization, agricultural uses, and maintenance of stream quality. Currently, irrigation is not the major consumer of water in the region due to sufficient amount of rainfall in the region. However, water use for irrigation has increased by 36% over the past decade and is projected to continue to increase throughout the coming decades (SERAT, 2002). Furthermore, previous studies (Mendolsohn et al., 1994; Adams et al. 1995; Darwin et al. 1995) indicate that climate change may also increase the quantity of irrigated land in much of the South exacerbating the water demand situation even further.

Weather and climate information is a vital factor in the decision making process of agricultural producers. Weather data play a critical role in decisions regarding new investments and modifications to existing systems, or regarding the day- to- day operation of existing facilities, particularly with respect to irrigation allocations. Thus, increasing the quality and usability of the available climate information and decision tools could have large economic and social benefits for the region. The objective of this study was to develop a methodology to aid managers in the design of irrigation facilities and determination of acres to devote to specific crops by including the uncertainty in weather and climate of the affected region. A decision tool was developed based on the objective of allocating limited available water among competing crops during the critical production period in a manner that would maximize the economic returns to the producer. The methodology can be employed to determine the optimal detention pond-to-drainage basin ratio and detention pond-to-irrigated acres ratio for the most efficient and profitable operation of the farm.

The method is based on analysis of the historic variability of climate (rainfall, temperatures) and streamflow for an area of interest. It relies on the availability of climate records of sufficient length such that a reliable picture of the variability of temperatures and rainfall of the area can be obtained. Normally, assuming exponential type I distributions (i.e., gamma, normal, lognormal, etc), this would require a record in excess of 50 years in length. The historic data were utilized in the simulation of runoff, soil moisture, and crop growth for the area. A hydrologic model was employed to simulate runoff over the historic period to provide inflows to storage facilities that were then used as constraints for the optimal allocation of the available water in the face of the uncertainty of future rainfall and runoff. Simulated irrigation decisions were made on a weekly basis and a crop simulation model was employed to derive crop response relationships for each week of the irrigation season. Based on the resulting crop response relationships, weekly irrigation requirements were determined to maximize total returns for an exhaustive suite of scenarios by varying storage pond sizes and acres planted, and initial soil moisture conditions.

2. Methodology

The procedure will be demonstrated for a typical farm located in the Chattahoochee River basin in Henry County, Alabama. The relevant agricultural data for this county from the 2000 census is given in Table 1.

For this demonstration, scenarios were developed assuming that the crops grown are corn, cotton, and peanuts. The goal is to develop a procedure based upon historic hydrologic and climate information for use by the farm manager to determine irrigation requirements, or optimal acreage of each crop, in order to maximize the returns from all three crops. In order to develop this tool, a large amount of data had to be generated to develop the hydrologic and climatological potential of the area as well as the crop response to various amounts of water applied during successive weeks of the growing season. In the development of this database, computer models of hydrology and crop growth were employed based on 62 years of observed climate data for Henry County. Once the database had been developed, then an optimization algorithm was employed to determine the optimal water allocations for each crop for each week, subject to the constraints of water availability; that would maximize the economic returns to the farmer.

This procedure can be repeated for as many ratios of pond size- to- catchment area or pond size- to- irrigated acres as desired.

2.1 Hydrologic Modeling

The US Agricultural Research Service model SWAT (Soil Water Assessment Tool; Arnold and Allen, 1993) was employed for the hydrologic simulations. SWAT is a basin scale continuous time hydrologic and water quality simulation model based on modifications of earlier ARS models such as GLEAMS, ROTO and SWWRB. The model runs on a daily time step; employs combination type evapotranspiration methods (e.g. Penman-Monteith), and a multi-layer vertical soil moisture routing. Surface runoff is computed by the NRCS curve number (CN) method. An improvement claimed in SWAT that is not available in the earlier models is the ability to simulate lateral soil moisture movement as a function of basin slope, subsurface flow lengths, and porosity (bulk density). SWAT methodology and practical applications have been thoroughly described by Arnold and Allen (1993), Srinivasan and Arnold (1994), Arnold, *et al*. (1998), Srinivasan, *et al*. (1998) and Rosenthal, *et al*. (1995). Present authors have employed the model in numerous studies throughout the southeastern U.S. (e.g., Ritschard, *et al*., 1999; Limaye, *et al*., 2001).

Required data inputs include daily precipitation and temperature, monthly solar radiation, soils data, land cover information (CN, Leaf Area Index (LAI)), and basin characteristics such as mean slope, stream length and subsurface flow length. Precipitation and temperature data were obtained from a NWS observation station located in the county at Blakely, AL and solar radiation data were available from the Agricultural Research Station at Griffin, GA. Topographic data were derived from 30 m resolution digital elevation model (DEM) datasets available from the USGS Eros Data Center. These data were used to determine slopes and flow lengths. Soil textures and characteristics were obtained from the NRCS State Geographic Soils (STATSGO) database. LAI for the simulated crop coverage were available from help files associated with the SWAT program and NRCS curve numbers were obtained from McCuen (1989).

The majority of Henry County is contained within the Abbie Creek tributary to the Chattahoochee River (Figure 1). A USGS gaging station was located on this stream at Haleburg, AL and was in operation from 1958 –1993. The gage was located near the downstream confluence of Abbie Creek with the Chattahoochee and encompassed an area of 375 km^2. The SWAT model was used to simulate the streamflow for this basin in order to provide runoff that would be available for capture and storage for irrigation purposes. The model was first calibrated using the last five complete years of the observed streamflow record at the gage. Only the last five years were used in this procedure so that the calibrated model would represent the contemporaneous land use of the basin to the extent possible. Model simulations are compared to observed runoff in Figure 2. The Nash-Sutcliffe Efficiency statistic, R^2 (ASCE, 1993) is a measure of the variance of model errors compared to the variance of the observed data. The R^2 value is given by 1 minus the ratio of the model error to the variance of the data and thus can vary from $-\infty$ to 1. The computed R^2 for the simulations shown in Figure 1 was 0.39, which compares favorably with values cited by Limaye, et al. (2001) for similar studies that employed the SWAT model. The calibrated model was then used to simulate the runoff from the basin for the entire 62 years of climate data available at the NWS climate station. The model produced daily runoff simulations for this period.

2.2 Crop Response Simulations

Although the daily water requirement of a plant depends on various factors including location, plant type, soil conditions, and weather conditions, the impact of water shortage at some critical stages of plant growth on crop yields can be particularly serious. For example, the impact of drought on corn during the tasseling period would be much more serious than at any other period of plant growth (Bryant et al. 1992). Thus, both timing as well as the rainfall and irrigation amounts have important bearing on crop yields. Therefore, the relationship between crop yields and the amount and timing of water received must be established before any optimal irrigation decision can be made. The empirical estimation of such relationships requires actual experimental data, which are rarely available. In the absence of real world data, various biophysical models have been used in the past to simulate different climatic conditions and water management practices and associated crop yield data.

The Erosion Productivity Impact Calculator (EPIC) model was initially developed to measure the cost of soil erosion or the benefits of soil erosion research. This model is capable of simulating the complex biophysical processes of plant growth using readily available data. It consists of nine components - weather, hydrology, erosion, nutrient cycling, soil temperature, tillage, crop growth, crop and soil management, and economics. In this study, EPIC was employed to determine crop response to pre-set amounts of applied water (whether from either rainfall or irrigation) in order to develop crop response functions to be used in the optimization analysis. Therefore, the weather generator of the model was not activated. In particular, daily rainfall, minimum and maximum temperature, and wind data were used to simulate the crop yield.

Bryant et al. (1992) used the EPIC model to simulate yield response of corn to soil water in the southern Texas High Plains. They used actual experimental data to validate the simulation results and found that simulated yield explained up to 86 percent of the variation in actual yields. Based on the soil moisture mapping results, the study area was divided into various homogeneous soil moisture units and for each unit; separate crop yield levels were simulated. The EPIC model was used to simulate crop yield levels associated with each soil type under various water management decision rules.

The soil moisture available to the plants at various growth stages can be defined as the amount of moisture transferred from the last to the current period plus the amount added externally (rainfall and irrigation) at the current decision period. The relationship between the level of soil moisture and final crop yield, within a relevant domain, is expected to be positive. This relationship between the level of soil moisture available to the plants at various growth stages and crop yield can be specified to be nonlinear and estimated using data on rainfall, supplemental irrigation, and associated crop yield levels.

EPIC was used to simulate the crop yield under different scenarios of water applied to the root zone. Four irrigation strategies were used to simulate crop yield in a representative soil in Henry County during an eight-week irrigation period running from week 24 through week 31 of the year. The EPIC model was calibrated so that it could reflect the county average yield for the conditions of irrigation and rainfall prevalent in the county. The calibrated EPIC model was then used to simulate corn, cotton, and peanut yields for four representative irrigation strategies for the southeastern US With the possible irrigation application of 0, 0.5, 0.75, 1 acre- inch in each of the eight-week window, 65536 ($4^{8)}$, Monte Carlo simulations were designed for each crop. Each simulation was run for the entire 62 years of observed rainfall data at the Blakely, AL station. However, during each run, the rainfall was randomly generated from a gamma distribution fitted to the Blakely data in order to account for the uncertainty in the climate. The appropriateness of the distribution function was tested using the Kalmanorov test and was found to be significant.

Crop yield and soil moisture at each week during the critical crop growing period were recorded from the EPIC simulations in order to derive regression equations between crop yield and soil moisture. Soil moisture and irrigation amounts at each week were also recorded to develop the soil moisture transformation equation. Soil moisture at the plow layer (30 cm) was employed for this purpose.

The crop response functions were of the following form:

$$\mathrm{Y_i} = \alpha_{i0} + \sum \alpha_{\mathrm{ij}} * \mathrm{M_{ij}} + \varepsilon(t_i) \qquad (1)$$

where

Y_i is the crop yield from crop I, the crop index (1 corn, 2 cotton and 3 for peanut)

Mij is soil moisture on crop i at end of week j, α_{ij} are the crop and week specific coefficients derived from regression of EPIC simulated yield and soil moisture data, and $\varepsilon(t)$ is the error term in the simulations. The upper bound on the production function is determined by the soil moisture holding capacity which cannot exceed the field capacity. The error term ($\varepsilon(t_i)$) represents the residuals between the regression modeled yields and the EPIC simulations for each crop (i). The ($\varepsilon(t_i)$) distribution was normal with zero mean and standard deviations of 0.06 (corn), 0.015 (cotton) and 0.016 (peanuts).

2.3 Non-Linear Optimization Model

An optimization model was written in optimization environment LINGO (Lingo, 2003) for this demonstration. The model estimates weekly irrigation water allotments for each crop with the objective of maximizing the total returns based on the crop yields derived from the carryover moisture, and irrigation water applied in each week. The mass balance of storage water in the pond is kept in the optimization, thus allowing maximum freedom in allotting water in critical weeks on crops. The model consists of three components: storage computations for the pond, soil moisture carryover function, and the yield and return estimator. The optimization model was run for several hundred thousand iterations to examine the effects of changes in storage pond sizes, acreage planted, and initial soil moisture conditions on the yields and total returns.

2.3.1 **Storage Computations for Irrigation Water**

For this demonstration, the pond surface area was allowed to vary, but the depth was kept fixed at 10 ft. Any runoff in excess of the amount needed to fill the pond during a given week was considered to be spilled from the pond and not available for storage. However, it was assumed that not all runoff from the stream would be available for capture at any individual farm site. For the demonstration discussed here, it was assumed that 5% of the total runoff would be available. This is equivalent to the assumption that an individual landowner would have access to 5% (18 km^2) of the total watershed area. A weekly mass balance was kept in the irrigation pond for each alternative as follows:

$$S_t = S_{t-1} + P_t + Q_t - E_t - I_t \quad (2)$$

Where: S_t = storage remaining at end of week t

S_{t-1} = storage remaining at end of week t-1, or beginning of week t

P_t = precipitation falling directly on the pond during week t

Q_t = runoff into the pond during week t

E_t = evaporation from the pond during week t

I_t = irrigation withdrawals from the pond during week t

The units of all quantities are m^2-mm. . The minimum streamflow requirements were subtracted from the runoff values before inclusion as pond inflow. Pond evaporation was also computed using the SWAT model. The storage operation was executed on a daily basis using daily precipitation, SWAT-generated runoff and estimated evaporation. All results were then aggregated on a weekly basis for the storage routing operation. The pond was considered to be full at the beginning of each irrigation cycle

2.3.2 Weekly soil moisture carryover

Soil moisture in week j is a function of the amount of moisture present in the soil at time period j-1, the irrigation applied during that week and the rainfall that occurred in that week. Because the amount of rainfall for any week during the simulation period is unknown at the beginning of the decision period, it was treated as a random variable in the Monte Carlo simulations as previously described. Furthermore, the climate and soil conditions cause soil moisture to transform differently for different weeks of the irrigation period thus necessitating the need to tabulate the data on a weekly basis.

Soil moisture carry-over term for each crop used in equation 1 is given by:

$$M_{ij} = \gamma_{i0} + \chi_{ij} * M_{ij-1} + \beta_{ij} * W_j + >(t) \qquad (3)$$

Where

M_{ij} is soil moisture from crop i at the end of week j

Wj is water applied during the week j

$\gamma_{i0}$are crop specific intercepts of the weekly moisture regression line.

χ_{ij} and β_{ij} crop specific and week specific coefficients derived from the simulation data.

>(t) is the error term derived in the same manner as in the crop model with average weekly standard deviations of 0.000683 (corn), 0.000841 (cotton), and 0.000763 (peanuts).

It can be noticed that the precipitation term does not explicitly occur in the above equation. However, rainfall uncertainty is incorporated in the random error component in the soil moisture function since it was derived from the Monte Carlo simulations using the EPIC results.

All three crop yields were fitted with the soil moisture function to find the effect of soil moisture applied in a given week on the crop yield. The coefficients of the regression were found to be significant at the five percent level for all three crops.

2.3.3 Maximizing crop returns based on optimal crop yields

The objective function is to maximize the total return, defined by the total revenue (price of crop multiplied by the total yield) minus the costs associated with irrigation (variable costs) and other expenses related to operation of the farm (fixed costs).

$$R = \sum P_i * y_i * Y_i - \sum C^* W_i{}^*Y_i\text{-fixed costs} \qquad (4)$$

Where R is the total return, P_i is price of crop i, C is cost of irrigation water per acre-inch, W_i is total irrigation water of crop i per acre, Y_i is acreage and y_i is per-acre yield of crop i. Crop prices derived from the October 15, 2003 edition of the National Agricultural Census data were employed in the analysis. These values were $71/ton for corn, $1500/ton for cotton, and $625/ton for peanuts. It is important to note that the value used for peanuts was price-supported numbers rather than free market prices. The costs (variable and fixed) for irrigation in this area of Alabama were obtained from a recent study performed by the Auburn University Extension Service. The values used were $3.85/acre-inch for the variable cost of irrigation and $72.16/acre for the fixed costs. These numbers represent the cost of applying the water to the crops and the amortization cost of the facilities respectively. Necessary unit conversions were performed carefully where needed. Maximum irrigation allowed in each week was limited to 2 inches. The other main constraint placed on the objective function was the irrigation water constraint.

$$\sum W_{ij} * Y_i \leq A_j \tag{6}$$

where A_j is available water for irrigation in week j.

The optimization model computed the most cost effective way of producing maximum returns given the constraints. Based on the yield – moisture relationships for all the crops (equation 1), the model optimizes the irrigation amounts given to each crop during each of the 8 simulation weeks in such a way that the returns would be highest. The resulting yield may not be the highest; however given the nonlinear relationship between yields and returns for different crops, the model optimized the yield to obtain maximum returns. The model was run for each of the 62 years for which the data are available, and the weekly statistics of each variable are computed. The model keeps track of the variables including weekly irrigation amounts for each crop, weekly water availability in the storage pond, crop yields and total returns. The weekly statistics include the average, minimum and maximum and standard deviation. The weekly average statistics for 62 years provide analysis on the average sense, however most of the variables exert bi-modality. Either the pond is full (or nearly full) in anticipation of irrigating a critical week for a crop, or is empty (or nearly so). Therefore in addition to the means, it is critical to examine the weekly statistics for the years in which the pond would have been nearly empty.

3. Results

The purpose of the exercise was to examine how water would be allocated among the three crops during periods of shortage. Water shortages could be generated in two ways, *i.e.,* through the use of a small irrigation pond or through the artifice of increasing the acreage planted. Exhaustive combinations of acres planted, pond size, and initial soil moisture conditions were employed in the analysis. For example, Figure 3(a) shows the average annual rate of returns per acre (over the 62 years of record) for three pond sizes as a function of total acres planted. The figure effectively demonstrates the relationship between available water for irrigation and effectiveness of the irrigation. For example, a pond size of 20 acres (*i.e*., 200 ac-ft) will maintain the maximum possible rate of returns for the three test crops under the prescribed soil and climate conditions of the area for up to about 400 acres of planted land. Similarly, a 400 ac-ft pond would maintain these returns for a maximum of about 700 acres, while a small 50 ac-ft pond would not supply enough irrigation to maintain the returns against any acreage above the minimum of 100 acres.

Of course, the results would not be complete without the inclusion of an alternative without any irrigation. These results are shown in Figure 3(b), which shows average annual rates of return versus pond size for 1000 acres planted and for initial soil moisture contents of 10% and 30%. The figure not only demonstrates the significant role played by the initial conditions assumptions, but also demonstrates that there is some value in even the smallest amount of irrigation for this farm. For example, a 50 ac-ft irrigation pond could result in an average net return increase of $100/acre under both initial condition scenarios when compared to the no irrigation alternative.

This concept is further developed in Figure 4, which shows contours of equal returns as a function of both pond size and acres planted for the two initial soil moisture conditions. The contour interval is $30 per acre on both figures. Landowners can use results such as these to determine the acres to be planted for an existing fixed capacity irrigation system or to aid in the design of irrigation facilities for a desired number of acres to be planted. One caveat to be mentioned in relation to these results is that the total acres planted are assumed to be divided equally among the three crops in all cases. For example, if one wished to maintain a rate of return of at least $450 per acre for a total of 1000 acres planted under a conservative assumption of 10% initial soil moisture (at the beginning of the irrigation cycle), then about 200 ac-ft of storage (20 ft of surface area of a storage pond 10 ft deep) would be required on an annual basis. Interestingly, if one is willing to assume 30% initial moisture content, then an average annual rate of return of better than $1050 per acre could be realized for 1000 acres planted with 200 ac-ft of irrigation storage. The results offer the producer a range of solutions depending on the resources at his disposal (land and money) and the degree of risk that one is willing to accept.

Figures 3 and 4 summarize the average results for the 62-year simulations. However that does not explain the annual variability in historic inflows, and precipitations in the light of associated returns. Figure 5 shows the relationship between returns as a function of acres planted, and collocated is the plot of fractional time the pond was nearly empty in the eight-week simulation period. Nearly empty pond at the beginning of any week is defined by water availability in the pond below 10% of the storage capacity. Figure 5 shows the results for a fixed pond size of 200 ac-ft and initial conditions of 10%. As expected, the returns are maintained as long as the water supply is not taxed and then begin a steep decline as the water shortage becomes increasingly severe. It should be noted that these results are influenced by economic factors beyond merely the availability of irrigation water. For example, one can see from the figure that the returns start to decline slightly even before the water shortage begins and continue to decline sharply after the water shortage has reached its maximum of 15% of the weeks dry. The figure clearly demonstrates the significant impact the water shortage has on the rate of returns.

It is also critical to examine the weekly distribution of water among the three competing crops and to determine the impact of this selection on the yield of each crop. These results are demonstrated in Figures 6 and 7 respectively. Again, these results are for a fixed 200 ac-ft pond size and for initial soil moisture conditions of 10%. As before, the water shortage is being generated by the increase in acres to be irrigated. Figure 6 effectively demonstrates how the optimization process selects the amount of water to place on each crop as the shortage grows. Basically, for cases of no shortage (*i.e.*, 100 acres planted), each crop gets as much water as it needs. Then, as the shortage begins (*i.e.*, 1000 acres planted), the irrigation is maintained on the more high value crops (peanuts and cotton) while the corn irrigation is decreased. Figure 7 can be used to evaluate the effects on the yield of these irrigation decisions. One can see from comparing the two figures that as the irrigation applied to the corn is decreased, its yield takes an immediate sharp drop. Thus, the relatively low value of the corn offsets its relative sensitivity to water supply. The process continues as the water shortage is increased to 2500 acres to be irrigated with the fixed supply. One can see from Figure 6 that the algorithm seeks to maintain irrigation on the peanuts and thus greatly reduces the amount of water placed on the cotton even though cotton is the higher value crop. The reason for this decision can be seen from Figure 7, *i.e*., cotton is obviously less sensitive to irrigation than are peanuts. Thus, the maximum total returns can be obtained by maintaining the yield of peanuts as much as possible because the cotton yield will not be as affected by decreasing the irrigation.

4. Summary and Conclusions

Water allocation in competing uses is an increasingly important issue in the Southeast USA. A decision tool was developed to maximize total economic returns from a typical farm by allowing optimal allotments of weekly irrigation water from a storage pond. The resulting optimization of yields would allow a farm operator to concentrate on optimization of irrigation water application in a few critical weeks for a given crop, instead of the entire growing season. Assessment of crop yields (and resulting net farm returns) was accomplished by conducting exhaustive combinations of storage pond surface area, acres planted (and irrigated), and initial soil moisture conditions. The algorithms appeared to generate reasonable results in light of the water sensitivity and economic value of the crops simulated. The methodology developed can be useful for other applications such as nutrient application, and can serve as a decision support tool to farm operators.

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Table 1. Agricultural Census Data for Henry County, AL

Number of Farms	325
Total Number of Farm Acres	103808
Total Irrigated Land Acres	2958
Corn Acreages	9621
Wheat Acreages	2327
Cotton Acreages	6474
Soybeans Acreages	313
Peanuts Acreages	42857
Hay Acreages	3838

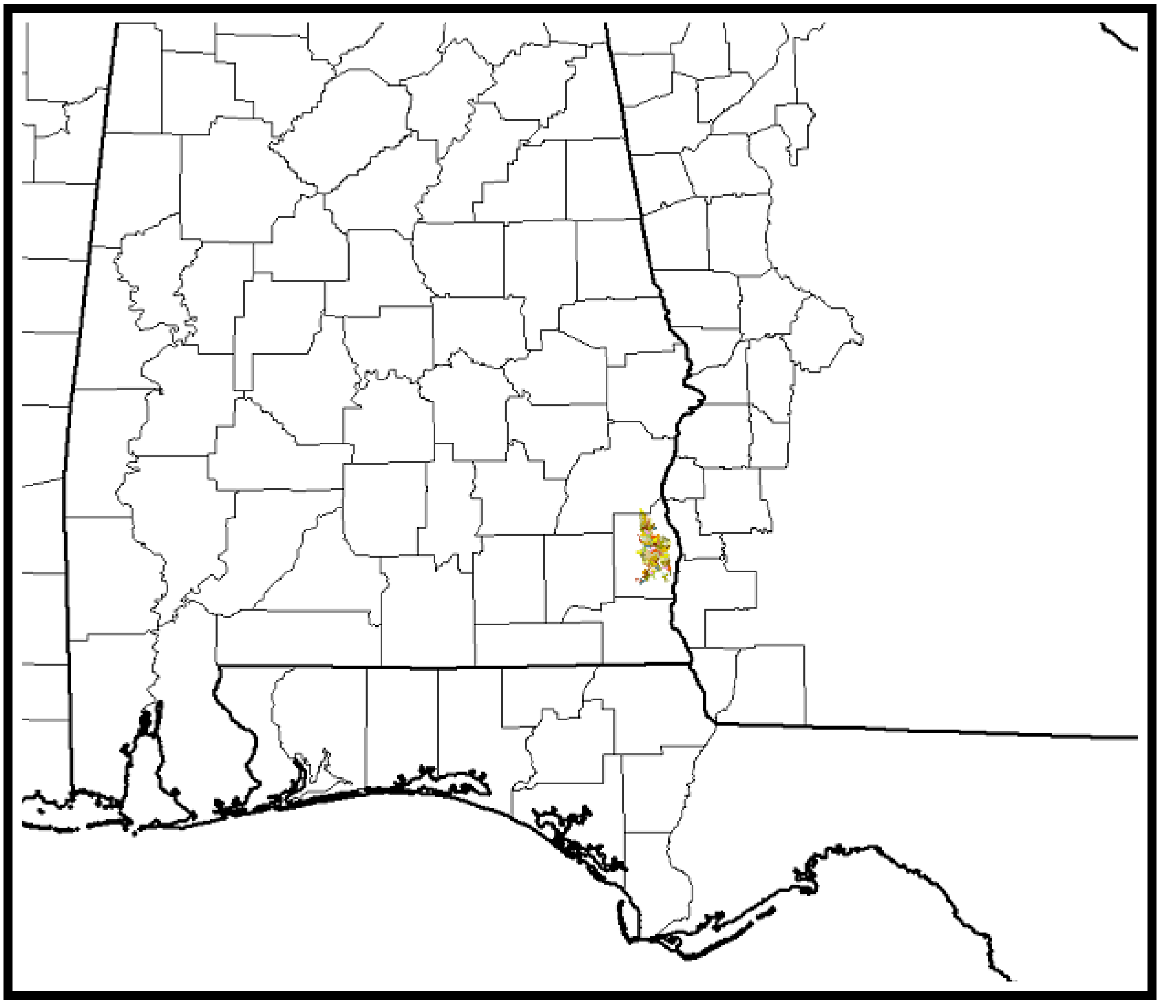

Figure 1. Location of Abbie Creek in Henry County.

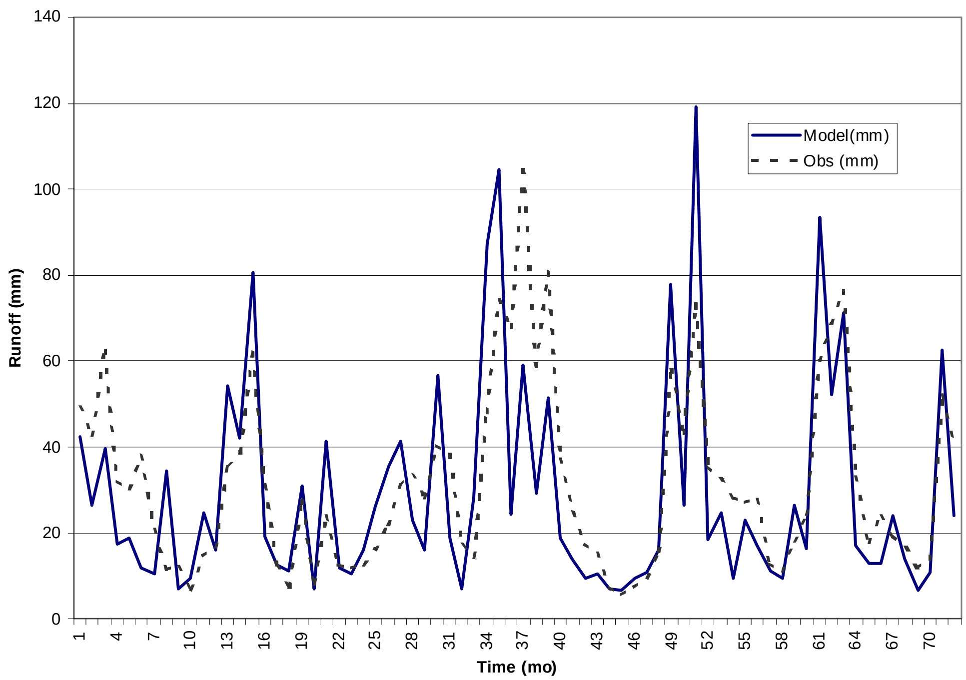

Figure 2. SWAT Simulations Comparisons for Abbie Creek: 1986-92

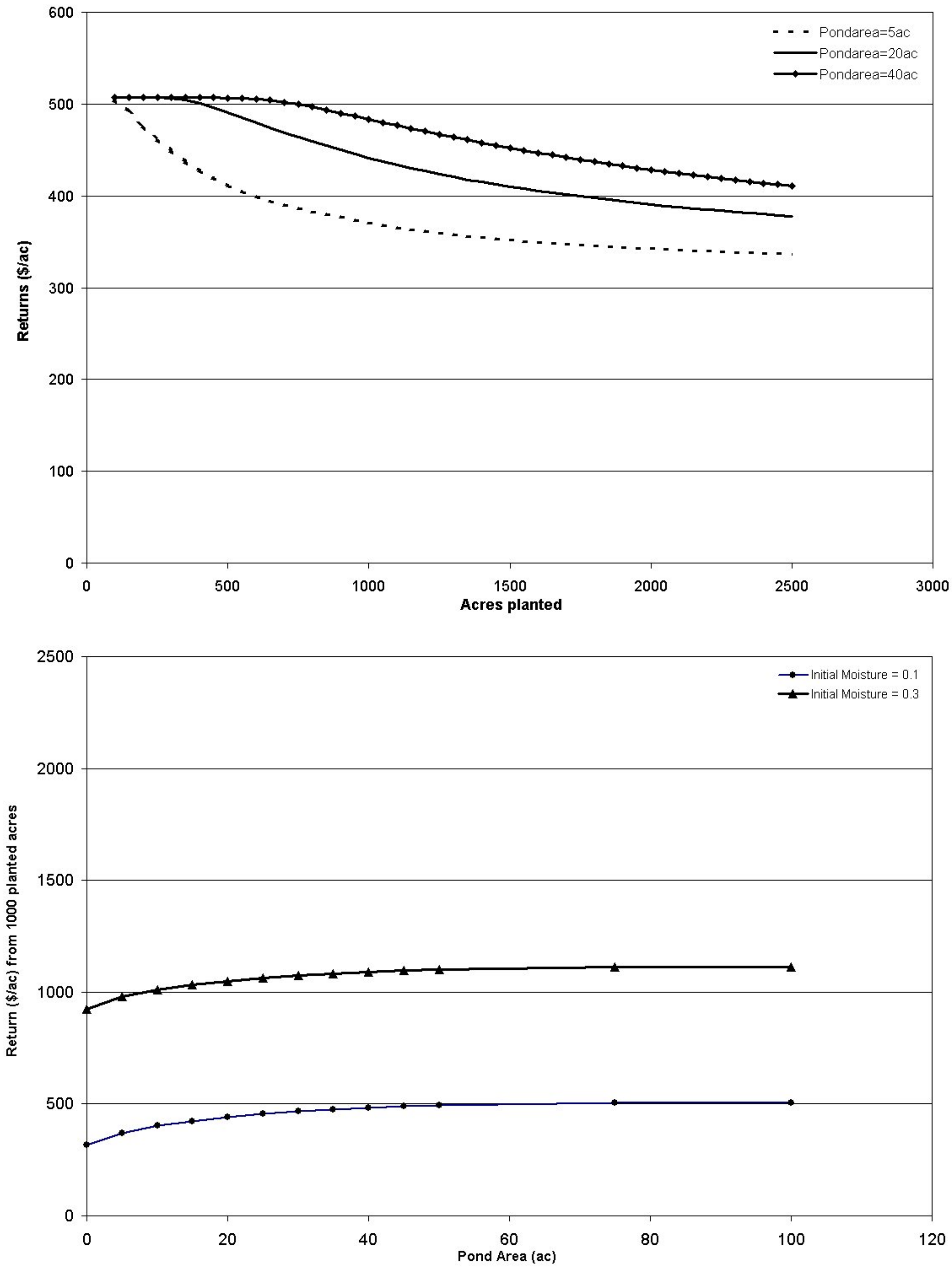

Figure 3. Total farm returns as a function of pond size and crop acreages.

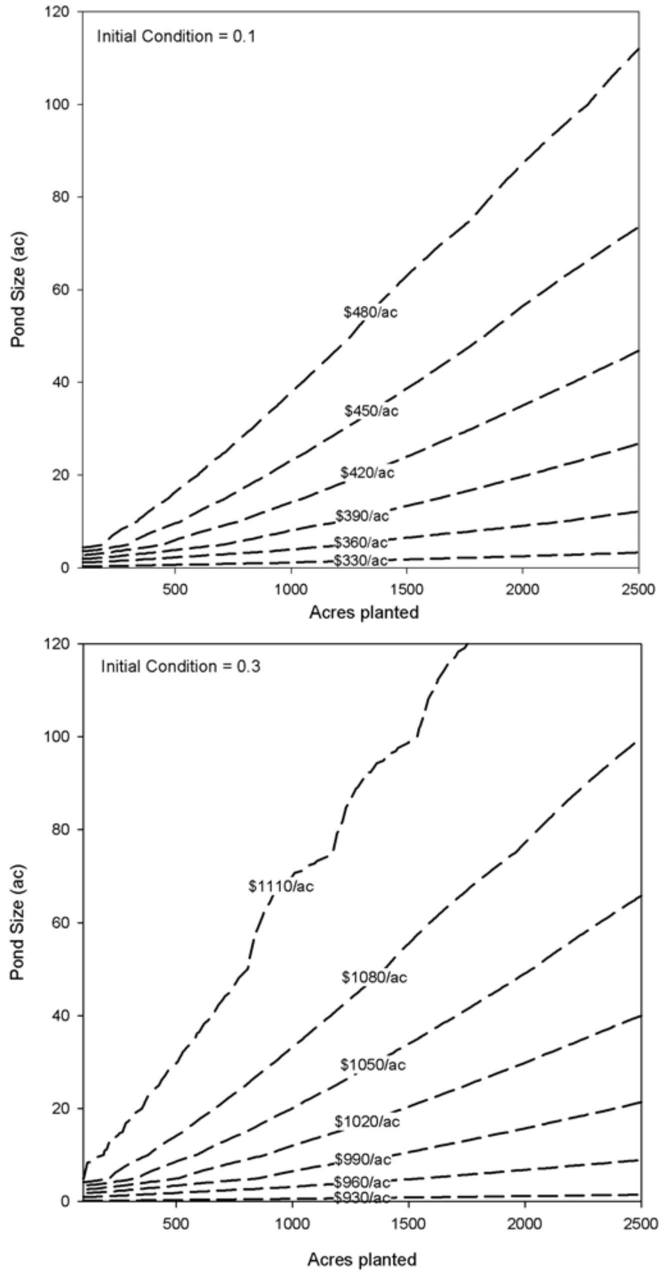

Figure 4. Contours of total returns as a function of pond size, total acreages and initial soil moisture conditions.

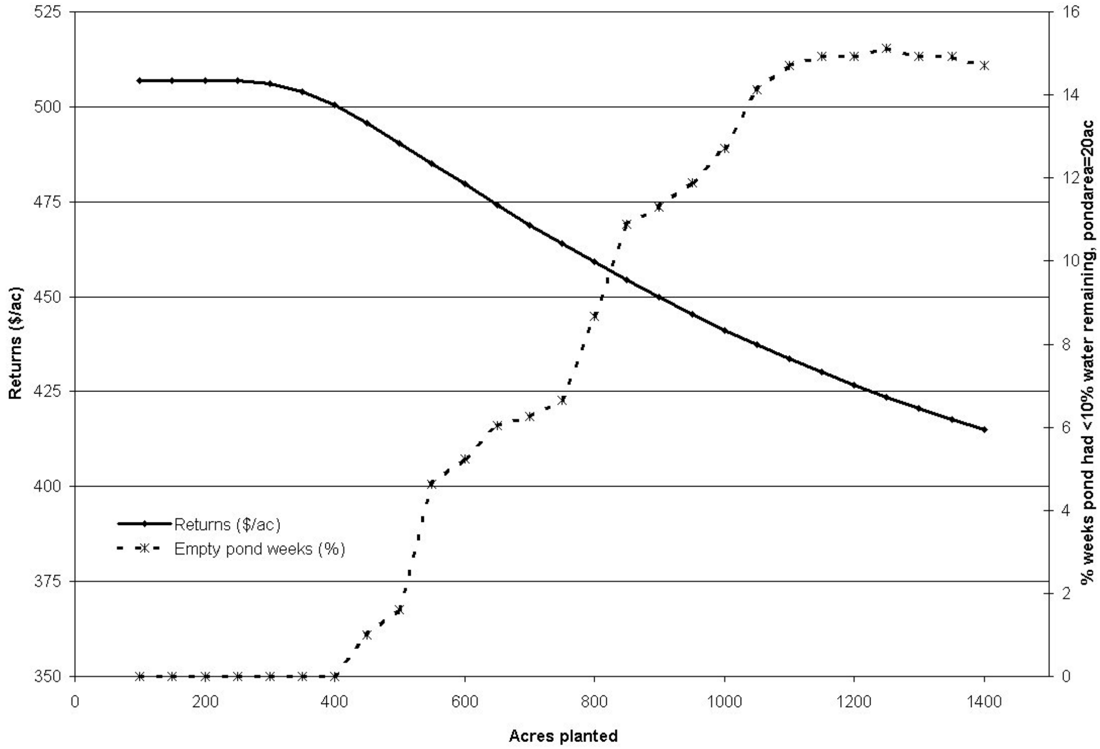

Figure 5. Assessment of total returns in relation with acres planted and corresponding % weeks the pond was nearly empty during the 62-year simulation period.

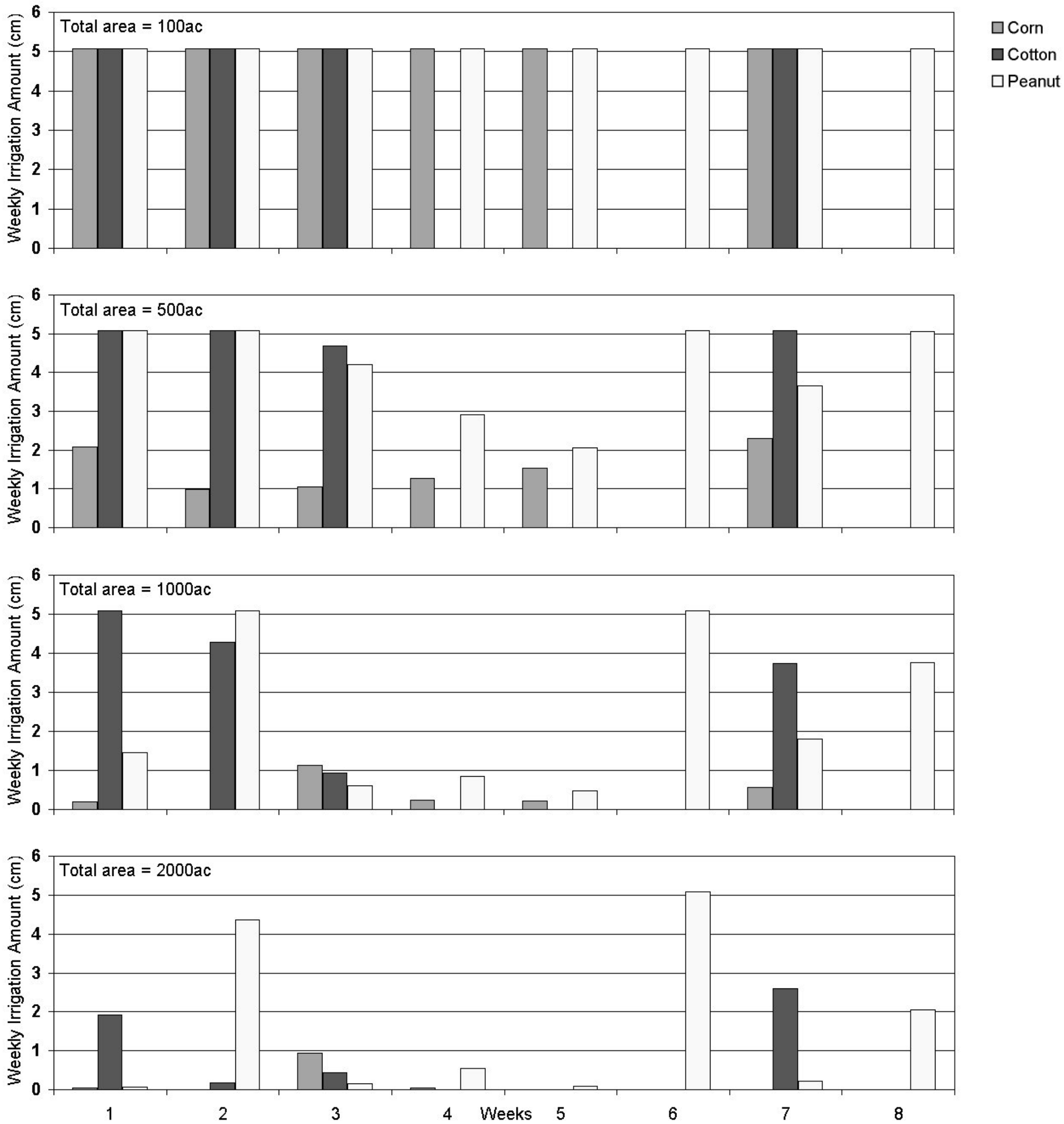

Figure 6. 62-year average weekly irrigation amounts for different acreages from a fixed 200 ac-ft pond size.

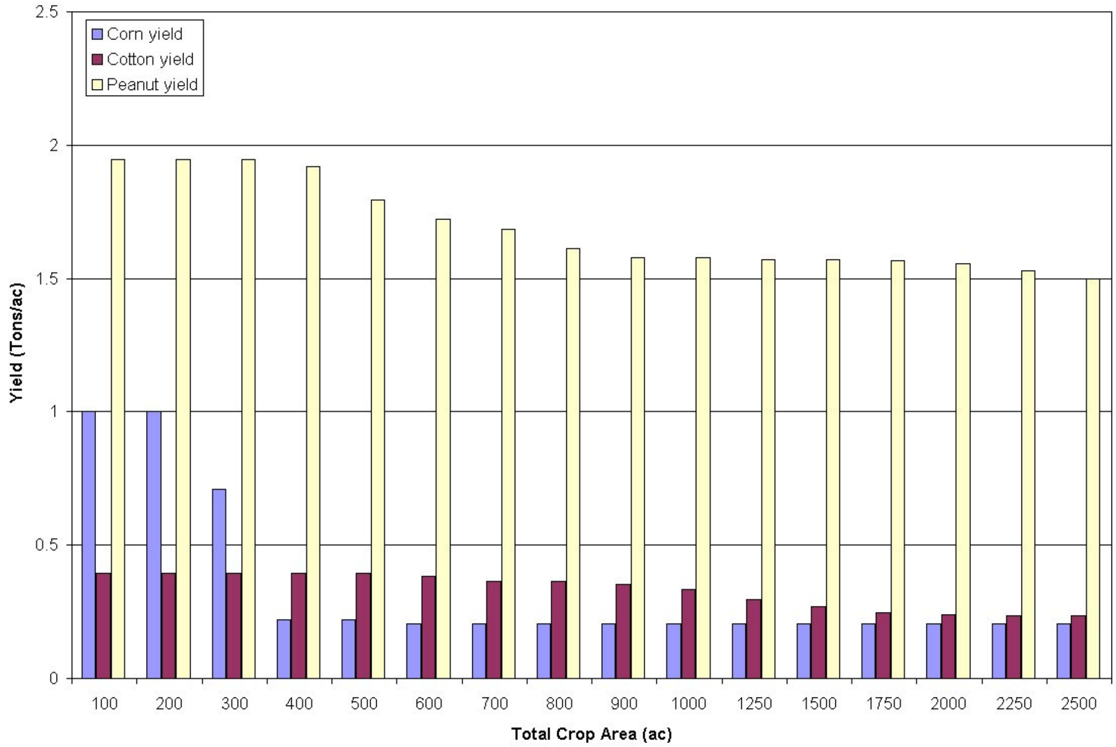

Figure 7. Yields from three crops as a function of total crop acreages.