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Development of a distributed artificial neural network for hydrologic modeling

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Development of a Distributed Artificial Neural Network for Hydrologic Modeling

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1. Background

1.1 Watersheds and Watershed Management

Water is one of the most important natural resources. It "drives all human systems and those of most other organisms as well" (Heathcote, 1998). Watersheds are particularly important in managing water resources, as they are broadly defined as the area of land that contributes runoff to a particular point. Managing a watershed is crucial for maintaining good ecosystem and human health. Runoff is an important aspect of watershed management. Runoff is precipitation that falls onto the earth but does not infiltrate into the soil, evapotranspire through plants, or get stored. Runoff carries with it nutrients, sediments, and pollutants until it eventually reaches a body of water. Nutrients, sediments, and pollutants that did not get deposited along the way may end up in water bodies. Simulation of runoff is an initial step in watershed management.

There has also been a push recently to organize governmental organizations and entities based on watershed boundaries. The watershed-based approach of policy-making, although not well known to most Americans, has been around since the time of John Wesley Powell. With growing human population and the corresponding growth of environmental concerns, the idea of watershed-based governmental organization is again being considered. Watershed boundaries are identified as good boundaries for political control because they "are meaningful ecologically, defined spatially, can be nested hierarchic ally, and because the health of an entire watershed generally can be measured by the health of the aquatic system" (McGinnis, 1999).

1.2 L'Anguille River Watershed (LRW) as a Case Study

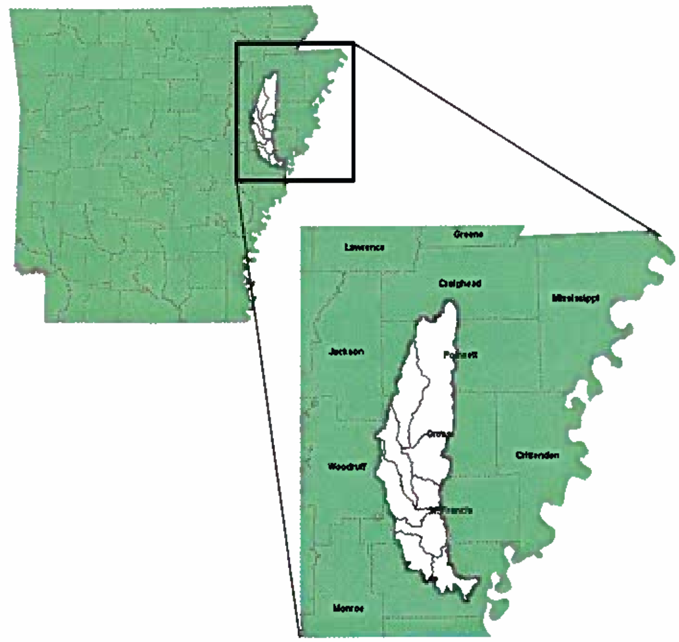

Fig. 1. Location of LRW in Arkansas and counties encompassed.

L'Anguille River Watershed (HUC 08020205) is located in Eastern Arkansas, United States (Appendix A). The watershed encompasses six counties in Arkansas: Craighead, Poinsett, Cross, Woodruff, St. Francis, and Lee (Figure 1). There are two main reasons the LRW was chosen as a case study for this research. First, the population of L'Anguille River Watershed in 2000 was 46, 169 giving a population density of only 49.39 people per square mile (AWIS). The watershed is mostly agricultural land, followed by forest and urban areas (Figure 2). Because of the large agricultural industry and the relatively small population, the main land-use/land-cover (LULC) changes in the watershed occur due to crop rotation, and little due to urbanization. The second reason the LRW was chosen as a case study was because, due to its large agricultural production, has some major pollution problems. Under section 303(d) of the Clean Water Act, states are required to develop a list of impaired waters that are too polluted or degraded to meet water quality standards set by that state (USEPA). The states are then required to establish rankings for the water bodies listed and develop Total Daily Maximum Loads (TMDLs) for the pollutant that is causing the water quality problems. Since 1995, there have been seven TMDL reports on the L'Anguille River, five for turbidity and two for fecal

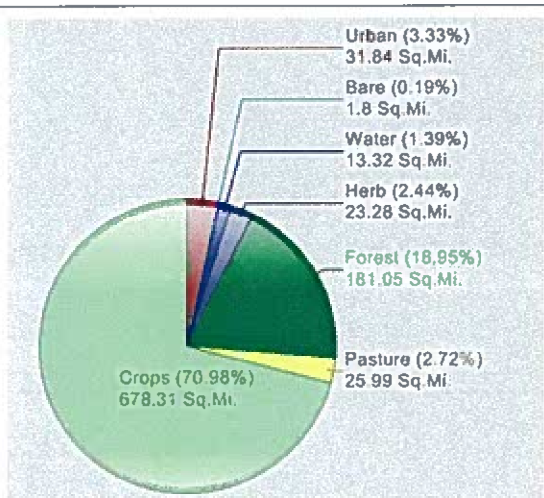

Fig. 2. 2006 land cover percentages for LRW (AWIS)

coliforms (USEPA). In 2008 the river had twelve of its reaches totaling over 98 miles designated as impaired (Class 5) by the Arkansas Department of Environmental Quality (ADEQ, 2008). Excess chloride and lead in these reaches as well as low dissolved oxygen levels were the main reasons these reaches were designated as impaired. Agriculture was the source of these pollutants and problems in all known cases (Appendix A). Five of the twelve reaches designated as impaired in 2008 were classified as 5a streams meaning they are "truly impaired" and TMDLs need to be developed for the given parameter.

The importance of being able to accurately monitor and predict the runoff in L'Anguille River Watershed is a crucial factor in being able to monitor and manage the pollutant loads of the L'Anguille River.

1.3 Hydrologic Models

Hydrological modeling is a field of study that attempts to utilize mathematical and analytical models to both model watersheds and predict watershed characteristics. Many hydrologic models have been developed in attempts to model different aspects of watersheds. One very common model is the Soil and Water Assessment Tool (SWAT). SWAT models are often used for modeling watersheds, but they have difficulty accounting for LULC changes other than crop rotation. This is a problem because these parameters not only vary within a watershed, but they are also interrelated to one another. For example, the runoff in one section of a watershed may contribute flow into a different section of the watershed. Therefore, typical models are incapable in handling complex relationships between large amounts of data efficiently.

1.4 Artificial Neural Networks

Artificial Neural Networks (ANNs) were designed to process and transfer information similarly to the neurons in a human brain. Broadly, a neural network is given a variety of inputs and corresponding outputs (Figure 3). These inputs enter into a hidden layer or layers that contain neurons. As the inputs pass through the hidden layer, weights and biases are added to the data. When the weighted data goes through a neuron, it is processed with a non-linear function in an attempt to relate the input data to the target data. Simply put, ANNs have the ability to relate input and output variables in complex systems (Dawson and Wilby, 2001).

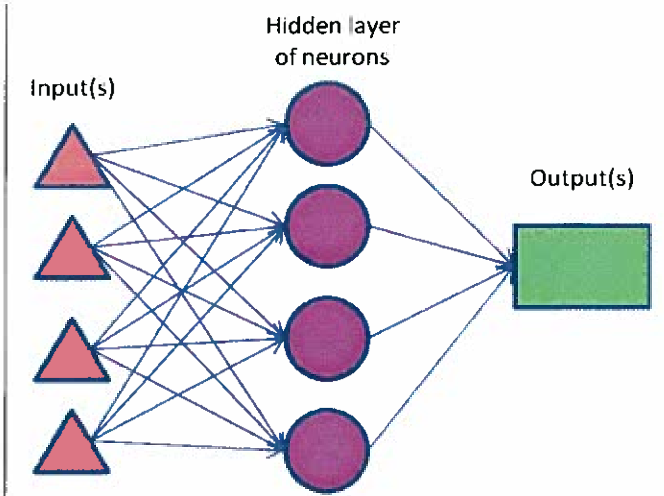

Fig. 3. Simple illustration of ANN.

Artificial Neural Networks (ANN) are relatively new to hydrologic modeling, but have the ability to handle multiple data inputs and relate them in non-linear spatial ways (Dawson and Wilby, 2001). ANNs also have the capability to account for dynamic changes in a watershed such as changes in land use and land cover. This property is especially important for watershed management, because increasing human population leads to a rapidly changing landscape. Typically, ANNs used in hydrologic models are feed-forward, back-propagation networks with one hidden layer of neurons. Input and target data along with network parameters are entered. Data flows forward through the network, where the network compares the computed output to the known target by calculating an error (usually mean squared error). If the error goal is not met, the network keeps re-running the data, changing the weights and biases until a given network parameter is met. The problem with this typical use of ANNs is that it does not have the ability to spatially relate the input parameters.

In this research, however, a pre-defined network in MatLab® was not used to model the LRW. Instead, a custom ANN with a specific architecture was defined in order to better capture the spatial dynamics of the flow within the watershed.

1. 5 Significance of research

Being able to accurately and efficiently model aspects of a watershed, particularly runoff is very important in monitoring and controlling non-point source pollution within the watershed. Unlike point-source pollution, non-point source pollution is difficult to pinpoint and quantify. It is carried through runoff and sediment flow in and out of watersheds. Because of the Clean Water Act (1972) and its regulations, it is important to be able to quantify pollutant and sediment transport in a given watershed. Water health and quality is a good indication of ecosystem health and health of the human population. Water is the most essential resource for human survival. It is needed for drinking, for growing food, and for cleansing purposes. Lack of clean water leads to many waterborne diseases and even death. Being able to quantify, monitor, and even predict runoff and the pollutant loads in the runoff is a great step towards conserving and managing watersheds and water resources.

2. Methods

2.1 Determining Inputs for ANN Model

It is widely understood that a general mass balance of water for a watershed is given by Equation 1:

Equ. 1: Precipitation = Runoff + Infiltration + Evapotranspiration + Change in storage

Rearranging Equation 1 to solve for runoff:

Equ. 1b: Runoff = Precipitation –Infiltration – Evapotranspiration –Change in storage

Thus, in order to accurately predict the runoff in a particular area, it would be ideal to have exact values of precipitation, infiltration, evapotranspiration, and change in storage. Current technology, however, does not allow for the exact calculation of all these parameters. Thus, there is a need to create hydrologic models that can take currently available data and mathematically relate them in order to estimate runoff. Precipitation can be measured fairly accurately in a region with rain gages or by using remote sensing. Infiltration is related to the land cover, slope/topography and soil type of a region.

Infiltration rates of different soils have been heavily studied by the Natural Resource Conservation Service (NRCS), and general infiltration of different land covers has been studied as well. Evapotranspiration is a term that encompasses the amount of water that is evaporated from the ground plus the amount of water that is transpired through plant respiration (USGS). Evapotranspiration is controlled mostly by climate, but also by plant species, fractional vegetation cover, vegetative health, and land cover. Change in storage is a parameter describing the amount of water "stored" in an area in the soil, man-made structures, ponds, and anything that will contain precipitation and prevent or delay it from going to runoff. Controlling factors of storage are topography, bedrock type, land use, infiltration rate, etc.

The complexity of the interactions of the water cycle justifies the need for a neural network model. Thus, the inputs selected for the model should be controlling factors that influence the water balance equation. For this research inputs chosen for the initial model were precipitation, average temperature, and SCS Curve Number. Precipitation was an obvious choice for an input as it is fairly accurately measured and a direct influence on runoff. Daily precipitation data (from January 1995 to December 2004) was taken from four weather stations in LRW at Beedeville, Mariana, Wynne, and Madison (Appendix A). The closest weather station to a subbasin was used for its precipitation data. Daily average temperature (from January 1995 to December 2004) was chosen as an input because it is a controlling factor for evapotranspiration and can influence infiltration rates of soils. Average temperature data was taken from the same four weather stations as the precipitation data. The third input chosen was SCS Curve Number. The SCS Curve Number is a method that was developed to predict the amount of runoff that would come from a certain area of land based on the soil type and LULC. Curve numbers range from 0-100 with a curve number of 100 corresponding to 100% of rainfall going to runoff. Therefore, a CN allows for a quantitative description of the soil type and land cover of an area of land in relation to infiltration and runoff. As mentioned previously, land cover and soil type are controlling factors in infiltration rates, evapotranspiration, and storage.

2.1.1 Cross-Correlation of RF-RO to Determine Lag

The lag time of a storm is defined as the time from the peak of a precipitation event to the time it takes for the hydrograph of a nearby stream or river to peak. This lag time can be anywhere from minutes, to days, to weeks depending on factors such as infiltration, topography, and ground water movement. Therefore, it is important to determine whether or not to use antecedent rainfalls as inputs into the model. In order to do this, a cross-correlation analysis of rainfall to runoff (RF-RO) was performed up to four previous days to determine if antecedent rainfall affected runoff. The correlation coefficient for same day and four day's previous was calculated using Excel® for each sub-basin and then plotted (Appendix A). The results for all nine subbasins showed that the highest correlation between rainfall and runoff occurred on the same day. Therefore, only the same day's precipitation was used for an input into the model.

2.1.2 Development of SCS Curve Number

The two pieces of information needed to formulate an SCS CN of an area of land are the hydrologic group of a soil and the land use/ land cover of an area of land. There are four hydrologic groups used for classifying soils based on the SCS CN method, which classifies soils by their relative runoff potentials. Hydrologic group A contains soils that are least likely to produce runoff when thoroughly wet and are typically 10% clay and 90% sand or gravel (USDA, NEH). Hydrologic group B contains soils that have "moderately low runoff potential when thoroughly wet" and is typically 10-20% clay and 50-90% sand (USDA, NEH). Hydrologic group C contains soils that have "moderately high runoff potential when thoroughly wet" and contain 20-40% clays and <50% sand (USDA, NEH). Lastly, hydrologic group D contains soils that have "high runoff potential when thoroughly wet" and are typically >40% clay and

<50% sand (USDA, NEH). LULC is also used to determine the SCS CN. All land cover types allow for a certain amount of rainfall to infiltrate and the rest to runoff. For example, pervious land covers such as cement and asphalt allow for zero infiltration, therefore all rain that falls on these surfaces goes to runoff.

Since the data for daily precipitation and daily average temperature was from 1995-2004, LULC and soil information were needed for approximately the same time period. LULC data for the spring, summer, and fall for 1999 was available from the Arkansas Soil and Water Conservation Commission and the University of Arkansas' Center for Advanced Spatial Technologies (CAST). Soils data for the six counties in LRW was available from the U.S. National Resource Conservation Service and the University of Arkansas' Center for Advanced Spatial Technology databases.

Using ESRI's ArcGIS and specifically ArcMap, the first step to developing the CN data was to dissolve the soil data based on the hydrologic group of the soil (Appendix B). Next, the LULC data for spring, summer, and fall of 1999 was dissolved based on the name of the land cover (Appendix B). The dissolved soil data and LULC data were intersected to form the soil-cover complex. The area of each unique soil-cover complex was calculated using a simple visual basic code in ArcMap. Then the soil-LULC complex was clipped to each subbasin so that each subbasin had its own soil-LULC complex data. Using the soil-cover complex database files along with NEH curve number tables (USDA NEH, 2008) the curve number for each soil-cover complex could be determined. Next, using Equation 2, the area weighted CN for each subbasin was calculated.

Equation 2: $$A_W CN = \sum_{i=1}^{n}\left(CN_i \times \frac{A_i}{A_T}\right)$$

where $A_w CN$ = area weighted CN

CN_i = CN of soil-complex *i*

A_i = Area of soil-complex *i*

A_T = Total area of subbasin

n = number of soil-complexes in subbasin

The area weighted CNs calculated for the spring, summer, and fall of 1999 for each subbasin were assumed to be similar enough to the spring, summer, and fall of 1995 to be used as the "base" CN for the beginning of the data.

2.1.3 Adjusting Curve Number for Crop Planting and Harvesting Dates

The data collected for the LULC was collected during the spring, summer, and fall of 1999. It is not very accurate to divide the 365 days of the year into these three time periods and assume that the LULC will not vary within each time period. This is especially true during the some of the winter months when only wheat is grown; the "fall" LULC data are not sufficient for the winter months. Thus, the LULC data were assumed to be true for the dates which the data was collected (Appendix C). Next, the LULC for each subbasin was adjusted based on planting and harvesting dates of crops. Data on common planting and harvesting dates from the USDA Agricultural Handbook No. 628 (USDA, 1997) was used to determine the earliest planting dates and latest harvesting dates for each crop (Appendix C). From the dates of the data collection and the planting and harvesting dates of each crop, what crops should be present on each day of the year could be estimated and the curve number adjusted accordingly (Figure 4). If a crop should not be present on a certain day, the area covered by that crop was assumed to be and changed to a land cover of bare soil/seedbed. The results of this CN adjustment was a full year of area weighted CNs for each subbasin, assumed to be for year 1995.

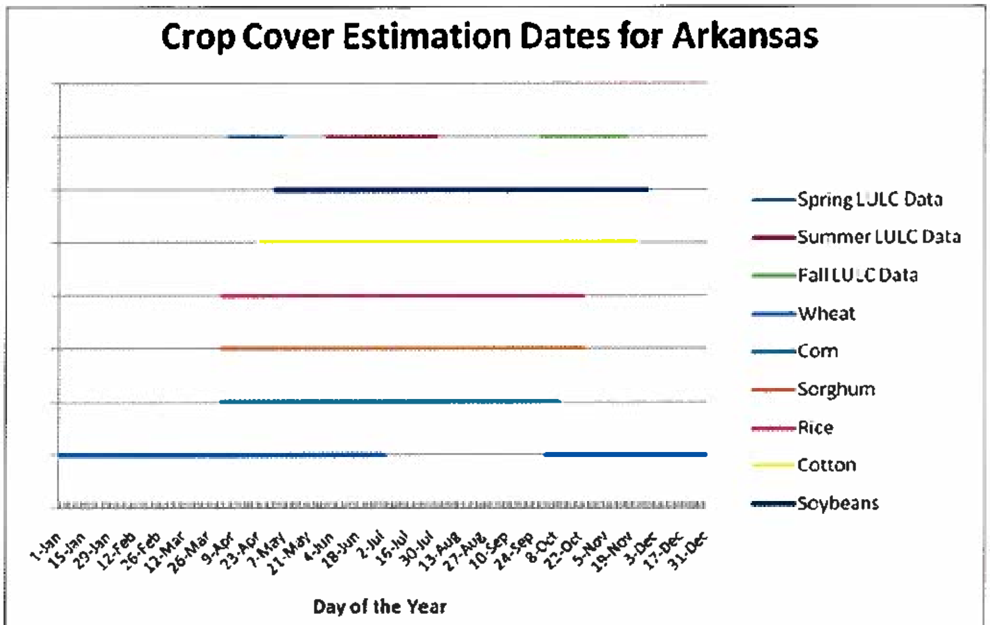

Fig. 4. Crop cover estimation dates based on USDA Agricultural Handbook 628.

2.1.4 Adjusting the Curve Number to Account for Crop Rotation

Now that crop variation within a year had been accounted for in the area weighted CN for each subbasin, the next step was to account for yearly crop rotation. Crop rotation practices vary from farm to farm and from region to region. Therefore, accurate data on exact crop rotation practices is not often recorded. However, crop rotation practices for counties in the LRW were estimated based on a focus group survey of University of Arkansas Cooperative Extension Service agents in six counties in Arkansas, conducted in January of 2001 (Hill, Popp, and Manning 2003). Two counties from LRW (St. Francis and Lee) were included in the survey and the crop rotation practices discussed for these two counties were assumed to be the same for all six counties in LRW. These data were then used to rotate certain percentages of each crop as stated based on Table 22 of the focus survey group report. The resultant data produced was 10 years (January 1995-December 2004) of daily, area-weighted CNs for each subbasin based on LULC and soil type and adjusted to account for crop planting and harvesting dates and crop rotation.

2.2 Determining Network Outputs and Target Data

Since the purpose of this research project was to predict the runoff in LRW at the outlet of each subbasin, naturally the target output for the model was discharge at each outlet. However, there are only two USGS gage stations along the entire reach of the L'Anguille River (at outlets of subbasins nine and eight). Therefore, simulated discharge data for subbasins 1-7 from previous research on L'Anguille River Watershed was used as target data for these subbasins (Srivastava et. al, 2005). The data were simulated using a SWAT model.

2.3 Constructing Preliminary Network Architecture

The goal of this research project was to create an ANN that could account for the spatial dynamics of flow of water within a watershed. This was accomplished by creating a custom ANN instead of using a pre-defined network within MatLab®. By custom defining the network, the architecture could be arranged in such a way that the output of one subbasin could be an input into the next subbasin if the first subbasin's flow added to the next subbasin's flow.

The network created contained three initial inputs for each subbasin, nine layers with one neuron each representing each subbasin, and one target output for each subbasin. The network was custom created to account for the spatial dynamics of the water flow between the subbasins within the watershed (Figure 5).

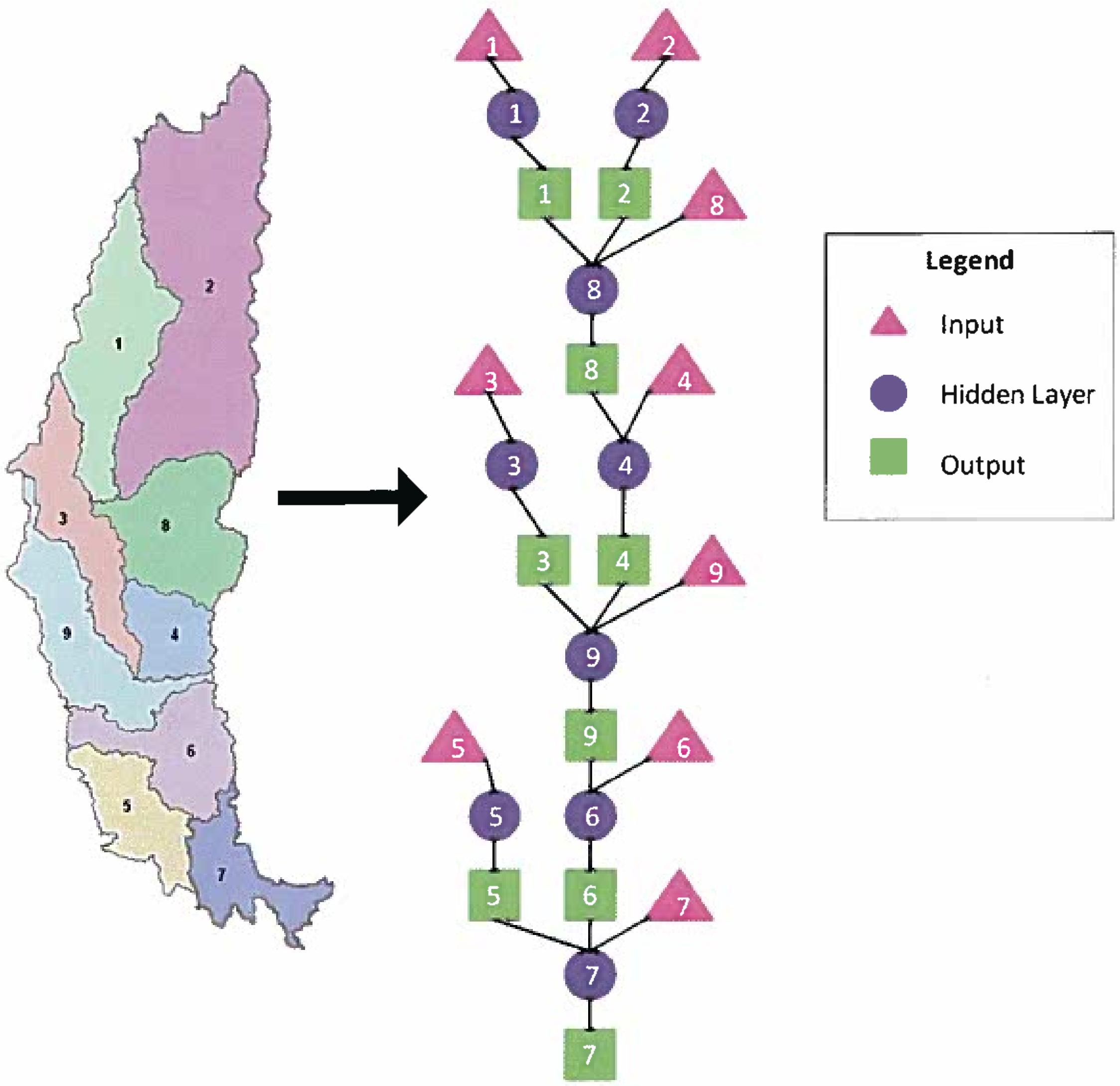

Fig. 5. Network architecture to account for spatial dynamics of low within the watershed.

To do this, subbasins 1 and 2 outputs became inputs for subbasin 8. Output from subbasin 8 became an input for subbasin 4. Outputs from subbasins 3 and 4 became inputs for subbasin 9. Subbasin 9 output was an input for subbasin 6. Outputs from subbasins 5 and 6 became inputs for subbasin 7.

For network training the Levenberg-Marquardt algorithm was used as the training algorithm and the performance of the network was measured by the Mean Squared Error (MSE). The data sets were also divided into training, testing, and validation data sets. Because the training of the network requires the most data, 60% (1997-2002) of the data set was used for training, whereas 20% (1995-1996) was used for testing and 20% (2002-2004) for validation.

2.4 Optimization of Network Parameters

Because only one neuron was used in each layer, it was not necessary to optimize the number of neurons. Thus, optimization was performed only on the training parameters. Since the training function chosen was Levenberg-Marquardt (trainlm), the only option for optimization of the network was the learning rate. A trial and error procedure was followed by varying learning rate at different increments. The optimized learning rate was identified as the one that resulted in the lowest mean square error (MSE). The R-square value, MSE, and Nash-Sutcliffe Model efficiency was used to determine the optimum learning rate value.

3. Results

The custom defined neural network was run, using the optimized learning rate. The model was evaluated using three different methods using the validation data set: (1) calculating the mean-squared error between the computed and observed results, (2) calculating the linear regression value between computed and observed results, and (3) calculating the Nash-Sutcliffe efficiency coefficient for hydrologic models.

3.1 Graphical Representation of Model Results

The computed values of each subbasin and the actual values, were reverse-normalized to get back to real values and then plotted versus one another in order to visually observe the results of the model (Figures 6-14).

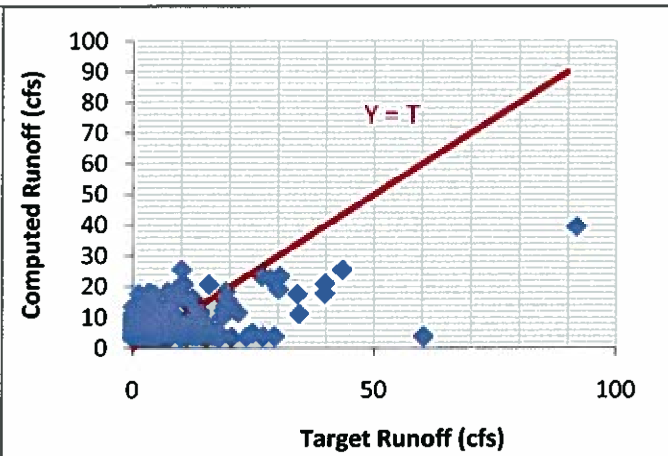

Figure 6. Computed versus actual runoff values for subbasin 1.

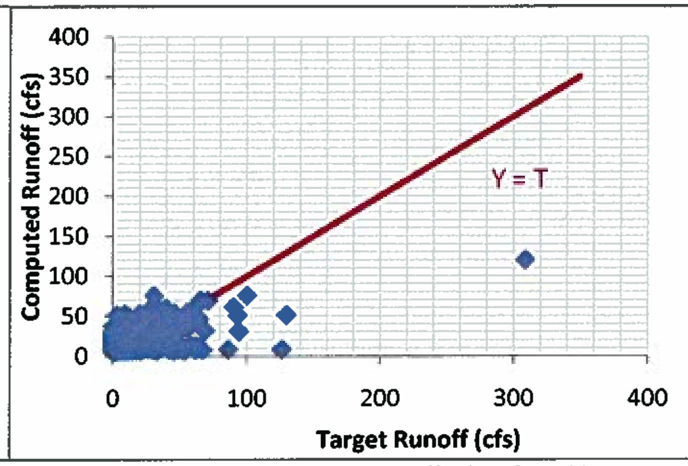

Figure 7. Computed versus actual runoff values for subbasin 2.

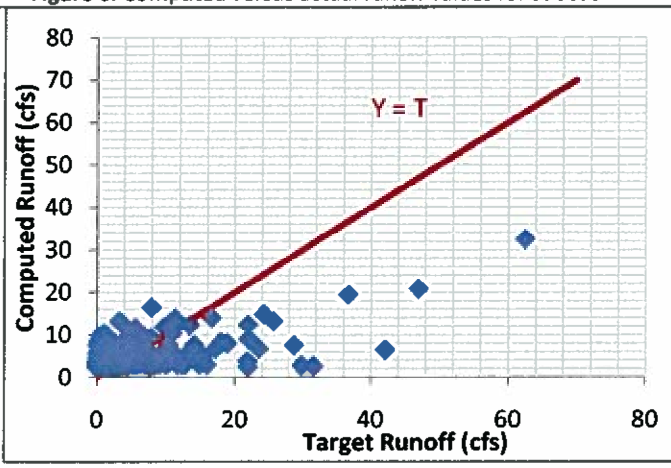

Figure 8. Computed versus actual runoff values for subbasin 3.

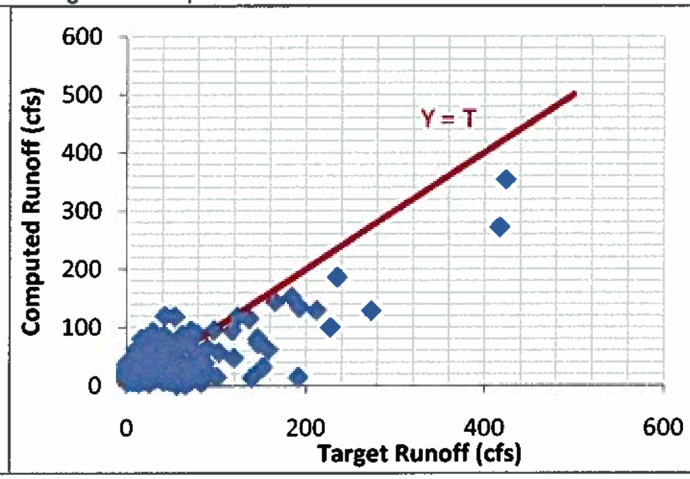

Figure 9. Computed versus actual runoff values for subbasin 4.

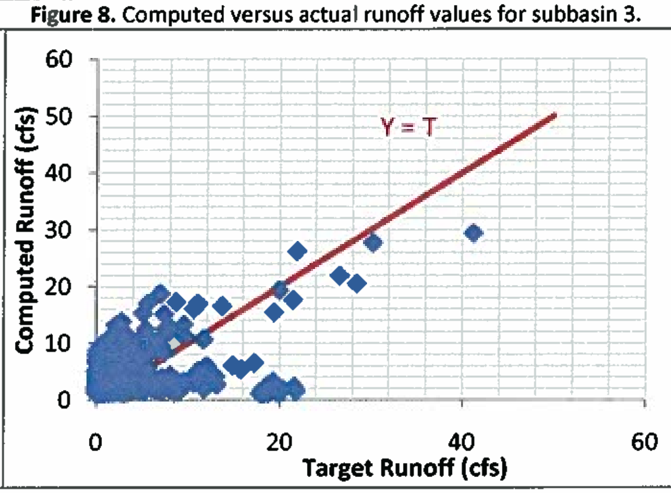

Figure 10. Computed versus actual runoff values for subbasin 5.

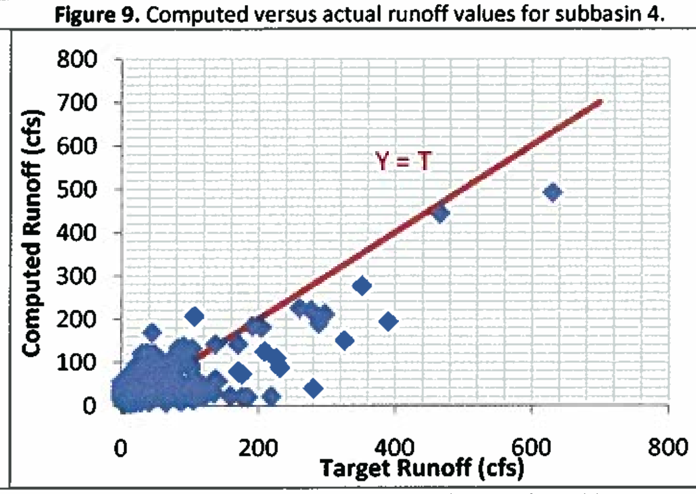

Figure 10. Computed versus actual runoff values for subbasin 6.

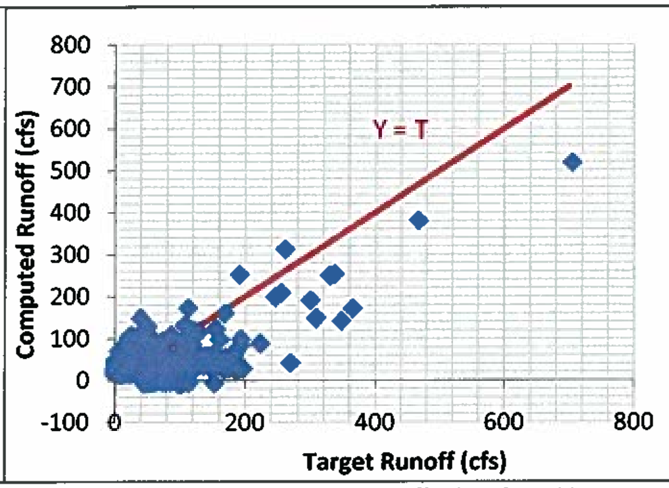

Figure 12. Computed versus actual runoff values for subbasin 7.

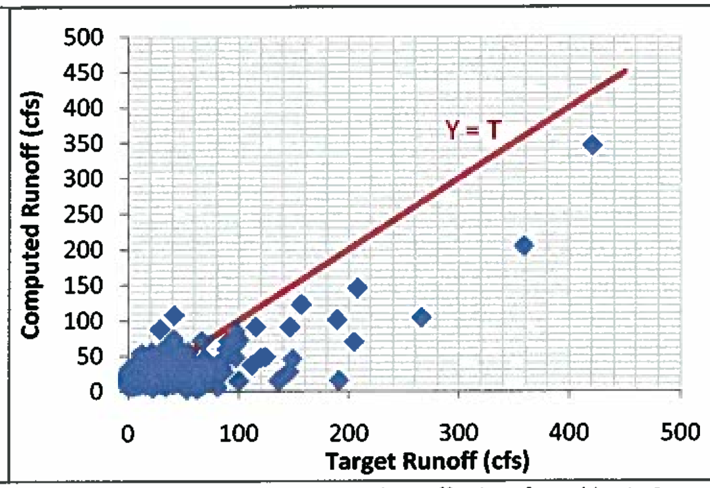

Figure 11. Computed versus actual runoff values for subbasin 8.

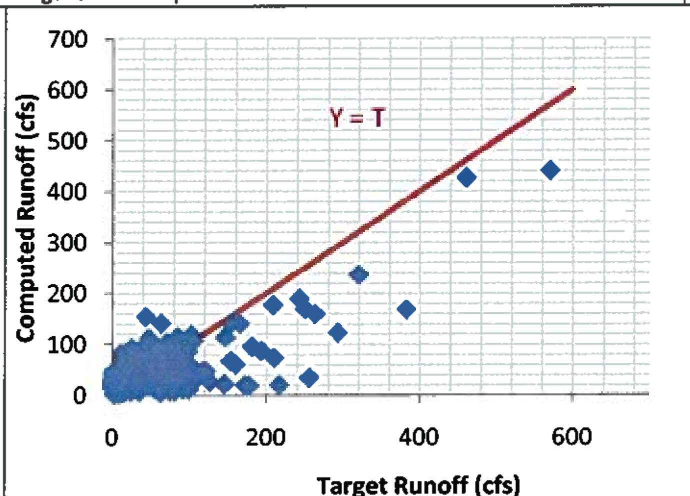

Figure 14. Computed versus actual runoff values for subbasin 9.

3.2 Mean Squared Error Results

The MSE was calculated between the model's computed results and the target results for each subbasin's data using Equation 3 (Table 1).

Equ. 3: $$MSE = \frac{\sum_{i=1}^{n}(obs_i - comp_i)^2}{n}$$

Where: obs_i = target value of data point, i

$comp_i$ = computed value of data point, i

n = number of data points

Table 1. Calculated mean-squared error values between model's computed results and target results for each subbasin.	
Subbasin	MSE
1	0.00243
2	0.00119
3	0.00404
4	0.00073
5	0.00206
6	0.00122
7	0.00131
8	0.00092
9	0.00093

3.3 Linear Regression Results

The linear regression value (R) between the model's computed value and the actual target data was calculated using the "postreg" function in MatLab® (Table 2).

Table 2. Calculated linear regression values between model's computed results and target results for each subbasin.	
Subbasin	Regression Value (R)
1	0.56304
2	0.58789
3	0.62414
4	0.78364
5	0.49596
6	0.77095
7	0.71937
8	0.76936
9	0.76878

3.4 Nash-Sutcliffe Model Efficiency Results

The Nash-Sutcliffe Efficiency value is often used for hydrologic models because it is "insensitive to additive and proportional differences between model simulations and observations" (Harmel and Smith, 2007). The Nash-Sutcliffe Efficiency value was calculated for each subbasin's results using Equation 4 (Table 3).

Equation 4: $$NSE = 1 - \frac{\sum_{i=1}^{n}(obs_i - comp_i)^2}{\sum_{i=1}^{n}(obs_i - \overline{obs})^2}$$

Where: obs_i = target value of data point, *i*

$comp_i$ = computed value of data point, *i*

$\overline{obs_i}$ = mean of target values

n = number of data points

Table 3. Calculated Nash-Sutcliffe Efficiency values between model's computed results and target results for each subbasin.

Subbasin	Nash-Sutcliffe Efficiency Value
1	0.27623
2	0.32273
3	0.33598
4	0.58762
5	0.17063
6	0.57973
7	0.50704
8	0.53865
9	0.56802

4. Conclusion

From the results it was concluded that the model was not very good based on the low linear regression values and Nash-Sutcliffe Efficiency values between computed output and actual data. Thus, the next step was to look at possible sources of error and means of improvement for the model.

4.1 Errors Due to Target Data

As previously mentioned, the target data for each subbasin was discharge. However, there was only available USGS gage station data at the outlets of subbasin eight and nine. Therefore, simulated data from previous research was used for the discharge at the outlets of subbasins 1-7 (Srivastava, 2005). In his SWAT model, Srivastava did not take into account rice field flooding. Since LRW is over seventypercent agricultural and rice makes up a large percentage of that land (Appendix C), not accounting for rice field flooding could have led to poor estimations of discharge for the outlets at subbasins 1-7.

4.2 Errors Due to Network Architecture

The custom neural network that was defined in MatLab® in order to account for the spatial dynamics of flow within the watershed was created so that each subbasin was represented by one layer containing one neuron. Then the layers were connected spatially based on which subbasins flowed into one another. Generally, for ANNs to model non-linear relationships more accurately, more neurons are required. Thus, the neuron constraint of the model could have been another large source of error for the network. The relationship between rainfall and amount of runoff is highly complex, so a single neuron is not adequate to represent this relationship.

4.3 Other Possible Sources of Error

There are also some other aspects of the research that could have lead to some minor errors in the model. First, crop rotation practices had to be estimated based on a survey that only incorporated two of the counties in LRW. This was because exact crop rotation practices for these counties in Arkansas were not available. Secondly, the LULC data used for generation of the curve number was based on the year of 1999. However, this data was assumed to be for the year of 1995 (the beginning of the precipitation and temperature data) so this could also have contributed error to the model.

5. Future Work and Improvements

It is recommended that to improve this model for future work that three things be done. First, the entire network architecture should be changed to allow for more than one neuron in each hidden layer so that the network can better relate output to target in non-linear ways. Second, better estimations of crop rotation practices should be determined. Lastly, it is recommended to only look at and compare the output of the model where the target values are actual collected field values.

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USGS. "The Water Cycle: Evapotranspiration." <http://ga.water.usgs.gov/edu/watercycleevapotranspiration.html>

Appendix A

Figure A.1 Location map of L'Anguille River Watershed
Table A.1 2008 Total Maximum Daily Load for L'Anguille River
Figure A.3 Map of Weather and USGS Gage Stations for L'Anguille River Watershed
Figures A.4-A.12 Results of Cross-Correlation of RF-RO to Determine Lag

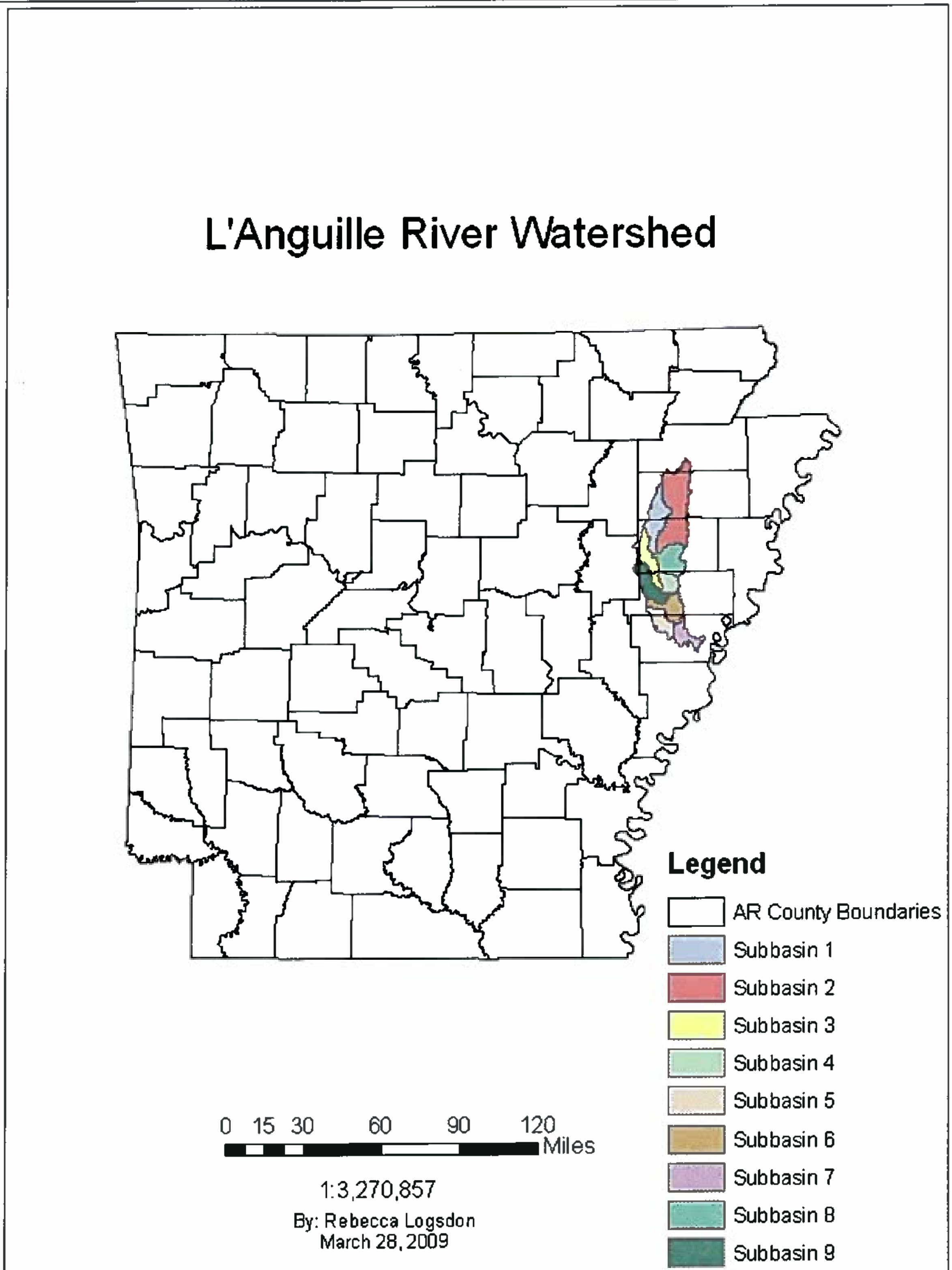

Figure A.1. Location map of L'Anguille River Watershed in Arkansas.

Category 5 Waters: Arkansas's Water Quality Limited Waterbodies (Streams) - 2008 303(d) list

STREAM NAME	HUC	RCH	PLNG SEG	MILES	MONITORING STATIONS	ASSESS TYPE	FISH COMSUMP	AQUATIC LIFE	PRIMARY CONTACT	SECONDARY CONTACT	DRINKING WATER	AGRI & INDUSTRY	SOURCE 1	SOURCE 2	SOURCE 3	SOURCE 4	CAUSE 1	CAUSE 2	CAUSE 3	CAUSE 4	Category	Priority
Spring River	11010010	-007	4H	4.0		E		N					UN				Temp				5f	L
Spring River	11010010	-006	4H	5.3	WHI0022	M		N					UN				Temp				5f	L
Warm Fork Spring R.	11010010	-008t	4H	3.1	WHI0006A	M		N				N	UN	UN			DO	TDS			5d	M
Eleven Point River	11010011	-001	4H	33.1	WHI0005B	M		N					UN				DO				5f	L
Crooked Creek	11010003	-048	4I	31.7	WHI0048A+	M		N					RE				Temp				5a	L
Crooked Creek	11010003	-048	4I			M						N	UN				TDS				5a	L
Crooked Creek	11010003	-049	4I	36.2	WHI0067+	M		N				N	UN	UN	UN	UN	TDS	CL	Be	SO4	5a	L
White River	11010003	-902	4I	3.0	USGS	M		N					HP				DO				5a	H
Bear Creek	11010003	-045	4I	25.9	WHI0174	M					N		UN				Be				5d	L
Bear Creek	11010005	-026	4J	23.9	UWBRK01+	M						N	MP				TDS				5d	L
Buffalo River	11010005	-001	4J	11.3	BUFR09	M		N					UN				Temp				5f	L
Buffalo River	11010005	-005	4J	6.9	WHI0009A	M		N					UN				DO				5f	L
Richland Creek	11010005	-024	4J	28.7	BUFT09	M		N					UN				Temp				5f	L
Holman Creek	11010001	-059	4K	9.1	WHI0070	M					N	N	MP				TDS				5a	L
Kings River	11010001	-037	4K	19.1	WHI0009A	M						N	UN				TDS				5d	L
Kings River	11010001	-042	4K	39.5	WHI0123	M		N			N	N	UN	UN	UN		Be	TDS	DO		5d	L
Dry Fork Creek	11010001	-043	4K	16.5	WHI0127	M					N		UN				Be				5d	L
Osage Creek	11010001	-047	4K	13.4	WHI0130	M					N		UN				Be				5d	L
Yocum Creek	11010001	-052	4K	16.2	WHI0137	M					N		UN				Be				5d	L
White River	11010001	-027	4K	23.8	WHI0106	M		N			N		UN	UN			DO	Be			5d	L
White River	11010001	-023	4K	6.2	WHI0052	M						N	UN	UN	UN		TDS	CL	SO4		5a	M
West Fork	11010001	-024	4K	27.2	WHI0051	M		N				N	UN				DO				5f	M
West Fork	11010001	-024	4K			M						N	UN	UN			SO4	TDS			5a	M
M. F. White River	11010001	-026	4K	8.1	WHI0103	M		N					UN				DO				5d	M
War Eagle Creek	11010001	-034	4K	22.2	WHI0116	M					N		UN				Be				5d	M
St. Francis River	8020203	-014	5A	22.8	FRA0008	M		N					UN				DO				5c	L
St. Francis River	8020203	-014	5A			M		N			N	N	UN	UN	UN	UN	Cu	Pb	CL	Be	5d	L
St. Francis River	8020203	-009	5A	17.1		E						N	AG				CL				5d	L
St. Francis River	8020203	-008	5A	55.9	FRA0013	M						N	AG				CL				5d	L
Caney Creek	8020203	-901	5B	9.0	FRA0034	M						N	MP				TDS				5b	L
~~Second Creek~~	~~8020205~~	~~-008~~	~~5B~~	~~16.4~~	~~FRA0012~~	~~M~~		~~N~~					~~AG~~				~~DO~~				~~5e~~	~~L~~
L' Anguille River	8020205	-005	5B	44.1	UWLGR02	M						N	AG	AG	AG		CL	SO4	TDS		5a	L
L' Anguille River	8020205	-005	5B			M		N					AG				Pb				5d	L
L' Anguille River	8020205	-005	5B			M		N					UN				DO				5f	L
L' Anguille River	8020205	-004	5B	16.0	UWLGR01	M						N	AG	AG			CL	TDS			5a	L
L' Anguille River	8020205	-004	5B			M		N					AG				Pb				5d	L
L' Anguille River	8020205	-004	5B			M		N					UN				DO				5f	L
L' Anguille River	8020205	-003	5B	16.8		E						N	AG	AG			CL	TDS			5a	L
L' Anguille River	8020205	-003	5B			E		N					UN				DO				5f	L
L' Anguille River	8020205	-002	5B	1.8		E						N	AG	AG			CL	TDS			5a	L
L' Anguille River	8020205	-002	5B			E		N					UN				DO				5f	L
L' Anguille River	8020205	-001	5B	19.7	FRA0010	M						N	AG	AG			CL	TDS			5a	L
L' Anguille River	8020205	-001	5B			M		N					UN				DO				5f	L

Table A.1. 2008 List of category 5 impaired streams for L'Anguille River (ADEQ).

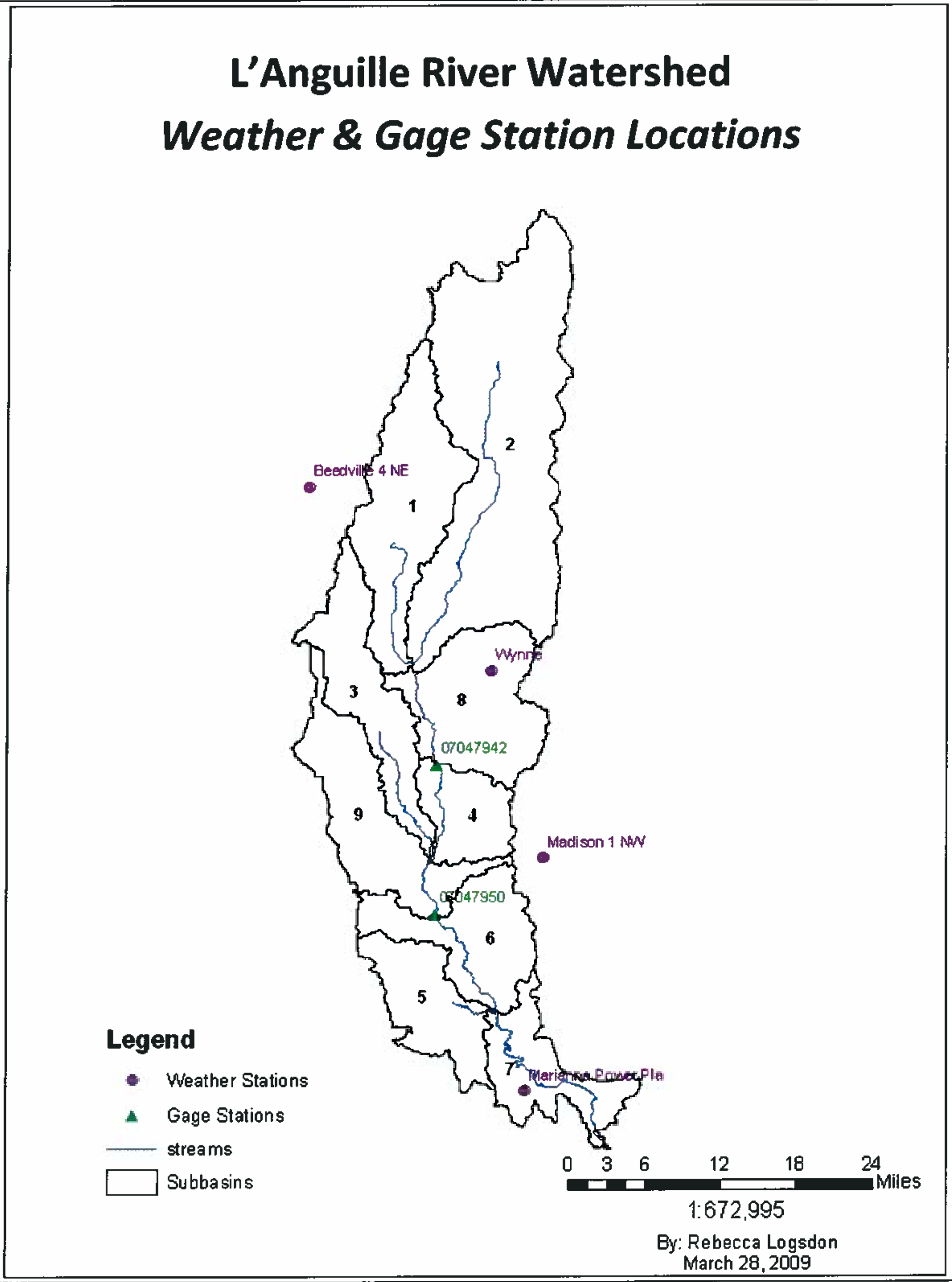

Figure A.3. Locations of weather and gage stations in LRW.

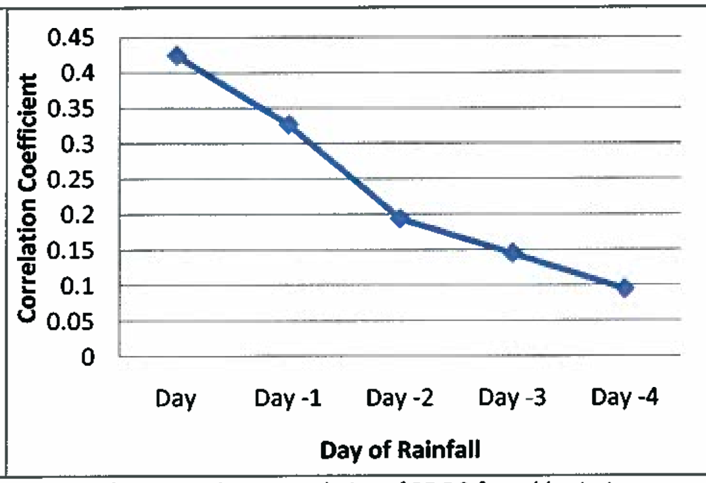

Figure A.4. Cross-correlation of RF-RO for subbasin 1.

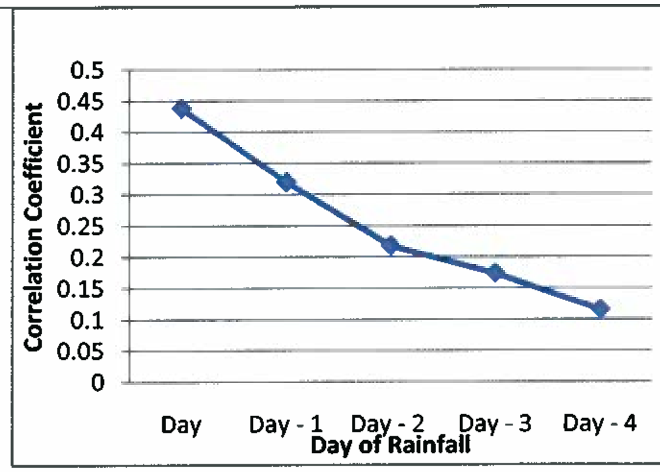

Figure A.5. Cross-correlation of RF-RO for subbasin 2.

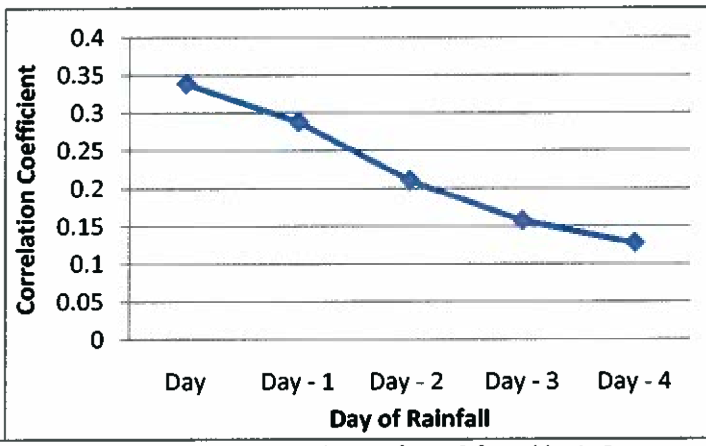

Figure A.6. Cross-correlation of RF-RO for subbasin 3.

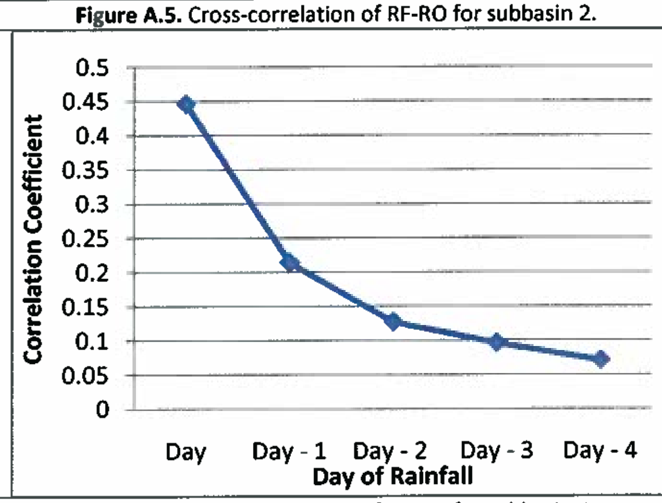

Figure A.7. Cross-correlation of RF-RO for subbasin 4.

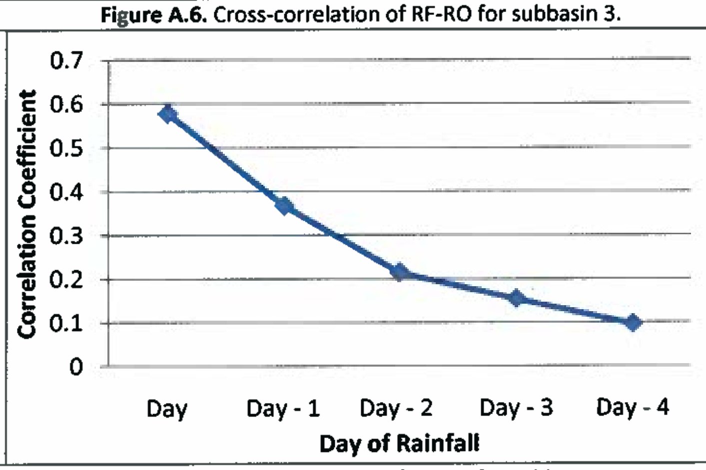

Figure A.8. Cross-correlation of RF-RO for subbasin 5.

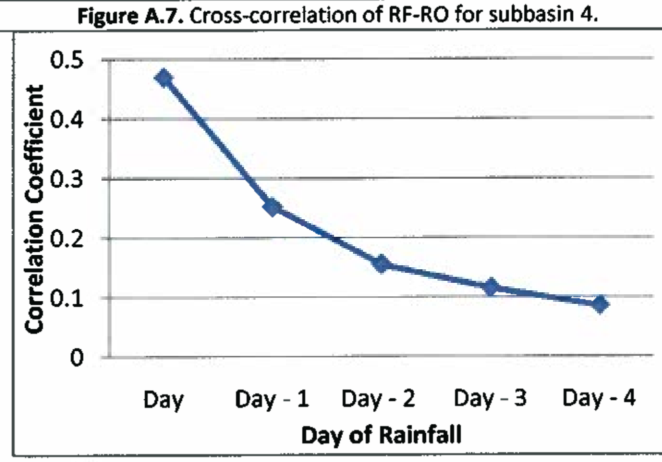

Figure A.9. Cross-correlation of RF-RO for subbasin 6.

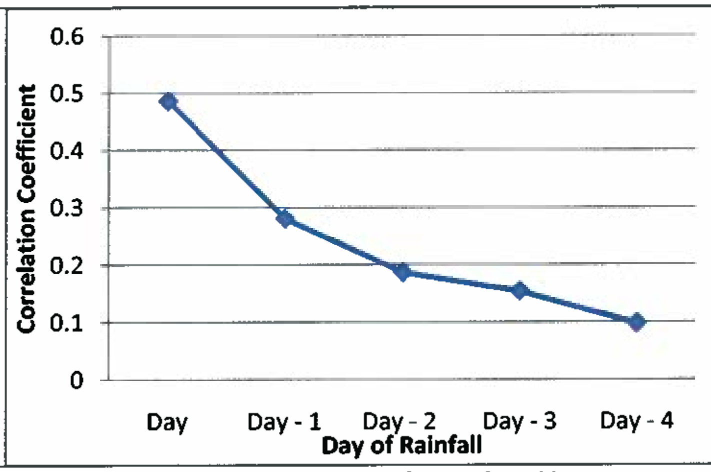

Figure A.10. Cross-correlation of RF-RO for subbasin 7.

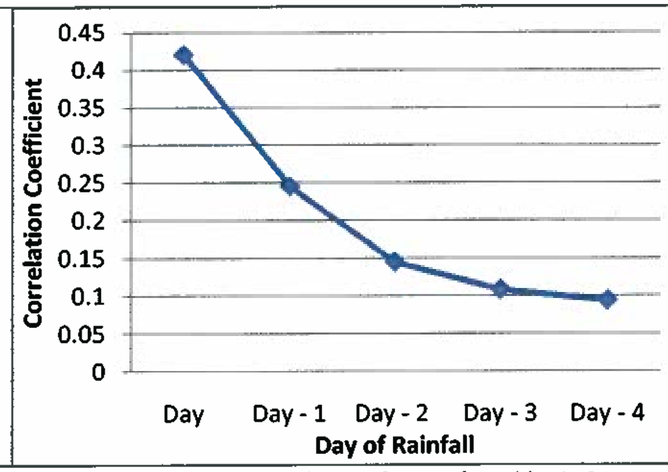

Figure A.11. Cross-correlation of RF-RO for subbasin 8.

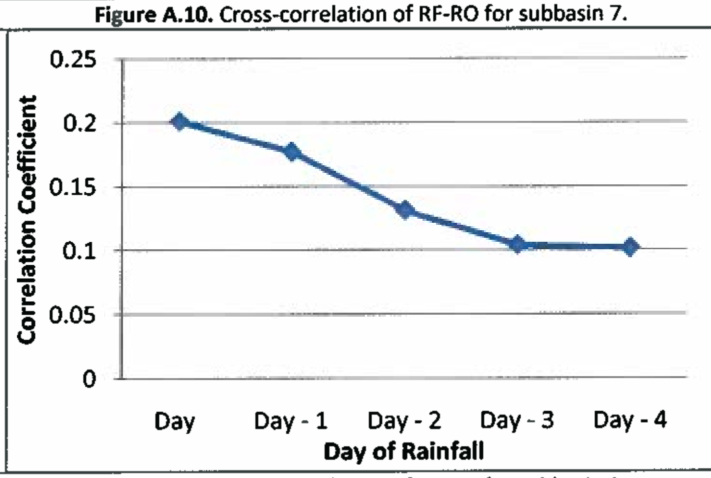

Figure A.12. Cross-correlation of RF-RO for subbasin 9.

Appendix B

Figure B.1 Soils Map of L'Anguille River Watershed
Figure B.2 LULC Map of L'Anguille River Watershed for Spring 1999
Figure B.3 LULC Map of L'Anguille River Watershed for Summer1999
Figure B.4 LULC Map of L'Anguille River Watershed for Fall 1999

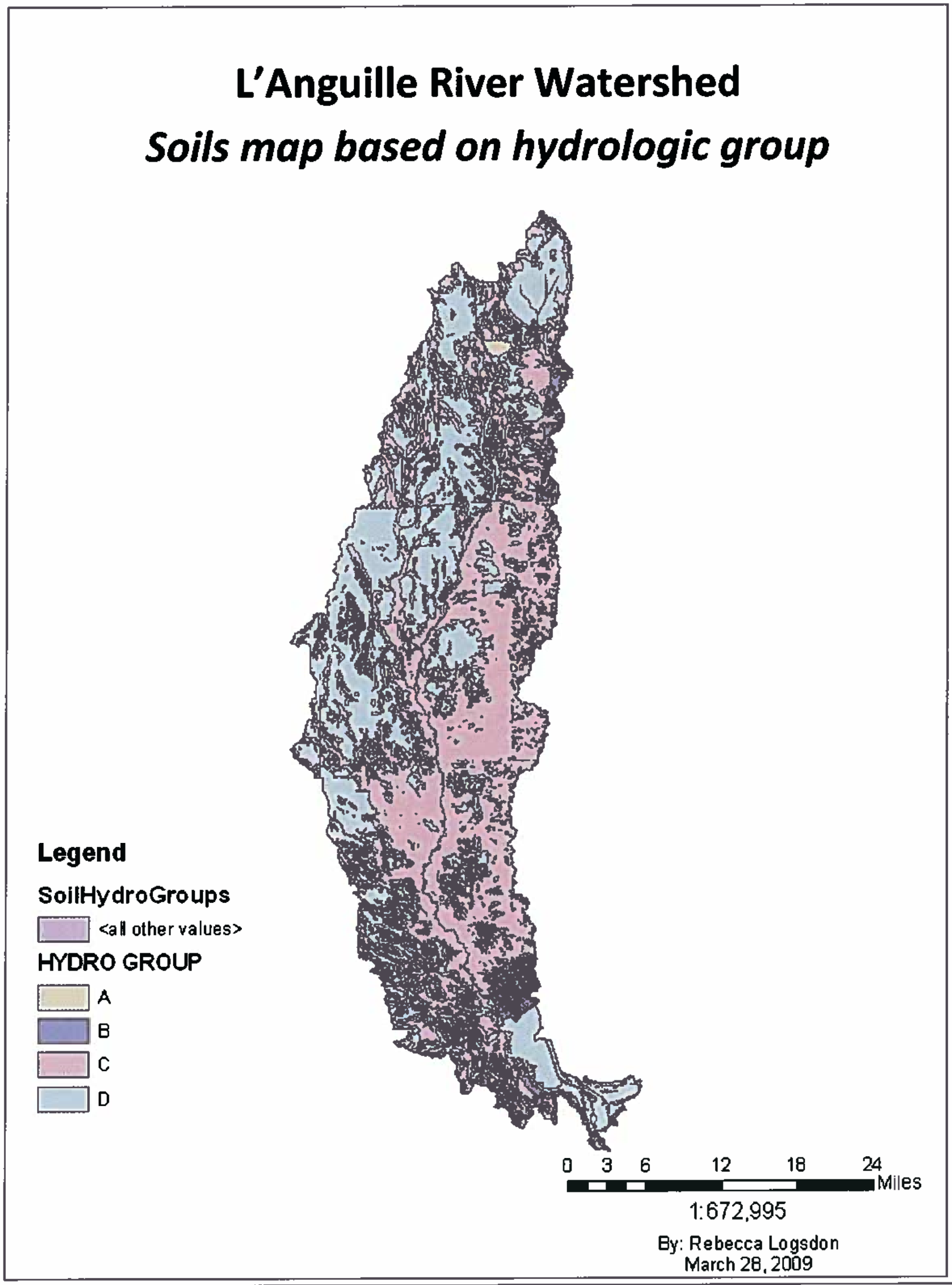

Figure B.1. Soils Map of L'Anguille River Watershed.

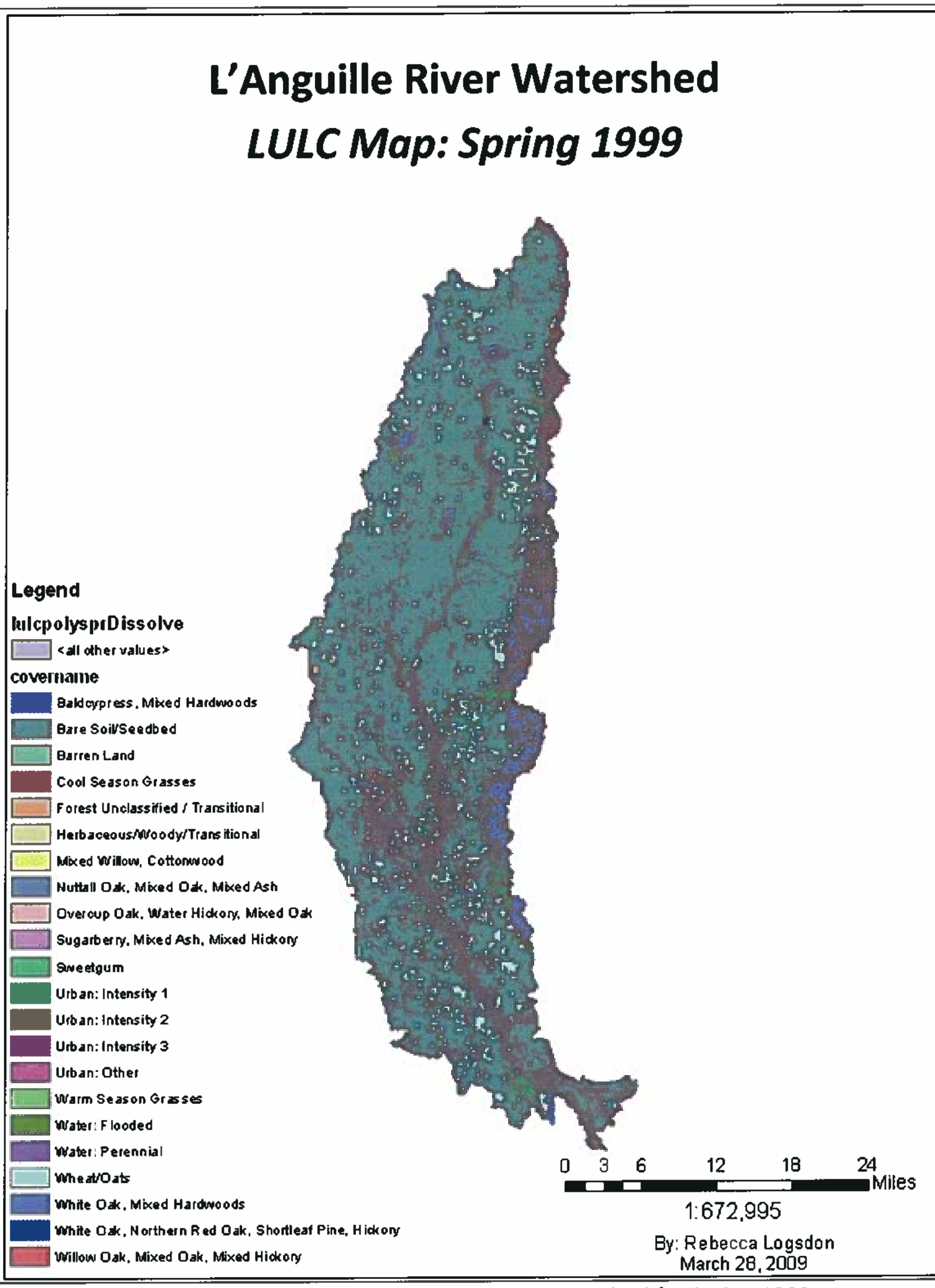

Figure B.2. LULC map of L'Anguille River Watershed for Spring 1999.

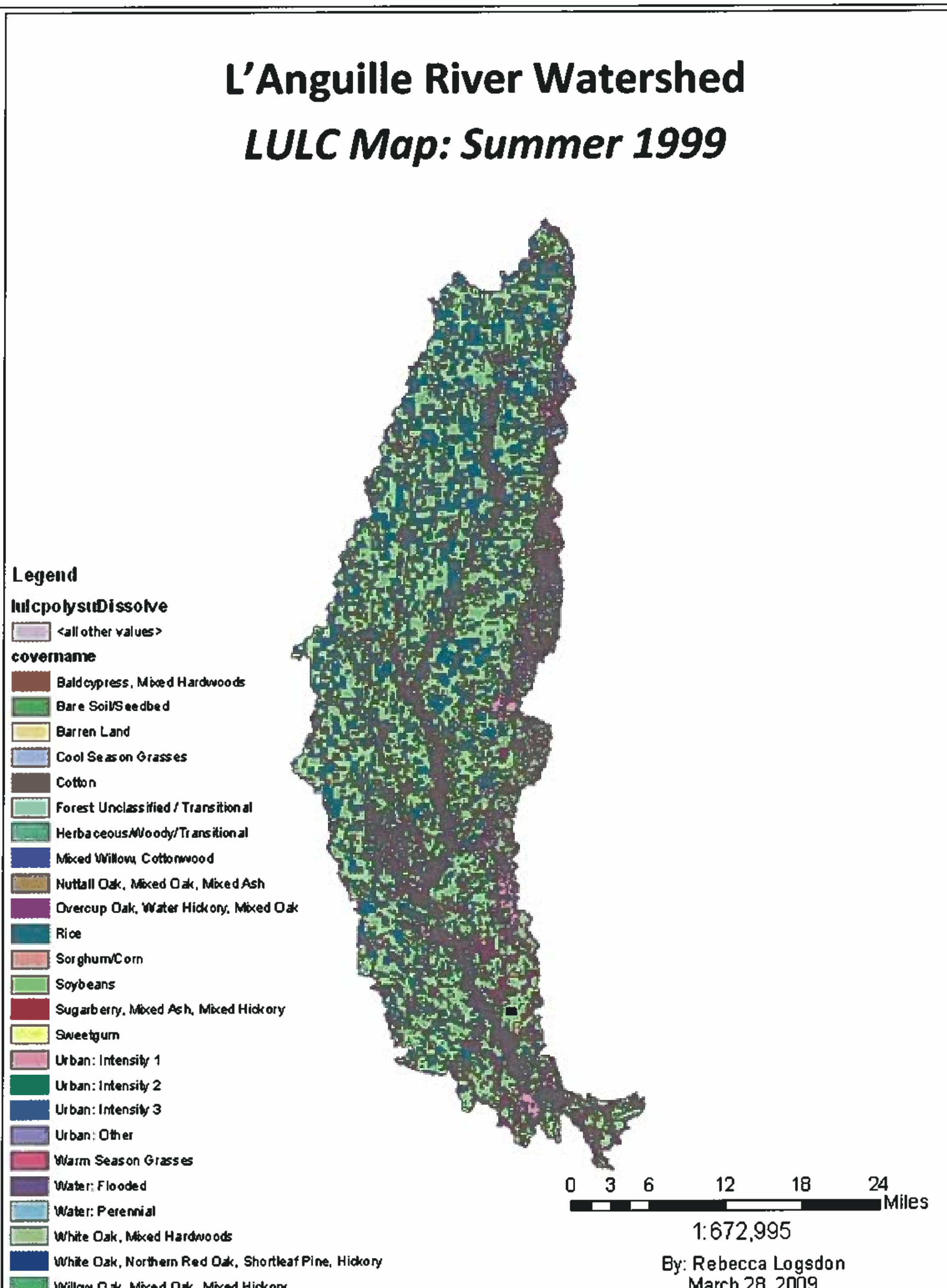

Figure B.3. LULC map of L'Anguille River Watershed for Summer 1999.

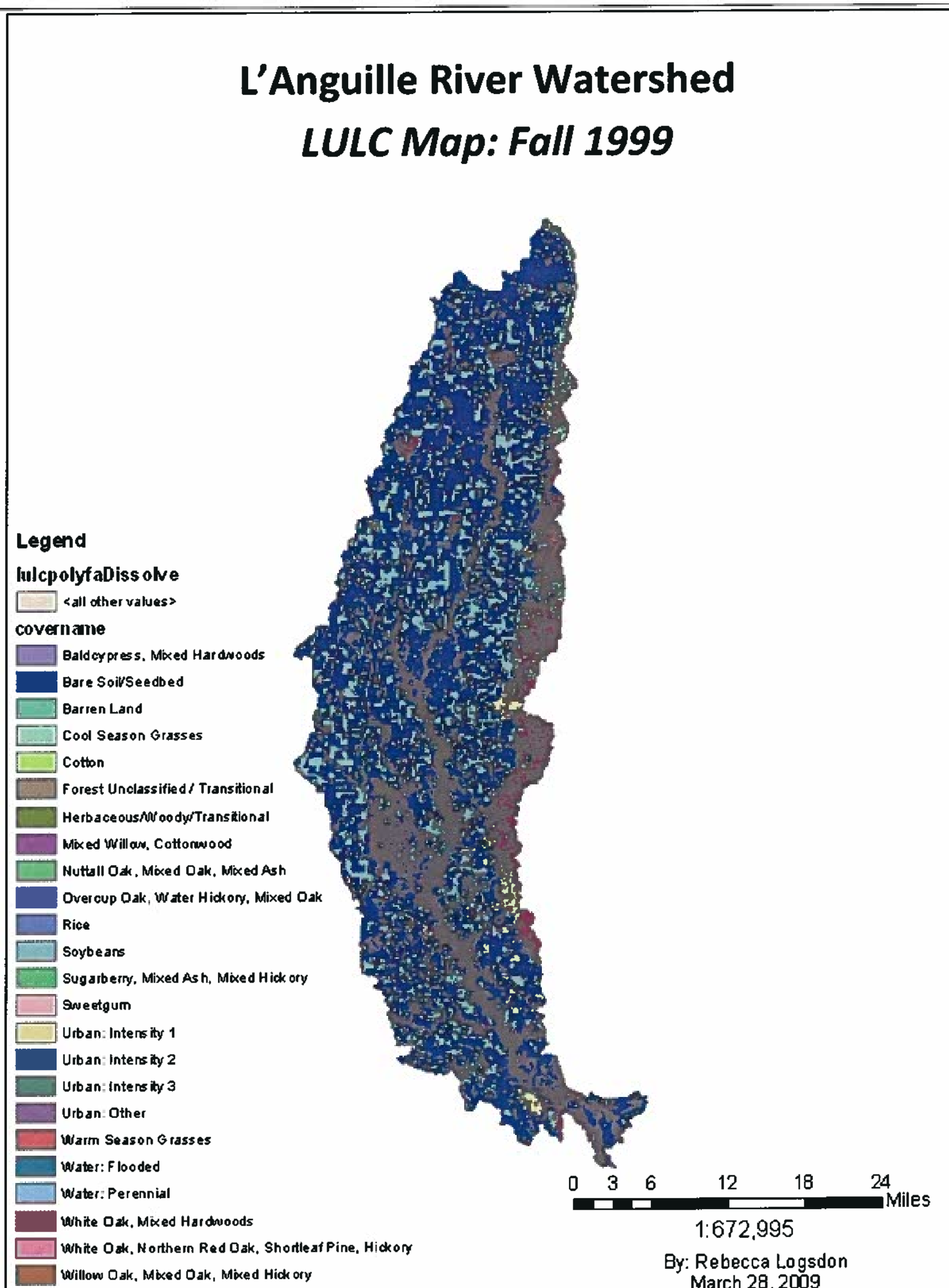

Figure B.4. LULC map of L'Anguille River Watershed for Fall 1999.

Appendix C

Table C.1 Dates for LULC Data Collection
Table C.2. Crop Planting & Harvesting Dates

Table C.1. Dates for data collection of spring, summer, and fall LULC for 1999.		
Data	Date Started	Date Ended
Spring 1999 LULC	April 7, 1999	May 7, 1999
Summer 1999 LULC	June 1, 1999	August 1, 1999
Fall 1999 LULC	September 30, 1999	November 16, 1999

Table C.2. Dates for Crop Planting & Harvesting Dates		
Crop	Earliest Planting Date	Latest Harvesting Date
Corn, for Grain	April 3	October 11
Cotton	April 24	November 24
Oats	October 2	July 5
Rice	April 7	October 25
Sorghum, for Grain	April 6	October 24
Soybeans	May 4	November 29
Wheat	October 3	July 5