AGRICULTURAL SYSTEM MODELS

in Field Research and Technology Transfer

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CHAPTER 10

Applications of Models with Different Spatial Scales

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INTRODUCTION

Simulation models integrate results from field research, providing valuable means of technology transfer. User-oriented models help agricultural producers, crop consultants, and policy makers make intelligent decisions based on current scientific knowledge and readily available soils and weather data. Such models integrate information from a wide range of sources into easily applied decision aids. The objective of this chapter is to describe some models of different scales, in such a way as to help users decide which is most appropriate for their situation.

Simulation models can be grouped into three categories based on spatial scale. Single-plant models simulate processes such as production of various yield components, leaf development, and reproductive development. They can be used to evaluate traits for optimizing yield production at different latitudes, in different rainfall zones, and on different soils. They can evaluate planting densities and planting dates as part of risk assessment in different environments.

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Canopy-level, single-field models share some common applications with single plant models, but tend to use more conservative and more general approaches to simulating plants. Leaf growth can be simulated as leaf area index (LAI) and yield can be simulated as harvest index (HI). Although they are often not able to describe the detailed differences among cultivars of a crop, such models can be readily applied to several crops by deriving realistic crop parameters. Within crop species differences may be confined to maturity types for such a model. Single field models can simulate the impact of management systems (crop rotations, tillage, irrigation, manure and fertilizer management, and drainage) on edge-of-field sediments and pollutant loadings.

Basin scale models simulate crop growth in a more aggregated fashion, allowing reasonable leaf area index development and reasonable biomass production in order to simulate yields of water, sediment nutrients, and pesticides from sub-basins. Basin scale models can be used to assess off-site impacts such as channel erosion, reservoir sedimentation, wetlands, riparian zones, water supply, water transfer, and stream and reservoir water quality. The scale is such that plant parameters describe generic processes of crop growth and development.

This chapter describes three models developed by USDA-ARS at Temple, TX. CERES-Maize (Crop Environment Resource Synthesis) (Jones and Kiniry, 1986) is a maize (Zea mays L.) simulation model for individual plants. ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria) (Kiniry et al., 1992) is a field-scale model that simulates a wide range of plant species and simulates competition among species. The SWAT model (Soil and Water Assessment Tool) (Arnold et al., 1998) simulates watersheds and subwatersheds and can also simulate many plant species. SWAT is an integral part of the HUMUS (Hydrologic Unit Model for the U.S.) (Srinivasan et al., 1993) hydrologic project. HUMUS combines SWAT with a geographic information system and with regional databases to simulate surface and subsurface water quantity and quality on a basin scale.

Several features shared by these models contribute to their widespread application. First, they were all developed with a high degree of cooperation with users and, since the models were developed by the USDA-ARS, they are available at no cost. The models, documentation, code, and example data sets can be obtained by contacting the authors. This has encouraged widespread application of the models and has increased feedback from users. Often users help decide which processes need to be simulated and what output is needed. As a result of this close cooperation, these models are easy to access and apply. They have been validated for a wide range of sites within the U.S. and throughout the world. Feedback from such users has been an important component of model improvement.

Second, the models rely on readily available daily weather data and on the extensive USDA-NRCS soils data. Commonly reported values of daily maximum and minimum temperatures, rainfall, and solar radiation are needed. This enables users to apply the models throughout the world by using data from the nearest weather station. In cases where weather data or portions of weather data are not available, realistic values can be generated, usually within the models themselves.

Third, the models use a daily time step, enabling rapid execution of multiple year runs. The models do not have iterative processes such as curve fitting or solving differential equations which can slow down execution. Users can make runs with several years of weather in a few minutes, enabling them to efficiently simulate an extensive range of management, crop, and soil scenarios.

Finally, the models share common features in their simulation of plant growth. The models simulate LAI, light interception with Beer's law, and potential daily biomass increase with a species-specific value of radiation use efficiency (RUE). The daily increases in LAI and biomass are reduced when plant available water in the current rooting depth is insufficient to meet potential evapotranspiration. Plant development is temperature driven, with duration of growth stages dependent on degree days. Each plant species has a defined base temperature and optimum temperature. Parameters for describing plant processes are easy to derive for a plant species or cultivar and easy to transfer among models.

DESCRIPTION OF ALMANAC AND CERES-MAIZE

The ALMANAC and CERES-Maize models simulate processes of crop growth and soil water balance including light interception by leaves, dry matter production, and partitioning of biomass into grain. A major difference between these models is their approach to simulating grain yields. ALMANAC simulates a grain yield based on HI, which is grain yield as a fraction of total aboveground dry matter at maturity. CERES simulates the seed number per plant (based on plant growth) and average mass per seed (based on potential seed growth rate).

CERES-Maize simulates phenology based on leaf development up to silking and on ear development thereafter. Leaf area is simulated on an individual leaf basis. Plants begin with six leaf primordia at seedling emergence and initiate an additional leaf for each 20 degree days base 8°C up to the date of tassel initiation. Prior to tassel initiation, plants are in the basic vegetative phase which is degree day dependent, the sum of which varies among hybrids. Plants are then in a photoperiod sensitive phase, which can be as short as 4 days in short days and is extended when photoperiods exceed 12.5 h. Hybrids differ in the sensitivity to photoperiod, with greater sensitivity causing greater delays in tassel initiation in long photoperiods. At tassel initiation, final leaf number is determined. The number of leaf tips that emerge from the leaf whorl requires 38 degree days base 8°C, after the second leaf. The first leaf is assumed to be present at seedling emergence and the last leaf emerges 20 degree days later. Silking is assumed to occur when the final leaf fully emerges. The degree days from silking to maturity is input as a hybrid-specific parameter. The effective filling period of the grain is assumed to be completed when 95% of these degree days have accumulated.

ALMANAC includes a generic LAI function. The maximum LAI of a crop species at high planting density is a parameter. This potential LAI is reduced as a function of planting density. The development of LAI as a function of fraction of seasonal degree day sum follows an "s" curve, with two input parameters defining the curve. Daily increments of LAI growth can be reduced by water stress. At a defined fraction of the seasonal degree days, grain growth is assumed to begin. A species specific value for HI defines the fraction of final above-ground biomass that is in grain. This potential HI can be reduced if drought stress occurs near anthesis (from 45 to 60% of the season degree days).

Recent improvements in the models include light extinction coefficients (k) based on row spacing for ALMANAC and a new seed number algorithm in CERES.

For ALMANAC, the extinction coefficient equation is a linear function of row spacing for maize and sorghum (Flénet et al., 1996):

$$k = 0.685 - 0.209 \quad \text{ROWS} \tag{10.1}$$

where ROWS is the row spacing for maize and sorghum and k is the extinction coefficient. This function is not included in CERES-Maize because it reduced yield simulation accuracy.

The number of seeds per plant (SEEDS) for CERES is now estimated by a linear function of GROWTH (g plant 1 d 1) from silking to the beginning of grain growth (Kiniry et al., 2001a):

$$\text{SEEDS} = 90\ \text{GROWTH}, \tag{10.2}$$

where SEEDS is constrained to not exceed a genotype-specific potential number of seeds per plant (G2). Although Andrade et al. (2000) and Otegui and Andrade (2000) described nonlinear seed number equations due to increased barrenness at abnormally high planting densities, we chose to use Eq. (10.2), which is similar to the function of Keating et al. (1988).

Since publication of CERES-Maize in 1986, some other studies have provided basic information about maize growth relationships described in the model. Improvements in the model based on

Crops such as maize and sorghum (Sorghum *bicolor* L. Moench) are grown in a wide range of soils and climatic conditions and can be vulnerable to late-spring freezes, drought, and high temperatures during grain growth.This sequence seemed more logical during the growing season. Producers make decisions on planting date, maturity type, planting rate, and fertilizer rates, attempting to maximize profit and minimize risks associated with unpredictable weather conditions. Crop models offer hope as tools to optimize such management practices. A robust crop model can provide a quantitative means to predict crop yields under different environmental and climatic conditions. Crop consultants, using accurate soil information and updated weather data, can provide producers with realistic predictions on the outcome of various management alternatives. Likewise, crop advisory information can be linked to soil type and measurements of soil layer depths in individual fields.

ALMANAC and CERES-Maize were developed to simulate critical growth processes. ALMANAC was developed to simulate the impacts of various field-level management on the soil and water environment, and on crop yields. The crop model in ALMANAC was designed to simulate a wide range of plant species efficiently. CERES-Maize was developed to simulate phenological processes and yield components of maize and to describe accurately how different hybrids produce grain in different environments. Adapted versions of CERES-Maize accurately simulated dryland and irrigated maize yields in Kenya at one to nine plants m^{-2} (Keating et al., 1988) and reasonably simulated maize yields with variable planting density, sowing dates, and nitrogen rates in Kenya (Wafula, 1995). CERES-Maize was used to simulate maize yields in Kansas with weed and insect stresses (Retta et al., 1991). The model "gave excellent predictions of yield trends" when used to simulate variability within a field in Iowa, proving to be "a viable and powerful tool in developing and evaluating management prescriptions across a field" (Paz et al., 1999). The model was tested in the semiarid tropics under conditions with measured yields of 1.7 to 8.3 Mg/ha^{-1} (Carberry et al., 1989). CERES failed to simulate differences among data sets for high yielding conditions in Argentina when yields ranging from 11.7 to 16.7 Mg/ha^{-1}, but was the mean simulated yield was only 5% greater than the mean observed yield (Otegui et al., 1996). An adaptation of CERES-Maize to simulate sorghum was tested in Australia using data with measured yields ranging from 1.6 to 6.3 Mg/ha^{-1} (Birch et al.. 1990). ALMANAC and CERES-Maize accurately simulated mean crop yields in nine states with diverse soils and climate (Kiniry et al., 1997) and at sites within Texas (Kiniry and Bockholt, 1998). ALMANAC accurately simulated spring wheat (Triticum aestivum L.) yields with different densities of competing oats (Avena sativa L.), oilseed rape (Brassica *napus* L.), and vetch (Vicia sativa L.) in France (Debaeke et al., 1997).

To be effective as tools, crop models must be capable of simulating crop yields in average rainfall years and in unusual rainfall years such as with drought or excess moisture. When applied to maize at eleven sites and sorghum at eight sites in Texas for the dry conditions of 1998, ALMANAC realistically simulated grain yields (Yun et al., 2001). In this study, the model demonstrated ability to simulate site-to-site differences in grain yields under dry climate conditions, showing it can be valuable for risk assessment of grain production.

ALMANAC is also capable of simulating grasses, both in monoculture and with multiple species growing together. Kiniry et al. (1996) successfully simulated Alamo switchgrass (Panicum *virgatum* L.) at several sites in Texas. In addition, ALMANAC realistically simulated range yields for 20 range sites representing the extremes of productivity for Texas (Kiniry et al., 2001b).

Crop models capable of accurately simulating long-term mean crop yields for diverse environments and capable of simulating annual crop yields in extreme climatic conditions would be valuable for risk assessment and management evaluation. Such models can greatly increase confidence in crop modeling. Of the models evaluated in this study, ALMANAC and SWAT simulate many crops by using different parameters, while CERES-Maize simulates individual maize hybrids with descriptive parameters.

these studies were described previously (Kiniry et al., 1997). The first change is that RUE is now reduced as mean daily vapor pressure deficit (VPD) exceeds 1.0 kPa (Stockle and Kiniry, 1990). Maize RUE is 4.33 g MJ^{-1} of intercepted photosynthetically active radiation for mean daily VPD less than 1.0 kPa and is reduced by mean daily VPD > 1.0 as:

$$RUE = 5.05 - 0.72\ VPD \tag{10.3}$$

The second change is that only 0.26 g of grain is produced for each g of carbohydrate lost from the stem and leaves (Kiniry et al., 1992b). Respiration, efficiency of conversion of glucose into grain, and translocation costs presumably are responsible for this being less than 1.0.

Critical for yield simulation in water-limited conditions is the simulated water demand. The three models calculate effects of soil water on crop growth and yield with similar functions. Potential evaporation (Eo) is calculated first, and then potential soil water evaporation (ES) and potential plant water transpiration (EP) are derived from potential evaporation and LAI. Based on the soil water supply and crop water demand, the water stress factor is estimated to decrease daily crop growth and yield, although some water balance equations differ between the two models. Each model has options on which technique is used to estimate Es, but for this study, Eo was estimated by the Penman method (1948) in ALMANAC, and by the Priestley–Taylor method (1972) in CERES-Maize. In ALMANAC, ES, and EP were estimated by:

$$E_P = E_o(LAI/3) \qquad 0 \le LAI \le 3.0 \tag{10.4}$$

$$E_P = E_o \qquad LAI > 3.0 \tag{10.5}$$

E_S is either $E_o \exp(-0.1BIO)$ or E_o – E„ whichever is smallest, where BIO is the sum of the aboveground biomass and crop residue (Mg ha^{-1}). In CERES-Maize

$$E_P = E_o(1 - \exp(-LAI)) \qquad 0 \le LAI \le 3.0 \tag{10.6}$$

$$E_P = E_o \qquad LAI > 3.0 \tag{10.7}$$

$$E_S = E_o(1 - 0.43LAI) \qquad 0 \le LAI \le 1.0 \tag{10.8}$$

$$E_S = E_o \exp(-0.4LAI)/1.1 \qquad LAI > 1.0 \tag{10.9}$$

If E, $< E_P + E_S$, then $E_P = E_o$ – E,.

Demonstration of CERES-Maize

CERES-Maize can simulate how changes in plant parameters affect grain yields in different weather conditions and on different soils. By evaluating the impact of changes in a plant parameter for a given set of conditions, users can efficiently determine how changes in hybrid characteristics can influence grain yields. These indicate the response of yield to changes in various plant characteristics. For this demonstration, we used a site near Ames, IA, on a Nicollet loam and a site near Temple, TX on a Houston Black clay, as described in Kiniry et al. (1997). Researchers used the weather data from 1983 to 1992 just as in the previous study and evaluated how changes in three traits altered grain yield.

Table **10.1** CERES-Maize Mean Simulated Grain Yields (Mg **ha^{-1}**) near Ames, **Iowa,** for **10** Years

P1 values	180	200	220	240	
	(100)[a]	(111)	(122)	(133)	
Mean yields	6.51	6.58	6.67	6.72	
	(100)	(101)	(102)	(103)	
G3 values	6	7	8	9	
	(100)	(117)	(133)	(150)	
Mean yields	5.23	5.99	6.72	7.33	
	(100)	(115)	(129)	(140)	
P5 values	550	600	650	700	750
	(100)	(109)	(118)	(127)	(136)
Mean yields	5.00	5.63	6.21	6.76	7.29
	(100)	(113)	(124)	(135)	(146)

Note: Crop parameters changed included the duration of the vegetative phase (P1, in GDD,), the rate of grain filling (G3, mg seed-' d^{-1}), and the duration of grain filling (in GDD,).

[a] Values in parentheses are relative percentages.

At 5 plants m^{-2}, degree days base 8°C (GDD,) from silking to maturity of 685 GDD,, and a grain filling rate of 7.8 mg per seed per day, the impact of change in number of leaves was measured by changing the heat units from seedling emergence to end of the juvenile phase. Each 20 GDD, increase in this "P1" causes an additional leaf primordia to be initiated and delays tasseling by 39 GDD,. Values tested were 180,200,220, and 240 GDD,. These allowed 9, 10, 11, and 12 leaves to be initiated during this stage resulting in final leaf numbers of 17, 18, 19, and 20 leaves.

The impact of changes in grain filling rate on final yield was evaluated next; rates of 6, 7, 8, and 9 mg seed-' d^{-1} were tested, assuming 5 plants m^{-2}, 685 GDD, from silking to maturity, and a grain filling rate of 7.8 as in the original study.

The final trait studied was the duration of grain filling, tried at values of 550, 600, 650, 700, and 750 GDD, from silking to maturity. All other parameters were held constant.

The relative sensitivity of these changes differed between the two sites (Tables 10.1 and 10.2). The more drought-prone site in Texas tended to show less yield increases than the site in Iowa, due to the dominant influence of drought stress in Texas.

At Ames, increases in number of leaves (greater P1) gradually increased mean simulated yields up to a maximum increase of 3%. At the more drought-prone Temple site, mean yields decreased for the largest two P1 values.

Increases in grain filling rate (G3) caused increases in mean yields at Ames of up to 40%. At Temple, these increases were almost as large, the maximum being 39%.

Finally, increases in duration of grain filling (P5) caused increases up to 46% in Iowa. Temple mean yields also increased, but only up to a maximum of 36%.

Demonstration of ALMANAC

Farmers face a number of management decisions when growing dryland maize. They try to optimize their management based on past experiences and expected weather. Two known variables on which they can base management decisions at planting time are the depth of their soil, and thus their potential plant available water at field capacity, and how much of their soil profile has been refilled since last year's growing season. Researchers examined the effect of plant spacing on yields on a deep (2.0 m) Houston black clay soil (fine, montmorillonitic, thermic Udic Palusterts) with 9 years of Temple, TX measured weather. This was repeated with a 1.5 m and a 1.0 m deep soil. Next they looked at planting density effects on a 5 d earlier and 10 d earlier maturity maize hybrids

Table 10.2 CERES-Maize Mean Simulated Grain Yields (Mg ha^{-1}) near Temple, Texas, for 10 Years

P1 values	180	200	220	240	
	(100)[a]	(111)	(122)	(133)	
Mean yields	5.54	5.52	5.35	5.26	
	(100)	(100)	(97)	(95)	
G3 values	6	7	8	9	
	(100)	(117)	(133)	(150)	
Mean yields	4.39	5.07	5.63	6.12	
	(100)	(115)	(128)	(139)	
P5 values	550	600	650	700	750
	(100)	(109)	(118)	(127)	(136)
Mean yields	4.35	4.82	5.23	5.60	5.89
	(100)	(111)	(120)	(129)	(136)

Note: Crop parameters changed included the duration of the vegetative phase (P1, in GDD,), the rate of grain filling (G3, mg seed^{-1} d^{-1}), and the duration of grain filling (in GDD,).

[a] Values in parentheses are relative percentages.

and finally simulated yields of different maturity hybrids and a sorghum hybrid when soil moisture was not entirely replenished.

For the first set of analyses, a 2.0 m deep Houston black clay soil that could hold 0.25 m of plant available water at field capacity was simulated. The three maturity types evaluated were normal maturity for this region (1600 GDD, from planting to maturity), 5 d earlier maturing (1500), and 10 d earlier maturing (1400). This range was based on the range of maturities measured at Temple, TX, for some hybrids of diverse maturity (Kiniry and Knievel, 1995). For each maturity type, investigators simulated four, five, six, and seven plants m^{-2} plant densities for years 1991 to 2000 at Temple.

The three statistics of interest were the average for the three lowest yielding years (as an indication of yields in dry years), the yields for the three greatest yielding years (as an indication of yield potential), and the average yields over the 10 years.

Results with different densities of different maturity types on a 2.0 m soil (Table 10.3) showed useful information on maturity type differences and grain yields. Optimum densities for greatest average yields were five plants m^{-2} for the normal maturity, six plants m^{-2} for the 3 d earlier hybrid, and seven plants m^{-2} for the 10 d earlier hybrid. For the normal maturity hybrid, decreasing planting density decreased yield potential but increased yield in the 3 driest years. Using the CV as an estimate of yield variability, CV values increased as population density increased above five plants m^{-2} for the earliest maturity results and above four plants m^{-2} for the other two. For any given density, earlier maturity caused a decrease in yield potential and an increase in yield stability (the CV decreased). The greatest yields in the 3 driest years were for the four plants m^{-2} density for the normal maturity, for the five plants m^{-2} density for the 5 d earlier maturity hybrid, and six plants m^{-2} for the 10 d earlier maturity hybrid.

Decreasing soil depth to less than 1.5 m decreased overall average yield and yield in the highest 3 years (Table 10.4). The change in soil depth from 2.0 m to 1.5 m had little or no effect on maize yields. These soil depths correspond to plant available water at field capacity of 250 mm, 206 mm, and 147 mm. The optimum planting density based on average yield was five plants m^{-2} for all three soil depths. Greater densities, although they had increased potential yields, had reduced values for the low yielding years and reduced yield stability (as indicated by large CV values).

Analysis of 89 years of Temple, TX, weather indicated the average rainfall during the period from maize harvest until the next year's planting was 483 mm. Ranking the 89 years for amount rainfall during this period, the average rainfall for the lowest 20% of these years was 254 mm. Our

Table **10.3** ALMANAC's Mean Simulated Grain Yields of Three Different Maturity Maize Hybrids on a 2.0-m deep Houston Black Clay with Temple, Texas, Weather Data from **1991** to **2000**, with Different Planting Densities

	4 Plants m^{-2} **16,200** Plants Acre-'	**5** Plants m^{-2} **20,200** Plants Acre-?	**6** Plants m^{-2} **24,300** Plants $Acre^{-1}$	7 Plants m^{-2} **28,300** Plants $Acre^{-1}$
		(Mg ha^{-1})		
		Normal Hybrid		
Low **3** avg.	3.5	2.7	2.4	2.5
High **3** avg.	5.0	7.4	8.4	9.2
Avg.	4.4(83)	5.2(97)	4.7(89)	5.1(96)
CV (%)	16	37	53	55
		Early Hybrid		
Low **3** avg.	2.6	3.1	2.6	2.6
High **3** avg.	3.6	6.2	7.5	8.1
Avg.	3.2(61)	4.9(92)	5.1(97)	4.9(93)
CV (%)	15	27	39	46
		Very Early Hybrid		
Low **3** avg.	1.7	3.1	3.3	2.9
High **3** avg.	2.2	4.2	5.8	6.8
Avg.	2.0(38)	3.8(72)	4.8(90)	5.0(95)
CV (%)	15	15	24	32

Note: The latter two maturity types reached maturity **5** d earlier and **10** d earlier than the common maturity type for the region. The value in parentheses is the yield in bushels per acre.

Table **10.4** ALMANAC's Mean Simulated Grain Yields for Three Soil Depths of a Houston Black Clay for a Common Maturity Maize with Temple, Texas, Weather Data from **1991** to **2000** with Different Planting Densities

	4 Plants m^{-2} **16,200** Plants $Acre^{-1}$	**5** Plants m^{-2} **20,200** Plants $Acre^{-1}$	**6** Plants m^{-2} **24,300** Plants $Acre^{-1}$	7 Plants m^{-2} **28,300** Plants $Acre^{-1}$
		(Mg ha^{-1})		
		2.0 m Soil Depth		
Low **3** avg.	3.5	2.7	2.4	2.5
High 3 avg.	5.0	7.4	8.4	9.2
Avg.	4.4 (83)	5.2 (97)	4.7 (89)	5.1 (96)
CV (%)	16	37	53	55
		1.5 m Soil Depth		
Low **3** avg.	3.4	2.6	2.4	2.5
High **3** avg.	5.0	7.5	8.4	9.2
Avg.	4.4 (83)	5.2 (98)	4.7 (89)	5.1 (96)
CV (Yo)	16	38	54	55
		1.0 m Soil Depth		
Low **3** avg.	2.8	2.3	2.3	2.4
High **3** avg.	5.0	6.7	7.6	7.7
Avg.	4.2 (80)	4.8 (91)	4.5 (84)	4.6 (86)
CV (%)	22	38	50	48

Note: The value in parentheses is the yield in bushels per acre.

Table 10.5 ALMANAC's Mean Simulated Grain Yields Following 254 mm of Rainfall during the Previous Fallow Period, for Three Different Maturity Maize Hybrids Simulated on a 2.0-m Deep Houston Black Clay with Temple, Texas, Weather Data from 1991 to 2000 with Different Planting Densities

	4 Plants m^{-2} 16,200 Plants $Acre^{-1}$	5 Plants m^{-2} 20,200 Plants $Acre^{-1}$	6 Plants m^{-2} 24,300 Plants Acre-'	7 Plants m^{-2} 28,300 Plants $Acre^{-1}$
	(Mg ha^{-1})			
	Normal Hybrid			
Low 3 avg.	1.1	1.3	1.4	1.4
High 3 avg.	3.8	3.6	3.6	3.9
Avg.	2.4 (44)	2.4 (45)	2.5 (47)	2.7 (51)
CV (%)	49	44	40	40
	Early Hybrid			
Low 3 avg.	1.2	1.2	1.3	1.3
High 3 avg.	3.5	3.7	4.0	3.7
Avg.	2.4 (46)	2.4 (44)	2.5 (47)	2.5 (47)
CV (%)	40	49	51	42
	Very Early Hybrid			
Low 3 avg.	1.7	1.2	1.2	1.2
High 3 avg.	2.2	3.8	3.7	3.7
Avg.	2.0 (38)	2.5 (47)	2.3 (43)	2.3 (44)
CV (%)	15	44	50	50
	Grain Sorghum (25 plants)			
Low 3 avg.	1.6			
High 3 avg.	4.0			
Avg.	2.8			
CV (%)	38			

Note: The average rainfall for this period for 89 years was 483 mm. The latter two maturity types reached maturity 5 d earlier and 10 d earlier than the common maturity type for the region. The value in parentheses is the yield in bushels per acre.

Grain sorghum results for a common pllanting density are included for comparison.

two scenarios for looking at management of maize following low winter rainfall were 254 mm and an intermediate value of 381 mm during the period. Fallow season rainfall was adjusted accordingly, using the growing season weather for 1991 to 2000 at Temple, as described previously.

With the lowest winter soil recharge (254 mm), there did not appear to be a benefit of reducing planting density but sorghum showed promise as having superior yields to maize (Table 10.5). Yields of the normal maturity maize hybrid were low, averaging 2.4 to 2.7 Mg/ha^{-1}. Again looking at planting densities of four to seven plants m^{-2}, the highest average yields were at seven plants m^{-2} for the normal maturity maize hybrid, at six to seven for the early hybrid, and at five for the very early hybrid. The sorghum average yield exceeded all of the maize average yields. Sorghum yields were more stable than those of maize, as indicated by the smaller CV values of sorghum.

With an intermediate amount of winter soil recharge (381 mm), optimum density of maize was reduced and maize average yields were greater than sorghum yields (Table 10.6). The optimum planting rates to achieve maximum average yields were four plants m^{-2} for the normal maturity maize, and five plants m^{-2} for the early and very early hybrids. With such soil moisture recharge, there appeared to be sufficient soil moisture to take advantage of reduced planting density. Yields in the 3 years with wettest growing season conditions were greatest for these low densities. Sorghum was not as competitive as it was with the 254 mm winter rainfall.

Table 10.6 ALMANAC's Mean Simulated Grain Yields Following 381 mm of Rainfall during the Previous Fallow Period for Three Different Maturity Maize Hybrids Simulated on a 2.0 m Deep Houston Black Clay with Temple, Texas, Weather Data from 1991 to 2000 with Different Planting Densities

	4 Plants m^{-2} 16,200 Plants $Acre^{-1}$	5 Plants m^{-2} 20,200 Plants $Acre^{-1}$	6 Plants m^{-2} 24,300 Plants $Acre^{-1}$	7 Plants m^{-2} 28,300 Plants $Acre^{-1}$
		($Mg\ ha^{-1}$)		
		Normal Hybrid		
Low 3 avg.	2.3	1.8	1.9	2.1
High 3 avg.	4.9	6.0	5.1	5.6
Avg.	3.8 (71)	3.6 (68)	3.4 (63)	3.6 (69)
CV (%)	32	48	46	47
		Early Hybrid		
Low 3 avg.	2.7	2.2	1.9	2.0
High 3 avg.	3.6	5.6	5.3	5.0
Avg.	3.3 (61)	3.9 (73)	3.3 (62)	3.2 (61)
CV (%)	15	37	48	46
		Very Early Hybrid		
Low 3 avg.	2.8	2.0	1.8	2.0
High 3 avg.	3.8	5.7	4.5	4.9
Avg.	3.4 (64)	3.9 (74)	3.0 (56)	3.2 (61)
CV (%)	15	38	44	46
		Grain Sorghum (25 plants)		
Low 3 avg.	2.2			
High 3 avg.	4.3			
Avg.	3.3			
CV (%)	28			

Note: The average rainfall for this period for 89 years was 483 mm. The latter two maturity types reached maturity 5 d earlier and 10 d earlier than the common maturity type for the region. The value in parentheses is the yield in bushels per acre.

Grain sorghum results for a common pllanting density are included for comparison.

DESCRIPTION OF THE SWAT MODEL AND THE HUMUS PROJECT

The SWAT model simulates water quantity and quality in large, complex basins. SWAT predicts the impact of topography, soils, land use, management and weather on water, sediment, nutrient (nitrogen and phosphorus), and agricultural chemical yields for large watersheds with an insufficient number of gages. To meet the design criteria SWAT:

1. Does not require calibration (which is impossible on ungaged watersheds).
2. Uses inputs that are readily available for large areas.
3. Efficiently simulates hundreds of interacting sub-basins using a daily time step.
4. Simulates hundreds of years in a continuous time model to assess long-term impacts.

The command structure routes water, nutrients and chemicals through streams and reservoirs and inputs measured data for point sources of water and nutrients (Figure 10.1). Basins are subdivided into grid cells or subwatersheds to increase input and output detail.

Model sub-basin components consist of components of hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management. The model simulates hydrologic processes including surface runoff estimated from daily rainfall using the USDA-NRCS

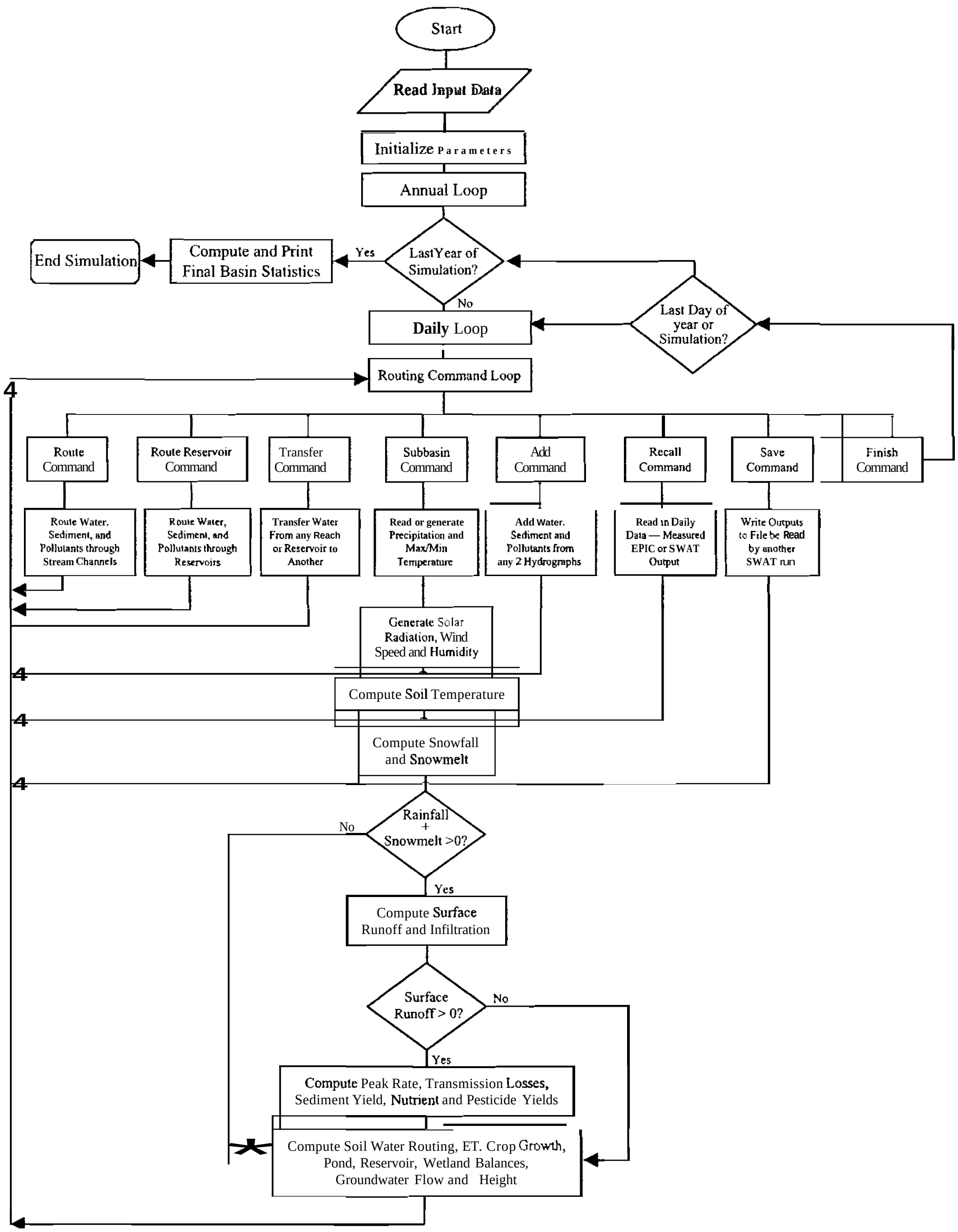

Figure 10.1 Flowchart of SWAT model operation.

curve number; percolation modeled with a layered storage routing technique combined with a crack flow model; lateral subsurface flow; groundwater flow to streams from shallow aquifers, potential evapotranspiration by the Hargreaves, Priestley–Taylor or Penman–Monteith methods; snowmelt; transmission losses from streams; and water storage and losses from ponds.

Daily precipitation, maximum and minimum air temperatures, solar radiation, wind speed, and relative humidity drive the hydrologic model. **A** weather generator simulates variables based on monthly climate statistics derived from long-term measured data. Weather data can differ among sub-basins.

SWAT computes sediment yield for each sub-basin with the modified universal soil loss equation. Soil temperature is updated daily for each soil layer as a function of air temperature; snow, plant and residue cover; damping depth; and mean annual temperature.

The model simulates crop growth with a daily time step using a simplification of the EPIC crop model which predicts phonological development based on daily accumulation of degree days, harvest index for partitioning grain yield, a radiation use efficiency approach for potential biomass, and adjustments for water and temperature stress. Both annual and perennial crops are simulated using crop-specific input parameters.

SWAT simulates nitrate losses in runoff, in percolation and in lateral subsurface flow. The model simulates organic nitrogen losses from soil erosion and an enrichment ratio. A nitrogen transformation model modified from EPIC includes residue mineralization, soil humus, mineralization, nitrification, denitrification, volatilization, fertilization and plant uptake. Phosphorus processes include residue and humus, mineralization, losses with runoff water and sediment, fertilization, fixation by soil particles and plant uptake. Pesticide transformations are simulated with a simplification of the GLEAMS model (Leonard et al., 1987) approach and include interception by the crop canopy; volatilization; degradation in soils and from foliage; and losses in runoff, percolation, and sediment.

The model simulates agricultural management practices such as tillage effects on soil and residue mixing, bulk density and residue decomposition. Irrigation may be scheduled by the user or applied automatically according to user-specified rules. Fertilization with nitrogen and phosphorus can also be scheduled by the user or applied automatically. Pesticide applications are scheduled by the user. Grazing is simulated as a daily harvest operation.

SWAT simulates stream processes including channel flood routing, channel sediment routing, nutrient and pesticide routing, and transformations modified from the QUAL2E model (Brown and Barnwell, 1987). Components include algae as chlorophyll-a, dissolved oxygen, organic oxygen demand, organic nitrogen, ammonium nitrogen, nitrite nitrogen, organic phosphorus, and soluble phosphorus. In-stream pesticide transformations include reactions, volatilization, settling, diffusion, resuspension, and burial.

The ponds and reservoirs component includes water balance, routing, sediment settling, and simplified nutrient and pesticide transformation routines. Water diversions into, out of, or within the basin can be simulated to represent imgation and other withdrawals from the system.

HUMUS was designed to improve existing technologies for making national and river basin scale water resource assessments, considering both current and projected future climatic characteristics, water demands, point-sources of pollution, and land management affecting non-point pollution. The project was implemented as part of the U.S. Resources Conservation Act Assessment completed in 1997. The major cooperators in the HUMUS project were the U.S. Department of Agricultural Research Service and the Texas Agricultural Experiment Station, part of the Texas A&M University System.

The major components of the HUMUS system were:

1. The basin-scale **SWAT** to model surface and sub-surface water quantity and quality
2. **A** geographic information system to collect, manage, analyze, and display the spatial and temporal inputs and outputs of **SWAT**
3. Relational databases used to manage nonspatial climate, soil, crop and management data required as input to and generated as output from **SWAT**

A SWAT/GRASS input interface (Srinivasan and Arnold, 1994) was used in this project. The Geographic Resource Analysis Support System-Geographic Information System (GRASS) (U.S.

Army, 1987) is a GIS system developed by the U.S. Army Corps of Engineers. The interface project manager is used to extract, aggregate, view, and edit model inputs. This manager helps the user collect, prepare, edit and store basin and sub-basin information to be formatted into a SWAT input file. Most of the SWAT input data are derived from GRASS map layers. The data collected by the interface include basin attributes such as area of the basin, its geographic location, and soil attributes needed for SWAT. These are extracted from the STATSGO (USDA-SCS, 1992) database. Topographic attributes include accumulated drainage area, overland field slope, overland field length, channel dimensions, channel slope, and channel length. Land use attributes include crop name, planting and harvesting date based on heat unit scheduling, and weather station information for the weather generator.

Digital Elevation Model (DEM) Topographic Attributes

The overland slope and slope length were estimated for each polygon using the 3-arc second DEM data for each state. Measuring the slope using the neighborhood technique (Srinivasan and Engel, 1991) for each cell within a sub-basin, a weighted average based on area for the entire sub-basin was then calculated. The USLE slope length factor was computed using the standard table from the USDA Handbook 537 (Wischmeier and Smith, 1978) and the estimated overland slope.

Land Use Attributes

The USGS-LUDA data were used to develop crop inputs to SWAT. The land use with the greatest area was selected for each sub-basin and the crop parameter database characterized each crop (Williams et. al, 1990). The broad classification categories used in the LUDA were urban, agriculture/pasture, range, forest, wetland, and water. Planting date of a land use was calculated with a heat unit scheduling algorithm using latitude and longitude of the sub-basin, monthly mean temperatures of the sub-basin, and land use type. This automated approach also identifies other operations associated with a cropping system. For this study maize as used in the agricultural areas because it is the most prevalent crop in many parts of the U.S.

Soil Attributes

The STATSGO-soil association map was used to select soil attributes for each sub-basin. Each STATSGO polygon contains multiple soil series and the areal percentage of each. The soil series with the largest area was selected by the GIS interface. The interface then extracted the physical properties of the soil series for SWAT from a relational data structure and wrote them to SWAT input files. The runoff curve number (CN) was assigned to each sub-basin based on the type of land use and the hydrologic condition of the soil series using a standard CN table (USDA-SCS, 1972).

Irrigation Attributes

This study used the STATSGO database to identify locations using irrigation. In the STATSGO "yldunits" table, irrigated crop yield is reported. Hence, if a STATSGO polygon had irrigated crop yield for any crop in this table, and if the sub-basin's land use (from USGS-LUDA) was agriculture, then that sub-basin was simulated as irrigated agriculture. Using the irrigation map layer, the interface created input parameters for automated irrigation application for each sub-basin. The model automatically irrigated a sub-basin by replenishing soil moisture to field capacity when crop stress reached a user-defined level.

Weather Attributes

The SWAT model accessed data from 1130 weather stations in the U.S. The input interface assigned the closest weather station for each sub-basin. The interface also extracted and stored the monthly weather parameters in a model input file for each sub-basin.

Once the data were gathered for all the sub-basins for each state, the SWAT model was executed for a 20-year simulation run. Using the SWAT/GRASS output interface, average annual output were created as layers, which included rainfall, water yield, actual ET, potential ET, biomass, grain production, water surplus (rainfall minus actual ET), and irrigation applied.

Demonstration of SWAT

The U.S. Environmental Protection Agency reported nutrient enrichment as the major cause for impairment of lakes and other water bodies in the U.S. (USEPA, 1994). EPA's water quality inventory of 1996 indicated that forty percent of the surveyed rivers, lakes, and estuaries were polluted relative to their designated uses (USEPA, 1998). To restore the quality of these water bodies, the Total Maximum Daily Load (TMDL) process was established by Section 303(d) of the Clean Water Act. A TMDL quantifies pollutant sources, and maximum allowable loads of contributing point and nonpoint sources so that water quality standards are attained for uses such as for drinking water and aquatic life (USEPA, 1998). Once necessary pollutant reduction levels are identified through the establishment of TMDLs, control measures such as best management practices are implemented. The USEPA Office of Science and Technology has developed a framework for states to analyze impaired water bodies called BASINS (Better Assessment Science Integrating point and Non-point Sources). BASINS consists of five components:

1. National databases
2. Assessment tools
3. Utilities
4. Watershed models
5. Post-processing and output tools

SWAT and its associated GIS interface have been integrated into BASINS and is being used in several states for TMDL analysis.

The SWAT model was applied to the 4277 km^2 Bosque River watershed in central Texas. This river flows into Lake Waco, which is the source of drinking water for the city of Waco, TX. The watershed is mostly range and pasture in the upper portion while cropland is widespread in the lower portion. Manure from the 41,000 dairy cows in this watershed is applied on an area of 9450 ha. There is a strong positive correlation between elevated levels of phosphorus, the number of cows and the total acreage of manure application fields (McFarland and Hauck, 1999). Other sources of pollution include runoff from cropland and urban areas and effluent from wastewater treatment plants.

SWAT was calibrated and validated at two USGS gaging stations in this watershed, at Hico and Valley Mills (Santhi et al., 2001). After the model was validated, several management practices were simulated to see which practices would reduce phosphorus concentrations in the river below water quality standards.

The calibrated model was used to study the long-term effects of various BMPs related to dairy manure management and municipal wastewater treatment plant loads in this watershed. Among several scenarios studied, four scenarios are discussed in this paper. Detailed description of the BMPs can be found in Santhi et al. (2002). The existing condition scenario simulates the watershed with the present dairy herd size, the present waste application fields, the average manure application rate of 13 Mg $ha^{-1}yr^{-1}$, the present discharge volumes from waste water treatment plants (WWTPs)

Table 10.7 Comparison of SWAT Corn Yields vs. Ag Census and National Ag Statistics Corn Yields (Mg ha^{-1})

State	FIPS-id	AGCENSUS (1987)	NASS (20 yr avg)	SWAT Yield
Illinois	17	6.6	6.0	6.7
Indiana	18	6.5	6.2	6.2
Iowa	19	6.6	6.2	6.6
Kansas	20	5.3	5.9	5.5
Kentucky	21	4.5	4.5	4.9
Michigan	26	4.0	4.5	2.9
Minnesota	27	5.1	4.5	3.6
Missouri	29	4.8	4.5	5.0
Nebraska	31	6.2	6.6	3.7
North Carolina	37	3.1	4.0	3.0
Ohio	39	5.7	5.6	5.8
Pennsylvania	42	4.9	4.9	2.6
South Dakota	46	3.3	3.1	3.6
Wisconsin	55	5.3	5.2	3.6

with the current median concentrations for nutrients and present urban and cropland areas (Table 10.7). The future condition scenario reflects the projected conditions of the watershed in year 2020 with a projected dairy herd size of 67,000 cows, manure application in waste application fields at the crop N requirement rate of 46 Mg of N $ha^{-1}yr^{-1}$, waste application field area calculated at N rate requirement, maximum permitted discharge volumes from WWTPs using nutrient concentrations defined by current median values, urban area increased by 30% to reflect the projected population growth in 2020, and cropland area at current levels (due to no increase in cropland over last two decades) (Table 10.7). Three additional WWTPs with 1 mg/L concentration of total P were input into the model as point sources along the North Bosque River to account for possible industrial future growth outside existing communities.

Several management practices on dairy manure and WWTP effluents were simulated to study the impact in reducing the mineral P loadings. Imposed dairy management practices included hauling solid manure from the watershed, applying manure at crop P requirement rate (P rate) of 6.3 Mg $ha^{-1}yr^{-1}$ (because the N rate allows more applied P than crops require), and reducing the dairy diet P to 0.4% (resulting in a 29% reducvtion in dairy manure P content as suggested by Keplinger, 1999). The concentrations of total P in WWTP effluents were reduced to 1 mg/L^{-1}. Scenario E was a modification of the existing condition scenario with additional conditions imposed on manure application rate (P rate), hauling off 38% of the manure, P diet reduction in animal feed, and 1 mg/L^{-1} limits of P in WWTPs (Table 10.8). Scenario F was a modification over the

Table 10.8 Assumptions of BMP Scenarios in the Bosque Watershed

	WWTP Flow Period	WWTP P Limit	Dairy Manure Application Rate	Reduced P in Diet	Haul-Off Manure
Existing scenario	1997–1998 (actual)	Median concentration	Btw N&P rate	No	No
Future scenario	2020 (permitted)	Median concentration	N rate	No	No
Scenario E	1997–1998	All WWTPs at Median concentration and Stephenville WWTP — 1mg/L	P rate	Yes	Yes
Scenario F	2020	All WWTPs with loads equal to Scenario E and Stephenville WWTP — with load equal to 1mg/L of future	P rate	Yes	Yes

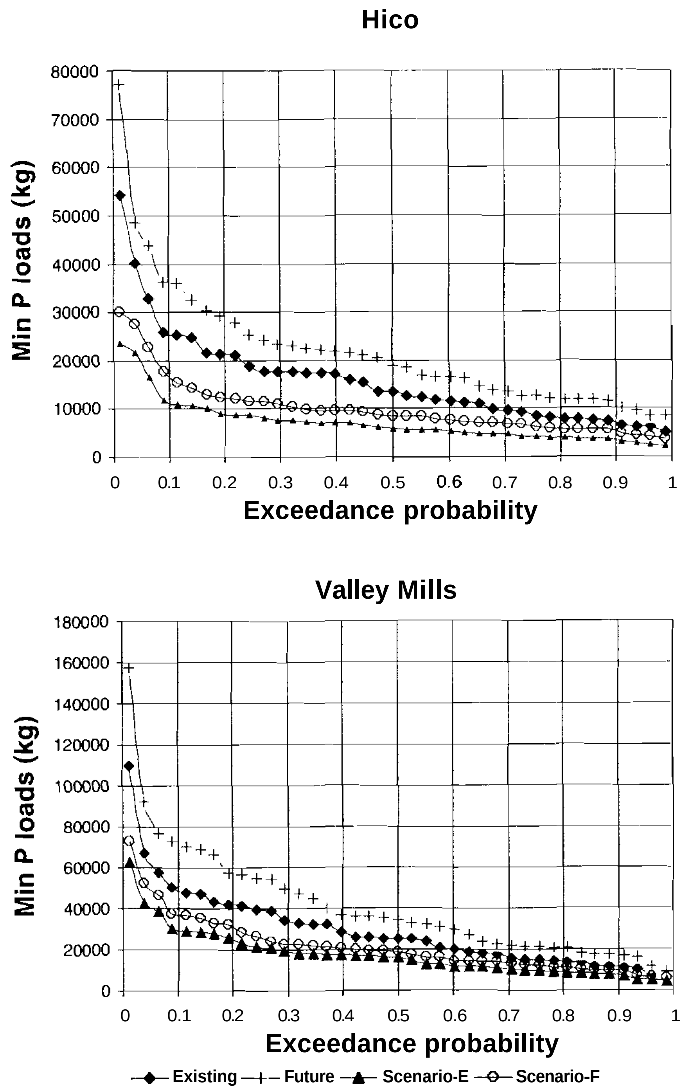

Figure 10.2 Exceedence probability of phosphorus loadings for various BMPs in the Bosque River.

future scenario with manure applied at P rate, hauling off 38% of the manure, P diet reduction, and 1 mg/L^{-1} P limits on all WWTPs.

Mineral P loadings are displayed as probability exceedance plots to analyze the effectiveness of BMPs. In these exceedance plots, annual mineral P loadings (y-axis) for the simulation period (1960 through 1998) were ordered and plotted with their associated exceedance probability values (x-axis) for Hico and Valley Mills (Figure 10.2). These plots provide information on the probability of achieving a particular load of mineral P through a BMP at a particular location. Mineral P loading curves for the scenarios varied from 10,000 kg to 40,000 kg at 10 probability at Hico whereas it varied from 20,000 kg to 80,000 kg at Valley Mills. These curves showed loadings within 10,000 kg at Hico at 90% probability and they showed loadings within 20,000 kg at Valley Mills for the same probability.

In general, the loading curves were wider at lower probabilities and become closer as they reach higher probabilities. The mineral P loadings were increased by about 27% at Hico and 29%

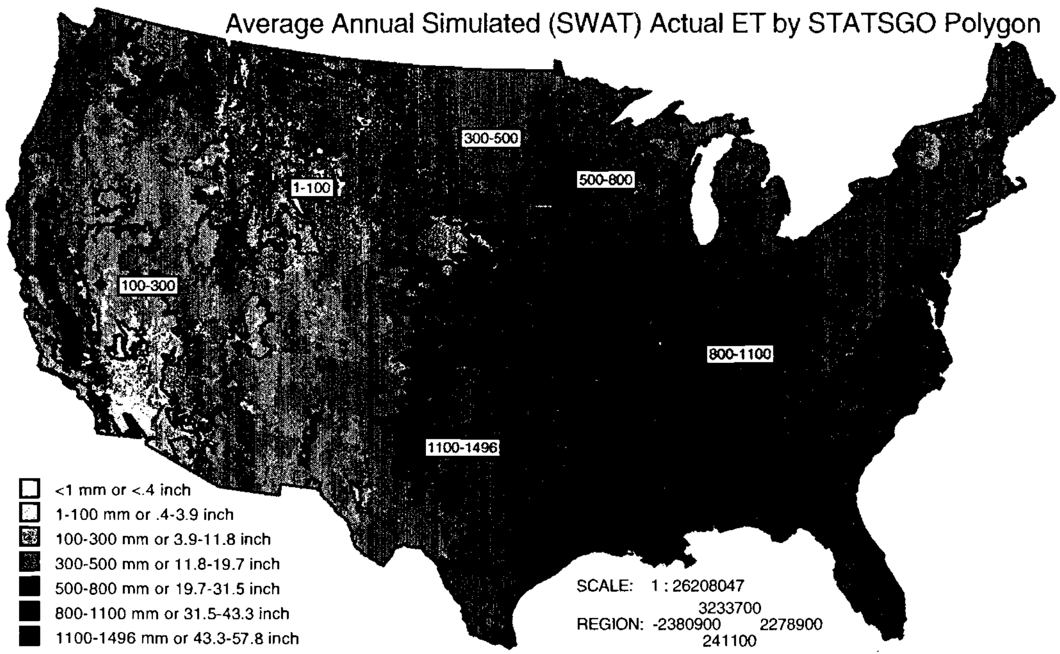

Figure 10.3 ET from HUMUS project.

at Valley Mills in the future condition scenario as compared to the existing condition scenario. These increases were predominantly caused by projected conditions for dairy and WWTPs in the future scenario (Table 10.7). Scenario E showed reduction in mineral P loadings of about 67% at Hico and 57% at Valley Mills from the future scenario. With scenario F, mineral P loadings were reduced 54% at Hico and 48% at Valley Mills from the future scenario. Scenario E indicated that with existing conditions, implementation of the BMPs would come closest to achieving the desired water quality goals; however, with year 2020 growth (future) conditions, more stringent controls will be required to meet the water quality goals.

Demonstration of HUMUS

Various hydrologic and crop growth outputs from the SWAT model simulation for the entire U.S. for the HUMUS project are given in Arnold et al. (1998). Penman-Monteith ET methodology was used in the simulation. Average annual ET generated from 20-year SWAT model simulations had highs and lows in parts of Kansas and Nebraska (Figure 10.3). These were due to the irrigation database used in this study. The high actual ET in most of Kansas was because the STATSGO database showed most of the state as irrigated land. With irrigation automatically triggered when plant available soil water was 50% of plant demand, irrigation of the agricultural cropland areas were greatest in parts of California, Kansas, and eastern New Mexico (Figure 10.4). The average annual biomass production (Figure 10.5) of irrigated cropland areas ranged from 25 to 32 Mg ha^{-1}. For non-irrigated cropland areas this ranged from 21 to 25 Mg ha^{-1}. For forest land areas values ranged from 16 to 21 Mg depending on their spatial and temporal distributions. Grains yields for irrigated land ranged from 9 to 11 Mg ha^{-1}, for non-irrigated land ranged from 6 to 9 Mg ha^{-1} in Midwest U.S. and 3 to 6 Mg in other grain production areas. These grain yields agreed reasonably well with state averages (Table 10.8).

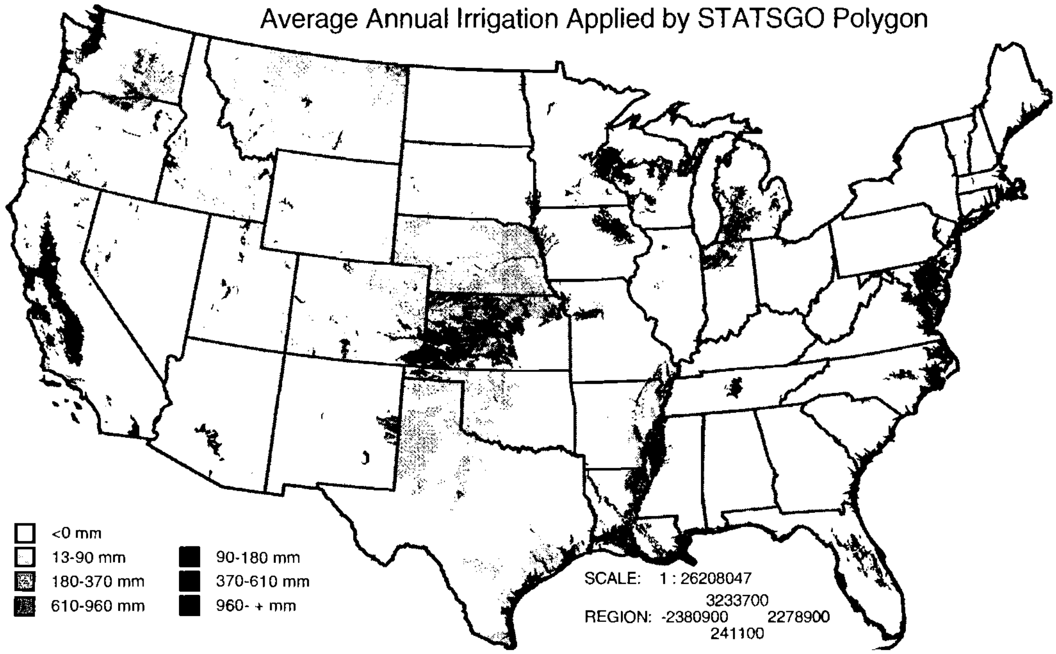

Figure 10.4 Irrigation applied from HUMUS.

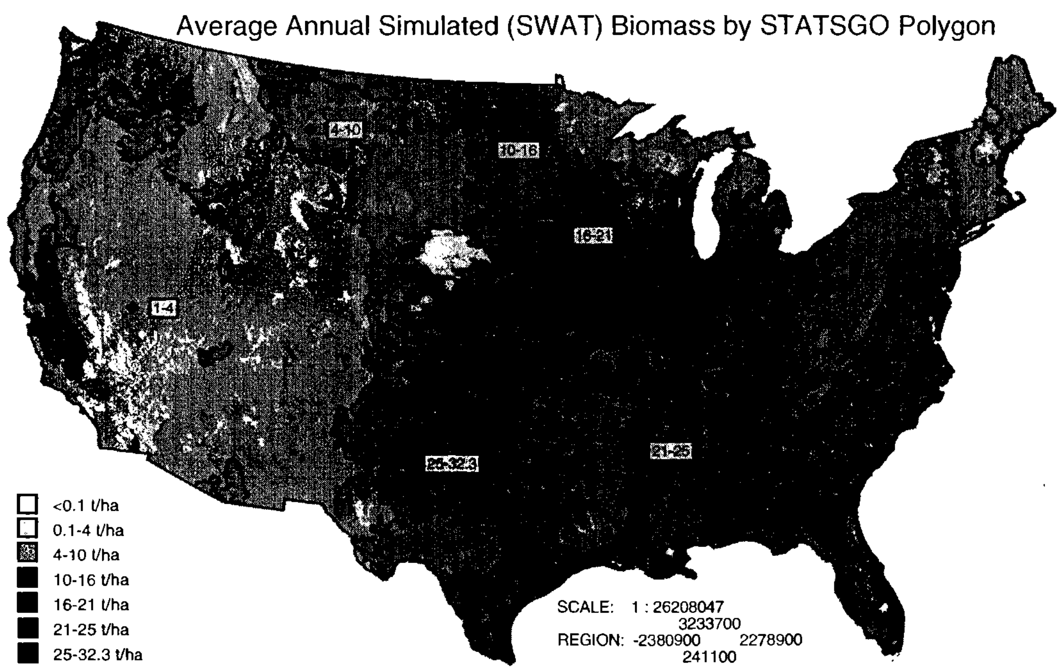

Figure 10.5 Biomass from HUMUS project.

CONCLUSIONS, RECOMMENDATIONS, AND AREAS FOR FUTURE STUDY

Model development and improvement are evolving processes, driven by users' needs while providing direction to basic research to fill knowledge gaps on key processes. Future work on model improvement is needed in several areas. We need to address limitations to model inputs, including availability of input data and problems with scale. Likewise, coding improvements can make models easier to understand and more modular. Interface tools for models and inputs of different scale are also needed. Especially challenging is the improvement in quantification of processes and process interactions in models. Finally, models need to be tested in environments distinct from the ones used for model development.

Limitations to inputs often become obvious when testing a model in a diverse group of sites. Precipitation data can be a problem because rain-gage density is insufficient to describe the spatial variability for accurate hydrologic simulation. Radar data (NEXRAD) can provide spatially detailed precipitation data for use in large scale models. Solar radiation data is often difficult to find, forcing model users to rely on weather stations several kilometers from field sites. Soil profile description can be derived from USDA-NRCS soil surveys, but actual description of layer depths within a field requires labor intensive soil sampling.

Making models modular allows portions to be easily transferred to new models. Once a model has been sufficiently validated and applied by many users, others may want to use only a portion, such as the plant growth. Thus, easily read code and favorable modularity become important. Often model developers, committed to working with users to apply models and develop reasonable inputs, may not have the resources and time to rewrite model code to make it modular. Such efforts may require outside funding and a special programmer to make the model code more object-oriented and user-friendly.

Interface tools are another area of promise for future work on modeling. GIS interfaces have been developed to automate spatial inputs and spatially display outputs of basin scale models. More research is needed to determine better basin discretization schemes (how to subdivide a basin, such as by sub-basins, on a grid scale, or by landuse overlays) and to assist users in developing management scenarios.

Functions within a model that quantify processes are usually the best available approximation at the time the model was developed and often can be improved by additional basic research. An example, for basin scale modeling, is the simulation of surface/groundwater interaction. Since groundwater can be a significant portion of stream flow at large scales, accurate simulation of groundwater flow and surface interaction (recharge) is essential. Likewise, functions to simulate bacteria fate and transport are needed for some basin scale models. Numerous TMDLs across the U.S. involve bacteria and basin scale bacteria processes which are not well understood or simulated. For single plant models there is a need for better description of many plant processes such as stress effects on plant phenology. For field scale and single plant models, there is a need for better description of root:shoot dynamics with and without drought or nutrient stress. Future research on the phenology and growth of perennial woody species in temperate and tropical environments will benefit application of these models to many areas.

The ultimate goal for process-based models is realistic simulation in a wide range of environments, not just those used for model development. Applying crop models developed in temperate conditions to new regions in the tropics can cause phenological simulations to fail. Maize leaf appearance rate as a function of degree days is much slower near the equator than in temperate zones. Careful analysis of simulations under high evaporative demand environments can identify weaknesses in soil water balance simulation and in plant responses to drought stress. Riparian zones and buffers are becoming important management tools with much need for accurate simulation. Realistic simulation of such zones is critical for many applications of large scale models.

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The SWAT model can be downloaded at http://www.brc.tamus.edu/swat/index.html. The other models are available directly from the authors.

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