Model Simulation of Soil Loss, Nutrient Loss, and Change in Soil Organic Carbon Associated with Crop Production

Introduction

About half of the land area in the United States, exclusive of Alaska, is cropland, pastureland, and rangeland owned and managed by farmers and ranchers. About 20 percent—377 million acres—is intensively managed to produce crops (USDA NRCS 2000). American farmers produce over 200 different crops, although five crops (cotton, hay, wheat, corn, and soybeans) account for about 70 percent of the total cropland acreage each year (USDA NASS 2004).

Soil properties and landscape characteristics vary considerably on land used to grow crops in the United States, as do climatic conditions. As a result, the crop mix and specific crop production practices (tillage, nutrient applications, pesticide applications, irrigation practices) differ substantially from one part of the country to another. If appropriate management activities and conservation practices are not used, the interaction between wind and water, soil and landscape characteristics, and crop production practices results in the loss of soil, nutrients, and pesticides from farm fields, contributing to water quality degradation in some watersheds. Moreover, onsite soil erosion and soil quality degradation, if not addressed, can jeopardize prospects for sustaining future crop production.

Science has shown that not all cropland acres are equally vulnerable to the forces of wind and water that cause the migration of potential pollutants from farm fields to lakes, rivers, streams, and ground water. The National Resources Inventory (NRI) documents how a minority of cropland acres (those most prone to erosion) are the source of the majority of the overall soil erosion (H.J. Heinz Center 2002). Various watershed modeling projects have shown that water quality degradation can be ameliorated by addressing resource concerns in only a portion of the watershed. Studies on the human dimension have also shown that the potential for environmental degradation can often be disproportionately influenced by a small group of land users (Shephard 2000). Nowak and Cabot (2004) argue that incorporation of this concept of disproportionality into water resource management is necessary to attain cleaner, healthy watersheds in agricultural areas. Understanding the characteristics and spatial distribution of the more fragile, or vulnerable, cropland acres can lead to more efficient and effective implementation of conservation programs.

The purpose of this study is to identify areas of the country that have the highest potential for sediment and nutrient loss from farm fields, wind erosion, and soil quality degradation—areas of the country that would likely benefit the most from conservation practices. To accomplish this, the National Nutrient Loss and Soil Carbon (NNLSC) database was constructed using the 1997 NRI to represent cropland land use patterns and resource conditions. The modeling results reported in this study were obtained using a system of databases and models built by the U.S. Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) and the Blackland Research Center, Texas Agricultural Experiment Station (TAES) during 2000 to 2004. The spatial distribution of the model outputs is shown in maps to identify areas of the country with the greatest potential for loss of soil and nutrients from farm fields and for changes in soil organic carbon as an indicator of the potential for deteriorating soil quality.

This report is the first in a series of reports on the cropland national assessment component of the Conservation Effects Assessment Project (CEAP). CEAP is a multi-agency effort initiated in 2003 by five USDA agencies (NRCS, ARS, CSREES, FSA, and NASS) to estimate the environmental benefits of conservation practices (Mausbach and Dedrick 2004). The purpose of the project is to quantify the benefits and effects of conservation practices. The project has two principal components: the watershed assessment studies component, designed primarily to measure the effects of conservation practices at the watershed scale, and the national assessment, designed to provide estimates of the benefits of conservation practices for reporting at the national and regional levels. (More information about CEAP can be found at http://www.nrcs.usda.gov/technical/nri/ceap.)

Subsequent CEAP reports on cropland will expand and extend the results presented in this first report.

A new farmer survey—the NRI–CEAP cropland survey—was initiated in 2003 to provide better and more current information on farming activities and conservation practices at NRI sample points (USDA NRCS 2004). In addition, significant refinements are currently underway in the models and modeling systems used to estimate effects. Preliminary results based on the new and expanded models and databases are scheduled for release in 2006, followed by a final report in 2007. Results in these forthcoming CEAP reports are expected to differ somewhat from results reported in the present study, benefiting from improved model routines, better information on farming activities, and a fuller accounting of conservation practices.

Modeling approach and methods

Overview of approach

The modeling approach used in this study is based on microsimulation modeling techniques that were originally developed to investigate the economic impact of public policy (Haveman and Hollenbeck 1980a, 1980b; Lewis and Michel 1989). Microeconomic simulation models consist of microdata on characteristics of individuals obtained from statistically designed surveys and response functions that predict behavior of individuals. Macroeconomic outcomes are then obtained by aggregating predicted outcomes of individuals represented in the sample. The statistical sample design provides the basis for the aggregation.

A similar modeling approach is used in this study. The 1997 NRI provides the microdata on natural resource characteristics for a representative set of sample points. The NRI is designed to assess conditions and trends of soil, water, and related resources on private land (see box inset—The National Resources Inventory). It consists of about 800,000 sample points, of which about 220,000 were cropland in 1997. NRI information on crop, soil characteristics, and other information for the year 1997 are combined with data on field management activities from farmer surveys and other sources for a comparable time period and used in conjunction with a field-level fate and transport process model to estimate the loss of materials from farm fields and other outcomes such as the change in soil organic carbon. The statistical sample weight associated with each sample point is used to aggregate the model outputs to the national or regional level. The resulting simulation model captures the diversity of land use, soils, climate, and topography from the NRI, estimates the loss of potential pollutants from farm fields at the field scale where the science is best developed, and provides a statistical basis for aggregating results to the national and regional levels. NRCS and TAES have used this approach in previous studies to estimate pesticide loss from cropland (Kellogg et al. 1992, 1994; Kellogg et al. 2002; Goss et al. 1998; Goebel and Kellogg 2002) and to identify priority watersheds for water quality protection from non-point sources related to agriculture (Kellogg 2000; Kellogg et al. 1997).

The physical process model Environmental Policy Integrated Climate (EPIC) is used to generate estimates of soil loss, loss of nutrients, and change in soil organic carbon for the 1997 NRI cropland sample points. (A description of the EPIC model is presented in a later section.) Version 3060 of EPIC was used. The Interactive-EPIC (I–EPIC) software (Campbell 2005; Gassman et al. 2003) was used to manage and automate batch model runs. An application program called RunBuilder was developed to automate data assembly. The integrated modeling system consists of the EPIC model, I–EPIC model management software, input databases, RunBuilder, and the model output database. The modeling system is documented in Potter et al. (2006).

The goal is to produce estimates of soil loss, nutrient loss, and change in soil organic carbon at NRI cropland points. However, it is not practical or necessary to run EPIC at each NRI sample point. Many of the sample points have the same crop grown on similar soils and in similar climates. Instead, a library of EPIC model results called the National Nutrient Loss and Soil Carbon (NNLSC) database was produced that provides estimates of EPIC model output for specific crops, soils, climates, and management characteristics. These EPIC model results were then matched to NRI sample points on the basis of the attributes associated with each sample point.

The National Resources Inventory

The National Resources Inventory (NRI) is a scientifically-based survey designed to assess conditions and trends of soil, water, and related resources of the Nation's non-federal lands at the national and regional level (USDA NRCS 2000; Goebel 1998).

The NRI sample is a stratified two-stage unequal-probability area sample (Nusser and Goebel 1997; Goebel and Baker 1987). The primary sampling units (PSU) are areas of land called segments. The segments vary in size from 16 to 256 hectares (40–640 a). Sampling rates vary across strata, but are typically between 2 and 6 percent. There are about 300,000 sample segments in the current national sample. Detailed data are collected at a randomized sample of points within each of these segments. Generally, there are three points per segment, but some segments only contain one or two points. Overall, there are about 800,000 sample points in the NRI, representing all land uses on privately owned land in the United States. The NRI sample was designed to provide national, state, and in some cases, sub-state assessments with statistical reliability.

At each sample point, information is collected on nearly 200 attributes including land use and cover, soil type, cropping history, conservation practices, erosion potential, water and wind erosion estimates, wetlands, wildlife habitat, vegetative cover conditions, and irrigation method. Detailed NRI data are collected for the specific sample points, but some items are also collected for the entire primary sampling unit. Some data, such as total surface area, federally owned land, and areas in large water bodies, are collected on a census basis external to the sample survey. Data are collected for PSUs using photo-interpretation and other remote sensing methods and standards. Data gatherers also use ancillary materials such as USDA field office records, information from NRCS field staff, soil survey and other inventory maps and reports, and tables and technical guides developed by local field office staffs. Data gathered in the NRI are linked to NRCS Soil Survey databases and can be linked spatially to climate databases.

The NRI approach to conducting inventories facilitates examining trends over time because the same sample sites have been studied since 1982, the same data have been collected since 1982 (definitions and protocols have remained the same), and quality assurance and statistical procedures are designed/developed to ensure that trend data are scientifically legitimate and unambiguous. Data undergo rigorous quality review. Statistical estimation procedures are used to assign acreage weights—called expansion factors—to sample points based on sampling (selection) probabilities, estimates from previous NRIs, and known land base attributes from the Census Bureau and other sources.

The 1997 NRI is the most recent published database. It includes sample point data for 4 years—1982, 1987, 1992, and 1997. The NRI is currently in transition from a 5-year cycle to an annual cycle of data collection. Summary statistics for the 2003 NRI have been released, but the sample point database is not yet available.

For more information on the NRI, visit http://www.nrcs.usda.gov/technical/NRI/.

The NNLSC database consists of EPIC model results for 25,250 Unique Resource Units (URU). Each URU consists of a climate zone, a soil cluster, a specific state, a specific crop, one of three irrigation types including no irrigation, and one of eight combinations of three conservation practices (contour farming, stripcropping, and terraces) including no practices (fig. 1). For modeling purposes, each URU is treated as a single homogeneous farm field. Several EPIC model runs are made for each URU, representing different tillage systems, different commercial fertilizer application schemes, and two types of manure applications. More model runs were conducted for URUs with a diverse collection of tillage and nutrient application possibilities than URUs with less diversity. Some crops, for example, have more tillage and nutrient application possibilities than other crops, and these can also vary for a given crop by region of the country. An average of 30 EPIC model runs were made for each URU to represent the various tillage options, commercial fertilizer application options, and manure application options. (The data inputs and assumptions used to generate these simulations are presented in later sections.) A total of 768,785 EPIC model runs were made to generate the NNLSC database.

The characteristics that define a URU (climate zone, soil cluster, state, crop, irrigation system, and conservation practice) were derived from characteristics of NRI cropland sample points. For example, the presence of irrigation, contour farming, stripcropping, and terraces was obtained from the NRI. Each URU represents at least one NRI cropland sample point. On average, a URU represents seven NRI sample points, with a maximum of 830 sample points in the largest URU. The acreage representation of each URU is the sum of the expansion factors for the NRI points corresponding to the URU. URUs with less than 1,000 acres were discarded because model simulation of these small areas would contribute little to the overall assessment; the corresponding NRI sample points were excluded from the sample domain.

Figure 1 Organizational scheme for construction of the NNLSC database

Climate zone (66 climate zones)
- Soil clusters (2,688 soils with 5,887 soil-climate combinations)
  - State (48 states with 6,043 state-soil-climate combinations)
    - Crop (15 crops)
      - Irrigation system (sprinkler, furrow, no irrigation)
        - Three conservation practices (8 combinations)

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25,250 URUs
- Tillage system (3 types)
  - Commercial fertilizer application
  - Manure application

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768,785 EPIC model runs

Each EPIC model run consists of 40 consecutive years of which the last 30 years of annual output were saved for analysis. The first 10 years of results are dropped because the model uses default starting values for various soil attributes and other input data (such as crop residue levels) that are not known, and therefore, the model is allowed to equilibrate before the annual output is recorded. A weather generator was used to provide estimates of daily weather. (Weather simulation is described in a later section.)

All crops were simulated as if they were grown in each year of the 40-year simulation (continuous cropping). Crop rotations can be modeled using EPIC, but the lack of information on the occurrence of the various crop rotations and the paucity of data on nutrient applications and tillage practices for crops grown in specific crop rotations precluded simulation of crop rotations in this study. However, sensitivity analysis showed that varying the crop from year to year sometimes has a significant effect on both the hydrologic cycle and the nutrient cycles, indicating that crop rotations will need to be taken into account in future modeling efforts.

EPIC model outputs were reported as 30-year annual averages. The results can be interpreted as outcomes averaged over a set of weather conditions that could reasonably occur. Alternatively, results represent expected outcomes for a future year where the weather conditions are not known. The cropping patterns and management activities are generally representative of 1997; however, the output results represent outcomes that would be expected after removing the year-to-year variability owing to weather. To estimate the 30-year change in organic carbon, the first and the 30th year values were used.

EPIC model outputs for each NRI cropland sample point were derived from the NNLSC database after obtaining 30-year annual averages for each model run. Model output results for NRI sample points were obtained by calculating the weighted average over all the management options in the NNLSC database for the URU corresponding to the NRI sample point. Each NRI sample point corresponding to a given URU was assigned the same model output results. The weights represent the probability that a particular option would occur. For example, if there were only three management options and the probability that the first option would occur was 20 percent, the probability that the second option would occur was 30 percent, and the probability that the third option would occur was 50 percent, then the model output estimate for the NRI sample point would be 0.2 times the model output estimated by EPIC for the first option plus 0.3 times the model output estimated for the second option plus 0.5 times the model output estimated for the third option. The probabilities that a particular management option applies to a URU (and the associated NRI sample points) were estimated based on the frequency of occurrence of each option obtained from national level databases (see app. A).

National and regional estimates of soil loss, loss of nutrients, and change in soil organic carbon were derived from the EPIC model outputs estimated for each NRI cropland sample point. Aggregated estimates were produced using the statistical sample weight (expansion factor, or acreage weight) associated with each NRI sample point. In the case of per-acre estimates, the expansion factors were used to derive weighted averages. In the case of total loss estimates, the expansion factors served as acreage estimates. In addition, maps showing the spatial distribution of EPIC model outputs were derived from estimates for NRI cropland sample points.

Seven geographic regions were established for reporting and summarizing the model results. The seven regions were determined on the basis of similar hydrologic characteristics (precipitation, runoff, and percolation). More traditional regional boundaries were tried initially, such as combinations of states or large watersheds, but the aggregate results for reporting in tables were in conflict with the information in the spatial distribution maps. These seven regions were selected so that the spatial trends in the maps were reflected in the regional tables. The boundaries for the seven regions are shown on all maps. The seven regions are the Northeast, Southeast, Upper Midwest, South Central, Northern Great Plains, Southern Great Plains, and West. Percent acres represented in the model simulations for each region are:

Region	Percent of total acres
Northeast region	4.6
Southeast region	4.5
South Central region	15.2
Upper Midwest region	37.7
Southern Great Plains region	10.8
Northern Great Plains region	24.3
West region	3.0

In the sections that follow, more details are provided on the EPIC model, the nature and extent of the NRI sample points included in the study, how soil and other characteristics were represented in the model, how weather was simulated, how farming practices and conservation practices were represented, how nutrient management activities were represented, and how the maps of the spatial distribution of the model output were derived.

EPIC model

For crop production, farmers prepare the soil (usually by loosening and mixing it), add fertilizer and organic amendments such as manure or lime, plant the seeds, cultivate, apply chemicals for pest control, irrigate as needed, and then harvest the crop. Throughout the year, weather events affect crop production both positively and negatively. Properties of the soil such as bulk density, organic matter, and water holding capacity affect crop growth and other processes. Over time, the chemical properties and physical structure of the soil can change. As a result of the interaction between the farmer's production activities, soil properties, and weather events, some soil particles are carried off the field by water runoff and wind. Adhered to these soil particles are residues of nitrogen, phosphorus, and pesticides. Nutrients and pesticides also migrate from the field dissolved in the water runoff and in the water that leaches beyond the root zone.

All of these processes are simulated in the EPIC model. A wide variety of soil, weather, and cropping practice data input options allow simulation of most crops on virtually any soil and climate combination. EPIC is used by scientists throughout the world for studying agro-environmental issues (Putman et al. 1988; Robertson et al. 1990; Sharpley et al. 1991; Stockle et al. 1992; Chang et al. 1993; Lacewell et al. 1993; Mapp et al. 1994; and Wu et al. 1996). EPIC was originally developed in the early 1980s for assessing the impact of agricultural management practices and the associated soil erosion on long-term productivity of United States soils (Putman et al. 1987, 1988; USDA SCS 1989; Williams 1990, 1995). Since then, the EPIC model has been extended to include the major soil and water processes related to crop growth and a broad array of environmental effects of farming activities. It continues to be modified and refined. The most recent version, version 3060, incorporates routines for soil carbon accounting that are nearly identical to those in the Century model, as well as other refinements (Izaurralde et al. 2005; Williams and Izaurralde 2005). Appendix B contains a summary of published literature on EPIC application and performance.

The major model components in EPIC are weather simulation, hydrology, erosion/sedimentation, nutrient cycling, pesticide fate, plant growth, soil temperature, tillage, economics, and plant environment control (fig. 2). EPIC operates on a daily time step, integrating daily weather data, soil characteristics, and farming operations such as planting, tillage, and nutrient applications. The plant growth model simulates the growth and harvest of a crop. All farming operations that take place on the field throughout the year are taken into account. On a daily basis, EPIC tracks the movement of water, soil erosion, and the cycling of nitrogen, phosphorus, and carbon.

EPIC is a point model that has been developed and parameterized on the basis of measured research data from experimental research plots and small fields. EPIC does not recognize field characteristics such as slope, shape, or concentrated flow paths. It does not route soil and water from one part of the field to another part of the field. EPIC assumes that the field area around the point is entirely homogeneous, including soil characteristics and all management activities. One of the ramifications of this is that EPIC does not estimate gully erosion. As a point model, it is ideal for use with NRI sample points because NRI sample points are also points in a field. Because of the nature of the measured data used to develop and parameterize EPIC, the model output represents about a 1-hectare area, or about 2.5 acres. The model outputs, such as surface water runoff or sediment yield, are similar to what would be found if actual measures could be taken from the edge of an area within a field about 1 hectare in size that was reasonably homogeneous. Vertically, EPIC simulates fate and transport processes through the soil profile, which is generally the boundary for crop roots. Thus, EPIC model output reported in this study is best represented as water, soil, and nutrient loss at the edge of a field or a small part of a field and at the bottom of the root zone (Williams 1990).

The potential list of output variables that can be generated by EPIC is large. Only a selection were tracked and reported in this study (table 1).

Figure 2 Schematic representing inputs to, processes in, and outputs from the EPIC model

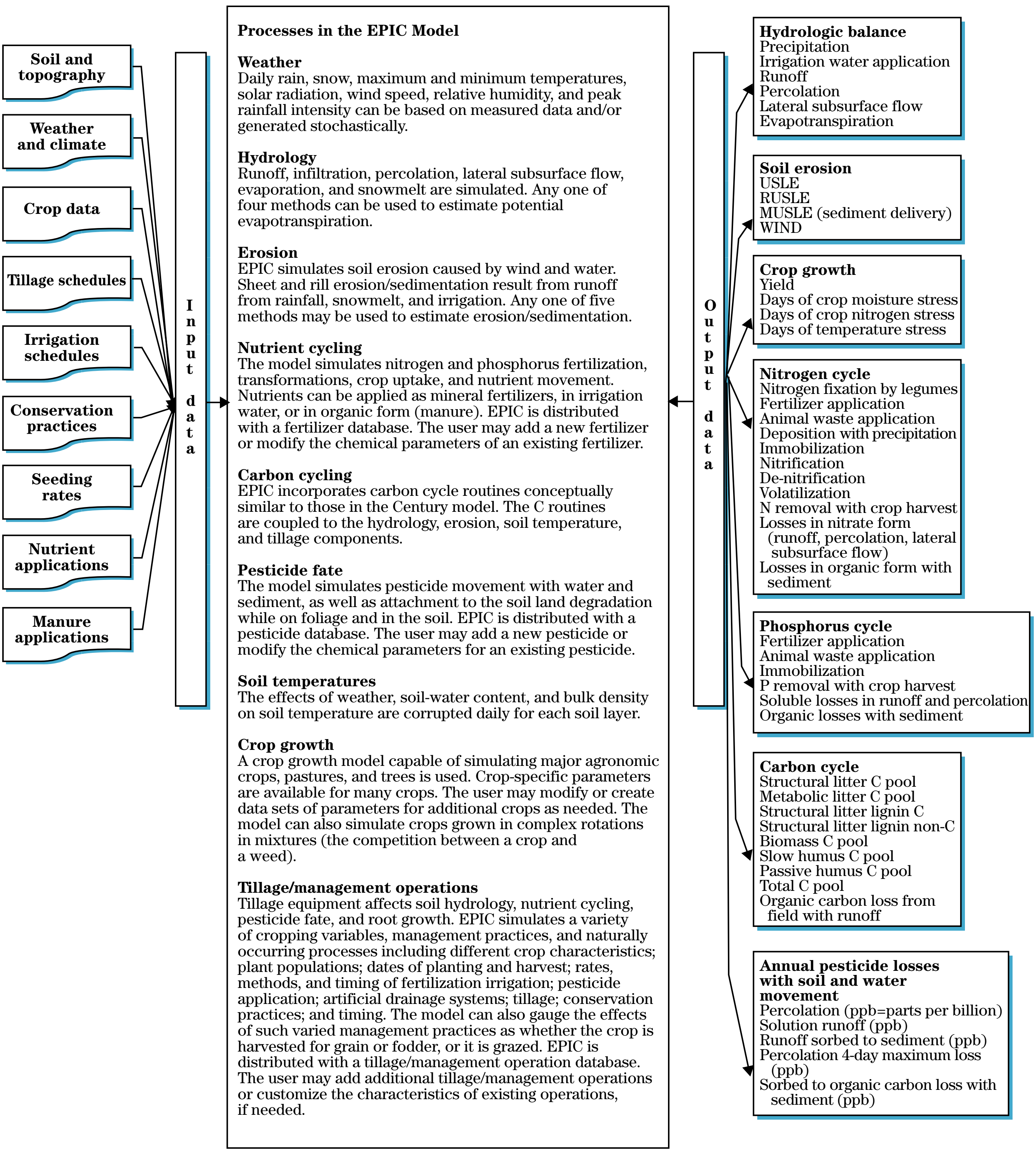


Table 1 EPIC-generated variables for NRI cropland sample points

Model component	Description	Reporting unit	
		Per acre	Total
Hydrology	Precipitation		in
Hydrology	Irrigation water applied		in
Hydrology	Evapotranspiration		in
Hydrology	Surface water runoff		in
Hydrology	Percolation		in
Hydrology	Subsurface lateral flow		in
Soil erosion	Water erosion, sheet and rill (USLE)	ton	ton
Soil erosion	Water erosion, sediment delivery (MUSLE)	ton	ton
Soil erosion	Wind erosion	ton	ton
Nitrogen cycle	Commercial nitrogen fertilizer applied	lb	ton
Nitrogen cycle	Manure nitrogen applied	lb	ton
Nitrogen cycle	Total nitrogen applied	lb	ton
Nitrogen cycle	Nitrogen fixation	lb	ton
Nitrogen cycle	Nitrogen added with rainfall	lb	ton
Nitrogen cycle	Nitrogen volatilized	lb	ton
Nitrogen cycle	NO_3 loss in runoff	lb	ton
Nitrogen cycle	NO_3 lost in leachate	lb	ton
Nitrogen cycle	NO_3 loss in subsurface lateral flow	lb	ton
Nitrogen cycle	Organic nitrogen loss with waterborne sediment	lb	ton
Nitrogen cycle	Organic nitrogen loss with windborne sediment	lb	ton
Nitrogen cycle	Sum of all nitrogen losses	lb	ton
Phosphorus cycle	Commercial phosphorus fertilizer applied	lb	ton
Phosphorus cycle	Manure phosphorus applied	lb	ton
Phosphorus cycle	Total phosphorus applied	lb	ton
Phosphorus cycle	Soluble phosphorus lost in runoff	lb	ton
Phosphorus cycle	Soluble phosphorus lost in leachate	lb	ton
Phosphorus cycle	Organic phosphorus loss with waterborne sediment	lb	ton
Phosphorus cycle	Organic phosphorus loss with windborne sediment	lb	ton
Phosphorus cycle	Sum of all phosphorus losses	lb	ton
Carbon cycle	Soil organic carbon (30-yr average)	ton	ton
Carbon cycle	Soil organic carbon (change over 30 yr)	ton	ton
Carbon cycle	Beginning soil organic carbon (yr 1)	ton	ton
Carbon cycle	Ending soil organic carbon (yr 30)	ton	ton
Other	Crop yield	Varies by crop	

Summary of crops and cropland acres included in the study

The domain of the NNLSC database was derived from the 1997 NRI. It includes NRI sample points with one of the following 13 crops recorded for 1997: corn, soybeans, wheat, cotton, barley, sorghum, rice, potatoes, oats, peanuts, legume hay, grass hay, and mixed legume-grass hay. Some crops such as summer fallow, tobacco, sugar beets, and sunflowers were not included because of the lack of information on farming activities from farmer surveys. In cases where the NRI crop classification scheme grouped several crops into a single group—such as other row crops, other close grown crops, other vegetable crops, and other crops—it was not possible to link farmer survey data on specific crops to the NRI points.

In the West, the domain was further restricted to include only the major agricultural areas. The western areas were delineated by 6-digit Hydrologic Unit Code (HUC) watersheds, and 19 were selected to represent cropland in the West. The selected areas consisted of 105 8-digit HUCs. Hawaii, Alaska, and United States territories were not included.

The total number of 1997 NRI sample points in the domain was 178,567. This coverage accounts for approximately 298 million acres, representing about 80 percent of the 377 million acres of cropland in the United States as estimated by the NRI for 1997 (tables 2 and 3). Map 2 shows the percentage of cropland acres that were included in the study. Approximately 92 percent of the NRI acreage for the 13 crops was included in the domain; acres of these crops not included were largely in the West. Over 98 percent of the NRI acres are represented in the domain for six crops—corn, sorghum, soybeans, cotton, peanuts, and rice. Map 3 shows the dominate crops for each of the seven regions.

Not all areas of the country are well represented by the 13 crops. Areas where summer fallow, tobacco, sugar beets, sunflowers, specialty crops, orchards, and vegetable crops are dominant crops are not covered in this study. Only about 18 percent of the cropland acreage in Florida is represented, mostly in northern Florida (table 3, map 2). Seven western states (Arizona, California, Nevada, Oregon, Utah, Washington, and Wyoming) are also poorly represented, with only about 26 percent of the cropland acreage included overall. Three New England states (Massachusetts, New Hampshire, and Rhode Island) had only 34 percent of the cropland included.

To properly account for management factors, it was necessary to break down NRI corn acres into corn for grain and corn for silage, and break down NRI wheat acres into winter wheat and spring wheat. County proportions for each of the crop breakdowns were obtained from the 1997 Census of Agriculture. For example, consider an NRI wheat point representing 2,600 acres in a county where 60 percent of the wheat was winter wheat and 40 percent was spring wheat. This point would be replaced with a winter wheat point with 1,560 acres and a spring wheat point with 1,040 acres. All other attributes of the original NRI point were assigned to each of the two derived points. Corn for grain, corn for silage, winter wheat, and spring wheat were set up as separate URUs for modeling. (number of points totaled 222,358 after the break down of corn and wheat).

Legume hay and mixed legume-grass hay were treated as the same crop as it was assumed they would both be managed as legume hay. Both were included in the same URU.

Table 2 Percent of NRI cropland acres included in the study–by crop

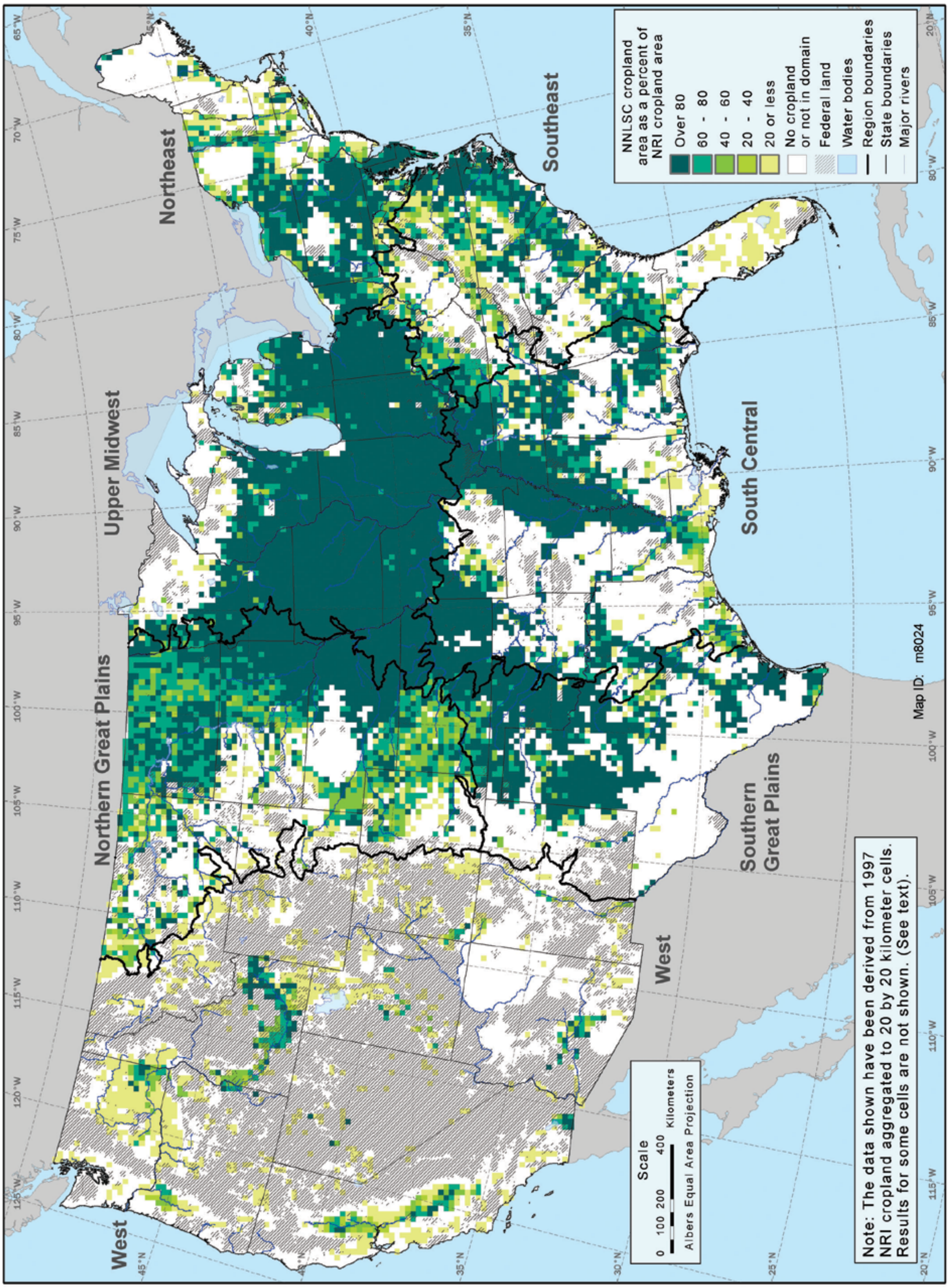
Crop	1997 NRI*		Domain of the NNLSC database		
	Number of NRI sample points	Acres (1,000s)	Number of NRI sample points	Acres (1,000s)	Percent NRI acres included in domain
Corn	56,285	84,549,200	55,105	83,416,000	98.7
Sorghum	5,502	10,972,600	5,406	10,897,300	99.3
Soybeans	45,379	67,767,600	45,039	67,542,800	99.7
Cotton	8,423	17,095,400	8,182	16,858,200	98.6
Peanuts	1,119	1,874,600	1,089	1,843,400	98.3
Potatoes	915	1,247,400	688	986,700	79.1
Tobacco	913	1,386,600	0	100	0.0
Sugar beet	742	1,228,800	0	0	0.0
Sunflowers	1,275	2,405,900	0	0	0.0
Other row crops	1,446	2,027,200	0	0	0.0
Other vegetable crops	2,691	3,990,900	0	0	0.0
Wheat	33,774	70,280,000	31,319	65,517,100	93.2
Oats	2,241	3,960,800	2,036	3,772,400	95.2
Rice	1,929	3,664,400	1,913	3,637,300	99.3
Barley	3,252	5,895,400	2,384	4,634,900	78.6
Other close-grown crops	3,077	6,040,200	0	0	0.0
Grass hay	14,094	21,500,500	9,447	14,596,300	67.9
Legume hay	9,986	14,982,700	6,879	10,980,400	73.3
Mixed hay	12,925	19,626,500	9,080	13,795,200	70.3
Summer fallow	7,663	20,677,600	0	0	0.0
Horticulture (fruits, nuts, berries, etc.)	4,477	6,458,600	0	0	0.0
Other crops	5,548	9,365,000	0	0	0.0
All crops	223,656	376,997,900	178,567	298,478,000	79.2

* Includes both cultivated and non-cultivated crop categories

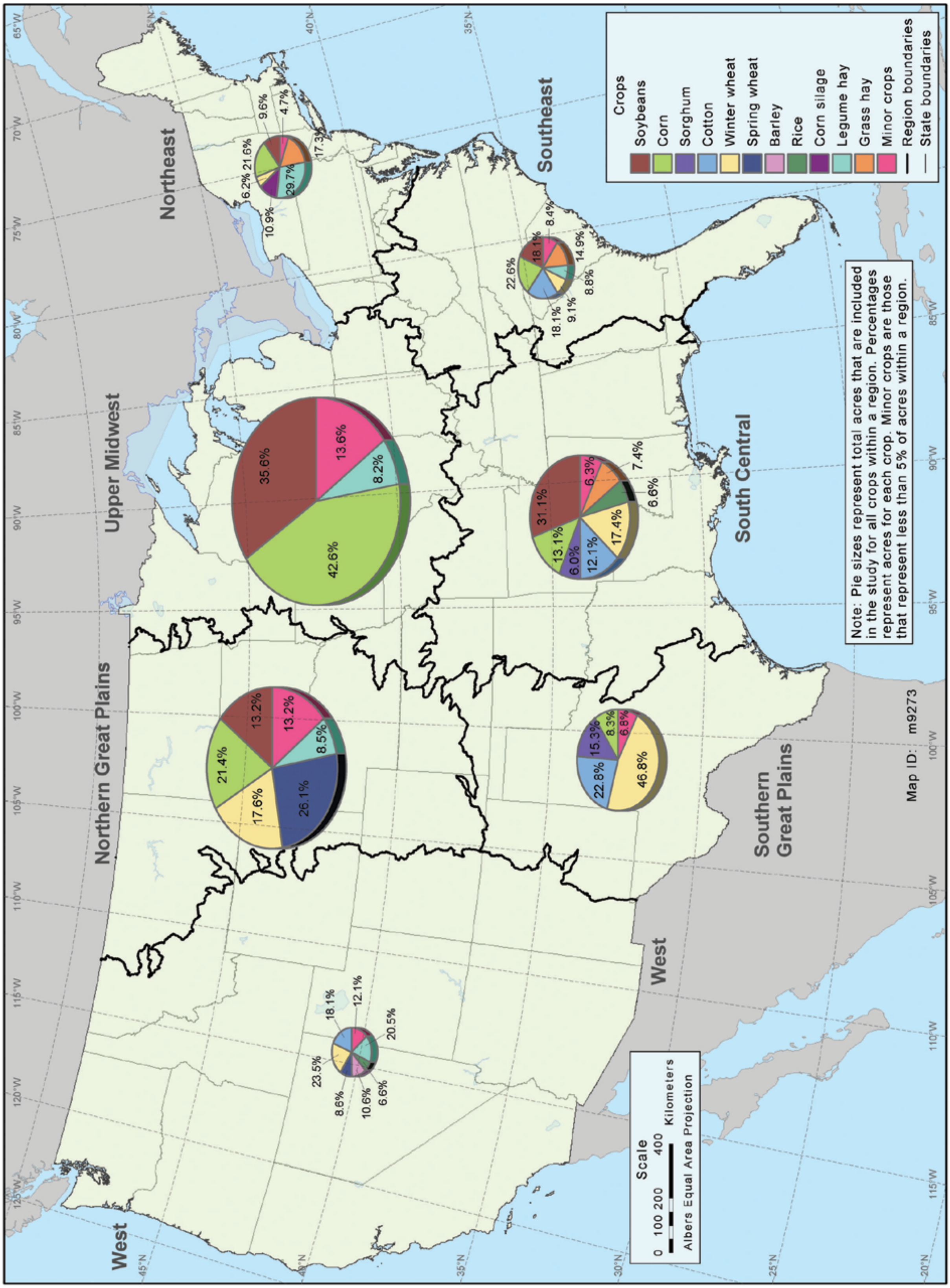
Table 3 Percent of NRI cropland acres included in the study–by state

State	1997 NRI Number of NRI sample points	1997 NRI Acres (1,000s)	Domain of the NNLSC database Number of NRI sample points	Domain of the NNLSC database Acres (1,000s)	Domain of the NNLSC database Percent NRI acres included in domain
Alabama	1,954	2,954	1,620	2,440	82.6
Arizona	1,004	1,212	284	439	36.2
Arkansas	3,986	7,625	3,837	7,375	96.7
California	4,844	9,635	1,560	3,566	37.0
Colorado	4,150	8,770	1,889	4,611	52.6
Connecticut	201	204	106	119	58.1
Delaware	504	485	459	448	92.5
Florida	1,659	2,752	283	497	18.1
Georgia	2,787	4,757	2,112	3,708	77.9
Hawaii	349	246	0	0	0.0
Idaho	4,737	5,517	2,451	2,683	48.6
Illinois	16,789	24,011	16,505	23,725	98.8
Indiana	9,751	13,407	9,391	12,961	96.7
Iowa	15,173	25,310	14,979	25,049	99.0
Kansas	13,595	26,524	11,404	21,115	79.6
Kentucky	4,132	5,178	3,432	4,343	83.9
Louisiana	2,453	5,659	1,535	3,793	67.0
Maine	294	413	147	248	60.1
Maryland	1,958	1,616	1,657	1,409	87.2
Massachusetts	256	277	94	106	38.3
Michigan	6,480	8,540	5,326	7,029	82.3
Minnesota	12,251	21,414	11,465	19,487	91.0
Mississippi	3,510	5,352	3,121	4,747	88.7
Missouri	9,202	13,751	8,571	12,680	92.2
Montana	4,254	15,171	1,795	7,215	47.6
Nebraska	11,434	19,469	10,230	17,073	87.7
Nevada	780	701	63	122	17.4
New Hampshire	149	134	46	39	29.2
New Jersey	661	589	363	327	55.5
New Mexico	1,640	1,875	841	1,107	59.0
New York	3,610	5,417	2,731	4,069	75.1
North Carolina	2,992	5,639	2,343	4,466	79.2
North Dakota	12,710	25,004	9,636	18,998	76.0
Ohio	8,958	11,627	8,373	10,945	94.1
Oklahoma	4,546	9,737	4,243	9,161	94.1
Oregon	2,475	3,762	398	610	16.2
Pennsylvania	4,493	5,471	3,867	4,776	87.3
Rhode Island	45	22	5	2	9.3
South Carolina	1,912	2,574	1,411	1,975	76.7
South Dakota	9,401	16,738	7,882	13,594	81.2
Tennessee	3,739	4,644	3,208	3,980	85.7
Texas	11,136	26,938	9,386	22,921	85.1
Utah	1,308	1,679	170	272	16.2
Vermont	624	607	394	359	59.1
Virginia	2,621	2,918	1,832	2,044	70.1
Washington	2,805	6,656	467	1,109	16.7
West Virginia	684	864	394	501	57.9
Wisconsin	6,468	10,613	5,851	9,597	90.4
Wyoming	1,500	2,174	410	643	29.6
Puerto Rico	692	368	0	0	0.0
All states	223,656	376,998	178,567	298,478	79.2

Map 2 Percent of cropland acres included in study



Map 3 Crop acreage–by region



Representing soil characteristics in the model

The soil's chemical and physical properties influence the movement of water, the cycling of nutrients and carbon, and crop growth. Soil is modeled in EPIC as a series of horizontal layers through which water and dissolved materials move through and which plant roots penetrate. The EPIC model uses information on the initial soil profile and soil properties (table 4). These are provided as inputs to the model or, if they are unknown, EPIC will estimate them. As the model simulation proceeds over several years, EPIC changes some of the soil properties in response to farming activities and weather. For example, the thickness of the surface layer decreases as soil is removed by erosion.

Soil data needed for the model were obtained from the NRCS Soil Survey databases linked to the NRI sample points. Soils represented by the NRI sample points were grouped into 2,688 soil clusters within which differences among soil properties would result in low variability among the major model output variables tracked in the study. For EPIC modeling, a single set of soil attributes was used to represent the NRI points in each of the 2,688 soil clusters (see box inset—Derivation of soil clusters).

For analysis and presentation of results, the 2,688 soil clusters were categorized into 25 groups defined by the combination of two variables—soil surface texture and hydrologic soil group. Surface texture was used to classify each soil into one of the following seven texture groups: coarse, moderately coarse, medium, moderately fine, fine, organic, and other. The coarse texture group consisted of soils with sandy surface textures including: coarse sand, sand, fine sand, very fine sand, loamy coarse sand, loamy sand, loamy fine sand, and loamy very fine sand. The moderately coarse texture group included soils with coarse sandy loam, sandy loam, and fine sandy loam surface textures. Medium textured soils were classified as those having very fine sandy loam, loam, silt loam, and silt surface textures. The moderately fine group included soils with clay loam, sandy clay loam, and silty clay loam surface textures. Fine textured soils were classified as those with sandy clay, silty clay, and clay surface textures. Peat and muck soils were classified as organic. Remaining soils were classified as other.

The hydrologic soil group is based on the NRCS classifications of soil runoff potential. Group A soils are primarily deep, well-drained sands or gravels having a low runoff potential and a high infiltration rate. Group B soils are moderately deep to deep soils with moderate infiltration rates when thoroughly wetted. Group C soils have slow infiltration rates when thoroughly wetted, sometimes with a soil layer impeding downward movement of water. Group D soils have a high runoff potential and a very slow infiltration rate when wet; these are soils with a high swelling potential, soils with a permanent high water table, or shallow soils over nearly impervious material.

Nearly 30 percent of the NRI cropland acres included in the study are classified as medium textured hydrologic soil group B soils (table 5). Soils with medium texture and hydrologic soil group C accounted for 17 percent, and soils with moderately fine texture and hydrologic soil group B accounted for 16 percent. The remaining 22 soil groupings accounted for 37 percent of the acres.

Table 4 Soil characteristics data required by EPIC

Soil attributes for each soil layer	Other soil attributes
Layer depth (m)	Number of soil layers
Bulk density (moist—ton/m^3)	Maximum number of layers
Bulk density (dry—ton/m^3)	Soils 5 ID
Water content at wilting point (1,500 KPA) (m/m)	Map unit symbol
Water content at field capacity (33 KPA) (m/m)	Hydrologic soil group (A,B,C,D)
Sand content (%)	Initial splitting thickness (m)
Silt content (%)	Weathering code
pH	Albedo (wet)
Sum of bases (cmol/kg)	Minimum profile thickness (m)
Organic carbon (%)	Minimum thickness of maximum layer (m)
Organic nitrogen concentration (g/ton)	Minimum depth to water table (m)
Calcium carbonate (%)	Maximum depth to water table (m)
Cation exchange capacity (cmol/kg)	Initial depth to water table (m)
Coarse fragment content (% volume)	Sub-surface flow travel time (mm/h)
Nitrate concentration (g/ton)	Initial ground water storage (mm)
Labile phosphorus concentration (g/ton)	Maximum ground water storage (mm)
Crop residue (ton/ha)	Runoff curve number (0–100)
Phosphorous sorption ratio	Return flow fraction of water percolating through root zone
Saturated conductivity (mm/h)	No. years of cultivation at start
Fraction of storage interacting with NO_3 leaching (g/ton)	Initial soil water content (% of field capacity)

Derivation of soil clusters

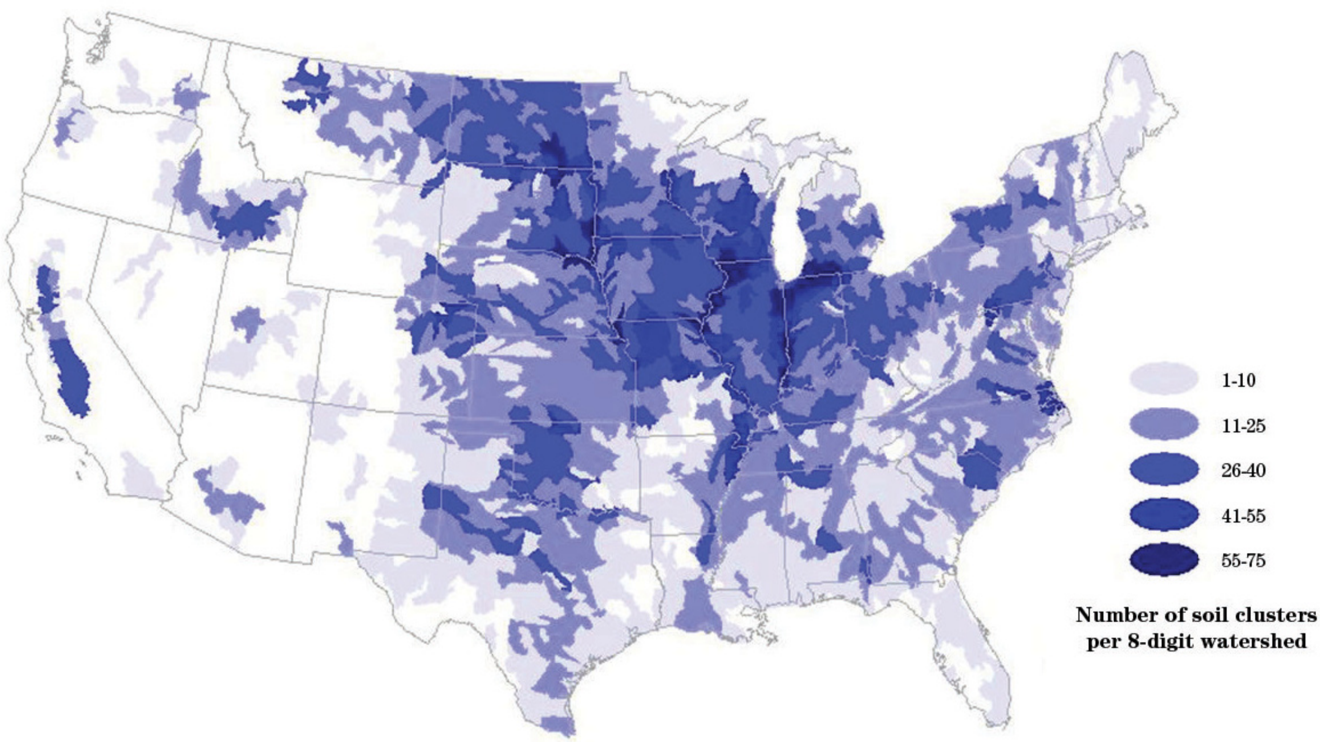
A statistical clustering procedure was used to define soil clusters with similar attributes (Sanabria and Goss 1997; Goss et al. 2001). Soil attribute data were obtained from soil characteristics defined for each of the NRI cropland sample points.

The clustering procedure was conducted using 27 soil attributes that are important for estimation of erosion and nutrient and carbon cycling. The soil attribute data were standardized to a mean of zero and a standard deviation of one prior to clustering to prevent attributes with large values from dominating the procedure. A factor analysis summarized the correlations and interactions of the properties into several underlying factors. Then each state's soils were clustered into groups of soils having similar factors using Ward's (1963) method in SAS (Statistical Analysis Software). This process placed a number of soils with similar properties into one cluster. Finally, the soil having the multivariate mean closest to the multivariate mean of the group was selected to represent the group. If the selected soil had peculiar properties, such as a very shallow depth, the next closest soil was used. The clustering procedure identified 2,688 soil clusters that represented all of the NRI cropland points included in the study.

The 2,688 soil clusters are not co-located spatially and include both dominant soils and relatively minor soils. A particular soil cluster could be found in several different watersheds in various locations throughout the United States. Some regions of the country have more diverse soils than other regions and, therefore, will have more soil clusters represented. As shown in figure 3, the number of soil clusters in watersheds defined by 8-digit HUCs can vary from less than 7 to as many as 75.

A specific example of the diversity of soils represented in the modeling is shown in figure 4, where the percentage of each soil cluster is presented for two watersheds in Iowa. Many of the soil clusters are found in both watersheds. In the Lower Iowa watershed (8-digit HUC 10230002), 31 different soils are represented. These 31 soils included three dominant soils, each representing more than 10 percent of the NRI cropland acreage in the watershed, and 28 relatively minor soils, each representing less than 7 percent of the acreage. The Floyd watershed (8-digit HUC 07080209) has 18 soils with 3 dominant soils and 15 minor soils. As will be shown later in the report, relatively minor soils can sometimes make a significant contribution to estimates of soil and nutrient loss from farm fields within a watershed.

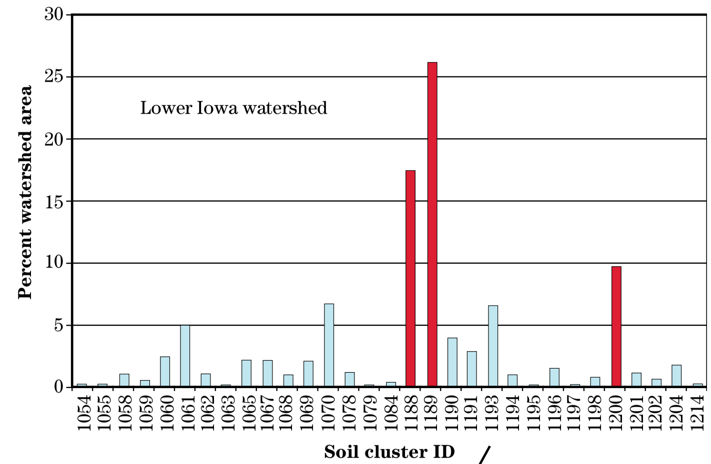
Figure 3 Number of soil clusters in each 8-digit watershed

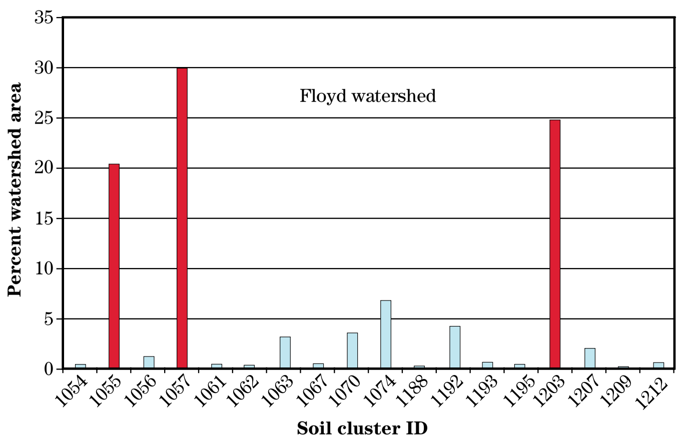


Note: White areas have no cropland or no NRI cropland sample points in the domain.

Figure 4 Diversity of soils represented in the model for two IA watersheds (dominant soils are colored red)

Soil cluster	Representative soil	Texture group	Hydrologic soil group	Soil cluster	Representative soil	Texture group	Hydrologic soil group
1054	Fairhaven	Medium	B	1189	Lagoda	Medium	B
1055	Kossuth	Moderately fine	B	1190	Sharpsburg	Moderately fine	B
1056	Alton	Moderately fine	C	1191	Adair	Medium	C
1057	Galva	Moderately fine	B	1192	Kenyon	Medium	B
1058	Hoopeston	Moderately coarse	B	1193	Marshall	Moderately fine	B
1059	Coland	Moderately fine	B	1194	Sparta	Coarse	A
1060	Tama	Medium	B	1195	Huntsville	Medium	B
1061	Coppock	Medium	B	1196	Downs	Medium	B
1062	Shelby	Moderately fine	B	1197	Village	Medium	B
1063	Turlin	Medium	B	1198	Lineville	Medium	C
1065	Fayette	Medium	B	1200	Humeston	Medium	C
1067	Nodaway	Medium	B	1201	Lamoni	Fine	C
1068	Gara	Medium	C	1202	Wabash	Moderately fine	D
1069	Lindley	Medium	C	1203	Terril	Medium	B
1070	Colo	Moderately fine	B	1204	Floyd	Medium	B
1074	Ida	Medium	B	1207	Monona	Medium	B
1078	Adair	Moderately fine	C	1209	Racine	Medium	B
1079	Lamont	Moderately coarse	B	1212	Spicer	Moderately fine	B
1084	Dickinson	Moderately coarse	B	1214	Chelsea	Coarse	A
1188	Ely	Medium	B				





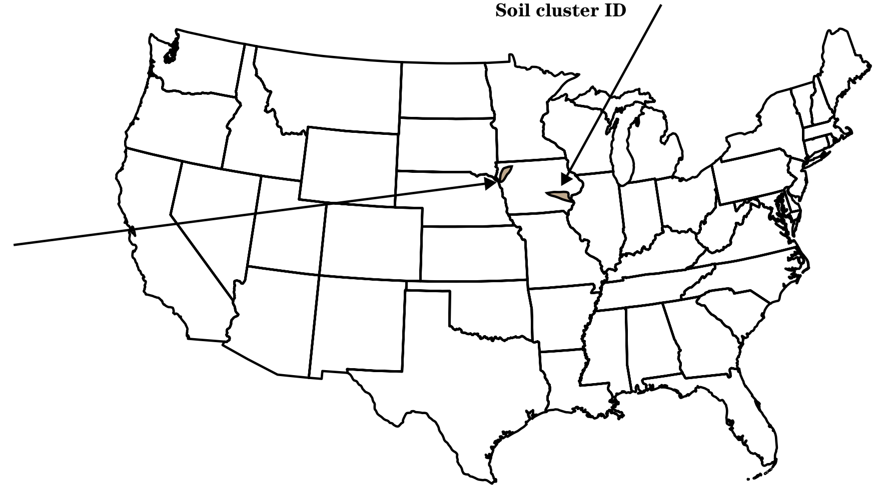


Table 5 Representation of 25 soil groups in cropland acres included in the study

Soil texture group	Hydrologic soil group	Number of soil clusters	Number of NRI sample points in soil clusters	Acres (1,000s)	Percent
Fine	B	8	310	300	0.1
Fine	C	25	1,988	2,715	0.9
Fine	D	128	7,694	14,935	5.0
	All	161	9,992	17,950	6.0
Moderately fine	B	132	27,216	46,690	15.6
Moderately fine	C	154	9,587	17,554	5.9
Moderately fine	D	110	7,229	14,005	4.7
	All	396	44,032	78,249	26.2
Medium	A	15	326	474	0.2
Medium	B	719	53,238	88,353	29.6
Medium	C	418	33,594	50,530	16.9
Medium	D	178	8,641	14,127	4.7
	All	1,330	95,799	153,484	51.4
Moderately coarse	A	24	696	1,257	0.4
Moderately coarse	B	293	14,785	25,062	8.4
Moderately coarse	C	120	2,956	4,469	1.5
Moderately coarse	D	40	811	1,665	0.6
	All	477	19,248	32,452	10.9
Coarse	A	145	4,938	8,724	2.9
Coarse	B	68	2,907	5,066	1.7
Coarse	C	36	761	1,218	0.4
Coarse	D	3	101	145	<0.1
	All	252	8,707	15,152	5.1
Organic	A	26	522	755	0.2
Organic	B	17	121	189	<0.1
Organic	C	3	37	72	<0.1
Organic	D	11	78	126	<0.1
	All	57	758	1,142	0.4
Other	B	11	21	31	<0.1
Other	C	2	2	3	<0.1
Other	D	2	8	15	<0.1
	All	15	31	49	<0.1
Totals	All	2,688	178,567	298,478	100.0

Representing weather in the model

Daily weather including precipitation volume, minimum and maximum temperatures, solar radiation, wind speed and prevalent direction, and relative humidity are necessary to run the EPIC model. Measured data can be input or the model can stochastically generate daily weather from the input of long-term monthly climate statistics. For this study, the weather generator option was used. The weather generator requires the average historical monthly maximum half hour rainfall and days per month with precipitation, which were derived from the EPIC climatic dataset. Thus, while the daily weather data used in this study are not actual weather, the simulated weather data are representative of historical weather patterns.

The weather generator, which is part of the EPIC model, operates stochastically. The estimate for precipitation involves two steps. First, the probability of precipitation is determined by using a random number generator to output a point between 0 and 1, which is then compared to the appropriate wet-dry probability distribution derived from climate records. If the random number is less than or equal to the wet-dry probability, precipitation occurs on that day. Secondly, the estimated precipitation is generated from a skewed normal daily precipitation distribution. On any given day, the input must include whether the previous day was dry or wet since the model provides for a higher probability of a wet day following a wet day. Determining whether the precipitation is rain or snow is based on air and soil temperatures. As configured for these simulations, EPIC did not account for rainfall intensity (storm duration or frequency within the day) or the interception and surface storage of precipitation.

Daily maximum and minimum air temperatures and solar radiation are generated from a normal distribution. A continuity equation is incorporated into the generator to account for temperature and radiation variations caused by dry versus rainy conditions. Maximum air temperature and solar radiation are adjusted downward when simulating rainy conditions and upwards when simulating dry conditions. The adjustments are made so that the long-term generated values for the average monthly maximum temperature and monthly solar radiation agree with the input averages.

A model routine developed by Richardson and Wright (1984) is used in EPIC to generate daily mean wind speed and direction given the mean monthly wind speed. This model is based on a modified exponential equation.

The relative humidity model routine uses a triangular distribution to simulate the daily average relative humidity from the monthly average. As with temperature and radiation, the mean daily relative humidity is adjusted to account for wet-day and dry-day effects.

Climate zones were derived from long-term weather data at about 1,000 weather stations to identify areas of the country with similar weather. A total of 35 climate zones were identified for the region east of the Rocky Mountains using a statistical clustering procedure similar to that used to identify soil clusters (see box inset—Derivation of climate zones for cropland east of the Rocky Mountains).

The western states were excluded from the statistical clustering due to large climatic variations within the 8-digit watersheds, usually due to orographic effects including elevation changes or rain shadows. A total of 31 climate zones were selected to represent cropland in the West by matching cropland areas within each 8-digit watershed to the most representative weather station available. Selection criteria included similarities in the cropland area and the weather station in elevation and topography, land cover, first and last freeze dates, mean temperatures and precipitation, and RUSLE rainfall erosivity. In most cases, a selected weather station represented cropland in several 8-digit watersheds.

The 66 climate zones are shown in map 4. Climate zones generally represent contiguous regions. There are some cases, however, where the climate clustering procedure identified similar climates in different regions of the country. These were grouped together into a single climate zone for purposes of EPIC modeling.

In each climate zone, a single weather station was selected to represent weather for EPIC model simulations. The selected weather station is also shown in map 4 and defined further in table 6. The weather statistics required by EPIC were derived from the weather records for the 66 selected weather stations. Solar radiation is estimated based on the latitude of the selected weather station. Wind speed and prevalent direction are based on long-term monthly averages for the weather station. Precipitation and temperature are based on the monthly statistics for the weather station.

Because multiple EPIC model runs were made for each URU to represent different management activities, and multiple URUs within a climate zone were used to represent different crops and soils, it was necessary to generate the same weather for all model runs conducted for a given climate zone. To accomplish this, the weather generator was set to start from the same random number seed in the initial year of the simulation for all model runs done in each climate zone. The stochastically generated weather sequences (precipitation, wind, and temperature events) for a given climate zone are independent of those for all other climate zones. Thus, the weather simulation does not capture a large storm as it moves across several climate zones. The weather station data are, however, usually correlated with nearby weather stations, so that the general spatial trends in weather are well represented.

Derivation of climate zones for cropland east of the Rocky Mountains

For cropland areas east of the Rocky Mountains, a statistical clustering procedure was used to define areas with similar weather (Goss et al. 2001). Climate records for approximately 680 weather stations were analyzed using a statistical clustering procedure, resulting in identification of 35 climate clusters for this region. All climate clusters were delineated by a collection of 8-digit HUC watersheds.

Ten variables were used in the clustering procedure: mean monthly precipitation, mean standard deviation of monthly precipitation, mean monthly maximum half hour precipitation (intensity), mean monthly dew point, mean monthly maximum temperature, mean monthly minimum temperature, mean monthly solar radiation, mean number of monthly rain days, mean percentage of wet days followed by dry days, and mean percentage of wet days followed by wet days. In addition to the annual variables, variables were constructed for each of four seasons: December to February, March to May, June to August, and September to November. In all, there were 50 climate variables. To reduce the impact of unusually high or low values, all variables were standardized to a mean of zero and a standard deviation of one prior to clustering.

The set of variables was processed with a multivariate factor analysis and one or more strongly weighted variables were chosen from each factor. These variables were: the monthly dew point for each season, mean monthly maximum and minimum temperature, and average standard deviation of the monthly precipitation and mean monthly precipitation. Also selected were mean monthly solar radiation for the spring and winter and mean and standard deviation of the annual precipitation. The number of climate clusters was optimized using a breakpoint determined by the improvement in the sum of deviations from the mean.

Selecting a weather station from each cluster that has characteristics best representing all the weather stations in the cluster was done by identifying the weather station with the lowest sum of the standardized absolute value of all the variables (the weather station with variable values most like the average over all the weather stations in the cluster).

Map 4 Climate zones used for model simulations

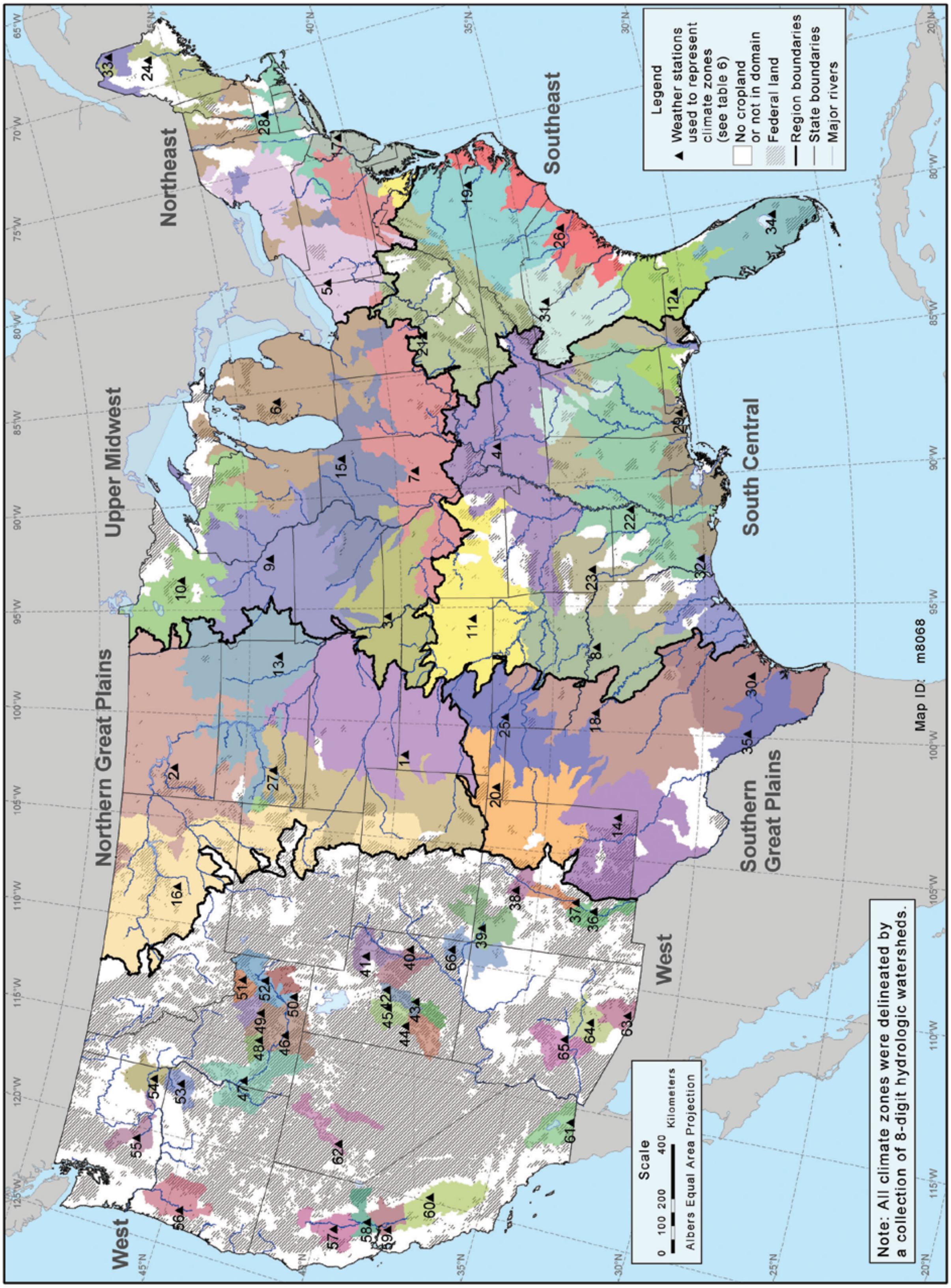


Table 6 Weather stations used to represent climate zones

Climate zone	Weather station name*	Percent of acres included in study
1	McDonald	7.3
2	Dunn Center	6.5
3	Tarkio Airport	5.4
4	Murray	5.6
5	Jamestown	2.1
6	Big Rapids Waterworks	6.4
7	Pana	8.7
8	Sherman	1.1
9	Zumbrota	8.7
10	Pokegama Dam	1.1
11	Chanute Airport	3.5
12	Live Oak	0.7
13	Madison Research Farm	6.7
14	Pearl	1.1
15	Aurora College	8.7
16	Flatwillow	2.2
17	Freehold	0.6
18	Seymour	3.1
19	Jackson	1.7
20	Boise City	1.9
21	Vanceburg Dam	1.0
22	Tallulah	2.6
23	Hope	1.4
24	Millinocket	0.1
25	Fort Supply Dam	3.2
26	Kingstree	0.9
27	Wasta	1.6
28	Amherst	0.2
29	Robertsdale	0.3
30	Beeville	1.3
31	Anderson	0.7
32	Lake Charles WSO	0.4
33	Caribou Airport	0.1
34	Belle Glade Experiment Station	<0.1
35	Carrizo Springs	0.3
36	Elephant Butte Dam	<0.1
37	Bosque Del Apache	<0.1
39	Fruitland	<0.1
40	Thompson	<0.1
41	Altamont	<0.1
42	Moroni	<0.1
43	Koosharem	<0.1
44	Black Rock	<0.1
45	Oak City	<0.1
46	Twin Falls WSO	0.3
47	Deer Flat Dam	0.2
48	Fairfield	<0.1
49	Craters Of Moon Nat'l Monument	<0.1
50	Arbon	0.1
51	Dubois Experiment Station	<0.1
52	Idaho Falls Airport	0.3
53	Wallowa	<0.1
54	Pomeroy	0.3
55	Yakima Airport	0.1
56	Corvallis St Col	0.1
57	Willows	0.2
58	Sacramento Airport	0.1
59	Tracy Pumping Plant	0.1
60	Fresno Airport	0.7
61	El Centro	0.1
62	Lovelock Airport	<0.1
63	Tumacacori	<0.1
64	Eloy	0.1
65	Litchfield Park	0.1
66	Blanding	<0.1
	Total	100.0

* Map 4 shows the locations of weather stations.
Note: Cluster 38, Jemez Springs, has no cropland points in the domain used in the study and is not listed.

Representing topographic characteristics and field drainage in the model

EPIC simulates effects within the boundaries of a field with a homogenous soil having a uniform slope and is bounded horizontally by the edges of the field and vertically from the soil surface down through the soil profile to the bottom of the root zone. Slope and slope length data are available directly from the NRI. Each NRI sample point was visited in 1982 and the slope and slope length determined for purposes of estimating sheet and rill erosion. Additional sample points added to the sample frame after 1982 were also visited to obtain slope and slope length. Protocols for measuring the slope and slope length are described in USDA NRCS (1997b). Slope and slope length were represented in the EPIC model for each URU as the average of the NRI cropland sample points associated with each URU.

Information on field drainage, such as drainage ditches and tile drains, was not available for the 1997 NRI sample points. (Data on tile drains were available for some of the 1992 NRI sample points, but as it was not a complete data record, the information was not used in this study.) EPIC can simulate these features, but without data indicating the extent to which they occurred, field drainage could not be included in the model simulations. Thus, all sample points were assumed to be adequately drained. This was simulated in the EPIC model by manipulating the water table depths. Initial water table depth was set to 2 meters for soils with an initial depth less than 2 meters. Also, for soils in which the minimum of the maximum water table depth was less than 2 meters, the minimum depth was set to 2 meters and the maximum depth was set to 3 meters.

Representing crop growth characteristics in the model

The crop growth model in EPIC is capable of simulating agronomic crops, pasture, and trees.

A single crop growth model is used in EPIC for simulating all 15 crops included in the study. However, each crop is uniquely characterized by over 50 parameters, listed in table 7. These crop growth parameters have been developed by scientists and model developers and are maintained as a database associated with the EPIC model.

Plant growth is simulated with a daily heat unit system that correlates plant growth with temperature. Accumulated heat units drive potential growth, and actual growth is reduced from potential growth by accounting for factors that constrain plant growth, including temperature, solar radiation, soil moisture, soil aeration, soil strength, and plant available nitrogen and phosphorus.

EPIC can simulate growth for both annual and perennial crops. Annual crops grow from planting date to harvest date or until the accumulated heat units equal the potential heat units for the crop. Perennial crops, such as alfalfa hay, maintain their root systems throughout the year, although they may become dormant after frost. In EPIC, a crop starts growing when the average daily air temperature exceeds the base temperature for the crop.

In addition to crop growth parameters, EPIC requires that the actual plant population be entered in plants per square meter. Plant population inputs vary from crop to crop and from state to state. Most available data from which plant population could be derived is for seeding rates. Conversion of seeding rates to plant population data requires information on seed germination and seedling survival rates. Since seeding rates are typically in units of volume or weight per acre, additional information was required on seed count per volume or weight, which varied to some extent across different regions of the country. For the majority of crops, seeding rate data were taken from the Cropping Practice Survey (1990–95) for both dry and irrigated production for each state (USDA ERS 2000). Data on seeds per pound, expected germination rates, and seedling survival were taken from Martin et al. (1976) and other published sources. Plants per square meter were estimated from these data sources for each crop and state for EPIC model input. Corn for grain values were used for corn silage. Plant populations for hay crops were set at the EPIC default levels. Barley and oat plant populations were assumed to be similar to spring wheat. The plant population calculation for cotton was based on Martin et al. (1976).

For peanuts in Texas and Oklahoma, particularly for dryland production, the plant populations derived using this standard approach were too low. Further in-

Table 7 Crop growth parameters required by EPIC

Crop name and number	Biomass-energy ratio and biomass-energy ratio decline rate parameter
Minimum and optimal temperatures for plant growth	Maximum potential leaf area index
Fraction of growing season when leaf area declines and leaf area index decline rate parameter	First and second points on optimal leaf area development curve
Aluminum tolerance index	Maximum stomatal conductance
Critical aeration factor	Maximum crop height
Maximum root depth	Parameter relating CO_2 concentration to radiation use efficiency
Minimum value of C factor for water erosion	Fractions of nitrogen, phosphorus, potassium, and water in yield
Lower limit of harvest index	Pest (insects, weeds, and disease) factor
Seeding rate and seed cost	Price for grain yield
Nitrogen uptake parameter (N fraction in plant at emergence, 0.5 maturity, and maturity)	Phosphorus uptake parameter (P fraction in plant at emergence, 0.5 maturity, and maturity)
Potassium uptake parameter (K fraction in plant at emergence, 0.5 maturity, and maturity)	Wind erosion factors for standing live residue, standing dead residue, and flat residue
First and second points on frost damage curve	Parameter relating vapor pressure deficit (VPD) to radiation use efficiency
VPD value and threshold VPD	Fraction of root weight at emergence and maturity
Heat units required for germination	Price for field forage
Plant population for trees, crops, or grass	Water use to biomass
Yield salinity ratio	Salinity threshold
Lignin fraction at half-maturity and maturity	Fraction turnout or lint for picker and stripper cotton

vestigation indicated that the predominant peanut type grown in Texas and Oklahoma is Spanish peanuts, with Runner types also occupying some acreage (Brooks and Ali 1994; Sanford and Evans 1995). Seed counts per pound of seed for the three types are approximately 500 for Virginia, 700 for Runner, and 1,200 for Spanish (Martin et al. 1976). Yields consistent with published statistics for Oklahoma and Texas were achieved by setting the plant population at 35 plants per square meter for dryland and 38 plants per square meter for irrigated acres.

EPIC yields obtained during this study are compared to historical crop yield data in table 8. Historic crop yield estimates by state and crop for a 5-year period from 1995 to 1999 were obtained from the National Agricultural Statistics Service (NASS) for the comparison. These estimates vary from year to year, in part reflecting variability in weather conditions. Yield estimates from the EPIC model simulations represent 30-year averages derived from probabilistically generated weather. Even if a comparable long-term average could be obtained from the NASS yield data, the comparison would be flawed because of technological advancements (such as improvements in seed varieties) that have occurred over time, which are manifested as an upward trend in the observed yield data over time that is not related to weather.

Overall, the 30-year EPIC average yield corresponded reasonably well to the 5-year historic average yield for most crops. The EPIC average national yield was relatively high compared to the 5-year NASS yield for corn silage, soybeans, grass hay, and legume hay. The EPIC yield was relatively low for peanuts and potatoes. Some of the differences in yields for some states will be due to differences between actual weather and the simulated weather used in the EPIC model runs, particularly in regions with prolonged drought conditions during 1995 to 1999. Other yield differences may be explained in part by the continuous crop simulations used to generate the EPIC results; crops commonly grown in rotation with other crops would be expected to have different yields than those determined under the continuous cropping conditions represented by the model simulations.

Table 8 Comparison of EPIC crop yields to NASS reported crop yields

Crop	Yield unit	NASS 5-year average annual yield (1995–99)	EPIC 30-year average annual yield	Difference from NASS yield estimate	Percent difference from NASS yield estimate
Barley	bu/a	59	56	-3	-5.3
Corn	bu/a	127	128	1	0.4
Corn silage	tons/a	16	22	6	38.5
Cotton	lb/a	626	681	55	8.7
Oats	bu/a	58	64	6	9.6
Peanuts	1,000 lb/a	2.6	1.7	-0.9	-34.6
Potatoes	100 lb/a	352	267	-85	-24.2
Rice	1,000 lb/a	5.8	5.2	-0.6	-11.1
Spring wheat	bu/a	33	39	6	17.4
Sorghum	bu/a	66	73	7	9.9
Soybeans	bu/a	38	55	17	46.1
Winter wheat	bu/a	43	40	-3	-5.7
Grass hay	ton/a	2	3	1	63.4
Legume hay	ton/a	3	5	2	59.7

Representing field operations in the model

All field operations used in the production of a crop are required inputs to the EPIC model. These include planting, a variety of tillage operations, irrigation, commercial fertilizer applications, manure applications, and harvesting. A generic set of field operation schedules was developed for each crop and irrigation system.

The timing of the operations was automatically determined during the model run on the basis of accumulated heat units. Year-to-year temperature differences preclude assigning specific dates prior to running the model; planting during a warm spring should occur earlier than during a cool spring, for example. Heat units are calculated as the difference between the average of the daily maximum and minimum temperatures and a specified base or developmental threshold temperature. Prior to running EPIC, heat units necessary for planting and heat units required for crop maturity are determined for each crop in each climate zone. As the model runs, heat units are accumulated for each year and the ratio of accumulated heat units to the required heat units is used to determine plant and harvest dates. The timing of other field operations is scheduled relative to plant date or harvest date and converted into heat units.

The heat unit scheduling code (HUSC) has two timing scales. For the first timing scale, the total expected heat units for any year is the sum of all daily average temperatures above 32 degrees Fahrenheit, derived from long-term climate records. This timing scale is used to schedule the plant date and operations occurring prior to planting.

As soon as planting occurs, a second timing scale becomes the applicable timing mechanism. For this second timing scale, the total expected heat units shift to the number of heat units required for the crop to reach maturity from the time of planting. The heat units required for the crop to reach maturity are calculated prior to the model simulation for each crop and climate zone based on the latitude and elevation of the weather station. During the model run, crop maturity heat units are accumulated when the daily average temperature exceeds a crop-specific base temperature, or threshold temperature.

A threshold date is also set that must be reached before any operation can occur regardless of heat units. Both conditions—accumulated heat units and threshold date—must be met before a field operation is simulated in EPIC.

A hypothetical example is provided in table 9 for corn. The month and day are the earliest date that the operation is allowed to occur. According to the example, a field cultivation will be simulated after March 15 when 12 percent of the annual heat units have accumulated. Corn is planted after April 1 when 15 percent of the annual heat units have accumulated. Once the corn begins to grow, the schedule is based on the fraction of heat units required for crop maturity. In this exam-

Table 9 Hypothetical example of an operations schedule for corn that demonstrates heat unit scheduling

Month	Day	Percent of annual heat units accumulated (above 32 °F)	Percent of crop maturity heat units (above 46 °F for corn)	Field operation
3	15	12	NA	Field cultivation
4	1	15	NA	Plant
5	1	NA	20	Application of commercial fertilizer
6	1	NA	35	Row cultivation
8	1	NA	115	Harvest
1	5	NA	None used	Kill crop (dummy operation for model)

NA = Not applicable

ple, corn requires 1,400 heat units. Crop maturity heat units are accumulated when temperatures are above the base temperature of corn—46 degrees Fahrenheit. Commercial fertilizer application is simulated when the plant is at 20 percent of maturity in this example. Cultivation is simulated at 35 percent of maturity. The corn is harvested at 115 percent of maturity to allow for grain drying. The crop is then terminated to allow these operations to repeat for the next year's crop.

Using the heat unit scheduling routine, specific field operation schedules were created for each crop and irrigation system in each climate zone. Irrigation operations, commercial fertilizer applications, and manure applications were incorporated into the specific field operation schedules according to rules presented in sections of this report addressing those topics. An example of a specific field operation schedule used for irrigated corn in Nebraska in climate zone 27 is shown in table 10.

Representing tillage in the model

Tillage equipment is used in agriculture to prepare the field for planting, weed control, and for irrigation management. Conventional tillage includes primary and secondary tillage operations performed in preparing a seedbed for planting, and typically includes plowing, chiseling, and disking operations that buries plant residue remaining from the previous crop. Conservation tillage is a system of field operations that attempts to reduce soil manipulation, thereby increasing the amount of crop residue remaining on the soil surface.

Table 10 Example of a specific field operation schedule for irrigated corn in climate zone 27 in NE (URU 7462) with conventional tillage and fall application of nitrogen

Month	Day	Proportion of annual heat units (accumulated above 32 °F)	Proportion of crop maturity heat units (accumulated above 46 °F)	Action
1	1	0.01	NA	Turns auto irrigate function on (model operation)
4	22	0.07	NA	Disk
4	29	0.09	NA	Disk
5	5	0.1	NA	Field cultivate
5	6	0.11	NA	Irrigate 75 mm 1 wk prior to plant
5	13	0.13	0	Row plant corn; heat units to maturity=1420, water stress factor= 0.85, plant population= 6.56 plants m^{-2}
6	3	NA	0.12	Row cultivate
6	17	NA	0.23	Row cultivate
7	29	NA	1	Turns auto irrigate function off when crop reaches maturity
9	25	NA	1.15	Harvest crop
9	26	NA	1.15	Kill crop (model operation)
10	16	NA	1.24	Chisel
10	25	NA	1.25	Anhydrous ammonia application at 173 lb/a injected at 150 mm
11	20	NA	1.25	Disk

NA = Not applicable
Note: This schedule is repeated for each year of the simulation to simulate continuous cropping; thus, the post-harvest operations are in preparation for the next year's corn crop.

This provides some protection against the erosive actions of wind and water. No-till is a system whereby the crop is planted directly into a seedbed undisturbed since harvest of the previous crop, providing the maximum erosion protection.

Three tillage systems were simulated in EPIC model runs—conventional tillage, mulch tillage (representing conservation tillage), and no-till. These three tillage systems are incorporated into the model in the field operation schedules, which are specific to each crop, irrigation system, and climate zone. An example generic field operation schedule for the three tillage systems for corn for grain is as follows:

Conventional tillage:

1. Tandem disk 2 weeks after harvest of previous crop.
2. Chisel 3 weeks after harvest of previous crop
3. Tandem disk 3 weeks before planting
4. Tandem disk 2 weeks before planting
5. Field cultivator 1 week before planting
6. Plant
7. Row cultivation 3 weeks after planting
8. Row cultivation 5 weeks after planting
9. Harvest

Mulch tillage:

1. Chisel 3 weeks after harvest of previous crop
2. Tandem disk 2 weeks before planting
3. Field cultivator 1 week before planting
4. Plant
5. Row cultivation 4 weeks after planting
6. Harvest

No-till:

1. Plant (No-till plant dates were set about one week later than the other tillage systems to account for the lower soil temperatures typically associated with no-till.)
2. Harvest

Each piece of equipment is associated with a set of model input parameters that include: mixing efficiency of operation, a random roughness coefficient, tillage depth, ridge height and interval, furrow dike height and interval, fraction of soil compacted (based on tire and tillage width), fraction of plant population reduced by operation, and harvest efficiency. Using these parameters, EPIC calculates standing, surface, and buried crop residue amounts, the extent to which soil mixing occurs, and other related outcomes that effect hydrology and erosion.

In addition to the equipment parameters, three other model parameters were adjusted to better represent the effects of the three tillage systems. Manning's roughness coefficient, which reflects surface roughness effects by reducing overland flow velocities, was set as follows: conventional tillage=0.1; mulch tillage=0.2, and no-till=0.3. Also two cover management factor parameters were adjusted to represent each tillage system. The Water Erosion Cover Coefficient reduces the effect of increasing canopy or residue for controlling erosion and was set as follows: conventional tillage=0.5; mulch tillage=0.8, and no-till=1.0. The Minimum Water Erosion Cover Factor is the lower limit that the USLE C-factor can be for any day and was set as follows: conventional tillage=0.25; mulch tillage=0.15, and no-till=0.05.

All three tillage systems were simulated for each URU for eight crops—corn, corn silage, sorghum, soybeans, barley, oats, spring wheat and winter wheat. For cotton, peanuts, and rice, only conventional tillage and mulch tillage systems were simulated, and only conventional tillage was simulated for potatoes. Hayland was treated as no-till. In addition, no-till was not simulated for any crops where gravity irrigation was used because of the need for land forming tillage operations associated with gravity irrigation systems.

The frequency of occurrence of the three tillage systems is needed to determine the probability associated with each tillage option for calculation of the weighted average for model outputs assigned to NRI cropland points (app. A). This information was obtained from county data by crop from the Crop Residue Management Survey (CRMS) (CTIC 2001) for the year 2000. The CRMS dataset includes five tillage classes for each crop grown within a county, state, or region—no-till, ridge till, mulch till, reduced till (15–30% residue), and conventional till (<15% residue). For this study, conventional till included both the CRMS reduced till and the CRMS conventional till to represent residue amounts of 30 percent or less. In addition, the CRMS ridge till and mulch till categories were combined. The percentage of each of the three tillage systems simulated in this study was then obtained for each NRI cropland point and each URU using the CRMS county data.

The extent to which the 3 tillage systems are represented in the NNLSC database is summarized in table 11. The percentage representation for each tillage type varies by region and crop. Overall, however, model simulation results represent conventional tillage on about 55 percent of the acres, mulch tillage on about 17 percent of the acres, and no-till on about 28 percent of the acres (including hayland).

A subset of the full database was used to assess how accounting for conservation tillage effected model estimates of sediment loss, wind erosion, nitrogen loss, and phosphorus loss. This tillage comparison subset of model runs included only those URUs (and associated NRI sample points) where all three tillage systems were present. The tillage comparison subset consists of 565,673 model runs representing 207.6 million acres (70 percent of the acres included in the NNLSC database). Eight crops that were either non-irrigat-

Table 11 Representation of three tillage systems in the NNLSC database

	Acres (1,000s)	Percent conventional till	Percent mulch tillage	Percent no-till
By region				
Northeast	13,642	34.7	6.7	58.6
Southeast	13,394	52.9	7.5	39.5
South Central	45,350	63.2	13.3	23.5
Upper Midwest	112,581	45.9	19.4	34.7
Northern Great Plains	72,397	57.1	20.0	22.9
Southern Great Plains	32,096	77.4	16.4	6.3
West	9,018	62.6	13.1	24.3
By crop				
Barley	4,635	73.6	20.6	5.8
Corn	78,219	63.2	18.8	18.0
Corn silage	5,197	75.8	11.5	12.7
Cotton	16,858	87.9	12.1	0.0
Grass hay	14,596	0.0	0.0	100.0
Legume hay	24,776	0.0	0.0	100.0
Oats	3,772	72.5	20.2	7.3
Peanuts	1,843	94.5	5.5	0.0
Potatoes	987	100.0	0.0	0.0
Rice	3,637	89.0	11.0	0.0
Spring wheat	20,503	72.3	17.2	10.5
Sorghum	10,897	69.6	18.4	12.0
Soybeans	67,543	44.6	24.8	30.6
Winter wheat	45,014	69.1	19.8	11.1
All regions and crops	298,478	54.9	17.0	28.1

ed or sprinkler irrigated are included: corn, soybeans, sorghum, winter wheat, spring wheat, barley, oats, and corn silage.

Four sets of model results were constructed using the tillage comparison subset of model runs. A tillage-effects baseline representing the mix of tillage systems reported by CTIC (2001) was estimated. Acreage representation of the three tillage systems in this tillage-effects baseline is: 59 percent for conventional tillage, 21 percent for mulch tillage, and 21 percent for no-till (table 12). A set of alternative results was obtained for each of the three tillage systems as if all acres had been modeled using a single tillage system. Comparisons among these four sets of results are used in later sections of this report to assess the effects that tillage had on estimates of sediment loss, wind erosion, nutrient loss, and phosphorus loss in model simulations.

Representing conservation practices in the model

Three conservation practices, designed primarily to reduce sheet and rill erosion and sediment transport, were simulated—contour farming, stripcropping, and terraces. Contour farming is a technique in which farming operations such as tillage and planting are conducted along the contour of the field slope so that ridges are formed to slow overland runoff and trap sediment. Stripcropping is a technique for growing crops in a systematic arrangement of strips across a field such that no two adjacent strips are in an erosion-susceptible condition at the same time during the crop growing season, usually done by growing different crops in adjacent strips. A terrace is an engineered earth embankment, or a combination ridge and channel, constructed across the field slope, diverting water and intercepting concentrated runoff flows.

Table 12 Representation of tillage systems in the tillage-effects baseline

	Acres (1,000s)	Percent conventional tillage	Percent mulch tillage	Percent no-till
By region				
Northeast	6,034	62.5	14.3	23.2
Southeast	4,442	61.8	8.0	30.2
South Central	24,879	64.7	14.5	20.8
Upper Midwest	96,330	51.3	22.2	26.5
Northern Great Plains	56,551	64.6	21.5	13.9
Southern Great Plains	17,746	72.5	21.7	5.8
West	1,661	62.9	26.6	10.5
By crop				
Barley	3,256	75.0	17.8	7.2
Corn	71,016	62.9	18.0	19.1
Corn silage	4,082	74.1	12.7	13.2
Oats	2,078	69.0	20.9	10.1
Spring wheat	18,074	71.2	17.0	11.7
Sorghum	7,697	65.5	18.7	15.8
Soybeans	62,967	42.3	25.8	31.9
Winter wheat	38,473	68.6	19.7	11.7
All regions and crops	207,642	59.0	20.5	20.5

The NRI database provided information on which sample points had these three conservation practices and combinations of the practices. Separate URUs were created for each of three structural conservation practices as well as separate URUs for all combinations of practices. Overall, these three conservation practices were simulated for about 11 percent of the cropland acres included in the study (table 13). The most frequently occurring practice combination was terraces with contour farming, which represented about 5 percent of the acres.

In the EPIC model, the primary mode of simulating the effect of conservation practices on soil erosion is through manipulation of the support practice factor, or P-factor. An integral component of the equation used to estimate sediment loss, the P-factor is the ratio of soil erosion with a conservation practice like contouring, stripcropping, or terracing to soil erosion with straight-row farming up and down the slope. Conservation practices are always represented by a P-factor of less than 1.0 while a setting of 1.0 indicates no conservation practice. In addition, for some terraces slope length is reduced resulting in a shorter slope length and lower steepness (LS) factor. Within the NRCS curve number method for estimating runoff, there are provisions for reducing the curve number for fields with contouring, stripcropping, or terracing, resulting in reduced surface water runoff and more infiltration. The model recognizes conservation practice codes and automatically adjusts the NRCS curve number in the model.

The NRI provides estimates of the P-factor for all sample points including those with conservation practices and combinations of practices (USDA NRCS 1997b). These NRI estimates were used in the EPIC model simulations to represent the effects of the three conservation practices. The average values of the P-factor for the NRI cropland sample points associated with each URU were used as model inputs.

Additional model runs were conducted to assess the effects of the conservation practices on model estimates of sediment loss, nitrogen loss, and phosphorus loss. Two scenarios were established:

- A conservation-practice baseline scenario, consisting of the original model runs in the NNLSC database for all NRI sample points with one or more conservation practice.

Table 13 Representation of stripcropping, contour farming, and terraces in the NNLSC database

Conservation practice	Number of URUs	Number of NRI sample points in URUs	Acres (1,000s)	Percent acres
Terraces only	1,111	3,268	6,285	2.1
Terraces with contour farming	1,361	7,883	14,728	4.9
Terraces with stripcropping	0	0	0	0
Terraces with contour farming and stripcropping	28	31	64	<0.1
Contour farming only	1,165	3,728	5,965	2.0
Contour farming with stripcropping	462	1,183	1,764	0.6
Stripcropping only	531	1,308	2,930	1.0
None	20,592	161,166	266,741	89.4
Totals	25,250	178,567	298,478	100.0

- A no-practices scenario, consisting of the results of revised model runs where the P-factor was set equal to 1.0 and the practice code was set such that the NRCS curve number represented conditions without conservation practices. All other model settings were the same as in the conservation-practices baseline scenario, including slopes and slope lengths and tillage practices.

Outputs from the no-practices scenario model runs were aggregated in the same manner as for the conservation practice baseline model runs. The two scenarios represent the same acreage. To determine the effects of the conservation practices, outputs for the URUs with practices were compared to the same set of URUs simulated without practices. Since the P-factor is not part of the wind erosion equation, the effects of the three practices on wind erosion was not assessed.

Representing irrigation in the model

Irrigation was simulated for URUs representing NRI sample points with irrigation. Irrigated land, as defined for NRI purposes, is land that shows physical evidence of being irrigated during the year of the inventory (presence of ditches, pipes, or other conduits) or having been irrigated during two or more of the four years preceding the inventory (USDA NRCS 1997b). Three types of irrigation are recorded in the NRI: gravity irrigated, pressure irrigated, or gravity and pressure irrigated.

For EPIC modeling, sprinkler irrigation was used to simulate pressure systems and furrow/flood irrigation was used to simulate gravity systems. The gravity pressure irrigation type was defined in the NRI as cases where water was delivered to the field by gravity flow and then applied through a pressurized sprinkler system (USDA NRCS 1997b); this was modeled in EPIC as a sprinkler system. When simulating no-till, however, a sprinkler system was always used. For rice, flood/furrow irrigation was always used. For URUs with average slopes greater than 3 percent, only sprinkler irrigation was used for non-hay crops.

Since information about the timing and amount of irrigation water used was not available, a generic irrigation schedule was simulated. A manual irrigation of 75 millimeters (3 in) for gravity and 50 millimeters (2 in) for sprinkler systems was applied prior to planting to ensure adequate moisture for seed germination. Subsequent irrigation events were simulated using the automatic irrigation feature of EPIC to irrigate during the growing season. The plant growth stress factor in this routine was set at 0.85, which caused the model to irrigate on any day that plant growth was less than 85 percent of potential growth if all other parameter conditions were met. Other parameters were set to: only irrigate to field capacity when irrigation was triggered; never irrigate more frequently than once in 5 days; irrigate with volumes between 25 and 75 millimeters (1–3 in); never irrigate more than 900 millimeters annually (35 in); limit irrigation volumes at each application so that no more than 5 percent is lost to runoff for sprinkler systems and no more than 20 percent is lost to runoff for gravity systems.

Overall, about 13 percent of the acres included in the study were irrigated (table 14). In the West, however, 79 percent of the acres were irrigated. The Southern Great Plains and South Central regions also had significant irrigation; 28 percent and 21 percent of the cropland acres included in the study were irrigated in these two regions, respectively. About 15 percent of the acres in the Northern Great Plains region were irrigated. Irrigated acres in the Southeast region represented 6 percent of the cropland acres included in the study. The Northeast and Upper Midwest regions had very few irrigated acres.

Representing commercial fertilizer applications in the model

Commercial fertilizer application is a critical factor for determining the amount of nitrogen and phosphorus loss from farm fields. The timing of application, the method of application (whether the materials are incorporated into the soil at application or not), and the amount applied all have significant influences on EPIC model results. Farmer surveys typically collect information on the number of applications, the timing of application, the amount applied at each application, and the method of application for both nitrogen and phosphorus. However, reports published by NASS and ERS seldom include summary statistics with this much detail because sample sizes from farmer surveys are usually too small to report these results on an annual basis.

Table 14 Representation of irrigation in the NNLSC database

Region	Irrigation type	Number of NRI sample points	Acres (1,000s)	Percent acres
Northeast	Pressure/sprinkler	161	164	1.2
	Gravity	3	2	<0.1
	No irrigation	11,118	13,475	98.8
	Subtotal	11,282	13,642	100.0
Southeast	Pressure/sprinkler	491	821	6.1
	Gravity	8	11	0.1
	No irrigation	8,456	12,563	93.8
	Subtotal	8,955	13,394	100.0
South Central	Pressure/sprinkler	2,673	4,914	10.8
	Gravity	2,571	4,786	10.6
	No irrigation	22,221	35,650	78.6
	Subtotal	27,465	45,350	100.0
Upper Midwest	Pressure/sprinkler	1,237	1,991	1.8
	Gravity	278	490	0.4
	No irrigation	73,176	110,100	97.8
	Subtotal	74,691	112,581	100.0
Northern Great Plains	Pressure/sprinkler	3,147	6,112	8.4
	Gravity	2,563	4,525	6.3
	No irrigation	30,325	61,759	85.3
	Subtotal	36,035	72,397	100.0
Southern Great Plains	Pressure/sprinkler	3,009	6,707	20.9
	Gravity	1,222	2,322	7.2
	No irrigation	10,264	23,067	71.9
	Subtotal	14,495	32,096	100.0
West	Pressure/sprinkler	2,153	3,550	39.4
	Gravity	2,474	3,600	39.9
	No irrigation	1,017	1,868	20.7
	Subtotal	5,644	9,018	100.0
All regions	Pressure/sprinkler	12,871	24,259	8.1
	Gravity	9,119	15,737	5.3
	No irrigation	156,577	258,482	86.6
	Totals	178,567	298,478	100.0

It was, therefore, necessary to obtain the raw data from farmer surveys conducted over several years, pool the data, and then aggregate the data according to the state, crop, and time of application. Most of the estimates were derived from the 1990–95 Cropping Practices Surveys (USDA ERS 2000). The Cropping Practices Survey was conducted by the National Agricultural Statistics Service (NASS) in the early 1990s to estimate total commercial fertilizer use on farms. The Cropping Practices Survey has since been integrated into the Agricultural Resource Management Study (ARMS) survey (USDA ERS 2001). A few additional samples were obtained from the 1991 to 1993 Area Studies Survey, a special study conducted by ERS and NASS in selected river basins (Caswell et al. 2001). Farmer survey results were available for 9 of the 15 crops included in this study: corn for grain, soybeans, winter wheat, spring wheat, cotton, sorghum, peanuts, and rice. A total of 75,465 separate farmer survey results were available. These surveys recorded the time of application as: fall application, spring application, application at plant, and application after plant. Since only a few farmers reported nitrogen applications during 3 or more of the time periods, and few farmers reported more than one time of application for phosphorus, the following 11 nitrogen application timing category possibilities were established for each crop, state, and irrigation category:

- Fall nitrogen application only
- Spring nitrogen application only
- At plant nitrogen application only
- After plant nitrogen application only
- Fall and spring nitrogen applications
- Fall and at plant nitrogen applications
- Fall and after plant nitrogen applications
- Spring and at plant nitrogen applications
- Spring and after plant nitrogen applications
- At plant and after plant nitrogen applications
- No nitrogen applications

All records with three or more combinations of nitrogen application times were discarded. In addition, the survey records whether or not manure was applied to the field (although not how much manure was applied). Since manure applications by crop were determined from another source (see next section), it was necessary that these estimates of commercial fertilizer represent the amount of nutrients applied without nutrient supplements from manure. Therefore, all survey records with manure applied were also discarded (about 5% of the available observations).

The application rate was then estimated for each application timing category. First, all multiple applications within a timing category were totaled to provide a total application rate for each timing category. Second, it was necessary to treat nitrogen application rates differently from phosphorus application rates. In many cases, nitrogen was applied but phosphorus was not. In other cases, only phosphorus was applied, usually at low rates. Nitrogen application rates were much more variable than phosphorus application rates. To account for this variability, three separate nitrogen application rate categories were established for each timing category on the basis of the total amount of nitrogen applied to the field for the year. The high application rate category was the highest third of the samples within each timing category, the low application rate category was the lowest third of the sample, and the medium category was the remaining third. Each of these three categories was then split into two categories to account for phosphorus use: cases with no phosphorus applications, and cases with phosphorus applications. An additional application rate category represented survey samples where no nitrogen was applied but phosphorus was applied. This scheme resulted in the following seven nutrient application rate categories:

- High N and average non-zero P
- High N and zero P
- Medium N and average non-zero P
- Medium N and zero P
- Low N and average non-zero P
- Low N and zero P
- Zero N and average non-zero P

After all the survey samples were assigned to a nitrogen timing category and to a nutrient application rate category, the average nitrogen application rate was estimated for the group. Where there was more than one time of nitrogen application (such as fall and spring applications), separate nitrogen application rates were calculated for each time of application. Where phosphorus was applied in more than one time period, the average rate of application was estimated using all the samples available and the time of phosphorus application was determined as the time period with the highest frequency of occurrence among the samples in the nutrient application rate category.

In all, there were 62 nutrient application possibilities defined for each crop, state, and irrigation category. Only the dominant combinations of timing and rate were chosen to represent commercial fertilizer applications for the model simulations. In many cases, it was necessary to combine states to get an adequate sample size to estimate application rates. Nutrient application possibilities with low sample sizes were discarded. For most crops and states, this resulted in one to four application timing categories, each with about three to six application rate categories. Table 15 provides a specific example of the nitrogen and phosphorus application rates used in the EPIC simulations for Nebraska corn. In most cases, the selected possibilities represented 70 percent or more of the observations for a given crop and state. Overall, 60,004 observations were used to estimate commercial fertilizer application rates, representing about 87 percent of the survey samples available for non-irrigated crops and about 74 percent of the survey samples available for irrigated crops. The number of farmer survey samples used to estimate application rates are shown by crop and state (or state combination) in table 16.

Phosphorus application rates in the farmer survey database (and in table 15) are as pounds of phosphate fertilizer equivalent (P_2O_5). The EPIC model requires that they be converted to pounds of elemental phosphorus (P). Thus, all commercial phosphorus application rates were multiplied by 0.44 (0.44 pounds of elemental phosphorus in one pound of P_2O_5).

The survey results were also used to estimate the probability that a specific nutrient application scenario would occur. These probabilities were estimated as the frequency of occurrence of each of the specific scenarios on the basis of the sample size. An example calculation is shown in table 15. In addition, the percentage of the observations that applied nitrogen by knifing it in or injection was recorded for each combination of categories.

Farmer survey data were not available for grass hay, alfalfa hay, mixed hay, barley, oats, or corn for silage. For alfalfa hay and grass hay, it was assumed that 40 percent of the acres would not receive commercial fertilizer applications. For the remaining 60 percent of the acres, alfalfa received 60 pounds per acre of nitrogen and 26.4 pounds P_2O_5 applied at plant, and grass hay received 110 pounds of nitrogen per acre and 17.6 pounds of P_2O_5 applied at plant. Separate model runs were made for the hayland that received commercial fertilizers and hayland that did not. For corn for silage, nutrient application scenarios for corn for grain were used. For barley and oats, nutrient application scenarios for spring wheat were used. A comparison was done between farmer survey results for oats and barley versus spring wheat for a small number of observations reported by NASS for years prior to 1990. Based on this comparison, the nutrient application rates for spring wheat in Minnesota closely approximated those for barley in major producing states, and nutrient application rates for spring wheat in Montana closely approximated those for oats in major producing states. Consequently, nutrient applications for Minnesota spring wheat were used for barley in Idaho, Minnesota, Montana, North Dakota, South Dakota, and Washington. Nutrient applications for Montana spring wheat were used for oats in Iowa, Minnesota, Montana, North Dakota, South Dakota, Texas, and Wisconsin.

There were several states and crops with acreage in the NRI that were not included in the farmer survey database. In some cases, nutrient application rates from other states were used for these crops; this imputation applied to 11.6 million acres (table 17). For other crops, commercial fertilizer applications were derived to emulate nitrogen applied at nitrogen-standard rates with phosphorus applications at levels that would typically be found in animal manures applied at these rates. The application time was at plant. A total of 5.8 million acres were handled in this manner.

For modeling the selected nutrient application possibilities with EPIC, fall applications were set at 30 days after the harvest of the previous crop, spring applications were set at 30 days before planting, and after plant applications were set at 30 days after planting. (Planting and harvest dates were set using the HUSC, but the timing relative to planting and harvest remained fixed.)

Table 15 Example of nutrient application rates used in EPIC model simulations for corn in NE, derived from Cropping Practice Survey data

	Application rate (lb/a)						
Nutrient application scenario	1st N application	2nd N application	P application (as P_2O_5)	Time of application for phosphorus	Average yield (bu/a)	Number of survey samples	Aggregation weight (probability of occurrence)
NON-IRRIGATED CORN							
FALL ONLY:							
High N rate and avg. non-zero P rate	139	NA	48	Fall	124.5	8	0.015
High N rate and zero P rate	126	NA	NA	NA	114.3	33	0.063
Medium N rate and avg. non-zero P rate	99	NA	43	Fall	111.2	8	0.015
Medium N rate and zero P rate	100	NA	NA	NA	103.6	37	0.071
Low N rate and avg. non-zero P rate	58	NA	34	Fall	67.4	19	0.036
Low N rate and zero P rate	56	NA	NA	NA	63.7	23	0.044
SPRING ONLY:							
High N rate and avg. non-zero P rate	144	NA	34	Spring	134.8	28	0.054
High N rate and zero P rate	141	NA	NA	NA	104.6	39	0.075
Medium N rate and avg. non-zero P rate	99	NA	41	Spring	104.3	32	0.061
Medium N rate and zero P rate	98	NA	NA	NA	108.4	37	0.071
Low N rate and avg. non-zero P rate	58	NA	41	Spring	85.6	24	0.046
Low N rate and zero P rate	67	NA	NA	NA	93.2	44	0.084
SPRING-AT PLANT:							
High N rate and avg. non-zero P rate	113	21	42	At plant	93.3	31	0.059
Medium N rate and avg. non-zero P rate	85	14	26	At plant	98.4	32	0.061
Low N rate and avg. non-zero P rate	51	10	32	At plant	83.1	30	0.057
AT/AFTER PLANT:							
High N rate and avg. non-zero P rate	20	120	36	At plant	100.0	24	0.046
Medium N rate and avg. non-zero P rate	14	80	29	At plant	63.5	27	0.052
Low N rate and avg. non-zero P rate	13	42	35	At plant	93.8	26	0.050
NO COMMERCIAL FERT. APPLIED	0	0	0	NA		21	0.040
Weighted average for non-irrigated corn	79.9	14.4	19.6		Sum =	523	1.000

Table 15 Example of nutrient application rates used in EPIC model simulations for corn in NE, derived from Cropping Practice Survey data—Continued

	Application rate (lb/a)						
Nutrient application scenario	1st N application	2nd N application	P application (as P_2O_5)	Time of application for phosphorus	Average yield (bu/a)	Number of survey samples	Aggregation weight (probability of occurrence)
IRRIGATED CORN							
FALL ONLY:							
High N rate and avg. non-zero P rate	197	NA	35	Fall	167.3	21	0.017
High N rate and zero P rate	198	NA	NA	NA	168.8	15	0.012
Medium N rate and avg. non-zero P rate	177	NA	67	Fall	137.0	12	0.010
Medium N rate and zero P rate	173	NA	NA	NA	150.3	32	0.026
Low N rate and avg. non-zero P rate	126	NA	27	Fall	139.0	16	0.013
Low N rate and zero P rate	129	NA	NA	NA	121.4	23	0.019
SPRING ONLY:							
High N rate and avg. non-zero P rate	197	NA	43	Spring	168.6	45	0.037
High N rate and zero P rate	197	NA	NA	NA	163.1	52	0.043
Medium N rate and avg. non-zero rate	163	NA	39	Spring	167.5	46	0.038
Medium N rate and zero P rate	161	NA	NA	NA	134.2	48	0.040
Low N rate and avg. non-zero P rate	111	NA	33	Spring	140.9	30	0.025
Low N rate and zero P rate	118	NA	NA	NA	148.8	56	0.046
FALL-AT PLANT:							
High N rate and avg. non-zero P rate	194	12	39	At plant	151.9	46	0.038
Medium N rate and avg. non-zero P rate	164	10	25	At plant	155.7	52	0.043
Low N rate and avg. non-zero P rate	122	9	25	At plant	140.3	45	0.037
SPRING-AT PLANT:							
High N rate and avg. non-zero P rate	188	15	34	At plant	161.7	105	0.086
Medium N rate and avg. non-zero P rate	149	18	31	At plant	147.3	105	0.086
Low N rate and avg. non-zero P rate	102	13	29	At plant	157.3	106	0.087
AT/AFTER PLANT:							
High N rate and avg. non-zero P rate	29	173	38	At plant	145.9	121	0.100
Medium N rate and avg. non-zero P rate	24	131	33	At plant	143.9	123	0.101
Low N rate and avg. non-zero P rate	21	73	31	At plant	131.0	116	0.095
Weighted average	116.8	42.7	27.2		Sum =	1,215	1.000

NA=not applicable.

Note: There were a total of 2,457 survey observations for corn in Nebraska: 1,681 were irrigated and 776 were non-irrigated. Of the 62 nutrient application possibilities for non-irrigated corn, 51 were represented in the survey observations; the dominant nutrient application possibilities were the 19 presented in the table, representing 523 of the original 776 survey observations (67%). Of the 62 possibilities for irrigated corn, 57 were represented in the survey observations; the dominant nutrient application possibilities were the 21 presented in the table, representing 1,215 of the original 1,681 survey observations (72%).

Table 16 Number of farmer survey samples used to estimate nutrient application rates used in EPIC model simulations

		Non-irrigated crops		Irrigated crops	
Crop	States or state combinations	Number of survey samples used	Percent of total survey samples	Number of survey samples used	Percent of total survey samples
Corn	IN	1,520	74	––	––
	AL, GA, FL, MS, AR, LA	492	87	27	21
	CO, KS	217	70	233	68
	MD, DE, VA, WV	161	76	––	––
	TX, NM, OK, AZ	321	72	173	72
	MT, ND, WY, SD	985	84	17	24
	NE	523	67	1,215	72
	MO	881	77	73	43
	CA, NV, UT, ID, OR, WA	––	––	90	75
	ME, CT, PA ,NY, NJ, MA, NH, RI, VT	316	72	––	––
	NC, SC	669	75	––	––
	KY, TN	632	74	––	––
	MI	772	76	79	75
	WI	673	74	––	––
	MN	1,418	79	––	––
	IA	2,364	79	––	––
	OH	1,151	69	––	––
	IL	2,204	75	––	––
Soybeans	AL, FL, GA	633	95	––	––
	AR	823	97	553	95
	DE, MD, PA, NJ, VA	293	81	––	––
	KY	671	96	––	––
	KS	539	95	17	43
	LA	634	98	––	––
	MN	1,504	98	42	78
	MI, WI	123	79	––	––
	ND, SD	533	95	––	––
	NC, SC	735	94	––	––
	MS	722	98	84	90
	MO	1,268	98	92	76
	NE	753	95	167	81
	OH	1,406	99	––	––
	TN	675	98	––	––
	TX, OK	46	82	––	––
	IN	1,526	99	––	––
	IL	2,089	99	––	––
	IA	2,001	99	––	––

Table 16 Number of farmer survey samples used to estimate nutrient application rates used in EPIC model simulations—Continued

		Non-irrigated crops		Irrigated crops	
Crop	States or state combinations	Number of survey samples used	Percent of total survey samples	Number of survey samples used	Percent of total survey samples
Winter wheat	WA	639	92	28	38
	TX	605	87	212	84
	SD	305	88	––	––
	OR	332	85	12	29
	OH	339	87	––	––
	OK	1,084	91	––	––
	NE	449	89	––	––
	MT	468	90	––	––
	MO	353	92	––	––
	KS	1,547	97	43	49
	IL, IN	443	85	––	––
	ID	213	77	123	79
	CO	366	90	24	63
	AR	175	89	––	––
	AL, GA, FL, NC, VA*	407	100	78	100
Spring wheat	ND	1,272	96	––	––
	MN	397	89	––	––
	MT	341	84	––	––
	SD	289	91	––	––
Cotton	CA	––	––	892	94
	AR	232	77	324	79
	AZ	––	––	352	85
	LA	267	87	130	72
	MS	642	89	150	66
	TX	1,565	93	1,038	91
	AL, GA, FL, NC, VA*	306	100	80	100
Sorghum	KS, NE, TX	544	77	42	46
Rice	LA	––	––	430	86
	AR	––	––	606	84
Peanuts	GA	192	97	52	93
	TX	104	90	89	82
	NC, VA	150	95	––	––
Potatoes	CO	––	––	271	80
	ID	––	––	1,159	73
	MN	394	84	93	80
	MI	85	61	226	69
	ME	779	96	66	70

Table 16 Number of farmer survey samples used to estimate nutrient application rates used in EPIC model simulations—Continued

Crop	States or state combinations	Non-irrigated crops		Irrigated crops	
		Number of survey samples used	Percent of total survey samples	Number of survey samples used	Percent of total survey samples
Potatoes	ND	330	78	130	63
	NY	214	87	213	90
	PA	246	84	49	77
	WI	33	52	594	93
	WA	24	62	733	83
	OR	––	––	499	68
All crops	All states	49,440	87	10,564	74

Note: Dashes denote that sufficient data were not available to estimate nutrient application rates.
* Derived from area studies survey data.

Table 17 Cases where nutrient application rates were imputed from other states or were based on nitrogen-standard application rates

Crop	States where nutrient application scenarios from other states were used	Acres (1,000s)	States where nutrient application scenarios were based on nitrogen-standard application rates	Acres (1,000s)
Corn for grain, non-irrigated	None	0	None	0
Corn for grain, irrigated	None	0	None	0
Soybeans, non-irrigated	None	0	CO, NY, WV	120
Soybeans, irrigated	SD, ND	138	CO	16
Sorghum, non-irrigated	AR, MO, OK, SD	741	AL, CO, DE, FL, GA, ID, IL, IN, IA, KY, LA, MD, MS, NJ, NM, NC, ND, OH, PA, SC, TN, VA, WI	749
Sorghum, irrigated	AR, MO, OK, SD	117	AZ, CA, CO, GA, IN, LA, MS	60
Cotton, non-irrigated	KS, MO, NM, OK, SC, TN	1,335	None	0
Cotton, irrigated	KS, MO, NM, OK, SC, TN	0	None	326
Peanuts, non-irrigated	AL, FL, OK	456	AR, MS, SC	15
Peanuts, irrigated	AL, FL, OK	118	AR, LA, NM, SC	29
Winter wheat, non-irrigated	KY, MI, MS, NM, TN, WY	1,684	CA, DE, LA, MD, MN, ND, NJ, NY, SC, UT, WV, WI	1,568
Winter wheat, irrigated	NM	135	AZ, CA, DE, IA, MD, NV, NJ, SC, UT	465
Spring wheat, non-irrigated	WY	21	CO, ID, NJ, OR, WA	202
Spring wheat, irrigated	None	0	AZ, CA, NV, OR, UT	200
Rice	MS, MO, TX	759	CA, MN	617
Potatoes, non-irrigated	None	0	AL, FL, GA, LA, MA, MS, MO, NJ, OH, TN, VT	63
Potatoes, irrigated	None	0	CA, DE, FL, IN, KS, LA, MO, NJ, NM, NC, TX, VA	101
Barley, non-irrigated	ID, MN, MT, ND, SD, TX, WI	3,436	CA, CO, GA, IA, KY, MD, ME, MI, MS, NC, NE, NJ, NY, OH, OR, PA, UT, VA, WY	295
Barley, irrigated	None	0	AZ, CA, CO, MD, MO, OR, UT, VA, WY	222
Oats, non-irrigated	IA, MN, MT, ND, SD, TX, WI	2,913	AR, CA, CO, FL, IL, IN, KS, LA, MD, ME, MI, MS, NC, NE, NY, OH, OK, OR, PA, SC, TN, VA, WY	683
Oats, irrigated	None	0	CA, CO, ID, KS, MI, NC, NE, NJ, NM, UT, WA, WY	97
Total acres (1000s)		11,583		5,827

EPIC requires information on the form of nitrogen applied—either applied as elemental nitrogen or as anhydrous ammonia. If the method of application was injection or knifed in, it was assumed that the form of nitrogen was anhydrous ammonia. If not, nitrogen was applied as elemental nitrogen using a broadcast method of application. Where a portion of the nitrogen applied was injected, two nitrogen applications were simulated in the EPIC model run—one for the injected portion and another for the amount broadcast applied. In EPIC, anhydrous ammonia was applied at the 150-millimeter depth while the elemental nitrogen was applied to the surface.

Representing manure applications in the model

Only an incidental amount of information on manure applications is available from farmer surveys, which was inadequate for representing manure applications for this study. Manure applications were derived from estimates of manure application rates created in a recent study on the costs of implementing Comprehensive Nutrient Management Plans (CNMP) (USDA NRCS 2003). In that study, a baseline scenario was constructed using information from the 1997 Census of Agriculture (USDA NASS 1999) that simulated manure applications for 1997, emulating pre-CNMP land application practices. County estimates were made of the total amount of manure nutrients available for land application, which were converted to crop-specific estimates of manure application rates and percentage of acres receiving manure. In estimating crop-specific application rates, manure was allocated to crops using a priority approach. The highest priority crops were allocated the manure first. The highest priority crops were corn, sorghum, silage crops, and hayland (USDA NRCS 2003, app. B.)

Separate estimates were made for land application on livestock operations (manure producing farms) and land application on surrounding properties (manure receiving farms). In deriving these manure applications, the following assumptions were made:

- manure receiving farms would apply manure at nitrogen-standard rates for all crops
- manure producing farms would apply manure at nitrogen-standard rates for alfalfa hay, soybeans, potatoes, cotton, and all close grown crops
- manure producing farms would apply manure at rates above the nitrogen-standard rates (determined in part by the amount of land available on the farm) for corn, sorghum, other hay land, and pastureland.

Because different application rates were available for manure producing farms and manure receiving farms, separate EPIC model runs were created for each of these two cases.

For this study, these county estimates were converted to estimates of application rates and percentage of acres treated for each crop in each state and climate cluster combination. To avoid distortions in the model results that would arise because of differences in crop yields between the EPIC model results and the crop yields from the Census of Agriculture, which were the basis for calculating application rates related to the nitrogen standard, application rates were adjusted to correspond to the yields produced using EPIC. This adjustment was based on the relationship between yield and application rate in the estimates derived from the Census of Agriculture. For each state, crop, and climate zone, five yield classes were created on the basis of yields obtained from EPIC model runs using only commercial fertilizer applications. Yield classes were constructed so as to roughly represent equal acreage. (In cases where there was little variability in EPIC yields, fewer yield classes were created.) For each yield class, a manure application rate was calculated using the yield-application rate relationship determined from the results of the previous study by NRCS. An additional adjustment was also made to the estimates of the percentage of acres with manure applied to make sure that the yield-based adjustment did not lead to the application of more or less manure in a region than was produced by livestock operations in that region.

An example of manure application rates used in the EPIC model simulations is shown in table 18 for Nebraska corn, where there are three climate clusters. The table shows how manure nitrogen (N) and manure phosphorus (P) application rates increase as yields increase. The application rates shown only apply to URUs in the corresponding yield class. The aggregation weights shown in table 18 are the proportion of acres receiving manure, and were used as estimates of the probability that the manure application option would occur in calculating EPIC model outputs for

Table 18 Example of manure application rates (irrigated and non-irrigated) and supplemental commercial fertilizer application rates for NE corn

			Manure producing farms			Manure receiving farms				Supplemental commercial fertilizer application rates (lb/a)**			
			Application rate (lb/a)*			Application rate (lb/a)*				Manure producing farms		Manure receiving farms	
Climate cluster	Yield class (bu/a)	NRI acres in yield class	N	P	Climate cluster aggregation weight	N	P	Climate cluster aggregation weight	Yield class index	N	P	N	P
1	66.3–77.0	1,400,938	146	64	0.019	79	37	0.034	0.549	1.5	0.0	15.3	0.0
1	77.0–145.5	1,283,418	226	99	0.019	122	58	0.034	0.851	2.3	0.0	23.8	0.0
1	145.5–153.4	1,414,904	304	134	0.019	164	78	0.034	1.144	3.1	0.0	32.1	0.0
1	153.4–157.2	1,273,095	316	139	0.019	170	81	0.034	1.189	3.3	0.0	33.8	0.0
1	157.2–178.6	1,317,104	342	150	0.019	184	88	0.034	1.287	3.5	0.0	36.5	0.0
	Total	6,689,459											
3	89.1–121.0	350,360	211	86	0.017	117	56	0.024	0.741	0.0	0.0	12.7	0.0
3	121.0–128.5	336,107	251	102	0.017	138	66	0.024	0.882	0.0	0.0	16.0	0.0
3	128.5–151.8	334,398	282	115	0.017	156	74	0.024	0.990	0.0	0.0	17.3	0.0
3	151.8–164.5	420,566	318	129	0.017	176	84	0.024	1.117	0.0	0.0	19.5	0.0
3	164.5–214.6	249,803	381	155	0.017	210	100	0.024	1.338	0.0	0.0	24.0	0.0
	Total	1,691,234											
27	64.8–142.4	53,551	218	106	0.028	119	60	0.080	0.721	0.0	0.0	8.5	0.0
27	142.4–152.6	76,628	311	151	0.028	170	85	0.080	1.029	0.0	0.0	12.0	0.0
27	152.6–154.6	32,459	324	157	0.028	177	88	0.080	1.072	0.0	0.0	12.6	0.0
27	154.6–158.9	53,453	330	160	0.028	181	90	0.080	1.092	0.0	0.0	12.3	0.0
27	158.9–164.1	43,987	340	165	0.028	186	93	0.080	1.125	0.0	0.0	13.0	0.0
	Total	260,078											

* Application rates are pounds of elemental N or elemental P.

** For nitrogen, the expected commercial fertilizer application rate is 135.6 pounds per acre if manure were not going to be applied (state average rate). For phosphorus, it is 10.7 pounds per acre as elemental P.

NRI cropland sample points. In cluster 1, for example, 1.9 percent of the corn acres received manure at rates associated with manure producing farms and 3.4 percent received manure at rates associated with manure receiving farms. In total, 5.3 percent of the corn acres in cluster 1 received manure in the EPIC model simulations. In cluster 3, a total of 4.1 percent of the corn acres received manure, and in cluster 27, a total of 10.8 percent of the corn acres received manure.

Commercial fertilizers are also applied on fields receiving manure in the model simulations, but at lower rates than on fields without manure applications. Since there was not enough data from farmer surveys to estimate commercial fertilizer application rates on fields receiving manure, the approach taken in this study was to estimate the amount of commercial fertilizer that might have been applied had manure not also been applied, and then reduce those commercial fertilizer rates by calculating a nutrient credit for the manure applied.

The first step was to estimate the amount of commercial fertilizer expected to be applied if no manure was applied. For this, the average annual nitrogen and phosphorus application rate was calculated for each state and crop from the farmer survey data used to estimate commercial fertilizer applications. For example, the following estimates were obtained for corn in Nebraska, derived as weighted averages from the commercial fertilizer rates shown in table 15.

	Annual N application rate (lb/a)	Annual P application rate (lb/a)	
		P as P_2O_5	Elemental P
Non-irrigated corn, NE	94.2	19.6	8.6
Irrigated corn, NE	159.5	27.3	12.0
Acreage-weighted average for state	135.6	24.4	10.7

NRI acreage for irrigated and non-irrigated crops was used to derive an acreage-weighted average application rate to represent the expected commercial fertilizer application if no manure was applied. Thus, for the Nebraska example, the state average nitrogen rate was 135.6 pounds per acre and the state average phosphorus rate was 10.7 pounds per acre (as elemental P). (According to the NRI, there were 3.239 million acres of non-irrigated corn and 5.599 million acres of irrigated corn in Nebraska in 1997.)

The second step was to convert the state average rate to an expected rate for each of the yield classes. This was done by constructing a yield index such that the acreage-weighted average yield would have an index value of 1. Multiplying this index times the state average application rate produced estimates for each yield class of the commercial fertilizer application rate that would generally be expected if no manure were to be applied.

The last step was to adjust these rates downward by applying a nutrient credit for the manure that was applied. It was assumed that manure producing farms would take a manure nutrient credit of 50 percent of the amount of manure nutrients applied. Thus, if the manure nitrogen application rate was 150 pounds per acre and the manure phosphorus application rate was 60 pounds per acre, the nitrogen credit would be 75 pounds per acre, and the phosphorus credit would be 30 pounds per acre. If the commercial fertilizer application possibility was 100 pounds per acre for commercial nitrogen fertilizer, the commercial fertilizer application rate would be reduced to 25 pounds per acre for model runs where manure was also applied. In some cases, this nutrient credit adjustment resulted in no commercial fertilizer applications. In the hypothetical example presented above, commercial nitrogen application rates less than 75 pounds per acre would be adjusted to zero. Because manure receiving farms are mostly crop producers, and therefore, do not need to address a manure disposal situation, a higher manure nutrient credit was used for manure receiving farms—75 percent of the amount of manure nutrients applied.

A specific example of how nitrogen and phosphorus credits affected supplemental commercial fertilizer application rates for cases where manure is applied is presented in table 18 for corn in Nebraska. The expected commercial fertilizer application rate for nitrogen is 135.6 pounds per acre if manure were not going to be applied. In the case of the lowest yield class in climate cluster 1, for example, the expected nitrogen application rate was 75 pounds per acre (135.6 times the yield index of 0.549), and the expected phosphorus rate was 5.9 pounds per acre as elemental P. Thus, the nitrogen credit was 73.5 pounds per acre for manure producing farms and 59.7 pounds per acre for manure receiving farms in this yield class, which resulted in estimates of supplemental commercial fertilizer applications of 1.5 and 15.3 pounds per acre for manure producing farms and manure receiving farms, respectively. For phosphorus, the credit was 32 pounds per acre for manure producing farms and 28 pounds per acre for manure receiving farms, but because the expected application rate was lower than the credit estimate, no supplemental phosphorus was applied in the model simulation in this case. Supplemental commercial fertilizer application rates for the other yield classes and climate clusters shown in table 18 were calculated similarly.

The manure credit assumptions were applied to all parts of the country. However, there is evidence that manure credits are not always taken into account by crop producers, especially on farms with livestock operations. For example, Gallepp (2001) and Shepherd (2000) report that beef and dairy farmers over applied nitrogen and phosphorus on average by 38 and 74 pounds per acre, respectively in Wisconsin, based on a survey of about 1,900 livestock producers. The results were skewed by extreme applications applied by about 20 percent of the producers; nevertheless, few producers were found to be crediting nutrients appropriately. Gassman et al. (2002) also report that a survey of livestock producers in the Upper Maquoketa River watershed in eastern Iowa showed that little or no crediting of manure nutrients was common in that area. Gassman et al. (2003) also report only modest manure nutrient crediting among livestock producers in the Mineral Creek Watershed, also located in eastern Iowa.

For EPIC model simulations, it is also necessary to establish application methods and times of application for manure applications. For the manure producing farm case, manure was surface applied without incorporation at three application times:

- 50 percent of the manure was applied in the fall 15 days after the harvest of the last crop
- 15 percent of the manure was applied on February 1
- 35 percent of the manure was applied in the spring 20 days before planting

For the manure receiving farm case, manure was surface applied 2 days before the primary tillage except for no-till simulations, where half of the manure was injected and half was surface applied 20 days before planting. For winter wheat, manure was applied 15 days before fall planting in both cases. For hayland in both cases, 15 percent of the manure was applied on February 1 and the remainder was applied at intervals following each cutting. All supplemental commercial fertilizer applications were applied at plant. (Planting and harvest dates were set using the heat unit scheduling code, but the timing relative to planting and harvest remained fixed.)

The 1997 Census of Agriculture database was also used to derive the proportion of manure nitrogen that was in mineral form, organic form, or available as ammonia, which is needed to run the EPIC model. These estimates were based largely on the livestock type and assumptions about manure handling technologies. The proportion of manure phosphorus in mineral form and organic form was also derived. These proportions were determined for each state-climate zone combination for use in making EPIC model runs.

Only about 4 percent of the acres had manure applications in the EPIC model simulations (table 19), representing about 11 million acres. The majority of manure applications were for corn silage, corn, and grass hay.

Maps of per-acre estimates of model output

The spatial distribution of per-acre model output is shown in maps created using a GIS-based approach developed specifically for mapping NRI variables. The mapping procedure is a grid-based approach that takes advantage of the coordinate locations of NRI sample points and involves calculation of weighted averages by grid cell areas and the application of interpolation and smoothing techniques. The purpose of the mapping technique is to illustrate spatial trends and patterns in the model results.

Prior to mapping, the database was censored slightly to reduce the number of isolated sample points. This was done primarily to ensure that the locations of the NRI sample points were not revealed in the map product, as the NRI sample frame is proprietary and protected by federal confidentiality rules and regulations. In areas where points are relatively close together, the data aggregation, interpolation, and smoothing procedures effectively conceal the precise location of individual sample points. NRI sample points were censored such that at least two primary sampling units (PSU), and a total of four cropland sample points were contained in each 20 by 20-kilometer (400 km^2) grid cell (12.4 by 12.4 mi, 154 mi^2). NRI cropland sample points not meeting these criteria were considered isolated points and were not included in the mapping analysis. A total of 6,196 NRI sample points were excluded from the results shown in the maps as a result of this censoring procedure, representing about 2.8 percent of the sample points in the NNLSC database and approximately 3.9 percent of the acres. Censoring applied only to the results shown in the maps; summary statistics presented in tables in this report include the full set of NRI sample points in the NNLSC database.

The mapping procedure is basically a three step process:

Step 1. Calculate grid cell values for cells that contain data.

Step 2. Interpolate (predict) values for cells that have no data.

Step 3. Perform a geographic transformation when representing the grid cells for display on a map.

Mapping was performed using ESRI's ArcGIS software version 9.0.

The first step is to calculate the weighted average (using the NRI expansion factor as the weight) of all data values associated with points found within each 25-

Table 19 Representation of manured acres in the model simulations

	No manure		Manure producing farms		Manure receiving farms		Total manured acres	
Crop	Acres	Percent	Acres	Percent	Acres	Percent	Acres	Percent
Barley	4,567,608	98.6	11,946	0.3	55,347	1.2	67,293	1.5
Corn	72,874,682	93.2	2,001,884	2.6	3,342,774	4.3	5,344,658	6.8
Corn silage	3,547,540	68.3	1,564,899	30.1	84,220	1.6	1,649,119	31.7
Cotton	16,169,723	95.9	32,285	0.2	656,191	3.9	688,476	4.1
Grass hay	13,500,009	92.5	677,288	4.6	419,003	2.9	1,096,291	7.5
Legume hay	24,710,636	99.7	39,612	0.2	25,352	0.1	64,964	0.3
Oats	3,745,858	99.3	2,988	0.1	23,554	0.6	26,542	0.7
Peanuts	1,820,542	98.8	4,374	0.2	18,484	1.0	22,858	1.2
Potatoes	966,180	97.9	473	0.1	20,047	2.0	20,520	2.1
Rice	3,636,996	100.0	146	<0.1	157	0.0	303	<0.1
Spring wheat	20,392,934	99.5	4,492	<0.1	105,713	0.5	110,205	0.5
Sorghum	10,511,384	96.5	31,177	0.3	354,738	3.3	385,915	3.5
Soybeans	67,131,262	99.4	99,092	0.2	312,446	0.5	411,538	0.6
Winter wheat	44,041,606	97.8	73,424	0.2	898,932	2.0	972,356	2.2
All crops	287,616,962	96.4	4,544,080	1.5	6,316,958	2.1	10,861,038	3.6

square-kilometer grid cell area (9.6-mi^2 grid cell area). The grid function sets the center point of each cell that contains one or more NRI points to the weighted average value. While many cells have multiple NRI points within them that get averaged together, many others cells have no NRI points and are referred to as unpopulated cells; the value for unpopulated cells remains null or undefined after this first step.

The next step is to use the mean values associated with the center points of populated cells in an interpolation function to generate values for the unpopulated cells. The goal of interpolating is to populate surrounding empty cells with predicted values in order to provide a smoother, easier-to-interpret look at the geographic distribution of the populated cell values. There are several commonly used types of interpolation models, including Inverse Distance Weighted (IDW), polynomial trend surface, spline, and Kriging. IDW was chosen for its relative simplicity of calculation and because of its suitability for representing surfaces that may at times be sharply varied rather than gently varied. All interpolation functions assume that spatially distributed phenomena are spatially correlated. If no populated cell center points are found within the neighborhood, as would occur in areas with little or no cropland, the cell value remains unpopulated. When a cell is populated by means of interpolation, it is not further used in the calculation of other unpopulated cells still to be interpolated.

Those points nearest to the prediction cell are given greater weight in the calculation of the predicted value than are those further away. This is implemented through what is referred to as an exponent of distance. The value 2 was chosen for the exponent, the default used by ESRI and also known as inverse distance squared interpolation. It causes the influence of surrounding values to decrease rapidly with increasing distance from the predicted cell. Smaller exponents result in smoother, more gradual trends and less detailed surfaces.

A 15-kilometer radius size (9.3 mi) was chosen as the neighborhood for the calculation of each interpolated value. The radius size was somewhat arbitrary, but was based upon experimentation with several different radii, and ultimately was a compromise of several objectives including:

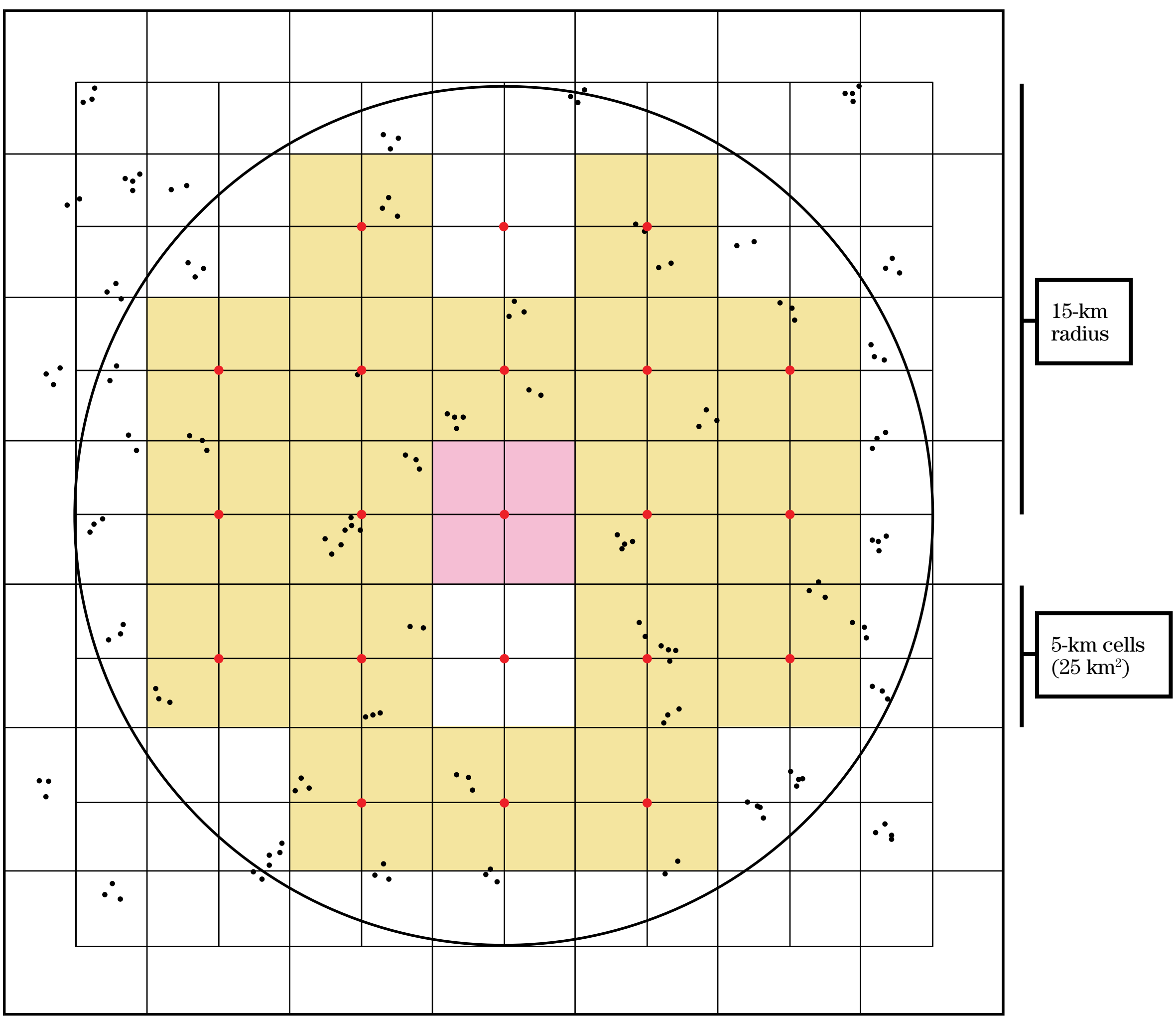
- encompassing the entire area of each 20- by 20-kilometer grid cell used in the censoring process (assuring that every interpolated value results from cropland points in at least two PSUs)
- limiting the area of influence impacting the predicted value of each cell
- limiting the number of surrounding unpopulated cells that would become populated in the course of interpolation
- limiting the cell size to provide a sufficiently high resolution in order to reveal detail in spatial trends across regional areas
- protecting the precise location of NRI sample points

The IDW function also requires input for a maximum number of points to examine, but that maximum was set high enough so that the limiting constraint would be the neighborhood size, effectively assuring that the smallest area mapped would be the size of the neighborhood.

Figure 5 illustrates how the value of each grid cell is determined in the process of interpolation. The black squares represent 5-kilometer length (25-km^2 area) cells of a small grid. The red cell is the prediction cell, the cell for which an interpolated value will be calculated. The lighter background grid simply serves as a measure for showing the center points of cells (shown as red points) that are completely contained within the 15-kilometer radius defined from the center point of the red prediction cell. The black dots represent NRI sample points, with locations that are approximately based upon an actual example. The yellow cells are those completely within the 15-kilometer radius that contain at least one NRI sample point and are therefore populated at the cell center with a weighted average value representing all point values in the cell. Each white cell completely within the radius is unpopulated and has no value until one is predicted for it as the interpolation process proceeds from the upper left cell to the lower right cell across a grid positioned over the United States. If no populated cells are found within the 15-kilometer radius, the prediction cell will remain unpopulated. Potentially, up to 20 cell centers (the red dots in the illustration, excluding the cell being interpolated) within a 15-kilometer radius may be populated with values.

In the final step, a geometric transformation is used to create the values in the output display grid. A resampling method is used to account for the fact that the origin of the output display grid does not line up exactly with the origin of the input point layer or with intermediate grids involved in the calculations. One of three possible resampling techniques can be selected —either nearest neighbor assignment, bilinear interpolation, or cubic convolution resampling. In the case of continuous data, the choice is mainly a matter of aesthetics. Bilinear interpolation resampling was selected for use on these maps because it produced the sharpest output. Bilinear interpolation uses the values of the four nearest cell centers to weight-average a cell value for display on the map.

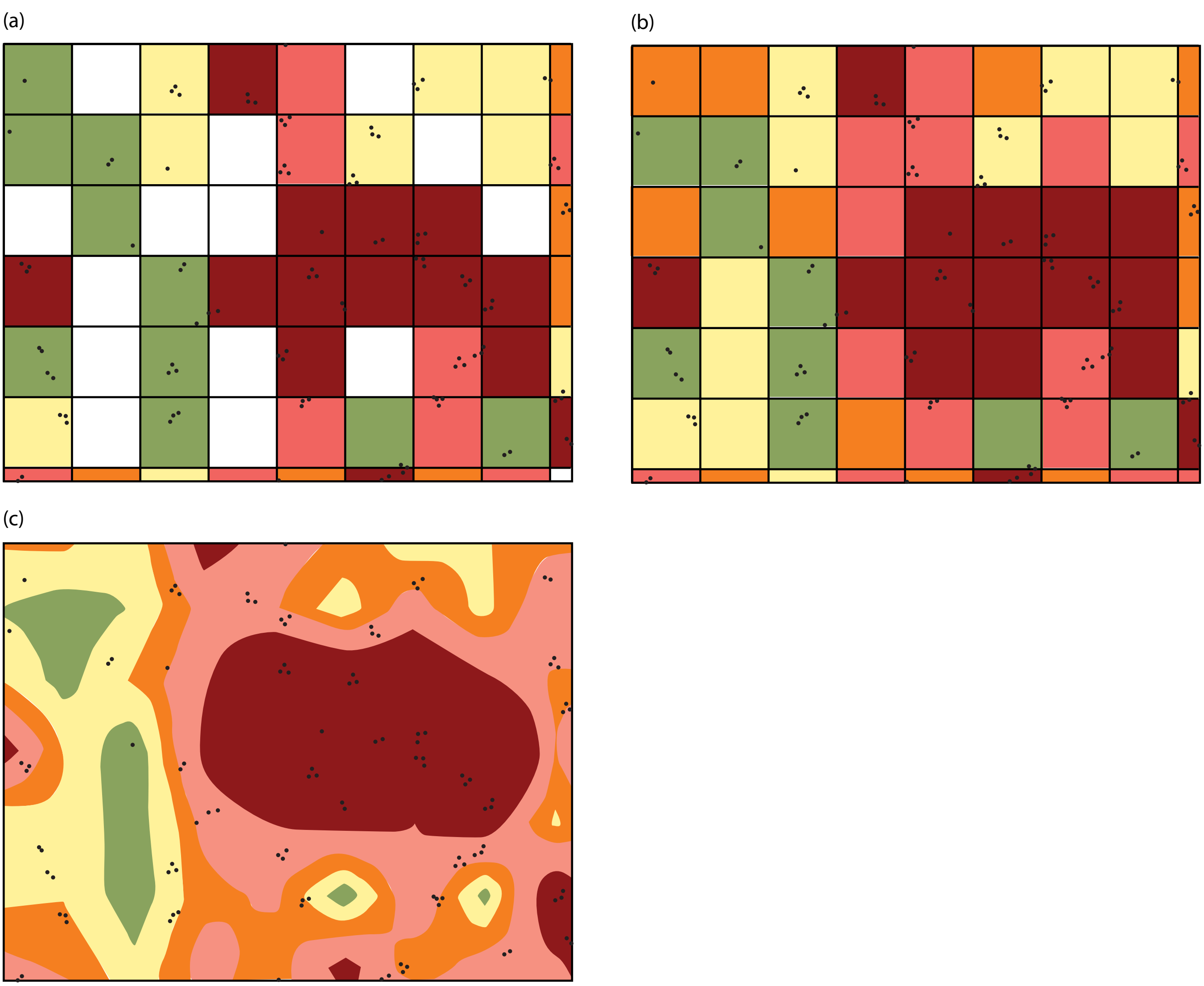
Figure 5 Schematic for illustrating the mapping technique used to display per-acre model output results



The three steps in the mapping process are illustrated in figure 6. Figure 6(a) shows that prior to interpolation, the values for points are weight-averaged and the resulting value is assigned to the cell, while cells lacking points are treated as null values (white cells); (b) shows that after interpolation, null cells within a limited radius of cells containing data are populated with values based upon the interpolation function; and (c) shows how the re-sampling algorithm (in this case, bilinear interpolation re-sampling, which examines 4 surrounding cell values) smoothes the data to represent a more continuous surface. Note that the colors represent classes to which the weight-averaged values are assigned.

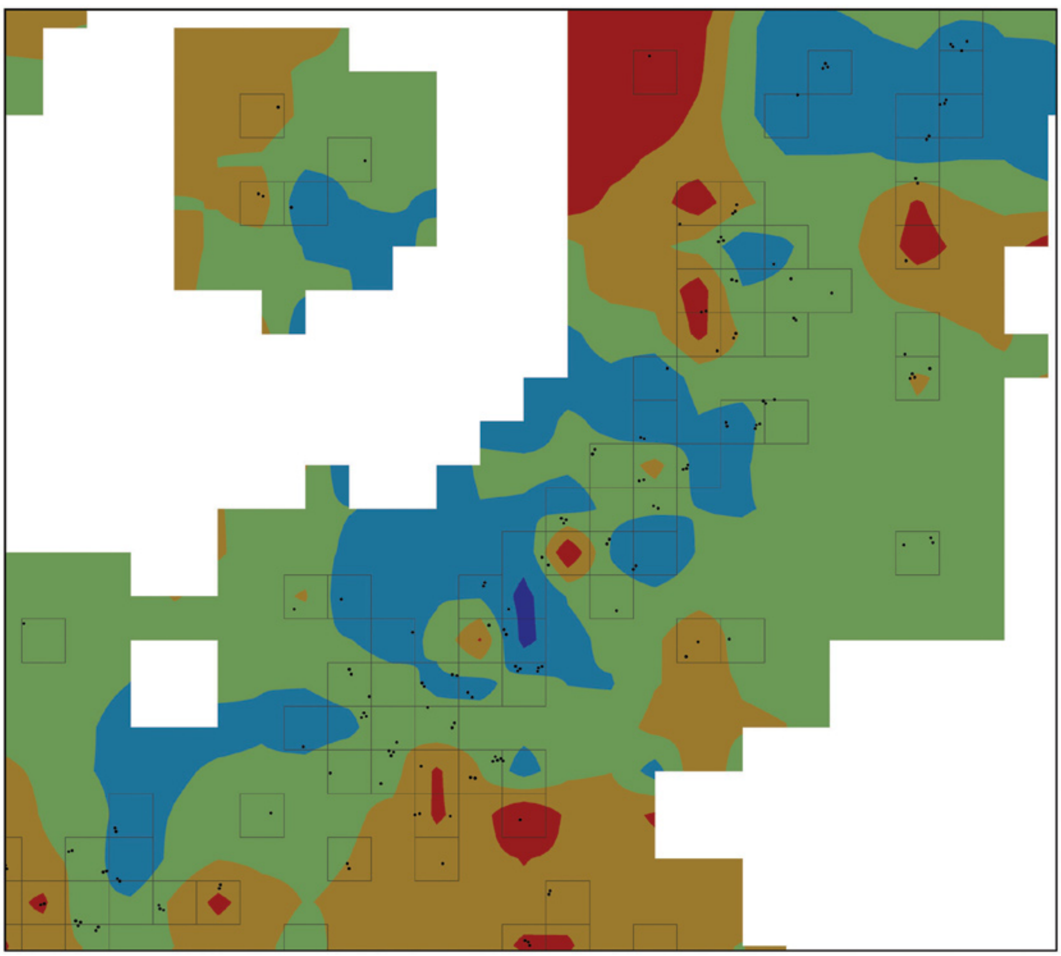
The result provides a geographic representation that is easier to interpret and offers clearer spatial trending than would be revealed by merely examining a map of the point values or by aggregating the data by irregularly shaped polygons. As with polygon-based maps, the numeric range of calculated values is divided into classes, and the classes are color coded to reveal spatial trends. Class breaks and colors were selected to highlight the spatial trends, or in some cases, to allow comparisons among maps of related variables.

Figure 6 Hypothetical example of interpolation and resampling process



The mapping method resulted in a visual representation that greatly overstates the total number of cropland acres. For example, the domain of NRI points used in this study represents a total of 298 million acres, only 287 million of which was used in the mapping after censoring. However, when displayed using the interpolation mapping technique, the spatial representation is equivalent to 925 million acres on the map. The over-representation is most pronounced in areas where land cover is diverse and cropland is not the dominant land use. In large areas where the percentage of the land cover is predominately cropland, the visual over-representation of acres is minimal. Figure 7 is a hypothetical example that demonstrates this over-representation of cropland acres in a setting where land cover is diverse. The EPIC model output estimates presented in the maps only represent the cropland portion of the land cover. Nearly all the colored areas in the maps also include other land covers, such as pastureland, forestland, rangeland, and urban. As shown in figure 7, cropland in some areas is only a small portion of the actual land cover.

Figure 7 Hypothetical example of area over-representation and under-representation



NRI sample points are not evenly distributed, and each sample point may represent anywhere from 100 to 49,500 acres (expansion factors). The median value is 1,500 acres. When NRI sample point expansion factors are summed for each 5-kilometer square grid cell, the total may substantially over-represent or in some cases under-represent the surface area of a 5-kilometer square cell (approximately 6,178 a). The interpolation method fills in additional areas, expanding well beyond the size of the grid cells that contain sample sites and results in a net over-representation of cropland (colored area) acres.

Another source of over-representation of acres occurs because some grid cells contain only a few NRI sample points, representing only a few acres of cropland, while other grid cells represent many more cropland acres. Since all grid cells are the same size, this has the visual effect of exaggerating the cropland representation in some areas of the country relative to other areas of the country. Areas where cropland is a small share of the land use on the landscape appear over-represented in the maps.

The percentage of acres associated with the class breaks used to construct the maps is reported in the map legend to provide a perspective on the extent of the over-representation of acres in the maps. These percentages were calculated on the basis of the individual NRI sample points, and not on the basis of the average values for the map cells. Thus, the percentages reported in the map legend do not account for the averaging effect originating from use of the mean values to represent model output for each map cell.

The NRI sample frame was designed to provide statistically reliable estimates at the national, state, and sometimes sub-state levels. However, it was not designed to provide statistically reliable estimates for the small grids used to construct the maps presented in this report. Therefore, caution must be exercised in interpreting the information depicted on the maps. The purpose of the maps is to show spatial trends; localized interpretations of results are inappropriate and may be misleading.

Maps of total loading estimates

Maps of per-acre model outputs are useful for identifying areas of the country where conservation practices would be expected to have the greatest impact on reducing sediment and nutrient losses from farm fields, wind erosion, and soil quality degradation. In some cases, however, the focus for implementation of conservation practices is on reducing the total loadings of nutrients and sediment within a region. An example would be to address downstream water quality degradation, such as impaired water quality in estuaries or in the oceans. For these concerns, cropland areas exporting the largest amounts of sediment and nutrients would constitute priority areas. Annual loadings estimates in total tons are shown in these maps, representing field-level losses of potential pollutants. These estimates were derived by multiplying the annual average per-acre model output times the number of acres represented by the NRI sample points.

A dot-map approach was used to display total loading estimates. Each dot on the map represents a specified number of tons. Each dot is randomly placed within a county. Dots are placed using ESRI's ArcMap non-fixed placement method (see ESRI publication Using ArcMap).

Surface water runoff, percolation, and evapotranspiration

Modeling the hydrologic cycle

Water is a potent force that interacts with or drives almost all environmental processes acting within an agricultural production system. There are six processes at work in the hydrologic cycle: condensation, precipitation, infiltration, runoff, evaporation, and transpiration.

The EPIC model simulates the hydrologic processes that operate at the field scale, with some simplifications. Evaporation and transpiration are combined into a single variable. Infiltration is partitioned into vertical and lateral flow, which results in changes in the soil-water storage. In reality, surface water runoff, infiltration, and evaporation occur simultaneously; in the EPIC model, however, surface water runoff occurs first, and only the portion that does not run off is available for infiltration or evapotranspiration (ET). EPIC models the hydrologic cycle only within the boundaries of a small field with a homogenous soil having a uniform slope. Ponding of water on the field is not simulated.

Given daily rainfall, surface runoff is estimated as a function of soil attributes, soil-water content, slope, land use and vegetative cover, antecedent moisture conditions, and management factors using a set of equations based on the NRCS curve number method (Mockus 1972). Each day the final estimate of the NRCS curve number is generated stochastically to account for the uncertainty of the deterministic estimate. Provisions are also made to reflect increases in runoff on frozen soils. For irrigation water, runoff was set as a fixed percent of the quantity applied; 5 percent is assumed to run off for sprinkler systems and 20 percent is assumed to run off for gravity or furrow applications.

Precipitation and irrigation water not removed from the field by surface water runoff is assumed to infiltrate into the soil. Vertical movement is simulated in EPIC using a storage routing technique that can be visualized as several vertically stacked buckets—each almost full of water. Rain fills and then overfills the top bucket which spills the excess into the bucket directly below, and so on. As infiltration occurs, soil water content in the top soil layer increases. When field capacity in a layer is exceeded, flow occurs vertically down through the soil layers and laterally off-field until the soil-water storage in that layer returns to field capacity. In each layer, vertical and lateral flows are calculated using flow rates estimated from travel times and the quantity of excess soil-water. Travel time for the vertical component (percolation) is a function of soil characteristics including porosity and saturated conductivity (or percent clay), while lateral subsurface flow is a fractional proportion of percolation estimated using the surface slope. Calculations for both flow components are performed simultaneously to avoid one dominating the other simply because of solution order. Interflow, the flow path in which lateral flow returns to the surface, is not considered in EPIC. Tile and surface drainage systems are also not taken into account in EPIC model simulations conducted for this study, as explained in a previous section.

Routines in EPIC alter water movement in certain cases. For instance, vertical routing usually moves water downward, but water can be routed upwards through capillary processes in cases where soil water exceeds storage capacity in a lower layer having a low saturated conductivity. Also, freezing temperatures can affect percolation because water is routed into a frozen layer but is not allowed to percolate out.

ET is the process that returns water vapor to the atmosphere by evaporation from the soil and transpiration by plants. EPIC estimates ET by first calculating the total quantity that could be transported under ideal circumstances, called potential evapotranspiration (PET). In these simulations, PET was estimated as a function of solar radiation and air temperature using the modified Hargreaves equation option in EPIC. PET is then partitioned into evaporation from soils and transpiration from plants using leaf area index and soil albedo. Actual plant water transpiration is some fraction of the potential, based upon leaf area index and soil water content. Actual soil water evaporation is some fraction of the potential, which is limited by exponential functions of soil depth and water content. Actual evaporation and transpiration are summed and reported as ET.

Land use decisions, field operations, and other management activities influence hydrology mainly by altering field characteristics, such as surface roughness or residue cover, that affect surface storage, infiltration, or runoff. EPIC simulates the effects of these management activities; for example, the EPIC tillage component mixes nutrients and crop residues within the plow depth, simulates changes in soil bulk density, converts standing residue to flat residue, and simulates ridge height and surface roughness. Other land use and conservation practices are simulated using the curve number and associated functions. The effects of management on the hydrologic response vary from field to field based on the inherent properties of each field.

Model simulation results for water inputs

The model simulates precipitation and irrigation water inputs, as explained in previous sections. Overall, precipitation for non-irrigated acres averaged 32 inches per year and 27 inches per year for irrigated acres (table 20). On average, irrigated acres received an additional 18 inches per year throughout the growing season. Precipitation was much lower in arid and semi-arid areas, averaging about 13 inches per year; irrigation water use in arid areas averaged 23 inches per year. In the most humid regions, precipitation averaged about 55 inches per year on cropland acres. Total water inputs were highest in the South Central region (51 in/yr) and the Southeast region (47 in/yr), and lowest in the Northern Great Plains region (21 in/yr) (table 21).

The spatial distributions of precipitation and irrigation water inputs as simulated by the model are shown in maps 5 and 6. Because weather inputs were the same within each climate zone, the precipitation map (map 5) is a reflection of the underlying climate zones. Irrigation water was applied in the model simulations only on the acres that the NRI indicated were irrigated; thus the irrigation map (map 6) reflects the spatial distribution of irrigated acres. The values for irrigation water shown in map 6 are the average over all cropland acres in each map cell, and do not reflect the rates applied only on the irrigated acres within the map cell. For example, the yellow areas in map 6 have, on average over all cropland acres, 1 inch or less of irrigated water applied. The amount of irrigation water applied to the acres that were irrigated within those map cells, however, would have been similar to amounts reported for irrigated acres in tables 20 and 21.

Table 20 Summary of model simulation results for the hydrologic cycle (average annual values)

	Water inputs				Evapotranspiration		Surface water runoff		Percolation		Subsurface lateral flow	
Precipitation class*	Percent acres	Precipitation (in)	Irrigation (in)	Precipitation and irrigation (in)	Inches	Percent of inputs	Inches	Percent of inputs	Inches	Percent of inputs	Inches	Percent of inputs
Irrigated cropland												
Arid	4.4	12	23	36	32	88.7	3.2	8.9	0.8	2.2	0.10	0.3
Semi-arid	4.3	20	18	39	33	85.4	3.7	9.5	1.9	4.8	0.15	0.4
Sub-humid	1.1	33	11	43	32	73.6	5.6	12.9	5.7	13.1	0.17	0.4
Moderately humid	2.2	49	14	63	36	57.2	12.9	20.4	13.8	21.9	0.13	0.2
Humid	1.4	56	16	72	39	54.9	16.6	23.2	14.8	20.6	0.14	0.2
All	13.4	27	18	45	34	74.1	6.5	14.2	5.1	11.1	0.13	0.3
Non-irrigated cropland												
Arid	4.8	14	0	14	13	96.3	0.4	2.8	0.1	0.5	0.05	0.4
Semi-arid	24.2	20	0	20	19	92.2	1.3	6.1	0.3	1.6	0.07	0.3
Sub-humid	36.1	33	0	33	26	76.9	4.7	14.1	2.8	8.4	0.21	0.6
Moderately humid	18.8	44	0	44	29	65.1	7.1	16.1	7.8	17.7	0.30	0.7
Humid	2.6	55	0	55	32	58.5	11.0	19.8	11.4	20.5	0.24	0.4
All	86.6	32	0	32	24	75.6	4.2	13.3	3.3	10.4	0.18	0.6
Totals	100.0	31.1	2.5	33.5	25.3	75.3	4.5	13.5	3.5	10.6	0.2	0.5

*Precipitation classes: arid is less than 400 millimeters (<15.7 in); semi-arid is 400 to 700 millimeters (15.7–27.6 in); sub-humid is 700 to 1,000 millimeters (27.6–39.4 in); moderately humid is 1,000 to 1,300 millimeters (39.4–51.2 in); and humid is greater than 1,300 millimeters (>51.2 in).
Note: Precipitation classes were assigned to NRI sample points based on the 30-year average annual precipitation as simulated by EPIC.

Table 21 Water inputs, ET, surface water runoff, and percolation–by region and crop within regions (average annual values)

Region	Crop	Acres (1,000s)	Precip-itation (in)	Irriga-tion (in)	Total water inputs (in)	Evapo-transpiration (in)	Evapo-transpiration Percent of inputs	Surface water runoff (in)	Surface water runoff Percent of inputs	Percolation (in)	Percolation Percent of inputs	Subsurface lateral flow (in)	Subsurface lateral flow Percent of inputs
Northeast	All crops	13,642	39.3	0.1	39.4	25.3	64.2	6.6	16.8	7.0	17.8	0.4	1.1
Northern Great Plains	All crops	72,397	18.7	2.6	21.3	19.5	91.6	1.5	6.9	0.3	1.4	0.1	0.4
South Central	All crops	45,350	47.9	3.1	51.1	32.3	63.2	10.1	19.7	8.4	16.5	0.2	0.4
Southeast	All crops	13,394	46.0	0.7	46.7	28.9	61.9	4.9	10.6	12.1	25.9	0.4	0.8
Southern Great Plains	All crops	32,096	21.2	5.7	26.9	24.4	90.6	1.6	6.0	0.9	3.2	0.1	0.3
Upper Midwest	All crops	112,581	33.8	0.2	34.0	25.8	75.8	4.8	14.1	3.2	9.3	0.2	0.6
West	All crops	9,018	12.6	19.7	32.3	26.9	83.1	3.9	12.0	1.5	4.6	0.1	0.3
All regions	All crops	298,478	31.1	2.5	33.5	25.3	75.3	4.5	13.5	3.5	10.6	0.2	0.5
By crop within region*													
Northeast	Corn	2,943	39.9	0.2	40.1	24.1	60.0	6.8	16.9	8.8	21.9	0.4	1.1
	Corn silage	1,482	38.6	<0.1	38.6	23.8	61.7	7.9	20.5	6.4	16.6	0.4	1.1
	Grass hay	2,369	38.8	<0.1	38.8	26.5	68.2	6.4	16.5	5.4	14.0	0.5	1.2
	Legume hay	4,052	38.2	<0.1	38.2	26.4	69.1	6.3	16.4	5.0	13.1	0.5	1.2
	Oats	362	38.5	<0.1	38.5	24.9	64.7	6.7	17.3	6.4	16.6	0.5	1.3
	Soybeans	1,305	41.5	0.4	41.9	23.8	56.9	6.8	16.1	11.0	26.3	0.3	0.7
	Winter wheat	853	41.0	0.4	41.4	26.3	63.6	5.7	13.8	9.0	21.7	0.4	0.9
Northern Great Plains	Barley	3,243	16.8	0.5	17.3	16.2	93.7	1.0	5.9	<0.1	0.2	<0.1	0.3
	Corn	15,466	20.2	7.4	27.5	24.3	88.4	2.3	8.4	0.8	3.0	0.1	0.5
	Corn silage	810	19.4	5.0	24.3	21.3	87.7	2.3	9.5	0.6	2.6	0.1	0.5
	Grass hay	2,443	17.8	0.3	18.1	17.0	93.9	0.9	5.2	0.1	0.6	0.1	0.4
	Legume hay	6,152	18.2	5.5	23.7	21.6	91.0	1.7	7.1	0.3	1.5	0.1	0.4
	Oats	1,255	18.4	0.3	18.6	17.3	92.7	1.2	6.3	0.1	0.7	0.1	0.4
	Spring wheat	18,916	17.4	0.1	17.5	16.4	93.5	1.1	6.1	<0.1	0.3	0.1	0.3
	Sorghum	1,595	19.9	2.5	22.4	20.9	93.0	1.3	5.6	0.3	1.3	0.1	0.4
	Soybeans	9,562	20.6	1.6	22.2	20.1	90.6	1.8	8.1	0.3	1.3	0.1	0.4
	Winter wheat	12,748	18.0	1.2	19.2	18.2	94.8	0.9	4.5	0.1	0.4	0.1	0.3

Table 21 Water inputs, ET, surface water runoff, and percolation–by region and crop within regions (average annual values)—Continued

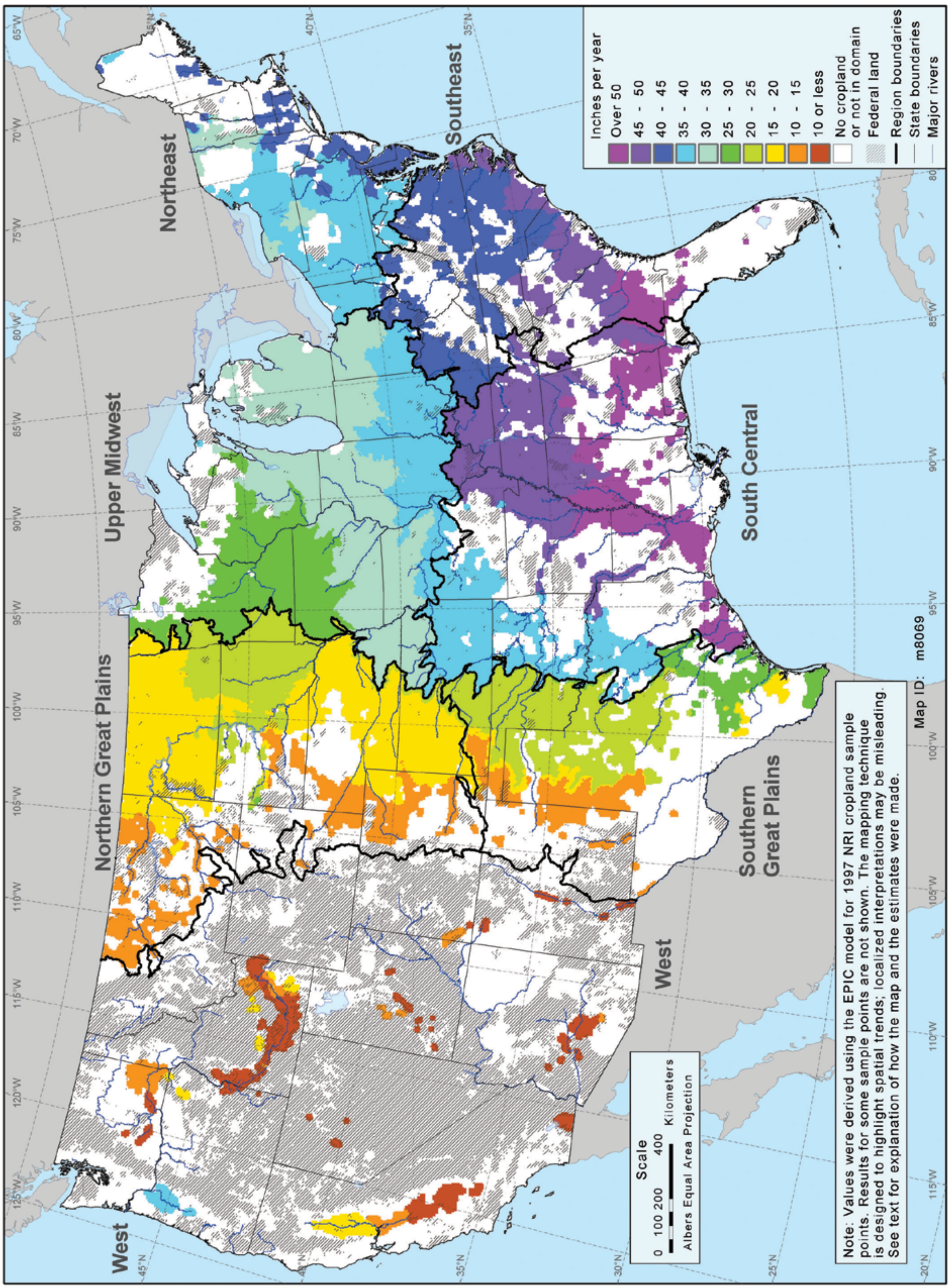
			Precip-itation	Irriga-tion	Total water inputs	Evapo-transpiration		Surface water runoff		Percolation		Subsurface lateral flow	
Region	Crop	Acres (1,000s)	(in)	(in)	(in)	(in)	Percent of inputs	(in)	Percent of inputs	(in)	Percent of inputs	(in)	Percent of inputs
South Central	Corn	5,956	50.1	1.2	51.3	31.4	61.3	10.6	20.8	8.8	17.2	0.3	0.5
	Cotton	5,487	52.0	4.0	56.0	31.9	57.0	10.4	18.6	13.2	23.6	0.2	0.4
	Grass hay	3,347	46.0	<0.1	46.0	31.1	67.7	7.2	15.5	7.3	15.8	0.4	0.8
	Legume hay	1,630	45.5	0.3	45.7	33.1	72.3	7.0	15.2	5.2	11.3	0.4	0.9
	Peanuts	880	51.1	2.6	53.7	33.1	61.6	5.0	9.3	14.6	27.2	0.5	1.0
	Rice	3,004	53.3	23.1	76.4	37.2	48.7	19.4	25.4	19.5	25.5	0.1	0.1
	Sorghum	2,729	41.0	0.4	41.5	31.0	74.7	6.4	15.4	4.0	9.5	0.1	0.3
	Soybeans	14,083	50.2	2.6	52.8	32.9	62.3	12.2	23.1	7.4	14.0	0.2	0.3
	Winter wheat	7,896	40.8	0.5	41.4	31.1	75.2	5.8	13.9	4.4	10.6	0.2	0.4
Southeast	Corn	3,028	46.0	0.7	46.7	29.3	62.7	5.4	11.6	11.4	24.4	0.3	0.6
	Corn silage	412	44.2	0.1	44.3	28.0	63.1	7.2	16.2	8.5	19.2	0.5	1.2
	Cotton	2,422	48.2	1.9	50.0	27.9	55.8	4.3	8.6	16.5	32.9	0.3	0.7
	Grass hay	2,000	44.6	<0.1	44.6	30.4	68.0	4.6	10.3	8.9	20.1	0.6	1.3
	Legume hay	1,183	42.6	<0.1	42.6	31.4	73.8	5.8	13.6	4.8	11.3	0.5	1.2
	Peanuts	479	48.9	2.4	51.3	31.9	62.2	4.4	8.5	13.2	25.7	0.4	0.8
	Soybeans	2,419	46.3	0.4	46.6	28.4	60.8	4.9	10.5	12.8	27.5	0.3	0.7
	Winter wheat	1,216	45.8	0.6	46.4	25.8	55.7	4.3	9.3	15.6	33.7	0.4	0.9
Southern Great Plains	Corn	2,665	20.8	13.1	33.9	30.2	89.2	2.8	8.3	0.7	2.2	0.1	0.3
	Cotton	7,316	19.9	8.5	28.4	24.9	87.8	1.9	6.8	1.5	5.4	0.1	0.2
	Legume hay	677	18.5	18.5	36.9	33.8	91.6	2.2	6.0	0.6	1.8	0.2	0.5
	Oats	503	26.8	0.6	27.4	22.8	83.2	3.1	11.5	1.4	5.2	0.1	0.3
	Peanuts	484	22.9	8.8	31.7	27.1	85.4	2.1	6.7	2.3	7.3	0.2	0.5
	Sorghum	4,895	22.2	3.9	26.0	23.3	89.6	2.0	7.8	0.6	2.4	0.0	0.2
	Winter wheat	15,037	21.4	3.1	24.5	22.8	93.3	1.0	4.2	0.6	2.3	0.1	0.3

Table 21 Water inputs, ET, surface water runoff, and percolation–by region and crop within regions (average annual values)—Continued

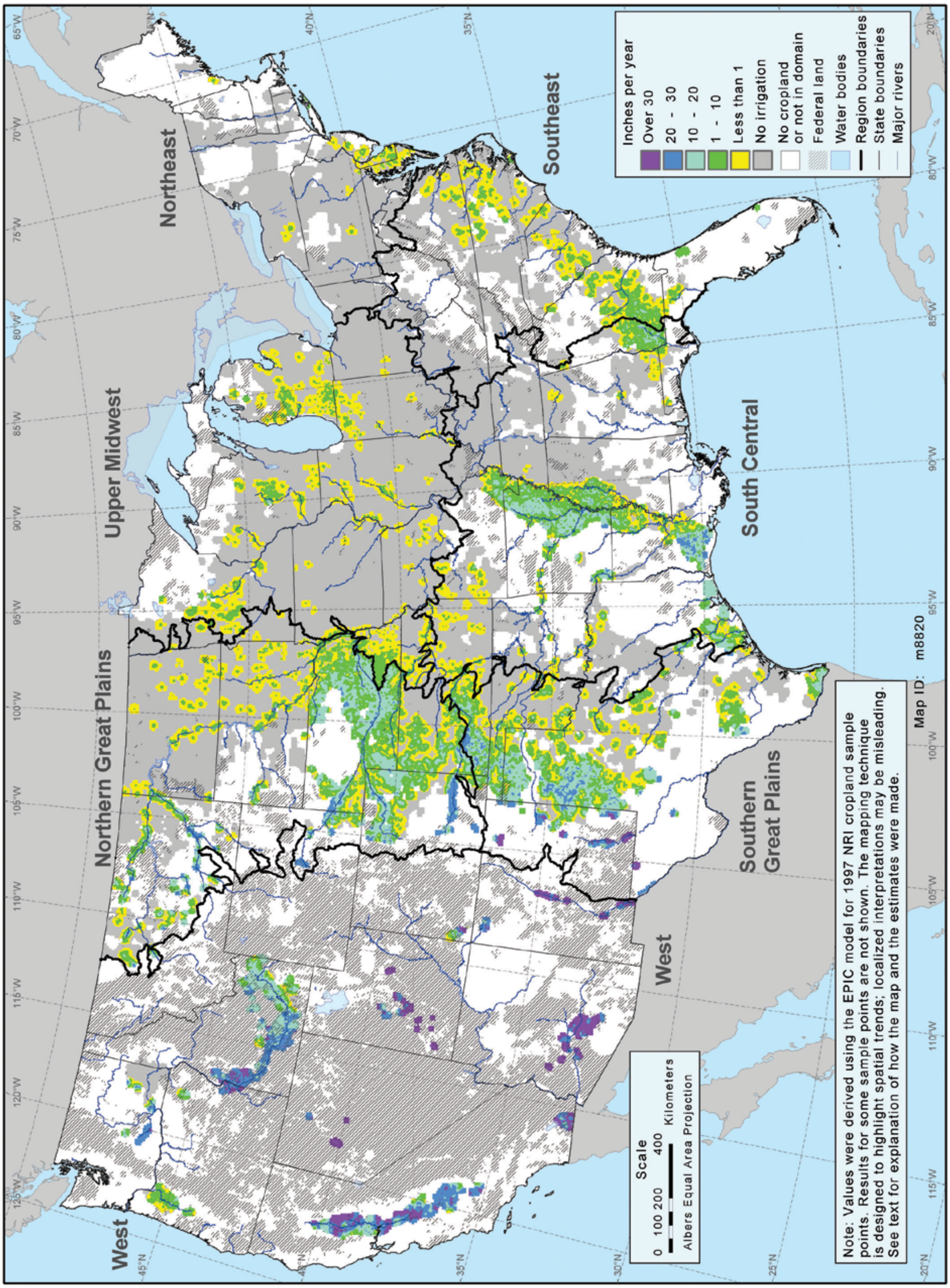
Region	Crop	Acres (1,000s)	Precip-itation (in)	Irriga-tion (in)	Total water inputs (in)	Evapo-transpiration (in)	Evapo-transpiration Percent of inputs	Surface water runoff (in)	Surface water runoff Percent of inputs	Percolation (in)	Percolation Percent of inputs	Subsurface lateral flow (in)	Subsurface lateral flow Percent of inputs
Upper Midwest	Corn	47,941	34.0	0.3	34.3	25.8	75.1	4.8	14.1	3.5	10.1	0.2	0.6
	Corn silage	1,947	31.4	0.1	31.5	22.6	71.7	5.3	16.9	3.4	10.8	0.2	0.7
	Grass hay	4,044	33.8	<0.1	33.8	26.9	79.8	4.3	12.8	2.1	6.3	0.3	0.8
	Legume hay	9,233	32.2	0.1	32.3	25.5	78.9	4.2	13.1	2.2	6.9	0.3	0.9
	Oats	1,388	31.0	0.1	31.1	24.2	77.9	3.9	12.4	2.7	8.7	0.3	0.9
	Spring wheat	815	27.0	<0.1	27.0	23.7	87.9	2.9	10.6	0.3	1.2	0.0	0.2
	Sorghum	1,604	33.2	0.2	33.4	27.7	82.9	3.6	10.8	1.8	5.4	0.2	0.7
	Soybeans	40,049	34.3	0.2	34.4	25.7	74.6	5.1	14.8	3.4	9.9	0.2	0.5
	Winter wheat	5,147	34.9	0.1	35.0	28.3	81.0	4.6	13.2	1.8	5.0	0.2	0.5
West	Barley	958	12.0	8.8	20.7	18.5	89.0	1.9	9.1	0.3	1.3	0.1	0.6
	Corn silage	297	14.5	21.9	36.4	28.7	79.0	4.3	11.9	3.2	8.8	0.1	0.3
	Cotton	1,631	10.1	31.3	41.3	36.0	87.0	4.7	11.4	0.6	1.4	0.0	0.1
	Legume hay	1,847	10.1	28.9	39.0	33.0	84.6	4.8	12.2	1.1	2.8	0.1	0.3
	Potatoes	329	10.5	14.6	25.1	22.8	90.7	2.1	8.3	0.2	0.7	0.1	0.4
	Rice	599	17.1	34.6	51.6	36.7	71.0	9.4	18.3	5.5	10.6	0.0	0.1
	Spring wheat	772	11.5	11.0	22.5	20.0	88.9	2.0	8.7	0.4	1.9	0.1	0.5
	Winter wheat	2,118	15.7	8.7	24.4	19.4	79.4	2.7	11.0	2.2	8.9	0.2	0.7

* Estimates for crops with less than 250,000 acres within a region are not shown. However, acres for these minor crops are included in the calculation of the regional estimates.

Map 5 Average annual precipitation input for model simulations



Map 6 Average annual irrigation input for model simulations



Model simulation results for surface water runoff, percolation, and ET

EPIC estimates the amount of water inputs that leaves the field through ET, surface runoff, percolation, and subsurface lateral flow. Model results for surface water runoff and percolation are key to understanding the estimates of potential pollutants from farm fields presented in subsequent sections.

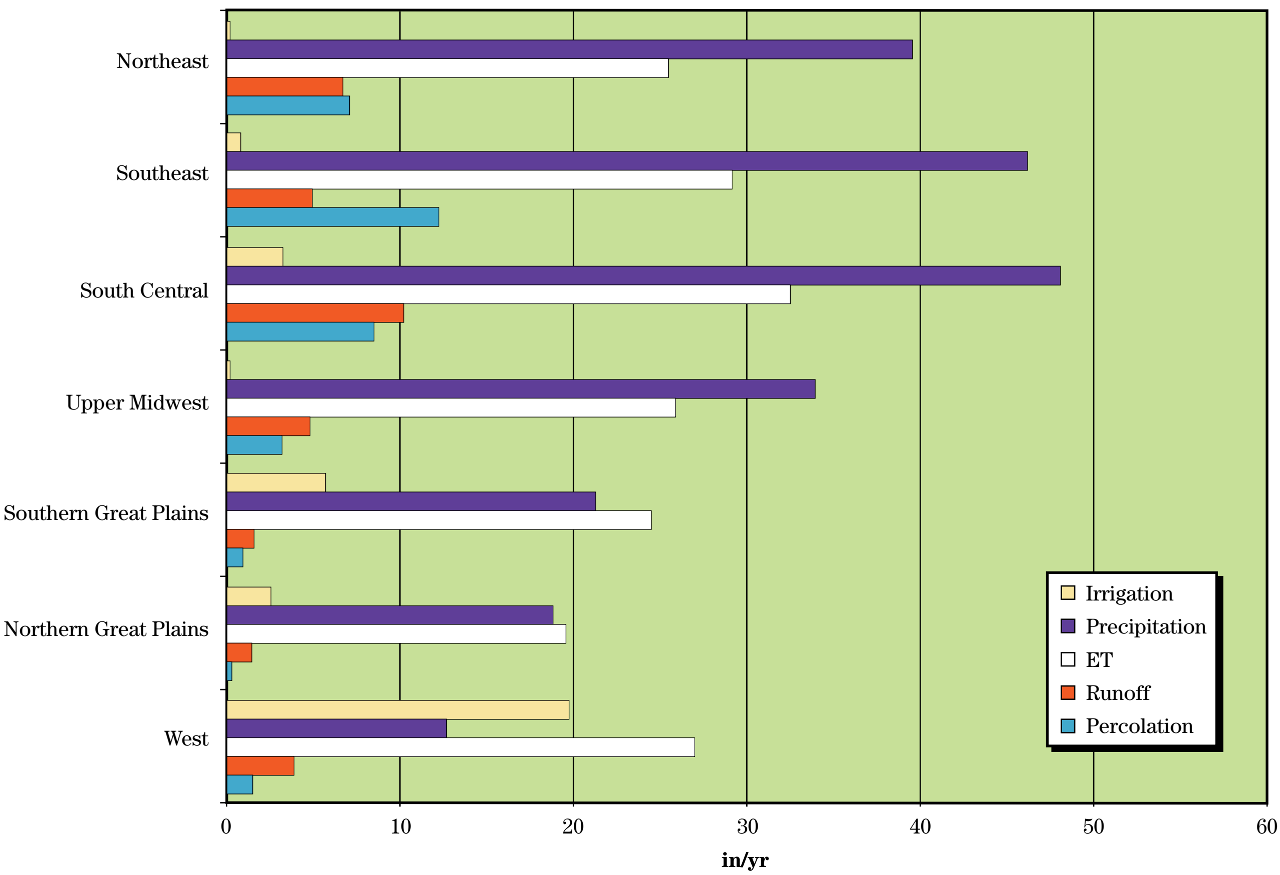
Most of the water that falls on farm fields or is added through irrigation passes back to the atmosphere through evaporation and transpiration (fig. 8). Model simulation results showed that on average about 75 percent of water inputs for cropland results in ET (tables 20 and 21). The percent of water inputs that result in ET is lower in areas where precipitation is higher, averaging 55 to 65 percent in moderately humid and humid cropland regions. In arid and semi-arid cropland regions, more than 90 percent results in ET on non-irrigated acres and more than 80 percent on irrigated acres. These results are consistent with research that shows that plants transpire a larger proportion of available water in arid regions (Garbrecht et al. 2004).

Model simulation results showed that the remainder of the water inputs—ranging from 8 to 38 percent among the seven regions (table 21)—results in either percolation or surface water runoff. A minor amount (less than 1% in most cases) leaves the field through subsurface lateral flow, which may either eventually return to the surface and discharge into a receiving water body or continue to percolate downward once a more porous soil is encountered. Nationally, surface water runoff is higher than percolation, averaging about 4.5 inches per year compared to 3.5 inches per year for percolation. At the regional scale, however, average percolation was higher than average surface water runoff in two regions—the Northeast and Southeast regions. For cropland acres in the Southeast region, percolation was more than twice the amount of surface water runoff (table 21).

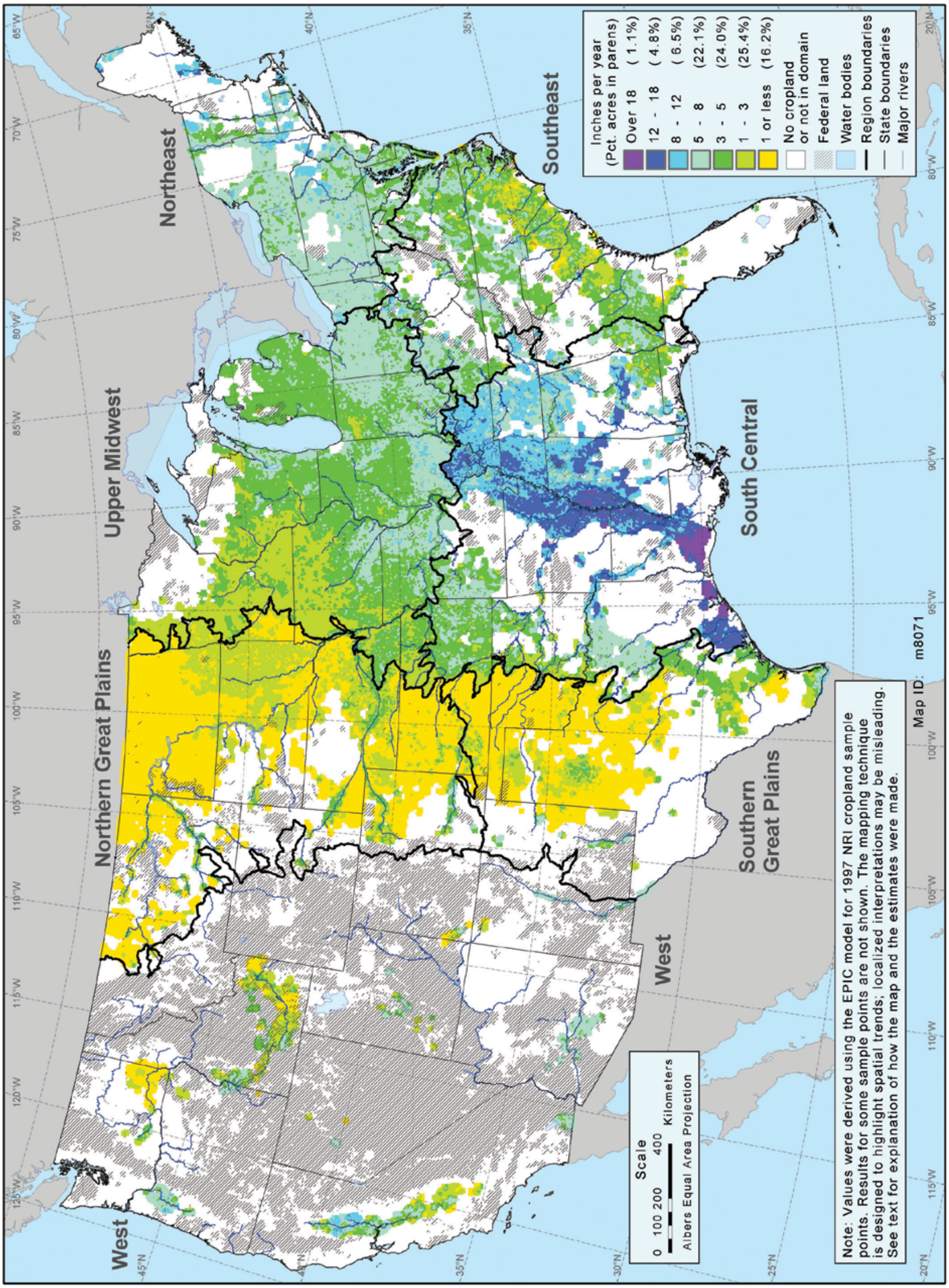
Spatial trends in surface water runoff and percolation are shown in maps 7 and 8. The cropland areas with the highest surface water runoff are found along the lower half of the Mississippi River Basin and portions of southeast Texas. While this area also had fairly high percolation, the highest percolation for cropland was in the eastern coastal plain extending from southern Alabama northward through the Delmarva Peninsula. The relationship between water inputs, surface water runoff, and percolation on cropland differs throughout the country, reflecting interactions between climate, soil and terrain characteristics, and agricultural practices.

Although the principal determinant of surface water runoff and percolation is precipitation and irrigation water use, management activities and soil characteristics can also have a pronounced influence on field hydrology.

Figure 8 Average water inputs, ET, surface water runoff, and percolation–by region



Map 7 Estimated average annual surface water runoff



Map 8 Estimated average annual percolation