96-08

Spring Wheat Yield Assessment Using Landsat TM Imagery And a Crop Simulation Model

Paul C. Doraiswamy
U.S. Department of Agriculture,
Agricultural Research Service, Beltsville, MD

Pedro Zara
SSAI Inc. Lanham, MD

Sophie Moulin
Centre d'Etudes Spatiales de la Biosphere,
Toulouse, France

Paul W. Cook
U.S. Department of Agriculture
National Agricultural Statistical Service, Fairfax

1996

Abstract

Monitoring crop condition and production estimates at the state and county level is of great interest to the U.S. Department of Agriculture. The National Agricultural Statistical Service (NASS) of the U.S. Department of Agriculture conducts field interviews with sampled farm operators and crop cuttings to obtain crop yield estimates at regional and state levels. NASS needs supplemental spatial data that provides timely information on crop condition and potential yields. In this research, the crop model EPIC (Erosion Productivity Impact Calculator) was adapted for simulations at regional scales. Satellite remotely sensed data provides a real time assessment of the magnitude and variation of crop condition parameters and this study investigates the use of these parameters as an input to a crop growth model. This investigation was conducted in the semi-arid region of North Dakota in the southeastern part of the state. The primary objective was to evaluate a method of integrating Landsat TM satellite data in a crop growth model to simulate spring wheat yields at the sub-county level. The input parameters derived from remotely sensed data provided spatial integrity, as well as a real-time calibration of model simulated parameters during the season to ensure that the modeled and observed conditions agree. A radiative transfer model (SAIL) provided the link between the satellite data and crop model. The model parameters were simulated at the satellite pixel level in a geographic information system, which was the platform for aggregating yield at local and regional scales. The simulation was run for each soil type within the county and the results integrated to provide county yields. The model simulated yields were similar to reported county averages and the farm level yields at selected NASS survey sites.

INTRODUCTION

Monitoring agricultural crop conditions during the growing season and estimating the potential crop yields are both important for the assessment of seasonal production. Accurate and timely assessment of particularly decreased production caused by a natural disaster, such as drought or pest infestation, can be critical for countries where the economy is dependent on its crop harvest. Early assessment of yield reductions could avert a disastrous situation and help in strategic planning to meet the demands. The National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA), monitors crop condition to provide monthly estimates of major crop yields and production in the United States. NASS has developed methods to assess crop growth and development from several sources of information including surveys of farm operators, crop condition reports from field surveys and local weather information.

Current NASS procedures require field sample interviews and crop cuttings to obtain crop yield estimates at multi-state (regional) or state levels. NASS needs supplemental spatial data to provide timely information on crop condition and potential yields. NOAA AVHRR data currently provides a means to evaluate crop condition biweekly from data supplied by EROS Data Center (Mueller et al., 1996). However, the images do not directly provide crop yields. The focus of this paper is to develop the groundwork for procedures to make yield forecasting process available at larger scales. The timely evaluation of potential yields is increasingly important because of the economic impact of agricultural products on the world markets.

The use of remote sensing technology for monitoring vegetation condition has been studied extensively during the past decade, providing timely assessment of changes in growth and development of agricultural crops. The normalized difference vegetation index (NDVI) derived from the visible and near-infrared reflectance of the NOAA AVHRR meteorological satellite have been successfully used to monitor vegetation changes at regional scales (Tucker et al.,1983). Temporal changes in the NDVI have been shown to relate to net primary production (Prince et al., 1986, Malingreau et al. 1986, and Goward et al., 1987). Tucker and Sellers (1986) provided a theoretical background to relate primary production estimates based on the absorption of photosynthetically active radiation (PAR) by the canopy. Satellite observations can provide an estimate of biomass. Earlier field studies conducted by Daughtry et al., (1983) and Asrar et al., (1985) provided experimental validation of this theory that relates spectral reflectance to biomass production of vegetation at field and regional scales.

Using the NDVI parameter derived form NOAA AVHRR data, to estimate crop yields is an extension of the above concept. Studies have shown that the seasonal accumulated NDVI values are correlated well with the reported crop yields in semi-arid regions (Groten, 1993). Doraiswamy et al., (1994) further demonstrated that accumulating the AVHRR derived NDVI values for spring wheat only during the grain-fill period improved the estimates of potential crop yields in North Dakota. Using a crop mask helped in deriving the NDVI values for primarily spring wheat crop. Although the results were encouraging, the relationships seemed to be valid only for the study areas and required adjustment for differences in soil background and the mixture of crops in the area because of the low resolution (one Km) of the NOAA AVHRR data.

Crop physiology based growth models have been used successfully for predicting crop yields at the field level. These models however, use numerous inputs that are specific to the crop, soil characteristics, management practices and local climatic conditions. These models have limited use because of the fewer number of inputs that are generally available at larger than field scales. Additionally, when considering large scale model applications, satellite remote sensing technology has been shown to be capable of providing certain crop characteristics and a real-time snapshot of changes in conditions affected by weather related events. The growth models simulate the biophysical processes in the soil-crop-atmospheric system to provide a continuous description of growth and development. Combining such a growth model with input parameters derived from remotely sensed data, provides spatial integrity as well as a real-time "calibration" to the simulations of model parameters (Maas et. al., 1988, 1992, 1993; Moulin et al., 1992 and Guerif et al., 1993). Earlier studies conducted at field scales have shown that remotely sensed data could be incorporated in simulations of agricultural crop yields to calibrate or adjust parameters during the simulation period to ensure that the modeled and satellite observed conditions agree.

The integration of remotely sensed data with a crop growth model can be achieved by using two distinct methods. In the first method, model initialization is done by estimating crop parameters from remote sensing data and using these parameters as a direct input to the growth model. Crop parameters successfully used in this method are measures of light interception by the canopy, namely, leaf area index (LAI) and crop canopy cover. In a second method, a time series of remotely sensed measurements is used to calibrate the crop growth model. Maas (1988) adjusts simulated values of LAI to match the LAI estimates from reflectance measurements observed by the Landsat TM satellite. Bouman (1992) linked X-band radar and canopy optical reflectance were used to link to a crop growth model so that canopy reflectance was simulated with crop growth. The calibration in this procedure is through the LAI and leaf optical properties that link the crop growth model with a radiative transfer model. Moulin et al., (1995) successfully showed that the temporal variation of spectral reflectance at field and regional scales can be linked to a crop model. The objective of our research was to simulate the crop leaf area index and vegetation parameters at the satellite pixel level and assess the spatial variability of crop yields. A radiative transfer model provided the link between satellite data and the crop growth model. The geographic information system (GIS) was used to aggregate the data layers and model parameters for determining the yields at the sub-county and county levels in North Dakota.

MATERIALS AND METHODS

Study Area

The predominantly spring wheat counties of Sargent, Ransom and Richland in the south-eastern corner of the state of North Dakota (Figure 1), were selected for this study during the 1994 crop season. The eastern part of the state has a greater amount of spring wheat because the soils and climatic conditions are less harsh than in the western part of the state. Farmers grow spring wheat in this area in soils generally dominated by the following soils: loams and clayloams with dark to black soil surface, limy subsoils, sandy loams and loams with sandy or gravelly substrata. The total seasonal rainfall in the eastern region (April to September) ranges from 355 to 457 mm. Since spring wheat is grown under non-irrigated conditions, the seasonal variability in rainfall patterns contributes to the variability in crop yields from season to season. The other predominant crops cultivated in the study area include spring barley, sunflower and corn. Pasture is generally found in the non-productive soil areas. The total acreage of spring wheat in Sargent, Ransom and Richland counties are, respectively, 120, 120 and 210 thousand acres.

Crop Growth Model

Several models were examined for their ability to provide a simulation for regional assessments with only a few input parameters. Since soil moisture conditions are a key factor in determining crop yields, the model was required to have a rigorous soil-water budget component. The EPIC (Erosion Productivity Impact Calculator) model developed by Williams et al., (1984) was selected to simulate the spring wheat crop growth and yield. The model components include weather simulation, hydrology, erosion-sedimentation, nutrient cycling, pesticide fate, plant growth, tillage, soil temperature, and crop and soil management. EPIC simulates these processes using a daily time step for several different crops using generally available inputs.

The EPIC model is a mechanistic growth model describing the potential growth of the crop as a function of solar irradiation, air temperature, precipitation and crop characteristics. The potential biomass is adjusted daily as a function of five plant stress factors (water, temperature, nutrient, aeration, and rootgrowth). . The EPIC model has evolved over the past decade into a widely used model and has gone through rigorous testing under various environmental conditions. Its ability to simulate yields of grain sorghum, wheat (Steiner et al., 1987) and corn (Bryant et al., 1992, Schneekloth et al., 1992) has been very satisfactory. In Southern France, simulation of yields for crops grown in complex rotation (corn, sorghum, sunflower, soybean and wheat) were reported to be within acceptable accuracy for many applications (Cabelguenne et al., 1990). In southern Alberta, Canada, yields of spring wheat and spring wheat rotations were simulated accurately by EPIC (Toure et al., 1995). Nutrient (total Nitrogen, organic Phosphorous and Carbon) predictions for a three-year rotation (cotton-grain sorghum-wheat) were also found satisfactory (Smith et al., 1990). Hydrologic processes, runoff, percolation and Evapotranspiration, simulated by the model were in good agreement with observed values (Edwards et al., 1994; Meisinger et al., 1991; Stiener et al. 1987). However, conducting validation procedures is critical for specific crops in the study region before using simulated data in further analyses (Addiscott and Wagenet, 1985; Tanji, 1982).

The SAIL model

The one dimensional radiative transfer model, SAIL (Scattering by Arbitrarily Inclined Leaves) (Verhoef, 1984), provided simulated canopy reflectance in the direction of the sensor. The SAIL model requires information on four canopy parameters: LAI, leaf angle distribution (LAD), the single leaf reflectance and transmittance. The leaf reflectance and transmittance parameters used in this study for the visible band were 0.12 and 0.01, respectively, and for the near-infrared were 0.46 and 0.50 respectively. The soil reflectance for the visible and near-infrared were 0.13 and 0.19 respectively. Other parameters required for the model included solar zenith and azimuth angles, sensor view angle, proportions of direct and diffuse shortwave solar radiation. Solar angles are computed as a function of latitude, date and time of satellite overpass time. Earlier investigators have shown that leaf optical properties differ with spring wheat varieties (Pinter et al., 1985; and Jackson et al., 1986). Optical properties of the spring wheat varieties grown in North Dakota were selected based on prior studies. The EPIC model simulated the daily LAI required as input to the SAIL model.

Processing of Satellite data

Satellite data used in this study were acquired by Landsat TM on two dates (May 28 and June 30). There were clouds present in the imagery on these dates, however the area covering the three counties were clear on both dates. The imagery data was in the UTM projection and registration to map control points in the Land Analyses System software. The digital counts were calibrated to radiances to obtain the surface reflectances. The normalized difference vegetation index for each pixel is calculated using the red and near infrared (NIR) reflectance as follows:

$$NDVI = (NIR-RED) / (NIR+RED) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Climate data

Daily weather data collected from a total of five climate stations within the three counties, however data from stations in the surrounding counties were used to extrapolate data for locations in the three county area. The daily data available were maximum and minimum temperatures, solar radiation and precipitation. The ARC/INFO geographic information system (GIS) was the platform for maintaining all the layers of data and spatial extrapolations were done within this environment.

Soils data

The major soil groups were identified from the General Soil Map of North Dakota and from the County Soil Survey Report published by the North Dakota Agricultural Experiment (USDA, SCS , 1990) Station and U.S. Soil Conservation Service. Soils physical and chemical properties were obtained from the EPIC soils5 database for North Dakota (Sharpley and Williams, 1990). The digital form of the data was brought into the GIS and the general soil association polygons (Figure 2) were identified as the basic unit to run the crop growth model to obtain a regional yield.

Figure 2 shows the major soil groups in the three county study area. The soils are generally nearly level to gently rolling with a thick black surface layer with calcareous, claypan or wet subsoils. Surface texture varied from fine to coarse. The dominant soil groups in the area are the moderately well drained loams and clay loams (Forman-Aastad, Barnes-Hamerly, Barnes-Svea, Garden-Glyndon and Overly-Bearden). Embden-Tiffany and Hecla-Hamar groups are moderately well drained fine sandy loams with rapid permeability and low water holding capacity. Renshaw (fine loamy over sandy) is somewhat excessively drained and had moderately rapid permeability. The Fargo series consists of deep poorly drained fine texture soils with slow permeability and high water holding capacity.

Landsat TM Crop Classification and Crop Data

Accurate location of the spring wheat in the county was an important consideration in obtaining accurate results. Therefore, classification of Landsat TM data into land use and crop types was targeted as the first input into the yield modeling effort. USDA/NASS developed an accurate crop classification using four overlaid dates of 1994 Landsat TM data for path 28, row 30 in southeastern North Dakota and northeastern South Dakota (Cook, et al.,1996).

The crop classification effort used ground information from NASS's June Agricultural Survey (JAS) to establish the crop categories and develop the clusters for the classification. Farm Services Agency (FSA) provided farmer supplied field data to verify the accuracies obtained. Spring wheat was the most accurately classified crop within the North Dakota counties with an accuracy of 87.2% for the NASS JAS data, but 79.2% correct for the FSA data. However, prints of the classified data clearly show field boundaries that delineate well the transition from one group of crops to the other. So the classification appears very map-like and does represent well the location of spring wheat in the area.

The land use map produced in cooperation with NASS was used to select spring wheat acreage for development of the spring wheat yield model. The crop mask of spring wheat acreage within each county is shown in figure 3. Crop information (acreage, yield) for the 1994 season was obtained from the North Dakota Agricultural Statistics Report. Information on crop phenology was obtained from weekly crop-weather bulletins of North Dakota Agricultural Statistics Service. Spring wheat yields from four field sites obtained by NASS during the 1994 season were used in further validation of the model results.

Data Organization

A geographical information systems (GIS), was used to organize, extract and analyze the spatially distributed layers of information. The predominantly spring wheat areas were delineated from the land use maps. The soils association map was registered to the NDVI map derived from the Landsat TM image. The NDVI statistics of the wheat pixels were extracted for each soil type, since this was the basic unit from which the model simulation was conducted.

Weather data required for the model simulation was generated by interpolation the data from existing weather stations located around the study area. The generation of these arrays provided the environmental data needed to execute the model and produce a simulation of LAI and yield for each soil type. The simulation results are presented in the GIS for each soil type, to facilitate the aggregation of the results to the county level.

Crop Simulation and Model Calibration

The crop simulation was conducted at the sub-county level by organizing the data layers of climate, soil physical properties, surface reflectances and NDVI in the GIS within each of the soil types, and represented as separate polygons. The crop growth model was run to estimate the leaf area index and the final wheat yield. First, location parameters, weather data for the 1994 growing season, soils data and crop specific parameters (default) were used as inputs to the model. In general when assessing yields at regional scales, no actual information on sowing and maturity dates are available. The model was initially run using the earliest reported dates (state averages) of planting and maturity to establish the number of growing degree days required from emergence to maturity. Once the growing-degree-days were established, only the sowing date is required as input while maturity dates were automatically determined according to the specified number of growing degree days from emergence.

Several model parameters are reinitialized in the calibration procedure of the crop growth model. In this study, calibrations were limited to adjusting the maximum potential LAI of the crop and leaf area decline rate parameters for each soil type. In addition, since sowing dates are not readily available, these dates were adjusted to provide the correct time of peak and seasonal pattern of LAI. The calibration procedure is shown schematically in Figure 4. The crop model was initially run using default (unadjusted) parameters to generate the LAI and crop yield. The resulting daily LAI was an input to the SAIL model, simulated reflectances in the RED and NIR spectral range equivalent to the Landsat TM. The NDVI values calculated using the reflectances obtained from the SAIL model are compared with NDVI derived from direct satellite measurements. Model parameters were adjusted until a reasonable fit with the observed data was attained.

RESULTS AND DISCUSSION

The general spring wheat crop calendar for North Dakota is shown in Figure 5 describing the earliest occurrences of the different phenological stages of development. Based on NASS state level reports, the sowing season begins in mid April and continues through the first week of June and the crop maturity begins in early July and continues through the end of August. For areas in the southern part of the state where the earliest sowing occurs, the crops emerge by the first week in May. Flowering occurs by the second week of June and the spring wheat crop matures by the first week in July for the earliest planting dates. Simulation of crop growth using the earliest planting date and growing degree days of 1300 from emergence to maturity agreed very well with the observed data provided by NASS reports.

The range and magnitude of the NDVI values for the classified spring wheat for May 28 is shown in figure 6 . This image represents the vegetative stage of crop growth. There was a wide variability in NDVI, with the eastern side greener (higher NDVI) compared to the western side of the study area. Figure 7 shows the increased NDVI values for June 30, the crop has passed or is at the flowering stage. The same pattern in NDVI occurred as in the May image, with the eastern side greener than the western side. This variability could be due to differences in sowing or emergence dates, weather (rainfall and air temperature) and soil moisture conditions.

Simulation of the crop growth calibrated with remotely sensed data was carried out for all soil types within each county. The crop model was run at the soil association level and figure 8 is an example of the daily output of satellite derived and simulated NDVI for different sowing dates, varied by 10 days starting with the earliest possible sowing date reported for this area. The sowing date selected for simulating yields for this particular soil type was April 30, based on the graphical representation which shows the mean and standard deviation of the satellite derived NDVI within each soil type. The second point of adjustment occurs past the flowering stage since earlier satellite data was not available. The calibration of the rate of decline in NDVI is also adjusted to match the satellite derived values. The final yields are simulated using crop parameters adjusted to provide the match for the daily NDVI values.

The analyses of soil moisture conditions obtained from model simulations suggest that more water stress days occurred in the western part of the study area compared to the eastern side. Figure 9 is a snap-shot representation of moisture conditions in the three county area for June 26,1994. The four graphs represent the time series of available soil moisture for selected soil types. Barnes and Forman soils in the western part of the study area reach lower levels of available soil moisture compared to Garden and Fargo soils in the east. This low availability of soil moisture during the vegetative phase reaches a minimum at the critical stage of flowering. The predicted lower LAI (NDVI) due to limitations in soil moisture conditions caused a greater than normal rapid rate of decline in leaf area due to premature senescence. Soil moisture availability appears to be the most critical factor influencing crop yields in dryland farming. Although the interpolated rainfall data in the four soil types are similar, the soil water holding capacity and the ability to maintain a continuous moisture supply throughout the growing season results in higher yields.

Figure 10 is a map of spring wheat yield distribution in the study area simulated within the GIS environment. The spring wheat yields varied from as low as 9.2 to a maximum of 44.8 b/ac, depending on soil types and seasonal patterns of rainfall. The yields were simulated for each soil type and aggregated to obtain the weighted county level yield. A comparison of the simulated and USDA/NASS reported yields are shown in figure 11. There are four farmer reported yields at the farm level that are presented along with the county level aggregated yield. The results of model yields are very encouraging and proved to be a beneficial technique for integrating remotely sensed data with crop models to monitor yields at field and county regional scales. This technique will be extended to monitor yields for the entire state and the surround spring wheat region using NOAA AVHRR data.

CONCLUSION

In this study, we have demonstrated the use of a crop simulation model (EPIC) together with remote sensing data (Landsat TM) in monitoring crop growth and estimating the final yields of spring wheat for three counties in Southeastern North Dakota. Model simulation calibrated with remotely sensed data obtained during the growing season predicted spring wheat yields with a high degree of accuracy, to within one bushel per acre of the USDA/NASS reported yields. The final adjustment to the crop model using remotely sensed satellite data took place about midway between the time of flowering and crop maturity. This is optimum period of crop development when the combined models can provide a good assessment of the potential yields.

Although only two satellite images were used to calibrate the model, this provided sufficient data for a successful calibration. The availability of cloud-free satellite data during a critical window of data acquisition is necessary to achieve optimum calibration of the crop model. The three optimum calibration periods occur during the early vegetative phase, flowering and senescence. However, only two effective Landsat TM overpass dates are usually available during the crop growing season This research has demonstrated two ways of improving crop yield assessments: 1). Landsat TM data can provide an effective means to calibrate the climate based crop growth model (EPIC) during the crop growing season when the satellite data is available at optimum times. 2). The models can generate crop yield predictions at the soil association level that can be aggregated to provide county yields.

REFERENCES

Addiscott, T.M. and R.J. Wagenet. 1985. Concept of solute leaching in soils: review of modeling approaches. J. Soil Sci. 36:411-424.

Asrar, G., Kanemasu, E.T., Jackson, T.D., Pinter, J.R. 1985. Estimation of total above-ground phytomass production using remotely sensed data. Remote Sens. Environ. 17:211-220.

Bouman. B.A.M. 1992. Linking physical remote sensing models with crop growth simulation models, applied for sugar beet. Int. J. Remote Sens. 13(14):2565-2581.

Bryant, K.J., V.W. Benson, J.R. Kiniry, J.R. Williams and R.D. Lacewell. 1992. Simulating corn yield response to irrigation timings: Validation of the EPIC model. J. Prod. Agric. 5:237-242.

Cook, P.W. Mueller, R. and P. C. Doraiswamy. 1996. Southeastern North Dakota Landsat TM Crop Mapping Project. Proc. Annual Convention & Exhibition, ASPRS/ACSM, April 22-25, Baltimore MD, vol 1:600-614.

Daughtry, C.S. , Gallo, K.P.,Bauer, M.E. 1983. Spectral estimation of solar radiation intercepted by corn canopies. Agron. J., 75:527-531.

Doraiswamy, P.C. and Cook, P.W. 1995. Spring wheat yield assessment using NOAA AVHRR data. Can. J. Remote Sens. 21 (1): 43-51.

Edwards,D.R., V.W. Benson, J.R. Williams, T.C. Daniels, J. Lemunyon and R.G. Gilbert. 1994. Use of the EPIC model to predict runoff transport of surface-applied inorganic fertilizer and poultry manure constituents. Transactions of the ASAE. (37(2):403-409.

Goward, S.N., Dye, D., Kerber,A. and Kalb, V. 1987. Comparison of North and South biomass from AVHRR observations. Geocarto International. 1:27-39.

Groten, S.M.E. 1993. NDVI- crop monitoring and early yield assessment of Brukina Faso. int. J. Remote sens. 14(8), 1495-1515.

Guerif, M., de Brisis, S., and Seguin, B. 1993. Combined NOAA-AVHRR and SPOT-HRV data for assessing crop yields of semiarid environements. EARsel Advances in remote sensing 2:(2)110-123.

Jackson, R.D., and Pinter, P.J., Jr. 1986. Spectral responses of architecturally different wheat canopies. Remote Sens. Environ. 20:43-56.

Maas, S.J. 1988. Using satellite data to improve model estimates of crop yield. Agron. J. 80:655-662

Maas, S.J. 1993. Parameterized model of gramineous crop growth: II. Within-season simulation calibration. Agronomy Journal. 85: 354:358.

Maas, S.J., Moran, M.S. and Jackson, R.D. 1992. Combining remote sensing and modeling for regional resource monitoring, Part II: Asimple model for estimating surface evaporation and biomass production. Technical Papers, ASPRS/CSM/RT92 Convention. American Society for Photogrammetry and Remote Sensing, pp.225-234.

Maas, S.J., Moran, M.S., Weltz, M.A., and Blanford, J.H. 1993. Model for simulating surface evaporation and biomass production using routine meteorological and remote sensing data. Annual ACSM/ASPRS Convention, American Society for Photogrammetry and Remote Sensing, pp. 212-221.

Malingreau, J.P. 1986. lobal vegetation dynamics: satellite observations over Asia. Int. J. Remote Sens. 7:1121-1146.

Meisinger, J.J., W.L. Hargrove, R.L. Mickelsen, J.R. Williams and V.W. Benson. 1991. Effects of cover crops on groundwater quality. In: Hargrove, H.L. (ed) Cover Crops for Clean Water. pp. 57-68. Soil and Water Conservation Society. Ankeny, Iowa.

Moulin, S., Fisher, A., Dedieu, G. and Delcolle, R. 1995. Temporal variation in satellite reflectances at field and regional scales compared with values simulated by linking crop growth and SAIL models. Remote Sens. of Environ. 54:261-272.

Muller, R., Wade, G. and Cook, P. 1996. Agricultural Statistics Board AVHRR and GIS product development. Proc. Annual Convention & Exhibition, ASPRS/ACSM, April 22-25, Baltimore MD, vol 1:625-635.

Pinter, P.J. Jr., Jackson, R.D., Ezra, C.E., and Gausman, H.W. 1985. Sun angle and canopy architecture effects on the spectral reflectance of six heat cultivars, Int. J. Remote Sens. 6:1813-1825.

Prince, S.D., 1991. A model of regional primary production for use with course resolution satelltie data. Int. J. Remote Sens. 7:1555-1570.

Schneekloth, J.P., N.L. Kclocke, R.T. Clark and D.L. Martin. 1992. Evaluation of the EPIC simulation model Using continuous corn under three water management strategies. Transaction of the ASAE.---

Smith, S.J., A.N. Sharpley and A.D. Nicks. 1990. Evaluation of EPIC nutrient projections using soil profiles for virgin and cultivated lands of the same soil series. Chapter 12, pp.

217-219. In: A.N. Sharpley and J.R. Williams (eds.) EPIC- Erosion/Productivity Impact Calculator: 1. Model Documentation. USDA Tech. Bull. No.1768. p.235.

Steiner, J.L., J.R. Williams and O.R. Jones. 1987. Evaluation of the EPIC simulation model using a dryland wheat-sorghum-fallow crop rotation. Agron. J. 79(4):732-738.

Tanji, K.K. 1982. Modeling of the soil nitrogen cycle. In: Stevenson F.J. (ed) Nitrogen in Agricultural Soils. pp. 721-772. Madison, Wisconsin: Am. Soc. Agron.

Toure, A., Major, D.J., and Lindwall, C.W. 1994. Comparison o ffive wheat simulation models in southern Alberta. Can. J. Plant Sci. 75:61-68.

Tucker, C.J., Vanpraet, C., Boerwinkel, E., Gaston, A. 1983. Satellite remote sensing of total dry matter productionin the Senegalese Sahel. Remote Sens. Environ. 13:461-474.

Tucker, C.J. and Sellers, P.J. and Sellers, P.J. 1986. Satellite remote sensing of primary production. Int. J. Remote Sens.7(11):1395-1416.

USDA Soil Survey Report, 1990. Soil Survey of North Dakota Counties. Published by the Soil Conservation Service in Cooperation with North Dakota Agricultural Experiment Station, North Dakota Conservation Extension Service, and North Dakota State Soil Conservation Committee.
Washington, D.C.

Williams, J.R., C.A. Jones and P.T. Dyke. 1984. A modeling approach to determining the relationship between erosion and soil productivity. Trans. ASAE. 27:129-144.