SPRING WHEAT YIELD ASSESSMENT USING NOAA AVHRR DATA

Paul C. Doraiswamy
Agriculture Research Service, USDA
Bldg. 007, Room 121, Beltsville, MD 20705

Paul W. Cook
National Agricultural Statistical Service, USDA
Research Division, 3231 Old Lee Hwy, Room 305
Fairfax, VA 22030

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SUMMARY

A potential application of the normalized difference vegetation index (NDVI) is to monitor crop yields over large areas. The study concentrated on the spring wheat areas of North Dakota and South Dakota for several years (1989-1992). The NOAA AVHRR data was carefully analyzed to minimize processing and sampling errors. Sums of biweekly NDVI county averages over an eight week period from heading to crop maturity (approximately, June 22 to August 16) were the independent variables in the linear regressions with spring wheat yields. Both single year and multi-year spectral regression models were developed for each state. Spring wheat yield predictions using both within year model and the multiple year models compared favorably with similar reported studies. The accuracies from this approach shows promise for forecasting yields at the Agricultural Statistics District (ASD) and state levels. NDVI remains a potentially useful parameter in an integrated crop model with other agrometeorological parameters to estimate yields at the county level.

INTRODUCTION

Monitoring of crop condition over extensive areas during the growing season is an important area of research where satellite remote sensing can play a major role. The National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) monitors the crop condition in the United States and provides monthly projected estimates of the crop yield and production. NASS has developed methods to assess the crop growth and development from several sources of information including several types of surveys of farm operators. Field offices in each state are charged with the responsibility to monitor the progress and health of the crop integrated with local weather information. This crop information is also disseminated in a biweekly report on the regional weather conditions. NASS provides monthly inputs to the Agriculture Statistics Board that assesses the potential yields of all commodites based on crop condition information acquired from different sources. This research complements the efforts to assess crop condition at the county, agricultural statistics district and state levels from an independent perspective.

Satellite remote sensing technology has the potential of providing real-time condition of the crop and can efficiently monitor rapid changes in weather related events such as flood, hail, freeze, excessive rain and other disasters. The satellites use a combination of sensors to measure reflectance in the visible, near infrared and thermal spectral bands. Since the size of the target area and type of investigation determine the selection of the satellite data, studies have used LANDSAT and SPOT only over geographically small areas. The cost of data combined with the minimal frequency of coverage have limited their use for the seasonal assessment of crop condition.

The National Oceanic and Atmospheric Administration (NOAA) has a five channel scanning sensor, the Advanced Very High Resolution Radiometer (AVHRR). The ranges of data collected from its five channels are in the visible, near infrared, and thermal infrared spectral bands (NOAA, 1988). Although the resolution of AVHRR satellite data is low at 1.1 Km compared with that of LANDSAT and SPOT satellites at 20 -30 meters, there is an increased use of the AVHRR data during the past decade. For large area applications the frequency of daily observation compensates for the lower resolution when compared to data from less frequent high resolution satellite sensors. In 1993, NOAA AVHRR data provided timely information about the extensive flooding that proved to be very beneficial for damage assessment. The goal of this research was to study the feasibility of using NOAA AVHRR data to assess crop condition during the growing season and estimate yields at harvest.

METHODS

Satellite spectral reflectance data is useful because the greenness or vegetation conditions of the crop changes predictably during the growing season. Each crop has a temporal profile based on its seasonality so that one can anticipate the same signature under "normal" conditions. However, drastic changes in weather conditions or a natural disaster such as flooding and drought can alter the vegetation's temporal profiles. The deviation from "normal" conditions can be monitored if they are severe enough to affect crop growth and productivity.

A vigorous and rapid growth of vegetation corresponds with a healthy crop production. For example, plants such as corn and wheat that have a low leaf area index as determined from remote sensing will have low grain yields (Tucker et al. 1980, 1981; Weigand and Richardson, 1990). Studies have shown that the seasonal accumulation of green vegetation or biomass is correlated with crop yields (Weigand and Richardson, 1984, 1987). Soil water deficit conditions early in the season reduce the rate of vegetative growth. Also, moisture stress during the post-flowering stages can reduce photosynthesis and hence the rate of grain development.

Applying the principles of crop physiology discussed above, Doraiswamy and Hodges (1990) reported correlating the normalized difference vegetation index (NDVI) from NOAA AVHRR data with corn yields reported by USDA/NASS. The NDVI time series profile for the season was developed for each county in Iowa using cloud free scenes. NDVI is an indication of the surface vegetation condition and total ground cover. The NDVI parameter can monitor the rate of increase in biomass production early in the crop season and the decline towards the end of the grain-fill period due to leaf senescence (Gallo and Flesch, 1990). Vegetation dynamics of various types of land systems has been investigated using the NDVI derived from the NOAA AVHRR satellite (Eidenshink, 1993; Tucker et al., 1986).
The visible (Ch1) and near infrared (Ch2) bands are effective in separating the soil and vegetation surfaces because of their spectral differences. The NDVI is low for bare soils and water surfaces and high for green vegetation. The index ranges from -1.0 to 1.0 and is computed as follows:

$$NDVI = (ch2 - ch1) / (ch1 + ch2) \quad \ldots\ldots\ldots\ldots(1)$$

Ashcroft, et al. (1990), studied the relationship of a one time estimate of NDVI and the final yields for winter wheat in the United Kingdom. They demonstrated a more positive correlation from ground measurements of NDVI than with aircraft data. Doraiswamy and Hodges (1990) integrated the area of the seasonal NDVI profile between silking and maturity for corn in Iowa and reported an r-square of 0.72 with the reported yields. The crop phenological stages were calculated from the CERES Maize model (Jones and Kiniry, 1986) run for the climate station data within each county. Quarmby, et al. (1993) studied the correlation of integrated seasonal NDVI with yields for several crops in carefully selected areas in Greece. Benedetti and Rossini (1993) developed a linear regression model relating spring wheat yield estimates with the summation of NDVI averages for agricultural regions (counties) in Italy. In their study, 10-day composite data were used over a sixty-day interval to correspond with the period between flowering and maturity stages. Their regression model developed at the agricultural regional level and summed to the Provence (ASD) level from a four-year data set had a stable prediction equation.

Spectral Regression Model

Knowledge of the phenological events of spring wheat is important in determining the period over which the SUM NDVI should be accumulated. However, since we are not using the daily NDVI values, the approximate periods that correspond to the phenological stages of flowering and maturity is selected. The NASS crop statistics report contains phenological stages at the state level and by percentages of development. Therefore, the sixty-day interval between heading and maturity should approximate four biweekly composite periods.

The linear regressions used the NASS reported yields and county averaged NDVI summed for four composite periods (SUM NDVI) starting either one biweekly period earlier than the period containing the date of heading or one period later. The set of periods with the highest r-square determined the selection of the best starting period. Three sets of four NDVI composite dates extended from periods 18 through 24, periods 20 through 26, and periods 22 through 28. EDC nomenclature for biweekly periods usually uses even numbers (except 1990). For 1990, the above periods corresponded to the following dates: June 8 - August 2 (period 18-24), June 22- August 16 (period 20-26), and July 6 - August 30 (period 22-28). Dates for the other three years varied within a few days of these dates.

Linear regressions between county averaged SUM NDVI and reported yields for counties were performed independently for North Dakota and South Dakota. The prediction intervals for the county predicted values were calculated for the predictions at the county level to obtain the upper and lower limits of the 68% confidence intervals. The results were then integrated to the ASD level and the final yield and production predictions made at the ASD levels.

Satellite Data Processing and Analysis

We acquired biweekly AVHRR maximum NDVI composite data (Holben, 1986) for the conterminous U.S. from the EROS Data Center (EDC) of the U.S. Geological Survey, Sioux Falls, South Dakota. The NDVI values are a maximum NDVI composite over a two week period to minimize cloud contamination in the data sets. This data represents the maximum value of each pixel during the composite period in a Lambert Azimuthal Equal Area Projection (Eidenshink, 1992). The processed data has a resolution of 1.0 Km and includes other auxiliary files to enable the overlay and extraction of data for states and counties.

These analyses use four years of data from 1989 to 1992. The data were provided by EDC on 9-track and 8mm tape. We used the Land Analyses System (LAS) image processing package (Ailts et al. 1990) that EDC uses for processing the raw digital NOAA AVHRR data. Further processing of the biweekly images provided statistical information such as the mean and standard deviation of NDVI for each county.

Study Area and Site Analysis

The predominantly spring wheat states of North Dakota and South Dakota in the northern great plains were selected for this study. The winters are generally very cold with adequate winter precipitation to support germination of spring crop. The spring wheat crop is planted between May 15 - June 1. The soil is generally not at field capacity early in the season although the maximum rainfall period is in late June. The total seasonal rainfall (April - September) ranges between 10 - 14 inches for North Dakota and between 15 - 20 inches for the spring wheat areas (eastern half) in South Dakota. Seasonal variability in rainfall pattern contribute to the regional and seasonal variation in crop yields.

The regional vegetation map of 167 categories developed by Brown et al.(1993) was useful in delineating the majority of the spring wheat area in North Dakota and South Dakota. Brown et al. (1993) developed this vegetation map by non-supervised classification of NDVI using an annual time-series from the biweekly data sets. The 13 categories selected for our analysis included spring wheat combined with those cropland categories that might be associated with spring wheat. Exact categories were not critical since the actual land under cultivation for spring wheat varies for any given year due to crop rotation plans and individual farmer decisions.

A preliminary assessment of the spring wheat acreage classification for North Dakota and South Dakota showed a favorable comparison with the NASS reported spring wheat acreage. This evaluation found the categories to be adequate for our analyses at the county level. Figure 1 shows the crop mask of spring wheat acreage within counties in North Dakota and South Dakota. The crop mask was applied to the image before extracting the NDVI for county statistics.

RESULTS AND DISCUSSION

Analysis of AVHRR data

A regression analysis of SUM NDVI and reported yields was conducted at the county level with a minimum limit of four pixels per county. A total of 53 counties were available from 1989 through 1992 for North Dakota and 60 counties for South Dakota. The total acreage of spring wheat was much less in South Dakota than in North Dakota (Figure 1). Statistical analyses used each set of the three starting biweekly periods of 18, 20, and 22. For North Dakota, the regression of SUM NDVI for periods 20 to 26 had r-squares ranging from 0.53 in 1989 to 0.63 for 1992. The remaining two groups of periods had r-squares that were lower. Similar analyses in South Dakota provided r-squares ranging from 0.02 for 1991 to 0.60 for 1989 and 1990. Based on these analyses, the SUM NDVI for periods 20 through 26 was established as the standard for the rest of the analyses in this paper.

The number of spring wheat pixels in a county that contributed to the county mean SUM NDVI is largely influenced by the accuracy of the crop mask and changes in the year to year management practices of farmers. A smaller spring wheat acreage in a county could greatly increase the error of the mean NDVI. Benedetti and Rossini (1993) used a limit of 30 % (planted spring wheat acres in the agricultural regions) to delete agricultural regions (counties) that had low acreage. Similarly, the effect in our study of pixel limits of 20, 100, 250, 700 and 850 pixels in the regression analysis was evaluated. In North Dakota the best r-squares were found to be when 100 pixels were used as the limit below which the counties were eliminated from the analysis.

The results were mixed for different pixel limits set in South Dakota. For 1989, the r-squares gradually increased from 0.60 to 0.81 after deleting 700 and 850 pixels. Since counties in South Dakota have fewer acres of spring wheat, the 700 and 850 pixel cutoff required deleting two-thirds of all counties and were therefore not acceptable for developing the prediction equations. When deleting counties for the 1990 data, r-squares continued to decrease from 0.60 to a low of 0.34. However, r-squares for the 1991 data stayed at a low of 0.01 or 0.02. The very low r-squares of 1991 required a close examination of the data. The State Statistician explained that in 1991 there were disaster payments to farmers because of poor weather conditions and so yields varied more than normal. Eliminating 1991 data from the South Dakota spring wheat crop yield analyses was necessary since the NDVI data could not relate to land planted to spring wheat but later plowed under without harvesting the crop.

The regression model parameters for within-year and combined-years are shown in Table 1 and Table 2 for North Dakota and South Dakota respectively. Deleting those counties with 100 or fewer pixels for North Dakota and 20 pixels or fewer for South Dakota provided regression parameter values comparable to those reported by other investigators (Benedetti and

Rissini, 1993). The r-squares for North Dakota ranged from 0.57 for 1989 to 0.69 for 1992 (Table 1). The four year combined regression r-square was 0.57. The r-squares for South Dakota ranged from 0.49 for 1992 to 0.58 for 1989 (Table 2), with a combined regression r-square of 0.55.

Within-year spring wheat yield and production relationships

North Dakota

The North Dakota spring wheat yield and production at the Agricultural Statistics Districts (ASD) and the State levels for both within-year and the four-year models are presented in Table 3. As expected, the percent change between NDVI yield and production estimates are much more variable at the county level than at higher levels of aggregation. The yield and production percent differences were within a 0.1% difference and so only the yield percent difference are reported. These differences were much higher for the similar analysis conducted by Beneditti and Rossini (1994).

The within year analyses showed that in 1990 only District 80 greatly exceeded a 20% (at 52.52%) difference from either yield or production levels of the standard survey. However, this district is the smallest district in North Dakota and therefore had only a marginal effect on the state yield and production levels. The remaining districts for all years are within a 21% difference with no district in 1991 or 1992 exceeding 16%. Clearly higher levels of aggregation provide evidence of a strong relationship between the SUM NDVI county averages and the county yield and production.

The within year state level yield and production show an even greater degree of correspondence with NDVI estimates from the regression. The 1989 difference is the greatest at -6.4% while 1992 is within 1.2%. These percentage differences compare favorably with the results Beneditti and Rossini (1993) obtained in the Emilia Romagna region of Italy. The comparison is made because North Dakota produces about 50% of the U.S. spring wheat while Emilia Romagma produces about 77% of Italy's spring wheat.

Figure 2A shows the regression of the model predicted yields and the NASS reported yields for North Dakota at the ASD level for individual years. For North Dakota the r-squares ranged from 0.73 in 1989 to 0.78 in 1992. The prediction intervals (68%) for the individual predicted values averaged plus or minus 5.0, 6.25, 3.25 and 3.75 bushels for 1989, 1990, 1991 and 1992 respectively.

South Dakota

The three year predicted yield and within-year analyses for South Dakota are presented in Table 4. Although South Dakota produces a large amount of spring wheat, its production is usually only 20-25% of that of North Dakota. The ASD yield and production levels for within-year analysis are comparable on a percentage basis to results in North Dakota. Only ASD 70 in 1990 exceeded a 26.9% difference (at 45.6%) from the survey values when regressed with NDVI county sums and aggregated yields to the ASD level. However, ASD 70 in South Dakota has only 0.2% of the spring wheat grown in South Dakota and so the large percentage difference is certainly of no consequence to the state estimate.

At the state level, within year regression yield and production estimates are within 10% of NASS values and two of the three years are within 2.4% of state survey levels. Within year estimates are reasonably accurate at both the ASD and state levels.

The relationship of the model predicted yields and the NASS reported yields for North Dakota at the ASD level and by individual years is shown in Figure 2B. For South Dakota, the r-squares were slightly lower than North Dakota and varied from 0.53 in 1992 to 0.65 in 1989. The prediction intervals of the individual predicted average values were plus or minus 4.25, 5.8 and 4.5 bushels for the 1989, 1990 and 1992 yields, respectively.

Spring wheat yield predictions with combined models

The yields between North Dakota and South Dakota were quite different and the need to exclude 1991 data from the South Dakota data set made combining the two states in the analyses difficult. The operational programs provided separate estimates for each state so that having individual models for each state was an ideal way to proceed with the analyses.

North Dakota

The ASD yield estimates for North Dakota shown in Table 3 also used the combined four year model coefficients. Of the four years used in the analysis, only ASD 80 in 1990 exceeded 50% (67.9%), but this ASD had only 5% of that year's total production and so did not adversely affect the state estimate. In the remaining ASDs, three exceeded 40% difference in the four years and four were between 30% and 40% different from the NASS reported value. The 28 ASD yields were within 30% or less and thereby gave reasonable yield estimates.

The state level estimates using the combined model were within

2.4% for two years, but at 13.9% and 16.8% for 1989 and 1992, respectively. Since the 1992 state estimate of 34.9 is 7.1 bushels lower than the NASS reported value, other improvements in making the model predictions for 1992 would be desirable. In examining yields from earlier years, the 1992 yield is higher than an average year. Therefore, developing models for extremely low or high yielding years will certainly be more difficult when using a regression procedure that relies on averages. Figure 3A is the combined data at the ASD level for the four years of data. The r-squares (0.61) is lower than that of the individual years. The prediction interval is larger than for the individual year analysis at plus or minus 6.6 bushels.

South Dakota

Table 4 presents yield predictions for South Dakota for three years using the combined three-year model. In contrast with North Dakota, there were two years in South Dakota, 1989 and 1992, when all ASD yields had less than a 22% difference with the NASS reported yields. There were three ASDs with large differences in 1990 (36.3 to 78%), two of these ADSs contributed a total of less than 1% to total production, while ASD 10 is only 5% of the total state's production for that year.

The state level model estimates for South Dakota were even more reasonable than were those for North Dakota. The estimates for the worst year, 1992, differed by 12.4%, but was within five bushels of the official NASS estimates. Although only three years were used in the analyses, the model appeared to produce estimates that were quite reasonable for South Dakota. Figure 3B is the combined data at the ASD level for the four years of data. The regression analysis shows an r-square of 0.53 which is equal to the lowest value obtained from the individual year regression (Figure 2B). The prediction interval averaged plus or minus 6.25 bushels. This interval is much larger than for the individual year estimates.

Spring wheat production prediction using the combined model

The evaluation of spring wheat production estimates followed that of the yields estimates for both states. The few counties excluded during the development of the regression model were used in making the ASD and state estimates for both within-year and combined-year models. Tables 3 and 4, respectively, also present the production estimates for North Dakota and South Dakota that use the combined models. As with the yield estimates, production estimates for both states follow the same percentage ranges at the ASD and the state level. However, only the 1992 North Dakota production estimates fell short by more than 60 million bushels: an amount that is certainly of concern.

The difference between model estimates and the NASS reports for North Dakota ranges from nearly six million to 24 million bushels. The production differences in South Dakota were smaller ranging from 4.7 million to 9.4 million bushels. These differences are within reasonable limits in relation to the total production for the two states. There is room for improvements in the combined regression model to obtain better estimates at all levels of integration. Although adding several years of data may aid in improving the fit to the data, very high or very low yielding years will continue to be difficult to estimate accurately.

CONCLUSION

This study was an evaluation of a simple crop yield regression model at a U.S. state level from satellite data. The reliability of the grain yield predictions appears to improve with an increased purity of pixels. Masking out areas without spring wheat and including those areas that are predominantly spring wheat appears to have improved the accuracy and usefulness of a spectral regression model.

The period for selecting the county averaged SUM NDVI is critical and is dependent on prevailing weather conditions among other factors. Therefore, the window for integration is variable even within a State. Since the 60 day window of integration changes in duration and starting date, these factors need adequate consideration. Physiologically, the rate of change in NDVI values at flowering and stages beyond must capture the extent of the grainfill period. The NDVI values during the vegetative phase do not seem to increase the NDVI correlation with the final yield. However, we know that high yields are associated with high vegetative cover but low yields are not necessarily related directly to low vegetative cover.

Spring wheat yield predictions using both within year model and the multiple year models compared favorably with the accuracies reported by Benedetti and Rossini (1993). To use this approach for forecasting yields in an operational mode, further research to improve the techniques is necessary. The spectral models do not provide adequate accuracy at the county level nor is it sufficiently accurate in those years for which yields are far from the historic average.

Finally, this study has shown the potential for using the NDVI parameter derived from NOAA AVHRR satellite data in large area crop yield and production estimates. Research efforts will continue to integrate the satellite data with surface climatological information to improve the utility of satellite derived parameters in crop yield models.

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Figure 3. Regression estimates of spring wheat yields (BU/AC) predicted by the multi-year spectral model regressed on the USDA/NASS reported yields in (A) North Dakota and (B) South Dakota.

Figure 2. Regression estimates of spring wheat yields (BU/AC) predicted by the spectral model for each year regressed on the USDA/NASS reported yields in (A) North Dakota and (B) South Dakota.

TABLE 3. North Dakota Spring Wheat Yield and Production
Estimates Using NOAA-AVHRR NDVI Spectral Regression Method

		WITHIN - YEAR						FOUR YEARS		
		HARVESTED	YIELD		PRODUCTION		NDVI-NASS	NDVI	NDVI	
YEAR	ASD	ACRES	NASS	NDVI	NDVI	NASS	DIFF %	YIELD	PRODUCTION	DIFF %
1989	10	690,000	17.9	19.5	13,465,000	12,368,000	8.9%	23.8	16,418,000	32.7%
	20	474,000	19.5	23.4	11,099,000	9,230,000	20.2%	28.5	13,497,000	46.2%
	30	1,365,000	34.5	29.1	39,741,000	47,090,000	-15.6%	35.3	48,207,000	2.4%
	40	496,000	18.5	16.3	8,067,000	9,176,000	-12.1%	19.9	9,866,000	7.5%
	50	894,000	18	20.8	18,577,000	16,092,000	15.4%	25.3	22,628,000	40.6%
	60	1,098,000	29.5	24.6	26,993,000	32,388,000	-16.7%	29.9	32,807,000	1.3%
	70	720,000	20	15.8	11,368,000	14,400,000	-21.1%	19.3	13,911,000	-3.4%
	80	480,000	12	13.4	6,414,000	5,760,000	11.4%	16.4	7,876,000	36.7%
	90	1,033,000	26.6	26.3	27,213,000	27,496,000	-1.0%	32.0	33,047,000	20.2%
ND		7,250,000	24	22.5	162,937,000	174,000,000	-6.4%	27.3	198,257,000	13.9%
1990	10	655,000	31	29.1	19,055,000	20,305,000	-6.2%	31.4	20,575,000	1.3%
	20	550,000	34.5	36.9	20,312,000	18,975,000	7.0%	37.1	20,408,000	7.6%
	30	1,520,000	41.6	36.2	54,980,000	63,307,000	-13.2%	36.6	55,561,000	-12.2%
	40	505,000	27	26.3	13,294,000	13,635,000	-2.5%	29.4	14,848,000	8.9%
	50	975,000	40.5	39.6	38,635,000	39,490,000	-2.2%	39.1	38,086,000	-3.6%
	60	1,215,000	49	43.1	52,319,000	59,535,000	-12.1%	41.6	50,491,000	-15.2%
	70	700,000	20.5	18.1	12,695,000	14,350,000	-11.5%	23.5	16,419,000	14.4%
	80	485,000	18	27.5	13,316,000	8,730,000	52.5%	30.2	14,658,000	67.9%
	90	1,095,000	35.5	36.4	39,898,000	38,873,000	2.6%	36.7	40,237,000	3.5%
ND		7,700,000	36	34.4	264,504,000	277,200,000	-4.6%	35.2	271,284,000	-2.1%
1991	10	595,000	28.5	28.7	17,102,000	16,960,000	0.8%	29.9	17,804,000	5.0%
	20	510,000	28	30.4	15,488,000	14,280,000	8.5%	31.9	16,288,000	14.1%
	30	1,315,000	36.8	34.8	45,753,000	48,350,000	-5.4%	37.4	49,207,000	1.8%
	40	440,000	25	24.2	10,669,000	11,000,000	-3.0%	24.4	10,714,000	-2.6%
	50	905,000	30.5	28.5	25,758,000	27,603,000	-6.7%	29.6	26,764,000	-3.0%
	60	1,005,000	38.5	33.3	33,464,000	38,692,000	-13.5%	35.6	35,744,000	-7.6%
	70	625,000	25	23.1	14,415,000	15,625,000	-7.7%	22.9	14,304,000	-8.5%
	80	585,000	22	25.6	14,990,000	12,870,000	16.5%	26.1	15,244,000	18.4%
	90	870,000	31	33.7	29,313,000	26,970,000	8.7%	36.1	31,370,000	16.3%
ND		6,850,000	31	30.2	206,952,000	212,350,000	-2.5%	31.7	217,438,000	2.4%
1992	10	864,000	39.5	36.4	31,481,000	34,093,000	-7.7%	27.0	23,368,000	-31.5%
	20	775,000	35.2	37.7	29,239,000	27,270,000	7.2%	29.1	22,516,000	-17.4%
	30	1,806,000	51.1	50.3	90,897,000	92,237,000	-1.5%	48.6	87,839,000	-4.8%
	40	625,000	36	34.0	21,220,000	22,523,000	-5.8%	23.2	14,491,000	-35.7%
	50	1,096,000	37.4	39.3	43,101,000	41,024,000	5.1%	31.5	34,563,000	-15.7%
	60	1,287,000	48.2	46.3	59,584,000	62,000,000	-3.9%	42.4	54,529,000	-12.1%
	70	827,000	34.5	32.2	26,598,000	28,507,000	-6.7%	20.4	16,873,000	-40.8%
	80	704,000	32.7	38.2	26,884,000	23,007,000	16.9%	29.8	20,956,000	-8.9%
	90	1,116,000	46.2	43.7	48,746,000	51,539,000	-5.4%	38.3	42,744,000	-17.1%
ND		9,100,000	42	41.5	377,750,000	382,200,000	-1.2%	34.9	317,880,000	-16.8%

TABLE 4. South Dakota Spring Wheat Yield and Production Estimates USing NOAA-AVHRR NDVI Spectral Regression Method

			WITHIN - YEAR					THREE YEARS		
		HARVESTED		YIELD	PRODUCTION		NDVI - NASS	NDVI	NDVI	
YEAR	ASD	ACRES	NASS	NDVI	NDVI	NASS	DIFF%	YIELD	PRODUCTION	DIFF %
1989	10	178,000	18.2	18.5	3,297,700	3,243,900	1.8%	19.4	3,447,200	6.3%
	20	878,900	20.5	20.8	18,260,400	18,014,800	1.3%	23.1	20,345,100	12.9%
	30	530,500	27.9	25.0	13,244,300	14,786,300	-10.5%	30.2	16,015,900	8.3%
	40	41,900	12.3	11.7	488,900	516,400	-5.1%	7.8	328,400	-36.4%
	50	233,600	15	18.3	4,274,900	3,508,400	22.0%	19.0	4,435,100	26.4%
	60	141,500	29.7	24.7	3,499,000	4,197,700	-16.7%	29.8	4,215,300	0.4%
	70	2,100	15	13.8	28,900	31,500	-8.3%	11.3	23,800	-24.4%
	80	5,100	16.3	14.3	73,100	83,300	-12.1%	12.4	63,100	-24.3%
	90	38,400	18.7	21.9	842,200	717,700	17.3%	25.1	963,600	34.3%
SD		2,050,000	22	21.5	44,009,400	45,100,000	-2.4%	24.3	49,837,500	10.5%
1990	10	135,400	16.5	14.6	1,980,600	2,234,500	-11.3%	22.5	3,046,000	36.3%
	20	918,000	32	27.2	24,978,400	29,345,100	-15.0%	29.0	26,658,400	-9.2%
	30	609,000	39.4	35.7	21,733,500	24,000,400	-9.4%	33.4	20,370,100	-15.1%
	40	17,600	16.9	21.4	377,400	298,300	26.9%	26.0	458,300	53.6%
	50	258,200	27.8	25.4	6,559,300	7,177,900	-8.6%	28.1	7,255,600	1.1%
	60	124,000	25.9	32.1	3,984,900	3,217,500	24.1%	31.6	3,918,600	21.8%
	70	1,600	14.6	21.3	34,000	23,300	45.6%	25.9	41,500	78.0%
	80	7,700	25.4	26.1	200,800	195,300	2.7%	28.5	219,100	12.0%
	90	28,500	24.8	24.5	698,700	707,700	-23.4%	27.6	787,700	11.3%
SD		2,100,000	32	28.8	60,547,600	67,200,000	-9.9%	29.9	62,755,300	-6.6%
1992	10	244,000	25	24.6	6,002,200	6,108,900	-1.6%	21.9	5,331,600	-12.7%
	20	1,020,000	34.9	33.3	33,959,200	35,648,300	-4.6%	29.6	30,208,500	-15.3%
	30	553,000	40.6	39.1	21,596,600	22,472,000	-3.8%	34.8	19,222,800	-14.5%
	40	76,000	27.4	25.1	1,908,200	2,084,000	-8.4%	22.3	1,695,200	-18.7%
	50	377,000	28.3	32.0	12,079,300	10,650,700	13.2%	28.5	10,743,500	0.9%
	60	120,000	38	39.0	4,682,600	4,564,000	2.7%	34.7	4,167,900	-8.7%
	70	6,000	26.9	27.2	163,500	161,500	1.3%	24.2	145,300	-10.0%
	80	58,000	27.8	29.8	1,727,000	1,611,300	7.1%	26.5	1,535,500	-4.7%
	90	46,000	36.9	33.7	1,552,200	1,699,300	-8.6%	26.5	1,380,800	-18.7%
SD		2,500,000	34	33.5	83,670,800	85,000,000	-1.6%	29.8	74,431,100	-12.4%

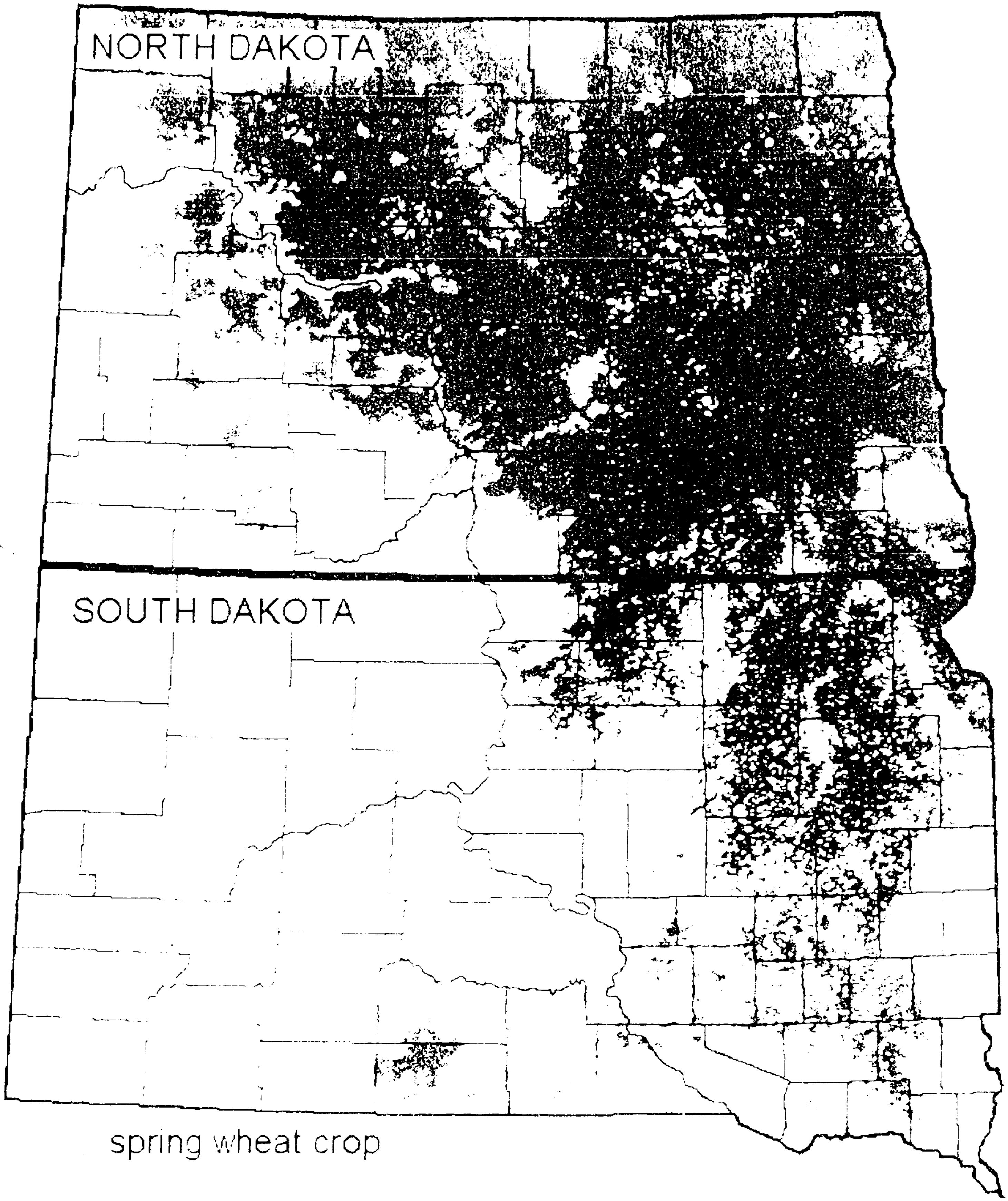
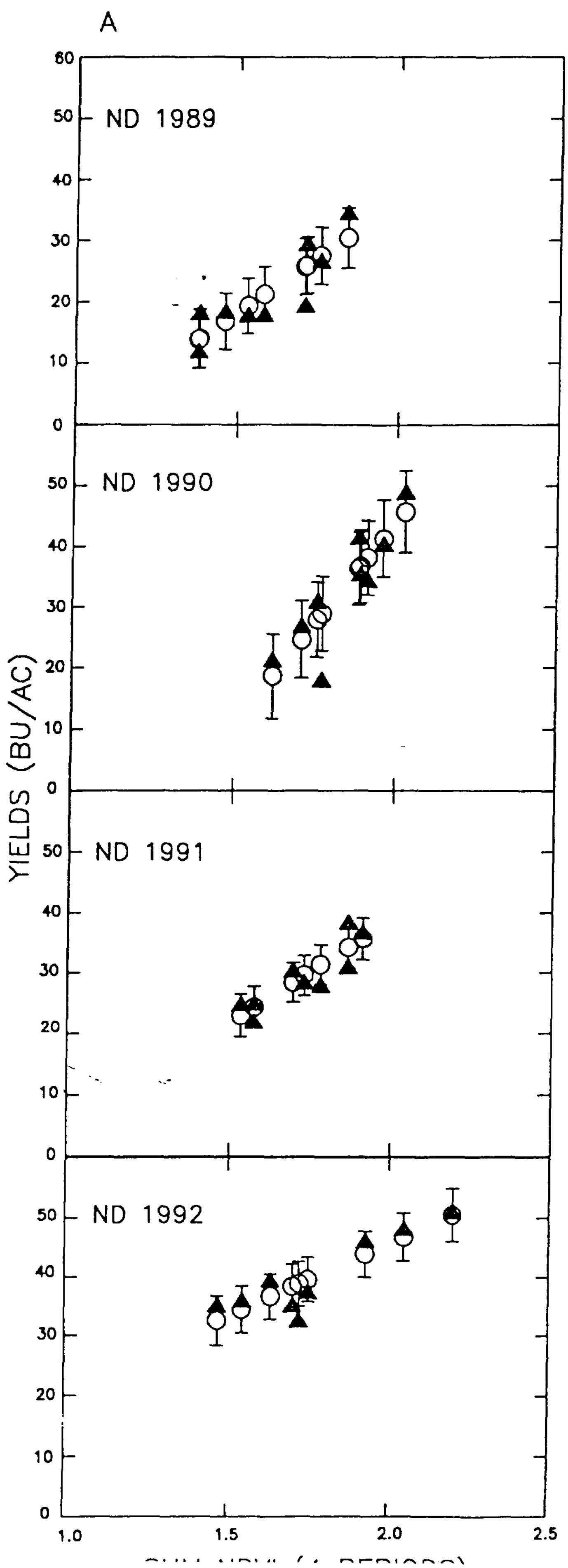


Figure 1 Spring wheat mask for North Dakota and South Dakota developed from NOAA AVHRR data (Brown et al. 1993)



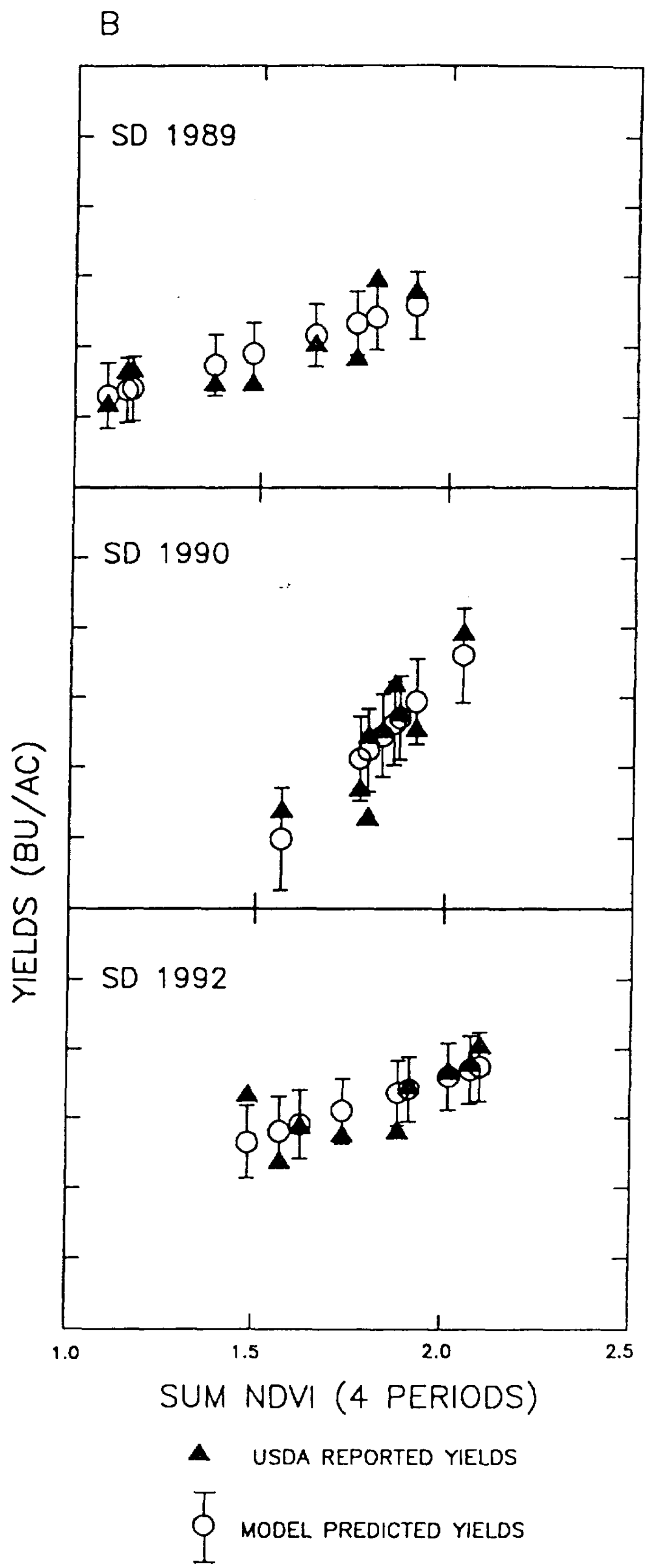


Figure 2. Regression estimates of spring wheat yields (BU/AC) predicted by the spectral model for each year regressed on the USDA/NASS reported yields in (A) North Dakota and (B) South Dakota.

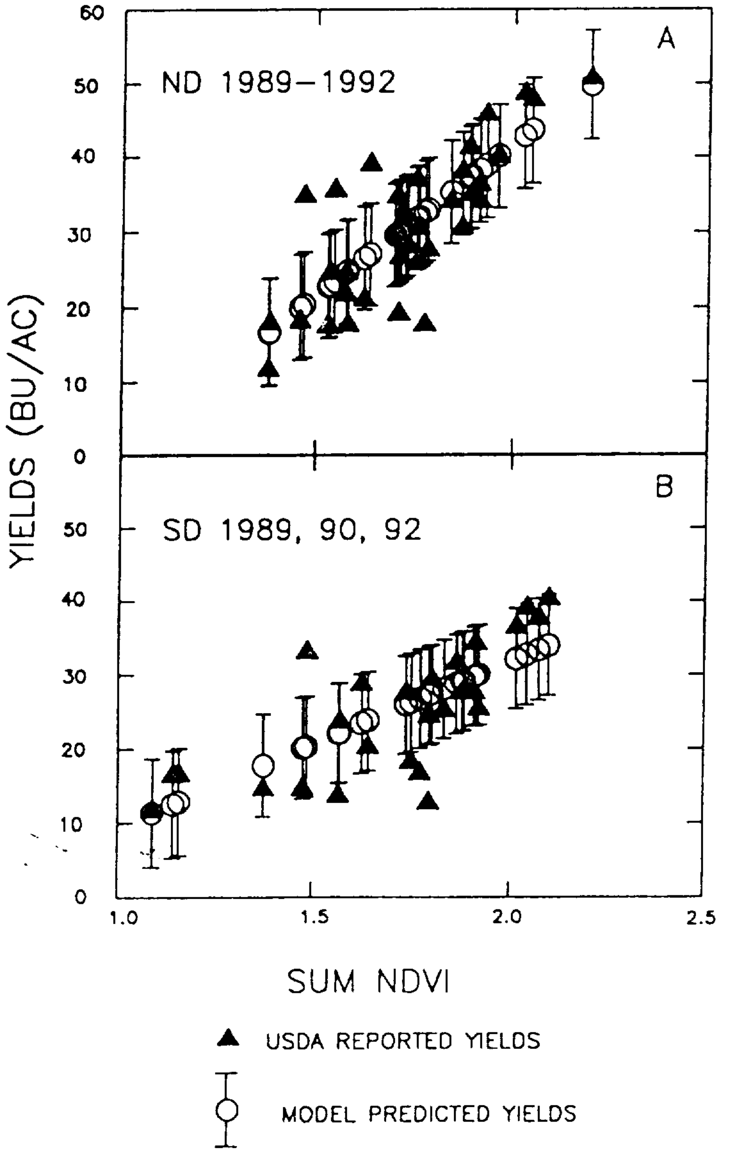


Figure 3. Regression estimates of spring wheat yields (BU/AC) predicted by the multi-year spectral model regressed on the USDA/NASS reported yields in (A) North Dakota and (B) South Dakota.