Using Satellite Imagery in Kansas Crop Yield and Net Farm Income Forecasts

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Paper presented at the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management
Chicago, Illinois, April 17-18, 2000

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Remotely sensed data have been used in the past to predict crop yields. This research attempts to incorporate remotely sensed data into a net farm income projection model. Using in-sample regressions, satellite imagery appears to increase prediction accuracy in the time periods prior to USDA's first crop production estimate for wheat and corn. Remotely sensed data improved model performance more in the western regions of the state than in the eastern regions. However, in a jackknife out-of-sample framework, the satellite imagery appeared to statistically improve only 8 of the 81 models (9 crop reporting districts by 9 forecasting horizons) estimated. Moreover, 41 of the 81 models were statistically better without the satellite imagery data. This indicates that perhaps the functional form of net farm income has not been well-specified since additional information should generally not cause a model to deteriorate.

Keywords: net farm income, remote sensing, satellite imagery

Introduction

Large ad hoc farm subsidies in 1998 and 1999, supplemental to the scheduled payments of the Federal Agricultural Improvement and Reform (FAIR) Act of 1996 demonstrate the increased variability about net farm income resulting from that Act. With the increased variability of farm income across years, different sectors require frequent estimates of farm income that assimilate new information as it becomes available. One such sector is the government. State and national legislatures routinely need net farm income forecasts to help guide their current and future policy decisions, and especially to help them deal with unusually bad years, economically. As an example, in the summer of 1999 the Revenue Planning Committee for the Kansas State Legislature recognized a severe tax revenue shortfall and called in agricultural economists (Kastens and Featherstone) to help them project Kansas net farm income. Knowing net farm income earlier in the year would be useful to agribusinesses as well, as they plan their inventory management programs for the following months. Furthermore, given that agricultural economic well being can be localized, due largely to weather-induced crop yield differences, it would be beneficial to have regional estimates instead of state estimates, especially for those whose businesses tend to be more regionalized.

The objective of this paper is to test whether satellite imagery data (i.e. remotely sensed data) might improve a simple net farm income projection model. With the use of remotely sensed data, crop yield forecasts can be provided earlier in the year than those currently available from the USDA, which suggests that such data might also be used to make early-in-the-year income forecasts. In addition, both income and production forecasts could be more location-specific than what is currently available from the USDA.

Previous Research

Based on a recent literature search, the USDA net farm income model is perhaps one of the only viable models readily available. However, that model is somewhat complex, using 32 individual livestock and crop variables, government program payments, and expenses to project net farm income. In addition, the USDA only projects U.S. net farm income at the national and regional levels. Therefore, the USDA's estimates are less than adequate for local businesses and governments.

Even though the USDA's net farm income projections are geographically broad, at least two states, Kansas and Minnesota, have estimates available at the state level. Kansas State University (KSU) provides annual estimates of future net farm income for both the crop and livestock sectors for the state of Kansas (Featherstone, Mintert, and Kastens; 1997, 1998, 1999). Bailey's (1999) model for Minnesota net farm income is based on projected prices and yields at both the state and national level.

Net farm income is sometimes estimated either to examine risk or when farm income is expected to be low. For example, Kastens and Featherstone (1997) examined the FAIR Act at the time of its inception to determine how net farm income risk would change as a result of this policy, and found it would likely increase the variability in net farm income. Featherstone and Kastens (2000) projected crop income for Kansas in 2000 to be the lowest since 1992. Olsen (1998) estimated the change in net farm income due to changes in crop prices. He found that 1998 farm income in Minnesota was expected to drop substantially due to lower crop prices. Having a forecasting model that could accurately and frequently predict net farm income earlier in the season would alert individuals to possibly low net farm incomes before a potential crisis emerges.

Intrinsically, net farm income is highly dependent on both production and price, both for grains and for livestock. Price projections are relatively easy to construct due to the efficiency and ubiquity of futures prices. Production forecasts are more difficult but might be based on historical production data or on USDA production forecasts as they become available.

Both the USDA and KSU net farm income models depend heavily on National Agricultural Statistics projections as they are made available. However, the relatively infrequent availability of such data often prevents rapid and current updates on net farm income models. The question is whether it is possible to use less conventional but readily available data to improve on net farm income projections, both in terms of frequency of provision and in terms of accuracy.

To estimate harvest time prices, it has been shown that futures markets are, in general, unbiased predictors of actual crop price. Kastens and Schroeder (1996) found that Kansas City wheat futures are especially efficient, and that the efficiency has been increasing over the past 50 years. Zulauf et al. (1996) concluded that futures prices are unbiased predictors of harvest time prices. Garcia, Hudson, and Waller (1988) studied previous research and found that, in general, the futures market is a reasonable indicator of future market price. Because futures prices provide reasonably accurate price forecasts, a reliable estimate of production is what is most needed to project net farm income.

Assuming a positive correlation between crop condition (cash crops and pastureland) and net farm income it seems reasonable to assume that earlier-in-the-year estimates of crop condition would enhance the accuracy of earlier-in-the-year net farm income projections. Until recently, estimates of crop condition early in the year were principally subjective, relying upon those surveyed to provide such information. However, with recent advances in remotely sensed imagery, it is now possible to obtain earlier estimates of crop conditions than before. Furthermore, these estimates will likely be more uniform and consistent than the estimates might be in the absence of such objective information. In the past 25 years, remote sensing techniques have been utilized by many scientists to assess agricultural crop yield, production, and condition. Although most of the related research has focused on estimating crop yield, the imagery and procedures from these efforts can additionally be used to estimate crop condition and progress.

Wiegand et al. (1979) and Tucker et al. (1980) first identified a relationship between the Normalized Difference Vegetation Index (NDVI) and crop yield using experimental fields and ground-based spectral radiometer measurements.[1] Final grain yields were found to be highly correlated with the time-integrated NDVI (TI NDVI) around the time of maximum greenness (Tucker et al., 1980). Such early experiments identified relationships between NDVI and crop response, paving the way for crop yield estimation using satellite imagery.

Since that time, numerous studies have reported an association between agricultural crop yields and satellite imagery (e.g., Rudorff and Batista, 1991; Das et al., 1993; Potdar, 1992; Rasmussen, 1992). Also a number of studies have focused on multi-year data sets as they have become available (e.g., Maselli, et al., 1992; Gupla et al., 1993; Quarmby, et al., 1993, Grolen).

In 1995, Doraiswamy and Cook used three years of advanced very high resolution radiometer (AVVHR) NDVI imagery to assess spring wheat yields in North Dakota and South Dakota. Although they concluded that spectral models based on NDVI values were not accurate enough to estimate absolute spring wheat yields at the county level, they believed that crop yields could be reliably estimated at the Agriculture Statistical District (ASD) level by improving the spectral model through the use of larger temporal data sets, better crop masks, and information about crop phenological development. Most recently, Lee (1999), used an eight year, bi-weekly AVHRR data set and information on vegetation phenological growth stages to forecast corn yields in Iowa. He found that the most accurate forecasts of crop yield were made using a crop mask and measurements of TI NDVI.

To date, the most accurate yield estimates from remotely sensed data have been reported in research that used models developed using regression analysis techniques and extensive multi-temporal data sets. The focus of this research is to determine whether similar data can be used directly as explanatory variables to improve the accuracy in net farm income projection models.

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[1] NDVI is defined in the data section.

Model

Conceptually, the net farm income model is

(1) *Net farm income=f(expected crop income, expected livestock income, costs of production).*

Because production costs vary much less than production and price, it is reasonable to ignore costs, focusing a regression-based empirical specification of (1) on only crop and livestock income measures. Further, a practical empirical specification might generalize or aggregate measures of crop and livestock income to accommodate ease of use and data availability.

To determine if satellite imagery has any impact on predicting net farm income both restricted and unrestricted models were specified. The restricted model was specified with data that are currently publicly available. This model is

(2) $$NFI_{ij} = \boldsymbol{b}_0 + \boldsymbol{b}_1 * CROPINC_{ijt} + \boldsymbol{b}_2 * CATTLEF_{jt} + \boldsymbol{e}_{ijt},$$

where NFI_{ij} is average net farm income, $CROPINC_{ijt}$ is a measure of total expected crop income, $CATTLEF_{jt}$ is a measure of expected livestock income, g_{ijt} is the error term, and i, j, t index region, week of year a projection is made, and year, respectively.[2] While it would be preferable to have a separate variable representing each crop's income, only 10 years of remotely sensed data were available, providing only 10 observations for each potential income model. Consequently, an aggregate crop income estimate was used. The aggregated crop income estimate for region i, estimated in week j, and for year t, was calculated as

(3) $$CROPINC_{ijt} = WHEATINC_{ijt} + CORNINC_{ijt} + SORGINC_{ijt} + SOYINC_{ijt},$$

where the individual crop income estimates are derived as follows, using wheat as an example:

(4) $$WHEATINC_{ijt} = PLANTACW_{ijt} * PERHARVW_{ijt} * ESTYLDW_{ijt} * FUTUREW_{jt}.$$

In (4), $WHEATINC_{ijt}$ is estimated wheat income for region i, week j, and year t. This estimate is comprised of $PLANTACW_{ijt}$, which is the estimated total planted acres of wheat for region i, at week j, for year t. Similarly, $PERHARVW_{ijt}$ is the estimated percent of planted acres of wheat that are harvested for grain in region i year t. Also, $ESTYLDW_{ijt}$ is the estimated yield in bushels per acre. $FUTUREW_{jt}$ is the Kansas City July Wheat futures price in week j, for year t. $CORNINC_{ijt}$ (estimated corn income) and $SOYINC_{ijt}$ (estimated soybean income) were calculated similarly to wheat income, only using Chicago December corn and November soybean futures prices. $SORGINC_{ijt}$ (grain sorghum income) was calculated

[2] Week 1 of a year begins January 1 and ends January 7, and so on. For this research a bi-weekly time period was used, so only even numbered weeks are relevant. The dates associated with these weeks are reported in table 1.

similarly, and used corn futures data. $CATTLEF_{jt}$ in equation (2) is the nearby futures price for live cattle in week j, for year t. This was used as a proxy to capture the livestock income effects.[3]

The unrestricted model for this research is as follows:

$$(5)\qquad NFI_{ij} = b_0 + b_1 * CROPINC_{ijt} + b_2 * CATTLEF_{ij} + b_3 * NDVI_{ijt},$$

where NFI_{ij}, $CROPINC_{ijt}$, *and* $CATTLEF_{ij}$, are the same as defined above, and $NDVI_{ijt}$ is the satellite imagery crop condition measure for region i, week j, and year t.

Data

By definition, remote sensing involves collecting data about an object without coming into direct contact with it. Satellite imagery is one type of remote sensing: satellites orbit the Earth continuously collecting surface information in multiple "bands." Each band records information about spectral reflectance in discrete wavelengths. Most satellites collect surface data for a minimum of three bands: red, green, and near-infrared (NIR).

Remotely sensed data have been used for over twenty-five years to assess and monitor vegetation condition. In particular, red and NIR reflectance have been used to measure vegetation health and vigor, based on the inverse relationship between red reflectance and chlorophyll content, and the direct relationship between leaf structure and NIR reflectance. Normalized Difference Vegetation Index (NDVI) values, calculated from the red and NIR bands as ((NIR - RED) / (NIR + RED)), are often referred to as "greenness" values because they are strong indicators of vegetation condition and quantity. Time-series analysis of NDVI imagery has allowed scientists to examine global-scale phenological phenomena such as green-up, duration of green period, onset of senescence, as well as changes in biophysical variables such as leaf area index, biomass, and net primary productivity (Eastman and Fulk, 1993; Tucker et al., 1985). Imagery from AVHRR sensor was used to develop the data underlying this research because information from this sensor is well suited for monitoring crop response due to its temporal and spatial resolutions, and because AVHRR data are relatively inexpensive.

The NDVI dataset was created by the Kansas Applied Remote Sensing (KARS) program from the U.S. Geological Survey's Earth Resources Observations Systems (EROS) for years 1989 to 1998. Nearly cloud-free AVHRR NDVI composites were created by saving the highest NDVI values from individual NDVI images over a two-week period. KARS provided these data at the county level. Since this research was conducted on a crop reporting district (CRD) level the county NDVI data were aggregated to the CRD level (there are nine CRD's in Kansas).

The remotely sensed NDVI data are assumed to be available on the last calendar day of the bi-weekly coverage period, which was considered to be the income projecting, or

[3] Future research will refine livestock income as well as the crop income variable.

model, date. Futures data used are Kansas City July wheat futures, Chicago December corn futures, Chicago November soybean futures, and Chicago nearby live cattle futures (Bridge Financial Data Center). The futures prices used were those observed on the calendar dates associated with the model date. If the date fell on a weekend, the futures prices used were the following Monday's prices.

CRD-level data for crop production estimates were from *Kansas Farm Facts*, and *Kansas Agricultural Statistics Monthly Crop Reports* from 1989-1998. The most recently published *Crop Report* provided the relevant information for a particular model date. If the monthly crop report did not have crop production estimates, then a 5-year historic average of crop production from *Kansas Farm Facts* data were used to estimate crop production for that date. The yearly average net farm income measure was obtained from the Kansas Farm Management Association (KFMA) *Annual Analysis and Management Information* for 1989-1998, and reported by KFMA region.[4] These data were assigned to each county in a KFMA region, and subsequently aggregated back to a CRD level using simple averaging across the counties in a CRD.

The model dates used in estimations were weeks 16-32 (see table 1 for the calendar dates associated with these weeks). Using a "greenness" measure, it is likely unreasonable to consider models beyond about week 32 because the new wheat crop would be emerging and would show up in the NDVI measure, causing spurious results.

Results

Descriptive statistics for the variables used in estimating the model are reported in table 2. An in-sample ordinary least squares regression of net farm income for the restricted and unrestricted models for each model date (9) and CRD (9) was estimated. F-values associated with the restricted and unrestricted (NDVI contribution) tests are reported in figures 1-3 along with the F-value associated with a 10% significance level. From the figures it can be seen that NDVI appears to add information value only in the western regions of Kansas. This is perhaps not too surprising given that, in that area, images of crop vegetation are likely less confounded by non-crop vegetation such as grassland or wooded land. Interestingly, it appears that the satellite imagery might significantly contribute to the accuracy of net farm income projections during two critical time periods, week 18 (end of April) and weeks 26-28 (end of June). The USDA provides its first monthly wheat yield projections for Kansas around the middle of May and begins making yield estimates for corn, grain sorghum, and soybeans around the middle of July. This suggests that satellite imagery might favorably impact net farm income projection models during such critical time periods. As an example of regression estimation, tables 3 and 4 report the OLS-estimated parameters of the restricted and unrestricted model for calendar weeks 18 and 26 for the NW region. It can bee seen that in week 18 for every $100,000 increase there is in predicted regional crop income, the net farm income for an individual farm in the NW region increases by $120 (restricted model -- table 3). Furthermore, one can see that NDVI added value for both of these weeks in this region.

[4] The Kansas Farm Management Program assigns farms to one of six geographical regions in Kansas.

To validate the regression model results, out-of-sample jackknife regressions were estimated for the models (predicting net farm income for each year using a regression estimated with all other years). The Ashley, Granger, Schmalensee (AGS) test was used to test the alternative forecasts (results are reported in table 5).[5] From this table it can be seen that the unrestricted model statistically outperformed the restricted model only 8 times. It would have been better to use the restricted model than the unrestricted model 41 times.

Examples of the RMSE's associated with the out-of-sample prediction errors are reported in figure 4. From figure 4 it can be seen that the RMSE's for both the restricted and unrestricted models for the NW region follow the in-sample regressions. Relative to the restricted model, the RMSE for the unrestricted (NDVI) model is at its minimum at weeks 18 and 26. It would be expected that the RMSE's for the unrestricted models would be less than the RMSE's for the restricted model earlier in the year when there is less information available, and as the season progressed the RMSE for the restricted model would equal the RMSE for the unrestricted model. However, this did not happen, except for a few crop regions. This result could be due to the predictive ability of the model, or it could be due to a crop mix issue. Fore example, if a CRD is mostly corn then it would be expected that the NDVI for that region would not have a large effect in April, and would have more of an impact in June or July.

Conclusion

Earlier in the year net farm income projections could be useful to many policy makers and businesses. This research attempted to predict Kansas crop reporting district average net farm income earlier in the year using remotely sensed satellite imagery (NDVI – normalized difference vegetation index). Using in-sample forecasts the model that included NDVI generally performed better in early May, just ahead of USDA's first crop production estimate for wheat. The model that incorporated NDVI also did better in late June, just prior to the USDA's first crop production estimates for corn, grain sorghum and soybeans. NDVI information was more important for western Kansas than eastern Kansas. This may be due to less woodlands and grasslands to mask the NDVI/crop relationships in western Kansas.

The Ashley, Granger, Schmalensee (AGS) test was used to examine the out-of-sample RMSE's from jackknife regression predictions. Based on the AGS tests, NDVI improved accuracy in only 8 of 81 scenarios (9 crop reporting districts by 9 forecasting horizons). Furthermore, 41 of the RMSE's were statistically higher when satellite imagery data were included in the model, implying that one might generally be better off without NDVI data. However, the basic net farm income model estimated was a simple model that made some strong assumptions about crop income, livestock income, and costs. Given that NDVI has been used to predict yields earlier in the season than the USDA, it seems reasonable that, given the correct functional form of the net farm income model, satellite imagery should improve net farm income projections. Consequently, what likely is needed in future research is more years of data and a more rigorous explorations of the prediction model.

[5] The AGS test is described in Brandt and Bressler.

Acknowledgements

Funding for projects is provided by the NASA Great Plains Regional Earth Science Applications Center (GP RESAC) at the Kansas Applied Remote Sensing (KARS) Program at the University of Kansas, Lawrence, Kansas.

NASA Grant: NAG13-99009
PI: Dr. Edward A. Martinko

Funding provided through sub-contract to Kansas State University Department of Agricultural Economics, Manhattan, Kansas.

Contract: FY99-072

PIs: Dr. Terry Kastens and Dr. Kevin Dhuyvetter

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Figure 1. F-Statistics of in-sample regressions testing contribution of NDVI to net farm income model: NW, WC, and SW Kansas, 1989-1998.

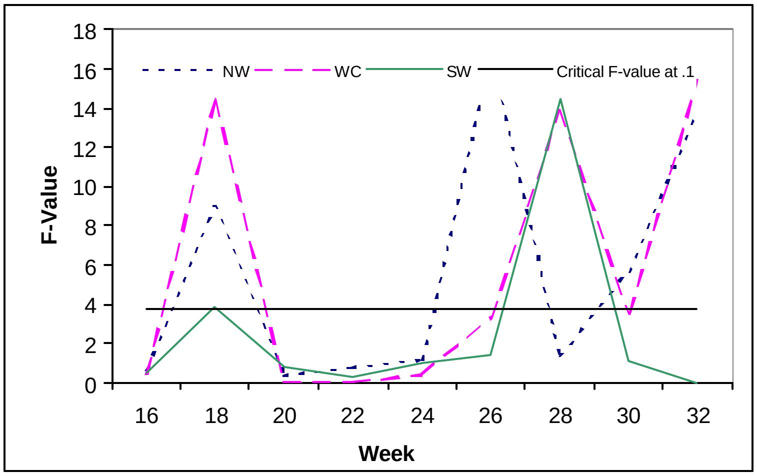

Figure 2. F-Statistics of in-sample regressions testing contribution of NDVI to net farm income model: NC, C, and SC Kansas, 1989-1998.

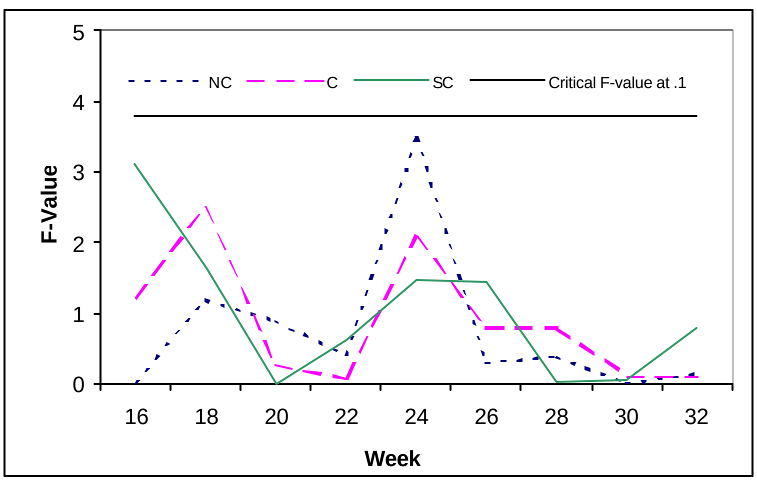

Figure 3. F-Statistics of in-sample regressions testing contribution of NDVI to net farm income model: NE, EC, and SE Kansas, 1989-1998.

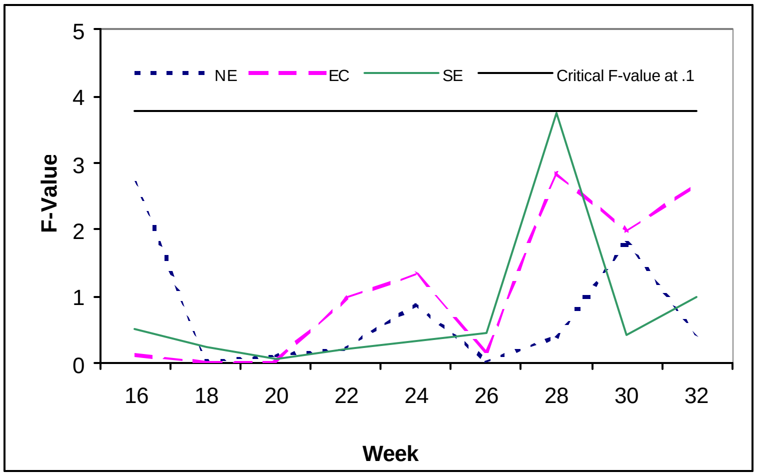

Table 1. Week of Year and Associated Calendar Dates

Week of year	Start	End
16	Apr 09	Apr 22
18	Apr 23	May 06
20	May 07	May 20
22	May 21	Jun 03
24	Jun 04	Jun 17
26	Jun 18	Jul 01
28	Jul 02	Jul 15
30	Jul 16	Jul 29
32	Jul 30	Aug 12

Table 2. Descriptive statistics for 1989-1998 across all regions

	Mean	St. Dev.
Net Farm Income	$35,730	15139
Crop Income ($100,000)	314.15	124.66
Livestock Price	69.50	5.60
NDVI	140.00	8.00

Table 3. In-sample OLS results for NW Region for week 18, 1989-1998

Variable	Restricted	Unrestricted
Intercept	-14112	-305363
	(0.89)	(0.04)
Crop Income ($100,000)	120	240
	(0.31)	(0.02)
Livestock Income	320.65	448.47
	(0.77)	(0.56)
NDVI		1861.58
		(0.02)
R-Square	0.20	0.68
RMSE	12875	8796
Regression F-Value	0.88	4.26
	(0.46)	(0.06)
F-value of Restriction Test	9.00	
	(.015)	

* Probability values are reported in parentheses

Table 4. In-sample OLS results for NW Region for week 26, 1989-1998

Variable	Restricted	Unrestricted
Intercept	-51711	-611765
	(0.63)	(0.01)
Crop Income	110	22
($100,000)	(0.38)	(0.76)
Livestock Income	881.34	1972.53
	(0.49)	(0.0349)
NDVI		3855.26
		(0.01)
R-Square	0.12	0.77
RMSE	13526	7509
Regression F-Value	0.47	6.59
	(0.64)	(0.03)
F-Value of Restriction Test	16.71	
	(.003)	

*Probability values are reported in parentheses

Table 5. AGS Test Results; Number of Kansas CRDs (out of 9) where the model that included NDVI (Unrestricted) outperformed the restricted model.

Week of Year	Restrict Model better	Unrestricted model better
16	8 (5)	1 (0)
18	5 (3)	4 (1)
20	9 (8)	0
22	9 (6)	0
24	5 (3)	4 (1)
26	6 (4)	3 (1)
28	5 (3)	4 (3)
30	6 (4)	3 (0)
32	7 (5)	2 (2)
Total	60(41)	21(8)

Note: numbers in parenthesis are the number of times where AGS test indicated statistically significant differences in RMSE

Figure 4. RMSE of Unrestricted and Restricted out-of-sample estimates testing contribution of NDVI to NW region net farm income model, 1989-1998.