HOW DO PRECIPITATION AND IRRIGATED RATIO INTERACTIVELY IMPACT CORN YIELD?

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Abstract. In this research, an econometric model has been constructed and estimated to study the relationship between precipitation, irrigated ratio and crop yield. The model was based on the weather and yield data in the southwest part of the State of Georgia. The econometric model includes three sets of explanatory variables: principal components of temperature and precipitation, precipitation distribution index (PDI) and de-trended irrigated ratio. The estimated results showed that de-trended irrigated ratio is significant in almost all of the models. PDI also helps improve the goodness-of-fit of the model. However, PDI is not highly correlated to de-trended irrigated ratio as expected. An explanation for this could be that Georgia irrigated ratio is still low and farmers' response to weather change is slow.

INTRODUCTION

Irrigation has been an important agricultural practice to protect the crop growth from drought. Irrigation systems provide extra water when precipitation fails to meet the crop growth water requirement. Irrigated acreage indicates the coverage of irrigation system. It also demonstrates farmers' ability to protect crops from drought. Therefore, irrigated acres are expected to be positively correlated with crop productivity. Nationally, irrigated corn yields are 30 percent greater than non-irrigated corn (Gollehon et al., 2006). Furthermore, irrigated acres are influenced by several factors including weather conditions, especially precipitation (Gollehon et al., 2006). When there is sufficient precipitation during the planting season, it becomes unnecessary to irrigate the crop. On the other hand, irrigated acres are expected to be higher in a year with severe drought. Therefore, it is interesting to see how irrigation effect correlates with crop productivity and how irrigation effect interacts with other weather conditions. Irrigation effect has rarely been considered in the previous weather-yield model where only weather conditions are considered.

Both high irrigated and adequate precipitation help improve the crop yield. Furthermore, it is hypothesized that irrigation and precipitation could interactively affect the crop growth and therefore productivity.

In this research, we developed and estimated an econometric weather-yield model explaining the variation of corn yield as a function of weather conditions and irrigation effects. Crop yield is actually a mixture of irrigated and non-irrigated (rainfed) yield. However, yield data differentiated by irrigated and non-irrigated are not available for all the states. Therefore, we choose to use average yield data for this study in the State of Georgia. Since we expect a negative statistical correlation between irrigated ratio and precipitation distribution, using both of these variables in the econometric model may lead to severe multicollinearity issue.

Instead of irrigated acres, we included the irrigated ratio (irrigated acres/harvested acres) as an additional explanatory variable to represent irrigation effects. Irrigated ratio is not directly used as an explanatory variable; instead, de-trended irrigated ratio is used. It is observed that irrigated ratio keeps increasing during the past 40 years. It is believed that the improvement of irrigated ratio is partially due to technological advances. Since we have already removed the technological effect from crop yield, we will also remove technological effect from irrigated ratio, leaving the part of the variation of irrigated ratio only related to precipitation water. It is hypothesized that a higher irrigated ratio offers agricultural producers better opportunities to protect crops from drought or irregular precipitation, and thus precipitation variables tend to be statistically insignificant in the model. However, no literature was found discussing the linkage between precipitation and an irrigated ratio in the yield-weather models.

Previous studies generally employed total precipitation as an explanatory variable in the yield-weather models, and did not include any indices to represent irregular precipitation (Horie et al., 1992; Garcia-Paredes et al., 2000). Specifically, assuming two months with the same amount of precipitation but

Table 1. Regression results for all four models

	Model 1	Model 2	Model 3	Model 4
Adjusted R-Square	0.5175	0.6041	0.7003	0.7201
F value	4.29	4.12	7.73	6.04
Root MSE	10.02	9.08	7.91	7.63

different distribution could have dissimilar impacts on crop yield. The month with more evenly distributed rainfall will result in higher yields than the month with several extreme rainfall events. Motivated by this fact, we included the distribution of precipitation within a month as an explanatory variable. A Precipitation Distribution Index (PDI) was calculated based on daily precipitation.

METHODS

In this study, a weather-yield principal component regression model is developed to study corn yield response to weather change. The following is a generalized expression of a crop yield response model for the regression analysis. It is a statistical function that demonstrates the historical relationship between weather variables and crop yields. After fixing all other inputs such as fertilizers, insect infestations, etc, the following equation estimates the connections between which crop yield response and weather conditions

$$Y_t = \beta_0 + \sum_{i=1}^{k} W_{it}\beta_i + \varepsilon \tag{1}$$

Where W_{it} represents weather variables, Y_t represents crop yield response, β is regression coefficients.

By introducing PDI and de-trended irrigated ratio into the model, we have the following equation

$$Y_t = \beta_0 + \sum_{i=1}^{k} W_{it}\beta_i + \sum_{j=1}^{l} PDI_{jt}\gamma_j + IRRI_t\delta + \varepsilon_t \tag{2}$$

Where PDI_{jt} represents precipitation distribution index, $IRRI_t$ represents de-trended irrigated ratio.

As mentioned earlier, principal components of weather variables will be used. PCA is a variable compression technique. It transforms a large number of interrelated variables to a new set of uncorrelated variables (principal components) which are linear combinations of original variables (Jolliffe, 2002). Therefore, each principal component contains information of all weather variables. By using PCA, none of the growing season months will be completely omitted no matter what variable selection method is applied. Besides, using PCA also helps solve possible multicollinearity problem. Some previous studies have used PCA components as explanatory variables in multiple regressions which are usually mentioned as Principal Component Regression (PCR) (Pandzic et al., 1992; Yu et al., 1997; Hansen et al., 2002). The final econometric model with PCA is

$$Y_t = \beta_0 + \sum_{i=1}^{k} W_{it}A_{ip} + \sum_{j=1}^{l} PDI_{jt}\gamma_j + IRRI_t\delta + \varepsilon_t \tag{3}$$

Where p^{th} principal component PC_W_{pt} is the summation of each weather variable W_{it} times its eigenvector A_{ip}. Each principal component is a linear combination of original weather variables. Each of the weather variables has its unique weights in each principal component where this weight is denoted by eigenvector. A de-trended yield adjusted to 2009 level has been used in order to remove the effect of technology.

Data. Monthly weather data of temperature and precipitation are obtained from Online Climate Data Directory of National Climate Data Center. Corn yield data are obtained from National Agricultural Statistical Service of USDA. 1960 is the first year with both yield data and desired weather data available, so we used the weather and yield data from 1960 to 2009 for econometric model estimation. Irrigated acres data is only available for every four or five years during those agricultural census years (1964, 1974, 1982, 1987, 1992, 1997, 2002, and 2007).

RESULTS AND DISCUSSION

The econometric weather yield model developed above was estimated for corn in the southwest part of the State of Georgia. To compare the effect of PDI and de-trended irrigation ratio, four models were constructed and compared. Model 1 is the model with only principal components of weather variables as explanatory variables. Model 2 is the model with both principal components and PDI as explanatory variables. Model 3 is the model with both principal components and de-trended irrigation ratio as explanatory variables. Model 4 is the model with principal components, PDI and de-trended irrigation ratio as explanatory variables.

The above table demonstrates that Model 4 has the highest adjusted R-square and lowest Root MSE among all four models. Therefore, it is the best fitted model. On the other hand, Model 1 is the worst fit model. Based on adjusted R-square and Root MSE, model 3 performs better than model 2. It indicates that de-trended irrigation ratio has larger impact on corn yield compared to PDI. This result indicates that irrigation is able to largely offset the water deficiencies associated from drought. Condition number for Model 4 is only 31.03 which indicate that multicollinearity is not a severe problem. Correlation matrix also shows low correlation between PDI and de-trended irrigation ratio. An explanation for this result is that irrigation ratio in Georgia is still low and farmers' responses to weather changes are lagged.

CONCLUSION

Overall, a yield-weather model was developed. The linkage between precipitation and an irrigated ratio in the model was also investigated. Both PDI and de-trended irrigation ratio helps explain more variance of crop yield. Compared to PDI, irrigation ratio has larger impact on crop yield. The results of this research provide valuable irrigation water usage information to agricultural policy makers in the State of Georgia. The methodologies developed in this study could be applied in other states as well. One major limitation of this study is that we ignore the fact that drought will bring down the availability of irrigation water and therefore irrigated acreage. Future related research could focus on the relationship between irrigated acreage, precipitation and irrigated water availability.

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