WEATHER INDEX FOR CROP INSURANCE TO MITIGATE BASIS RISK

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ABSTRACT

Weather index insurance against severe weather and flooding is an important research issue to protect both people and agriculture in developed and developing countries. This study utilized remote sensing data and climate data to find the relationship between crop yield and different indicators, like EVI, crop stage at flooding, inundation period, and other climate factors to reduce the basis risk. In this study, MODIS and PALSAR imageries are analyzed for flood detection using SVM in Illinois state. Results indicate that flood mostly destroyed those cropped areas which were near the river. Remote sensing clears the affect of weather, crop phenology and flooding on crop harvest loss, which is key to lower basis risk for weather index insurance.

Index Terms— Wavelet transformation, SVM, Flood, MODIS, Crop yield, EVI

1. INTRODUCTION

In recent years, the demand of agricultural insurances has increased because enormous crop damage has been wreaked by recurrent abnormal weather events[1]. The global market size of agricultural insurances is $25 billion [2]. The largest country is the United States ($12 bn.), the second is China ($4 bn.) and the third is Canada ($1.6 bn.). The market has been grown more than three times in four years, and also it is expected to expand in the future. This study develops more accurate weather index for agricultural insurances.

Unlike conventional agricultural insurance, weather index insurance does not include any assessment or survey. The mechanism of index insurance is that an indemnity is paid automatically if observed index becomes under the specific condition. The indemnity is based on realizations of a specific weather parameter measured over a pre-specified period of time at a particular weather station. The insurance can be structured to protect against index realizations that are either so high or so low that they are expected to cause crop losses [1]. The biggest challenge of weather index insurance is basis risk. Basis risk refers to the differences that may occur between the actual loss incurred by the farmer and the loss determined by the index, entailing claims for nonexistent losses and no claims for effective losses [2]. Since the demand of agricultural insurance has increased, highly accurate weather index which has low basis risk, is required.

In agricultural insurance, crops are damaged by drought, hail and flood mostly [3]. In contrast of drought and hail, weather observation stations cannot estimate flooded area. Flood damage has been rapidly increasing from the past two decades and causing huge agricultural loss. Huge flood caused $5 billion economic damage in Pakistan (2010) and $10 billion loss to agricultural crops in China (2013). In addition, in June, 2008, much of the Midwestern U.S. received heavy rain and it caused flood which was historical record high streamflows. It was expected that crop losses will increase more than $8 billion and half of it will loss only in Iowa state[4]. Fortunately the weather changed to ideal weather and help to recover the crop.

A flood hit U.S. in 2008 is important to understand basis risk. Wetter soil and cooler weather situation before 2008 flood reasoned for late planting of all crops in Iowa, Illinois, Indiana, Wisconsin and other states. More than one million acre of land was replanted after flooding and total wash out [5, 6]. Therefore, corn silking and maturity dates were also delayed due to late planting, and fortunately weather (temperature, solar radiation and rainfall) was similar to the best year which resulted in a good harvest[5]. So, it is not easy to estimate crop damage and diminish basis risk for weather index insurance.

This study used satellite remote sensing to detect flooded area, inundation duration and crop phenology to quantify loss of crop harvest. Previous studies have used threshold for indices or different band combinations using machine learning[7, 8, 9] to detect flood. This study applied Support Vector Machine (SVM) for flood detection using Enhance Vegetation Index (EVI), Land Surface Water Index (LSWI) and Difference value between EVI and LSWI (DVEL). For crop phenology monitoring, wavelet smoothing on EVI was performed to reduce influence of cloud contamination[10]. Finally, following two points were achieved to mitigate basis risk for weather index insurance. 1) Utilize higher resolution data than station data in spatial and time series. 2) Clarify a weather condition of causing harvest loss.

2. DATA AND METHODOLOGY

The objective of this study is designing a good weather index which has lower basis risk. To accomplish this goal, we established 4 main steps.1) Calculate a crop yield index to evaluate annual crop yield anomaly 2) Apply wavelet smoothing on EVI to extract phenology 3) Analyze relationships between crop growth and meteorological data 4) Estimate flooded area and inundation duration with satellite data 5) Assess crop damage by flood 6) Estimate harvest loss by severe weather

2.1. Data acquisition

Table 1 shows detail of data using for this research.

2.2. Crop yield index

Crop production per unit area (yield) is on the upward trend, since cultivation and its technology has been improving. Therefore, even though a relationship between weather and crop harvest is analyzed, an impact of severe weather on the crop cannot be figured out quantitatively. In this study, we calculate crop index which shows annual

Table 1. Detail of data using in this study

Date item	Period	Spatial res.	Remarks
MOD09A1	2001 - 2010	500 m	8-day surface reflectance
PALSAR	2008	13 m	L band SAR data
CRU	2001 - 2010	50 km	Max. temp, Min. temp, precipitation, Potential Eto
Crop yields	1970 - 2012	County level	Harvested area, production statistics
CDL	2008 - 2012	35 m	crop classification

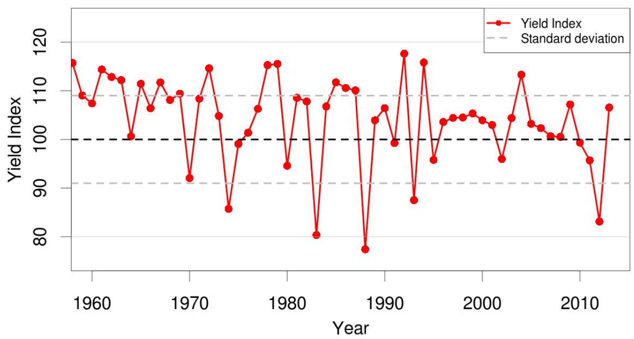

Fig. 1. Corn yield index in the United States

crop yield anomaly Eq. (1).

$$I_t = 100\frac{Y_t}{A_t} \tag{1}$$

I_t is crop index in year t. Y_t is a yield of crop in year t. A_t is a simple move average of a crop yield in year t. We make simple move average as average annual harvest. Fig. 1 shows crop yield index of corn in U.S. If the index is 100, it is average annual harvest. If it is lower than 100, it is a bad harvest. If it is higher than 100, it is an abundant harvest.

2.3. Analysis of crop growth and meteorological data

Weather conditions directly affects crop growth, and ultimately control crop harvest. Influence of weather conditions to crops is analyzed in time series, since crop growth conducts differently at each growth stage. We analyzed MODIS EVI, yields and weather data to comprehend a condition of crop sequentially.

2.4. wavelet transformation and crop phenology pattern

We estimated EVI from MOD09A1. Data smoothing by wavelet transformation was applied on MODIS EVI to remove noisy data. MODIS data have been disturbed ground observation by clouds because it is an optical sensor. Hard threshold method was selected for data smoothing algorithm. Clouds is obstacle in detecting a pattern of crop phenology from satellite image. Wavelet transformation is very useful to remove noise from time-series data. It has been already used to estimate important crop phenology events, such as emergence, maturity and harvest [10]. we detected corn planting date and silking stage of corn by the lower and upper peaks of smoothed EVI.

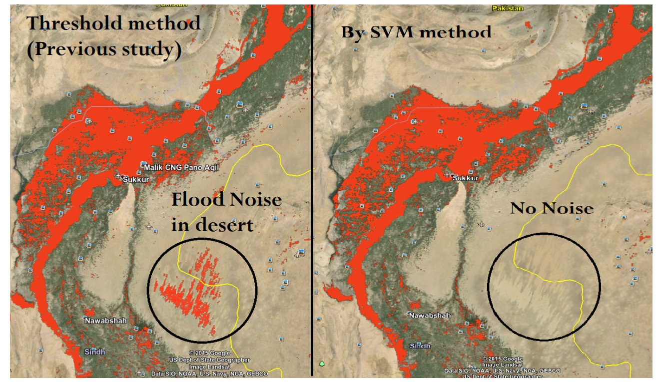

Fig. 2. Flood detection by using threshold method (left) and SVM (right)

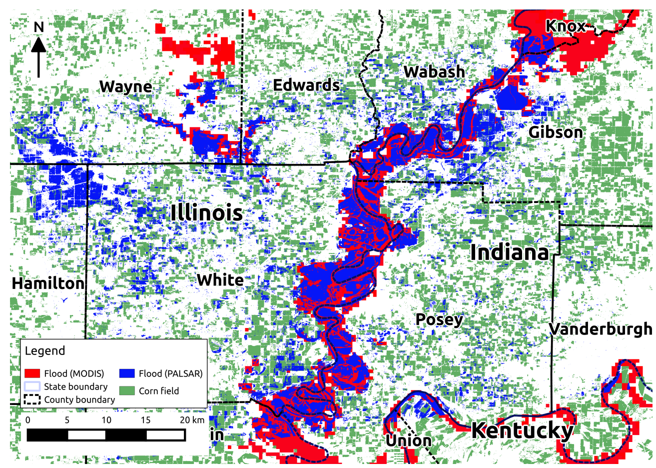

Fig. 3. Crop under flood water MODIS flood (red), PALSAR flood (blue)and crop area (green)

2.5. Flood detection with remote sensing

Floods cause serious damage to crops. Since inundation occurs in wide area when heavy rain water remains at the surface, a weather observation station which is constructed sparsely, cannot detect it [11]. We used satellite remote sensing data, to estimate inundation duration and flooded area.

For flood detection, previous study [7, 8] apply different thresholds to EVI, LSWI and DVEL values. Cloud cover area is removed, if reflectance value of blue band (MODIS band3) is higher than or equal to 0.27. A pixel having (EVI$\leq$ 0.3 and DVEL$\leq$ 0.05) or (EVI$\leq$ 0.05 and LSWI$\leq$ 0.0) is classified as flooded area. However using these threshold for Pakistan showed some noise in deserted area even in dry seasons. Therefore, we utilized SVM to train flood model.

2.5.1. *Support Vector Machine (SVM)*

SVC (Support vector classification) with RBF (Radial Basis Function) 3rd degree of the polynomial kernel function [12] was applied to train flood model by providing some EVI, LSWI and DVEL index values as training data and 2010 Pakistan flood map as training result near Sakhar barrage. These indices significantly differentiate between water, vegetation and flooded vegetation. By utilizing SVM, we could able to remove flood noise in desert area. Fig. 2 shows comparison of flood detection with previously suggested threshold method (left) and newly developed SVM method (right) which considerably remove noise in desert area.

After analyzing time series of EVI, LSWI and DVEL indices by SVM, inundation duration and flood receding map is plotted. Using optical sensor, estimating inundation period is difficult because cloud coverage interrupts ground observation. To mitigate cloud influence PALSAR (Phased Array type L-band Synthetic Aperture Radar) images were also acquired for flood area detection. SVM model was trained to detect flood area by using PALSAR backscatter as input data. These MODIS and PALSAR Flood inundation maps were overlaid on Cropland Data Layer (CDL) which is very precise crop classification data distributed by USDA, to determine crop types in flooded area [13] and to estimate flood damage to different crop types. Fig. 3 shows flood area on the boundary of Indiana & Illinois which is overlaid on CDL. Red and blue color represents flood inundation area detected by SVM using MODIS and PALSAR respectively.

3. RESULT AND DISCUSSION

Using SVM trained model we acquired flood map by MODIS and PALSAR satellite images. Fig. 3 shows mostly near river cropped area is effected by flood. However, far river area also received significant amount of rain which causes inundation for short period and effected crop growth. Fig. 4 represents peak EVI dates for the different counties in Illinois state from year 2001 to 2010. Difference of peak EVI indicates which area was planted first and which area was planted later. Late EVI peak in 2008 and 2009 explained that, due to wet climate condition farmers delayed the planting of crops to ensure the better harvest. This late planting resulted in better harvest in the southern counties of Illinois, but the northern counties shows converse result. Fig. 4 and 5 clearly indicate difference of crop maturing date in northern and southern counties of Illinois and its affect on crop yield in year 2008 and 2009. In 2008, flood hit Illinois state during late planting season, therefore those areas which were planted in early days, effected more.

Fig. 6 indicates correlation of monthly mean maximum temperature, monthly mean minimum temperature, monthly mean precipitation and monthly mean potential evapotranspiration with the annual crop yield. These data are averaged at state level. Temperature and potential evapotranspiration shows negative correlation with the crop yield, whereas precipitation shows positive correlation with crop harvest from may to august. we acquired these correlation between climate data and crop yield at state level but there was no significant correlation at county level.

Flood timing and duration is critically important for the crop yield, therefore; we plotted EVI, flood duration and crop yield index. Fig. 7 represents time series of EVI, flood signal, inundation duration and yield anomaly at a county, it is evidently observed that longer duration flood severely effects on crop EVI and crop growth. 2008 flood flushed some cropped area just after planting so many farmers replanted the area. However, Fig. 7 shows the drop and regain of EVI after June flood due to good weather conditions, which resulted in normal crop harvest. In 2009 farmers planted there crops very late due to highly wettest season (Fig. 4) and fortunately that year flood did not occur and Illinois received very good harvest (Fig. 7).

From these results we found that spatial data clears the effect of weather and flood damage on crops due to spatial disparity of counties in Illinois. Using weather data, spatial non integrity and remote sensing information we can mitigate basis risk.

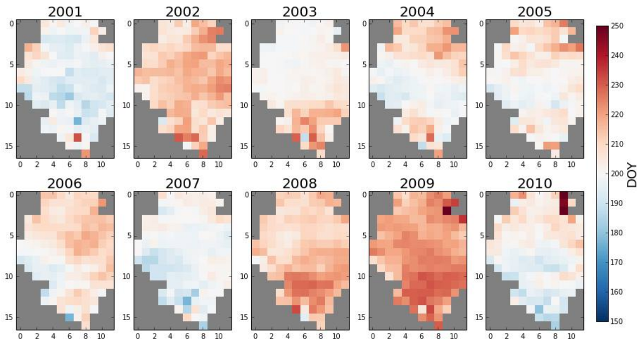

Fig. 4. Illinois peak EVI day of year for 2001-2010

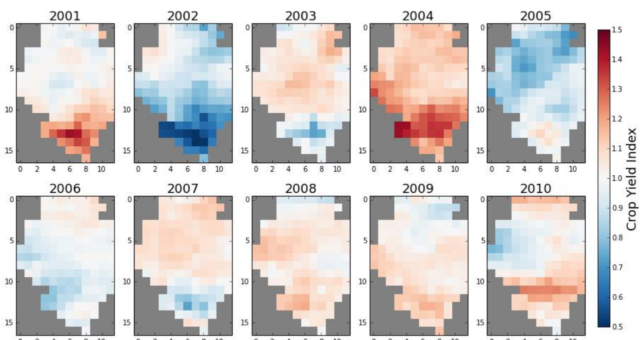

Fig. 5. Illinois county level crop yield index for 2001-2010

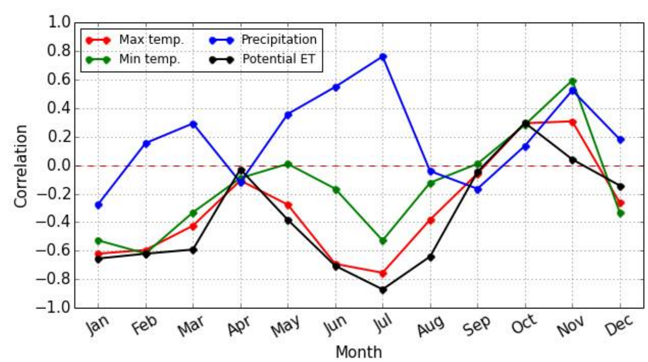

Fig. 6. Correlation of crop yield index with climate data at state level

4. CONCLUSION

By calculating the crop yield index, annual crop yield anomaly is acquired and influence of severe weather is evaluated. By using spatial data, a distribution of relationship between crops and weather data becomes clear. Fig. 6 shows that maximum temperature, minimum temperature and potential evapotranspiration have negative correlation with crop yield from Jun to August at state level. In contrast,

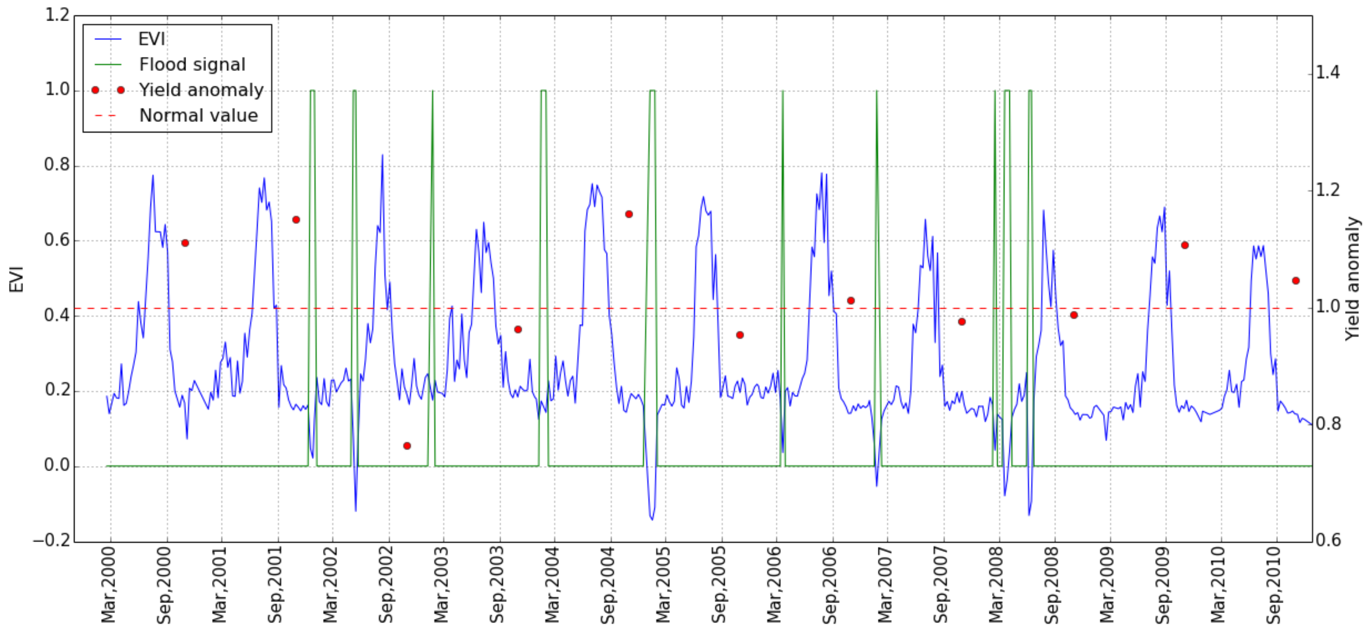

Fig. 7. Time series of EVI and flood signal with yield anomaly

precipitation has positive correlation. However, no such correlation is observed at county level. A possible cause is weather condition, that is different due to spatial disparity even with in a state. Peak EVI provides us the information of crop growth and weather effect. Furthermore, EVI time series give us the combined effect of weather and other damaging factor on crop growth. Using SVM for flood detection helped to remove noise in the desert area. By utilizing time series of EVI, flood signal and flood duration we can assess the flood affect on crop and crop growth after combined effect of flood and weather damage. These result are effective to design weather index insurance with reduced basis risk.

5. REFERENCES

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