International Journal of Remote Sensing
Vol. 26, No. 11, 10 June 2005, 2325–2336

Modelling corn production in China using AVHRR-based vegetation health indices

FELIX KOGAN*†, BANGJIE YANG‡, GUO WEI§, PEI ZHIYUAN‡ and JIAO XIANFENG‡

†NOAA, National Environmental Satellite Data and Information Services, Camp Springs, Maryland 20746, USA

‡Center for Agricultural Resource Monitoring, Ministry of Agriculture, Beijing 100026, China

§IM System Group Inc., Washington, DC, USA

(*Received 22 March 2004; in final form 25 October 2004*)

Weather-related crop losses have always been a concern for farmers, governments, traders and policy makers for the purpose of balanced food supplies, demands, trade, and distribution of aid to nations in need. Therefore, early crop loss assessment in response to weather fluctuations is an important issue. This paper discusses the utility of Advanced Very High Resolution Radiometer (AVHRR)-based vegetation health indices as a proxy for modelling corn yield and for early warning of drought-related losses of agricultural production in China. The indices were tested in Jilin province on corn yield during 1982–2001 using correlation and regression analysis. A strong correlation between corn yield and the vegetation health indices were found during the critical period of corn growth, which starts 2–3 weeks before and 2–3 weeks after corn tassel. Following the results of correlation analysis, several regression equations were constructed where vegetation health indices were used as independent variables. The estimates of corn yield can be carried out well in advance of harvest and the errors of the estimates are 7–10%. The errors become smaller when the estimations are related to losses in corn yield due to drought.

1. Introduction

Having a quarter of the world's population, one of China's most important agricultural priorities is aiming to provide enough domestic food and feed, and commodity for trade. Although China has only 7% of the world's arable land, the country is one of the largest producers of agricultural commodities including such an important food source as grain. In recent years, nearly 20% of the global total grain, including the largest amount of rice and wheat, have been produced by China's farmers. For example, in 2002, China's contribution to the total world production of wheat, corn and rice accounted for 16, 20 and 31%, respectively (FAO 2002). Therefore, in addition to domestic use, the amount of grain produced in China annually is very important for global supply and demand and food security.

The Northern Plains (north-east) are the main agricultural areas of China. Thirty-eight per cent of China's arable land and 35% of total number of people are located there (Ning 1998). Although the lands are generally productive, semi-arid climate

*Corresponding author. Email: felix.kogan@noaa.gov

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2005 Taylor & Francis Group Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160500034235

with frequent droughts limit agricultural output. By the amount of natural water resources, China is ranked number six in the world. However, the distribution of water is unbalanced geographically. The Northern Plains makes up only 7.5% of the total water resources available in China (Ning 1998). Therefore, irrigation can not offset dry climate in that area. In drought years, up to 25% of agricultural production might be lost in the Plains. Therefore, the Chinese Government is giving increasing importance to an early assessment of crop losses.

Since climate controls a large portion of variation in China's agricultural production, weather data are normally used for assessment of the losses. However, the weather-station network in China is not dense enough for a very large agricultural area and the number of farmers growing crops. Therefore, China's Government is considering using satellite sensor data for these purposes. The recent advances in the application of operational satellites proved that observed radiances are an excellent tool for monitoring the environment and agricultural activities. Vegetation health indices were found to be very useful for an early drought detection and monitoring their impacts on crop and pasture production in Greece, Mongolia, Brazil, Poland, Argentina, Morocco and other countries (Kogan 2002, Liu and Kogan 2002, Dabrowska-Zielinska *et al.* 2002, Kogan *et al.* 2003, Domenikiotis *et al.* 2004). The objective of this paper was to investigate the potential of vegetation health indices for monitoring agricultural production and assessment of crop losses in Jilin province, located in the China Northern Plains breadbasket.

2. Data

Both satellite and *in situ* data were used in this study. *In situ* data were corn production (tons, t), area (ha) and yield ($\mathrm{t\,ha^{-1}}$) during 1980–2001 obtained from the China's Central Statistical Administration. The data were collected from farmers at the end of agricultural year and aggregated to the total Jilin province level. Yield was calculated by dividing total Jilin province corn production by the sown area.

Satellite sensor data included Advanced Very High Resolution Radiometer (AVHRR)-measured solar energy reflected/emitted from the land surface (in 8-bit counts) collected from the National Oceanic and Atmospheric Administration (NOAA) Global Vegetation Index (GVI) dataset from 1981 through 2001. Spatial data resolution was 4 km, sampled to 16 km and temporal 1 day sampled to 7-day composite (Kidwell 1997). The GVI counts in the visible (VIS), near-infrared (NIR), and infrared (IR, 10.3–11.3 μm, Ch4) spectral regions were used in this research. Post-launch-calibrated VIS and NIR counts were converted to reflectances (Kidwell 1997) and used to calculate the normalized difference vegetation index ($\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS})/(\mathrm{VIS} + \mathrm{NIR})$). The Ch4 counts were converted to brightness (radiative) temperature (BT).

The strategy was (1) to separate weather component in corn yield, NDVI and BT values and (2) to correlate weather-related component of yield with the corresponding component of vegetation health indices. The goal was to investigate the strength of the relationship and whether the strongest correlation coincides with the corn's critical period. It is important to emphasize that NDVI and BT quantify both spatial difference between productivity of ecosystem (ecosystem component) related to the influence of long-term factors (climate, topography, etc.) and year-to-year variations in each ecosystem related to weather fluctuations (weather component). Since weather component values are much smaller than the ecosystem, separation of weather component is an important procedure prior to correlation analysis. Other indices (cumulative, maximum, etc.), representing both ecosystem and weather components are very useful for characterization of vegetation distribution rather then for analysis of weather-related fluctuations, which are small compared to ecosystem component (Kogan *et al.* 2003).

3. Methodology

3.1 *Corn yield*

Over a long period of time, yield of any crop normally increases because technology of crop cultivation (breeding, mechanization, fertilizers, etc.) is constantly improving. The technology-related yield increase can be approximated by a polynomial (either linear or non-linear depending on longevity of yield series and climate contribution), which describes a trend in yield time series. At a general background of the technology-related trend, yield fluctuates around the trend from year to year due to weather variation. If weather is favourable for crop growth yield exceeds the level estimated from the trend and in case of unfavourable weather yield drops below the trend. In sum, yield time series were separated into two components: technology-related trend and yield deviation from the technological trend. The first characterizes long-term yield tendency associated with technology change and the second characterizes variation of yield around the trend due to year-to-year weather fluctuations. The second component is normally expressed as a ratio of actual to trend-estimated yield.

The 1980–2001 Jilin province corn yield (Y) time series are shown in figure 1. They experience stable technology-related growth, which was approximated by the following linear equation:

$$Y_{\text{trend}} = 0.112 \text{ year} - 216.71 \tag{1}$$

Fluctuations around the trend (δY) were expressed as a ratio of deviation from trend:

$$\delta Y = Y / Y_{\text{trend}} \tag{2}$$

For any year, trend estimates that yield level which is associated with the contribution of agricultural technology to crop production line provided that the

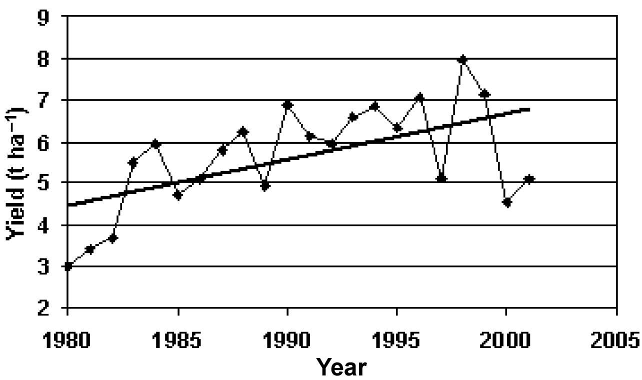

Figure 1. Corn yield time series for Jilin province, China.

weather was near normal (close to many-year mean).Yield deviation from the trend is associated with weather fluctuations. For example, Jilin province's deviation of corn yield from the trend in 1997 and 1998 were estimated at 0.79 and 1.23, respectively, indicating 21% yield reduction in 1997 due to unfavourable and 23% increase due to favourable weather in 1998.

3.2 *AVHRR-based vegetation health indices*

The principle for constructing vegetation health indices stems from the properties of green vegetation to reflect visible and emit thermal solar radiation. If vegetation is healthy it reflects little radiation in the VIS part of solar spectrum (due to high chlorophyll absorption), much in the NIR part (due to scattering the light by leaf internal tissues and water content), and emits less thermal radiation in IR spectral bands (because the transpiring canopy is cooler). As a result NDVI becomes large and BT small. Conversely, for unhealthy vegetation, NDVI becomes small and BT large.

The vegetation health indices were calculated from NDVI and BT. Details of the algorithm are presented in Kogan (1997). Here, only the important steps are mentioned, which include (a) complete elimination of high frequency noise from NDVI and BT annual time series, (b) approximation of annual cycle, (c) calculation of multi-year climatology, and (d) estimation of medium-to-low frequency fluctuations during the seasonal cycle (departure from climatology) associated with weather variations. The indices Vegetation Condition (VCI), Temperature Condition (TCI) and Vegetation Health (VHI) were approximated as:

$$\mathrm{VCI} = 100(\mathrm{NDVI} - \mathrm{NDVI}_{\min})/(\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min}) \tag{3}$$

$$\mathrm{TCI} = 100(\mathrm{BT}_{\max} - \mathrm{BT})/(\mathrm{BT}_{\max} - \mathrm{BT}_{\min}) \tag{4}$$

$$\mathrm{VHI} = a\ \mathrm{VCI} + (1 - a)\mathrm{TCI} \tag{5}$$

where NDVI, $\mathrm{NDVI}_{\max}$ and $\mathrm{NDVI}_{\min}$ (BT, $\mathrm{BT}_{\max}$ and $\mathrm{BT}_{\mathrm{tmin}}$) are the smoothed weekly NDVI (BT) and their 1985–2003 absolute maximum and minimum (climatology), respectively; a is a coefficient quantifying a share of VCI and TCI contribution in the VHI. Since this share is not known for a specific location it was assumed that the share is equal and a=0.5. The range of vegetation health indices changes from 0 quantifying severe vegetation stress to 100 quantifying favourable conditions. The application of these indices in a number of countries (Poland, Brazil, Argentina, Zimbabwe, Morocco, Russia, India) showed that they correlate highly with productivity of crops and pastures and can be used as numerical weather-related indicators of agricultural losses in advance of harvest (Kogan 1997, Unganai and Kogan 1998).

4. Corn and the environment

Although Jilin province is the largest producer of corn in China (USDA 1994), geographic location and the environmental conditions are not favourable there. The major area of corn planting in the central and western Jilin province (figure 2) receives 500–700 mm of annual precipitation (P), 80% of which falls during May–September (Hou 1990). This amount is generally marginal for corn growth. Moreover, because of the hot summer, potential evapotranspiration (PET) in this

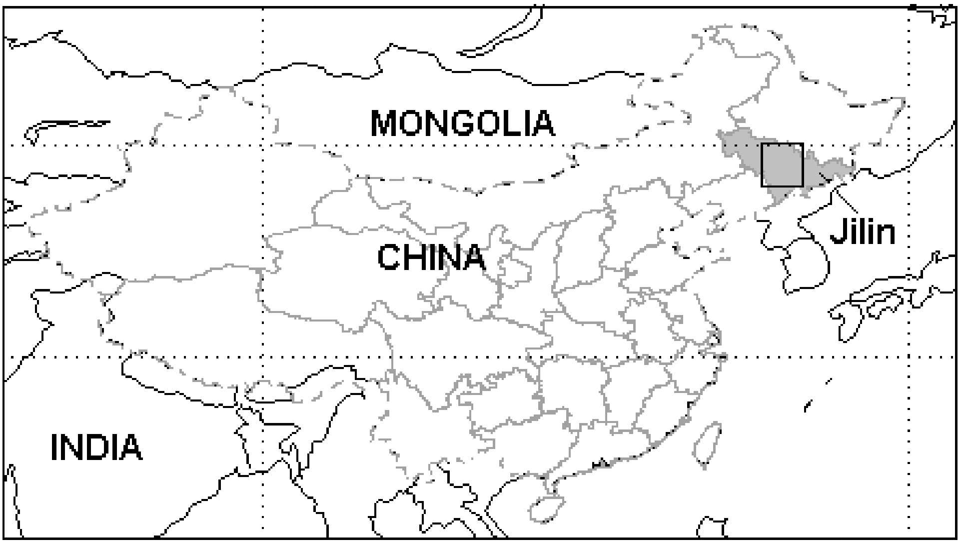

Figure 2. Location of Jilin province and the area of satellite sensor data collection.

area is large, exceeding the amount of precipitation. As a result, the natural annual water balance (P – PET) in Jilin province is 200–400 mm short. Ninety per cent of this deficit occurred during warm period. Therefore, corn, which is planted in Jilin province during May through mid June and harvested in September and October is affected severely (USDA 1994).

Since the exact coordinates of the major corn area in Jilin province are not available, this area was derived based on general distribution of corn indicated in Hou (1990) and USDA (1994). Weekly vegetation health indices data were collected for all pixels inside the major area of corn growth (46° to 42.5° N and 122° to 126° E) shown shaded in figure 2. Weekly average Jilin province indices (VCI, TCI and VHI) were calculated from the total number of 600 pixels inside the indicated area.

5. Results and discussion

The Y_{trend} analysis shows that during 1980–2001, technology-related corn yield increased 30% (from 4.5 to 5.8 t ha^{-1}). This growth was moderate considering large investments of China's Government in agricultural technology of Jilin province (Ning 1998). Besides, moderate growth emphasizes also that climate put considerable constraints on agricultural productivity and limits the efforts of technology to overcome shortage of water. At the background of yield increase, weather-related fluctuations of yield around the trend or de-trended yields (δY) were large and as seen in figure 1, in the latest 2 years (2000, 2001) corn yield dropped to the level of the early 1980s because Jilin province was affected by large area, intensive drought.

Since δY corn yield and vegetation health indices were similarly expressed as a deviation from climatology (from trend for corn and from max-min for vegetation health indices), further investigation included correlation and regression analysis

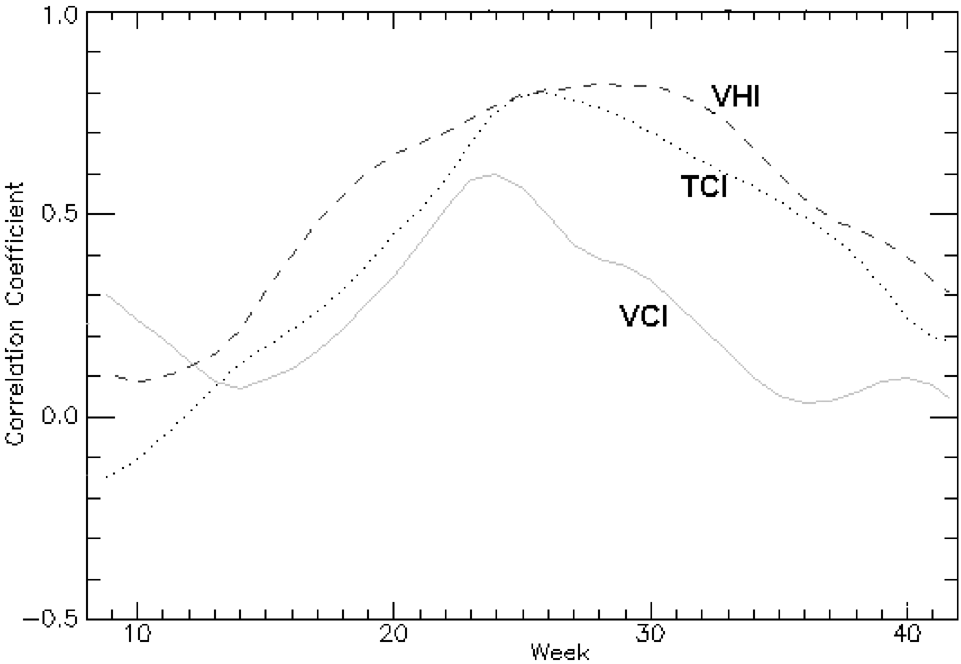

Figure 3. Dynamics of correlation coefficients for corn yield departure from trend with VCI, TCI and VHI.

of these deviations. Figure 3 shows dynamics of correlation coefficients of δY versus VCI, TCI and VHI between weeks 10 (mid-March) and 40 (end of October).

These results were analysed first, to interpret the response of corn productivity to moisture (VCI) and thermal (TCI) conditions expressed by the vegetation health indices. As seen in figure 3, in the early period of the corn growing season, which is pre-planting, planting and emergence (weeks 15–20, April to early June), the correlation for both indices is small. It increases sharply during the corn's green mass accumulation (weeks 22–28), reaching maximum in late June for VCI and mid July for TCI. This maximum correlation coincides with the critical period in corn development, which starts 2–3 weeks prior to and ends 2–3 weeks after corn tassels (Chirkov 1969). During this period, plentiful water supply and cooler temperatures stimulate larger corn production. Figure 3 confirms that positive correlation with VCI and TCI indicates that below trend yield is associated with moisture and thermal stress (both VCI and TCI below 40) and above trend yield is associated with favourable (moist and cool) conditions (VCI and TCI above 60).

Although the correlation dynamics were in line with corn response to the environment, it should be noted that even for the weeks of the highest correlation, VCI explained only 30% of δY variance (Pearson correlation coefficient, CC=0.55); TCI explained 50% (CC=0.73). However, this relationship increased for the VHI (figure 3). Analogous to the other two indices, the correlation of δY with VHI had similar dynamics reflecting the described corn response to the environment (low correlation during the earlier stages of corn development, sharp increase during biomass accumulation and high correlation during the critical period, around tasselling (Chirkov 1969)). Concerning the critical period, the peak of the correlation shifted slightly to the later weeks and show high CC (0.75) at week 31. This emphasizes the importance of combining VCI (moisture conditions) and TCI (thermal conditions) together even if their contribution to VHI was approximated as equal (equation (5)).

It is known that crop response to moisture and thermal conditions is not equal during the growing season. Corn is more moisture-dependent in the period of green leaf formation and more temperature dependent during the reproductive stages (Chirkov 1969). However, in the environment of Jilin province, thermal conditions are more important, especially during and after corn tassels (weeks 26–36, June–July). For example, for week 22 (leaf formation), the contribution of VCI and TCI are almost the same ($CC_{vci}=0.52$ and $CC_{tci}=0.59$), while for week 32 (reproductive stage), TCI contribution considerably exceeds VCI ($CC_{vci}=0.16$ and $CC_{tci}=0.60$).

In addition to equal VCI and TCI contribution (equation (5)), the test was performed for non-equal contribution. The later was calculated based on weights (W) estimated from the CC following the approximation below. Squares were used in order to give slightly more weight to the index with the larger CC. It would be appropriate to indicate that Ws do not change from year-to-year since they are derived from CC, which characterize the entire period of observations (1982–2001).

$$
\begin{aligned}
W_{\mathrm{vci}} &= \mathrm{CC}_{\mathrm{vci}}^2 / \left(\mathrm{CC}_{\mathrm{vci}}^2 + \mathrm{CC}_{\mathrm{tci}}^2\right) \\
W_{\mathrm{tci}} &= \mathrm{CC}_{\mathrm{tci}}^2 / \left(\mathrm{CC}_{\mathrm{vci}}^2 + \mathrm{CC}_{\mathrm{tci}}^2\right)
\end{aligned} \tag{6}
$$

Table 1 compares CC dynamics for weighted and non-weighted VHI. For the critical period (weeks 25–35), the strength of the correlation remains the same for both indices. This is an important conclusion because it is normally unknown how to weight VCI and TCI contribution to VHI for a pixel and even an area. This task requires calibration of satellite indices based on ground data, which are often not easily available.

Figure 4 shows a scatter plot of δY versus VHI for week 31 (early August) which is the peak of the correlation (figure 3). This relationship approximated by equation (7) explains 64% of δY variance at 5% level of significance:

$$
\begin{aligned}
&\delta Y = 14.888 + 1.6561\,\mathrm{VHI}_{31} \\
&\mathrm{CC} = 0.81;\ R^2 = 0.64;\ E = 15\%
\end{aligned} \tag{7}
$$

Since the 31st week is in the middle of critical period for corn and has the strongest δY versus VHI relationship, this 1-week equation can be used for estimation of δY. However, the shortcomings in using equation (7) include high error of estimation (15%) and low R^2 (64%). Besides, other weeks around 31, as seen

Table 1. Pearson correlation coefficients for δY versus weighted VHI and non-weighted VHI.

Parameter	Week 15	Week 20	Week 25	Week 30	Week 35
Weighted	0.120	0.492	0.776	0.799	0.581
Non-weighted	0.269	0.646	0.792	0.743	0.555

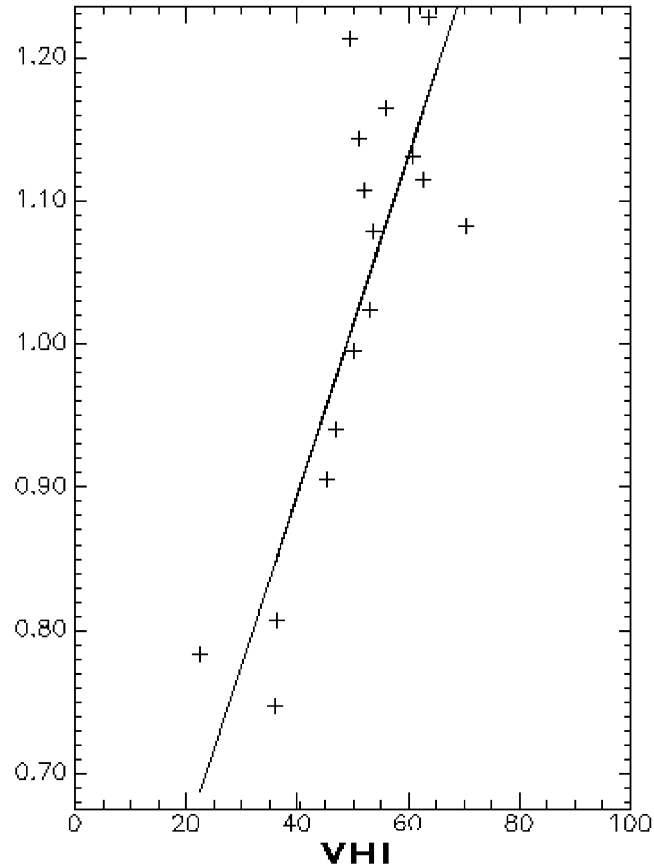

Figure 4. Scatter plot of corn yield departure from trend versus VHI.

in figure 3, are also highly correlated with δY. Therefore, in addition to 1-week analysis, the tests were also performed regressing δY with several weeks (with the highest CC) of the same independent variable or their combination. The tests included building regression equations and investigation of the contribution of different weeks into total δY variance.

The criteria used for this analysis were partial correlation coefficients (PCC), which estimate the contribution of each independent variable when other variables are fixed at the average level (Snedecor 1965). The PCC indicator is important to use for selection of the parameters with the largest contribution to variability of a dependent (predictant) variable. This analysis is necessary because independent variables (predictors) are correlated with each other (collinear), duplicating their contribution to variability of a dependent variable. If two variables are collinear, the regression coefficients of such an equation become unstable and the equation becomes less accurate. In order to improve the equation stability one of the variables should be removed.

Table 2 presents the results of PCC analysis. The first test included all weeks with the highest CC and in the following tests, the independent variable which had the lowest PCC was removed and PCCs were re-estimated for the remaining variables. As seen in table 2, VCI_{25} had the largest contribution (PCC=0.468) if week 26 was

Table 2. Assessment of independent variables' contribution based on partial correlation coefficients.

Parameter	Partial correlation coefficients		
	First test	Second test	Third test
VCI_{25}	0.289	0.468	0.518
VCI_{26}	0.149	− 0.366	
VCI_{27}	0.055		− 0.342
MCC for VCI regression	0.625	0.637	0.628
TCI_{24}	0.030	0.077	
TCI_{25}	0.001		
TCI_{26}	0.002	0.102	0.321
TCI_{27}	0.099	0.162	0.235
TCI_{28}	0.200	0.207	0.207
TCI_{29}	0.174	0.173	0.156
MCC for TCI regression	0.629	0.810	0.811
VCI_{25}	0.131		
VCI_{27}	0.132	0.503	
TCI_{26}	0.430	0.437	
TCI_{27}	0.436	0.434	
TCI_{28}	0.426	0.424	
TCI_{29}	0.347	0.341	
MCC for VCI and TCI regression	0.865	0.863	

included in regression analysis. The PCC for week 25 increased to 0.518 if week 27 was included and 26 excluded (third test). The tightness of the relationship between δY and all independent variables (equation (8)) is estimated with the multiple CC (MCC). The MCC is calculated based on PCC of δY with each of the independent variables and PCC between all pair of independent variables (Dlin 1958). Following the third test of δY versus VCI only in table 2, the MCC for the entire regression was not large (0.628). The MCC increased to 0.811 (third test) when TCIs for weeks 26–29 were included in the regression. A combination of VCI and TCI together further increased MCC to 0.863 (second test). However, the highest MCC and the lowest error were received when VHIs were used as independent variables.

These results were used to build and test regression equations. Two equations were developed the first, with VCI and TCI combination used as independent variables (equation (8)) and the second, VHI (equation (9)). The variables in these equations were selected based on the largest values of PCC:

$$\delta Y = 0.502 + 0.005\ \mathrm{VCI}_{27} + 0.034\ \mathrm{TCI}_{26} - 0.106\ \underline{\mathrm{TCI}}_{27} + 0.107\ \underline{\mathrm{TCI}}_{28} - 0.03\ \mathrm{TCI}_{29}$$
$$\mathrm{MCC} = 0.86;\ R^2 = 0.75;\ n = 20;\ \mathrm{d.f.} = 15 \tag{8}$$

$$\delta Y = 0.501 + 0.114\ \mathrm{VHI}_{26} - 0.316\ \underline{\mathrm{VHI}}_{27} + 0.289\ \underline{\mathrm{VHI}}_{28} - 0.076\ \mathrm{VHI}_{29}$$
$$\mathrm{MCC} = 0.90;\ R^2 = 0.81;\ n = 20;\ \mathrm{d.f.} = 16 \tag{9}$$

In addition, in order to improve the stability of regression coefficients (Snedecor 1965), the number of independent variables was reduced to one-two resulting in the degree of freedom (d.f.) increase. Following the transformation in equation (6) the

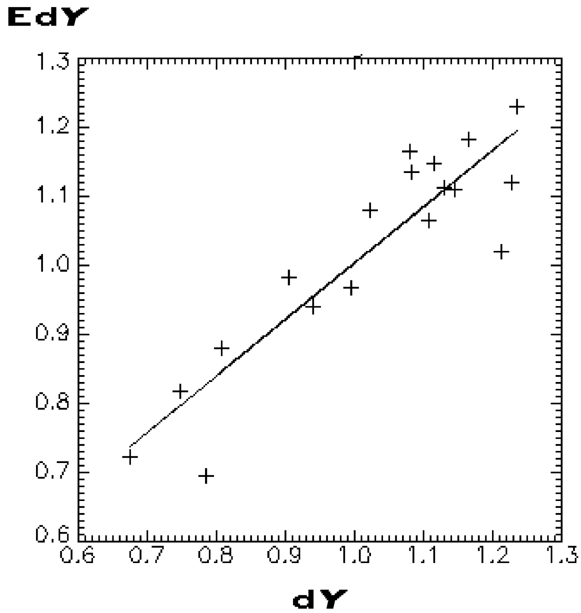

Figure 5. Scatter plot of VHI-based $E\delta Y$ and δY for corn yield.

equations (8) and (9) were presented in the following form:

$$\begin{aligned} \delta Y &= 0.462 + 0.004\ \mathrm{VCI}_{27} + 0.006\ \mathrm{TCI}_{26-29} \\ \mathrm{TCI}_{26-29} &= 0.269\ \mathrm{TCI}_{26} + 0.257\ \mathrm{TCI}_{27} + 0.246\ \mathrm{TCI}_{28} + 0.229\ \mathrm{TCI}_{29} \end{aligned} \tag{10}$$

$$\mathrm{MCC} = 0.83;\ R^2 = 0.69;\ n = 20;\ \mathrm{d.f.} = 18$$

$$\begin{aligned} \delta Y &= 0.496 + 0.006\ \underline{\mathrm{VHI}}_{26-29} \\ \mathrm{VHI}_{26-29} &= 0.246\ \mathrm{VHI}_{26} + 0.249\ \mathrm{VHI}_{27} + 0.253\ \mathrm{VHI}_{28} + 0.252\ \mathrm{VHI}_{29} \end{aligned} \tag{11}$$

$$\mathrm{MCC} = 0.86;\ R^2 = 0.74;\ n = 20;\ \mathrm{d.f.} = 19$$

Regarding significance, underlined variables and all MCC indicate probabilities equal to or less than 0.01, without underline indicates probabilities between 0.05 and 0.01. Equation (8) was used to calculate the estimated δY ($E\delta Y$) and the scatter plot of $E\delta Y$ versus δY in figure 5 confirms that this relationship is quite strong.

The MCC and R^2 estimations of equations (8) and (9) show that the relationships are strong explaining 75 and 81% of the δY variance, respectively. The scatter plot of $E\delta Y$ versus δY shown in figure 5 confirms this strong relationship for equation (9). The weighted variables (equations (10) and (11)) have smaller MCC and R^2. However, all four equations (8)–(11) were tested independently. For that a 'Jacknife' approach was used when years were eliminated one by one from the dataset, in each case, new equation (with the same variables) was developed (without an eliminated year) and each equation was tested using independent variables of the eliminated years. This procedure was performed 19 times and estimated δY ($E\delta Y$) was calculated for each year not included in the development of the regression. Finally,

Table 3. Statistics of an independent testing of equations (8)–(11).

Parameter	8	9	10	11
Mean bias (MB)	0.101	0.087	0.028	0.067
SD of MB	0.70	0.59	0.66	0.57
Mean Square Error (MSE)	0.478	0.333	0.409	0.314
Systematic Error	0.071	0.018	0.041	0.014
Non-systematic Error	0.408	0.314	0.368	0.300
R^2 between simulated (*S*) and observed (*O*) yield	0.782	0.860	0.813	0.861

EδY was used to estimate simulated (*S*) corn yield, which was compared with the observed (*O*) yield.

The statistics of an independent testing of *S* versus *O* corn yield in Jilin province is shown in table 3. Following R^2 and Mean Square Error (MSE) values the best models are 9 and 11, which are based on VHI variables (both weighted and non-weighted). This again emphasizes importance of combining together VCI (calculated from NDVI and estimating moisture conditions) and TCI (calculated from BT and estimating thermal conditions). Although the R^2 for these equations are the same, equation (11) (weighted VHI) has 6% smaller (0.314 versus 0.333) MSE and 28% smaller systematic error (0.014 versus 0.018), which is an important indicator of how good might be model performance. It is important to mention that in 'good' models systematic error should approach zero while non-systematic error should approach MSE (Willmont 1981). In this sense, models 9 and 11 showed the best performance because systematic errors are low, 5 and 4%, respectively. Regarding the models 8 and 10, their systematic errors (0.071 and 0.041) as well as MSE (0.478 and 0.409) are larger (15 and 10%, respectively) compared with models 9 and 11. It should be mentioned again that compared with (8) the model (10), which is based on weighted TCI variables, has 17% smaller MSE and 42% smaller systematic error. Finally, figure 6 displays corn yield time series of observed versus independently simulated corn yield in Jilin province, which showed that except for two years (1984 and 1991) the two time series match quite well.

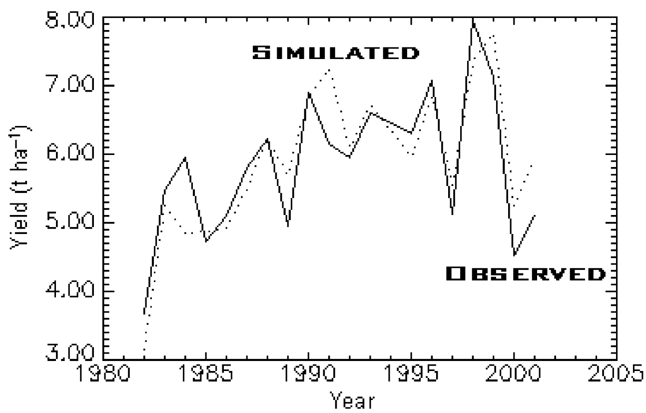

Figure 6. Observed versus independently simulated Jilin province corn yield (t ha^{-1}), China 1982–2001.

6. Conclusions

This globally universal technique for monitoring vegetation health, including drought, from AVHRR data was applied for statistical modelling of corn yield in Jilin province, one of the major producers of corn in China's Main Plains. Correlation and regression analysis relating corn yield deviation from the technological trend (δY) with three vegetation health indices (VCI, TCI and VHI) during 1982–2001 showed strong correlation during the critical period of corn growth, which starts 2–3 weeks before and end 2–3 weeks after corn taselling. These estimates can be carried out well in advance of harvest. From the two indices characterizing moisture (VCI) and thermal (TCI) conditions, the second was found to be more sensitive to corn yield.

Further investigation might include combining satellite sensor data with weather data specifically during winter and early spring when vegetation is still dormant and the application of VCI is limited. The vegetation health indices and data are delivered in real time (every Monday) to http://orbit.nesdis.noaa.gov/smcd/emcb/vci. They show global and regional vegetation health, moisture and thermal conditions, and fire risk potential. They also demonstrate climate issues and utility of vegetation health indices in global observing systems.

References

Chirkov, Y.I., 1969, *Agrometeorological Conditions and Productivity of Corn* (Hydrometiszdat: Leningrad).

Dabrowska-Zielinska, K., Kogan, F., Ciolkosz, K.A., Gruszczynska, M. and Kowalik, W., 2002, Modeling of crop conditions and yield in Poland using AVHRR-based indices. *International Journal of Remote Sensing*, **23**, pp. 1109–1123.

Dlin, A.M., 1958, *Mathematical Statistics in Engineering* (Moscow: Soviet Science).

Domenikiotis, C., Spiliotopoulos, M., Tsiros, V. and Dalezios, N.R., 2004, Early cotton yield assessment by the use of the NOAA/AVHRR derived Vegetation Condition Index (VCI) in Greece. *International Journal of Remote Sensing*, **25**, pp. 2807–2819.

FAO, 2002, Crop production. Available online: http://fao.org (Rome Italy: FAO).

Hou, R. (Ed.), 1990, *Maps of China's Agriculture and the Environment* (Beijing: Zhongguo, Zonghe and Dituji).

Kidwell, K.B., 1997, Global Vegetation Index user's guide. NOAA Technical Report, Department of Commerce, Washington DC.

Kogan, F., 2002, World droughts in the new millennium from AVHRR-based Vegetation Health Indices. *Eos*, **83**, pp. 557–564.

Kogan, F., Gitelson, A., Zakarin, E., Spivak, L. and Lebed, V., 2003, AVHRR-based spectral vegetation indices for quantitative assessment of vegetation state and productivity: calibration and validation. *Photogrammetry Engineering and Remote Sensing*, **69**, pp. 899–906.

Kogan, F.N., 1997, Global drought watch from space. *Bulletin of the American Meteorological Society*, **78**, pp. 621–636.

Liu, W.T. and Kogan, F., 2002, Monitoring Brazilian soybean production using NOAA/AVHRR based vegetation condition indices. *International Journal of Remote Sensing*, **23**, pp. 1161–1179.

Ning, S., 1998, Scientists: water transfer feasibility. *China Daily*, p. 9, 20 July 1998, Beijing.

Snedecor, G.W., 1965, *Statistical Methods* (Ames, Iowa: The Iowa State University).

Unganai, L.S. and Kogan, F.N., 1998, Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. *Remote Sensing of Environment*, **63**, pp. 210–232.

USDA (United States Department of Agriculture), 1994, *Major World Crop Areas and Climate Profile*, Agricultural Handbook, No 664 (Washington, DC: USDA).