

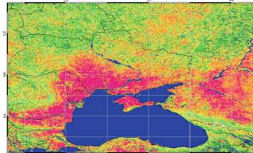
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STRESSED NORMAL FAVORABLE
DROUGHT July 2007
Global Water Board of Operations Study
Stress countries are affected: UKRAINE, RUSSIA, MOLDOVA, ROMANIA and BULGARIA.

Edited by
Felix Kogan, Alfred Powell, and Oleg Fedorov

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Satellite-Based Crop Production Monitoring in Ukraine and Regional Food Security

Felix Kogan, Tatiana Adamenko, and Mikola Kulbida

Abstract Every year weather vagaries have caused shortfalls of agricultural production regionally and every 3–4 years these shortfalls occurred globally. Therefore, early assessment of crop losses in response to weather fluctuations is an important task for the estimation of global, regional and countries food supply/demand, donor's decision to assists the nations in need and to those receiving the assistance. The new satellite-based technology has been recently developed to provide timely and accurate crops' monitoring and assessments. This technology includes the theory, algorithm, data base and operational implementation of vegetation health (VH) assessments from observations provided by the Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA operational polar-orbiting satellites. Several AVHRR-based VH indices were developed and used to provide weekly cumulative estimation of moisture, thermal and health conditions of vegetation canopy throughout the growing season. The indices were calculated for the entire 1981–2010 period of the AVHRR sensor in space and were compared with regional crop yields in the two dozens of countries. Strong correlation between wheat (both winter and spring), corn, soybeans and sorghum yield and VH indices was found during the critical period of the tested crops. The test results showed that VH indices can be used as proxy for early (2–5 months in advance of harvest) assessment of crop yield with the errors of estimation less than 10%. This paper discusses utility of space observations for early forecasting regional crop yield in Ukraine, with specific emphasis on 2–5 months warning of weather-related losses in agricultural production and their impact on agricultural supply/demand and food security.

Keywords Food security • Operational satellites • Vegetation health • Modeling crop losses

F. Kogan (✉)

NOAA, NESDIS, Center for Satellite Application and Research (STAR), Washington DC, USA
e-mail: felix.kogan@noaa.gov

T. Adamenko and M. Kulbida

Ukrainian Hydrometeorological Centre, Kyiv, Ukraine

Introduction

Weather-related crop production assessments, especially losses, have always been a concern for farmers, governments, traders and policy makers for the purpose of balanced food supplies/demands, trade, food aid to the nations in need and food security in general. This is also a very important issue for Ukraine which is a country where agriculture is the major sector of the economy. Every 2–3 years, weather vagaries in Ukraine have caused shortfalls of agricultural production. In some years such as 2003 or 2007, the losses might be staggering. Therefore, assessment of early crop losses in response to weather fluctuations is an important issue for the estimation of global, regional and countries food supply/demand, donor's decision to assist the nations in need and to those receiving the assistance.

Ukraine has the best in the world chernozem soils to produce excellent harvest if the weather is supportive. Unfortunately, Ukraine's misfortune is to be located in a dry climate zone, where annual shortage of water due to lack of precipitation and excessive thermal resources (leading to elevated evapotranspiration) accounts for 200–400 mm. Droughts affect Ukraine every 2–4 years. The largest agricultural losses occur when drought is preceded by a very cold winter with a lack of snow to cover winter wheat crop. Therefore, monitoring weather impacts on agriculture in Ukraine is a very important component for assessment of agricultural production, food supply/demand, potential trade and food security in general.

Weather data are traditionally used in Ukraine for agricultural assessments. One hundred and eighty operational weather stations is a very good source of information about precipitation, temperature, snow and other weather parameters used for the assessments. However, for the 223,000 square miles of Ukrainian territory this number is not sufficient for state and county level analysis since each station covers nearly 1 million acres of land. Therefore, an attempt was made to test the NOAA/NESDIS Vegetation Health (VH) technology which has spatial coverage of every 4 km². This paper discusses application of VH indices for monitoring crops and early assessment of yield in Ukraine.

Satellite Data and Method

Satellite data were retrieved from the NOAA/NESDIS global archive. The observations from the Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA polar-orbiting satellites created the basis for this data set. The AVHRR-based Global Area Coverage (GAC) data set were produced by sampling and mapping the AVHRR 1-km daily reflectance/emission in the visible (VIS, 0.58–0.68 μm), near infrared (NIR, 0.72–1.1 μm), and two infrared bands (IR4, 10.3–11.3 and IR5, 11.5–12.5 μm) to a 4-km map. The daily GAC data were aggregated to 7-day composite saving those pixels, which have the highest (during 7-day period) Normalized difference vegetation index ($NDVI = (NIR - VIS)/(NIR + VIS)$). The 4 km and 7-day VIS and NIR reflectance were pre- and post-launch calibrated and the IR4

counts were converted to brightness temperature (BT), which was corrected for non-linear behavior of the AVHRR sensor (Kidwell 1997).

The 1981–2010 NDVI and BT weekly time series were processed to remove high frequency noise, identify seasonal cycle, calculate climatology and extract medium-to-low frequency variations associated with weather impacts during the growing season. The new method is based on estimation of green canopy stress/no stress from AVHRR-derived indices, characterizing moisture, thermal conditions and total vegetation health (Kogan 1990, 1995, 1997, 2001). Unlike the two spectral channel NDVI-based approach applied for vegetation monitoring, the new numerical method in addition to NDVI, uses also BT from 10.3 to 11.3 μm IR4 channel, which estimate the hotness of the vegetation canopy. In dry years, high temperatures, at the background of insufficient water supply, lead to overheating the canopy, which intensifies negative effects of moisture deficit impact on vegetation. The VH procedure was formalized by equations 1–3, where climatology was represented by the difference between 22-year absolute maximum and minimum both NDVI and BT values for each pixel and week.

$$\text{VCI} = 100 * (\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min}) \quad (1)$$

$$\text{TCI} = 100 * (\text{BT}_{\max} - \text{BT}) / (\text{BT}_{\max} - \text{BT}_{\min}) \quad (2)$$

$$\text{VHI} = a * \text{VCI} + b * \text{TCI} \quad (3)$$

where NDVI, NDVI_{\max} , and NDVI_{\min} (BT, BT_{\max} , and BT_{\min}) are the smoothed weekly NDVI (BT) their multi-year absolute maximum and minimum, respectively; a and $b = 1 - a$ are coefficients quantifying a share of VCI and TCI contribution in the total vegetation health. The VCI (Vegetation Condition Index), TCI (Temperature Condition Index) and VHI (Vegetation Health Index) are indices estimating cumulative moisture, temperature and total vegetation health conditions, respectively on a scale from 0 (extreme stress) to 100 (favorable condition) with 50 corresponding to the average condition.

Results and Discussion

In order to understand if VH carries the information about regional crop production in Ukraine the values of the indices were compared with crop yield. Figure 1 shows 2002–2004 VH for mid-May and also Ukraine's average yield of cereals (winter and spring wheat, barley, oats and corn).

The 2002 and 2004 images taken by NOAA-16 polar-orbiting satellite identified favorable vegetation condition (green) resulted in high yields, 2.75 and 2.84 t/ha, respectively. Opposite to these 2 years, the 2003 indicates a very severe vegetation stress (red color) in the principal agricultural area due to severe drought, which caused 35% losses in cereal yield (1.84 t/ha) versus the years before and after.

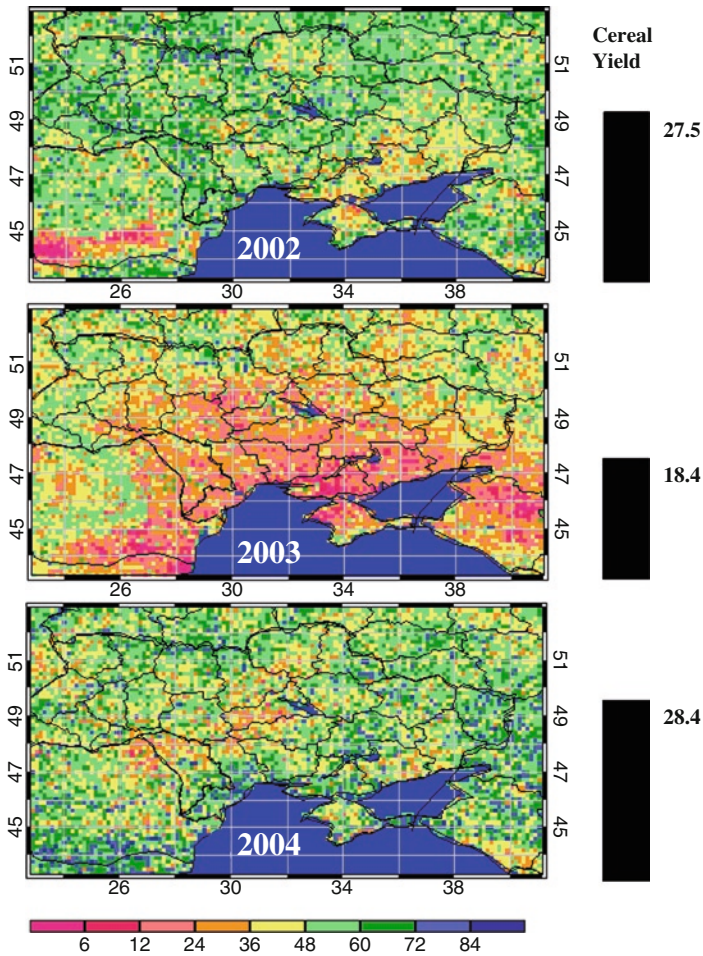


Fig. 1 Mid-May VH and Ukraine's average cereal yield, 2002–2004 (Color figure is in Appendix 2)

Statistical Modeling of Regional Yield

Following these encouraging results, correlation and regression analysis were employed to investigate numerically regional yield dependence on VH. Average winter wheat yield for Odessa oblast during 1980–2006, shown in Fig 2, were collected from Ukrainian Statistical Administration. According to Obuhov (1949), the long-term yield time series are normally separated into two components: technological (TEC), driven by agricultural technology (fertilizers, genetics, plant protection, irrigation etc.) and weather (WETH), controlled by variations in meteorological parameters from year to year. The TEC component is approximated by trend (straight line in Fig. 2) and WETH by deviation from the TEC trend.

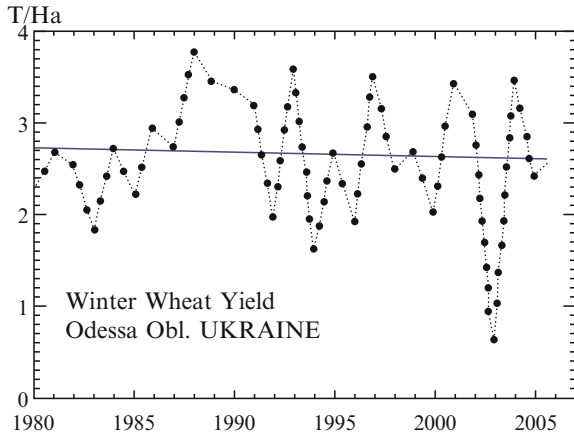


Fig. 2 Winter wheat yield and trend, 1980–2006, Odessa oblast, Ukraine

The equations 4 and 5 represent the approximation procedure, respectively.

$$\hat{Y}_t = a_0 + a_1 Y_t \tag{4}$$

$$dY_t = Y_t / \hat{Y}_t \tag{5}$$

where Y_t is measured yield, \hat{Y}_t is the trend yield – the deterministic component regulated by the agricultural technology, dY is a random component regulated by weather fluctuations and t is year number.

The random component can be approximated by either a difference or ratio of actual and trend (estimated from equation 5) yields. In this paper the ration was used (Obuhov 1949; Salazar et al. 2007).

Figure 3 shows the dynamics of correlation coefficients for the end-of-season winter wheat dY with every week from the first week in January to the last week in June. As seen, (a) during January and February the correlation is close to zero; (b) thereafter, it is increasing; (c) reaches maximum (0.5–0.6) during the critical period (2–3 weeks before and after winter wheat heading (April–May); and (d) drops thereafter, almost to zero at the grain filling and beyond.

Based on the results presented at Fig. 3, VH variables for several weeks of critical period were selected to build regression model. The equation was written as

$$dY = 0.286 - 0.057VH5 + 0.067VH6 - 0.041VH18 + 0.044VH19, \tag{6}$$

where dY is winter wheat yield deviation from trend and VH is vegetation health index for the weeks indicated by the attached number.

This equation indicates that 4 weeks were selected as independent variables: 2 weeks in February reflecting moisture (VCI) contribution and 2 weeks in May reflecting thermal contribution. This equation was validated independently using “Jack-Knife” or “one-in-one-out” techniques. Following this technique (a) each year

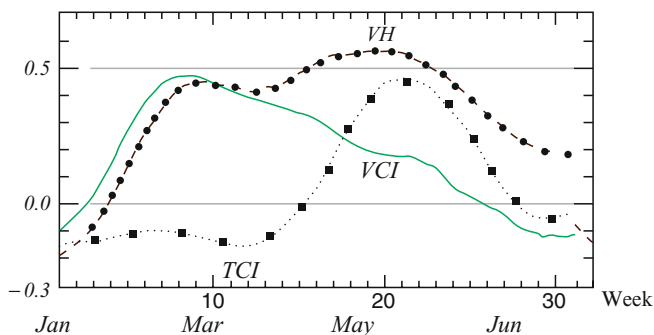


Fig. 3 Correlation dynamics of winter wheat dY versus VH indices (VCI, TCI and VHI)

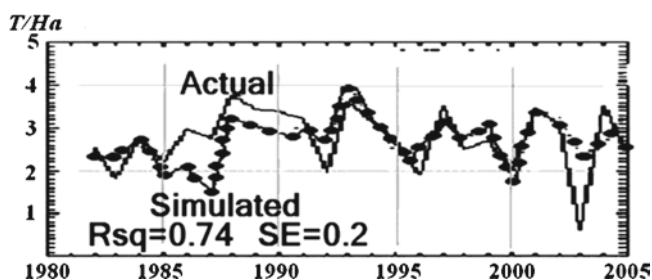


Fig. 4 VH-simulated and actual winter wheat yield, Odessa oblast, Ukraine

yield data are removed from the time series one by one, (b) new model is developed without removed year and (c) the model is applied to the removed year. This procedure is repeated until all years were independently tested. Comparison of measured and independently simulated winter wheat yield are shown in Fig. 4. The two time series are well correlated ($R = 0.86$) with the error of estimation 0.2 t/ha.

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