International Journal of Applied Earth Observation and Geoinformation 28 (2014) 181–192

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Estimating soil moisture and the relationship with crop yield using surface temperature and vegetation index

M.E. Holzman[a,*], R. Rivas[a,b], M.C. Piccolo[c]

[a] Consejo Nacional de Investigaciones Científicas y Técnicas – Instituto de Hidrología de Llanuras "Dr. Eduardo J. Usunoff", República de Italia 780, B7300 Azul, Buenos Aires, Argentina
[b] Comisión de Investigaciones Científicas de la provincia de Buenos Aires, Argentina
[c] Departamento de Geografía y Turismo, Universidad Nacional del Sur, Bahía Blanca, Argentina

ARTICLE INFO

Article history:
Received 5 September 2013
Accepted 11 December 2013

Keywords:
Soil moisture
MODIS
Optical-thermal
Crop yield forecasting
Remote sensing

ABSTRACT

Soil moisture availability affects rainfed crop yield. Therefore, the development of methods for pre-harvest yield prediction is essential for the food security. A study was carried out to estimate regional crop yield using the Temperature Vegetation Dryness Index (TVDI). Triangular scatters from land surface temperature (LST) and enhanced vegetation index (EVI) space from MODIS (Moderate Resolution Imaging Spectroradiometer) were utilized to obtain TVDI and to estimate soil moisture availability. Then soybean and wheat crops yield was estimated on four agro-climatic zones of Argentine Pampas. TVDI showed a strong correlation with soil moisture measurements, with R^2 values ranged from 0.61 to 0.83 and also it was in agreement with spatial pattern of soil moisture. Moreover, results showed that TVDI data can be used effectively to predict crop yield on the Argentine Pampas. Depending on the agro-climatic zone, R^2 values ranged from 0.68 to 0.79 for soybean crop and 0.76 to 0.81 for wheat. The RMSE values were 366 and 380 kg ha^{-1} for soybean and they varied between 300 and 550 kg ha^{-1} in the case of wheat crop. When expressed as percentages of actual yield, the RMSE values ranged from 12% to 13% for soybean and 14% to 22% for wheat. The bias values indicated that the obtained models underestimated soybean and wheat yield. Accurate crop grain yield forecast using the developed regression models was achieved one to three months before harvest. In many cases the results were better than others obtained using only a vegetation index, showing the aptitude of surface temperature and vegetation index combination to reflect the crop water condition. Finally, the analysis of a wide range of soil moisture availability allowed us to develop a generalized model of crop yield and dryness index relationship which could be applicable in other regions and crops at regional scale.

1. Introduction

With the increase in global food and energy demand, the monitoring of crop yield is essential for the food security. Argentina is one of the six most important producers of wheat, maize and soybean (UNDP, 2009). However, like in several countries, the main cause of instability in crop yield is the dependency on soil moisture variability, as the crops grow without irrigation. Since these crops play a considerable role in global food security, their pre-harvest yield prediction is fundamental for supporting export-import policies.

Despite the importance of soil moisture for crop yield, reliable determination of this variable at regional scales through conventional point measurements is complex. Generally, these methods are expensive and available at a limited number of stations. Moreover, high uncertainties may exist because many factors affect the spatial variability of soil moisture (e.g. changes in topography, types of soil and depth of water table). Thus, the applicability at regional scales is limited (Crow et al., 2005; Grayson and Western, 1998). In this context, it is fundamental to develop independent methods of ancillary data for soil moisture assessment and the impact on crop yield.

In the last decades several satellite-based techniques have been developed for soil moisture sensing (Batlivala and Ulaby, 1977; Chauhan et al., 2003; Du et al., 2000; Dubois et al., 1995; Jackson et al., 1977, 1996; Moran et al., 1994; Sandholt et al., 2002; Wang and Qu, 2009). These are based on information of optical-thermal and microwave bands of the electromagnetic spectrum. Microwave sensors have the capability to monitor the surface under all-weather conditions, while optical-thermal sensors can sense only in clear skies. The main disadvantage of passive microwave sensors is the coarse spatial resolution (25–40 km), so they can be used only to estimate large-area soil moisture. This limitation has been overcome partially with active microwave sensors, which have better spatial resolution (10–30 m), although with repeat intervals

* Corresponding author. Tel.: +54 2281432666.
E-mail address: mauroh@faa.unicen.edu.ar (M.E. Holzman).

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http://dx.doi.org/10.1016/j.jag.2013.12.006

between 15 and 25 days (Mallick et al., 2009). On the other hand, microwave sensors can monitor only near-surface soil moisture (0–10 cm) (Eagleman and Li, 1976; Jackson et al., 1982; Shutko, 1982). This is an important variable that influences the interactions between the land surface and atmospheric process (Brubaker and Entekhabi, 1996), but it is not decisive for the process determining the crop yield, as vegetation can extract deeper soil moisture. Even though information of diverse bands of electromagnetic spectrum can be combined, efforts should be made in optical-thermal infrared bands since they have an adequate spatial and temporal resolution for monitoring soil moisture and crop condition.

In this sense, several authors have analyzed canopy water stress based only on thermal infrared band data (Boulet et al., 2007; Nemani et al., 1993; Carlson et al., 1995; Sandholt et al., 2002). A direct relationship between soil moisture and land surface temperature (LST) is not evident, as LST shows sensitivity differently for vegetation and for soil below it. However, soil moisture content is an essential factor that affects the LST (Mallick et al., 2009; Sandholt et al., 2002). These concepts were originally proposed by Jackson et al. (1977, 1981) and Jackson (1982) who defined the crop water stress index (CWSI), which is based on the difference between canopy and air temperature as a function of vapor pressure deficit. About this index, Moran (2004) has shown that it would be applicable only over full vegetated areas where sensed temperature is equal to the temperature of the vegetation.

On the other hand, different authors (e.g., Carlson et al., 1994; Goetz, 1997; Han et al., 2010; Mallick et al., 2009; Moran et al., 1994; Nemani and Running, 1997; Sandholt et al., 2002) have examined the capability of capturing information about surface water and energy availability combining satellite data of land surface temperature (LST) and vegetation indices (VI). LST and vegetation condition largely depend on water availability. Soil moisture controls the partitioning of energy between latent (evapotranspiration) and sensible heat fluxes (Monteith, 1981). The lower latent flux, the more energy available for sensible heating of the surface. In addition, plants can exert physiological control over the stomatal resistance to transpiration according to the soil moisture availability. Thus, LST increases in early stages of water stress process (Goetz, 1997). In advanced stages of water stress, root zone soil moisture is minimal and the photosynthetic systems (e.g. pigments content) are affected, decreasing the VI. Thereby, short and long-term variations of soil moisture and the impact on vegetation condition could be monitored through stress indices combining LST, visible and NIR information. One of them is the Temperature Vegetation Dryness Index (TVDI), based on a parameterization of the relationship between LST and a vegetation index (Sandholt et al., 2002), being calculated from satellite imagery without ancillary data and can be applicable over partially vegetated surfaces.

Earlier works have analyzed the relationship between TVDI and soil moisture. Sandholt et al. (2002) showed that TVDI from NOAA-AVHRR (Advanced Very High Resolution Radiometer) can reflect the spatial variation of simulated soil moisture at landscape scale in a semiarid area of Senegal. Patel et al. (2009) estimated soil moisture in a sub-humid area of India with TVDI from 8 day MODIS (Moderate Resolution Imaging Spectroradiometer) reflectance and surface temperature products. Mallick et al. (2009) estimated near-surface soil moisture (0–5 cm) in India through the soil wetness index (SWI), an index similar to TVDI. Using data from ASTER (Advanced Space borne Thermal Emission and Reflection Radiometer) for field scale and MODIS AQUA for landscape scale, they found better results at landscape scale than in field scale as ASTER fails to capture the wide range of surface soil wetness and vegetation cover required in this method. Han et al. (2010) estimated surface soil moisture in China with MODIS TERRA data products of 16-day composite NDVI and 8-day composite LST. These authors found a strong correlation between TVDI and relative soil moisture, with $R^2 = 0.76$. Chen et al. (2011) also reported a strong relationship between TVDI, rainfall data, phenological development and surface soil moisture (10–20 cm) in China. In Argentina, Holzman and Rivas (2011) reported that TVDI is suitable to reflect the spatial and temporal variability of soil moisture in Argentine Pampas at regional scale.

About crop yield estimation, plants condition and forecast yield have been extensively analyzed in many countries through the traditional Normalized Difference Vegetation Index (NDVI) (Boken and Shaykewich, 2002; Doraiswamy and Cook, 1995; Mkhabela et al., 2005, 2011; Moriondo et al., 2007; Quarmby et al., 1993). These studies are based on that photosynthetic capacity of vegetation, spectrally estimated through these indices, is directly related to crop yield. Most of these works have reported linear correlation between NDVI and crop yield. Mahey et al. (1993) reported that NDVI during maximum vegetation cover stage is linear and closely related to wheat yield. Baez-Gonzalez et al. (2002), through NOAA-AVHRR, determined that yield of maize can be estimated in Mexico 1–2 months before harvest. Also Unganai and Kogan (1998) had found that NDVI from NOAA-AVHRR correlated significantly with maize yield in Zimbabwe during the grain filling stage. Prasad et al. (2006) estimated crop yield in United States with rainfall, NDVI, surface temperature and soil moisture data and reported $R^2 = 0.78$ for corn and $R^2 = 0.86$ for soybean crops. In spite of the extensive use of NDVI, this index can saturate at Leaf Area Index values between 2 and 6 (Carlson and Ripley, 1997; Wang et al., 2005), with limitations for monitoring vigorous vegetation. Moreover, vegetation indices are conservative indicators of vegetation condition, as vegetation remains in good conditions after initial water shortages (Gillies and Carlson, 1995).

In spite of numerous works about surface soil moisture estimation through TVDI, the relationship with crop yield has yet to be examined. Therefore, the main objective of this work was to evaluate the ability to estimate regional crop yield using the TVDI. Furthermore, there were two specific objectives. The first was to validate the relationship between surface soil moisture and TVDI and finally to assess the level of precision that could be expected from this method to estimate crop yield.

2. Temperature Vegetation Dryness Index

2.1. Theory

The LST mainly depends on soil moisture and fractional vegetation cover. In bare soil and vegetated surfaces, soil moisture determines surface temperature through evaporative control, thermal inertia and the amount of energy involved in the evapotranspiration process (Mallick et al., 2009), with differences in radiative temperature between soil and canopy. Thus, combination of fractional vegetation viewed for the sensor through VI and LST allows the estimation of soil water availability from bare soil to full vegetated surfaces.

Typically, there is a strong negative relationship between LST and VI (Gillies et al., 1997). With increasing VI, the soil signal becomes increasingly masked by vegetation, with decreases in temperature. On the other hand, with high soil moisture availability LST decreases becoming similar on both bare soil and vegetation (Nemani et al., 1993). Thus, several authors (Carlson et al., 1994; Han et al., 2010; Price, 1990; Sandholt et al., 2002; Stisen et al., 2008; Wang et al., 2006) have proven that if a wide range of fractional vegetation cover and soil moisture contents are represented in the data, the scatterplot of LST and VI frequently shows a triangular shape. Some studies have interpreted this triangular space from the energy balance concept (e.g. Mallick et al., 2009), other considering different inter-related aspects (e.g. Sandholt et al., 2002).