Potential of using satellite based vegetation indices and biophysical variables for the assessment of the water footprint of crops

Conference Paper *in* Proceedings of SPIE - The International Society for Optical Engineering · September 2014

DOI: 10.1117/12.2066392

Potential of using satellite based vegetation indices and biophysical variables for the assessment of the water footprint of crops

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ABSTRACT

Satellite remote sensing techniques play an important role in crop identification, acreage and production estimation, disease and stress detection, and soil and water resources characterization because they provide spatially explicit information and access to remote locations. The main objective of the study is to highlight the potential of using remote sensing techniques in the research field of water management, especially for "water footprint" assessment. In this paper, several vegetation indices (NDVI, NDWI, etc) and biophysical variables (LAI, fAPAR) are key variables to potentially be estimated by remote sensing and used in water footprint studies. The combination of these input parameters brings several limitations regarding the discrepancies in temporal and spatial resolution and data availability, which are described and discussed in detail. MODIS, Landsat, SPOT Vegetation and Meteosat data were used in order to estimate evapotranspiration and vegetation indices. The results of this study show the usefulness of satellite data for water footprint assessment and were obtained by the Remote Sensing Working Group in the framework of the ESSEM COST Action ES1106, "Assessment of EUROpean AGRIculture WATer use and trade under climate change" (EURO-AGRIWAT).

Keywords: satellite, water footprint, evapotranspiration, vegetation indices, NDVI, NDWI, LAI

1. INTRODUCTION

Among the challenges Europe is facing at the beginning of the third millennium, the reduction of the water resources, their degrading quality and the occurrence of ever more severe and frequent droughts are of critical importance. Causes the complex, some pertaining to the climate change, especially as regards southern Europe, where the trend has already been noticed for diminished precipitation, which leads to diminished accumulated water resources. Experiments carried-out with climatic models have shown that this situation will worsen in future. In southern and south-eastern Europe the precipitation deficit will keep enhancing, in step with the global warming. For the summer time models predict drought-connected hardships in Central Europe and ever more intense and more frequent droughts as the global warming process continues. However, there is also the issue of managing the water resources. Practically, water resources are used to an ever greater extent for development in agriculture and industry and for public consumption. The general development of the society as a whole has not taken into account the sustainability side of the issue, so that preoccupations to use the water with a high efficiency have never been as important as they are today. When the "development" issue was at stake, more and more water was used, without trying to render its use efficient and without seeking for those solutions that could lead to its sustainable use. Reaching the objectives of a sustainable development largely depends on the integrated management of water resources, since water is an essential factor to the existence of life and the development of human society. The water resources integrated management concept merges the issues of using the water with those of protecting the natural ecosystems through integrating the water uses at basin level. In contrast to the traditional approach of the water resources, this concept assumes an integrated approach of the resources, both at the technical and physical

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Second International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2014),
edited by Diofantos G. Hadjimitsis, Kyriacos Themistocleous, Silas Michaelides, Giorgos Papadavid,
Proc. of SPIE Vol. 9229, 92290K · © 2014 SPIE · CCC code: 0277-786X/14/$18 · doi: 10.1117/12.2066392

level and at the management and planning one. The integration level is the hydrographic basin, the natural unit where water resources are formed. The integrated management of the water resources promotes the development and coordination of the water, the land and their resources, in view to optimize balanced social and economic development, without compromising the sustainability of the ecosystems. The achievement of EU water policy goals is challenging due to, inter alia, a number of old and emerging water management issues. Pollution of water resources, degradation of hydro-morphology, over-abstraction, decline in soil organic matter are still occurring and have detrimental impacts on freshwater ecosystems and on economic activity, in particular through the nexus between water, food and energy production. Demographic evolution, land use change and economic development are projected to increase pollution and water shortages. This is expected to be exacerbated by climate change, particularly in the Mediterranean region, while increasing the intensity and frequency of floods in many parts of Europe. All this makes it increasingly difficult to achieve the Water Frame Directive objective of good water status for all EU waters by 2015. Climate change predictions point to a warmer world within the next 50 years, yet the impact of rising temperatures on rainfall distribution patterns in much of the world remains far less certain. Agriculture is currently accountable for 85% of the global water consumption, and irrigated areas are expected to raise by a factor of 1.9 by 2050, globally in the highest percentages where water-scarcity is most intense, namely South Europe Countries [10].

In this context the concept of “Water Footprint” (WF) was introduced by Hoekstra in 2003 as an indicator of water use which relates human consumption with global water resources. The concept was improved and computing methods were established through several publications from two lead authors A.K. Chapagain and A.Y. Hoekstra. One of the most important studies about how to estimate water footprints are a 2004 report on the "Water footprint of nations" from UNESCO-IHE Institute of Water Education[5], the 2008 book Globalization of Water[20] and the 2011 manual “The water footprint assessment manual: Setting the global standard”[18].

Remote sensing techniques are an important tool for applications in various fields such as agriculture, meteorology, hydrology, land cover dynamics, geology or global climate studies. These techniques allow examining the properties and processes of ecosystems and their inter-annual variability at multiple scales because remote sensing observations can be obtained over large areas of interest almost every day.

The main objective of present study is to discuss and analyze the potential use of remote sensing techniques in the field of water footprint studies, in order to improve the understanding and estimation of water footprint.

2. WATER FOOTPRINT CONCEPT

According to the exiting studies, WFs and virtual water have been estimated for crops, goods, services and on generic levels [4, 21, 22, 27, 32, and 43].

The WF of a product is defined as the s the volume of freshwater used to produce the product along the supply chain of a product [19]. A WF has three components: blue, green, and grey. The blue WF is defined as the volume of freshwater that evaporated from the global blue water resources (surface water and ground water) to produce the goods and services consumed by the individual or community. The green water footprint represents the volume of water evaporated from the global green water resources (rainwater stored in the soil as soil moisture). The grey WF means the volume of polluted water that associates with the production of all goods and services for the individual or community that can be estimated as the volume of water that is required to dilute pollutants to such an extent that the quality of the water remains at or above water quality standards[4].

2.1 Water footprint of crops – State of the art

According to Romaguera et al. [39], the blue WF for crops assumes irrigation water usage and green WF is the rain water usage. In the case of irrigation, a part from the water withdrawn from surface or groundwater system is evaporated from the point of withdrawal and the field. Another part infiltrates and returns to the water source, can be reused. Another part reaches the field and a part turns into drainage flow, can be reused too. Blue WF refers to the amount of evaporation from the storage reservoirs, transport channels and evapotranspiration from the field.

The main input parameters for WF (blue and green) estimation are: crop evapotranspiration (reference/actual), area and volume of irrigation, water storage (soil moisture, ground water), runoff, crop characteristics (crop type, crop health, cropping intensity, etc), climatic data (radiation, precipitation and temperature), crop production data (crop yield).

The total water footprint of the process of growing crops can be calculated according to the following equation (1) [18]:

$$WF_{crop} = WF_{crop,green} + WF_{crop,blue} + WF_{crop,grey} \tag{1}$$

In the Ec. 1, the green component ($WF_{crop,\ green}$ - m^3/ton) is calculated dividing the green component of crop water use (CWU_{green} – m^3/ha) by the crop yield (Y – ton/ha) (2). The blue component ($WF_{crop,\ blue}$ - m^3/ton) is estimated similarly (3).

$$WF_{crop,green} = \frac{CWU_{green}}{Y} \qquad \left[\frac{volume}{mass}\right] \tag{2}$$

$$WF_{crop,blue} = \frac{CWU_{blue}}{Y} \qquad \left[\frac{volume}{mass}\right] \tag{3}$$

The grey component is calculate as the ratio the chemical application rate to the field per hectare (AR, kg/ha) times the leaching-run-off fraction (α) divided by the maximum acceptable concentration (c_{max}, kg/m^3) minus the natural concentration for the pollutant considered (c_{nat}, kg/m^3) the crop yield (Y, ton/ha) (4).

$$WF_{crop,grey} = \frac{(\alpha \times AR)/(c_{max} - c_{nat})}{Y} \qquad \left[\frac{volume}{mass}\right] \tag{4}$$

In the last years, several studies are focused on water footprint estimation for crops. In their study, Hoekstra and Hung[22] have been estimated the amount of water needed to produce crops in different countries of the world, to quantify the volume of virtual water flows between nations during 1995–1999, and to analyze national virtual water balances related to national water needs and water availability. Data on crop water requirements for different crop types were calculated using CropWat model available from FAO (Food and Agriculture Organization). The CROPWAT model uses Penman–Monteith equation for calculating reference crop evapotranspiration. It assumes that crops are planted under optimum soil water conditions, disease-free, well-fertilized, and grown in large fields with 100% coverage, having a single cropping pattern. The climatic data used as input in CROPWAT model was extracted from FAO's climatic database ClimWat and data referring on crop yields, from FAOSTAT database.

Many studies focused on water footprint estimation for crops was made coarse spatial resolution (global, continental or at country level). In recent years many researches try to assess global water consumption in agriculture at high spatial resolution. Crop production requires a high consumption of green and blue water. Siebert and Doell[43, 44] developed a new global crop water model (GCWM) to compute consumptive water use (evapotranspiration) and virtual water content (evapotranspiration / harvested biomass) of crops at a spatial resolution of 5 arc minutes by 5 arc minutes for 26 different crops, for the 1998-2002 period. GCWM is based on soil water balances performed for each crop and each grid cell, according to Allen et al. [1]. Growing areas of 26 crop classes and related cropping periods were derived from the MIRCA2000 data set [37]. Climate data were derived from the Climate Research Unit (CRU) of the University of East Anglia dataset [33] and crop coefficients according to Allen et al.[1]

Liu et al. [26, 27] have been estimated both the blue and green water components of consumptive water use (CWU) for 17 agricultural crops, during 1998-2002, with a spatial resolution of 30 arc min on the land surface. They have been quantified CWU in food production and investigated CWU-virtual water trade relations. To simulate crop yield, total evaporation (E), and crop water productivity (CWP) for each crop in each grid cell at the mentioned spatial resolution covering the entire world Liu et al. used GEPIC model (is a GIS-based EPIC model designed to simulate the spatial and temporal dynamics of the major processes of the soil crop-atmosphere-management system[28-30]. Two sources of data was used for harvested area: the center for sustainability and the global environment (SAGE) of the University of Wisconsin at Madison, USA [38] and Institute of Physical Geography of the University of Frankfurt (Main), Germany (MIRCA2000). Climate data (maximum temperature, minimum temperature, precipitation and number of wet days) were derived from the Climate Research Unit of the University of East Anglia (CRU)[33].

Recent developments in global hydrological models containing both physically based hydrological and anthropogenic activity modules allow us to simulate the virtual water content for major crops. Hanasaki et al. [16] used the global hydrological model H08 to assess the two major sources of virtual water: green and blue water, for the period 1985-1999, at a spatial resolution of 0.5° × 0.5° (longitude and latitude). They have been used H08 model for five crops and three livestock products. Mekonnen and Hoekstra [32] have been quantified the green, blue and grey water footprint of global crop production in a spatially-explicit way for the period 1996–2005. This study improves previous research because the evaluation of the three components of WF was made at 5 by 5 arc minute spatial resolution for 126 crops and for the period 1996-2005. The model is based on the daily soil water balance and climatic conditions for each grid cell. The grid-based dynamic water balance model used in this approach computes daily soil water balance and calculates crop water requirements, actual crop water use (both green and blue) and actual yields, for 126 primary crops. For another 20 crops which are grown only in a few countries, the CROPWAT model was used. Several sources of data were used: crop planting dates and intervals for cropping seasons were obtained from FAO[9], Sacks et al.[42], Portmann et al.[37] and USDA[46] , monthly long-term average reference evapotranspiration data from FAO[8] , crop coefficients (K_c) was obtained from Chapagain and Hoekstra[4] , total available water capacity of the soil from ISRIC-WISE, yield data (for the period 1996–2005) obtained from FAO[7].

As it can be observed, all the above mentioned approaches are based on the concept of evapotranspiration to estimate the blue, green and/or gray water use. The results are at different spatial resolutions, namely country scale, 5 or 30 arc minutes and various data sources are considered in the methods, such as climatic databases and crop-related maps at different spatial and temporal resolutions¸ national statistics, and reports, covering different period of time. Several limitations arising from these researches: (1) existing of different spatial resolution of input data, mainly extracted from various statistical databases; (2) temporal resolution differs from one set of source data to another, interpolation techniques being necessary to estimate different input parameters; (3) the algorithms used in such kind of studies need assumption of ideal conditions, such as optimum soil water conditions without any effective rainfall during their life or crop coefficients used by water balance models are selected depending on the single crop coefficient approach; (4) the outputs are given for a certain interval of time.

Remote sensing techniques can improved the WF estimation providing global coverage, various temporal and spatial resolution of information. Even having its limitations, remote sensing techniques are an important tool for actual evapotranspiration retrieval, to quantify precipitation and surface runoff estimation, to quantify water storage or land use mapping.

2.2 Water footprint from remote sensing

Irrigation mapping is important information in blue and green WF estimation. In the last decade many studies were focused on the problem of global irrigation mapping, considering national statistical data as input or taking into account spectral and temporal remote sensing information for classification. A detailed review over the methods and results of existing remote sensing studies regarding using satellite data in irrigated agriculture was made by Ozdogan et al.[35]. They have been evaluated the ability of remote sensing to provide synoptic and timely coverage of irrigated lands in several spectral regions and grouped the existing studies based on location, scale, inputs, and methods in order to classify different approaches within a logical framework (Tabel 2). Their review identifies passive and active microwave observations (Tabel 1), advanced image classification methods, and data fusion including optical and radar sensors or with information from sources with multiple spatial and temporal characteristics as key areas where additional research is necessary.

Tabel 1. Current operational optical sensors and their technical/logistical capacities for irrigation mapping [35]

Satellite observation system/ program	Technical observation challenges solved	Access to information/ data worldwide	Continuous observation program with global coverage	Preprocessed datasets accessible	Image data cost	Technical difficulty required to produce maps	Frequency of use in irrigation studies
RapidEYE	yes	no	yes	yes	high	medium	low
Landsat	yes	yes	yes	yes	low	medium	high
SPOT	yes	yes	yes	yes	high	medium	medium
AWiFS	yes	no	no	yes	high	medium	low
LISS	yes	no	no	yes	high	medium	low
ASTER	yes	yes	no	yes	low	medium	low

CBERS	no	no	no	no	low	medium	low
THEOS	yes	no	no	yes	mediu	medium	low
MODIS	yes	yes	yes	yes	low	high	medium
MERIS	yes	yes	yes	yes	low	high	low
AVHRR	yes	yes	yes	yes	low	high	medium
SPOT VEG.	yes	no/yes	yes	maybe	low	medium	low

Tabel 2. Summary of spatial scales, sensors, methods, and example applications[35]

Spatial scale	Sensors used	Method of mapping
local	Landsat TM/ETM+, SPOT, LISS, ASTER, AWiFS, CBERS, THEOS	Photo interpretation, Image arithmetic, Image classification, segmentation, image fusion
regional	Landsat TM/ETM+,MODIS, MERIS, AVHRR, SPOT VGT	Times-series analysis, Supervised/unsupervised classification, masking
continental	Landsat TM/ETM+, MODIS, MERIS, AVHRR, SPOT VGT	Times-series analysis with other ancillary data, data fusion
global	MODIS, MERIS, AVHRR, SPOT VGT	Unsupervised clustering, machine learning algorithms applied to timeseries data, also employ other ancillary data(statistic, ground truth data…)

A global Irrigated Area Map (GIAM) was developed by Thenkabail et al.[45] consisting in 28 classes with 10 km spatial resolution, for the year 1999. The algorithm is based on classification and identification techniques to establish different classes of irrigated areas and to differentiate irrigated areas from non-irrigated areas. As input data was used temporal series for reflectance values, brightness temperatures and Normalized Difference Vegetation Index (NDVI) obtained from the Advanced Very High Resolution Radiometer (AVHRR). NDVI was also obtained from Système Pour l'Observation de la Terre Vegetation (SPOT VGT). Precipitations were provided by the Japanese Earth Resources Satellite-1 Synthetic Aperture Radar (JERS-1 SAR). Landsat Enhanced Thematic Mapper Plus (ETM+) mosaics were used as background for the classification process. The resulting map differs from another GIAM developed by Siebert et al.[41] . The method used by Siebert at al. combined sub-national statistical data with land cover information to produce output at a grid resolution (5 arc minutes spatial resolution). They used data from several sources as FAO reports, United Nations, World Bank, Ministries of Agriculture, irrigation associations, printed maps, digital datasets and the land cover data set of the United States Geological Survey (USGS) for the year 2000.

Romaguera et al. [39] have been proposed an innovative approach to retrieve actual irrigation on a global scale, using, as input parameters, water cycle components (evapotranspiration, precipitation, and surface runoff and water storage) estimated from remote sensing techniques. The volume of irrigation was calculated using a mass water balance model. Green and blue WF was obtained from the green and blue evapotranspiration components. Evapotranspiration was estimated from data provided by Meteosat, while precipitation estimates obtained with the Climatic Prediction Center Morphing Technique (CMORPH). They used Earth Observation data to estimate precipitation, evapotranspiration, surface runoff and water storage (Figure 1).

Precipitation was obtained from different sources: Climatic Prediction Center (CPC) Morphing Technique (CMORPH), which produces global precipitation estimates at every 30 minutes with 8 km resolution at the equator, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) system that uses neural network techniques to estimate rainfall rate at six hourly intervals for each 0.25° × 0.25° pixel (cca. 30 km at the equator) of the infrared brightness temperature image provided by geostationary satellites, and from Meteosat satellite. Evapotranspiration was obtained from from the Land Surface Analysis-Satellite Applications Facility (LSA-SAF) at a temporal resolution of 30 minutes, for the disk of Meteosat Second Generation (MSG) satellites. Global data on water storage were obtained from the satellite GRACE (Gravity Recovery and Climate Experiment) at a resolution of 400 km on a monthly basis, while global data on runoff were provided by the Global Land Data Assimilation System (GLDAS).

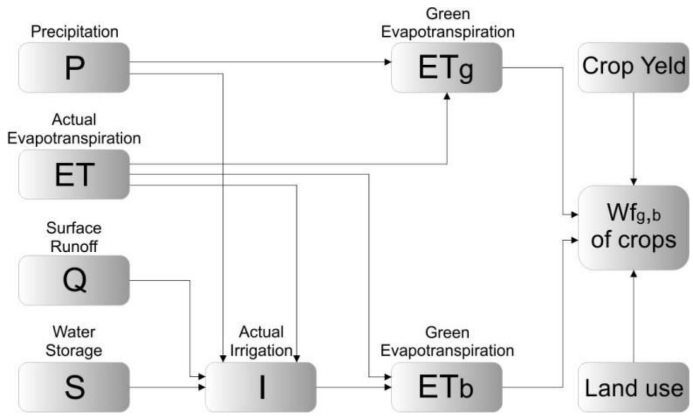


Figure 1. Flowchart proposed for obtaining WF of crops from remote sensing data. (After Romaguera et al. 2010)

As it can be observed most studies use as input several remote sensing data like evapotranspiration, precipitation, surface runoff, water storage, temperature, land cover/land use maps, etc.

In the following section will be discuss the usefulness of vegetation and biophysical parameters obtained from remote sensing data that are directly related to various input parameters used for WF estimation.

3. BIOPHYSICAL PARAMETERS AND VEGETATION INDICES FOR WATER FOOTPRINT ESTIMATION

The potential of remote sensing in agriculture is very high because multispectral reflectance and temperatures of the crop canopies are related to two important physiological processes: photosynthesis and evapotranspiration.

3.1. Vegetation Indices

Spectral vegetation indices (VI) are among the most commonly used satellite data products for the evaluation, monitoring, and measurement of vegetation cover, condition, biophysical processes, and change. The quantitative description of water, energy fluxes between the land surface and the atmosphere have an important role in current hydrological and climate research studies, especially at large spatial scales. Vegetation Indices (VIs) are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. Some vegetation indices are able to detect the presence and relative abundance of pigments, water, and carbon as expressed in the solar-reflected optical spectrum (400 nm to 2500 nm). Each category of indices typically provides multiple techniques to estimate the absence or presence of a single vegetation property. For different properties and field conditions, some indices within a category provide results with higher validity than others. In order to monitor the vegetation statement, the medium and high resolution satellite images can be used to obtain the dedicated vegetation indexes, which are good indicators of drought and they are used also by the scientific community (European Drought Observatory). The most important VIs for vegetation monitoring include the "broadband greenness" category (e.g.: Normalized Difference Vegetation Index - NDVI, Soil Adjusted Vegetative Index - SAVI, Ratio Vegetative Index - RVI, Enhanced Vegetation Index - EVI, Atmospherically Resistant Vegetation Index, Perpendicular Vegetative Index , Difference Vegetative Index, Modified Soil Vegetation Index - MSAVI, Weighted Difference Vegetative Index - WDVI) and the "canopy water content" category (e.g.: Normalized Difference Water Index - NDWI, Normalized Moisture Index - NMI, Normalized Difference Drought Index - NDDI)[14] .

3.1.1. Normalized Difference Vegetation Index - NDVI

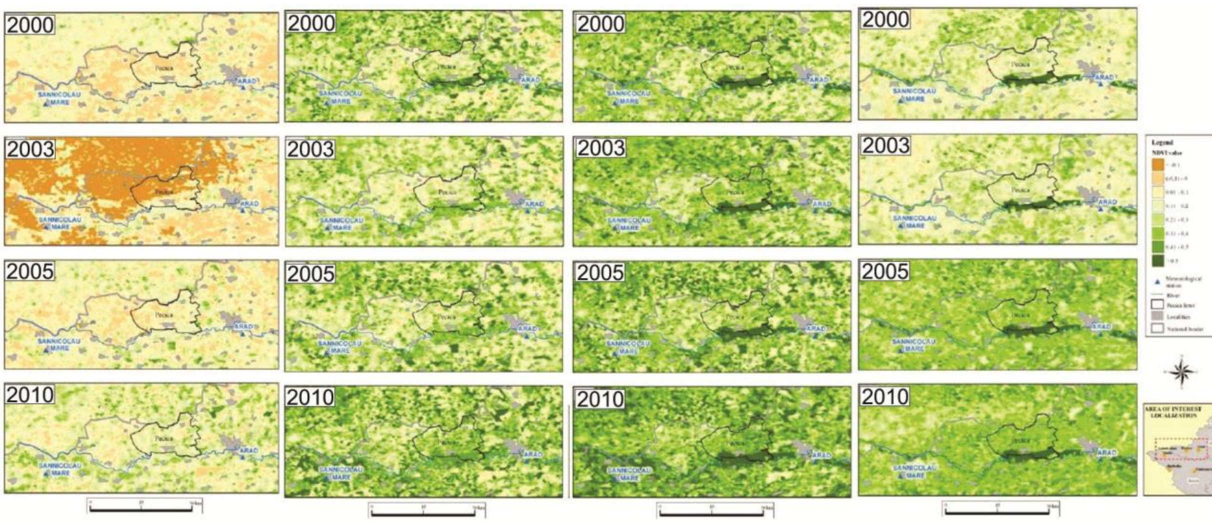
NDVI is a numerical indicator used for a wide application in vegetative studies as crop yield estimation, precision agriculture, drought monitoring, etc. being a measure of the amount and vigor of vegetation. It can be calculated according to the equation (5).

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (5)$$

ρ_{NIR} and ρ_{RED} are the reflectance in near infrared spectral band and red band, respectively.

NDVI varies between -1 to 1, negative values indicating clouds and water, positive values near zero indicating bare soil. Higher positive values of NDVI range from sparse vegetation (0.1 - 0.5) to dense green vegetation (0.6 and above). Several studies proved that NDVI is directly related to other important ground parameters like percent of ground cover, photosynthetic activity of the plant, surface water, leaf area index and the amount of biomass estimation. It was used for the first time in 1973 by Rouse et al. [40]. Indirectly, NDVI has been used to estimate the cumulative effective of rainfall on vegetation over a certain time period, rangeland carrying capacity, crop yields for different crop types, and the quality of the environment as habitat for various animals, pests and diseases. The NDVI observation data in operational or pre-operational programs increased in the last years. The information provided by different platforms is used for monitoring the environment, global change studies, management of productions (agriculture, forestry, etc The main missions are to describe spatial and temporal distribution of radiative properties, monitor productions (agriculture, forestry, grasslands, etc) and understand and modulate functioning of ecosystems, their interactions with the atmosphere and with human activities.

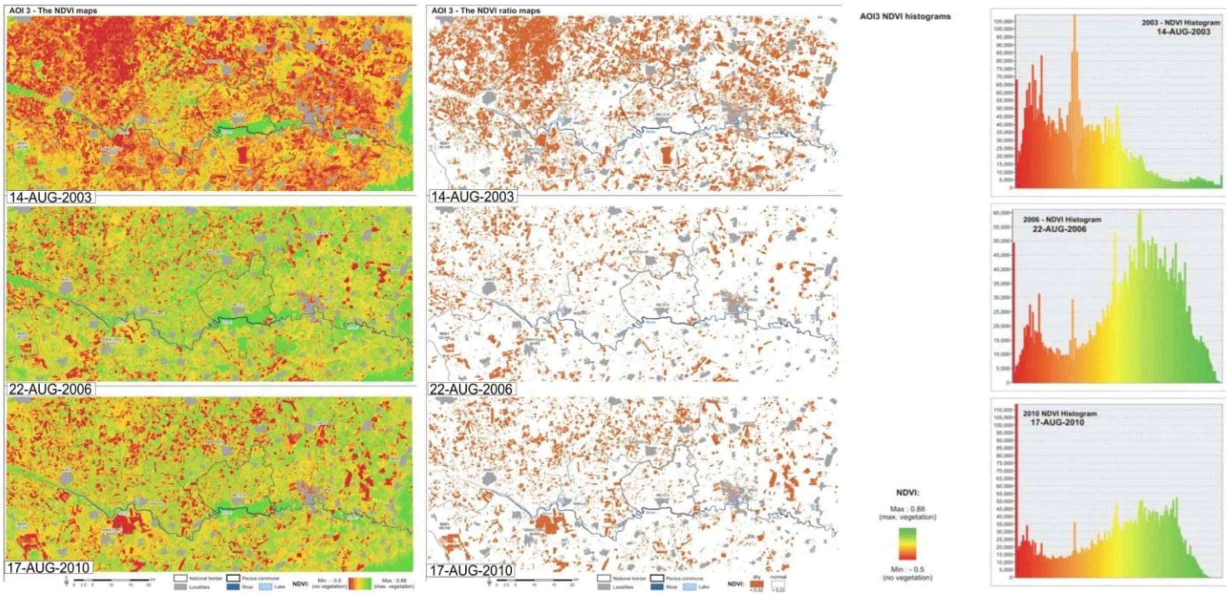
The NDVI time series analysis is very important for crop state monitoring. An example of a complex analysis was made using MODIS/TERRA NDVI products (MOD13A1) for the following years: 2000 and 2003 (as drought years), 2005 (as normal year) and 2010 (as rainy year), for different vegetation phases, for a study area situated in the lower basin of the Mures River, in the Western part of Romania. The NDVI data show a rather equal set of values between the four years, with a slight grow in 2005 and 2010 compared to 2000 and 2003 for the next periods: from 7th of April to 8th of May and from 9th of May to 9th of June (Figure 2a, 2b). Only during the last vegetation phenophase a visible difference occurs between 2000 and 2003 on one hand and 2005 and 2010 on the other hand (Figure 2c). Except some wooded land along Mures the vegetation shows the effect of low precipitation and high temperature in 2000 and 2003 (Figure 2d). The analysis clearly shows the effect of low precipitation and high temperatures in 2000 and 2003 (very droughty years) over the agricultural areas.



(a) (b) (c) (d)

Figure 2. Spatial variation of NDVI values from 6th of March - 6th of April (a), 7th of April - 8th of May (b), 9th of May - 9th of June (c) and from 10th of June - 28th of August (d)

Another example was made using high resolution data (Landsat) over the same study area. NDVI images were created for the years 2003, 2006 and 2010 (Figure 3). In the Figure 3a the areas with low NDVI values doesn't necessary mean that drought occurred there; the index's value can be also associated with an early harvest or with the lack of vegetation due to various regions. A good example for such a situation can be found south from Mures River in the vicinity of Sinnicolau Mare when very low NDVI values were recorded in the year 2010 (rainy year), although not associated with drought phenomena. In order to isolate only the parts affected by drought a two classes can be applied, using a "low-vegetation" NDVI threshold (Figure 3b). For this example an NDVI value of 0.22 was used as "drought threshold". This bi-color representation excludes the "normal" NDVI values while keeping the low ones. Areas represented in orange in Figure 3b can be therefore associated with dry land. Another approach in evaluating the NDVI maps is by using the histograms (Figure 3c). The NDVI histograms can be divided in 2 zones: dry and normal. The values for the year 2003 are grouped in the "dry" part while for 2006 and 2010 the opposite situation is recorded.



(a) (b) (c)

Figure 3: The NDVI maps extracted from LANDSAT data (a), NDVI ratio maps (b) and NDVI histograms (c)

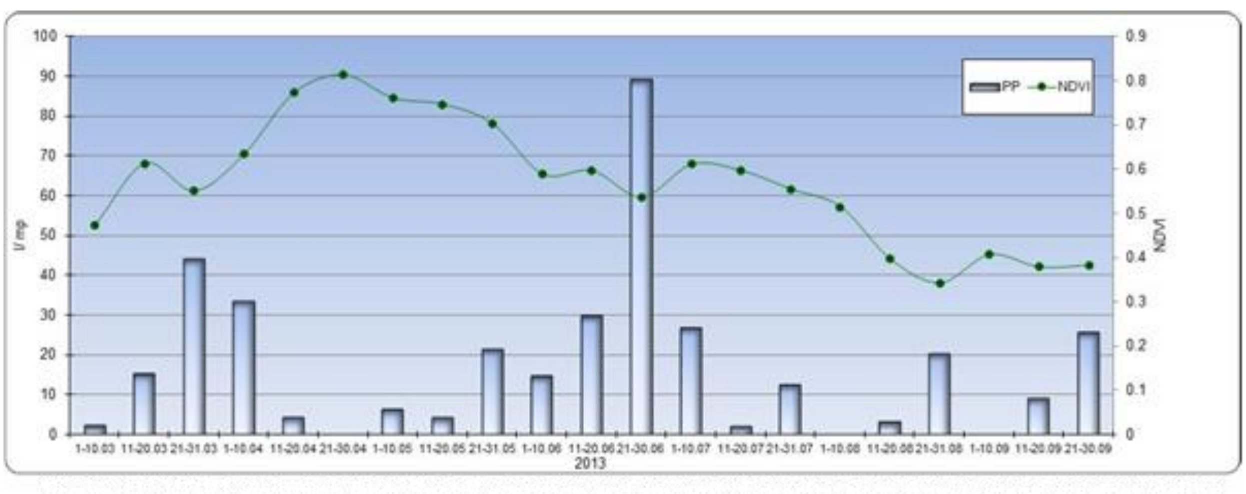


Figure 4. NDVI evolution from Spot Vegetation and amount of precipitation from Caracal weather station

It can be noticed that, although in the April-May period the precipitation amounts were small, the NDVI values increased, due to the existed in-soil water reserve, accumulated from the precipitation fallen in March through 10 April, 2013. However, due to the scarce amount of precipitation (in the periods 11 April – 10 June 2013 and 11.07 – 20 August 2013) the vegetation state of the crops was affected by drought, situation highlighted by the NDVI decrease trend. Owed to the spatial resolution of the SPOT Vegetation image products (1 km) and to the small size of the parcels, no clear delimitation can be made between the various crop types.

3.1.2. Normalized Difference Water Index - NDWI

The NDWI is a satellite-derived index from the Near-Infrared (NIR) and Short Wave Infrared (SWIR) reflectance channels , defined by the Equation 6:

$$NDWI = \frac{\rho NIR - \rho SWIR}{\rho NIR + \rho SWIR} \qquad (6)$$

where: ρNIR is spectral reflectance from near infrared (NIR) band and ρSWIR is spectral reflectance from short wave infrared (SWIR) band.

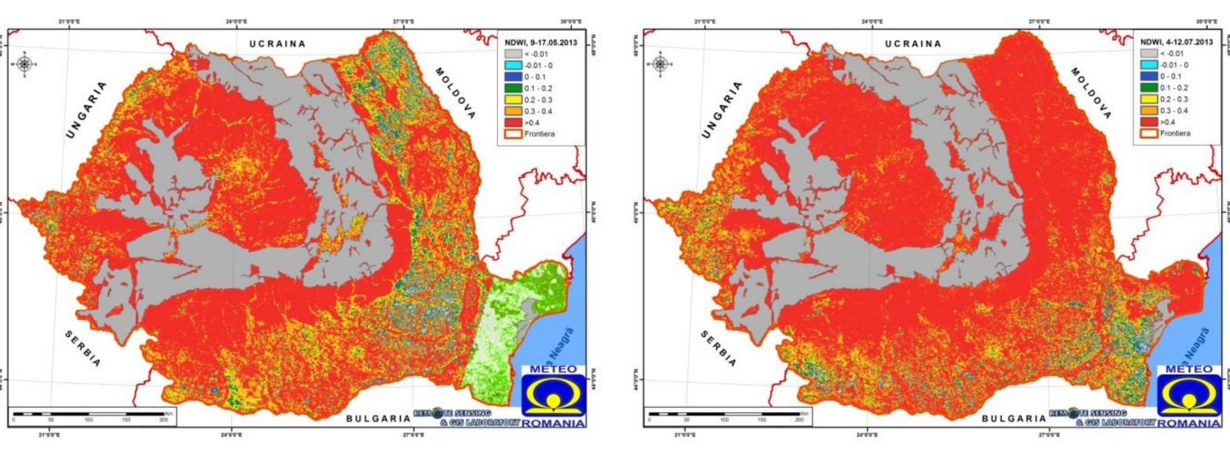
The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure of vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination these two spectral channels removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content. The amount of water available in the internal leaf structure largely controls the spectral reflectance in the SWIR interval of the electromagnetic spectrum. SWIR reflectance is therefore negatively related to leaf water content.

NDWI index is a good indicator of water content of leaves and is used for detecting and monitoring the humidity of the vegetation cover. It is well known that during dry periods, the vegetation is affected by water stress, which influence plant development and can cause damage to crops. NWDI holds considerable potential for drought monitoring because the two spectral bands used for its calculation are responsive to changes in the water content (SWIR band). As a consequence, NWDI is influenced by both the desiccation and wilting of vegetation and may be a more sensitive drought indicator than traditional remote sensing-based indices such as the NDVI, which do not account for changes in the vegetation's water content. This index increases with vegetation water content or from dry soil to free water[14] . The NDWI value varies from -1 to 1. The common range for green vegetation is -0.1 to 0.4.

Figure 5 presents an example for NDWI maps over Romania, obtained from MOD09A1 products (8-day composite) for the year 2013, during agricultural year.

As NDVI, NDWI index can be correlated with other vegetation indices or with agrometeorological parameters for different crop types.

The Figure 6 renders the evolution of NDVI and NDWI derived from MODIS data, for the wheat crop, from May to September 2013, for the Caracal agricultural area situated in the Southern Part of Romanian Plain. Through comparing it with the precipitation recorded at Caracal weather station, a minimum NDVI value was noticed at the beginning of May, due to the lack of precipitation. Further, due to the precipitation recorded in May and June, the NDVI values returned to normal (> 0.6). A NDVI decrease trend can be noticed over the interval when wheat was harvested (July). The same trend can be seen in the course of NDWI. NDWI correlates well with the moisture measured at the stations and in the test area. According to the Figure 6, the maximum values of NDWI (~0.4) correspond to medium vegetation water content and to medium vegetation fraction cover.



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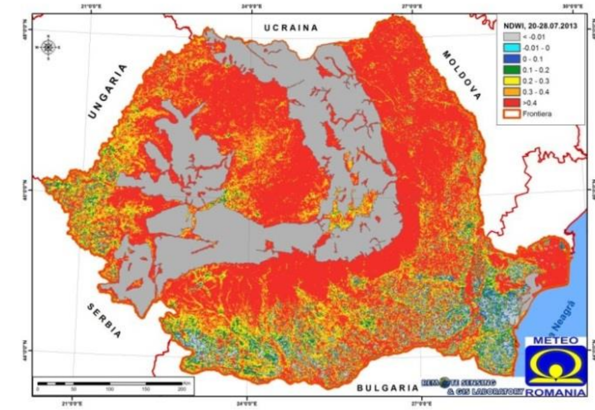


(20-28.07.2013)

Figure 5. NDWI maps obtained from MOD09A1 product for the year 2013

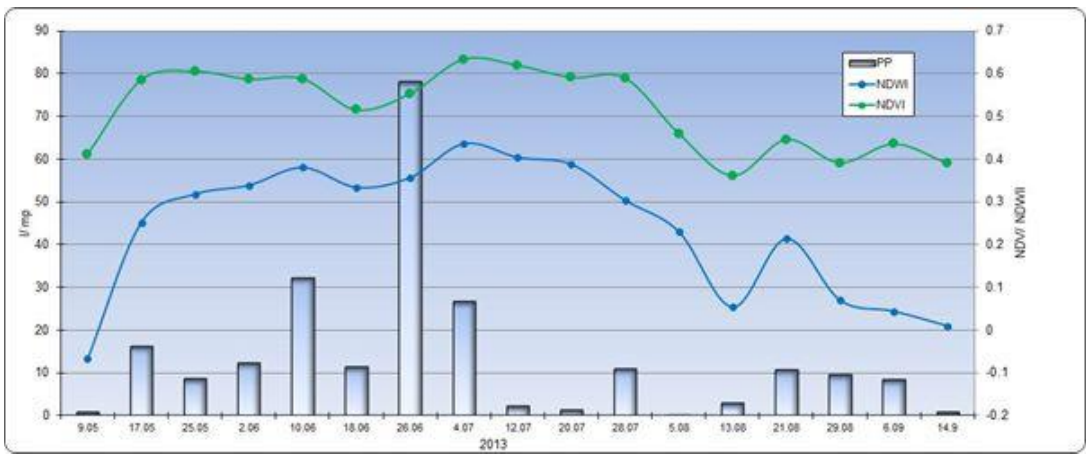


Figure 6. NDVI and NDWI evolution from MODIS and the amount of precipitation registered at Caracal weather station (wheat)

3.2. Crop biophysical characterization

Remote sensing can play a major role in agriculture by providing timely spectral reflectance information which can be linked to biophysical indicators of plant health: fraction of vegetative cover, chlorophyll content, green leaf area index, and, other measurable biophysical parameters.

3.2.1. Leaf area index – LAI and fraction of absorbed photosynthetically active radiation index (fAPAR)

The LAI variable defines the number of equivalent layers of leaves relative to a unit of ground area. The LAI variable is used as satellite-derived parameter for calculating surface photosynthesis, evapotranspiration, and net primary production, which in turn are used to calculate terrestrial energy, carbon, water cycle processes, and biogeochemistry of vegetation.

fAPAR is the solar radiation reaching the canopy in the 0.4–0.7μm wavelength region. fAPAR is a biophysical variable directly correlated with the primary productivity of the vegetation, since the intercepted PAR is the energy (carried by photons) underlying the biochemical productivity processes of plants. FAPAR ranges in space and time due to differences between species and ecosystems, weather and climate processes, and human activities. It is an important variable to document the intensity of the terrestrial carbon cycle and thus to assess of greenhouse gas forcing. The fAPAR is one of the 50 Essential Climate Variables recognized by the UN Global Climate Observing System (GCOS) as necessary to characterize the climate of the Earth.

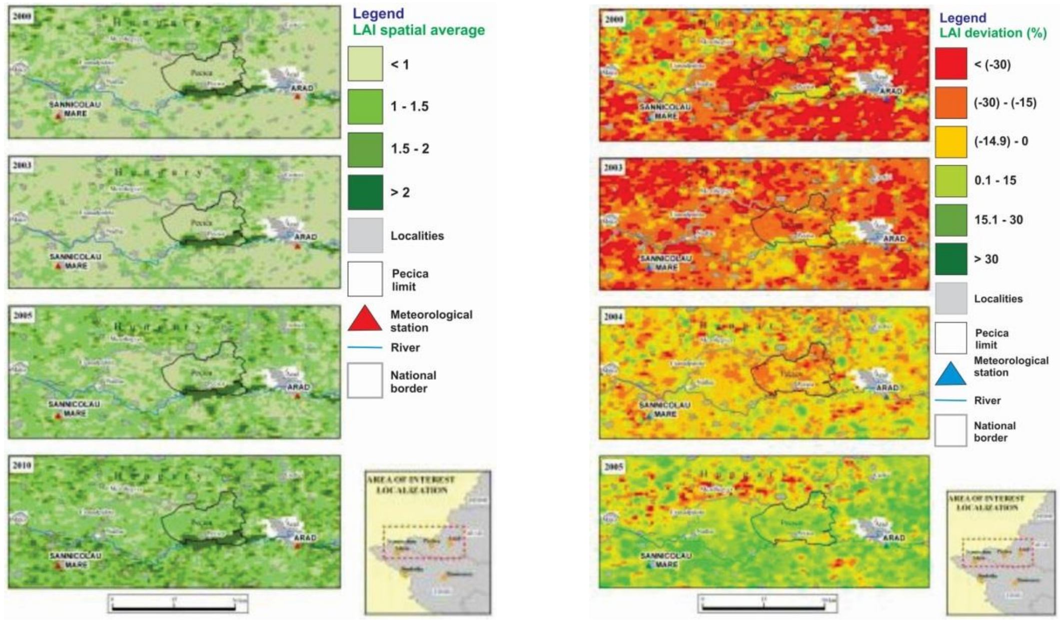
Gitelson et al. [12] proposed a technique to estimate LAI and green leaf biomass using spectral reflectance either in the green region (around 550 nm) or at the red edge (near 700 nm) along with the near-infrared (beyond 750 nm).Close relationships were found between the spectral indices tested (NDVI, SAVI, VARI) and LAI (ranging from 0 to more than 6) as well as green leaf biomass (ranging from 0 to 3500 kg/ha). Numerous other authors have addressed the topic of remote sensing of LAI. Haboudane et al. presents a method to minimize the effect of leaf chlorophyll content on the prediction of green LAI, and to develop new algorithms that adequately predict the LAI of crop canopies. The analyses was based on both simulated and real hyperspectral data in order to compare performances of existing vegetation indices (NDVI, Renormalized Difference Vegetation Index - RDVI, Modified Simple Ratio MSR, SAVI, Soil and Atmospherically Resistant Vegetation Index - SARVI, MSAVI, Triangular Vegetation Index - TVI, and Modified Chlorophyll Absorption Ratio Index - MCARI) and to design new ones (MTVI1, MCARI1, MTVI2, and MCARI2) that are both less sensitive to chlorophyll content variations and linearly related to green LAI. Hyperspectral images were acquired by the Compact Airborne Spectrographic Imager (CASI, Calgary, Canada). Leaf optical properties were simulated using the PROSPECT model[23, 24], which simulates upward and downward hemispherical radiation fluxes in the interval [400 – 2500] nm, and relates foliar biochemistry and scattering parameters to leaf reflectance and transmittance spectra. Canopy reflectance spectra were simulated using SAILH radiative transfer model, which is a variant of SAIL that taking into account the “hot spot” effect or the multiple scattering in the canopy [48, 49, and 51]. Several studies are focused on evapotranspiration estimation using a leaf area index-based surface energy and water balance model [6, 25,343, and 36].

Gitelson et al. [12] made an estimation of green LAI from MODIS 250-m vegetation index (VI) data for irrigated and rained maize and soybeans. In this regard, was evaluated the performance of both MODIS-derived NDVI and Wide Dynamic Range Vegetation Index (WDRVI) across three growing seasons during 2002-2004 over a wide range of LAI and also compared to the performance of NDVI and WDRVI derived from reflectance data collected across the same field locations. A time series of 16-day composite MODIS 250-m NDVI data (MOD13Q1 V004) spanning from May through October for each study year were acquired over the three study areas. The results proved that WDRVI estimated more accurately LAI across a much greater LAI range than the NDVI and can be used for assessing even slight variations in LAI that is an indicator of the early stages of plant stress. WRDVI can be calculated from other satellite-based sensors (e.g., AVHRR, Landsat TM and ETM+, MERIS, SPOT) that have bands in the red and NIR spectral regions.

In a recent study, Yan et al.[50] developed an air-relative-humidity-based two-source (ARTS) evapotranspiration (E) model that simulates the surface energy balance, soil water balance (SWB), and environmental constraints on E. They made a global estimation of evapotranspiration using a leaf area index-based surface energy and water balance model. The first step of ARTS model estimate plant transpiration and soil evaporation under the assumption of plentiful soil water. The second taking into account the effects of soil water stress, using SWB model. LAI was derived from NDVI calculated from Pathfinder Advanced Very High Resolution Radiometer (AVHRR) Land (PAL) channel 1 and 2 data.

Drought monitoring (corresponding to the state and dynamics of vegetation) in a given time may be accounting for LAI values derived from satellite data for a study time period. To mark out the plant water stress using LAI products will take into account the main land cover classes, according to Land Cover Classification.

In the Figure 7 shows the spatial evolution of lea area index for the reference years 2000, 2003, 2005 and 2010 in the lower basin of the Mures River (Romania). According MODIS Land Cover Classification (MCD12Q1 product), main classes for land cover/land use in the study area are agricultural crops, urban areas and broadleaf forests. 8 day LAI (MOD15A2/ LAI 1km) products have been used with an area extent approximately 101km wide by 21 km high. The LAI values was calculated as a sum of the total MODIS intervals during the vegetation phases (beginning of March – end of August). For the time period beginning of March – end of August, the LAI values confirm the result obtained when observing the NDVI (presented in sub-subsection 3.1.1) evolution during the fourth phenophase. More visible this time, are the forest lands, noticeably with higher values of LAI. From May 25, 2011 LAI values began to decrease and lasted about 1 month until June 26, 2011 (Figure 8) mark out the beginning of drought. This time period matches with latest phenological stages of winter crops (winter wheat), early milk and harvesting (end of June-beginning of July). During this period were recorded small amount of precipitation that affected the crops and led to lower values of LAI. A critical period can be observed from August to October when precipitation amounts were very low and soil moisture anomalies occurred thus setting up the droughts (Figure 9).



(a) (b)

Figure 7. (a) - Spatial variation of average LAI values (from the 6th of March to the 28th of August); (b) - The LAI deviation from the multi-annual average (2000 – 2009) (from 6 March to 28 August).

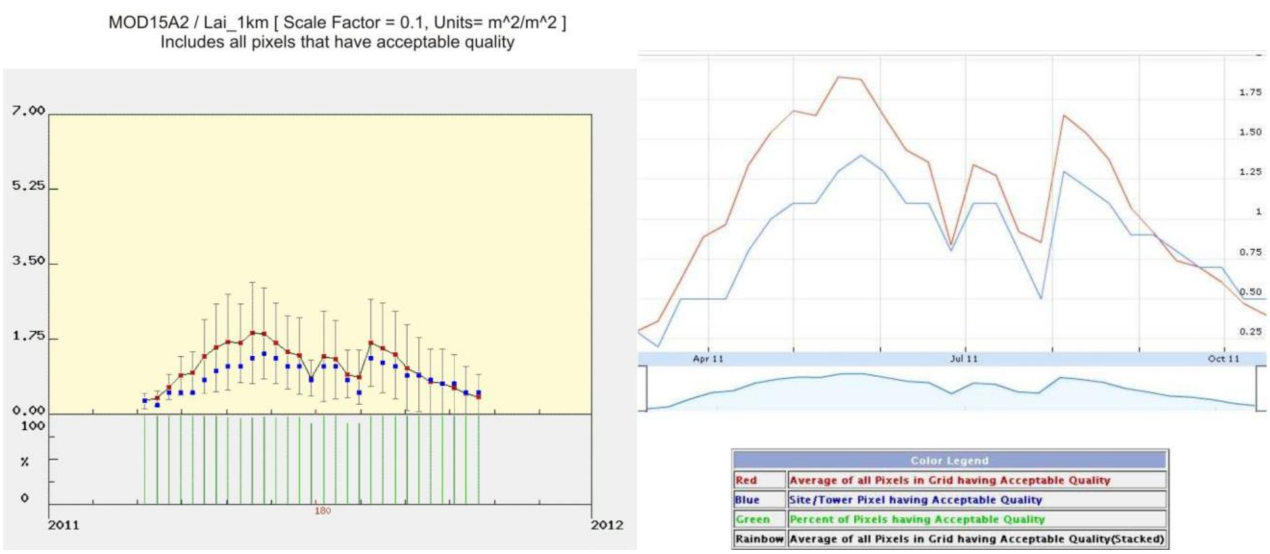


Figure 8. LAI evolution from March 6 to October 16, 2011

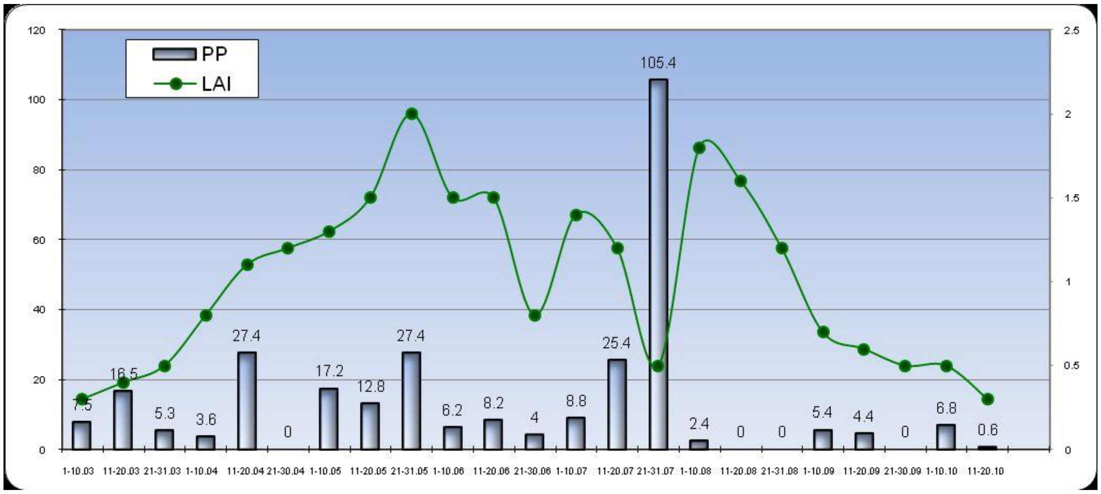


Figure 9. The correlation between LAI (extracted from TERRA/MODIS) and precipitation (recorded at ARAD meteorological station)

4. CONCLUSIONS

To have complex agro meteorological information it is necessary to improve the operational capabilities of monitoring using advanced remote sensing techniques. Remote sensing techniques play an important role in crop identification, acreage and production estimation, disease and stress detection, soil and water resources characterization because they provide spatially explicit information and access to remote locations. These techniques allow examining the properties and processes of ecosystems and their inter-annual variability at multiple scales because remote sensing observations can be obtained over large areas of interest almost every day.

Data sets provided by satellite systems can be used in global, regional or local studies, to obtain input data used to produce various models of energy balance, water balance, etc.

It is proved that remote sensing techniques can enhance and improve the drought analysis, especially considering the scarce availability of measured ground truth data. The advantage of multi-annual imagery availability allows the overlay and cross-checking of droughty, normal or rainy years.

The satellite-derived vegetation indices data and biophysical parameters proved to be good indicators of vegetation condition, being relevant for the installation, duration and intensity of drought.

Vegetation indices and biophysical parameters could be an important tool for evapotranspiration estimation. A lot of studies proved that LAI obtained from remotely sensed data can be used together with surface meteorological data to calculate evapotranspiration. Many studies proved the relationship between LAI and NDVI, as well between fAPAR and NDVI, especially when biophysical parameters are measured on the field or obtained using radiative transfer models. The results suggest that the LAI-NDVI relationship can vary both seasonally and inter annually, depending on phenological development. By combination of different types of data involves limitations in terms of differences in spatial and temporal resolution and data availability. One of the major limitations consists in the lack of operative global ET from remote sensing. In this regard, the future work aims to investigate in detail the relationship between different parameters used for water footprint estimation and vegetation indices and biophysical parameters obtained from remote sensing data, in order to compensate the lack of data.

The presented work was done in the frame of STAR 2012 (Space Technology and Advanced Research Program), project DROMOSIS *(Drought monitoring based on space and in-situ data).*

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