A MULTITEMPORAL TS-VI (MTVI) METHOD FOR SURFACE SOIL MOISTURE ASSESSMENT AT REGIONAL SCALE

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ABSTRACT

The Multitemporal Ts-VI (MTVI) method proposed in this paper originates as a conceptually modified approach of the well known TVDI method. The MTVI method takes advantage of the self-consistency of TVDI and consequently of its large operational applicability but, at the same time, tries to overcome its greatest limitation, which represent also its central assumption, that is the requirement, hardly verified in a single satellite acquisition, for a full range of soil moisture conditions and fractional vegetation cover. By processing satellite imagery in a multitemporal sequence, the MTVI approach seems to better characterize the environment in its natural spatial and temporal variability than TVDI can do. The spatial patterns and temporal evolution of MTVI values have been generated for a multitemporal sequence of Landsat TM imagery acquired in the same period of the year (July) from 1998 up to 2011 over the Little Washita River experimental watershed in Oklahoma, USA. Preliminary results show a good agreement between MTVI values and ground measurements (rainfall and near-surface soil water content), suggesting the potential use at operative level of the MTVI approach for monitoring surface soil moisture distribution over large and heterogeneous areas.

INTRODUCTION

The relationship between land surface temperature (Ts) and satellite-derived Vegetation Index (VI) has been long investigated for evaluating moisture conditions of land surfaces and several methodologies have been proposed for this purpose. Many of the preliminary studies focused on the slope of Ts-VI line and the main environmental factors driving this particular relationship for providing information about vegetation and surface soil moisture. During the 1990s a new approach was developed to map surface soil moisture. The 'Triangle method', as it is usually referred in literature, was introduced by Price (1) and then elaborated and modified by other authors. (2, 3, 4, 5). The triangle method gets its name from the triangular distribution of pixels in the Ts-VI space, assuming that a sufficiently large number of pixels representing almost the whole range of moisture conditions and vegetation cover are considered after having removed from satellite imagery those corresponding to clouds, water bodies or outliers (Figure 1a). The emergence of the triangular shape in the Ts-VI space can be physically explained by the higher sensitivity of Ts to soil moisture variations over bare soils than over dense vegetation. The right-hand limit of the triangle (called 'warm edge') is defined as locus of pixels characterized by the highest temperatures at different VI values. Likewise, the left-hand limit (called 'cold edge') represents the cooler pixels at varying vegetation fraction. Since vegetation canopy temperature can be considered close to air temperature and does not vary in space, temperature variations in the Ts-VI space reflect only *soil* temperature variations and consequently *soil* moisture availability and so the warm and cold edges correspond, respectively, to pixels with limited soil moisture availability (dry edge) and pixels with the maximum soil water content (wet edge). The base of the triangle is the result of the combined effects of soil water content and topography variations for pixels corresponding to bare soils, while the apex at the highest VI value implies a relative insensitivity of temperature of full vegetated areas to soil moisture. The presence of a trapezoidal (rather than triangular) scatter plot, with an upper narrow limit represented by a little variation of Ts at the maximum VI value, is the result of variations in thermal inertia of soil as soil moisture content changes.

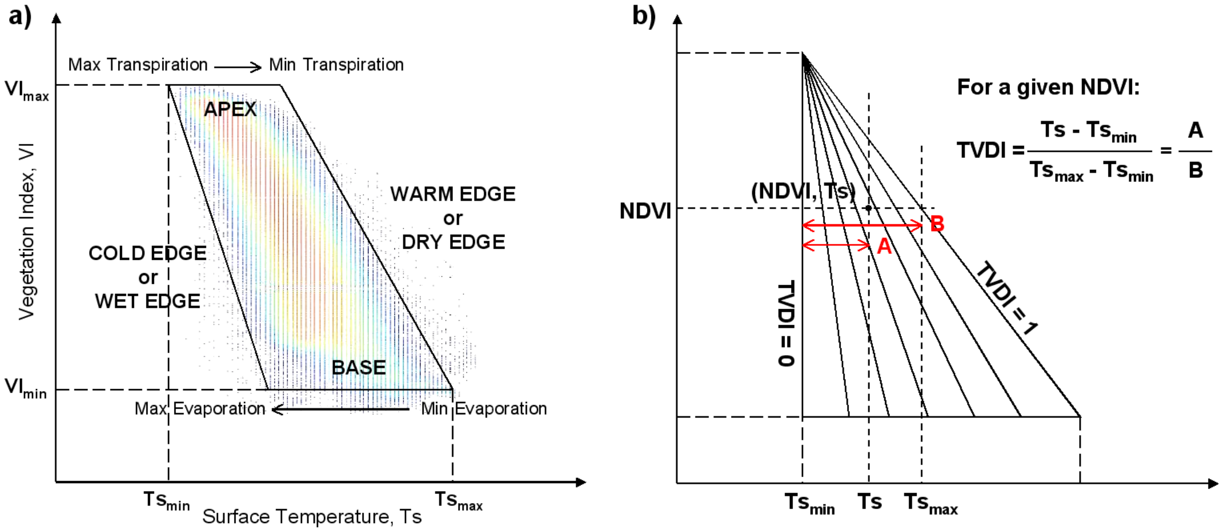


Figure 1: Ts-VI scatter plot: the main features of the Ts-VI space and the Ts-VI (TVDI) method introduced by Sandholt et al. are represented in a) and b), respectively.

Moreover, as vegetation fraction increases, bare soil signal is gradually masked by vegetation contribution and then the Ts-VI scatter plot slopes towards lower temperatures. For pixels having the same VI, Ts can considerably range; pixels with the minimum Ts represent the condition of the strongest evaporative cooling, while those with the maximum Ts are associated to weakest evaporative cooling. The most attractive advantage of the triangle method lies in its self-consistency, that is the boundary conditions of the model were fixed by pixel distribution itself and so there was no need for ancillary surface and atmospheric data. Nevertheless, its central assumption, that is the prerequisite for a large number of pixels representing a full range of variability in soil moisture conditions (from completely wet to completely dry) and vegetation cover (from bare soil to dense vegetation) in each considered image, inhibits mostly the estimation of surface soil moisture at operative level, since this particular condition is hardly verified in nature. Furthermore, because the Ts-VI space is empirically defined for each satellite image, comparison between surface soil moisture estimates retrieved from images acquired at different times are not possible. The new approach proposed in this paper aims to overcome these constraints and to better estimate spatial and temporal patterns of surface soil moisture at regional scale, extending operational applicability of the Ts-VI method to multitemporal monitoring.

METHODOLOGY

The Multitemporal Ts-VI (MTVI) method

The Multitemporal Ts-VI (MTVI) method introduced in this paper arises as a multitemporal extension of Temperature-Vegetation Dryness Index (TVDI) proposed by Sandholt et al. (6). TVDI represents a simplification of previous formulations (e.g., Water Deficit Index, WDI) (2). The method is conceptually and computationally straightforward and it is only based on satellite-derived information, Ts and NDVI. The basic assumption for the empirical estimation of TVDI is that soil moisture, by means of its control on surface thermal properties and evapotranspiration, is the main source of variation of Ts. For a given NDVI, TVDI is defined as:

$$TVDI = (Ts - Ts_{min}) / (Ts_{max} - Ts_{min}) \qquad (0 \leq TVDI \leq 1),$$

where Ts is the retrieved surface temperature for a given pixel, Ts_{min} is the minimum surface temperature in the Ts-VI space, defining the 'wet edge' (TVDI = 0) and Ts_{max} = a + b*NDVI represents the maximum surface temperature in the Ts-VI space, defining the 'dry edge' (TVDI = 1). The parameters a and b are modeled as linearly fit to the data. For pixels having the same NDVI, TVDI ranges from 0 (cold/wet edge) to 1 (warm/dry edge). Considering the full range of NDVI, isolines of TVDI can be drawn from the apex of the triangle in the Ts-NDVI space.

Graphically, TVDI for a given NDVI is estimated as a proportion between lines A and B (Figure 1b). The requirement of the Ts-VI methods for a full range of variability in soil moisture conditions and fractional vegetation cover in each satellite image, limits its use at operative level, especially in extreme circumstances. In fact, if the image is acquired soon after a rainy season, when soils are completely saturated, it can be expected that in the Ts-NDVI space pixels scatter in a narrow range, tendentially towards lower Ts values and so near the wet edge. The application of the TVDI method in this extreme case determines that pixels near the dry edge of the Ts-VI envelope are classified as completely dry, even if they are really wet. The MTVI method is inspired by this type of considerations. It suppose to have available at least two images acquired at different times, during a rainy and a dry period respectively (indicated in blue and in red in Figure 2). After extracting Ts and NDVI information from each image, the two scatter plot are overlapped in the same Ts-NDVI space. The two TS-NDVI envelope are shifted to each other; in particular, pixel distribution related to wet period is placed at lower Ts values than that corresponding to drier one. By considering the point C(Ts, NDVI) related to the image 1 acquired during the rainy period, the method introduced by Sandholt et el. returns a TVDI value calculated as segment AC out of segment AB and equal to 0,4. Since TVDI is a dryness index, the moisture index TVI is here defined as TVI = 1 – TVDI ($0 \le TVI \le 1$). For TVDI = 0,4, TVI is equal to 0,6, indicating medium wet conditions between purely wet (point A on the 'wet edge' of trapezoid 1) and purely dry (point B on the 'dry edge' of trapezoid 1). Nonetheless, actual meteorological conditions are in general wet. Paradoxically, the pixel represented by point B of the trapezoid 1 is classified by the TVDI method as completely dry (TVI = 0).

According to the previous considerations for the Multitemporal Ts-VI (MTVI) method, if we consider the segment AD (instead of the segment AB as regards the TVI method), MTVI value for point C assumes a 0,8-0,9 value against the 0,6 of TVI, which is more consistent with actual surface soil moisture. In this case, the pixel in point B shows a MTVI value equal to 0,3-0,4 and is classified by the MTVI method as intermediate between completely dry and completely wet conditions. The generic segment AD constructed from a suitable set of multitemporal images corresponds to an estimate of surface soil moisture, in its whole temporal variability, as fractional vegetation cover changes, allowing to satisfy the central assumption for a full range of surface soil moisture status and vegetation cover. Effectively, the 'multitemporal trapezoid' (Figure 2) is defined from a multitemporal sequence of N satellite imagery selecting the minimum and the maximum values of Ts_i (i = 1,…, N) corresponding to both the highest and lowest NDVI values and so to obtain the abscissa Ts_j (j = 0,…, 3) of the four vertices. The multitemporal dry and wet edges are thus determined by the lines passing respectively through the two couple of points (Ts_{1max}; $NDVI_0$) ,(Ts_{2max}; $NDVI_1$) and (Ts_{0min}; $NDVI_0$), (Ts_{3min}; $NDVI_1$), while the multitemporal base and apex are defined by $NDVI_0$ and $NDVI_1$ ordinates, respectively.

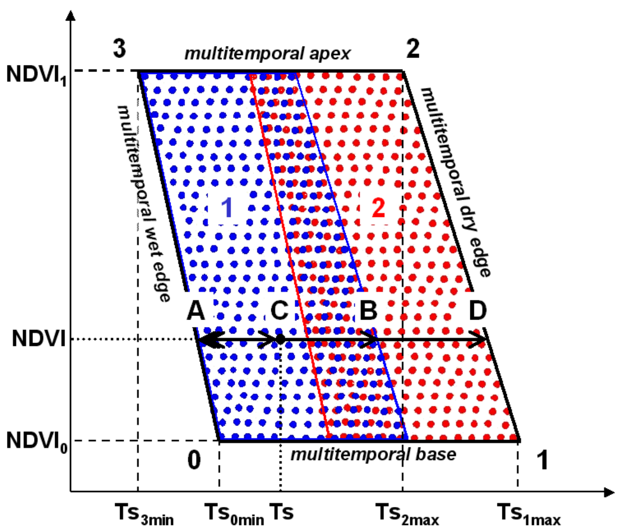


Figure 2: MTVI method: multitemporal trapezoid.

Study area and satellite data set used

The study area is situated in the Little Washita River watershed, extending over 610 km^2 in the Southern Great Plains, Oklahoma, USA. Topography is gently rolling with elevation varying from 300 to 500 meters with a mean slope of about 10 m per kilometer. Soils are from moderately well- to well-drained fine sands (in the central part of the watershed) and silty loams (in the western and eastern part of the watershed), ranging in thickness from 0,25 to 1,5 m, at the top of sandstone and shale bedrock (7). Climate is considered moist and sub-humid; much of the annual precipitation occur in spring and fall. The soil and climate have encouraged agriculture in the region and so most of the land cover is represented by grass rangeland and crops. Little Washita watershed is well instrumented. Hydrological and meteorological measurements of the watershed have been conducted for decades, providing a long-term data source to study basin hydrology. At present, the USDA-ARS monitors the environmental conditions of the Little Washita watershed with a 20-station network, called the Little Washita Micronet (http://ars.mesonet.org/) This network records many hydrological variables, including rainfall, air temperature, solar radiation and, recently, profile soil temperature and volumetric water content at different depths. For validation of surface soil moisture estimates retrieved by the application of the MTVI method, rainfall and volumetric water content data from eight selected ARS Micronet stations homogeneously distributed over the Little Washita watershed, are considered.

A series of eight Landsat-5 Thematic Mapper imagery, recently free-downloadable at the *Earth Resources Observation and Science (EROS) Center* website (http://glovis.usgs.gov), has been selected according to seasonal homogeneity criteria, all belonging to the same month (July) of different years (from 1998 to 2011). The original raw data have been geometrically corrected, radiometrically calibrated and converted to reflectance and temperature Ts values. Then, NDVI have been extracted from each image of the multitemporal sequence and combined with temperature information in the MTVI method to obtain the spatial patterns and the temporal evolution of surface soil moisture.

DATA PROCESSING AND RESULTS

The coordinates of the vertices in the Ts-VI space have been computed for each Landsat image and then for the multitemporal trapezoid. As shown in Figure 3, the trapezoid envelope for each acquisition date has a different position in the multitemporal Ts-NDVI space according mainly to weather condition changes.

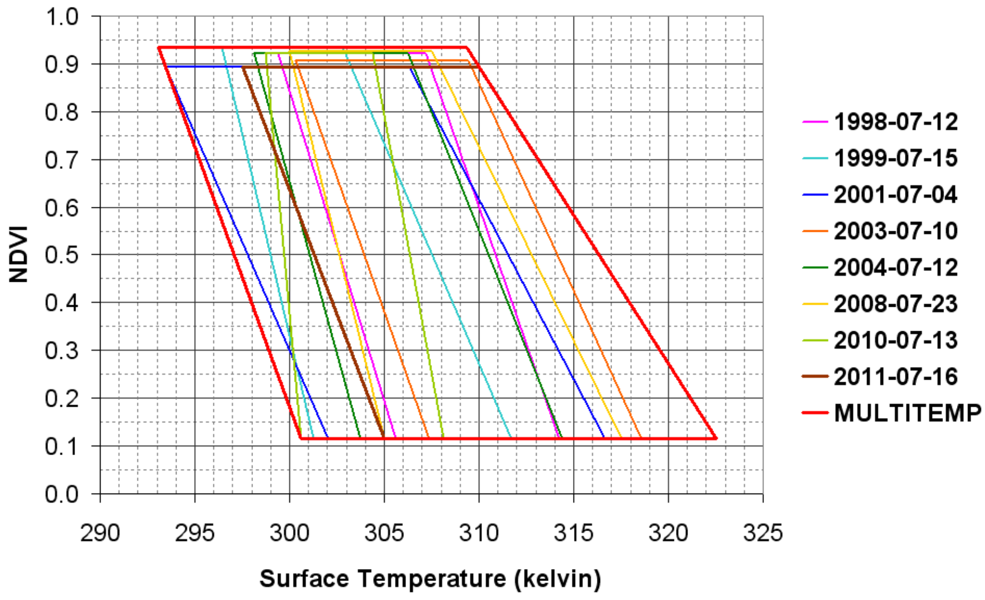


Figure 3: Multitemporal trapezoid processed from Landsat data set.

Afterwards, the TVI and MTVI maps of surface soil moisture have been produced for each acquisition date. Figure 4 shows an example of the obtained TVI and MTVI maps related to the TM5 image acquired on 10 July 2003, after a very dry period. Finally, the point values of soil moisture at the selected stations of the ARS Micronet network and a global mean value for the whole Little Washita River basin were extracted from the multitemporal sequence of TVI and MTVI maps and compared with the corresponding precipitation values accumulated within the last 7 days before the acquisition date. Rainfall spatial distribution is in general homogeneous in the whole wide watershed, except for 1999 and 2010.

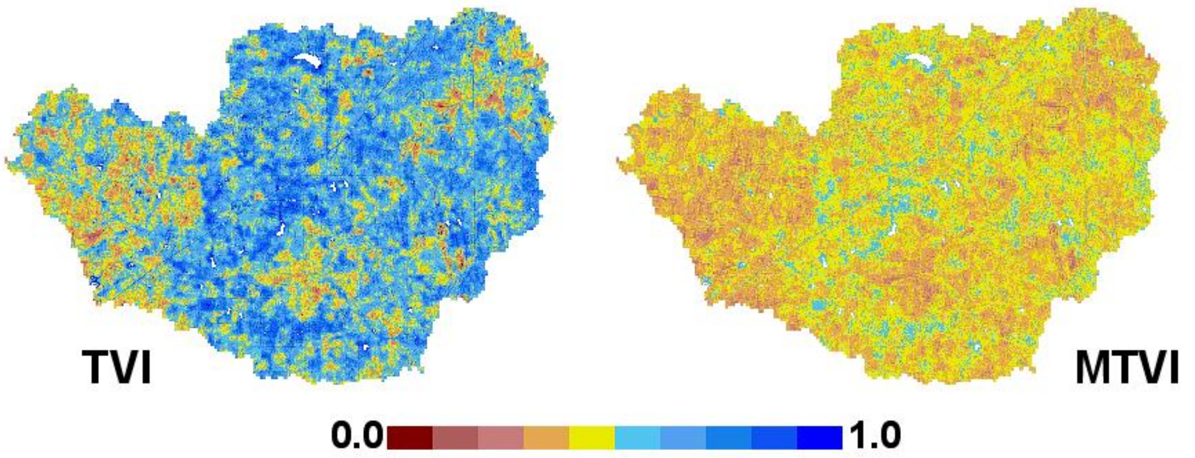
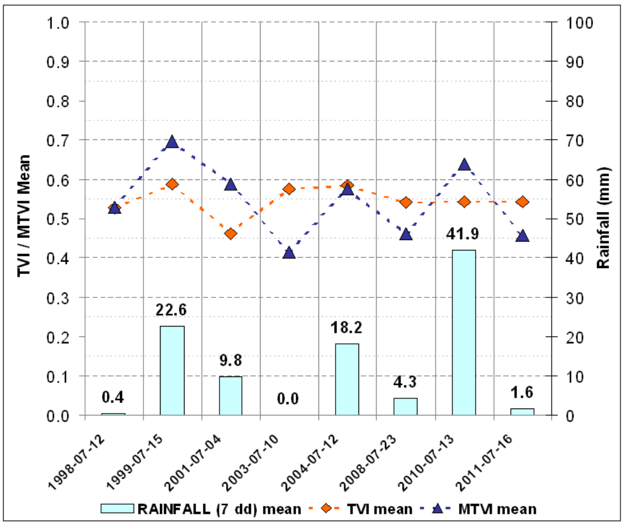


Figure 4: TVI and MTVI images processed from TM5 image on 10 July 2003.

The results obtained by the application of the MTVI method show better consistency with data trend from rain gauges for the whole period of the image sequence considered (Figure 5 on the left), than the corresponding TVI estimates. TVI and MTVI estimates have been compared also to the ground measurements of water content in the top 5 cm of soil (VW05) registered at ARS Micronet stations since 2008. Normalized MTVI values plotted as a function of normalized VW05 show a greater correlation than TVI values do. Linear regression exists between MTVI and VW05 with a correlation factor R^2 of 0,61 (Figure 5 on the right).



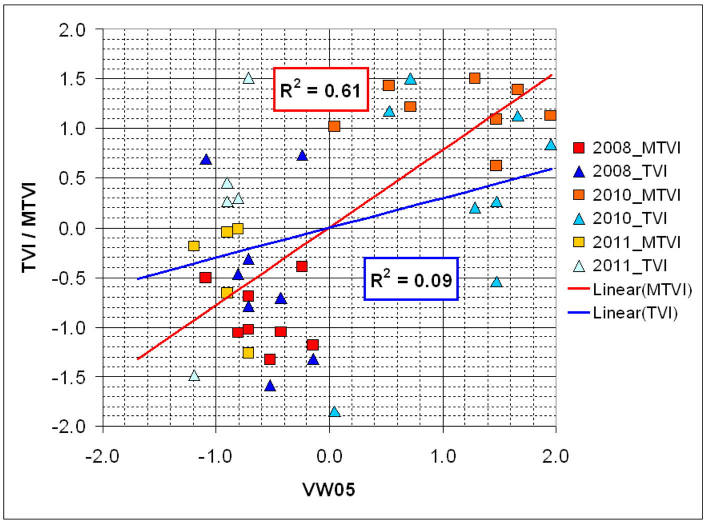


Figure 5: Results: on the left, comparison between TVI and MTVI mean values and mean precipitation accumulated in the last 7 days before the image acquisition; on the right, normalized TVI / MTVI values plotted as function of normalized VW05.

CONCLUSIONS

The MTVI method proposed in this paper takes advantage of Ts-VI relationship but, at the same time, tries to overcome its greatest constraint to operational applicability by means of a multitemporal approach that allows a better characterization of the environment in its natural variability both in space and time. The preliminary results are promising and suggest the potential employment at operative level of the MTVI method, as an indicator of surface soil moisture over large and heterogeneous areas for monitoring purposes. Moreover, land surface temperature validation represents an absolutely necessary step to assess how much the differences existing between remotely sensed retrieved temperatures and ground measurements affect the MTVI surface soil moisture estimation. In order to better test the performance and the robustness of the proposed multitemporal approach, further experimentation using hydrological distributed ground model or weighted rainfall data for validation of the MTVI method, applied also in different environmental contexts, are in progress.

ACKNOWLEDGEMENTS

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