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Prediction of soil moisture from remote sensing data

Eftychia Taktikou[a], George Bourazanis[b,c], Georgia Papaioannou[a,]* and Petros Kerkides[c]

[a]*National and Kapodistrian University of Athens, Department of Physics, University Campus Phys-5 Build., 15784 Zografos, Greece*
[b] *Department of Rural Economy and Veterinary of Regional Government of Laconia, Sparta, Laconia, 23100, Greece*
[c]*Agricultural University of Athens, Department of Natural Resources Development and Agricultural Engineering, Iera Odos 75, 11855 Athens, Greece*

Abstract

This study evaluates the capability of soil water content predicted from remote sensing to indicate the soil/canopy water content at short time and space scale, through comparisons with daily soil moisture data determined in situ, using dielectric devices. Daily aqua moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) and the diurnal (daytime and night time) land surface temperature difference (DLST) are employed to retrieving daily volumetric soil moisture content (θ) at Sparta experimental station, during the period June-August, of the years 2010, 2011, 2012 and 2014. Using the concept of apparent thermal inertia (ATI) in the remotely sensed topsoil moisture saturation index, daily θ is obtained from DLST and the volumetric saturated and residual soil moisture content and is compared with the experimental values of volumetric soil moisture content (SM) measured at various depths (10, 20, 30, 40, 60, 80 and 100 cm). Simple relationships are also calibrated between SM and ATI or DLST or NDVI during the years 2010, 2011 and 2014 and are tested for predicting θ, during the year 2012. Especially the three first models predict θ satisfactorily as compared with the measured SM and hence they can offer a considerable guidance in irrigated agriculture and other related fields.

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Keywords: Soil moisture, apparent thermal inertia, NDVI, land surface temperature, MODIS data

* Corresponding author. Tel.: +30 210 727 6925; fax: +30 210 729 5281.
E-mail address: gpapaioa@phys.uoa.gr

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1. Introduction

Soil moisture is an important parameter in hydrological modeling that influences the energy transfer between the land surface and the atmosphere by controlling the partition of available energy, further affecting the climate. Soil moisture (SM) determination is of paramount importance for a rational application of irrigated agriculture, especially in arid or semi-arid regions, where water scarcity and low quality waters may seriously affect crop development and productivity. Despite of their reliability, conventional point measurements are complex, labor-demanding, time-consuming and hence expensive. The recent development and wide-spread application of the so called dielectric sensors which exploit the amazing feature of water's dielectric constant to be exceptionally high (~80), while all other soil's constituents expose dielectric constant values not larger than 5, made the whole process of SM determination much easier. However, even this methodology cannot be used in large areas, since the spatial and temporal variations of soil properties, terrain, and vegetation cover, make the selection of representative field sites difficult. In contrast with the field methods, remote sensing is an effective tool for estimating soil moisture and drought monitoring at various scales because of large coverage, and multispectral and multitemporal observations from satellite sensors.

Estimating soil moisture from remotely sensed data has covered a wide spectrum ranging from visible to microwave bands. Despite the benefits of microwave methods (mainly capability to be used at night and even under cloudy skies), optical and thermal methods are also fundamental in remote sensing of soil moisture, especially because they can provide high spatial resolution maps. At optical and thermal infrared domains, land-surface temperature, vegetation index, and albedo are good indicators of soil moisture dynamics. Thermal inertia is a physical variable describing the impedance to variations of temperature and is defined as $TI = \sqrt{\rho Kc}$, where K is soil thermal conductivity [W m-1 K−1], ρ is soil bulk density [kg m−3], and c is heat capacity [J kg−1 K−1] [1]. When thermal inertia values increase, the variation of temperature is small, for a given transfer of heat, while when thermal inertia values are low, the variation of temperature is high for the same transfer of heat. In addition, the specific heat capacity of water being equal to 4.18 kJ kg−1 K−1, is much higher than dry soil (e.g. 0.8 kJ kg−1 K−1) and as a consequence, high soil moisture values lead to high thermal inertial values of soil which result in lower diurnal temperature fluctuation. Due to the difficulty of measuring ρ, K and c, thermal Inertia has been approached from the estimations of Apparent Thermal Inertia (ATI), by using remote sensing data. Various methods have been referred for estimating SM either based upon ATI [2-3] or DLST or NDVI [4-6].

This study evaluates the capability of volumetric soil water content predicted from remote sensing data to indicate the soil/canopy water content at short time and space scale through comparisons with measured (by dielectric devices) soil moisture data. Thus, daily aqua moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) and the diurnal (daytime and night time) land surface temperature difference (DLST) are used to estimating daily volumetric soil moisture content (θ) in an olive orchard at Sparta, during the period June-August, of the years 2010, 2011, 2012 and 2014. Daily θ is estimated from the soil moisture saturation index (SMSI) and is compared with the experimental values of volumetric soil moisture content (SM) measured at various depths (10, 20, 30, 40, 60, 80 and 100 cm). Simple relationships between SM and ATI or DLST or NDVI are also calibrated, during the years 2010, 2011 and 2014 and they are tested for predicting θ, during the year 2012.

2. Data and methods

2.1. Data

In this study, soil volumetric water content measurements (SM) taken from an olive orchard at the rural area of Sparta (Lat. 37° 04΄ N, long. 22° 05΄E and altitude 0.212Km) during the period June – August, of the years 2010, 2011, 2012 and 2014 were used. Soil moisture monitoring tubes had been properly installed in order to measure SM at 10, 20, 30, 40, 60, 80 and 100 cm depths (SM_{10}, SM_{20}, SM_{30}, SM_{40}, SM_{60}, SM_{80} and SM_{10}, respectively). ML2 Theta Probe was used, which is an impedance dielectric sensor with an operating frequency of 100 MHz.

Remotely sensed data obtained by the Moderate Resolution Imaging Spectroradiometer (MODIS), during summer of the years 2010, 2011, 2012 and 2014 were also used in this study. The MYD11A1 MODIS Aqua land product (version 5), was used, which offers daily daytime (LST_{day}) and nighttime (LST_{night}) Land Surface Temperature (LST) data stored on a 1-Km spatial resolution and gridded in the sinusoidal projection. The MODIS product (MYD09GA) data, with band1 (red wavelength) and band 2 (near-infrared wavelength), were used to calculate daily NDVI at 500m resolution in the selected station of Sparta, during summer periods of the years 2010, 2011, 2012 and 2014.

2.2. Methods

This study focuses on the estimation of daily *s*oil moisture content from various remote sensing data and the evaluation of the resulting estimates by their comparisons with SM experimental data averaged, as daily means for each depth. In all analyses, the 2010-, 2011- and 2014-data are used for the calibration procedure, while 2012-data are kept for the validation procedure. In the analysis, soil moisture content is estimated either from the soil moisture saturation index (SMSI), expressed as a function of maximum and minimum apparent thermal inertia (based upon the diurnal land surface temperature difference), or from ATI, DLST or NDVI by using calibrated predicting equations.

Apparent Thermal Inertia

ATI [7] is estimated according to the following equation:

$$ATI = C\frac{1-\alpha_0}{DLST} \quad (1)$$

Where: ATI is apparent thermal inertia [K^{-1}], α_0 is the surface albedo, DLST, is the diurnal land surface temperature difference [K] estimated as: DLST = $LST_d - LST_n$ (LST_d is daytime land surface temperature [K], LST_n is night time land surface temperature [K]) and C is solar correction factor estimated as:

$$C = \sin\vartheta \sin\varphi\ (1-\tan^2\vartheta \tan^2\varphi) + \cos\vartheta \cos\varphi\ \arccos\ (-\tan\vartheta \tan\varphi) \quad (2)$$

Where: ϑ is latitude, φ is the solar declination.

Estimation of soil moisture content based on apparent thermal inertia and soil moisture saturation index

Soil moisture saturation index (SMSI) is determined as:

$$\mathrm{SMSI} = \frac{\theta-\theta_{res}}{\theta_{sat}-\theta_{res}} \quad (3)$$

Where: θ is volumetric soil moisture content [m^3m^{-3}], θ_{res} is volumetric residual soil moisture content [m^3m^{-3}], θ_{sat} is volumetric saturated soil moisture content [m^3m^{-3}].

Based on the rationale that the maximum and minimum value of apparent thermal inertia, derived from remote sensing, correspond to the residual and saturated soil moisture content (θ_{res} and θ_{sat}, respectively), the soil moisture saturation index ($SMSI_0$) is determined as:

$$\mathrm{SMSI_0} = \frac{\mathrm{ATI}-\mathrm{ATI_{min}}}{\mathrm{ATI_{max}}-\mathrm{ATI_{min}}} \quad (4)$$

Considering that SMSI0 equals to SMSI and combining the Equation 3 and the Equation 4, the soil moisture content θ(SMSI) is estimated as a linear function of SMSI0:

$$\theta(\mathrm{SMSI}) = \mathrm{SMSI0}*(\theta\mathrm{sat} - \theta\mathrm{res}) + \theta\mathrm{res} \quad (5)$$

In this study, ATImax and ATImin are estimated from all the data of the calibration years (2010, 2011 and 2014) and the saturated (θsat) or the residual (θres) soil moisture content is determined under laboratory conditions, as equal to 0.415 or 0.119, respectively.

Calibration of predicting expressions for soil moisture content based on diurnal surface temperature difference or normalized difference vegetation index or apparent thermal inertia

Soil temperature is depended on the soil moisture and vegetation cover and inversely, a lot of studies have indicated that soil moisture is depended on soil temperature and vegetation status. Therefore, NDVI and Land Surface Temperature (LST) could provide information about the condition of soil moisture content. Especially, soil moisture and NDVI have been reported as well correlated, during growing periods [8]. Thus, in this study, daily experimental values of SM for each depth are linearly regressed with the corresponding DLST or NDVI or ATI. The results from the linear regressions [determination coefficient (R^2) and slope (a)], are taken into account to form predicting expressions for soil moisture content, as a linear function of ATI or DLST or NDVI (for each depth). The predicting expressions are obtained from the data during the period June – August of the calibration years 2010, 2011, and 2014.

Validation of soil moisture content predictions

The calibrated predicting equations of soil moisture as a function of ATI or DLST or NDVI are used for estimating soil moisture (θ_{DLST}, θ_{NDVI} and θ_{ATI}, respectively) for each depth, during the year 2012 (validation year). In addition θ_{SMSI} (based on ATI_{min} and ATI_{max} calculated from the data of the calibration period) is estimated during the year 2012. The estimated soil moisture values (θ_{SMSI}, θ_{DLST}, θ_{NDVI} and θ_{ATI}) are compared with the corresponding values of SM measured at various depths. The comparisons are evaluated by the results of linear regressions [determination coefficient (R^2) and slope (a)] and "difference measures" [root mean square error (RMSE), mean bias error (MBE) and index of agreement (IA)].

3. Results

Figure 1, shows the time evolution of the predicted volumetric soil moisture content θSMSI and the volumetric soil moisture content measured at depths of either 10 cm (SM10) or 100 cm (SM100) or its average value from all depths (SMAver), during the period June – August of the calibration years. It is evident that the best agreement exists between θSMSI and the surface volumetric soil moisture.

Similarly, the time evolution of the diurnal surface temperature difference (DLST) or the normalized difference vegetation index (NDVI) or the apparent thermal inertia (ATI) and the experimental values of SM10 and SMAver are apparent in Figure 2, during the period June – August of the calibration years. In general, the time evolution of SM10 or SMAver presents a rather similar pattern with the time evolution of DLST, NDVI and ATI. Thus, the corresponding predicting expressions of soil moisture content for each depth, are obtained by the linear regressions between SM10 (or SM20 or SM30 or SM40 or SM60 or SM80 or SMAver) and DLST (or NDVI or ATI). All slopes are found statistically significant (at 99.9 % confidence level) and the determination coefficients (R2) are quite high in all regressions although, the values of NDVI seem to show a time lag, when they are compared to the corresponding SM10 or SM Aver (Figure 2). For example, the linear regressions between SM10 and DLST (or NDVI or ATI) resulted in slopes equal to 0.817 (or 0.291 or 258.681, respectively) and R2 equal to 0.881 (or 0.897 or 0.912, respectively). The linear regressions between SMAver and DLST (or NDVI or ATI) have shown slopes equal to 0.956 (or 0.342 or 299.991, respectively) and R2 equal to 0.937 (or 0.939 or 0.950, respectively).

All predicted (either by SMSI or by the previously calibrated predicting equations based on ATI, or DLST or NDVI) soil moisture contents (θ_{SMSI}, θ_{ATI}, θ_{DLST}, θ_{NDVI}, respectively) are compared with the values of SM, measured at various depths, during the validation year. Table 1 shows the results of their linear regressions [determination coefficient (R^2), slope (a)] and their "difference measures" [root mean square error (RMSE), mean bias error (MBE) and index of agreement (IA)]. The comparisons between θ_{SMSI} or θ_{DLST} or θ_{ATI} or θ_{NDVI} and measured SM in various depths, show very high values of R^2 (0.91 to 0.98), reasonable (16%) up to quite high (35%) RMSE and MBE smaller than 10% in most depths, or smaller than 10% at 10 and 20 cm depths, or larger than 10% at 10 cm depth, or larger than 10% at 10 and 20 cm depths, respectively. IA is different for each depth, with the higher value estimated at 10 cm depth (0.41 or 0.34 or 0.45 or 0.31), respectively. Figure 3 shows the time evolution of either SM_{10}, and the predicted θ_{SMSI} and θ_{ATI} (a), θ_{DLST} and θ_{NDVI} (b) or SM_{Aver} and the predicted θ_{SMSI} and θ_{ATI} (c), θ_{DLST} and θ_{NDVI} (d), during the year 2012. It is evident that θ_{SMSI} and θ_{ATI} have a more similar evolution line with SM_{10} as compared with θ_{DLST} and $\theta_{NDVI.}$ θ_{SMSI} and θ_{ATI} also approach quite satisfactorily the evolution line of SM_{Aver} in contrast with θ_{DLST} and θ_{NDVI}. Generally, it is evident that θ_{SMSI} is in a better agreement with SM as compared to θ_{DLST}, θ_{NDVI} and θ_{ATI} and all predictions of θ are in a better agreement with SM_{10}.

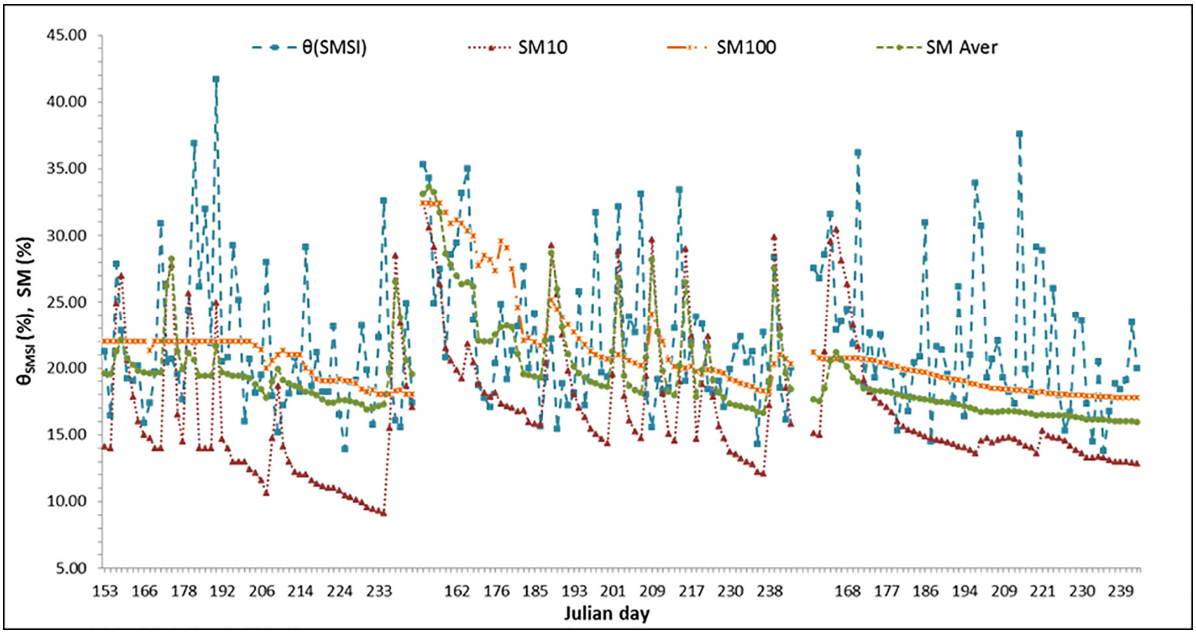

Fig. 1. Time evolution of predicted (by SMSI) volumetric soil moisture content (θ_{SMSI}) and values of volumetric soil moisture content measured at depths of either 10 cm (SM_{10}) or 100 cm (SM_{100}) or its average value from all depths (SM_{Aver}), during the calibration years.

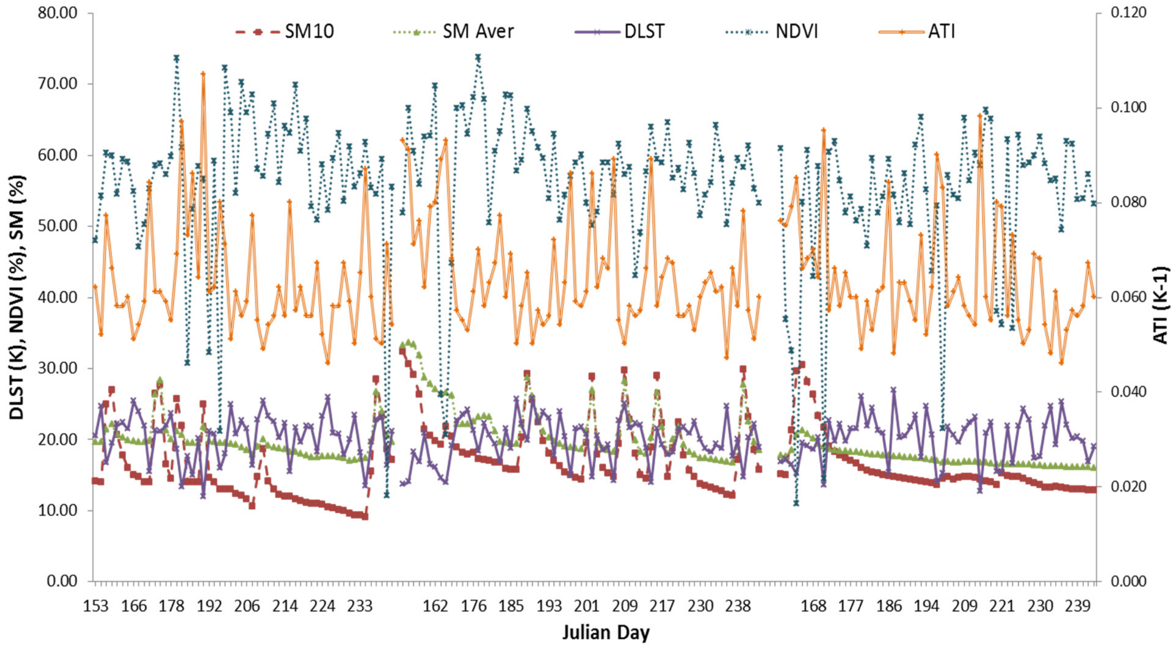

Fig. 2. Time evolution of diurnal surface temperature difference (DLST) or normalized difference vegetation index (NDVI) or apparent thermal inertia (ATI) and values of soil moisture content measured at depths of 10 cm (SM10), or its average value from all depths (SMAver), during the calibration years.

Table 1. The results of the linear regressions [determination coefficient (R^2), slope (a)] and the "difference measures" [root mean square error (RMSE), mean bias error (MBE) and index of agreement (IA)] between predicted (by SMSI or ATI, or DLST or NDVI) soil moisture contents (θ_{SMSI}, θ_{ATI}, θ_{DLST}, θ_{NDVI}, respectively) and the values of volumetric soil moisture content (SM) measured at various depths, during the validation year.

Depth (cm)	R^2	Slope α	RMSE	MBE	IA
	θ_{SMSI} - SM				
10	0.922	**1.043** ±0.036	31.189	8.418	0.405
20	0.946	**1.087** ±0.031	27.713	10.188	0.286
30	0.951	**1.009** ±0.020	25.118	1.298	0.172
40	0.952	**1.106** ±0.020	29.198	10.814	0.095
60	0.956	**0.945** ±0.018	20.951	-5.481	0.115
80	0.956	**1.158** ±0.020	29.438	15.859	0.080
100	0.955	**0.991** ±0.019	21.559	-0.785	0.168
Aver.	0.956	**1.057** ±0.020	23.786	5.926	0.181
	θ_{ATI} - SM				
10	0.940	**0.813** ±0.025	28.323	-15.350	0.445
20	0.964	**0.898** ±0.021	20.212	-8.936	0.382
30	0.971	**0.988** ±0.021	17.083	-0.767	0.213
40	0.972	**1.027** ±0.021	17.425	3.019	0.138
60	0.976	**0.950** ±0.018	15.638	-5.000	0.149
80	0.976	**1.028** ±0.019	16.304	2.817	0.144
100	0.975	**0.961** ±0.019	15.894	-3.770	0.226
Aver.	0.975	**0.957** ±0.019	16.153	-4.084	0.277
	θ_{DLST} - SM				
10	0.938	**0.958** ±0.025	25.456	0.169	0.341
20	0.968	**1.073** ±0.021	21.137	9.009	0.339
30	0.981	**1.181** ±0.021	24.459	18.445	0.253
40	0.982	**1.229** ±0.021	28.242	23.028	0.175
60	0.983	**1.141** ±0.018	20.637	14.062	0.120
80	0.983	**1.228** ±0.019	27.996	22.787	0.099
100	0.982	**1.150** ±0.019	21.576	15.114	0.205
Aver.	0.980	**1.143** ±0.019	21.637	14.560	0.238
	θ_{NDVI} - SM				
10	0.907	**0.750** ±0.029	35.403	-21.116	0.305
20	0.945	**0.846** ±0.025	25.857	-14.023	0.255
30	0.962	**0.934** ±0.022	19.806	-6.446	0.242
40	0.962	**0.970** ±0.023	19.526	-2.863	0.195
60	0.963	**0.899** ±0.021	20.252	-10.124	0.112
80	0.964	**0.970** ±0.023	19.124	-3.032	0.150
100	0.964	**0.908** ±0.021	19.756	-9.251	0.198
Aver.	0.959	**0.901** ±0.023	21.220	-9.621	0.161

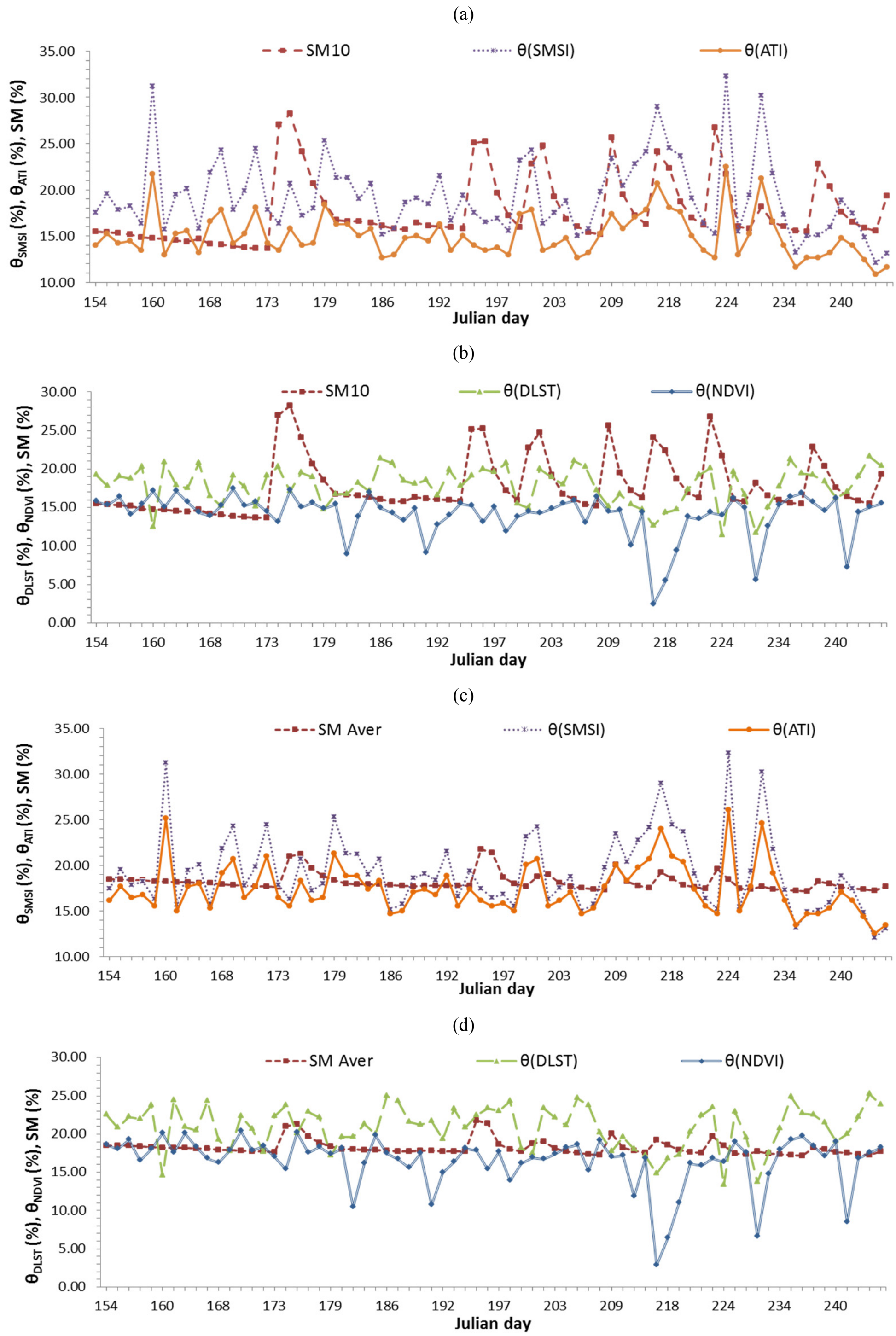

Fig. 3. Time evolution of predicted (by SMSI or ATI, or DLST or NDVI), soil moisture contents (θ_{SMSI}, θ_{ATI}, θ_{DLST}, θ_{NDVI}, respectively) and the experimental values of volumetric soil moisture content measured at depths of 10 cm (SM_{10}), or its average value from all depths (SM_{Aver}), during the validation year 2012.

4. Conclusions

The study focuses on the estimation of daily *s*oil moisture content from various remote sensing data, during the warm period as it is recommended [6]. Furthermore, the olive orchard at Sparta has been selected for applying the apparent thermal inertia concept, as rather sparsely vegetated region [9-12].

The evaluation of all resulting predictions, indicate that there is an appreciable proximity of the experimental values of soil moisture averaged, as daily means for the depth of 10 cm. Especially, θ_{SMSI} seems to predict quite accurately SM_{10} (MBE<10%, IA=0.41, RMSE ~31% and R^2=0.92) as compared to θ_{DLST}, θ_{NDVI} and θ_{ATI}. Moreover, θ_{ATI} verify also more satisfactorily the experimental values of SM_{10} than θ_{DLST} and θ_{NDVI} do. NDVI evolution, during the calibration years, does not show similar variations with the average experimental value of soil moisture (SM_{Aver}), but DLST or ATI do, either with SM_{10} or SM_{Aver}.

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