



# Consideration of seasonal variations on water radiometric indices estimation of soil moisture content in arid environment in Saudi Arabia

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## ABSTRACT

Remote sensing applications in agricultural practices are comprehensively reliable and cover a multidisciplinary fundamental interest both in local and regional level. Significantly, vegetation indices are the foremost essential in remote sensing applied for agricultural activities related to vegetation and/or water, particularly in an arid environment. Adequate water resources management plans are based on better fulfilling the water demand and supply equation. In arid environments, this equation is barely achieved due to water resources limitations. Remote sensing techniques improve the water resources management schemes by using five different water radiometric indices of Sentinel-2. Each of them plays a specific role in the quantification of soil/plant water content based on the interpretation of map surface water features and monitors the dynamics of surface water. The study area is located within the main agricultural region of Wadi As-Sirhan. The area is characterized by flourishing agricultural activities. Remote sensing data acquired by Sentinel-2 proved to be statistically sufficient to estimate soil water content in two different climatic conditions. Statistically, estimated winter indices are with better fit than summer indices. Modified Normalized Difference Water Index and second Normalized Difference Water Index best fitted winter soil water content estimations. Meanwhile, RMSE showed no differences between Normalized Difference Water Index and Normalized Difference Turbidity Index for both climatic conditions.

*Keywords:* Integrated water resources management; Sentinel-2; Soil water content; Remote sensing; Water radiometric indices

## 1. Introduction

The Kingdom of Saudi Arabia (KSA) has very low annual precipitation, high temperature, no lakes or flowing rivers and is classified as an arid region. Water, therefore, is infrequent and extremely valuable. With the rapid country growth and increasing water demand, the effect becomes cumulative. The scarcity of fresh water resources presents the most severe problem for the existence of biotic life in Saudi Arabia (Elhag 2016). Generally, the average annual rainfall is closely less than 80 mm, with a sporadic maximum annual rainfall that exceeds 500 mm, particularly in the south-western region (Bahrawi et al. 2016)

Saudi Arabia has experienced an elevated development in all divisions over the last four decades. As a result, a swift intensification in agricultural, industrial and domestic water

demands has been perceived. Agriculture is the major water consumption sector as it consumes about 85% of the total national water use (Elhag et al. 2017). The government of Saudi Arabia subsidized the agricultural sector during the period 1974–2006 to improve the standard of living in rural areas and to attain self-sufficiency.

Soil water content depends on many parameters that are spatially and temporally variable such as soil type, vegetation cover, crop type, topography and precipitation. Considering all these variable factors, in collecting enough measurements for the account of the spatial variations of the vadose zone, soil water content is neither financially nor technically practical.

Soil water content is the amount of water available for plants uptake at the root zone; coarsely this zone is less than 50 cm of depth (Zhu et al. 2008). Within this thin layer, several

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essential biological and hydrological processes take place (Crippen 1990 and Walker 1999). It is very crucial to monitor this layer to ensure plants survival (Su et al. 1999). Traditional methods of soil water content estimation are usually valid for a small local level similar to a farm but it always costs time and effort and is not a sufficient method to estimate spatial and temporal variations of soil water content on a regional scale (Engman 1991 and Wood et al. 1992).

Remote sensing techniques are now widely used to forecast, monitor and estimate soil water content (Ochsner et al. 2013 & Psilovikos and Elhag 2013). Estimation of soil water content using remote sensing practices is different and divided generally into two groups of methods: (1) passive remote sensing method of estimation and (2) active remote sensing method of estimation (Palecki and Bell 2013). Both techniques depend on the capability of a certain wavelength to penetrate the root zone and register its reflection (Myneni et al. 1995 and Dasgupta 2007). Short wave infra-red (SWIR) wavelength can penetrate in the shallow root zone as it is either registered passively from the sun or actively using ground penetration radar (GPR) systems (Gao 1996 and Moghadas et al. 2013).

Low crop productivity is highly related to the availability of water resources. To optimize the use of limited water resources in arid environments unconventional methods of planning are required (Elhag and Bahrawi 2017). Soil water monitoring is a crucial feature of managing water requirements of agricultural fields founded on advanced irrigation techniques (Muñoz-Carpena et al. 2002). The main goal and challenge for farmers and decision makers is to keep soil water content within optimized range for better and efficient crop production and unsaturated soil (Muñoz-Carpena et al. 2005 and Elhag and Bahrawi 2014).

Relevant research studies were conducted in similar arid environments. Modified Normalized Difference Water Index (MNDWI) was applied by Zhang and Huai-Liang 2016 to monitor drought condition. Mathieu et al. 1998 was the pioneer in studying the relationship between laboratory reflectance data and remote sensing data. Other significant scholarly work was conducted by Elhag and Bahrawi 2017 who assessed the hydrological drought indices in other parts of Saudi Arabia.

Several radiometric water indices have been developed within the past few decades. Principally, McFeeters 1996 projected the Normalized Difference Water Index (NDWI). The index uses the green and the near infrared bands of remote sensing data. The index was projected to improve the extracted information from the remote sensing data regarding the soil moisture content. Later, MNDWI was developed by Xu 2006 to improve the limitations of NDWI, where the shortwave infrared was used instead of NIR band. Several academic research works were conducted by Xu 2006, Li et al. 2013, Du et al. 2014 and Singh et al. 2015 where MNDWI was considered to be a better radiometric water index over NDWI.

Remote sensing techniques provide the tool to estimate soil water content on a large scale in time and effort cost-effective manner (Chauhan 2003). Irrigation network in the designated area relies on advanced sprinkling irrigation systems. The huge plant water requirement in the study region is supplied from the underlying groundwater aquifer. Spatial

correlation between soil water content and vegetation stress may alter the strategy of water management in the study area. Image correction is a preliminary procedure in digital image analysis. Atmospheric and radiometric correction techniques are also essential steps. According to Chavez 1996, atmospheric correction depends on the calibrated radiance value of these offset consents to decide the  $\kappa$  value. The  $\kappa$  decision rule is based specifically on the flying height. The  $\lambda^{-\kappa}$  determines the offset values for the green, red and near infra-red band calibration (Beisl et al. 2008). Moreover, radiometric correction is required to harmonize the conducted measurements made with a variety of different satellite sensors under different environmental conditions (Zhu et al. 2015).

The current research work is based on founding a regression correlation between values of remote sensing water radiometric indices conducted from satellite images and ground truth data. Therefore, accurate synchronization of ground truth data collection and satellite bypassing were exercised to maximize the use of the irrigational water in the study area.

## 2. Materials and methods

### 2.1. Study area

The Wadi As-Sirhan or Sirhan Valley is a quadrangle wadi which lies in the Northwestern part of Saudi Arabia at about 1,000 km north of Jeddah. It expands from Sakakah city up to Jordan and lies between Lat 30 45–29 30 N and Long 37 50–39 30 E on the border with the Kingdom of Jordan (Fig. 1). It is in the west-central part of the Sirhan turayf basin and is underlain by Silurian to Miocene-Pliocene sedimentary rocks that are partly covered by volcanic flows. The map area also contains large areas of surface sand and gravel. Wadi As-Sirhan is characterized by 5 Million Cubic Meter (MCM) annual flow and 18 MCM annual discharge and safe yield of 7–10 MCM/y (Bahrawi and Elhag 2016). Hydrogeological investigations in Saudi Arabia demonstrate that groundwater is stored in more than 20 primary and secondary aquifers (Hoetzi 1995). It has been estimated that the groundwater reserves are about  $1,919 \times 10^9 \text{ m}^3$  of which  $160 \times 10^9 \text{ m}^3$  stored in deeper secondary reserves (Al-Rashed and Sherif 2000). The total volume of groundwater abstracted for irrigation in the designated study area has increased from 23 MCM in 1973 to 2,051 MCM in 2006, while the annual recharge does not exceed 10% (Elhag and Bahrawi 2014). The climate in the study area is confined to the semi-arid climate. About 80% of the study area receives precipitation less than 100 mm/y, mostly during the spring months. The area of Wadi As-Sirhan, situated at an altitude of around 650 m.a.s.l., is characterized by very hot summers with average monthly maximum/minimum in July: 33.9°C/17.7°C, and mild winters with average monthly maximum/minimum in January: 14.7°C/3.8°C. The calculated annual potential evapotranspiration (ET<sub>o</sub>), Penman-Monteith approach (FAO) for Wadi As-Sirhan is 2,643 mm/y. The soil of the study area is generally sandy with pH from 6.65 up to 7.4 and with electric conductivity (EC) from 0.031 up to 1.634 ms/cm. There were no significant differences in soil colors either in dry summer soils or wet winter soils. Organic matter content is low around (2.11%). The study

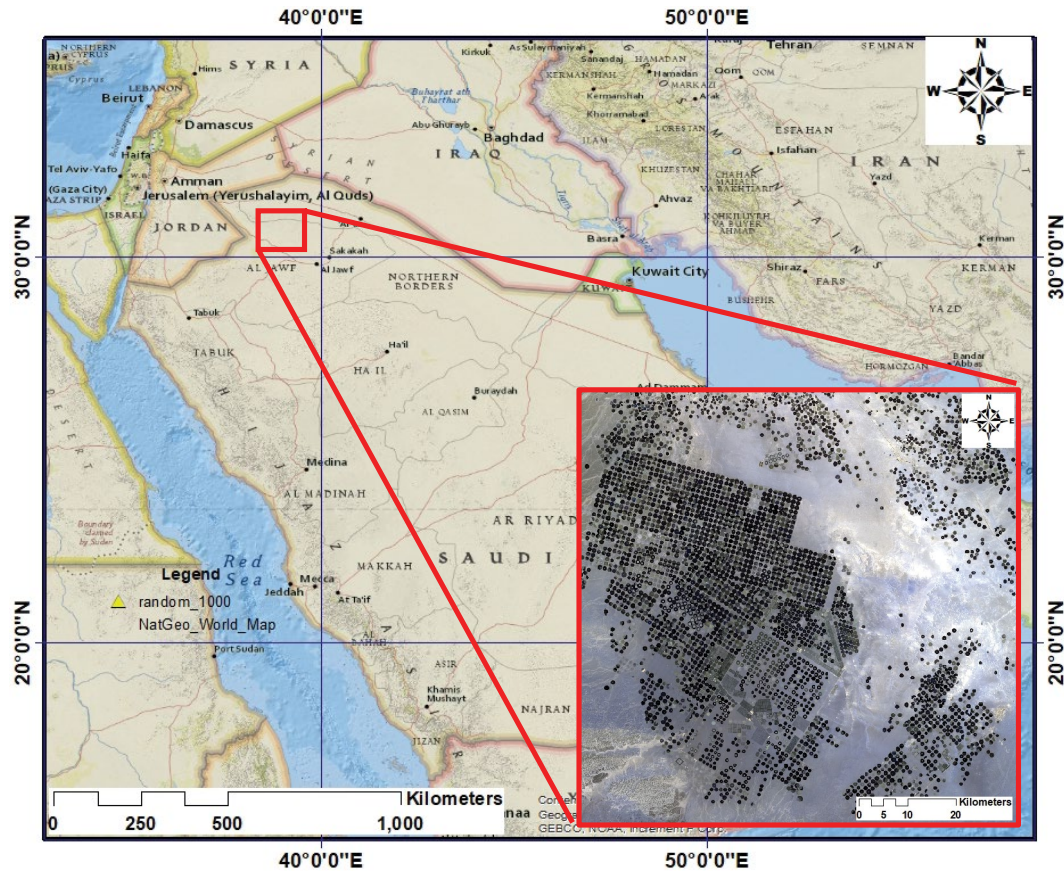


Fig. 1. Study area location in false-color composite over a natural color base map.

area is not covered by natural vegetation. It is reclaimed land for crop production mainly. Water radiometric indices interpretation is exercised on the ratio between red, near infra-red and infra-red bands of Sentinel-2 over the study area acquired in 2016.

## 2.2. Methodological framework

### 2.2.1. Dataset and soil sampling

A total number of 150 random soil samples were collected from the cultivated land in Wadi As-Sirhan area with a minimum distance of 1,000 m between the location of the sample to avoid data clumping and only bare soil locations without crop cover were considered. Soil samples were taken from 0 to 10 cm depth then mixed well for soil moisture estimation in triplicates to obtain the average sample. The standard procedure of determining soil extract salinity in terms of electrical conductivity (EC) was followed according to Rhoades and Chanduvi 1999 under laboratory condition and validated against soil salinity values estimated from remote sensing data according to Elhag 2016. Location of winter samples was marked with wooden sticks for summer data collection (Fig. 2). Sentinel-2 images acquired in January and July 2016 were downloaded and processed to represent the winter and the summer seasons correspondingly. Sentinel-2 is made of 12 spectral bands with a 10-m resolution of visible bands (VI), 20 m resolution of vegetation

red edge (VRE) bands and SWIR bands in addition to three bands related to coastal aerosols and water vapor of 60-m resolution. The remotely sensed water radiometric indices are conducted from several algorithms' exercises, basically VI, VRE and SWIR bands.

### 2.2.2. Estimation of soil water content

This study adopted the common gravimetric method of soil water content estimation. The soil water content is expressed either in terms of weight or volume. In the current research study, the soil water content is expressed in terms of weight as a ratio of the mass between dry and wet soil. Determination of the soil water weight ratio is carried out by drying the soil to a constant weight and calculating the soil sample mass after and before drying. The criterion for drying the soil samples to a constant weight is considered after heat treatment in an oven at a temperature between 100°C and 110°C. Within this range of temperature, it is assured that the water content in the examined samples will be evaporated without any alteration that may occur to the physical or the chemical characteristics of the soil samples. The soil water content in dry weight approach is calculated according to the formula (Klute 1986).

$$\theta_d = \frac{\text{wt of wet soil} - \text{wt of dry soil}}{\text{wt of dry soil}} \quad (1)$$

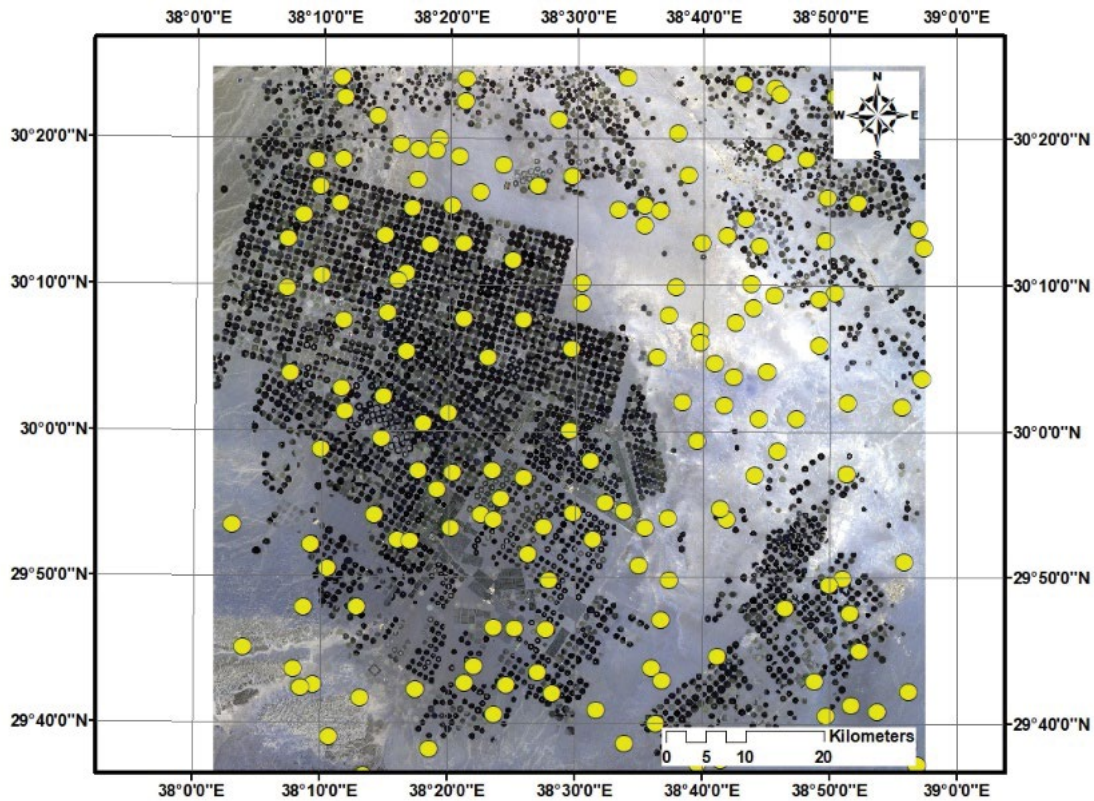


Fig. 2. Soil sample location in a false color composition of Sentinel-2.

Soil water content is calculated as the ratio between water mass and the mass of wet soil ( $\theta_w$ ). The alteration from  $\theta_d$  to  $\theta_w$  can be calculated as follows:

$$\theta_d = \frac{\text{wt of water}}{\text{wt of dry soil}} \quad (2)$$

After manipulation, the water content in wet and dry basis can be expressed as follows:

$$\theta_d = \frac{\theta_w}{1 - \theta_w} \quad (3)$$

and

$$\theta_w = \frac{\theta_d}{\theta_d + 1} \quad (4)$$

### 2.2.3. Remote sensing analysis

The amount of water present in leaf internal structure mainly affects the spectral reflectance in the SWIR interval (ca. 1.2–1.7  $\mu\text{m}$ ). The SWIR reflectance is also sensitive to the canopy internal structure. Because the NIR is exaggerated by leaf internal structure and leaf dry matter, but not by the water content, the combination of SWIR and NIR into NDWI calculation removes the leaf dry matter and internal structure and retains the water content. NDWI is less susceptible to atmospheric scattering than NDVI, but it cannot

eliminate totally the effects of the background soil reflectance's comparable with NDVI.

The MNDWI algorithm was developed by Xu 2006 to improve the open water features through an efficient elimination of land noise as well as vegetation and soil noise. MNDWI is calculated by the following equation:

$$\text{MNDWI} = \frac{\text{Green} - \text{SWIR}}{\text{Green} + \text{SWIR}} \quad (5)$$

The Normalized Difference Pond Index (NDPI) was developed by Lacaux et al. 2007 to distinguish the vegetation cover apart for its aquatic surroundings. NDPI is calculated by the following equation:

$$\text{NDPI} = \frac{\text{SWIR} - \text{Green}}{\text{SWIR} + \text{Green}} \quad (6)$$

The Normalized Difference Turbidity Index (NDTI) was developed by Lacaux et al. 2007 to estimate water turbidity. NDTI is calculated by the following equation:

$$\text{NDTI} = \frac{\text{Red} - \text{Green}}{\text{Red} + \text{Green}} \quad (7)$$

The NDWI was found by Gao 1996 and after that improved by Ganaie et al. 2013 to measure the liquid water molecules at the top of canopy level. NDWI is calculated by the following equation:

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (8)$$

The second Normalized Difference Water Index (NDWI-2) was developed by McFeeters 1996 to detect and measure the surface water extent in addition to the surface water of wetland environments. NDWI-2 is calculated by the following equation:

$$NDWI - 2 = \frac{Green - NIR}{Green + NIR} \quad (9)$$

where

- B3 "G" is the green band of Sentinel-2.
- B4 "R" is the red band of Sentinel-2.
- B8 "NIR" is the near infra-red band of Sentinel-2.
- B11 "SWIR" is the short-wave infra-red band of Sentinel-2.

The final step in image data analysis in the current study is data normalization. The above-mentioned Water Radiometric Indices are calculated within a range of -1 to +1. Therefore, Water Radiometric Indices were transformed into the same range of soil water content weights for comparability reasons using Hawkins and Pole 1989 transformation:

$$Z = \frac{1}{2} \ln \left( \frac{1+r}{1-r} \right) = \text{arctanh}(r) \quad (10)$$

where

- ln is the natural logarithm function.
- arctanh is the inverse hyperbolic tangent function.
- r is the Fisher's z-transformation.

### 2.3. Regression analyses

The purpose of the regression analyzes is to envisage the regression potentials between soil salinity index from one side and the rest of the hydrological drought indices from the other side. Principle component analysis (PCA) is performed to transform a set of likely correlated with unlikely correlated variables. Principal components number is less/equal to the variables original number. Following Monahan 2000, PCA fundamental equations are:

First vector  $w_{(1)}$  should be answered as follows:

$$w_{(1)} = \arg \max_{\|w\|=1} \left\{ \sum_i (t_i)_{(1)}^2 \right\} = \arg \max_{\|w\|=1} \left\{ \sum_i (x_i \times w)^2 \right\} \quad (11)$$

The matrix form of the above equation gives the following:

$$w_{(1)} = \arg \max_{\|w\|=1} \left\{ \|Xw\|^2 \right\} = \arg \max_{\|w\|=1} \left\{ w^T X^T X w \right\} \quad (12)$$

$w_{(1)}$  should be answered as follows:

$$w_{(1)} = \arg \max \left\{ \frac{w^T X^T X w}{w^T w} \right\} \quad (13)$$

Originated  $w_{(1)}$  suggests that first component of a data vector  $x_{(i)}$  can then be expressed as a score of  $t_{(i)} = x_{(i)} \times w_{(1)}$  in the transformed coordinates, or as the corresponding vector in the original variables,  $(x_{(i)} \times w_{(1)}) w_{(1)}$ .

### 2.4. Validation

Validation of Water Radiometric Indices values was carried out using the ground truth data collection. 150 soil samples were analyzed for gravimetric soil water content and plotted against the remotely sensed values. The average accuracy is estimated by a horizontal function of the tested dataset. The average reliability is estimated by a vertical function of the tested dataset. The overall efficiency estimated the diagonal function of the tested dataset. Following Congalton et al. 1983, a correspondence analysis was constructed as follows:

$$CA = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{ij} \times x_{ji})}{N^2 - \sum_{i=1}^r (x_{ij} \times x_{ji})} \quad (14)$$

where

- r, the number of rows in the error matrix
- $x_{ij}$ , the number of observations in row i and column j (the diagonal cells)
- $x_{i+}$ , total observations of row i
- $x_{+j}$ , total observations of column j
- N, total of observations in the matrix

## 3. Results and discussion

Realization of different water radiometric indices was computed succeeding to adequate atmospheric and radiometric corrections. Spatial distribution of the implemented water radiometric indices and their corresponded temporal acquisitions are illustrated in Figs. 3a-e. The first dataset was comprehended for winter Water Radiometric Indices (January 2016) then six months later (July 2016) the analysis procedures were repeated for the summer dataset (Figs. 3f-j).

Field data collection and remote sensing techniques were applied with precise synchronization to optimize the results. Soil water content collected from summer and winter seasons shows a significant correlation RMSE 0.01. Therefore, the agricultural practice in the designated study area suggests an equivalent amount of the irrigation water utilized in both seasons (Elhag and Bahrawi 2017).

Water radiometric indices conducted from remote sensing data showed inconsistent responses between winter and summer seasons (Table 1 and Figs. 4a and b).

The estimated radiometric indices tend to respond preferably to winter rather than to summer climatic condition (Fig. 5a). MNDWI shows a coherent pattern of estimation in different seasons. Such behavior could be considered as a lack of the index sensitivity in summer season rather than winter season (Wang et al. 2013 and Gautam et al. 2015).

NDPI shows an idealistic correlation between the two seasons (Fig. 5b). Henceforward, the only foreseen explanation is that there is no ponds formation in the study area and

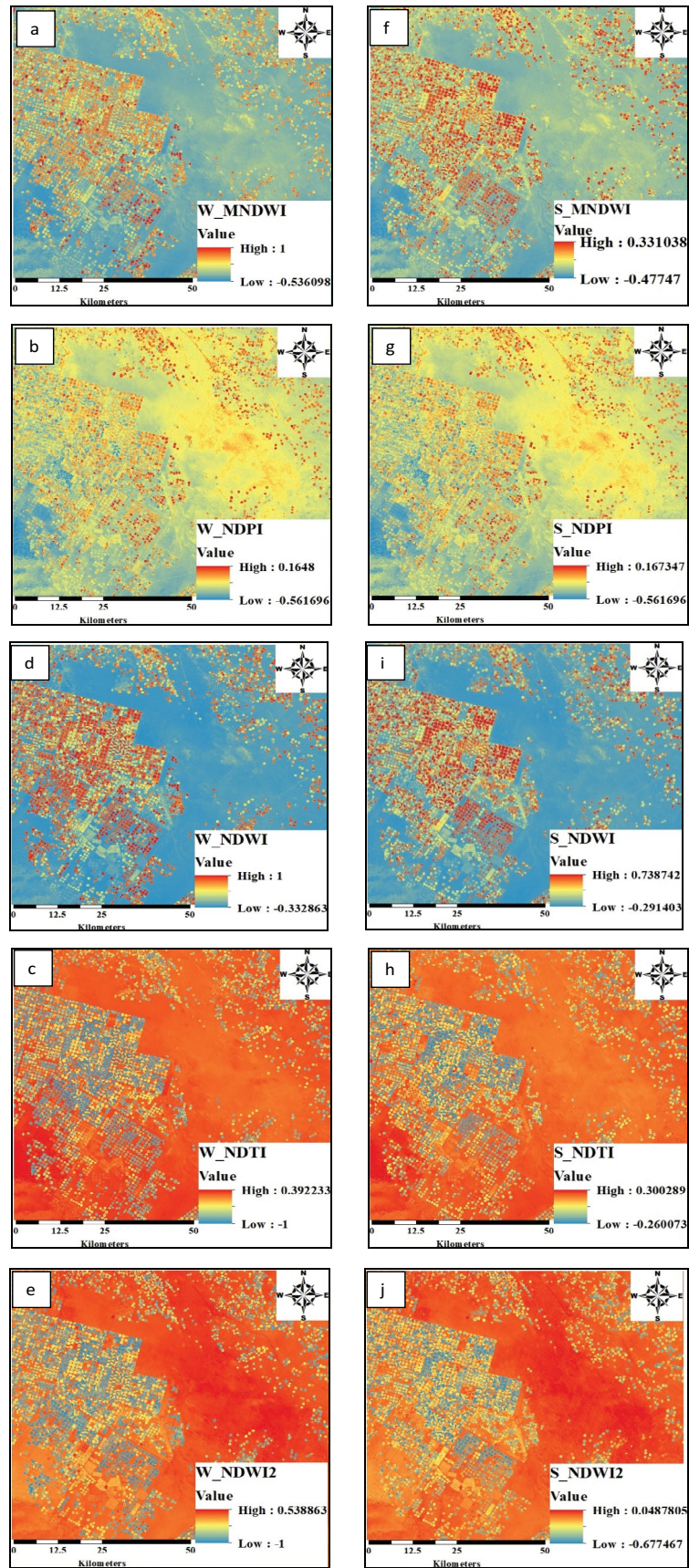


Fig. 3. Spatial distribution of five different water radiometric indices in two different seasons (January/July-2016).

Table 1  
Statistical analysis of the estimated radiometric water indices

	Summer indices			Winter indices		
	$R^2$	RMSE	Equation	$R^2$	RMSE	Equation
MNDWI	0.6117	0.08	$0.3232x - 0.4061$	0.7146	0.06	$0.3813x - 0.4643$
NDPI	0.9046	0.01	$0.1432x - 0.4365$	0.9476	0.01	$0.1642x - 0.4439$
NDTI	0.5397	0.07	$0.258x + 0.0287$	0.5859	0.08	$0.3574x - 0.0029$
NDWI	0.4916	0.15	$0.5033x - 0.1983$	0.5501	0.15	$0.6539x - 0.2522$
NDWI-2	0.5718	0.07	$0.2702x - 0.4212$	0.6455	0.07	$0.3747x - 0.5051$

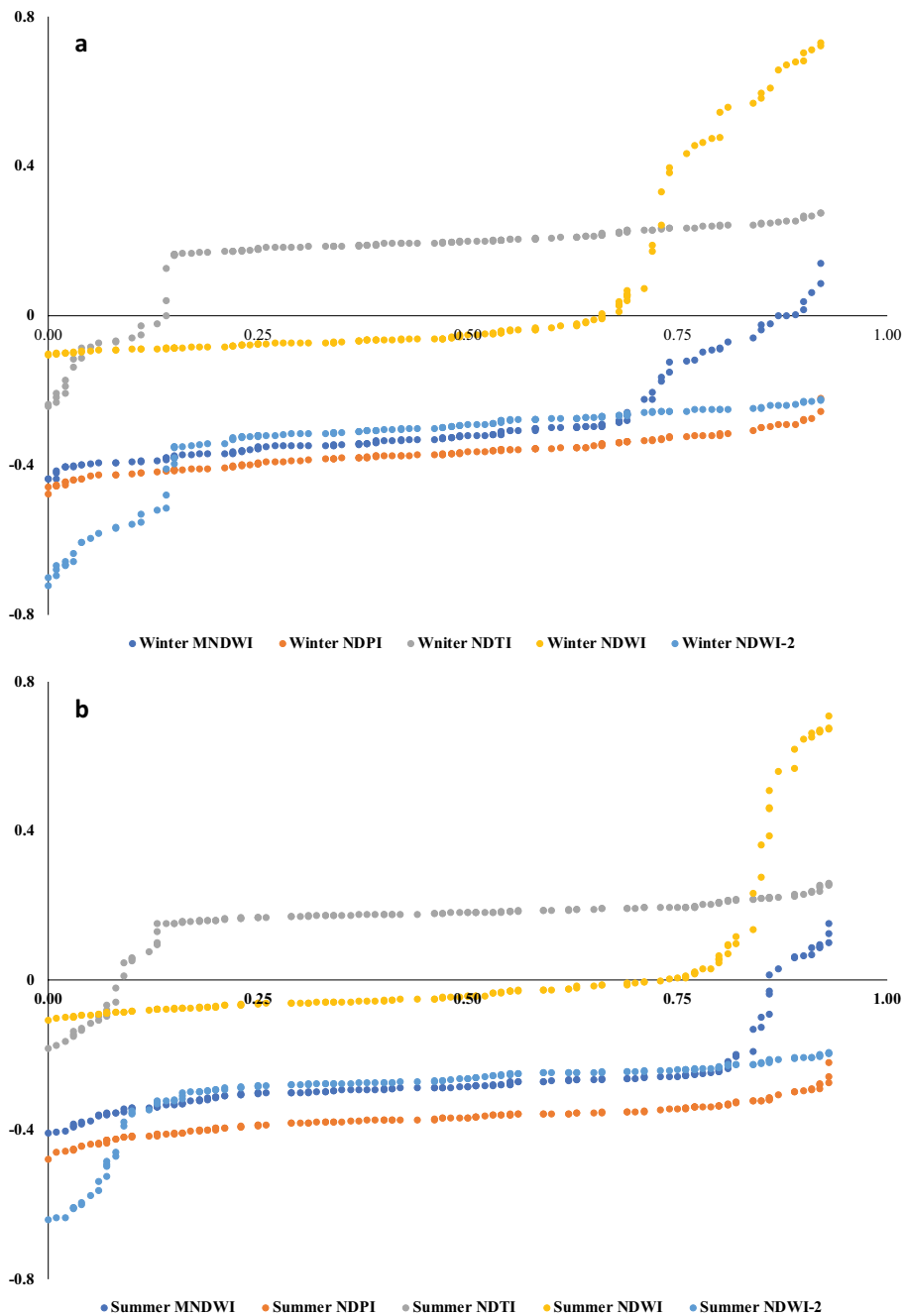


Fig. 4. Seasonal variation of the estimated radiometric water indices (a for winter and b for summer).

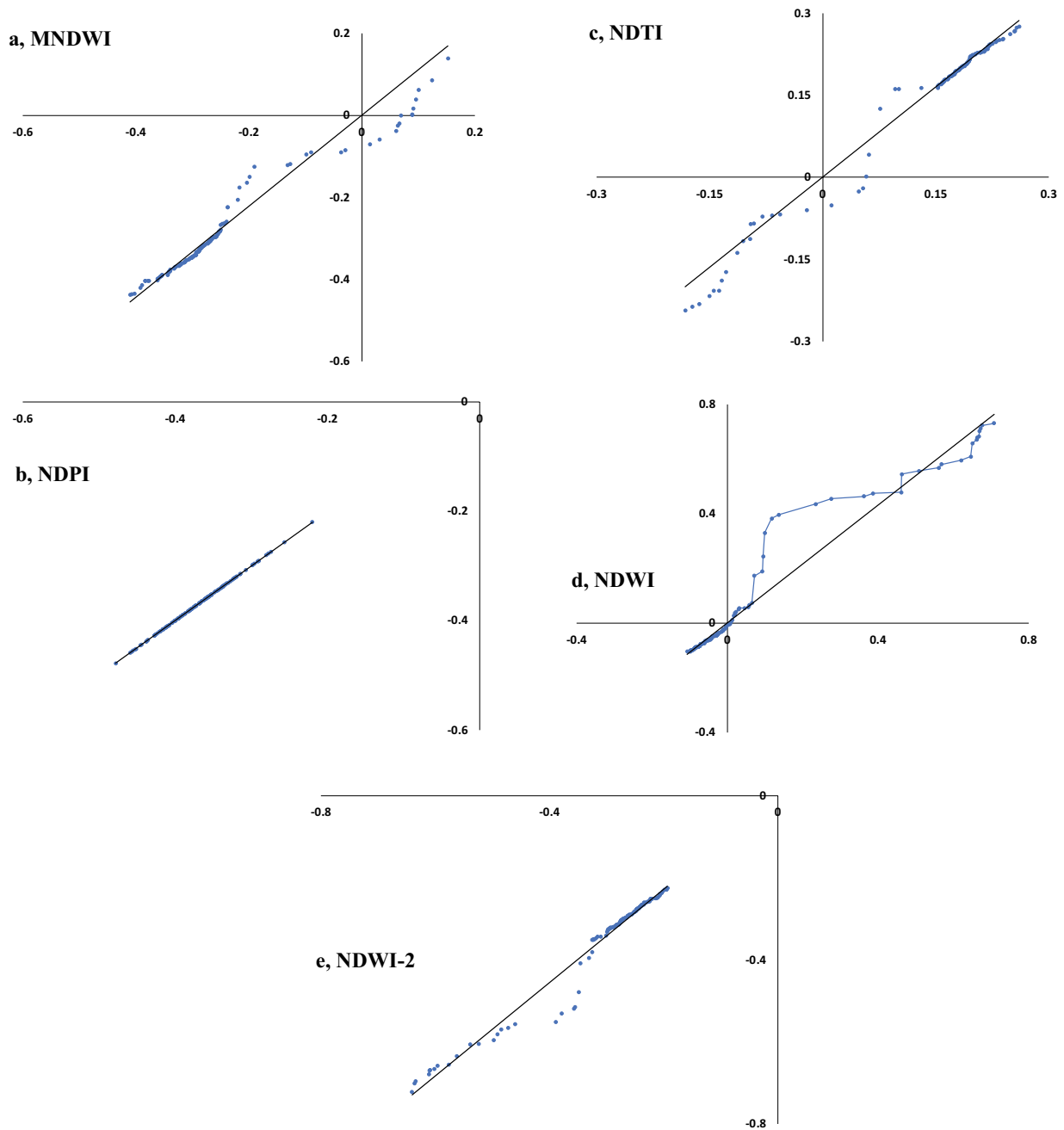


Fig. 5. Seasonal radiometric water indices intercorrelation (x axis is the winter measurements; y axis is the summer measurements).

hence the index cannot differentiate the seasonality dissimilarities. Consequently, NDPI can be exercised all year long with no season preferences (Ji et al. 2009 and Dambach et al. 2012).

On the other side, NDTI shows steady correlation along with the seasonal variations (Fig. 5c). NDTI is the only index that showed optimum correlation stability among the other radiometric water indices. Accordingly, NDTI behavior is explained by the lack of pure water surfaces and the irrigational water is considered as turbid water as it is mixed with soil particles at the surface level (Daughtry et al. 2005 and Serbin et al. 2009).

Similar behavior to NDTI but with less accuracy is expressed by NDWI. NDWI shows a robust correlation between lower NDWI values rather than the higher values (Fig. 5d). Such results may promote NDWI to be used in winter rather than in summer conditions (Chen 2006 and Gu et al. 2007).

In contrary, the improved index of NDWI was exercised to contradict the sensitivity of the index to the seasonal conditions. NDWI-2 shows significant correlations in summer conditions with no winter condition preferences (Fig. 5e). Therefore, NDWI-2 could be considered as a summer index (Soti et al. 2009 and Sánchez-Ruiz et al. 2014).



Principally, the Water Radiometric Indices used in the current research varied based on the utilized bands in each rationing. Therefore, categorization of different indices using principal component analysis will help to examine the indices discrepancies. Fig. 5 presents the grouping of different indices according to the PCA on covariances in both seasons.

Generally, different water radiometric indices fell into two groups in both seasons. The first group contained NDPI and it showed no seasonal variation and kept a neutral behavior. Meanwhile, NDTI from one side and NDWI and MNDWI from the other side showed an alternative behavior across the two seasons (Fig. 6). Additionally, NDWI-2 significantly correlated and grouped together (Table 2). Consequently, NDWI-2 is a superposed group (Dehni and Lounis 2012). Lack of correlation is the main reason of NDTI and NDWI insignificance (Table 2). The implemented band length is the driving force of the correlation inconsequentiality between the previously mentioned indices (Lillesand et al. 2014).

The dynamics of the soil water content dissimilarities proved by the seasonal variations added further complications to designate soil water content in a systematic uniform perspective. The use of different algorithms based on implementing different combinations and/or ratios of Sentinel-2 bands in the form of water radiometric indices evidenced to be more efficient to overcome water dynamicality problems (Lei et al. 2014 and Zhang et al. 2015).

Moreover, higher soil water content was related to the improper and intense irrigation systems which are based on the lack of an operative water resource management plan in the designated study area (Koshal et al. 2012).

The selection of the profound satellite bands adequate for accurate water radiometric mapping is not systematically comprehensive (Lei et al. 2014 and Zhang et al. 2013). Spatial inconsistency and land cover dissimilarities are the main controlling factors of the band sensor selection (Zhang et al. 2015 & Allbed and Kumar 2013). Consequently, the

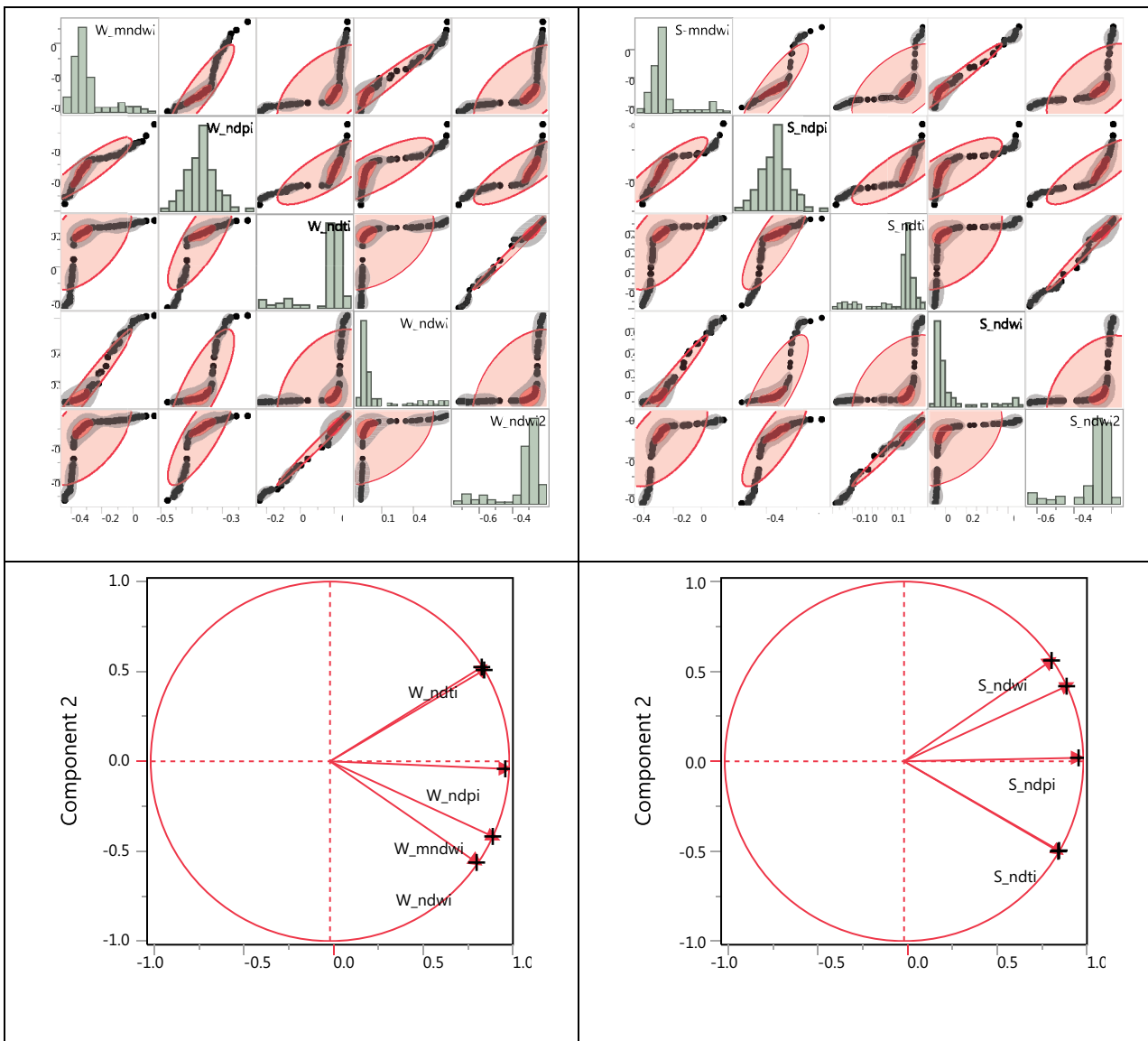


Fig. 6. Principal Component Analysis and its correlation matrix of the different water radiometric indices.

Table 2  
Descriptive statistical analysis and covariant matrix

	W_mndwi	W_ndpi	W_ndti	W_ndwi	W_ndwi2	S_mndwi	S_ndpi	S_ndti	S_ndwi	S_ndwi2				
W_mndwi	1.0000	0.9025	0.5499	0.9766	0.5677	1.0000	0.8796	0.5742	0.9832	0.5787				
W_ndpi	0.9025	1.0000	0.7874	0.7985	0.8125	0.8796	1.0000	0.8085	0.7919	0.8214				
W_ndti	0.5499	0.7874	1.0000	0.4068	0.9943	0.5742	0.8085	1.0000	0.4338	0.9917				
W_ndwi	0.9766	0.7985	0.4068	1.0000	0.4208	0.9832	0.7919	0.4338	1.0000	0.4370				
W_ndwi2	0.5677	0.8125	0.9943	0.4208	1.0000	0.5787	0.8214	0.9917	0.4370	1.0000				
Column	N	DF	Mean	Std Dev	Sum	Minimum	Column	N	DF	Mean	Std Dev	Sum	Minimum	Maximum
W_mndwi	150	149	-0.293	0.116	-44.003	-0.437	S_mndwi	150	149	-0.256	0.120	-38.480	-0.410	0.152
W_ndpi	150	149	-0.370	0.043	-55.538	-0.478	S_ndpi	150	149	-0.370	0.043	-55.538	-0.478	-0.219
W_ndti	150	149	0.157	0.121	23.6101	-0.243	S_ndti	150	149	0.148	0.102	22.2081	-0.182	0.260
W_ndwi	150	149	0.041	0.228	6.1484	-0.104	S_ndwi	150	149	0.034	0.208	5.1805	-0.106	0.708
W_ndwi2	150	149	-0.337	0.120	-50.563	-0.722	S_ndwi2	150	149	-0.296	0.103	-44.436	-0.640	-0.224

utilized water radiometric indices may have different results in specific areas using different band ratios other than the use of Sentinel-2 as a source of remote sensing data (Zhu et al. 2015 and Drusch et al. 2012).

#### 4. Conclusions

The groundwater resources in the Wadi As-Sirhan are the only water source for the agricultural practices that take place. Therefore, to sustain such agricultural activities in the designated study area, an adequate technique of monitoring soil water content is crucial. Remote sensing data acquired by Sentinel-2 proved to be statistically sufficient to estimate soil water content in two different climatic conditions. The implemented water radiometric indices in the current study can be primarily divided into two groups, climatic condition non-sensitive/ sensitive group. The non-sensitive group contains only the NDPI, while the sensitive group contains the rest of the Water Radiometric Indices. Within the second group, there are indices which are less accurate in summer rather than in winter. MNDWI and NDWI-2 best fitted winter soil water content estimations. Meanwhile, NDWI and NDTI least fitted winter estimations. However, NDTI was statistically proved to be the most defined water radiometric index for estimating soil water content. The current irrigational schemes in Wadi As-Sirhan are not taking into consideration the temporal changes in the climatic conditions, where both summer and winter irrigational schemes are almost the same. Thus, the existing agricultural strategy in Wadi As-Sirhan needs to be revised precisely by the decision makers. Moreover, coherent groundwater resources consumption and soil water content monitoring need to be implemented.

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