THE ROLE OF REMOTE SENSING, GEOPHYSICS AND CROP MODELING IN IRRIGATION MANAGEMENT: REVIEW AND FUTURE PERSPECTIVE

WANG, L. H.[1] – GUAN, J. N.[2] – WEI, J.[3*] – RASHEED, A.[4] – MAHMOOD, A.[5] – HASSAN, M. U.[6] – AKRAM, M.[7] – AL-KHAYRI, J. M.[8*] – ALDAEJ, M. I.[8] – SATTAR, M. N.[9] – REZK, A. A.[8,10] – ALMAGHASLA, M. I. [11,12] – SHEHATA, W. F.[8,13] – SHALABY, T. A.[11,14]

[1]*College of Tourism and Geographic Science, Baicheng Normal University, Baicheng, 137000 Jilin, China*

[2]*Rice Research Institute, Shenyang Agricultural University, Shenyang, China*

[3]*School of Agriculture, Jilin Agricultural University, Jilin, China*

[4]*College of Agronomy, Hunan Agricultural University, Changsha 410128, China*

[5]*Department of Agronomy, University of Agriculture, Faisalabad, Pakistan*

[6]*Research Center of Ecological Sciences, Jiangxi Agricultural University, Nanchang, China*

[7]*Agronomy (Forage Production) Section, Ayub Agricultural Research Institute, Faisalabad, Pakistan*

[8]*Department of Agricultural Biotechnology, College of Agriculture and Food Sciences, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

[9]*Central Laboratories, King Faisal University, PO Box 420, Al-Ahsa 31982, Saudi Arabia*

[10]*Department of Virus and Phytoplasma, Plant Pathology Institute, Agricultural Research Center, Giza 12619, Egypt*

[11]*Department of Arid Land Agriculture, College of Agriculture and Food Sciences, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

[12]*Plant Pests and Diseases Unit, College of Agriculture and Food Sciences, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

[13]*Plant Production Department, College of Environmental Agricultural Science, Arish University, PO Box 45511, North Sinai, Egypt*

[14]*Kafrelsheikh University, Faculty of Agriculture, Horticulture Department, Kafr El-Sheikh 33516, Egypt*

**Corresponding authors*
e-mail: 14800459@qq.com, jkhayri@kfu.edu.sa

(Received 12th Aug 2023; accepted 30th Oct 2023)

Abstract. The food and water security are the most critical issues across the globe owing to the continuous growing population. The agriculture sector is a largest consumer of fresh water and unwise use of water and poor irrigation systems are leading to rapid depletion of freshwater sources. Recently precision agriculture has emerged as an effective tool to improve the crop productivity while saving irrigation water. Agriculture is a complex system owing to different soil and climatic conditions, crops

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

and topography and its interconnections with scarcity and availability of water. Thus, it is mandatory to understand these variables as well as spatial and temporal behavior which is essential to support precision agriculture through the implementation of optimum use of irrigation water. Different cost and time effective methods have been developed to optimize the crop productivity' without affecting the quality as well as quantity of different resources. Recently, remote sensing (RS) has emerged as an excellent tool to improve the crop productivity while saving the irrigation water. The application of remote sensing provides the information about the areas of interest from regional to farm scales while geophysics can investigate the sub-surface soil which can help to save the irrigation with improving crop productivity. Therefore, in present review we highlighted the role of remote sensing, geophysics and crop modelling in improving irrigation management to get maximum productivity while saving water.
Keywords: *agriculture, crop growth, irrigation, modeling, water*

Introduction

Food is a basic and essential requirement for humans; however, the limited land and water resources will negatively affect food production in the future (Scheierling et al., 2014). The global population is continuously increasing and it has been projected that food production has to increase by 60% from 2005 to 2050 to meet the global food needs (Tilman et al., 2011). Water is a lifeline for agriculture however, water is a limited source, and therefore, in this context, the wise use of water for agriculture is a crucial factor (Alvino and Marino, 2017). Agriculture is the main user of water and it uses 70% of total water with drawls (Fereres, 2008; Samreen et al., 2023) and this sector will also see an increase of 20% in water use by the end of 2025 (Singh et al., 2016). Thus, it is projected competition for water resources will increase in the coming time therefore, it is essential to adopt wise practices to carefully manage the water to improve water use efficiency (WUE) and agricultural productivity (Scheierling et al., 2014; Alvino and Marino, 2017). At the same time, the rapid urbanization, market volatility, and climate variability linked with an increase in drought intensity and drought periods have forced to reduce the water withdrawals and improve the WUE (Rosa et al., 2020; Tramblay et al., 2020).

Precise irrigation refers to supply water and nutrients to crops at the desired with in a right place to ensure the better plant growth and development by using irrigation sensors. This system is emerged as an excellent and efficient way to apply the crops with addition additional benefits of water saving. Precision irrigation systems include diverse technologies of filtration and emitters with higher clogging resistance. In precision irrigation water can be applied drip irrigation, sub-surface drip irrigation and micro-sprinklers which ensures better use of water (Tramlay et al., 2020). In this context, remote sensing (RS) has emerged as an excellent strategy to improve the WUE and properly manage the applied irrigation water. The ability to monitor a variety of processes, such as soil moisture, land cover, and vegetation, is made possible by the Earth observation satellites. In the last century, there has been an appreciable improvement in the use of earth observation to retrieve information on the amount, frequency, and extent of irrigation application (Massari et al., 2021). In the last 20 years, there has been a significant improvement in the RS ability to recognize, and monitor crop growth and other bio-physical properties, yet there are many problems that need to be fixed in the future. Remote sensing techniques are identified as efficient and effective measures to manage irrigation water (Kanda and Lutta, 2022).

The technologies including RS, computing, satellite monitoring and mobile computing are providing the solution to manage the irrigation problems (Conrad et al., 2021). For diverse crops it is imperative to maintain a powerful connection among the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

crop production and farm water application (Alvino and Marino, 2017). The use of RS technique has increased the characterization, of water bodies, forecasting of rainfalls, and temperature and estimation of soil moisture, and evaporation. Further, with use of satellite data is also possible to monitor the drought, flood and irrigation management in real time (Massari et al., 2021).

Precise irrigation refers to the precise and accurate application of irrigation water to meet the specific requirements of crops and minimize the adverse impacts of environmental conditions (Raine et al., 2007; Alvino and Marino, 2017). To create effective measures, it is crucial to monitor water use and crop water status in the field, for which specific indicators are required.

Therefore, it is crucial to identify indicators to track the water quality at farm levels to develop successful irrigation methods (Alvino and Marino, 2017; Samreen et al., 2023). For this purpose, the agriculture information can be derived from the remote sensing data (Alvino and Marino, 2017). Besides RS, geophysics and hydrological modeling have been also used globally as an important tool for the management of irrigation water. These tools are part of precision agriculture which can help to make wise decisions at the farm level to achieve precision irrigation management. Therefore, in present review, we discussed the role of RS, geophysics, and hydrological modeling in WUE and the management of farm irrigation water.

Irrigation and crop monitoring in precision agriculture

The adequate measurement of crop water needs is the first step to improving the WUE and evapotranspiration (ET), soil water balance, and crop water needs all play a role in determining the appropriate amount of water for irrigation (Calera et al., 2017). ET is the soil evaporation and transpiration from plants and it can also be defined as the amount of water needed by plants (Evans and Sadler, 2008). Since ET is the most important outgoing water flux and changes to ET have a direct impact on the availability of water, precise knowledge of ET is essential for understanding the relationship between the balance of water and energy. Conventional practices like lysimeter, pan measurement, sap flow and eddy co-variance offer an effective way to estimate the ET at the field and crop scales. However, it is very challenging to extrapolate many of the aforementioned techniques to a larger scale to discover on-farm spatial variability while maintaining the land surface heterogeneity (*Table 1*). As a result, in this context, RS is a useful technique to get around this because it is accurate geographical and temporal information (Pradipta et al., 2022).

At the field scale, the shallow soil properties including soil texture and structure affect the nutrient availability, distribution of irrigation water, and root growth. Likewise, coarse soils can be irrigated with less irrigation water but they dry easily, thus resulting in frequent irrigation conversely, fine-textured soils can hold the water for a long period (Pradipta et al., 2022). The poor structure reduces the water infiltration and the runoff of water which could be due to compaction owing to the use of heavy machinery. These soil properties might affect irrigation water management, thus a precise assessment of sub-surface soil at the farm level is needed to support precise irrigation (Pradipta et al., 2022). Hydrological status and flux, such as SM and root water uptake (RWU), are the other variables needed for precise irrigation, and both of these variables are significantly affected by one another. Consequently, it is advantageous to have a better understanding of the spatial and temporal variability of SM and RWU to aid in the decision-making process for precision irrigation (Garré et

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

al., 2011). SM is the amount of water in soil and it is an important variable that affects the carbon, energy, and water in the soil-plant-atmosphere continuum. Crops require a particular quantity of SM, which may be measured using a variety of methods at various scales, from the local to the regional.

Table 1. *Different remote sensing methods use for estimation of evapotranspiration*

RS methods	Applications	Pros and cons	References
Surface energy balance algorithm for land	Used for estimation of ET in Huaihe River Basin	Needs ground bases information	Tan et al. (2021)
Single source surface energy balance	Used to estimate the ET in conterminous USA	It can reduce uncertainty in land surface temperature	Bhattarai et al. (2018)
Two source surface energy balance	Used to estimate the ET in China	It can calculate energy balance of soil canopy atmosphere	Song et al. (2016)
Modified surface energy balance	Used to estimate the ET in USA	It can estimate impact and importance of dry and wet soil evaporation on the total ET	Long and Singh (2012)
Simplified surface energy balance	Used for ET in the Netherlands	No additional meteorological data are needed to calculate energy flux	Roerink et al. (2000)
Water balance method	It can detect the irrigation induced ET	Temporal and spatial boundaries are not defined	Pan et al. (2017)
VI-Ts triangle method	Used to estimate of ET in China	It gives accurate results	Tian et al. (2013)

Another important technique at point scale is development of electromagnetic sensors inside the soil to measure the volumetric water content (Babaeian et al., 2019). At the proximal scales, geophysics techniques like resistivity, ground-penetrating radar (GPR) and electromagnetic induction (EMI) can be used to measure the volumetric water (Power et al., 2015; Babaeian et al., 2019). Crop monitoring, which entails retrieving metrics like the leaf area index (LAI), chlorophyll content, and plant hydration status, is a crucial task in precision agriculture (*Table 2*). Early crop yields can be calculated based on this knowledge to influence farm planning and decision-making. Water and nutrients are most important variable that affect the crop productivity;besides this, insect pests and disease monitoring should also be considered as they affect the crop yield (Gebbers and Adamchuk, 2010; Pradipta et al., 2022).

The implementation of crop monitoring can reduce the risk of economic losses. The measurement of chlorophyll contents can assist farmers in defining the concentration of nitrogen (N). Among different nutrients N is an essential nutrient needed for plants thus, farmers must make, and balance N to meet crop needs (Pradipta et al., 2022). The excess N supply could result in N losses in the form of run-off and leaching that cause eutrophication in soil and water bodies and the deficiency of N can reduce the crop yield (Yamashita et al., 2020). Early growth is a critical period and it affects the crop yield; therefore, a sufficiency N must be applied

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

across the field and must be properly determined (Yamashita et al., 2020). The concentration of leaf chlorophyll can be estimated through in situ measures or using remote sensing data (Parry et al., 2014; Elarab et al., 2015; Gago et al., 2015).

Table 2. *Different remote sensing indexes used to monitor the crop development*

RS index	Applications	Benefits	Disadvantages	References
Normalized difference water index (NDWI)	Monitor moisture condition of plant vegetation over large area	High resolution and good spatial coverage	Difficult to discern stress imposed by other than drought	Sun et al. (2021)
Difference spectral index (RSI)	Measure relative abundance and lack of land covers	Minimize the soil background influence	Saturation	Chen et al. (2023)
Plant biochemical index (PBI)	It indicates plant photosynthetic and biochemical process	Quick and easy method	Sometimes wavelengths not always being related to the compounds	Tao et al. (2020)
Structure insensitive pigment index (SIPI)	Monitors vegetation health and detect physiological stress	Maximize sensitivity to the bulk carotenoids to chlorophyll ratio	Minimize the impact of the variable canopy structure	Verrelst et al. (2008)
Chlorophyll index red edge (CIRE)	It indicates crop health when chlorophyll contents are high	Advantage of a narrow spectral band between the red and NIR	Saturation	Gitelson et al. (2003)
Enhanced vegetation index (EVI)	It is used to indicate vegetation greenness	More responsive to canopy variations, canopy type and architecture	The period of record for satellite data is short	Huete et al. (1994)
Soil-adjusted vegetation index (SAVI)	It is used to correct the normalized difference vegetation index	High-resolution and high-density	Exhibits asymptotic behaviors	Chang et al. (2019)
Green normalized difference vegetation index (GNDVI)	It is used to estimate plant photo-synthetic activity	Identify moisture deficit and saturation in the crop	If there is low vegetation cover then it will be sensitive to soil	Kanatas et al. (2023)
Red-edge normalized difference vegetation index (RENDVI)	It is used to measure amount of chlorophyll	Suppress undervaluation when vegetation cover is high	It cannot accurately detect the health of dense vegetation	Evangelides et al. (2020)
Normalized difference spectral index (NDSI)	Used to quantify forest supply and indicate drought		It is sensitive to soil when there is low vegetation	Chen et al. (2023)

The use of solvent extraction is the most accurate technique to estimate chlorophyll (Hosikian et al., 2010). However, new advances in optical sensors provide quick and non-destructive ways to measure reflectance to determine the chlorophyll concentration (Gitelson et al., 2005). The latter technique is more advantageous and it can also be used in RS observation and in-situ. In addition, RS provides an opportunity in precision

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

agriculture and it could monitor large areas (Delegido et al., 2010; Clevers et al., 2017). Nonetheless, chlorophyll measurement by RS at a large scale is challenging owing to the fact canopy reflectance is affected by canopy architecture, distribution of chlorophyll, and plant LAI (Prudnikova et al., 2019). Therefore, even with the same canopy and similar chlorophyll concentration, the obtained leaf reflectance may vary (Liu et al., 2016; Simic et al., 2018).

Since N, temperature, and water have a substantial impact on the amount of green leaf tissue, LAI may be a useful tool for determining responses to irrigation plans. The LAI can be utilized for crop growth and production prediction, fertilizer management, trimming, and spraying (Son et al., 2013). Remote sensing-based observations can overcome the limitations of ground-based measures; however, this practice still needs calibration and validation. RS-based LAI measures involve satellites and unmanned aerial vehicles (UAV). Similarly, measurement of vegetation water contents (VWC) is also imperative for precise irrigation. VWC refers to the total water volume in the stem and canopy and VWC is the production of LAI and leaf water content (Hunt et al., 2011). Recently, RS-based VWC estimation has become population owing to rapid monitoring, high efficiency, and cost effectiveness (Xu et al., 2020).

Remote sensing to support precision agriculture in irrigation management

For the management of precision agriculture, different crop production zones lack adequate field hydrological observations. Field data is spatially limited and has different record lengths. Recent developments in the field of RS can address these challenges by involving airborne and space-borne observations. The remote sensing-based measurements have the advantage of spatial and temporal resolutions and they can be used from farm to regional scales (Alexakis et al., 2016; Clevers et al., 2017).

Evapotranspiration

Different methods, including surface energy balance (SEB), vegetation index-surface temperature (VI-Ts), and water balance methods, are used to quantify ET through the RS (Zhang et al., 2016). The quantity of energy entering the earth is equal to the amount of energy emerging from it, according to SEB models, which calculate the ET as a residual of the surface energy budget equation (Liou and Kar, 2014; Senay et al., 2007). The SEB technique can be divide into single and double source models (Li et al., 2009). Globally, a large number of single source SEB algorithms have been developed for the calculation of ET through RS including the use of surface energy balance algorithm for land (SEBAL; Bastiaanssen et al., 1998), mapping evapotranspiration at high resolution using internalized calibration (METRIC), the surface energy balanced system (SEBS), and the surface temperature initiated closure (STIC; Mallick et al., 2015). The usage of single source SEB mode has limits across the various surface conditions, although single-source models are typically extremely simple to implement and do not handle the soil and vegetation as separate components (Li et al., 2009). The basic principle in two source SEB model involves the quantification of both vegetation and soil components to the total heat flux. The two source models are also successful because they do not require input data or ground base calibration in advance (Colaizzi et al., 2012). Globally, different two source models including atmosphere land exchange inverse (ALEXI), disaggregated atmosphere land exchange inverse model (DISALEXI), and two source energy balance (TSEB) model are most widely used for estimation of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

ET (Mecikalski et al., 1999; Norman et al., 2003). However, the accuracy of these models may be impacted by water availability and fractional soil vegetation cover.

Near infrared, visible, and thermal infrared RS bands ranging from land surface temperature, albedo, and VI could be used as the input for SEB. Then, using ground-based information such as air temperature and wind speed, these variables are integrated to determine net radiation, heat flue, and ground heat (Li et al., 2009). Various satellite platforms, such as land-sat data and moderate resolution image spectro-radiometer (MODIS), demonstrate their appreciable capacity to retrieve the data required for SEB input (Rwasoka et al., 2011; Senkondo et al., 2019; Tasumi, 2019). The major issues with visible, near-infrared, and thermal infrared RS have also been addressed by the use of microwave sensors (Bastiansseen et al., 2012; Mostafa et al., 2019). Additionally, the land surface temperature (LST), which can also be determined from RS, and VI-Ts triangle procedures are based on RS and LST. To estimate ET and the evaporative fraction (EF), VI-Ts construct scattered plots of LST vs LI and create a triangular shape with a dry and wet edge (Minacapilli et al., 2016); Zhang et al., 2016). VI-Ts is not a complex technique and it does not need a surface, meteorological and land surface model as an ancillary dataset (Carlson, 2007). Additionally, contrast fluctuations of VI and land surface temperature are required to get the best results from VI-Ts, and this method could not work well in some locations with homogenous land surface, such as desert (Zhu et al., 2017). Additionally, atmospheric factors like cloudiness can stop the LST, which further restricts this technique (Li et al., 2021).

Water balance is a very simple approach to estimating the ET (*Table 3*). By deducting runoff (R) and changes in water mass storage (WMS) from the precipitation, ET values can be obtained (Rodell et al., 2004). WMS is currently also accessible via gravity recovery and climate experiment (GRACE) satellite retrieval, but its utility is restricted to basin size due to its coarse geographic resolution and frequent data gaps (Long et al., 2014). Moreover, for the implementation of water balance methods in small and sub-basin areas, many attempts are focused on improving the spatial resolution of GRACE through the downscaling process (Wan et al., 2015; Yin et al., 2018).

Table 3. *Different geophysical methods used to determine the water availability of soil*

Geophysical method	Applications	Advantages	Disadvantages	References
Electrical resistivity tomography (ERT)	It is used to assess the soil compaction, monitor the soil variability's and impact of irrigation schemes	It can identify areas of potential instability or slope failure	Failures in nonhomogeneous soils	Keller et al. (2017)
Ground penetrating radar (GPR)	It is used to determine the soil water availability	It allows to highlight underground utilities without disturbing the ground	Sometimes it cannot tell the composition of a target	Klotzsche et al. (2018)
Time domain reflectometry (TDR)	It is used to determine the soil moisture contents	Superior accuracy	Undefined frequencies	Evett (2003)
Cosmic-ray neutron (CRN)	It is used to determine soil moisture contents	It does not disturb agricultural field operations	Low accuracy	Andreasen et al. (2017)

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

Electromagnetic induction (EMI)	It is used to measure soil compaction and soil moisture variability	Heat up very fast	Cheap, simple and reliable	Schmäck et al. (2021)
Seismic	It is used to assess the soil compaction	It can produce detailed images of structural features	Expensive to acquire	Mcanallen et al. (2018)

Crop chlorophyll and LAI

For estimating chlorophyll content and LAI, optical RS in the VIS, NIR, and SWIR spectra are frequently utilized (Delegido et al., 2010; Elarab et al., 2015; Kanning et al., 2018). Spectral signatures can be used to differentiate the different materials and objects. Optical RS can be divided into many imaging systems based on spectral bands, with multi-spectral and hyper-spectral imaging sensors being the most popular imaging sensors. Microwave RS is additionally used in addition to optical RS to extract the LAI and chlorophyll contents (Clevers et al., 2017). The multi and hyper spectral bands do work by recording the electromagnetic energy reflected from the surface of earth in 3 to 10 bands or more than 10 bands. In recent years the use of hyper-spectral RS has increased in recent years as compared to multi-spectral owing to its ability to continuous spectral coverage (Liu et al., 2016).

Generally, the estimation of chlorophyll concentration and LAI depends on empirical spectral vegetation indices and radiative transfer models (RTM) (Houborg and Boegh, 2008; Croft et al., 2014). The farmer is the more popular and simplest method that use a statistical technique to determine the correlation among the vegetation indices and observed objects (Croft et al., 2014). The spectral reflectance varies in time and space due to complicated internal and external influences, therefore the link between the seen item and its reflectance may not be adequate under heterogeneous settings (Colombo et al., 2003). In contrast, RTM can use the physical rules to explain how radiation interacts within the plant canopy (Houborg and Boegh, 2008). The major limitation in this method is that it needs in-situ specific information that are not always available (Elarab et al., 2015). VIS, NIR and SWIS domains can be used to quantitatively estimate the LAI and chlorophyll concentration. The spectral reflectance is assumed to be linked with chlorophyll concentration and these spectral domains can be used to develop different VI (Sims and Gamon, 2002).

The most widely used VI among the numerous developed VIs is the normalized difference vegetation index (NDVI), which is less influenced by the soil background and has good accuracy and dependability (Prudnikova et al., 2019). The most effective spectral reflectance use to estimate the LAI are located in NIR and SWIR regions at wavelengths of 820, 1040, 1200, 1650, 2100 and 2260 nm (Gong et al., 2003). The wavelengths of 520, 550, 643, 695, 705, 715 and 795 nm are closely linked with concentration of chlorophyll in all leaf species (Daughtry et al., 2000; Gitelson et al., 2003; Delagido et al., 2010).

Vegetation water content

In vegetation water content (VWC), remote sensing assesses different indicators including stomata conductance, water potential of leaf, water content of canopy, moisture content, and relative water contents (Zhang and Zhou, 2019). Generally, optical and microwave RS are mostly commonly used to measure VWC (*Table 3*),

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

besides, thermal RS is also being used to assess the VWC. Among the aforementioned methods, optical RS is a common method for determining VWC (Ullah et al., 2014; Jin et al., 2017). For instance, spectral reflectance of 926, 1397, 1600 and 1940 nm are related to leaf water content (Ullah et al., 2014; Jin et al., 2017).

Thus, different vegetation indices on the basis of reflectance such as NDVI, normalized difference infrared index (NDII), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and canopy temperature are being used to assess the VWC (Quemada et al., 2021) and amid these NDWI provides a best estimation of VWC (Huang et al., 2009). In recent time active microwave RS is also being used to assess the VWC. In this system radar based VI is used to monitor the crop properties which is used employed to VWC (Kim et al., 2012; Huang et al., 2016). This VI is also applied to vegetation greenness and LAI and it can also provide estimation of VWC (Kim et al., 2012; Ma et al., 2017).

The RVI’s sensitivity of radar measurement to soil moisture and roughness is one of its limitations. Thus, it is suggested that updated RV-II and RV-II must be used to lessen the effect of soil moisture and soil roughness (Szigarski et al., 2018). Despite the differences between RV-I and RV-II, alternative radar bases called VI are also developed to enhance the effectiveness of VWC measurement (Mandal et al., 2020). The results of many authors also demonstrated that thermal infrared remote sensing (TIRS), particularly at the leaf level, can be used to determine VWC. Despite its appreciably potential TIRS in VWC have not used due to different reasons. Likewise, relationship among TIRS and VWC is very weak as compared NIR and SWIR (Gerber et al., 2011). In case of space born platform the number of TIRS satellites is also very limited to a few satellites (MODIS, Landsat-8 and sentinel-3) which limits the use of TIRS (Xue and Su, 2017; Neinavaz et al., 2021).

Geophysical acquisitions

Geophysical applications have widespread uses and they are being used to assess the characterization of soil structure to SM assessment. This approach is considered noninvasive non-destructive and economical to investigate the soil properties. This application allows to investigate the sub-surface without disturbing the soil dynamics and structure of soil (Tabbagh et al., 2000). Additionally, the geophysical survey also maps a big spatial and temporal variation that bridges the gap between the RS and point-based measurements. Additionally, data derived from geophysical surveys can be utilized to validate and calibrate RS observations. Generally, EMI, GPR, and resistivity are the most commonly used geophysical methods in agriculture applications (Allred et al., 2008). Various soil characteristics like soil porosity, density, clay, SM, and salinity can studied through geophysical applications (Romero-Ruiz et al., 2018). Additionally, the most significant geophysical techniques that can be applied in the future include seismic, self-potential, and magnetometry (Allred et al., 2008). However, because of its ambiguity, the interpretation step is the most difficult phase in geophysical applications. Thus, a combination of diverse geophysical methods and RS can be used to minimize these uncertainties.

Soil characteristics

The soil sub-surface properties are the prerequisite step in agriculture management and different soil properties like soil texture and structure govern the distribution of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

water that can be monitored through geophysics application. The resistivity and seismic geophysical methods have strong signatures for soil texture and structure. Electrical resistivity (ER) is an important practice used in agriculture for the identification of soil structure, however, ER is sensitive to soil bulk density (BD) where an increase in soil BD due to compaction can reduce the soil porosity, air volume, pore spaces with subsequent reduction in soil ER (Ntarlagiannis et al., 2016; Ranjy et al., 2019). Nonetheless, soil degree of compaction cannot be directly measured with ER (Kowalczyk et al., 2014), therefore, in this context, an extension of ER named electrical resistivity tomography (ERT) is developed that can be used to study the soil facies on the bases seasonal water content (Chrétien et al.., 2014; Nielson et al., 2021). Besides ERT also offers to study soil rock interface and soil organic matter delineation (Cheng et al., 2019; Turki et al., 2019; Siddiq et al., 2021) (*Table 4*).

Table 4. *Different crop, and hydrologic models used in agriculture*

Crop model	Applications	Advantages	Disadvantages	References
Soil and water assessment tool (SWAT)	It is used to stimulate the effect of climate change on hydrology and crop yield	It can simulate at the basin scale water	Calibration process tedious	Chen et al. (2019)
Decision support system for agro-technology transfer (DSSAT)	It is used to stimulate the crop yield under different practices	It provides specific tools for entering weather, soil, crop management	The main limitations of DSSAT is to include crop models	Corbeels et al. (2016)
Simple and universal crop growth simulator (SUCROS)	Used to simulate the dynamics of crop growth	It can help to drive efficiency in agricultural production systems	Limited precisions	Vanden et al. (2011)
Environmental policy integrated climate (EPIC)	It used to simulate the soil moisture and evapotranspiration	It predicts impacts of management decisions on soil, water, nutrient and pesticide movements	They need large amounts of computer power and resources	Zhang et al. (2021)
Aquacrop	It is used to simulate crop-water productivity	Suited to address conditions where water is a key limiting factor in crop production	It predicts crop yields at the single field scale	Steduto et al. (2009)
General large area model for annual crops (GLAM)	It simulate the impacts effect of climate variability and change on crops	It simulates the impact of climate variability on crops	Calibration process tedious	Challinor et al. (2004)
HERMES	It simulates soil water and N dynamics and crop growth	It simulates soil water and N dynamics	Calibration process tedious	Palosuo et al. (2011)
Soil water atmosphere plant (SWAP)	This model simulates water and solutes transport in interaction with development of vegetation	It can generate soil water fluxes for pesticide and nutrient models	It presents parameters uncertainty	Huang et al. (2015)

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

Cropsyst	This model is used to effect of cropping systems on crop productivity	Simulates the soil water and nitrogen budgets	It has limitations due to the simplicity of its crop growth descriptions and related biophysical processes	Stöckle et al. (2003)

The soil's apparent electrical conductivity (AEC) measured through EMI can also directly show the different soil properties (Brogi et al., 2019). In irrigated regions, EMI has become an important approach to map the sub-surface owing to higher mobility. The sub-surface characterization by EMI is faster than other instruments (Martini et al., 2017) however, confounding geophysical interpretation can affect the AEC. Moreover, other techniques like wavelet and statistical correlations are being used to solve this issue. The examination of soil structure paid greater attention to reducing permeability whereas the assessment of soil texture by the EMI concentrated on soil clay composition rather than sand and silt (Schmäck et al., 2021). The antenna frequency must be properly selected by considering the aim of use and field conditions (Zajícová and Chuman, 2019). Another important aspect of geophysics application in soil structure is based on dielectric permittivity (Lombardi and Lualdi, 2019; Akinsunmade et al., 2019). In general, the state of the soil affects how well GPR measures the qualities of the soil. For instance, due to the strong absorption of radar signals, GPR application in soil that is primarily composed of clay is highly challenging (McAnallen et al., 2018; Romero-Ruiz et al., 2021).

Soil water availability and dynamic

The higher resolution SM mapping in 2D and 3D models most use resistivity, EMI and GPR (Chambers et al., 2014; Barca et al., 2019; Zhou et al., 2019). The scale disparity between point-scale SM sensors, such as RS observation and time domain reflectometry, can be closed using these geophysical methods (Klotzsche et al., 2018). Through the measurement of soil EC, ERT is regarded as a crucial procedure for observing the spatiotemporal resolution of SM at the field scale. Because soil water content has a significant impact on soil EC variability, it is possible to estimate SM variability (Michot et al., 2003). Therefore, in situ ERT calibration at a specific horizon is required to transform the bulk soil EC into water contents (Garré et al., 2014). The spacing between the electrodes that are placed into the soil determines how much of the subsurface is covered by the supplied resistivity measures (Calamita et al., 2012).

The relationship between soil water distribution and AEC-SM measurements serves as the foundation for SM measurements made using the EMI method (Moghadas et al., 2010). The various agriculture treatments like fertilizers application results in complex relation between SM and AEC (Altdorff et al., 2018). EMI was initially developed to assess the soil salinity as in saline soils soluble salts are the major factors that affect the soil EC and soil physicochemical properties. In areas with lower concentration of salts AEC is highly affected by SM variations (Brevik et al., 2006). Another technique for estimating the SM is GPR, where SM is thought to be a dominant factor that influences the wave's attenuation and velocity of GPR in electromagnetic signals that influence the soil's dielectric constant (Zhou et al., 2019). GPR is thought to be inferior to ERT

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

because it performs significantly worse in places that carry electricity, such as fine-textured soils (Klotzsche et al., 2018; Barca et al. (2019).

Irrigation modellings to support precision agriculture

In recent times the use of agriculture modelling has been substantially increased and use of these models have increased to greenhouse gases emissions, climate change mitigation, food and water security and carbon sequestration (Holzworth et al., 2015). The agricultural modelling can overcome the insufficient on farm dataset needed in space as well as time for increasing the farm management decisions. Generally, crop yields, soil, natural resources and human practices are essential to understand the behavior of agriculture system (Jones et al., 2017). The spatio-temporal score of agriculture models varies depending the problems to be addressed by the farmers, scientists and decision makers (Vereecken et al., 2016; Jones et al., 2017).

The raised concern of food and water has increased the need of crop growth models and coupled and hydrological models (Siad et al., 2021). The numerical representation of soil water distribution in soil and plant atmosphere is shown in the hydrological simulation. The Richards' equation and convection dispersion equations are the foundations of the majority of hydrological models, which are used to stimulate water flow and solute motions in granular media (Šimůnek et al., 2003). Globally, diverse hydrological models (HYDRUS, SUTRA, TOUGH, UNSAT-1, UNSAT-2, SATURN, 3DFEMWATER, SVAT, SWAP, and SWAT) have been developed (Pradipta et al., 2022). Amid these models, HYDRUS is the most commonly used model for stimulation of 1D, 2D and 3D hydrological movements in saturated as well as unsaturated zones.

The efficiency of computation, higher spatial resolution, availability of input data, capability to simulate the land management scenarios and provide the results are most important parameters for building of reliable hydrological models (Arnold et al., 1998). Likewise, crop growth models are also used to stimulate the biophysical process and predict the crop yields which is affected by the weather conditions, soil, irrigation and fertilizers application (Huang et al., 2019; Brogi et al., 2020). Generally, crop growth model is stimulated on the basis of mathematical expressions that explain the flow as well as the conversions process of carbon, nitrogen and water (Shelia et al., 2018). Globally, different crop models (DAISY, DSSAT, DSSAT-CERES, SUCROS, and WOFOST) have been developed and used for various purposes ((Pradipta et al., 2022). Additionally, the real-time calibration of model parameters can be achieved by integrating crop growth and hydrological models with other things like RS. Additionally, it is crucial for the agriculture system to couple crop and hydrological models in terms of geographical and temporal variation and without coupling the efficiency of both these models can be decreased (Siad et al., 2019; Zhang et al., 2021).

Precision agriculture and future challenges concerning proper irrigation

The active, optical, passive, and thermal RS have been proved viable approaches to support precision irrigation. Besides providing a higher resolution image; the atmospheric conditions and solar illuminations constrain the ability of optical satellites. Likewise, microwave, RS can accompaniment the conventional RS in precise irrigation (Pradipta et al., 2022). Although the capacity of microwave RS to penetrate clouds is its main benefit, though, characterizing vegetation features due to irrigation and radar

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

surveillance is still a difficult issue in this sector (Kim et al., 2012). Yet, each aforementioned sensor has its limitations in monitoring agriculture and they are complementary to each other therefore they can integrate to get good results. Unmanned aerial vehicles (UAV) also offer an economical solution to monitor agriculture for small farms where the resolution is large to see the variability of soil and plant characteristics (Pradipta et al., 2022).

The lack of quantitative data linked with sub-surface soil spatial data is a major problem in developing hydrological models. However, by utilizing data based on geophysics, this gap can be closed. A quick, affordable, and trustworthy method of characterizing soil is provided by the geophysical survey. This method makes it simple to comprehend the intricate interaction between flows and hydrological conditions in the subsoil (Pradipta et al., 2022). However, the non-uniqueness of the signal response that results in misleading interpretation is a big challenge that must be addressed. ERT higher resolution is still restricted to shallow depth also limits its use for larger surveys (Gourdol et al., 2018). Conversely, the vertical resolution of soil properties is also low and it can be improved with the development of new EMI instruments (Romero-Ruiz et al., 2018; Brogi et al., 2019). As a result, combining various geophysical techniques can increase resolution and decrease ambiguity in interpretation (Romero-Ruiz et al., 2018).

Additionally, agriculture modeling can overcome the insufficient data needed in the space as well as time to increase farm management. Both agricultural and hydrological models can account for the water condition as well as soil fluxes and water demand. As a result, linking agricultural and hydrological models can increase both models' effectiveness and enable decision-makers to forecast crop yields based on irrigation and fertilizer application (Pradipta et al., 2022). Additionally, the upscaling from field scales to regional dimensions can give decision-makers a better grasp of how to manage resources and maximize crop yield. However, this procedure needs details demonstrating the biological, chemical, and physical characteristics of the locations under study. Besides this paucity of ground-based data used to calibrate can limit the model's accuracy (Pradipta et al., 2022). Further, uncertainty can also come from the modeling approach rather than the input data. Thus, the wise use of input data and modeling techniques is a crucial step to obtaining modeling objectives (Manivasagam and Rozenstein, 2020).

Conclusions

The integration of RS, geophysics, and modeling is an imperative approach to on-farm irrigation application and WUE. The use of these techniques can help to monitor the different variables including soil texture, soil structure, ET, chlorophyll contents, SM, ET, LAI, and VWC. To increase WUE in precision agriculture, these variables must be routinely monitored. Additionally, the demarcation of agricultural zones based on data from RS, geophysics, and modeling at the decision-making levels can assist farmers in managing scarce resources and maximizing crop yield by applying the actual amount of water required for plants and soil. To maximize the benefits of RS, geophysics, and modeling in the future, improvements must be made to data processing methods and acquisition costs. Since the idea of precision agriculture is tied to the geographical and temporal variability of soil and plant features, knowledge of these factors needs to be increased to give farms a strong foundation to achieve their ultimate

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

objectives. In recent years there has been a significant improvement in spatial, spectral, and temporal resolution of earth-based observation. This progress has allowed a more accurate assessment of irrigated areas. The use of microwave-based observation and combining them with optical data and models can provide a way to map the irrigated areas. Moreover, microwave, near infrared, and visible methods have shown the ability to quantify the volumes of irrigation applied to the field. Nonetheless, VNIR observations can only provide the theoretical consumptive water use owing to their inherent limitations because of cloud covers. The frequency of irrigation water depends on water availability, crop type, and climatic conditions, however, lower frequency data is often not able to detect the irrigation event. The improvement of irrigation efficiency and prediction of impacts on diverse reservoirs needs knowledge of water inputs and time of decision making.

Funding. This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia [Project No. GRANT5057].

REFERENCES

[1] Akinsunmade, A., Tomecka-Suchoń, S., Pysz, P. (2019): Correlation between agrotechnical properties of selected soil types and corresponding GPR response. – Acta Geophys 67: 1913-1919.
[2] Alexakis, D. D., Sarris, A., Kalaitzidis, C., Papadopoulos, N., Soupios, P. (2016): Integrated use of satellite remote sensing, GIS, and ground spectroscopy techniques for monitoring olive oil mill waste disposal areas on the island of Crete, Greece. – Int. J. Remote Sens 37: 669-693.
[3] Allred, B. J., Ehsani, M. R., Daniels, J. J. (2008): General Considerations for Geophysical Methods Applied to Agriculture. – In: Handbook of Agricultural Geophysics. CRC Press, Boca Raton, FL.
[4] Altdorff, D., Galagedara, L., Nadeem, M., Cheema, M., Unc, A. (2018): Effect of agronomic treatments on the accuracy of soil moisture mapping by electromagnetic induction. – Catena 164: 96-106.
[5] Alvino, A., Marino, S. (2017): Remote sensing for irrigation of horticultural. – Horticulturae 3(2): 40.
[6] Andreasen, M., Jensen, K. H., Desilets, D., Franz, T. E., Zreda, M., Bogena, H. R., Looms, M. C. (2017): Status and perspectives on the cosmic-ray neutron method for soil moisture estimation and other environmental science applications. – Vadose Zone 16: 1-11.
[7] Arnold, J. G., Srinivasan, R., Muttiah, R. S., Williams, J. R. (1998): Large area hydrologic modeling and assessment. Part I: Model development. – J. Am. Water Resour. Assoc 34: 73-89.
[8] Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., Tuller, M. (2019): Ground, proximal, and satellite remote sensing of soil moisture. – Rev. Geophys 57: 530-616.
[9] Barca, E., De Benedetto, D., Stellacci, A. M. (2019): Contribution of EMI and GPR proximal sensing data in soil water content assessment by using linear mixed effects models and geostatistical approaches. – Geoderma 343: 280-293.
[10] Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., Holtslag, A. A. M. (1998): A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. – J. Hydrol 212: 198-212.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[11] Bastiaanssen, W. G. M., Cheema, M. J. M., Immerzeel, W. W., Miltenburg, I. J., Pelgrum, H. (2012): Surface energy balance and actual evapotranspiration of the transboundary Indus Basin estimated from satellite measurements and the ETLook model. – Water Resour. Res 48: 11512.
[12] Bhattarai, N., Mallick, K., Brunsell, N. A., Sun, G., Jain, M. (2012): Regional evapotranspiration from an image-based implementation of the Surface Temperature Initiated Closure (STIC1.2) model and its validation across an aridity gradient in the conterminous US. – Hydrol. Earth Syst Sci 22: 2311-2341.
[13] Brevik, E. C., Fenton, T. E., Lazari, A. (2006): Soil electrical conductivity as a function of soil water content and implications for soil mapping. – Precis. Agric 7: 393-404.
[14] Brogi, C., Huisman, J. A., Pätzold, S., von Hebel, C., Weihermüller, L., Kaufmann, M. S., van der Kruk, J., Vereecken, H. (2019): Large-scale soil mapping using multi-configuration EMI and supervised image classification. – Geoderma 335: 133-148.
[15] Brogi, C., Huisman, J. A., Herbst, M., Weihermüller, L., Klosterhalfen, A., Montzka, C., Reichenau, T. G., Vereecken, H. (2020): Simulation of spatial variability in crop leaf area index and yield using agro-ecosystem modeling and geophysics-based quantitative soil information. – Vadose Zone J 19: 20009.
[16] Calamita, G., Brocca, L., Perrone, A., Piscitelli, S., Lapenna, V., Melone, F., Moramarco, T. (2012): Electrical resistivity and TDR methods for soil moisture estimation in central Italy test-sites. – J. Hydro l454: 101-112.
[17] Calera, A., Campos, I., Osann, A., D'Urso, G., Menenti, M. (2017): Remote Sensing for Crop Water Management: From ET Modelling to Services for the End Users. – Sensors 17: 1104.
[18] Carlson, T. (2007): An overview of the "triangle method" for estimating surface evapotranspiration and soil moisture from satellite imagery. – Sensors 7: 1612-1629.
[19] Chambers, J. E., Gunn, D. A., Wilkinson, P. B., Meldrum, P. I., Haslam, E., Holyoake, S., Kirkham, M., Kuras, O., Merritt, A., Wragg, J. (2014): 4D electrical resistivity tomography monitoring of soil moisture dynamics in an operational railway embankment. – Near Surf. Geophys 12: 61-72.
[20] Chang, X. Y., Chang, Q. R., Wang, X., Chu, D., Guo, R. X. (2019): Estimation of maize leaf chlorophyll contents based on UAV hyperspectral drone image. – Agric Res Arid Areas 37: 66-73.
[21] Chen, X., Li, F. L., Shi, B. T., Fan, K., Li, Z. F., Chang, Q. R. (2023): Estimation of winter wheat canopy chlorophyll content based on canopy spectral transformation and machine learning method. – Agron 13: 783.
[22] Chen, Y., Marek, G. W., Marek, T. H., Moorhead, J. E., Heflin, K. R., Brauer, D. K., Gowda, P. H., Srinivasan, R. (2019): Simulating the impacts of climate change on hydrology and crop production in the Northern High Plains of Texas using an improved SWAT model. – Aric Water Manag 221: 13-24.
[23] Cheng, Q., Tao, M., Chen, X., Binley, A. (2019): Evaluation of electrical resistivity tomography (ERT) for mapping the soil–rock interface in karstic environments. – Environ. Earth Sci 78: 439.
[24] Chrétien, M., Lataste, J. F., Fabre, R., Denis, A. (2014): Electrical resistivity tomography to understand clay behavior during seasonal water content variations. – Eng. Geo 1169: 112-123.
[25] Clevers, J. G. P. W., Kooistra, L., van den Brande, M. M. M. (2017): Using Sentinel-2 data for retrieving LAI and leaf and canopy chlorophyll content of a potato crop. – Remote Sens 9: 405.
[26] Colaizzi, P. D., Kustas, W. P., Anderson, M. C., Agam, N., Tolk, J. A., Evett, S. R., Howell, T. A., Gowda, P. H., O'Shaughnessy, S. A. (2012): Two-source energy balance model estimates of evapotranspiration using component and composite surface temperatures. – Adv. Water Resour 50: 134-151.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[27] Colombo, R., Bellingeri, D., Fasolini, D., Marino, C. M. (2003): Retrieval of leaf area index in different vegetation types using high resolution satellite data. – Remote Sens. Environ 86: 120-131.
[28] Conrad, C., Usman, M., Morper-Busch, L., Schönbrodt-Stitt, S. (2021): Remote sensing-based assessments of land use, soil and vegetation status, crop production and water use in irrigation systems of the Aral Sea Basin. – A review. Water Secur 11: 100078.
[29] Corbeels, M., Chirat, G., Messad, S., Thierfelder, C. (2016): Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. – Eur J Agron 76: 41-53.
[30] Croft, H., Chen, J. M., Zhang, Y. (2014): The applicability of empirical vegetation indices for determining leaf chlorophyll content over different leaf and canopy structures. – Ecol. Complex 17: 119-130.
[31] Daughtry, C. S. T., Walthall, C. L., Kim, M. S., De Colstoun, E. B., McMurtrey, J. E. (2000): Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. – Remote Sens. Environ 74: 229-239.
[32] Delegido, J., Alonso, L., González, G., Moreno, J. (2010): Estimating chlorophyll content of crops from hyperspectral data using a normalized area over reflectance curve (NAOC). – Int. J. Appl. Earth Obs. Geoinf 12: 165-174.
[33] Elarab, M., Ticlavilca, A. M., Torres-Rua, A. F., Maslova, I., McKee, M. (2015): Estimating chlorophyll with thermal and broadband multispectral high resolution imagery from an unmanned aerial system using relevance vector machines for precision agriculture. – Int. J. Appl. Earth Obs. Geoinf 43: 32-42.
[34] Evangelides, C., Nobajas, A. (2020): Red-Edge Normalised Difference Vegetation Index (NDVI705) from Sentinel-2 imagery to assess post-fire regeneration. – Remote Sens Appl Soc Environ 17: 100283.
[35] Evans, R. G., Sadler, E. J. (2008): Methods and technologies to improve efficiency of water use. – Water Resour. Res 44: W00E04.
[36] Evett, S. R. (2003): Soil Water Measurement by Time Domain Reflectometry. – In: Stewart, B. A., Howell, T. A. (eds.) Encyclopedia of Water Science. Marcel Dekker, Inc., New York.
[37] FAO (2016): AQUASTAT Database. – https://www.fao.org/aquastat/en/ (accessed on 29 July 2021).
[38] Fereres, E. (2008): The future of irrigation in horticulture. – Chron. Horticult 48: 9-11.
[39] Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J., Escalona, J., Medrano, H. (2015): UAVs challenge to assess water stress for sustainable agriculture. – Agric. Water Manag 153: 9-19.
[40] Garré, S., Javaux, M., Vanderborght, J., Pagès, L., Vereecken, H. (2011): Three-dimensional electrical resistivity tomography to monitor root zone water dynamics. – Vadose Zone J 10: 412-424.
[41] Gebbers, R., Adamchuk, V. I. (2010): Precision agriculture and food security. – Science 327: 828-831.
[42] Gerber, F., Marion, R., Olioso, A., Jacquemoud, S., Ribeiro da Luz, B., Fabre, S. (2011): Modeling directional-hemispherical reflectance and transmittance of fresh and dry leaves from 0.4 μm to 5.7 μm with the PROSPECT-VISIR model. – Remote Sens. Environ 115: 404-414.
[43] Gitelson, A. A., Gritz, Y., Merzlyak, M. N. (2003): Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. – J. Plant Physiol 160: 271-282.
[44] Gitelson, A. A., Viña, A., Ciganda, V., Rundquist, D. C., Arkebauer, T. J. (2005): Remote estimation of canopy chlorophyll content in crops. – Geophys. Res. Lett 32: 403.
[45] Gong, P., Pu, R., Biging, G. S., Larrieu, M. R. (2003): Estimation of forest leaf area index using vegetation indices derived from Hyperion hyperspectral data. – IEEE Trans. Geosci. Remote Sens. 41: 1355-1362.

[46] Gourdol, L., Clément, R., Juilleret, J., Pfister, L., Hissler, C. (2018): Large-scale ERT surveys for investigating shallow regolith properties and architecture. – Hydrol. Earth Syst. Sci. Discuss. https://doi.org/10.5194/hess-2018-519.

[47] Holzworth, D. P., Snow, V., Janssen, S., Athanasiadis, I. N., Donatelli, M., Hoogenboom, G., White, J. W., Thorburn, P. (2015): Agricultural production systems modelling and software: current status and future prospects. – Environ. Model. Softw 72: 276-286.

[48] Hosikian, A., Lim, S., Halim, R., Danquah, M. K. (2010): chlorophyll extraction from microalgae: a review on the process engineering aspects. – Int. J. Chem. Eng. 391632.

[49] Houborg, R., Boegh, E. (2008): Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data. – Remote Sens. Environ 112: 186-202.

[50] Huang, J., Chen, D., Cosh, M. H. (2009): Sub-pixel reflectance unmixing in estimating vegetation water content and dry biomass of corn and soybeans cropland using normalized difference water index (NDWI) from satellites. – Int. J. Remote Sens 30: 2075-2104.

[51] Huang, J., Ma, H., Su, W., Zhang, X., Huang, Y., Fan, J., Wu, W. (2015): Jointly assimilating MODIS LAI and et products into the SWAP model for winter wheat yield estimation. – IEEE J Sel Top Appl Earth Observ Remote Sens. 8: 4060-4071.

[52] Huang, J., Gómez-Dans, J. L., Huang, H., Ma, H., Wu, Q., Lewis, P. E., Liang, S., Chen, Z., Xue, J. H., Wu, Y. (2019): Assimilation of remote sensing into crop growth models: current status and perspectives. – Agric. For. Meteorol 276: 107609.

[53] Huang, Y., Walker, J. P., Gao, Y., Wu, X., Monerris, A. (2016): Estimation of vegetation water content from the radar vegetation index at L-Band. – IEEE Trans. Geosci. Remote Sens 54: 981-989.

[54] Huete, A., Justice, C., Liu, H. (1994): Development of vegetation and soil indices for MODIS-EOS. – Remote Sens Environ 49: 224-234.

[55] Hunt, E. R., Li, L., Yilmaz, M. T., Jackson, T. J. (2011): Comparison of vegetation water contents derived from shortwave-infrared and passive-microwave sensors over central Iowa. – Remote Sens. Environ 115: 2376-2383.

[56] Jin, X., Shi, C., Yu, C. Y., Yamada, T., Sacks, E. J. (2017): Determination of leaf water content by visible and near-infrared spectrometry and multivariate calibration in Miscanthus. – Front. Plant Sci 8: 721.

[57] Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S. (2017): Brief history of agricultural systems modeling. – Agric. Syst 155: 240-254.

[58] Kanatas, P., Gazoulis, I., Antonopoulos, N., Tataridas, A., Travlos, I. (2023): The potential of a precision agriculture (PA) practice for in situ evaluation of herbicide efficacy and selectivity in durum wheat (*Triticum durum* Desf.). – Agron13: 732.

[59] Kanda, E. K., Lutta, V. O. (2022): The status and challenges of a modern irrigation system in Kenya: a systematic review. – Irrig. Drain 71: 27-38.

[60] Kanning, M., Kühling, I., Trautz, D., Jarmer, T. (2018): High-resolution UAV-based hyperspectral imagery for LAI and chlorophyll estimations from wheat for yield prediction. – Remote Sens 10: 2000.

[61] Keller, T., Colombi, T., Ruiz, S., Manalili, M. P., Rek, J., Stadelmann, V., Wunderli, H., Breitenstein, D., Reiser, R., Oberholzer, H. (2017): Long-term soil structure observatory for monitoring post-compaction evolution of soil structure. – Vadose Zone J. 16: 118.

[62] Kim, Y., Jackson, T., Bindlish, R., Lee, H., Hong, S. (2012): Radar vegetation index for estimating the vegetation water content of rice and soybean. IEEE Geosci. – Remote Sens. Lett 9: 564-568.

[63] Klotzsche, A., Jonard, F., Looms, M. C., van der Kruk, J., Huisman, J. A. (2018): Measuring soil water content with ground penetrating radar: a decade of progress. – Vadose Zone J. 17: 1-9.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[64] Kowalczyk, S., Maślakowski, M., Tucholka, P.(2014): Determination of the correlation between the electrical resistivity of non-cohesive soils and the degree of compaction. – J. Appl. Geophys 110: 43-50.
[65] Li, B., Cui, Y., Geng, X., Li, H. (2021): Improving the evapotranspiration estimation under cloudy condition by extending the Ts-VI triangle model. – Remote Sens 13: 1516.
[66] Li, Z. L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., Zhang, X. (2009): A review of current methodologies for regional evapotranspiration estimation from remotely sensed data. – Sensors 9: 3801-3853.
[67] Liou, Y. A., Kar, S. K. (2014): Evapotranspiration estimation with remote sensing and various surface energy balance algorithms-a review. – Energies 7: 2821-2849.
[68] Liu, K., Zhou, Q. B., Wu, W. B., Xia, T., Tang, H. J. (2016): Estimating the crop leaf area index using hyperspectral remote sensing. – J. Integr. Agric 15: 475-491.
[69] Lombardi, F., Lualdi, M. (2019): Step-frequency ground penetrating radar for agricultural soil morphology characterisation. – Remote Sens. 11: 1075.
[70] Long, D., Singh, V. P. (2012): A modified surface energy balance algorithm for land (M-SEBAL) based on a trapezoidal framework. – Water Res Res. 48: W02528.
[71] Long, D., Longuevergne, L., Scanlon, B. R. (2014): Uncertainty in evapotranspiration from land surface modeling, remote sensing, and GRACE satellites. – Water Resour. Res. 50: 1131-1151.
[72] Ma, J., Huang, S., Li, J., Li, X., Song, X., Leng, P., Sun, Y. (2017): Estimating vegetation water content of corn and soybean using different polarization ratios based on L-and S-band radar data. – IEEE Geosci. Remote Sens. Lett 14: 364-368.
[73] Mallick, K., Boegh, E., Trebs, I., Alfieri, J. G., Kustas, W. P., Prueger, J. H., Niyogi, D., Das, N., Drewry, D. T., Hoffmann, L. (2015): Reintroducing radiometric surface temperature into the Penman-Monteith formulation. – Water Resour. Res 51: 6214-6243.
[74] Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J. M., McNairn, H., Rao, Y. S. (2020): Dual polarimetric radar vegetation index for crop growth monitoring using sentinel-1 SAR data. – Remote Sens. Environ 247: 111-954.
[75] Manivasagam, V. S., Rozenstein, O. (2020): Practices for upscaling crop simulation models from field scale to large regions. Comput. – Electron. Agric 175: 105-554.
[76] Martini, E., Werban, U., Zacharias, S., Pohle, M., Dietrich, P., Wollschläger, U. (2017): Repeated electromagnetic induction measurements for mapping soil moisture at the field scale: validation with data from a wireless soil moisture monitoring network. – Hydrol. Earth Syst. Sci 21: 495-513.
[77] Massari, C., Modanesi, S., Dari, J., Gruber, A., De Lannoy, G. J., Girotto, M., Quintana-Seguí, P., Le Page, M., Jarlan, L., Zribi, M. and Ouaadi, N. (2021): A review of irrigation information retrievals from space and their utility for users. – Remote Sensing 13(20): 4112.
[78] McAnallen, L., Doherty, R., Donohue, S., Kirmizakis, P., Mendonça, C. (2018): Combined use of geophysical and geochemical methods to assess areas of active, degrading and restored blanket bog. – Sci. Total Environ 621: 762-771.
[79] Mecikalski, J. R., Diak, G. R., Anderson, M. C., Norman, J. M. (1999): Estimating fluxes on continental scales using remotely sensed data in an atmospheric-land exchange model. – J. Appl. Meteorol 38: 1352-1369.
[80] Michot, D., Benderitter, Y., Dorigny, A., Nicoullaud, B., King, D., Tabbagh, A. (2003): Spatial and temporal monitoring of soil water content with an irrigated corn crop cover using surface electrical resistivity tomography. – Water Resour. Res 39: 1138.
[81] Minacapilli, M., Consoli, S., Vanella, D., Ciraolo, G., Motisi, A. (2016): A time domain triangle method approach to estimate actual evapotranspiration: application in a Mediterranean region using MODIS and MSG-SEVIRI products. – Remote Sens. Environ 174: 10-23.
[82] Moghadas, D., André, F., Slob, E. C., Vereecken, H., Lambot, S. (2010): Joint full-waveform analysis of off-ground zero-offset ground penetrating radar and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

electromagnetic induction synthetic data for estimating soil electrical properties. Geophys. – J. Int 182: 1267-1278.
[83] Mostafa, J., Ali, B., Mohsen, G., Masoud, T. (2019): METRIC and WaPOR estimates of evapotranspiration over the Lake Urmia basin: comparative analysis and composite assessment. – Water 11: 1647.
[84] Neinavaz, E., Schlerf, M., Darvishzadeh, R., Gerhards, M., Skidmore, A. K. (2021): Thermal infrared remote sensing of vegetation: current status and perspectives. – Int. J. Appl. Earth Obs. Geoinf 102: 102415.
[85] Nielson, T., Bradford, J., Pierce, J., Seyfried, M. (2021): Soil structure and soil moisture dynamics inferred from time-lapse electrical resistivity tomography. – Catena 207: 105553.
[86] Norman, J. M., Anderson, M. C., Kustas, W. P., French, A. N., Mecikalski, J., Torn, R., Diak, G. R., Schmugge, T. J., Tanner, B. C. W. (2003): Remote sensing of surface energy fluxes at 101-m pixel resolutions. – Water Resour. Res: 39-1221.
[87] Ntarlagiannis, D., Robinson, J., Soupios, P., Slater, L. (2016): Field-scale electrical geophysics over an olive oil mill waste deposition site: evaluating the information content of resistivity versus induced polarization (IP) images for delineating the spatial extent of organic contamination. – J. Appl. Geophys 135: 418-426.
[88] OECD (2015): Drying Wells, Rising Stakes: Towards Sustainable Agricultural Ground-Water Use. – OECD, Paris.
[89] Ozdogan, M., Yang, Y., Allez, G., Cervantes, C. (2010): Remote sensing of irrigated agriculture: opportunities and challenges. – Remote Sens 2: 2274-2304.
[90] Palosuo, T., Kersebaum, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., Patil, R. H., Ruget, F., Rumbaur, C., Takáˇc, J. (2011): Simulation of winter wheat yield and its variability in different climates of Europe: a comparison of eight crop growth models. – Eur J Agron 35: 103-114.
[91] Pan, Y., Zhang, C., Gong, H., Yeh, P. J. F., Shen, Y., Guo, Y., Huang, Z., Li, X. (2017): Detection of human-induced evapotranspiration using GRACE satellite observations in the Haihe River basin of China. – Geophys Res Lett 44: 190-199.
[92] Parry, C., Blonquist, J. M., Bugbee, B. (2014): In situ measurement of leaf chlorophyll concentration: analysis of the optical/absolute relationship. – Plant Cell Environ 37: 2508-2520.
[93] Power, C., Gerhard, J. I., Tsourlos, P., Soupios, P., Simyrdanis, K., Karaoulis, M. (2015): Improved time-lapse electrical resistivity tomography monitoring of dense non-aqueous phase liquids with surface-to-horizontal borehole arrays. – J. Appl. Geophys 112: 1-13.
[94] Pradipta, A., Soupios, P., Kourgialas, N., Doula, M., Dokou, Z., Makkawi, M., Alfarhan, M., Tawabini, B., Kirmizakis, P. and Yassin, M. (2022): Remote sensing, geophysics, and modeling to support precision agriculture—Part 2. – Irrigation Mang Water 14(70): 1157.
[95] Prudnikova, E., Savin, I., Vindeker, G., Grubina, P., Shishkonakova, E., Sharychev, D. (2019): Influence of soil background on spectral reflectance of winter wheat crop canopy. – Remote Sens 11: 1932.
[96] Quemada, C., Pérez-Escudero, J. M., Gonzalo, R., Ederra, I., Santesteban, L. G., Torres, N., Iriarte, J. C. (2021): Remote sensing for plant water content monitoring: a review. – Remote Sens 13: 2088.
[97] Raine, S. R., Meyer, W. S., Rassam, D. W., Hutson, J. L., Cook, F. J. (2007): Soil water and solute movement under precision irrigation: knowledge gaps for managing sustainable root zones. – Irrig. Sci 26: 91-100.
[98] Ranjy, R. H., Hafizi, M. K., Soleymani Kermani, M. R., Ghorbani Nik, M. R. (2019): Electrical resistivity method for water content and compaction evaluation, a laboratory test on construction material. – J. Appl. Geophys 168: 49-58.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[99] Rodell, M., Famiglietti, J. S., Chen, J., Seneviratne, S. I., Viterbo, P., Holl, S., Wilson, C. R. (2004): Basin scale estimates of evapotranspiration using GRACE and other observations. – Geophys. Res. Lett 31: 10-13.

[100] Roerink, G. J., Su, Z. and Menenti, M. (2000): S-SEBI: A simple remote sensing algorithm to estimate the surface energy balance. – Physics and Chemistry of the Earth—Part B: Hydr Oceans Atmos 25: 147-157.

[101] Romero-Ruiz, A., Linde, N., Keller, T., Or, D. (2018): A review of geophysical methods for soil structure characterization. – Rev. Geophy 56: 672-697.

[102] Romero-Ruiz, A., Linde, N., Baron, L., Solazzi, S. G., Keller, T., Or, D. (2021): Seismic signatures reveal persistence of soil compaction. – Vadose Zone J. 20: 20140.

[103] Rosa, L., Chiarelli, D. D., Sangiorgio, M., Beltran-Peña, A. A., Rulli, M. C., D'Odorico, P., Fung, I. (2020): Potential for sustainable irrigation expansion in a 3°C warmer climate. – Proc. Natl. Acad. Sci. USA 117: 29526-29534.

[104] Rwasoka, D. T., Gumindoga, W., Gwenzi, J. (2011): Estimation of actual evapotranspiration using the Surface Energy Balance System (SEBS) algorithm in the Upper Manyame catchment in Zimbabwe. – Phys. Chem. Earth 36: 736-746.

[105] Samreen, T., Ahmad, M., Baig, M. T., Kanwal, S. and Nazir, M. Z. (2023): Remote sensing in precision agriculture for irrigation management. – Environ. Sci. Proce. 23(1): 31.

[106] Scheierling, S. M., Treguer, D. O., Booker, J. F., Decker, E. (2014): How to Assess Agricultural Water Productivity? Looking for Water in the Agricultural Productivity and Efficiency Literature. – Policy Research Working Paper 6982. Water Global Practice Group and Agriculture Global Practice Group. The World Bank, Washington, DC.

[107] Schmäck, J., Weihermüller, L., Klotzsche, A., Hebel, C., Pätzold, S., Welp, G., Vereecken, H. (2021): Large-scale detection and quantification of harmful soil compaction in a post-mining landscape using multi-configuration electromagnetic induction. – Soil Use Manag 38: 212-228.

[108] Senay, G. B., Budde, M., Verdin, J. P., Melesse, A. M. (2007): A coupled remote sensing and simplified surface energy balance approach to estimate actual evapotranspiration from irrigated fields. – Sensors 7: 979-1000.

[109] Senkondo, W., Munishi, S. E., Tumbo, M., Nobert, J., Lyon, S. W. (2019): Comparing remotely-sensed surface energy balance evapotranspiration estimates in heterogeneous and data-limited regions: a case study of Tanzania's Kilombero Valley. – Remote Sens 11: 1289.

[110] Shelia, V., Šimunek, J., Boote, K., Hoogenbooom, G. (2018): Coupling DSSAT and HYDRUS-1D for simulations of soil water dynamics in the soil-plant-atmosphere system. – J. Hydrol. Hydromech 66: 232-245.

[111] Siad, S. M., Iacobellis, V., Zdruli, P., Gioia, A., Stavi, I., Hoogenboom, G. (2019): A review of coupled hydrologic and crop growth models. Agric. – Water Manag 224: 105-746.

[112] Siddiq, M. O., Tawabini, B., Kirmizakis, P., Kalderis, D., Ntarlagiannis, D., Soupios, P. (2021): Combining geophysics and material science for environmental remediation: real-time monitoring of Fe-biochar arsenic wastewater treatment. – Chemosphere 284: 131390.

[113] Simic, M. A., Romanko, M., Reil, P., Abeysinghe, T., Marambe, A. (2018): The importance of leaf area index in mapping chlorophyll content of corn under different agricultural treatments using UAV images. – Int. J. Remote Sens 39: 5415-5431.

[114] Sims, D. A., Gamon, J. A. (2002): Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. – Remote Sens. Environ 81: 337-354.

[115] Šimůnek, J., Jarvis, N. J., Van Genuchten, M. T., Gärdenäs, A. (2003): Review and comparison of models for describing non-equilibrium and preferential flow and transport in the vadose zone. – J. Hydrol 272: 14-35.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[116] Singh, A. K., Dubey, O. P., Ghosh, S. K. (2016): Irrigation scheduling using intervention of Geomatics tools. A case study of Khedli minor. – Agric. Water Manag 177: 454-460.
[117] Son, N. T., Chen, C. F., Chen, C. R., Chang, L. Y., Duc, H. N., Nguyen, L. D. (2013): Prediction of rice crop yield using MODIS EVI-LAI data in the Mekong Delta, Vietnam. – Int. J. Remote Sens 34: 7275-7292.
[118] Song, L., Liu, S., Kustas, W. P., Zhou, J., Xu, Z., Xia, T. and Li, M. (2016): Application of remote sensing-based two-source energy balance model for mapping field surface fluxes with composite and component surface temperatures. – Agric Forest Meteorol 230: 8-19.
[119] Steduto, P., Hsiao, T. C., Raes, D., Fereres, E. (2009): Aquacrop—The FAO crop model to simulate yield response to water. – Agron J 101: 426-437.
[120] Stöckle, C. O., Donatelli, M., Nelson, R. (2003): Cropsyst, a cropping systems simulation model. – Eur J Agron 18: 289-307.
[121] Sun, H., Liu, H., Ma, Y., Xia, Q. (2021): Optical remote sensing indexes of soil moisture: evaluation and improvement based on aircraft experiment observations. – Remote Sense 13: 4638.
[122] Szigarski, C., Jagdhuber, T., Baur, M., Thiel, C., Parrens, M., Wigneron, J. P., Piles, M., Entekhabi, D. (2018): Analysis of the radar vegetation Index and potential improvements. – Remote Sens 10: 1776.
[123] Tabbagh, A., Dabas, M., Hesse, A., Panissod, C. P. (2000): Soil resistivity: a non-invasive tool to map soil structure horizonation. – Geoderma 97: 393-404.
[124] Tan, L., Zheng, K., Zhao, Q., Wu, Y. (2021): Evapotranspiration estimation using remote sensing technology based on a SEBAL model in the upper reaches of the Huaihe river basin. – Atmosp. 12: 1599.
[125] Tang, R., Li, Z. L. (2017): An end-member-based two-source approach for estimating land surface evapotranspiration from remote sensing data. – IEEE Trans. Geosci. Remote Sens 55: 5818-5832.
[126] Tao, H. L., Xu, J.-L., Feng, H. K., Yang, G. J., Dai, Y., Niu, Y. C. (2020): Estimation of plant height and leaf area index of winter wheat based on UAV hyperspectral remote sensing. – Trans Chin Soc Agric Mach 15: 193-201.
[127] Tasumi, M. (2019): Estimating evapotranspiration using METRIC model and Landsat data for better understandings of regional hydrology in the western Urmia Lake Basin. – Agric. Water Manag 226: 105805.
[128] Tian, J., Su, H., Sun, X., Chen, S., He, H., Zhao, L. (2013): Impact of the spatial domain size on the performance of the ts-vi triangle method in terrestrial evapotranspiration estimation. – Remote Sens 5: 1998-2013.
[129] Tilman, D., Balzer, C., Hill, J., Befort, B. L. (2011): Global food demand and the sustainable intensification of agriculture. – Proc. Natl. Acad. Sci. USA 108: 20260-20264.
[130] Tramblay, Y., Llasat, M. C., Randin, C., Coppola, E. (2020): Climate change impacts on water resources in the Mediterranean. – Reg. Environ. Chang 20: 83.
[131] Turki, N., Elaoud, A., Gabtni, H., Trabelsi, I., Khalfallah, K. K. (2019): Agricultural soil characterization using 2D electrical resistivity tomography (ERT) after direct and intermittent digestate application. – Arab. J. Geosci 12: 423.
[132] Ullah, S., Skidmore, A. K., Ramoelo, A., Groen, T. A., Naeem, M., Ali, A. (2014): Retrieval of leaf water content spanning the visible to thermal infrared spectra. – ISPRS J. Photogramm. Remote Sens 93: 56-64.
[133] Vanden, H. C., Hanert, E., Vidale, P. L. (2011): Simulating dynamic crop growth with an adapted land surface model-JULES-SUCROS: model development and validation. – Agric For Meteorol 151: 137-153.
[134] Vanella, D., Cassiani, G., Busato, L., Boaga, J., Barbagallo, S., Binley, A., Consoli, S. (2018): Use of small scale electrical resistivity tomography to identify soil-root interactions during deficit irrigation. – J. Hydrol 556: 310-324.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394

[135] Vereecken, H., Huisman, J. A., Bogena, H., Vanderborght, J., Vrugt, J. A., Hopmans, J. W. (2008): On the value of soil moisture measurements in vadose zone hydrology: a review. – Water Resour. Res 44: W00D06.
[136] Vereecken, H., Schnepf, A., Hopmans, J. W., Javaux, M., Or, D., Roose, T., Vanderborght, J., Young, M. H., Amelung, W., Aitkenhead, M. (2016): Modeling soil processes: review, key challenges, and new perspectives. – Vadose Zone J 15: 1-57.
[137] Verrelst, J., Schaepman, M. E., Koetz, B., Kneubühler, M. (2008): Angular sensitivity analysis of vegetation indices derived from CHRIS/PROBA data. – Remote Sens Environ 112: 2341-2353.
[138] Wan, Z., Zhang, K., Xue, X., Hong, Z., Hong, Y., Gourley, J. J. (2015): Water balance-based actual evapotranspiration reconstruction from ground and satellite observations over the conterminous United States. – Water Resour Res 51: 6485-6499.
[139] Xu, C., Qu, J. J., Hao, X., Cosh, M. H., Zhu, Z., Gutenberg, L. (2020): Monitoring crop water content for corn and soybean fields through data fusion of MODIS and Landsat measurements in Iowa. – Agric. Water Manag 227- 105844.
[140] Xue, J., Su, B. (2017): Significant remote sensing vegetation indices: a review of developments and applications. – J. Sensors 13: 53-691.
[141] Yamashita, H., Sonobe, R., Hirono, Y., Morita, A., Ikka, T. (2020): Dissection of hyperspectral reflectance to estimate nitrogen and chlorophyll contents in tea leaves based on machine learning algorithms. – Sci. Rep 10: 17360.
[142] Yin, W., Hu, L., Zhang, M., Wang, J., Han, S. C. (2018): Statistical downscaling of GRACE-derived groundwater storage using ET data in the North China Plain. – J. Geophys. Res. Atmos 123: 5973-5987.
[143] Zajícová, K., Chuman, T. (2019): Application of ground penetrating radar methods in soil studies: a review. – Geoderma 343: 116-129.
[144] Zhang, F., Zhou, G. (2019): Estimation of vegetation water content using hyperspectral vegetation indices: a comparison of crop water indicators in response to water stress treatments for summer maize. – BMC Ecol 19: 18.
[145] Zhang, K., Kimball, J. S., Running, S. W. (2016): A review of remote sensing based actual evapotranspiration estimation. – Wiley Interdiscip. Rev. Water 3: 834-853.
[146] Zhang, Y., Wu, Z., Singh, V. P., He, H., He, J., Yin, H., Zhang, Y. (2021): Coupled hydrology-crop growth model incorporating an improved evapotranspiration module. – Agric. Water Manag 246: 106691.
[147] Zheng, G., Moskal, L. M. (2009): Retrieving leaf area index (LAI) using remote sensing: theories, methods and sensors. – Sensors 9: 2719-2745.
[148] Zhou, L., Yu, D., Wang, Z., Wang, X. (2019): Soil water content estimation using high-frequency ground penetrating radar. – Water 11: 1036.
[149] Zhu, W., Jia, S., Lv, A. (2017): A universal Ts-VI triangle method for the continuous retrieval of evaporative fraction from MODIS products. – J. Geophys. Res. Atmos 122: 10206-10227.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_373394