



UAV-based remote sensing in plant stress imagine using high-resolution thermal sensor for digital agriculture practices: a meta-review

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Abstract

Water management is becoming a critical issue for sustainable agriculture, especially in the semi-arid region, where problems with water scarcity are rising. More accurate water status recovery in crops is required for precise irrigation through remote sensing technologies. These technologies have a lot of potential in intelligent irrigation because they allow for real-time environmental data collection. Nowadays, digital practices have been used, such as unmanned aerial vehicle (UAV), which plays an essential role in various applications related to crop management. Drones offer an exciting opportunity to track crop fields with high spatial and temporal resolution remote sensing to enhance water stress management in irrigation. Farmers have historically depended on soil moisture measurements and weather conditions to detect crop water status for irrigation scheduling. This review paper summarizes the use of UAV remote sensing data in crops for estimating the water status and gives a detailed summary of the potential capacity of UAV remote sensing for water stress application. The remote sensing techniques help modify agricultural practices to meet this significant challenge by providing repeated information on crop status at different scales and various performances during the season. UAVs successful implementation in water stress estimations depends on UAV features, such as flexibility of use in flight planning, low cost, reliability, autonomy, and capability of timely provision of high-resolution data. UAV with a thermal sensor is considered the most effective technique for detecting water stress using specific indices. Thermal imaging can identify water status variations and crop water stress index (CWSI). This CWSI acquired through UAV thermal sensors imagery can be acceptable for managing real-time irrigation to achieve optimum crop water efficiency.

Keywords Unmanned aerial vehicle (UAV) · Crop water stress index · Precision agriculture · Vegetation index · Image processing · Intelligent irrigation

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Abbreviations

UAV	Unmanned Aerial Vehicle
PA	Precision Agriculture
DSS	Decision Support System
GIS	Geographic Information System
GPS	Global Positioning System
RS	Remote Sensing
CT	Canopy Temperature
VIT	Vegetation Index Temperature
CWSI	Crop Water Stress Index
SWIR	Shortwave Infrared
MWIR	Midwave Infrared
LWIR	Longwave Infrared
VI	Vegetation Indices
IR	Infrared Region
RGB	Red–Green–Blue
TIR	Thermal Infrared
EM	Electromagnetic Spectrum
IRR	Reflected Infrared Region
T_{kin}	Kinetic Temperature
T_{rad}	Radiant Temperature
ϵ	Emissivity
NDVI	Normalize Difference Vegetation Index
DGPS	Differential Global Positioning System
RGRI	Red–Green Ration Index
DSM	Digital Surface Model
FFC	Flat Field Correction
VHR	Very High Resolution
WDI	Water Deficit Index
R_n	Net Radiation
SMC	Soil Moisture Content
MS	Multi-spectral
V	Visible
W	Water Vapor
LAI	Leaf Area Index
PRI	Photochemical Reflectance Index
RDN	Raw Data Number
T_{wet}	Wet Reference Temperate
T_{dry}	Dry Reference Temperature
T_{air}	Air Temperature
ET	Evapotranspiration
Ψ_L	Leaf Water Potential
FIR	Finite Impulse Response
RM	Regional Maxima
VPD	Vapor Pressure Deficit
RWC	Relative Water Content
EWT	Equal Water Thickness
LWT	Leaf Water Thickness
GCP	Ground Control Points
SfM	Structure from Motion
SWC	Soil Water Content
gs	Stomatal Conductance
Tr	Transpiration Rate

RH	Relative Humidity
FVC	Fractional Vegetation Cover
TDR	Time-Domain Reflectometer
RTK	Real-Time Kinematic
DEM	Digital Elevation Model
Ψ	Water Potential
VIS	Visible
ETc	Crop Evapotranspiration
RI	Red Edge Indices
3D	3 Dimensional

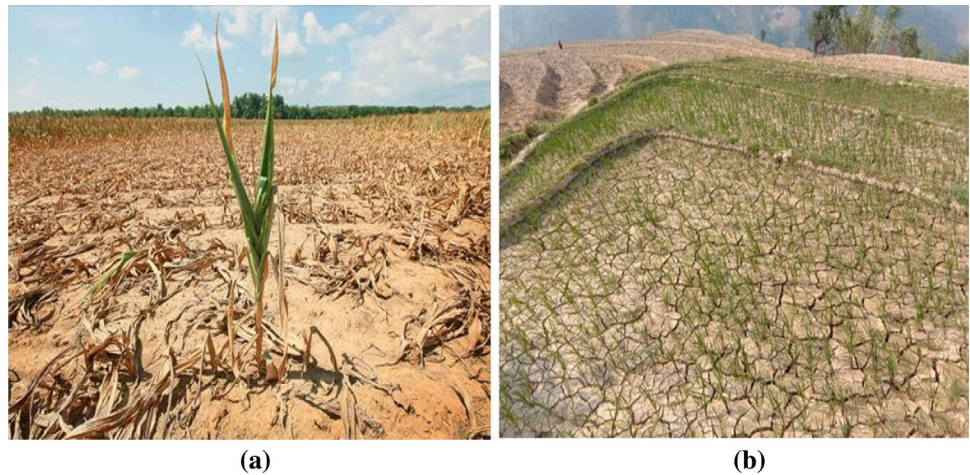
Introduction

Applications of water for sustainable farming have become a precarious problem worldwide because of water shortage and climate change, so specific water management strategies for irrigation are needed (Zhang et al. 2016). Water scarcity is a critical factor that limits agricultural production. In general terms, much of the world water supplies are used by agriculture (Karakoçak et al. 2013). Over the last few decades, land and water management for agriculture has met rapidly rising demands. However, a lack of available water for sustainable crop production is a growing concern in the semi-arid region (Loka et al. 2011). Due to climate change and water shortage, water application in sustainable farming has become a significant problem in all developed countries, so effective water management strategies are the perfect solution. Precision agriculture (PA) generally seeks to improve the quantity and quality of agricultural production with different resources (e.g., fertilizer, energy, water, herbicides, and pesticides). Throughout the world, civilization is formulating a growing population that will hit 10 billion in 2050 (United Nations, 2017). China agricultural water use is still in a state of low efficiency and severe waste, which seriously restricts China economic development. China is a vast country with a severe shortage of water. Mainly, agriculture (e.g., the arable land in the north part of China) takes 62.06% of fresh water (Becker 2015).

Drought is widely recognized as the world most expensive and imminent natural disaster, resulting in substantial economic, ecological, and environmental losses (Nicholson et al. 1998; Mishra and Singh 2010). Since the late 1990s, central and eastern region of china has several severe droughts (Fig. 1). Unfortunately, the current irrigation efficiency in China is only about 52%, which is well below advanced countries, achieving an efficiency of about 70–80% of water usage. It is therefore essential to control irrigation with optimum water use. Worldwide, farmers face various difficulties, especially in semi-arid areas of agricultural water supplies (Gonzalez-Dugo et al. 2010; Jin et al. 2018). Global food production has projected to increase by 70%



Fig. 1 Drought condition in China eastern and central regions; **a** wheat, **b** rice (He et al. 2011)



over the upcoming years to keep up with this development (Thornton et al. 2018; Sonnino et al. 2019; Amorim 2019).

Agriculture is under water stress

Agricultural water use is the primary variable for increased water scarcity, and irrigation accounts for about 70% of the world's freshwater extractions (Tshwene and Oladele 2016). Crop water productivity (CWP) correlates with the water and crop production used for agricultural production. Monitoring crops at different development stages is essential for several applications, such as water stress, decisions on crop inputs (fertilizers, water, and pesticides), and modeling of crop yields (Sakamoto et al. 2005). With China rapid development, agricultural water resources are becoming more and more critical. Intelligent irrigation is characterized to increased yield, water scarcity, and low agricultural practice results. Climate change on plant transpiration and soil water balance substantially impact crops quality and productivity under limited water resources (Sakamoto et al. 2005). The latest earth observation technologies (e.g., unmanned aerial vehicles) make it possible to monitor plant health (e.g., canopy temperature) in real time.

With the growth of the Internet of Things, a wide variety of data and knowledge about the world is becoming readily available (Awais et al. 2021). In addition, there is also substantial improvement in the production of irrigation machines that conserve water (Li et al. 2020). Timely and effective irrigation decision making and the application of irrigation will increase the quality of water use. Imageries from satellites were previously occupied, processed, and analyzed for getting water status. This review reflects the modern remote sensing experience acquired from UAV-based technology to achieve sustainable development and the potential ability to evaluate crop water stress induces and plant physiological parameters.

Precision farming and remote sensing

Precision agriculture (PA) aims to optimize and expand agricultural processes to certify final production and involves fast, consistent, and circulated measurements to farmers aware and gives a supplementary overview of their current situation in the cultivated land (Kacira et al. 2005; Körner and Straten 2008). The technology frequently used includes integrated electronic communication, wireless sensor network, precision positioning systems, machine learning methodology, variable rate technology, unmanned aerial vehicle (UAVs), and geographic information systems for well-timed crop management (Liaghat and Balasundram 2010). The PA cycle is shown in (Fig. 2). The different specific remote sensing applications are (e.g., yield prediction, irrigation, weed detection, and precision farming) on the primary platform of remote sensing (e.g.,

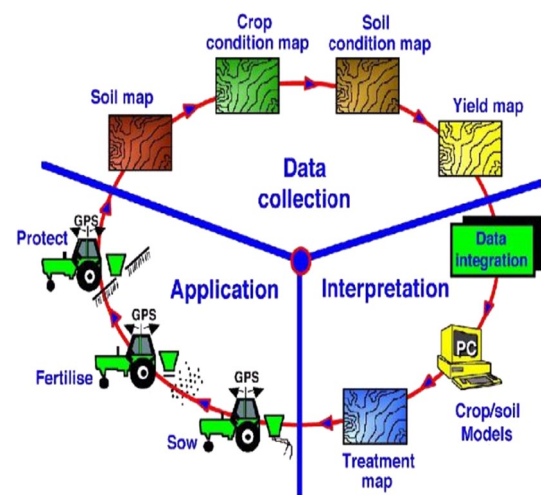


Fig. 2 The precision agriculture cycle (Berni et al. 2009a)

unmanned aerial vehicles—UAV, satellite, and sensors). These techniques working process requires a vast knowledge of the fertilizer map, quality of soil, nutrients, and weeds (Moran et al. 1997). Many farmers used nutrient requirement data and compared them with spatial variations of the playing area (Robertson et al. 2007). These alterations must be pushed the farmers to move from conservative farming (Vellidis et al. 2008) to precision agriculture farming.

The primary importance of precision agriculture is management collection and data utilization to make an automatic decision (Pham and Stack 2018). PA is expanding this change and is the primarily driven force for big data analytics (Wolfert et al. 2017; Poppe et al. 2015). Precision farming includes special features of remote sensing that are not present in traditional platforms, such as satellites and airborne platforms. The different specific applications of precision agriculture are (e.g., yield prediction, irrigation, weed detection, and precision farming) on the primary platform of remote sensing (e.g., unmanned aerial vehicles—UAV, satellite, and sensors). The working process of these techniques requires a vast knowledge of the map of fertilizer, quality of soil, nutrients, and weeds (Moran et al. 1997). Many farmers used nutrient requirement data and compared them with spatial variations of the playing area (Robertson et al. 2007). These alterations must be pushed the farmers to move from conservative farming to precision agriculture farming (Vellidis et al. 2008). The primary importance of precision agriculture is the management collection and data utilization to make an automatic decision (Pham and Stack 2018). PA is expanding this change and is the primarily driven force for big data analytics (Wolfert et al. 2017; Poppe et al. 2015). UAVs capture aerial photographs of agricultural fields in precision agriculture applications to track crop health, estimate nutrient status, estimate yield, and calculate crop water demand. Five essential points that need to be addressed by the research community depend on increasing the adoption of precision farming among farmers.

Identify the management problems that producers regularly face, including agricultural, environmental, or economic challenges.

Improve the processing of data from automated photogrammetric applications to calibration of instruments and image enhancement.

Develop algorithms in the processed data that can extract and interpret the information.

Adopt high spatial resolution and cost-effective platforms that can collect data to resolve the problems found.

Communicate these results by developing decision-making mechanisms that can support the best management practices for operations into a better informed management decision.

Fundamental principle of thermal remote sensing

In precision agriculture and smart farming, remote sensing is widely regarded as one of the most significant technologies. In the last 35 years, it has been widely used for tracking cultivated fields and providing successful precision agriculture solutions (Mulla 2013). Many crops and vegetation parameters can be monitored using remote sensing images at different wavelengths. RS techniques used to track vegetation status at various growth stages using satellite imagery or images captured by manned aircraft (Mora et al. 2017). There are two significant characteristics to define electromagnetic radiation, frequency, and wavelength. These data are transformed into temperatures (Khanal et al. 2017). Inside the IR zone (0.7–100 μm), two classes are distinguished, which are reflected—IRR (0.7–3.0 μm) and TIR (3.0–100 μm). Typically, the surface objects, such as trees, water, soil, and humans, emit TIR radiation within the range of (3.0–14.3 μm) of the EM spectrum (Jensen 2009). Part of the IR energy is transmitted to the earth's surface within the range of the EM spectrum, ranging from 3 to 5 μm and 8 to 14 μm (Vinet and Zhedanov 2011). Atmospheric gases (i.e., ozone, carbon dioxide, and water) absorb almost all radiations between 5 and 8 μm , as shown in (Fig. 3) (Jensen 2009).

Stefan–Boltzmann, Kirchhoff's, Wien, and Planck's physical law better understand EM behavior. According to the physical law of Plank's, frequency (f) is proportional to its energy factor (Q), while h is the constant that can be used to alter this equation.

$$Q = hf \quad (1)$$

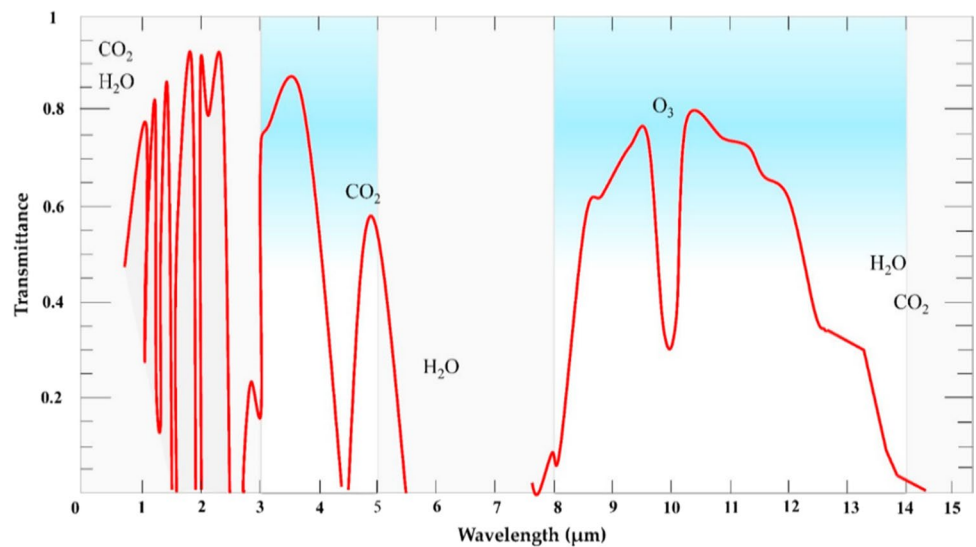
Equation (2.1) can be rewritten as follows after assuming that the wave frequency (f) is inversely proportional to its length (λ) and proportional to the speed of light (c).

$$Q = \frac{hc}{\lambda} \quad (2)$$

On the other hand, the wavelength is inversely proportional to its quantum energy. Therefore, less energy has a greater wavelength. The laws of Wien and Boltzmann define the relationship of black body radiations. Wien's displacement law describes the relationship between a black body's actual temperature in Kelvin degrees and its maximum spectral wavelength. The overall output changes into shorter wavelengths as the temperature increases (Kuenzer and Dech 2013).

$$\lambda_{\text{max}} = \frac{b}{T} \quad (3)$$

Fig. 3 Thermal region of atmospheric transmittance with standard gaseous and water-induced absorption bands (Richter and Schläpfer 2019)



Remote sensing in agriculture

Remote sensing is the technique of material and object inferences from measurements made at a distance to the objects under analysis without physical contact. Remote sensing systems for PA and agriculture, in general, can be divided into two categories: (i) sensor platform and (ii) sensor type. Satellites, aerial platforms, and ground-based

platforms are popular places for installing sensors (Fig. 4). Although the conventional techniques for acquiring weather and crop growth status are effective, they involve manual scouting, intensive, and time-consuming labor (Latif et al. 2018). It is also impossible to follow traditional approaches under adverse climate-changing conditions. Geospatial technology is, i.e., under certain conditions. Remote sensing and GIS are helpful for broad spatial and temporal data collection and tracking (Shanmugapriya

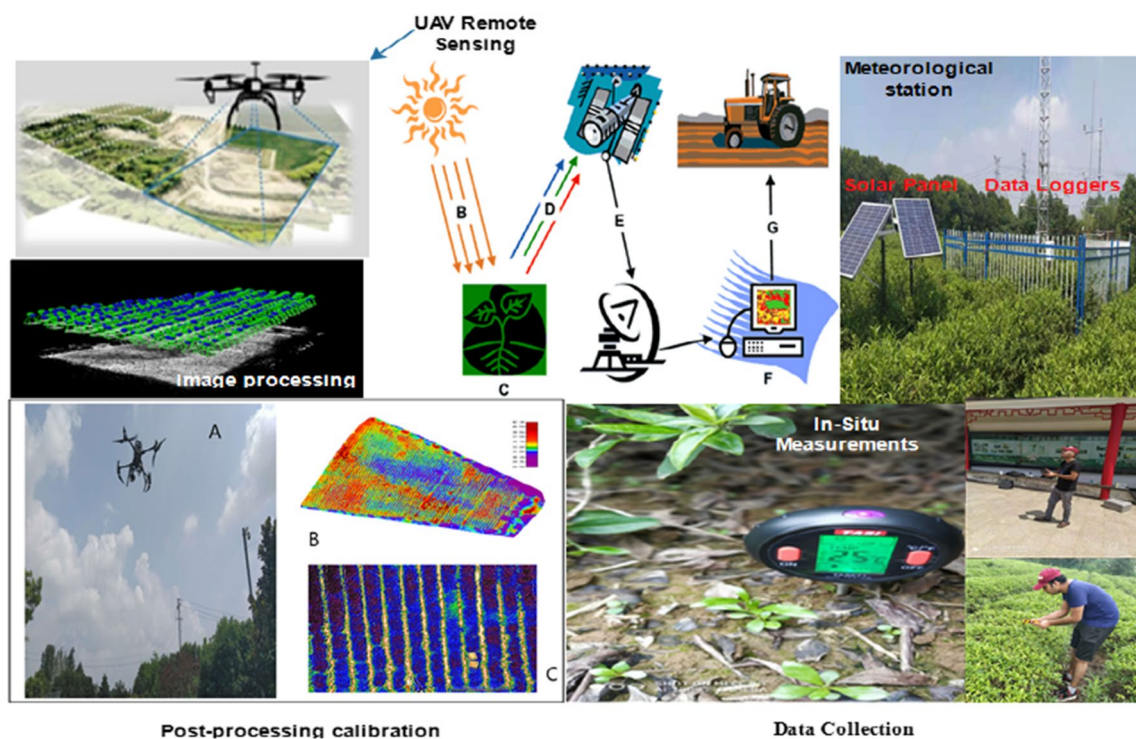


Fig. 4 A typical layout for the remote, UAV, and ground sensing systems deployed for precision agriculture

et al. 2019). RS technology can potentially revitalize the study of contributing factors to agricultural productivity based on crops and soils (Liaghat and Balasundram 2010; Hussain 2019). Remotely sensed satellite data are used to identify stress crops' early-stage identification and any disruptions for crop-specific yield estimation (Bernardes, et al. 2011; Gu, et al. 2007). With the advent of technologies generally referred to as drones, such as unmanned aerial vehicle (UAV), agricultural problems such as plant disease or pest control can now be solved by sprinkling pesticides, fertilizer, and water on them.

Satellite systems remote sensing

Remote sensing techniques are used to collect data through different satellites. The satellite RS systems started with the Landsat-1 launch in 1972 (Belward and Skøien 2015; Markham and Helder 2012). The eventual launching of SPOT-1 in 1986 and Ikonos in 1999 introduced the era of commercial satellite systems, resulting in rapidly increasing image efficiency, including high spatial resolution (Toth and

Józków 2016). Different airborne sensors and satellite used for digital application are given in (Table 1).

Numerous studies (Hatfield and Prueger 2010; Jordan 1969) (Huete et al. 2002) on agriculture sector monitored the condition of crops. Some vegetation indices (VIs) were established, depending on the grouping of waveband, to measure the various plant parameters, e.g., biomass, residue cover, leaf area, leaf chlorophyll, and ground cover, while these VIs provide symptoms of vegetable conditions. The earth observation satellite system, such as sentinel-1, Landsat, GeoEye, and Spot, has been used to study crops water status (Table 2). Most images of satellite-based remote sensing are used for biomass estimation (Yang et al. 2000) and prediction of crop output (Doraiswamy et al. 2003) with the help of (NDVI).

UAV-based remote sensing

A series of studies have been performed using UAV technology. The most examined crops were olive (Berni et al. 2009b; Agam et al. 2013; Poblete-Echeverría, et al. 1112), citrus (Gonzalez-Dugo et al. 2014; Stagakis et al. 2012),

Table 1 Satellite and airborne thermal sensors attached to platforms

Sensor satellite	Wavelength (μm)	Spatial resolution (m)	Waveband (Thermal)	Temporal resolution	Reference
AATSR/ENVISAT	11.0–12.0	1000	6–7	1	Llewellyn-Jones et al. 2001)
CBERS/Landsat	14.4–12.5	80	4	25	
ASTER	8.122–12.65	90	09–14	15	
MODIS	3.65–4.55	10,000	20–26,29–36	1	
GOES-R	10.1–13.6	2000	13–16	Hourly	
AVHRR	3.5–3.93	1100	3	0.5	
SENTINEL-3	0.555–10.85	500	9	27	
VIIRS	0.41–12.01	750	21	16	
<i>Airborne*</i>					
TIMS	8.32–12.02	50	1–6		Kealy and Hook 1993)
ATLAS	8.32–12.02	10	10–15		Lo et al. (1997)

*Human operated

Table 2 Types of satellite systems used to estimate the water status

Satellites	Spatial resolution (m)	Revisit cycle	Band number & designation
Spot-6 and -7	1.5	1 day	5: NIR ¹ , RE ¹
GeoEye-1	0.40–2	3 Days	5: Pan ¹ , NIR ¹
Landsat 8	15–100	16 days	11: NIR ¹ , SWIR ² , TIR ² , C ¹
Landsat 7	15–60	16 days	8: NIR ¹ , V ³ , SWIR ² , TIR ¹ , PAN ¹ ,
Sentinel-2	10–50	5 days	13: C ¹ , V ³ , NIR ² , SWIR ² , WV ¹
Sentinel-3	20–70	2 days	15: C ¹ , V ³ , NIR ² , SWIR ² , WV ¹

Note Integers^{1,2,3} represent the band number; NIR near infrared, RE red edge, Pan panchromatic, SWIR short-wave infrared, TIR thermal infrared, C costal, V visible, WN water vapor

almond (García-Tejero, et al. 2018; Zhao et al. 2017; Zhao et al. 2017), vineyards (Bellvert et al. 2016a; Baluja et al. 2012; Matese et al. 2018), and peach (Bellvert et al. 2016b; Park et al. 2017). The most commonly used UAV in agricultural water status studies is shown in (Fig. 5). Agricultural application of agro-chemicals is required for particular circumstances, such as location, site-specific management, and a particular time. These applications are completed with ground sprayers, which is not an accurate application of agro-chemicals. An indigenous UAV for the spraying of pesticides for standardized and site-specific applications of pesticides is therefore necessary. Also, the picture obtained from UAV will help the present state of crop, irrigation management and be a potential application for detecting diseases and pest attacks. Therefore, UAV secured prime importance to obtain a picture at the right time.

Types of remote sensor used in UAV

Images from the drone platform were used for vegetation mapping in the visible and IR spectrum. These sensors can be utilized to calculate water stress, LAI, growth stages, biomass, and crop healthiness. Different other parameters, such as the farm survey, insect identification, and mapping, are

also accomplished using various sensors. The list of sensors attached to the UAVs drone for sensing cameras is shown below.

RGB camera

An RGB camera usually contains a digital and conventional uniform sensor. RGB cameras use spectral bandwidth of red, green, and blue spectral circles to collect energy from the visible EMS. The RGB camera lens depends on image sharpness, while the camera's spatial resolution regulates its decision within an image (Fig. 6a). The pictures extract the dimensional properties of the crop, such as height, size, and parameter (Johansen et al. 2018; Mu et al. 2018; Tu et al. 2019). In general, water resources for the more abundant crop are expected to be available quickly, resulting in a shortage of agricultural crop water. The production structure, such as width, height, spacing, missing plant, and ground cover fraction, is remotely identified (Castro et al. 2018; Weiss and Baret 2017).

Multi-spectral camera

The multi-spectral sensor has various bands in the electromagnetic spectrum. The multi-spectral camera contains

Fig. 5 Types of (UAVs) used for evaluating water stress in the agricultural field. Note: **a** quadcopter attached with RGB thermal sensors (Santesteban et al. 2017), **b** fixed-wing eBee agriculture drone equipped with the multi-spectral and thermal camera, **c** DJI (S900) multi-rotor UAV drone, fitted with RGB, and thermal cameras (Zenmuse XT, FLIR System, Inc., USA), **d** hexacopter fitted out with RGB, thermal, and multi-spectral sensors

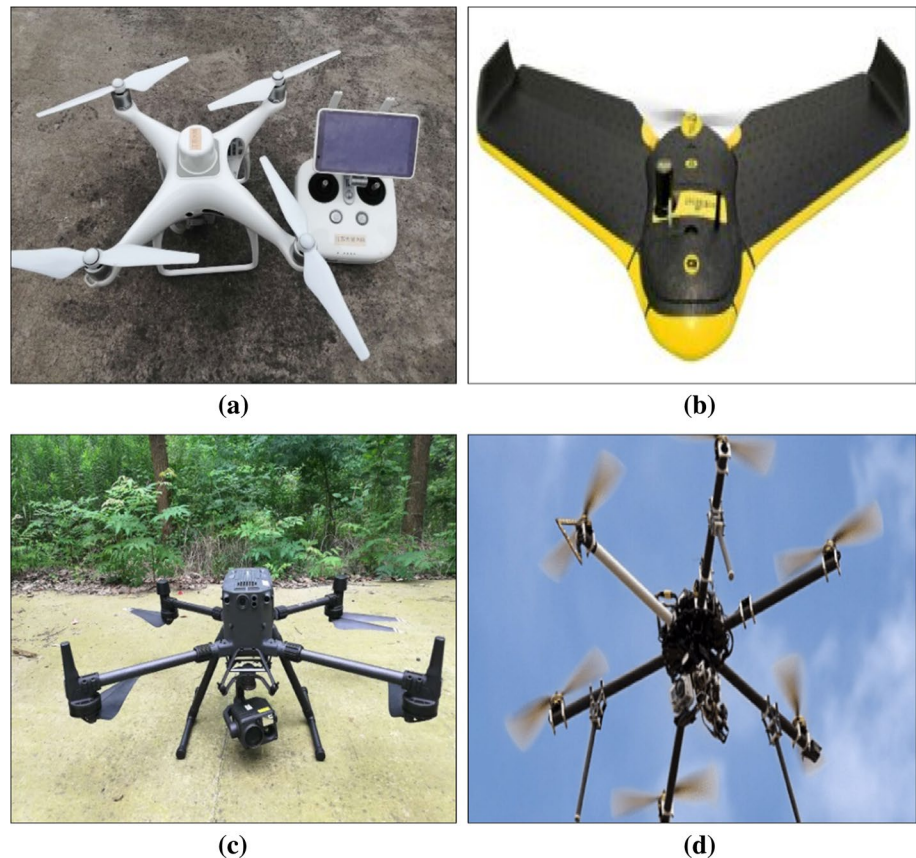


Fig. 6 Models of sensors used on UAV platforms for thermography in crops. Note: **a** a multi-sensors setup with an RGB, multi-spectral, and a thermal camera (Santesteban et al. 2017). **b** Multi-spectral sensor (Tetracam.Mini-MCA-6, Inc., Chatsworth, USA) (Turner et al. 2011). **c** Hyperspectral camera (Headwall. Photonics, MA, USA). **d** Thermal sensors (FLIR System, Inc., USA) (Zarco-Tejada et al. 2012)



Table 3 Some important specifications of sensor parrot sequoia

Sensor	Wavelength (nm)	Band width (nm)	Pixel size Mpx
Red	660	40	1.2
Green	550	40	1.2
Red edge	735	10	1.2
Near infrared	790	40	1.2
RGB camera	–	–	16

4–6 groups with about 10–15 nm bandwidth in the electromagnetic spectrum region blue, green, red, red edge, and NIR. The multi-spectral sensor Parrot Sequoia revolutionizes the agricultural sector and provides a reliable, adaptable solution compatible with all types of drones. Their geographic resolution is acceptable for RS applications, allowing the spectral response to be observed at the canopy level. For this purpose, multi-spectral sensors are frequently used in RS agricultural applications with reasonably low costs (Fig. 6b). The multi-spectral sensor detects the plants' light and absorbs in four different parts: green and red lights and two bands of infrared invisible to the human eye (Berni et al. 2009a). Some necessary specifications of the multi-spectral sensor are given (Table 3).

The spatial resolution of multi-spectral sensors is adequate in agricultural RS applications, enabling the spectral response at the canopy level. When the vegetation starts in stress condition, its refractive is decreased at the NIR band, while the reflectance of the plant is increased at the red band. Due to this intention, NDVI has shown a strong relationship with chlorophyll content, crop water stress index (CWSI), leaf area index (LAI), yield, and vigor (Matese et al. 2018; Espinoza et al. 2017; Poblete et al. 2017; Jorge et al. 2019).

Hyperspectral

Airborne hyperspectral imagery delivered detailed information of the spectral reflection of the earth's surface and can be used for RS applications. e.g., mineral mapping, land cover assets, and the coastal environment (Im and Jensen 2008; Ghiyamat and Shafri 2010; Govender et al. 2007). Such sensors can acquire images from a visible to IR region of EMs in many narrow bands (Fig. 6c). A hyperspectral sensor formed three-dimensional data called a cube of hyperspectral information. These hyperspectral cube images contain pixels of spatial information entire spectral reflectance curve (Aasen et al. 2018). In precision farming applications, specific biotic and abiotic stresses are monitored due to the high resolution of hyperspectral data (Rodríguez-Pérez et al. 2007). Another research suggested that hyperspectral data

were used to identify the water stress in the citrus orchard using the photochemical reflectance index (PRI) and fluorescence measurements (Zarco-Tejada et al. 2012). However, high-resolution images from the hyperspectral sensor were further used to establish the canopy map between CWSI and (gs) in olive orchards with different irrigation managements (Berni et al. 2009b; Gerhards et al. 2019). The specification of images taken from hyperspectral sensors is shown in Table 4.

Thermal

In the 1960s, the use of thermal data to detect water stress at field scale with thermal remote sensing became prominent (Tanner 1963). The thermal sensor uses thermal radiation to read passive thermal rendition with a wavelength range of 7–12 μm (Fig. 6d). An array of microbolometers inside the sensors is being used to store and received the thermal rendition signal and stored these signals as raw data number (DN) values on the image pixel. On the other hand, a thermal sensor monitored the surface temperature (Anderson et al. 2013; Stark et al. 2014). Thermal RS is a mechanism by which the heat released from an object is measured and transformed into temperature readings without contact with a body (Khanal et al. 2017). A comprehensive list of commercial thermal cameras on UAV platforms for RS application in precision agriculture was found in the literature (Khanal et al. 2017; Alvino and Marino 2017; Sepulcre-Cantó et al. 2006).

Application of thermal imaging

Thermal imaging as a plant stress monitoring tool

Applying thermal input to classify plant water stress with thermal sensors became common in the 1960s (Tanner

Table 4 Specification of hyperspectral imaging through UAVs

Specifications	Value	
Wavelength range	450–770 nm	
Field view	90°	
Pixels number	656×494 pixel	
Band width	6–24 nm (FWHM)	
Wavelength interval	1 nm	
Rate of frame	1–2 frames/s	
Component	Size (mm)	Weight (g)
Regulator	115×80×40 mm	220
Computer	124×59×24 mm	95
Battery	108×74×24 mm	230
Imager	220×90×90 mm	780
Total weight	–	1450

1963). The thermal sensor uses thermal radiation to read passive thermal rendition with a spectral range of 7–12 μm . An array of microbolometers inside the thermal sensors was used to identify and receive the thermal rendition signal and store these signals as raw data number (DN) values on the image pixel. Padhi et al. (2012) stated that various irrigation treatments could use thermal imaging to differentiate soil water deficits in cotton fields. The proposed thermal imaging can be used in cotton fields to assess the soil water deficit (Padhi et al. 2012). Pou et al. (2014) conducted a study on grape vines to examine the potential of using thermal imaging to evaluate the plant water stress (Pou et al. 2014). Grant et al. (2007) have used thermal imaging to diagnose the stress responses in grapevine under various irrigation regimes. They noticed that thermal imaging should differentiate between irrigated and non-irrigated plant canopies and noticed a disparity between plants and treatments for deficit irrigation (Grant et al. 2007). Jones et al. (2002) investigate thermal imaginations to evaluate the stomatal closure at the field level. They stated that by using infrared thermography, the water relationship of grapevine canopies could be studied. The inclusion of non-leaf material in the analysis of the images must be avoided to make this methodology more precise. It is possible to avoid non-leaf material by selecting suitable areas in the canopy plots or using dry and wet temperature thresholds to define the range outside which temperature values are rejected. They further stressed the potential benefits of thermal imaging. Thermography enables the semi-automated analysis of large canopy areas to study plant stomatal behavior with much more efficient replication than those achieved by porometry (Table 5).

Development of data processing system

Thermal imaging and image processing often allow automatic image correction, such as removing pixels representing the sky or soil. In addition, because of the potentially high accuracy in image comparisons, they concluded that thermal imaging has the potential to obtain measurements that are best suited for comparative studies (Jones et al. 2002). It should be noticed that remote sensing can observe plants' reactions to water stress rather than the stress itself. Unfortunately, related plant responses can give rise to several different environmental stresses. For example, water stress, mineral deficiency, disease, and insect damage contribute to stomatal closing, and many stresses appear to decrease the leaf area. Therefore, the effect of water tension from just one recorded reaction is difficult to track. Fortunately, remote sensing techniques from previous literature are offered to identify distinct stress responses (Jones and Vaughan 2010). Therefore, it is easier to combine multiple ways of prejudice against water tension attributable to other factors. Over the past

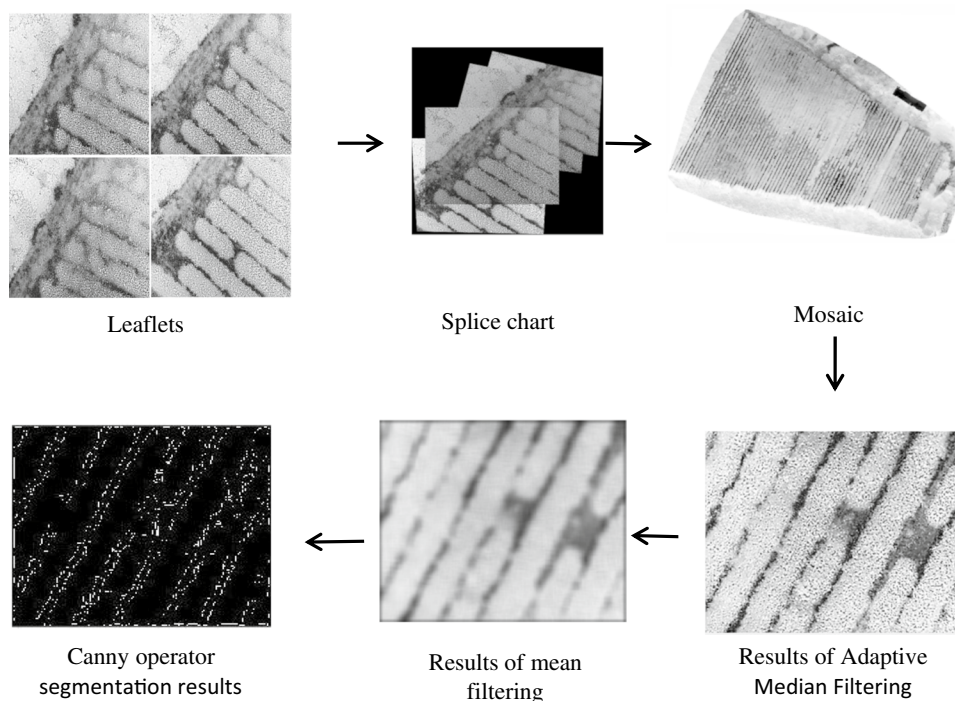
Table 5 Commonly used sensors on UAV platform

Sensors	Functions	Resolution	Accuracy
Red edge M	Multi-spectral	1280×960 pixel	8.2 cm/ pixel (per band) at 120 m
ThermalCAM SC640	Thermal infrared	640×480 pixel	±2 °C or ±2%
MAPIR Survey 2	Multi-spectral	4608×3456 pixel	4.05 cm / pixel at 120 m
ThermoMAP	Thermal infrared	640×512 pixel	14 cm / pixel at 75 m
Optris PI 450	Thermal infrared	640×512 pixel	±2 °C or ±2%
Sequoia	Multi-spectral	4608×3456 pixel	17 cm/ pixel at 100 m
ICI 9640 P	Thermal infrared	640×480 pixel	±1 °C
ISI SWIR 640 P	Short-wave infrared	640×512 pixel	±1 °C

few years, research on the estimation of water stress in various crops has been investigated, and RS imagery has increased. First of all, the research adopting both VIS and TIR imagery has been attempted to estimate crop water stress (Möller et al. 2006; Leinonen and Jones 2004). The co-registration method of VIS and TIR images has been widely accepted to calculate pure crop temperature, excluding soil temperature. This makes it possible to differentiate the canopy cover area and the soil surface in the VIS image and then compute the canopy cover in the TIR image co-registered with the VIS image. Despite the versatility of two kinds of image data combined, co-registration instead involves time-consuming work. A histogram-based approach has been implemented to eliminate the CT from soil background temperature using TIR imagery (Park et al. 2017). The method combines the TIR image pixel histogram and uses a constant threshold to obtain

canopy-related temperatures (e.g., the coldest 33% of the histogram).

The threshold in the histogram describes the border between vegetation and soil distribution, and mathematical and analytical methods calculate the value. The study shows that the CWSI estimation process has been facilitated and optimized, removing the need for VIS image processing. However, based on site-specific crop types, proper determination of threshold values to discard non-canopy pixels in histogram analysis is needed. The mixed pixels of thermal imagery will cause significant bias in canopy temperature at midday, as they are included in the canopy pixel clusters. As an indicator of crop water stress, the determination of T_{wet} and T_{dry} for CWSI has a significant effect on the accuracy of CWSI values. The thermal sensor uses thermal radiation to read passive thermal rendition with a spectral range of 7–12 μm . An array of microbolometers inside the thermal sensors was used to identify and receive the thermal

Fig. 7 Data processing flow-chart

rendition signal and store these signals as raw data number (DN) values on the image pixel. The thermal camera and UAVs allow data collection to be more versatile and lower cost than conventional remote sensing methods. Figure 7 shows the example of picture processing for irrigation management. In UAV-based CWSI analysis, an attempt was made to find an optimal UAV flight time, showing that mid-day UAV sensing promises optimal data collection, minimizing shadow effects on the earth (Quebrajo et al. 2018; Bellvert et al. 2014). These UAV-based techniques would be a promising method with optimized technologies to detect plant water status, integrating sophisticated image analytic algorithms and upgraded camera systems (Gago et al. 2015; García-Tejero et al. 2018).

Time for taking thermal images

Various guidelines can be used for genotype selection and stress monitoring processes on how and when to measure canopy temperature (Pinter et al. 1990). The first model hypothesizes that temperature readings should be done, while there is less water content in the soil. The explanation is that if the plants can transpire at a higher rate under low soil moisture levels, they will sustain comparatively higher growth and yield (Gardner et al. 1981). The second hypothesis is that, in well-watered settings, temperature readings should be done. The explanation for this is that since plants under this situation have higher temperatures, they transpire less and conserve water in the soil profile that can be used later during the reproductive process and have greater yields. It is essential to determine the optimum time of taking thermal images considering the stage of the crop, time of day, and weather conditions. In most of the studies, canopy temperature was measured around midday. Zia et al. (2012) took hourly thermal images to study the impact of the time of day on image acquisition and found that midday can be the most suitable time to take thermal measurements due to the highest canopy temperature and lowest stomatal conductance during solar noon and said that this would help to find the most significant difference between the treatments (Zia et al. 2012). Zia et al. (2012) analyzed the canopy temperature measurements taken during the day and found that the optimal time for calculating canopy temperature is 11:00–13:00 and 16:00 h (Zia et al. 2012). About growth point, time of day, and atmosphere, attempted to establish optimum measurement times for canopy temperature. They find that about 09:00 in the morning and 13:00 was the perfect time to measure the canopy's temperature (Balota et al. 2007). A weak relationship between the depression of canopy temperature (CTD) and other parameters was also noted when the measurements were taken during low solar radiance with high wind speed and rain events.

Aerial images acquisition and software solutions

The soil properties and vegetation indices can be measured using various airborne sensors through remote sensing techniques. Such as LAI and NDVI are the two most common indices to identify crop health. Also, the thermal sensor is used to calculate water stress from horticulture crops (Berni et al. 2009a). The canopy reflectance is used to classify the biochemical and biophysical properties with different methods, such as machine learning methodology, which shows superior outcomes in many studies. The flight path is planned to confirm the overlapping side > 70% between the images of flight strips. The SfM (structure from motion) technique is used to analyze the series of imageries to generate a 3D orthomosaic (Aasen et al. 2018; Colomina and Molina 2014). The Pix4D and Agisoft PhotoScan were used to process the UAV images. The standard output of SfM software includes the (DSM), orthomosaic, and 3D cloud (Weiss and Baret 2017; Turner et al. 2011). Different spectral, thermal indicators can be calculated from the equation below (Jones 2013; Costa et al. 2013).

$$\Delta T_{\text{canopy-air}} = T_C - T_{\text{air}} \quad (4)$$

$$\text{CWSI} = \frac{T_{\text{canopy}} - T_{\text{wet}}}{T_{\text{dry}} - T_{\text{wet}}} \quad (5)$$

$$\text{IG} = \frac{\Delta T_{\text{dry}} - \Delta T_{\text{canopy-air}}}{\Delta T_{\text{canopy-air}} \Delta T_{\text{wet}}} \quad (6)$$

where $\Delta T_{\text{canopy-air}}$, ΔT_{wet} , and ΔT_{dry} are variations in air and canopy temperature. The T_{dry} and T_{wet} values were the subjects of the CWSI calculated using simplified, statistical, and analytical methods.

Spectral and normalized indices

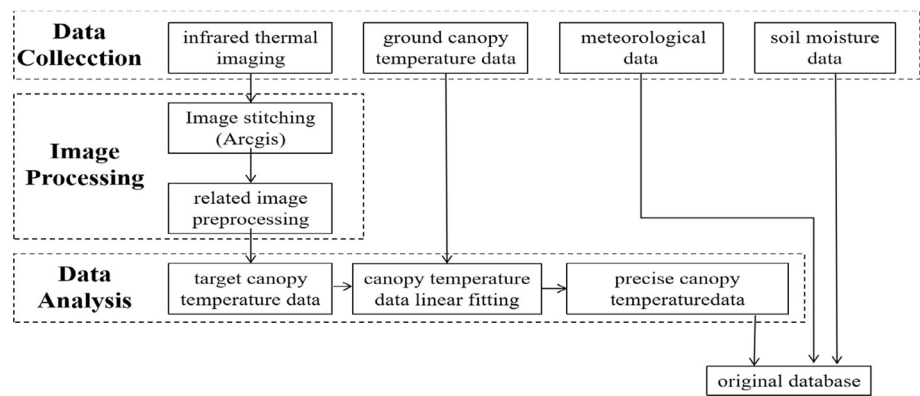
To estimate the various crop characteristics, i.e., biochemical and biophysical by vegetation indices, is one of the popular methods. However, NDVI and LAI have the sensitive issue. These indices are shown reasonable accuracy with satellite data. Leaf area index is a biological practice of the crop (Tahir 2018). It can be used to study plants transpiration growth and photosynthesis. LAI can also be used in water balance modeling and crop yield prediction (Jonckheere, et al. 2004). Many researchers (Baluja et al. 2012; Zarco-Tejada et al. 2012; Zarco-Tejada et al. 2009; Jones and Vaughan 2010) measured this specific reflectance using RGB, multi-spectral, and hyperspectral cameras. Several solutions were built to resolve this situation. One potential solution is the use of an extensive dynamic vegetation index



Table 6 Different thermal and vegetations indices used for water stress identification

Type	Indices	Formula	Reference
Chlorophyll indices	Combined TCARI/OSAVI	$TCARI/OSAVI = \frac{TCARI}{OSAVI}$	Haboudane et al. 2002)
	Red edge reflectance index	$RFI = \frac{R750}{R710}$	Zarco-Tejada et al. 2001)
	Carotenoid index	$CI = \frac{R515}{R570}$	Zarco-Tejada et al. 2001)
	TCARI (transformation chlorophyll absorption in reflectance index)	$TCARI = 3 \cdot \{(R700R670) - 0.2 \cdot (R700 - R550) \cdot (R700/R670)\}$	Kim et al. 2002)
Structural indices	NDVI	$NDVI = \frac{[NIR-R]}{[NIR+R]}$	Jackson 1980)
	Renormalized difference vegetation's index	$RDVI = \frac{(R850-R670)}{[R850+R670]^{0.25}}$	Rondeaux et al. 1996)
	Optimized soil adjusted · vegetation index	$OSAVI = \frac{(R800+R690+0.16)}{(1+0.16)(R800-R670)}$	Roujean and Breon 1995)
Leaf equivalent water thickness	NDWI (Normalized Difference Water Index)	$NDWI = \frac{R860-R1240}{R860+R1240}$	Stimson et al. 2005)
	MDWI (maximum difference water index)	$MDWI = \frac{R860-R1240}{R860+R1240}$	Eitel et al. 2006)
	MSI (Moisture Stress Index)	$MSI = \frac{R1600}{R550}$	Hunt and Rock 1989)
	NGRDI	$NGRDI = \frac{(Green-Red)}{(Green+Red)}$	Hunt and Rock 1989)
Biomass · Estimation	Photochemical Reflectance Index	$PRI = \frac{R570-R539}{R570+R531}$	Gago et al. 2015)
	Normalized · PRI	$PRInorm = \frac{R515-R531}{R515+R531}$	Gago et al. 2015)
Water stress index	CWSI	$CWSI = \frac{(Tc-Tb)LL-(Tc-Tb)UL}{(Tc-Tb)LL-(Tc-Tb)UL}$	Bellvert et al. 2014)



Fig. 8 Original database establishment flowchart

(WDRVI). For this index, 0 to 1 ranging factors are fixed with NIR reluctance (Gitelson 2004).

$$NDVI = \frac{NIR - R}{NIR + R} \& WDRVI = \frac{a * NIR - R}{a * NIR + R} \quad (7)$$

The relationship between LAI and WDRVI appears linear and tends to increase when the weighting factor approaches zero values. Another enhanced vegetation index is designed to show better sensitivity with LAI and blue band.

$$EVI = 2.7 \times \frac{NIR - R}{[(7.5 * B) + 1] - [NIR + (6 * R)]} \quad (8)$$

UAV operations can also acquire temperature, fluorescence, and water stress condition identification linking with a multi-spectral and thermal cameras sensor. Table 6 outlines the significant indices of vegetation studied through comprehensive literature.

A Case studies on UAV-based thermal sensor for precision agriculture

The image data collection works are carried out at 9:00am, 10: 00am, 11: 00am, 12: 00 pm, 1: 00 pm, 2: 00 pm in every experimental day in this field. The UAV flies at a relative altitude of 25 m. No irrigation is carried out during the experiment. By the thermal camera (Zenmuse XT2) on DJI multifunctional UAV (M300RTK), the infrared thermal images with resolution of 640×512 are captured. The wavelength range is 7.5–13.5 μm . The UAV is turned on 30 min before the measurement (Pham and Stack 2018). All flight missions are uploaded to the drone platform through the controller. The infrared thermal imaging camera is triggered regularly during the UAV flight, and the UAV platform has a fixed GPS module, which can automatically record the location coordinates of the shooting point in each image (tiff format). Finally, a single photograph is spliced into a orthomosaic map of the study area

by PIX-4D software. And the redundant image information is effectively removed through image preprocessing methods such as edge detection and filtering. The twenty soil moisture sensors are uniformly arranged in the field study area, and the coordinates of the 20 locations are obtained by GPS with the accuracy of 0.1 m. During UAV shooting, the soil moisture sensor collects soil moisture content data (θ) at these points. The field meteorological station collects relevant data every 1 h. Predictive values of canopy temperature of these locations are extracted from the infrared thermal image after removing the soil background. The true canopy temperature values of these 20 points are observed by hand-held thermometers (TN410LCE), and the average of the three measured values near each point is regarded as the real temperature value. The canopy prediction and real temperature observation are synchronized with soil moisture data acquisition. The experimental data collection and processing flowchart is shown in Fig. 8.

Real-time irrigation management and future perspectives

The current development in irrigation automation provides a framework for continuous data transfer across irrigation controllers, mounted field sensors, and variable irrigation equipment (Quebrajo et al. 2018). UAV thermal sensors approaches are used in the assessment of water status of crops, i.e., the temperature of the canopy, threshold temperature, and CWSI (theoretical and empirical) threshold, and CWSI (theoretical and practical) (Bian et al. 2019). Osroosh et al. established a theoretical CWSI algorithm to irrigate the apple trees automatically (Osroosh et al. 2015). They used a central pivot and linear irrigation system, and thermal imageries camera. The CWSI acquired from UAV thermal cameras would be optimized for real-time scheduling of irrigation. Hutton and Loveys 2011 established and validated UAV thermal images for assessing the plant water

status, which does not require the operator's involvement. Estimation of CWSI from thermal imaging has a great potential for quickly detecting changes in water stress and is used for detecting evapotranspiration (Bellvert et al. 2016a; Santesteban et al. 2017; Osroosh et al. 2016). The obtained information of evapotranspiration remained gathered to the irrigation valve zone assisted by the irrigation equipment. Accordingly, accurate data and information collated quickly are essential to assess the effectiveness of water usage. More effort is needed to make these UAVs user-friendly and accessible for all types of users for precise crop assessment. Automatic irrigation is a promising technology to increase the farm irrigation management of agricultural crops for sustainable production (Osroosh et al. 2016; Piao et al. 2010; Webb et al. 2010; Beare and Heaney 2002; McBratney et al. 2005). The future of automatic irrigation is expected to have included UAV, satellite-based RS, and ground-based sensors connected with WSN.

Many researchers predict more advances in temporal downscaling in satellite remote sensing to achieve daily measurement. Also, seasonal models for water stress detection were developed to schedule irrigation (Semmens et al. 2016; Sun et al. 2017; Biggs et al. 2016). Another method for upcoming precision irrigation is to track the irrigation water directly in automated pipelines near the sub-block. These automated pipelines depend on proximal data collection, analysis, specifications estimation, crop water status interpretation, and irrigation system regulation. Recent advances in cloud computing and wireless technologies could help process remote sensing data quickly after acquisition (Lakhwani et al. 2019; Ojha et al. 2015; Hori et al. 2010). Finally, automation and computational resources will ultimately combine and create intelligent technologies for artificial intelligence and real-time processing for decision-making tools. Soon, farmers benefit from precise irrigation guidance using UAV maps regularly, weather stations, and direct sensors. These data can be collected and almost instantly stored on the cloud and combined with post-processing algorithms to decide advanced irrigation applications (Goap et al. 2018). Furthermore, it is expected that technological advancements in the coming years will result in smaller and more affordable devices, making thermal sensing a widespread practice in agriculture, irrigation management, and related fields.

Conclusion

This research highlighted the state of the art, possibilities, and drawbacks for detecting crop water stress with thermal remote sensing. UAV technology improved CWP for these widely used sensors: multi-spectral, hyperspectral, and thermal. UAV with thermal sensors is a valuable tool for monitoring and assessing crop water status among these cameras. Therefore, regular tracking of crops for characterizing the water condition is better achieved using a UAV network. Researchers recently tried to increase crop productivity by an adaptive irrigation planning algorithm, which depends on simulated CWSI of thermal imageries sensors mounted on a central pivot and linear irrigation systems. Also, UAVs with remote sensors provide a cost-effective solution and data actuations. The current review paper has open new pathways for applying UAV-based thermal remote sensing techniques, potentially used in precision irrigation systems. Furthermore, research will show the extent to which the presented techniques are applicable in precise agriculture, and various crop-cultivar-site and time-specific experiments will remain for further work. Several limitations are preventing the broader use of UAVs for PA. For PA applications installation, the main reason for adopting the ad hoc procedure is the absence of a standardized workflow. It is also the fact that discourages the pertinent stakeholders. In addition, as PA requires data-intensive procedures for the image's manipulation, experts and skilled personnel are also needed. This leads to training or hiring an expert to assist them with image processing that is also a costly option for an average farmer. The fact mentioned above may proscribe the adoption of UAV technologies from farmers with small agricultural fields.; however, this is not the case for most of the fields in Asia.

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Muhammad Faheem helped in fabrication and optimization. Sajjad Hussain English edited the manuscript. Adeel Ahmad Nadeem wrote the review and edited. Muhammad Mannan Afzal curated the data. Chenchen Liu investigated the study and curated the data.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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