Review

An overview of current and potential applications of thermal remote sensing in precision agriculture

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Abstract

Precision agriculture (PA) utilizes tools and technologies to identify in-field soil and crop variability for improving farming practices and optimizing agronomic inputs. Traditionally, optical remote sensing (RS) that utilizes visible light and infrared regions of the electromagnetic spectrum has been used as an integral part of PA for crop and soil monitoring. Optical RS, however, is slow in differentiating stress levels in crops until visual symptoms become noticeable. Surface temperature is considered to be a rapid response variable that can indicate crop stresses prior to their visual symptoms. By measuring estimates of surface temperature, thermal RS has been found to be a promising tool for PA. Compared to optical RS, applications of thermal RS for PA have been limited. Until recently (i.e., before the advancement of low cost RS platforms such as unmanned aerial systems (UAVs)), the availability of high resolution thermal images was limited due to high acquisition costs. Given recent developments in UAVs, thermal images with high spatial and temporal resolutions have become available at a low cost, which has increased opportunities to understand in-field variability of crop and soil conditions useful for various agronomic decision-making. Before thermal RS is adopted as a routine tool for crop and environmental monitoring, there is a need to understand its current and potential applications as well as issues and concerns. This review focuses on current and potential applications of thermal RS in PA as well as some concerns relating to its application. The application areas of thermal RS in agriculture discussed here include irrigation scheduling, drought monitoring, crop disease detection, and mapping of soil properties, residues and tillage, field tiles, and crop maturity and yield. Some of the issues related to its application include spatial and temporal resolution, atmospheric conditions, and crop growth stages.

Keywords:
Precision agriculture
Monitoring
Remote sensing
Thermal sensing

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Contents

1. Introduction .......................................................................................................... 23
2. Remote sensing in precision agriculture .............................................................. 23
3. Thermal remote sensing and its application in agricultural sector ...................... 25
   3.1. Irrigation scheduling ..................................................................................... 25
       3.1.1. Soil moisture detection ........................................................................ 25
       3.1.2. Crop water stress monitoring ............................................................... 25
       3.1.3. Evapotranspiration and drought stress monitoring .............................. 26
   3.2. Plant disease detection .................................................................................. 26
   3.3. Soil texture mapping ..................................................................................... 26
   3.4. Residue cover and tillage mapping .............................................................. 26
   3.5. Field tile mapping ....................................................................................... 27
   3.6. Crop maturity mapping ................................................................................ 27
   3.7. Crop yield mapping ..................................................................................... 27

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1. Introduction

With rising concerns regarding agriculture's role in surface and groundwater quality combined with increasing fertilizer prices and the need to meet an expected 50–70% increase in global food demand with limited resources, there is an immediate need to improve agricultural systems into highly resource-efficient systems that are both profitable and environmentally sustainable (Donner and Kucharik, 2008; Zhang et al., 2015; Zillén et al., 2008). Agricultural systems can be made resource-efficient by integrating tools, technologies and information management systems that come under the precision agriculture PA concept. Precision agriculture (PA) is a site-specific form of agriculture that aims to optimize farm inputs, improve efficiency, and reduce environmental footprints by focusing on the right management practice at the right rate at the right time in the right place (Gebbers and Adamchuk, 2010). Unlike conventional farming practices where fields receive blanket applications of farm inputs, with PA, fields receive varying rates of inputs based on soil type, landscape position, and management history. Recent technological advancements, including global positioning system (GPS) for machine guidance, grain yield monitors, variable rate technologies (VRT), sensor networks, and remote sensing (RS), have helped farmers to identify in-field variability of crop and soil conditions and implement site-specific farming practices.

Varying the application of inputs with VRT can reduce inputs and labor costs, maximize productivity, and reduce the potential environmental impacts from over-application of farm inputs. However, the success of VRT requires accurate and reliable information on the location and magnitude of crop and soil health conditions, such as crop nutrient deficiencies, soil and plant water stress, and damage caused by insects, weeds, or diseases. While field sampling provides in-field variabilities on crop and soil health conditions, it is infeasible and costly due to current trends towards increasing farm size. Remote sensing is the most cost effective method for large scale monitoring and analyses in agriculture. To date, the dominant RS tools that agricultural sector has utilized are visible, near infrared (NIR), and short wave infrared (SWIR) sensors. Use of thermal sensors in agriculture is somewhat limited by its wide application in the areas of medicine (Ring and Ammer, 2012), intelligence/military (Hinz and Stilla, 2006), and food processing (Vadivambal and Jays, 2011). In recent years, due to the improvements in technologies as well as reduction in sensor costs, its use in PA has gained popularity. By providing temperature measurements of soil and crop surfaces, thermal RS has the potential to be used for various applications, including (1) monitoring of crop stresses, crop diseases and soil water stress, and (2) planning for irrigation scheduling and harvesting operations. The objectives of this paper are to review and summarize the current and potential applications of thermal RS in PA, and discuss some of the concerns and challenges related to its use.

2. Remote sensing in precision agriculture

Remote sensing in PA is used for collecting and analyzing information about crop and soil characteristics using sensors mounted on satellites, aircrafts, or ground equipment. Sensors collect energy that is reflected (visible and NIR), emitted (thermal infrared (TIR)), or backscattered (microwave) from the surface or atmosphere in different portions of the electromagnetic spectrum. Applications of RS in PA are typically influenced by the type of platform (ground, air, or satellite), region of the electromagnetic spectrum (visible, infrared, and microwave), number and width of the spectral bands (panchromatic, multispectral, hyperspectral), spatial resolution (high, medium and low), temporal resolution (hourly, daily, and weekly revisit frequency), radiometric resolution (8, 12, and 16 bits), and the source of energy (passive or active sensors) used by sensors to collect the data (Metternicht, 2008).

One of the most commonly exploited RS systems in the agricultural sector is optical RS. It utilizes visible, NIR, and SWIR sensors to create images of the earth’s surface by detecting the energy reflected by the surface of the target area (Prasad et al., 2011). Using visible and NIR images collected by satellite, traditional aircraft, and unmanned aerial vehicles (UAVs), several studies (Hatfield and Prueger, 2010; Gitelson et al., 2003; Huete et al., 2002; Jordan, 1969) have examined vegetative conditions in agriculture. Several vegetation indices (VIs) have been developed based on the combination of different wavebands to estimate various plant parameters, e.g., leaf area, ground cover, biomass, leaf chlorophyll content, residue cover, etc. Although these VIs provide indications of vegetative cover conditions, they are relatively slow response variables that typically adjust only after notable crop damage occurs. In contrast, surface temperature detected by thermal sensors is found to be a rapid response variable for monitoring crop growth and stresses (Stark et al., 2014; Anderson et al., 2013).

Thermal RS is a process of measuring the radiation emitted from an object's surface and converting it into temperature without establishing direct contact with the object. All objects with a temperature above 0 K or –273 °C or –459 °F emit radiation, and the amount of radiation is a function of the emissivity of the surface and the surface temperature (Prakash, 2000). The higher the temperature of the body, the greater is the intensity of radiation emitted by the object. Thermal RS provides important measurements of energy fluxes and temperatures from the earth’s surface, which are integral to understanding landscape processes and responses (Quattrochi and Luvall, 1999; Weng, 2009). Thus, a series of satellite and airborne thermal sensors (Table 1) have been developed and used directly or indirectly for many agricultural applications. In general, the crop canopy surface temperature is a function of transpiration rate, and that, itself, is a function of atmospheric evaporative demand and crop available soil water status. Stress (i.e., water, weed, nutrient) in crops influences its canopy temperature, which can be measured during critical phenological stages.
Table 1
Thermal infrared sensors deployed on satellite and airborne platforms.

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Wavelength (µm)</th>
<th>Waveband (Thermal)</th>
<th>Spatial Resolutions (meter)</th>
<th>Temporal Resolution (days)</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Satellite</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AATSR/ENVISAT</td>
<td>11.0–12.0</td>
<td>6–7</td>
<td>1000</td>
<td>1</td>
<td>Llewellyn-Jones et al. (2001)</td>
</tr>
<tr>
<td>ASTER</td>
<td>8.125–11.65</td>
<td>10–14</td>
<td>50</td>
<td>16</td>
<td>NASA (2016a)</td>
</tr>
<tr>
<td>AVHRR</td>
<td>3.5–3.93,</td>
<td>3,</td>
<td>1100</td>
<td>0.5</td>
<td>NOAA (2016)</td>
</tr>
<tr>
<td>10.50–12.5</td>
<td>4–5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBERS</td>
<td>10.4–12.5</td>
<td>4</td>
<td>80</td>
<td>26</td>
<td>CBERS (2016)</td>
</tr>
<tr>
<td><strong>Landsat</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>USGS (2016)</td>
</tr>
<tr>
<td>TM</td>
<td>10.40–12.50</td>
<td>6</td>
<td>120</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>7 ETM+</td>
<td>10.40–12.50</td>
<td>6</td>
<td>60</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>10.60–11.19,</td>
<td>10,</td>
<td>100</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>11.3–12.51</td>
<td>11</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MODIS</td>
<td>3.66–4.55,</td>
<td>20–25,</td>
<td>1000</td>
<td>1</td>
<td>NASA (2016b)</td>
</tr>
<tr>
<td>8.4–14.08</td>
<td>25–35</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Airborne</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ATLAS</td>
<td>8.32–12.02</td>
<td>10–15</td>
<td>10</td>
<td>*</td>
<td>Lo et al. (1997)</td>
</tr>
<tr>
<td>TIMS</td>
<td>8.2–12.2</td>
<td>1–6</td>
<td>50</td>
<td>*</td>
<td>Kealy and Hook (1993)</td>
</tr>
</tbody>
</table>

* Human operated.

Table 2
Applications of thermal imaging at various geographic scales in the agricultural sector.

<table>
<thead>
<tr>
<th>Areas in agriculture</th>
<th>Problem</th>
<th>Results</th>
<th>Geographic scale</th>
<th>Platform</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irrigation scheduling</td>
<td>Soil moisture</td>
<td>Map the spatial distribution of soil moisture conditions and monitor its change over time</td>
<td>Coarse resolution airborne thermal images performed better than a handheld thermal gun; thermal images can be used for operational monitoring of soil moisture conditions at the field or regional scales</td>
<td>Regional, vineyards, fields</td>
<td>Satellite, aerial, ground</td>
</tr>
<tr>
<td>Evapotranspiration (ET) and drought stress</td>
<td>Improve confidence in signals of emerging drought; need for a diagnostic fast-response indicator describing ET deficits</td>
<td>RS based ET estimates compare well with ET recorded at field level; provide early warning of drought conditions</td>
<td>National, regional, field</td>
<td>Satellite, aerial</td>
<td>Anderson et al. (2013), Barbagallo et al. (2009), Chávez et al. (2008) and Gowda et al. (2008)</td>
</tr>
<tr>
<td>Plant disease detection</td>
<td>Need for higher pesticide application efficiency through early detection of pathogens</td>
<td>An early stage of pathogen development can be detected using thermal images</td>
<td>Greenhouse, orchard</td>
<td>Ground, aerial</td>
<td>Mahlein (2016), Berdugo et al. (2014), Calderón et al. (2014), Oerke et al. (2011, 2006), Calderón et al. (2013), Stoll et al. (2008) and Chaerle et al. (2004)</td>
</tr>
<tr>
<td>Soil texture mapping</td>
<td>Better understanding of the relationship between soil texture and land surface temperature during different periods of the day</td>
<td>Thermal images could be used for digital mapping of regional soil texture variations</td>
<td>Regional</td>
<td>Satellite</td>
<td>Wang et al. (2012, 2015)</td>
</tr>
<tr>
<td>Residue cover and tillage mapping</td>
<td>Existing methods that measure crop residues are laborious, and largely inappropriate for field-scale to regional estimates; quantify residue effects on soil temperature and water</td>
<td>Thermal images can be used for crop residue variability assessment; plots with greater amounts of residue cover have lower surface temperature</td>
<td>Regional</td>
<td>Airborne</td>
<td>Sullivan et al. (2004) and Kozak et al. (2007)</td>
</tr>
<tr>
<td>Crop maturity mapping</td>
<td>Characteristics of produce (i.e., fruit and vegetables) at pre- and post-harvest stages are unknown</td>
<td>Thermal imaging could be used for analysis of pre-harvest conditions, evaluation of post-harvest climate, microbial infestation, freshness status of produce</td>
<td>Laboratory, ground</td>
<td>Ground</td>
<td>Linke et al. (2000)</td>
</tr>
<tr>
<td>Crop yield mapping</td>
<td>Hand harvesting of specialty crops is expensive; fruit recognition is difficult; need for an easy method for counting of fruits and estimating their yield</td>
<td>Possible to predict the yield of fruit; aids in developing robotic fruit harvesting</td>
<td>Orchard</td>
<td>Ground</td>
<td>Bulanon et al. (2008) and Stajnko et al. (2004)</td>
</tr>
</tbody>
</table>
for use in planning, management and optimization of agricultural inputs and activities.

3. Thermal remote sensing and its application in agricultural sector

Thermal RS can be used in many aspects of crop and soil monitoring in the agricultural sector, including estimating soil and crop water stress for irrigation scheduling, determining disease and pathogen infected crops, mapping soil texture, estimating of residue cover, locating tiles in fields, monitoring crop maturity for harvesting, and mapping crop yield. This section discusses studies conducted to determine the potential use of thermal images in agriculture. Table 2 summarizes some of the studies of the application of thermal imaging in agriculture.

3.1. Irrigation scheduling

Irrigation is an essential part of agricultural production in regions where in-season rainfall is inadequate to meet crop water demand. Knowing where, when and how much to irrigate helps to minimize crop yield loss related to water stress, maximize yield response to other management practices, and optimize yield per unit of water applied (i.e., irrigation efficiency) which in turn can maximize farmer’s profit. The need for irrigation is determined primarily by four factors – availability of water in soil, crop water need, rainfall amount, and efficiency of the irrigation system (Rhoads and Yonts, 2000). There are many approaches to quantify these factors, including measurement of soil moisture, plant-based temperature, and evapotranspiration. Studies have explored the possibility of using thermal images from various platforms (i.e., satellite, aerial and UAV) as a tool for measuring these variables (Shafian and Maas, 2015; Hillel, 2013; Soliman et al., 2013; Chávez et al., 2008; Carlson, 2007) (discussed below), and demonstrated that the timely availability of these data during critical crop phenological stages could optimize both frequency and timing of irrigation schedules.

3.1.1. Soil moisture detection

Timely monitoring of soil moisture is critical because it serves as a solvent and carrier of nutrients for plant growth, regulates soil temperature, supports microbial activities, influences farm operations (e.g., planting fertilization, irrigation), and acts as a nutrient itself (Ramachandra, 2006). Studies have used thermal RS for detecting soil moisture to aid in irrigation scheduling (Shafian and Maas, 2015; Soliman et al., 2013; Carlson, 2007). The soil moisture index and triangle method are widely used approaches for measuring soil moisture using thermal images. The triangle method is based on an interpretation of the image (pixel) distribution in surface radiant temperature to fractional vegetation cover space. A triangle emerges because the range of surface radiant temperatures decrease as the vegetation cover increases; a vertex emerges showing the narrow range of surface radiant temperature over the dense vegetation (Carlson 2007). Vegetation subject to water stress usually experiences an increase in its radiant temperature compared to vegetation that is well watered. Shafian and Maas (2015) developed the Perpendicular Soil Moisture Index (PSMI) using raw digital count data in the red, NIR, and thermal bands from Landsat satellite images, and demonstrated that PSMI is strongly correlated with observed soil moisture. Soliman et al. (2013) evaluated two sensors, an airborne thermal camera and a handheld thermal gun, to examine spatial variability in soil moisture in vineyards, and found that airborne thermal images performed better than data from the handheld thermal gun. Using high-resolution multi-spectral imagery (visual, near infrared, infrared/thermal) acquired by a UAV in combination with ground sampling, Hassan-Esfahani et al. (2015) demonstrated the application of thermal images in accurately estimating the spatial distribution of surface soil moisture in an Utah farm planted with alfalfa and oats.

3.1.2. Crop water stress monitoring

Crop canopy temperature and stomatal conductance have long been known to be important proxies for monitoring crop water stress and thus potential tools for irrigation scheduling. Except for some plant species, such as citrus and olive (discussed in the Section 4.5), significant elevation of canopy temperature above air temperature usually indicates stomatal closure and water deficit stress (Hillel, 2013; Jones, 2004). Using thermal images, studies have monitored canopy temperature and stomatal conductance to identify crop water stress. Using canopy temperature, Jackson and coworkers (Jackson et al., 1981) proposed the concept of Crop Water Stress Index (CWSI) to detect crop water stress. It is defined as the difference between air (Ta) and canopy temperature (Tc), normalized for the evaporative demand as determined by the means of a lower limit (when the canopy transpires at its potential rate) and an upper limit (a non-transpiring canopy), as shown in the Eq. (1).

$$\text{CWSI} = \frac{(T_c - T_a) - (T_c - T_a)_{UL}}{(T_c - T_a)_{LL} - (T_c - T_a)_{UL}}$$

where UL and LL are the upper and lower limits, respectively. There are several formulations to determine CWSI, and they vary based on the approach used to determine UL and LL (Agam et al., 2013; Gonzalez-Dugo et al., 2014). There are analytical (Berni et al., 2009a,b; Gonzalez-Dugo et al., 2014) and empirical (Cohen et al., 2005; Möller et al., 2007) approaches to determine UL and LL. These approaches have their own strengths and limitations (Agam et al., 2013), and have been used widely to determine crop water stress. Studies have estimated CWSI using thermal measurements acquired from various sources, including manually handled infrared thermometers (Jackson et al., 1981), sensors mounted on a mast or a crane (Wang and Gartung, 2010; Testi et al., 2008), unmanned aircraft (Gonzalez-Dugo et al., 2013; Berni et al., 2009a), or satellite (Barbagallo et al., 2009). Stoll and Jones (2007) explored the use of thermal imaging as a tool to distinguish different water stress treatments. The experiments involved grapevines that received two irrigation treatments: no irrigation and full irrigation. Images were taken from both sun-exposed and shaded leaves from both irrigated and non-irrigated vines. The study found canopies of non-irrigated vines to be significantly hotter than the fully irri-

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**Table 3** Examples of plant diseases identified by thermal sensors.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Disease/pathogen</th>
<th>Geographic scale</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cucumber</td>
<td>Downy mildew (Pseudoperonospora cubensis)</td>
<td>Greenhouse</td>
<td>Berdugo et al. (2014)</td>
</tr>
<tr>
<td>Apple</td>
<td>Apple scab (V. inaequalis)</td>
<td>Greenhouse</td>
<td>Oerke et al. (2006)</td>
</tr>
<tr>
<td>Rose</td>
<td>Downy mildew (Peronospora sparsa)</td>
<td>Greenhouse</td>
<td>Gomez (2013)</td>
</tr>
<tr>
<td>Olive</td>
<td>Verticillium wilt (Verticillium dahliae)</td>
<td>Orchard, Spain</td>
<td>Calderón et al. (2013)</td>
</tr>
<tr>
<td>Grape</td>
<td>Downy mildew (Plasmopara viticola)</td>
<td>Grapevines, Portugal</td>
<td>Stoll et al. (2008)</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>Leaf rust (Puccinia triticina)</td>
<td>Plot, Germany</td>
<td>Lenthe et al. (2007)</td>
</tr>
</tbody>
</table>
gated vines. They observed a greater difference in temperature between the sunlit and shaded canopies, and a wider range of temperature variation in sunlit leaves compared to shaded leaves. The study recommended the measurement of shaded leaves’ temperature as a reliable indicator of leaf temperature and hence the stomatal conductance. Further, it demonstrated that the temperature differences between stressed and non-stressed plants could be very helpful for identifying water stress in plants, and thus useful for irrigation scheduling. Using UAV acquired thermal images, Gonzalez-Dugo et al. (2013) estimated the CWSI to identify water stressed areas within a commercial orchard, and demonstrated that this approach is viable for precision irrigation management.

### 3.1.3. Evapotranspiration and drought stress monitoring

Evapotranspiration (ET) transfers a large volume of water from the soil, through evaporation, and vegetation, through transpiration, into the atmosphere. Reliable ET estimates thus are essential for improving crop water management at both field and regional scales. Under an ET-based irrigation scheduling approach, ET losses are replaced in the root zone to meet plant water requirements. Evapotranspiration is an energy-demanding process; higher ET rates decrease the surface temperature of leaves and plants. Numerous ET algorithms have been developed to utilize surface temperatures derived from thermal images from satellite based sensors (Maes and Steppe, 2012; Chávez et al., 2008; Gowda et al., 2008). While Maes and Steppe (2012) provided a review on the theoretical relation between surface temperature and ET/energy balance at leaf and crop scales, Gowda et al. (2008) provided a review of the numerous commonly used remote sensing based algorithms to estimate regional ET. In a study conducted by Barbagallo et al. (2009), satellite-based ET estimates compared well with ET flux recorded at field level. To determine whether ET algorithms originally derived using images from satellite platforms could be adapted to thermal images from other platforms, Chávez et al. (2008) applied ET algorithms to airborne thermal and multispectral images, and demonstrated their use in successful estimation of instantaneous ET and its extrapolation to daily ET for corn and soybean fields. Using thermal images, studies have also estimated empirical indices such as vegetation health index (VHI) and the evaporative stress index (ESI) that provide signals of emerging drought (Anderson et al., 2013). The ESI describes anomalies in the actual/reference ET ratio, and is derived based on leaf surface temperature (LST) and leaf area indices. The VHI shown in Eq. (i) is a composite of the vegetation condition index (VCI), computed from the normalized difference vegetation index (NDVI) (Eq. (ii)), and (ii) the temperature condition index (TCI) (Eq. (iii)) computed from brightness temperature (TB) from thermal data. It can be used as a proxy for monitoring vegetation health, drought, moisture, and thermal conditions (Choi et al., 2013).

\[
VHI = \frac{(VCI + TCI)}{2}
\]

\[
VCI = 100\left(\frac{NDVI - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}}\right)
\]

\[
TCI = 100\left(\frac{TB_{\text{max}} - TB}{TB_{\text{max}} - TB_{\text{min}}}\right)
\]

#### 3.2. Plant disease detection

Plant disease results in major production and economic losses in agriculture. For example, in the U.S., it is estimated that crop losses due to plant pathogens result in about $33 billion in lost revenue every year (Pimentel et al., 2005). It is estimated that farmers may reduce this loss by approximately $11 million just by eliminating 20% of the soybean rust, a prevalent disease. Using thermal RS, studies have shown the possibility of assessing and monitoring the spatial and temporal patterns of crop diseases pre-symptomatically during various disease development phases (Table 3).

Impairments due to root pathogens (e.g., *Rhizoctonia solani* or *Pythium* spp.), systemic infections (e.g., *Fusarium* spp.) or foliar pathogens, such as leaf spots or rusts, often influence the transpiration rate and the water flow of the entire plant or plant organs (Mahlein, 2016). Chaerle et al. (2004) reported changes in local temperatures due to pathogen infections or defense mechanisms for plant-virus interactions in tobacco, and for leaf spot disease in sugar beet at their early growth stage, before damage appeared. Also, studies (Mahlein, 2016; Mahlein et al., 2012; Stoll et al., 2008) have shown thermal sensors to be more effective in detecting disease-induced early modifications in plant respiration, water status, and leaf temperature compared to optical, multi and hyperspectral sensors. Using CWSI derived from aerial thermal images, Calderón et al. (2013) demonstrated the detection of early stage development of soil-borne fungus (i.e., *Verticillium Wilt*) in two olive orchards. Thermal images could also be used to evaluate environmental conditions (e.g., leaf wetness and the duration of wetness periods) favorable for pathogen infections, which can be used in models quantifying the potential of crop disease risk (Mahlein et al., 2012).

#### 3.3. Soil texture mapping

Some soil properties, such as soil texture, can be indicative of other physical and chemical soil properties, including structure, porosity, hydraulic properties, and nutrient retention ability, and all of these factors affect soil quality which in turn influences crop productivity. The ability to quickly determine accurate soil texture is thus important for agricultural decision-making. Land surface temperature has a strong relationship with soil texture; soil texture influences soil water content (i.e., amount of water soil can hold) and this in turn influences the land surface temperature (Mattikalli et al., 1998). For example, during dry periods, a sandy soil with a lower water holding capacity is expected to have a faster water depletion rate and a lower soil water content, and this leads to a higher land surface temperature. A clay soil with a higher water holding capacity is expected to have a slower depletion rate and higher soil water content, resulting in a lower land surface temperature (Wang et al., 2015). By examining the differences in land surface temperature under a relatively homogeneous climatic condition, studies (Wang et al., 2012, 2015) demonstrated the use of thermal RS in quantifying soil texture at a regional scale. Wang et al. (2015) developed linear regression models using daily LST data from MODIS satellite and observed sand (>0.05 mm), clay (<0.001 mm), and physical clay (0.01 mm) contents, and produced maps showing the spatial distribution of soil texture in the Yangtze-Huai River Plain in East China.

#### 3.4. Residue cover and tillage mapping

Crop residues play an important role in soil and water conservation by providing a protective layer on agricultural fields that shields soil from wind and water, prevents erosion, reduces moisture loss, and increases soil quality. Accurate assessment of the extent of crop residue is necessary for proper monitoring and implementation of conservation tillage practices (Hively, 2015). By examining the differences in soil surface temperature between conventional and no-till systems, studies (Kozak et al., 2007; Sullivan et al., 2004; Potter et al., 1985) have shown the potential of thermal images for mapping residue cover and tillage practices. Sullivan et al. (2004) used high resolution images from the Airborne Terrestrial Application Sensor (ATLAS) to differentiate between residue coverage from treatments that consisted of five
wheat (*Triticum aestivum* L.) straw cover rates (0, 10, 20, 50 and 80%) in the Coastal Plain and Appalachian Plateau physiographic regions of Alabama. All other conditions being equal, heat capacities of residue and soil surfaces varied depending on the residue cover rate. Their study demonstrated that thermal images could explain >95% of the variability in crop residue cover amount compared to >77% using visible and near IR images.

3.5. Field tile mapping

Tile drainage systems remove excess water from agricultural fields, which result in both ecological and economic benefits (Hofstrand, 2010). However, at the same time, substantial concentration of nutrients (mainly nitrogen and phosphorus) can be contained in tile drainage water which can contribute to poor water quality (King et al., 2015; Smith et al., 2015). The ability to better monitor tile drains would help farmers and natural resource managers to better predict and mitigate any adverse environmental and economic impacts. It could also allow farmers to identify and repair or replace missing or broken tiles. Improved drainage helps increase crop productivity and thus farm revenue. Studies have shown that visible and NIR images, studies (Naz et al., 2009; Naz and Bowling, 2008; Verma et al., 1996) can be used to identify tile locations in small-sized fields. However, because crop residues and soils have spectrally similar visible and NIR wavelengths between, these studies had limited success in field tile mapping. On bare agricultural land, tile drain locations usually appear lighter in color than the surrounding soil because drained soils dry more quickly. Due to the soil drying faster in tile drained fields, it is likely that there are differences in temperature between tile and naturally drained fields (Yanru and Xiaohong, 1990). By assessing temperature differences within a field, thermal images may provide additional opportunities in field tile mapping (Hoffman and Erb, 2016).

3.6. Crop maturity mapping

The ability to monitor crop maturity is useful for determining the harvesting, particularly when weather condition deteriorate and the entire area cannot be harvested in the time available. An early assessment of crop maturity in the growing season is also useful for screening the adaptability of a crop to potentially poor growing seasons such as drought (Jensen et al., 2009). Using the visual and infrared images acquired by UAV from barley trial areas at Lundavra, Australia in the late growing season, Jensen et al. (2009) used discriminant function analyses to map two primary growth stages of barley and demonstrated classification accuracy of 83.5%. It is the physiological stage and the crop type that influence the transpiration and respiration in crops, which in turn influences their thermal condition (discussed in Section 4.5). For most row crops, as they reach maturity, the degree of respiration rate decreases compared to the initial growth phase (Linke et al., 2000). Less respiration usually leads to higher temperatures. For fruit trees, fruit load plays an important role in controlling transpiration and respiration. Trees with zero fruit load have elevated canopy temperatures compared to those with fruit load. Thus, using thermal images to monitor differences in crop temperature during the growing season, the maturity phase of row crops and fruit yield of tree crops can be determined.

3.7. Crop yield mapping

An accurate and early estimate of crop yield is useful for farmers for a number of reasons, including crop insurance, planning of harvest and storage requirements, and cash flow budgeting. Utilizing images from satellite and airborne sensors at regional (Sakamoto et al., 2013; Mkhabela et al., 2011) and field scale levels (Geipel et al., 2014; Swain et al., 2010), a large number of studies...
have been carried out to predict crop yield. Sakamoto et al. (2013) developed a corn yield estimation model that was used to estimate the spatial distribution of corn grain yield for the entire U.S. for more than a decade using 8-day time series datasets (i.e., visual and near infrared) from an MODIS satellite. Mkhabela et al. (2011) forecasted crop yields, such as barley, canola, field peas and spring wheat, on the Canadian Prairies using vegetation indices derived from MODIS time series data. Using UAV acquired images, Swain et al. (2010) estimated yield and total biomass of a rice crop in Thailand, and Geipel et al. (2014) predicted corn grain yields in the early to mid-season crop growth stages in Germany. These studies however have focused on vegetation indices derived from visible and NIR images (i.e., optical RS). Thermal images are found to have a close relationship with crop yield, and thus could be utilized for crop yield monitoring and estimation (Fig. 1). Currently, only a few studies have used thermal images to estimate crop yield. Stajnko et al. (2004) developed a fruit detection algorithm using thermal images to estimate the number and diameter of apples for estimating apple yield. This algorithm is based on the temperature difference between fruits and the background. The study showed a close correlation ($R^2 = 0.83–0.88$) between the manually measured fruit number and estimated number, and ($R^2 = 0.68–0.70$) between the manually measured diameter and estimated diameter, based on the algorithm. Using thermal imaging, Bulanon et al. (2008) demonstrated that citrus fruit can be differentiated from its canopy. They demonstrated that the night temperature of fruit is about $1.6\,^{\circ}\mathrm{C}$ higher than of leaves, whereas during the day, the temperature differs by less than $0.5\,^{\circ}\mathrm{C}$. Utilizing UAV or aerial platforms, thermal sensors can be a valuable resource in crop yield monitoring in PA.

4. Challenges and future perspectives on the use of thermal images for precision agriculture

Although thermal RS has the potential to provide spatial and temporal information of crop and soil surface temperature, there are certain issues that need to be considered while making use of thermal RS images. These include the influence of: (1) spatial and temporal resolutions of acquired images, (2) atmospheric conditions, (3) viewing angle and altitude of thermal sensors, and (4) crop growth stage and crop species variation (Fig. 2).

4.1. Spatial and temporal resolution

To date, thermal images from satellite platforms have been used extensively to measure crop and soil surface temperatures at regional and global scales. However, the pixel sizes of these images are larger than an individual field in most agricultural regions, and thus, these images have limited applications for site-specific agricultural applications (Mahlein, 2016; Gowda et al., 2008). For example, some satellite-based thermal sensors with daily coverage, such as moderate-resolution imaging spectroradiometer (MODIS), geostationary environmental satellite (GOES), and advanced very high resolution radiometer (AVHRR) provide thermal images at the range of 1000–4400 m resolution (Table 1) compared to visible, NIR and SWIR images that have 250–1000 m resolution. There have been some improvements in the spatial resolution of thermal sensors in some satellites (e.g., Landsat 7 ETM provides 60 m, Landsat 8 provides 100 m, and ASTER provides 90 m pixel size) but these satellites have a revisit time of 16 days (Table 1). For producers or farmers willing to use satellite images for in-season crop and soil monitoring, the low spatial resolution and temporal frequency thus become major limitations.

Images from aerial platforms have demonstrated advantages over satellite images due to their high spatial (i.e., pixel sizes between 0.5 and 2 m), spectral (i.e., 2–20 nm bandwidths in the 400–2500 nm spectral range) resolutions (Berni et al., 2009a,b) and temporal resolutions (i.e., can be acquired when needed). Studies by Sepulcre-Cantó et al. (2006, 2005) demonstrated that high-resolution thermal images acquired aerially are useful for detecting crop water stress for site-specific management. However, manned aerial systems have high operating costs, and due to the limited presence of companies providing cost-effective products, use of manned aerial systems is limited in PA.

Due to recent developments in UAVs, thermal images are now available at high spatial, spectral and temporal resolutions at a lower price compared to the past few years. A typical thermal imager will range in price from $2000 to $50,000 depending on the...
quality and functionality, and the majority of thermal cameras have resolution of 640 pixels by 480 pixels. Although these are significant advancements in thermal technology, compared to commercial off-the-shelf optical sensors used in UAVs, thermal cameras are still more expensive and have poor resolution. Commercially available off-the-shelf optical cameras have resolutions of above 4200 pixels by 2800 pixels (Stark et al., 2014). Table 4 provides a list of thermal cameras currently available.

### 4.4. Atmospheric condition, viewing angle, altitude and timing for image acquisition

Haze and cloud cover conditions can influence the thermal data collected from aerial and satellite platforms. Thus these conditions should be carefully monitored while acquiring thermal images. Relative humidity, altitude and viewing angle at which images are acquired should also be considered. Thomson et al. (2012) collected canopy temperatures of soybean crops at both cloud and cloud-free conditions at varying altitudes near Stoneville, Mississippi, and demonstrated that thermal images collected aerially on cloudy days were of poor quality (i.e., lower contrast and poor radiometric resolution). They also found that altitude alone accounted for 58% of the variability in canopy temperature, solar radiation and altitude together accounted for 73%, and altitude and relative humidity accounted for 76%. Also, remote measurements of canopy temperature were shown to be influenced by viewing angle of thermal sensors (Berni et al., 2009a; Fuchs et al., 1967). Fuchs et al. (1967) demonstrated a temperature difference of +3 °C in soybean crops when the angle of incidence of the sensing beam changed from 0 to 180 deg. Alchanatis et al. (2010) developed regression models using thermal indices derived from thermal images for two different dates (i.e., July and August) and points in time (i.e., morning [10–12] and midday [12–14]) to estimate water status in cotton, and demonstrated that midday was the optimal time for thermal image acquisition. However, Sepulcre-Cantó et al. (2006) found temperature from airborne thermal images acquired early in the morning to be less affected by background effects than those acquired at noon.

### 4.5. Crop growth stage and crop species variation

Measurements of canopy temperature through RS can be influenced by crop growth stages. Early in the growing season, when plants are small and sparse, temperature readings can be affected by reflectance from the soil surface. With measurements obtained...
from partial canopy cover, accurate representation of crop stress thus becomes difficult (Thomson et al., 2012). For accurate representation and management of crop stress under partial ground cover, research should be focused on developing algorithms that help determine the relative influence of canopy and soil on remotely sensed thermal data. For example, Bai et al. (2016) used Otsu’s adaptive thresholding algorithm to segment green pixels from the background to estimate vegetation biomass early in the growing season before canopy closure for soybean and wheat field trials.

In addition to the crop growth stage, it is important to understand how the stomatal response to the environment varies across crop species while using canopy temperature as a proxy for plant water status (Ballester et al., 2013). For example, some species such as olive and citrus display significant stomatal closure at midday, even under well-watered conditions (Testi et al., 2008; Moriana et al., 2002), while for almond species, the stomatal behavior varies between cultivars (Gonzalez-Dugo et al., 2012). There is currently a gap in understanding of whether the indicators derived based on thermal images from various platforms (i.e., manned-aerial, UAV and satellite) can detect and differentiate behavior of contrasting species (Gonzalez-Dugo et al., 2013). Perhaps the integration of visual, thermal and NIR may provide a better understanding in this area, and thus further research is needed in this area.

4.6. Data processing time and data analytics

The usefulness of RS for in-season soil and crop monitoring depends on the turn-around time between image acquisition and dissemination of image-derived products. At present, image processing is still a very time consuming step that requires expert knowledge (Maes and Steppe, 2012). The turn-around time is between 1 and 3 weeks depending on the RS platform and/or sensor, algorithm utilized, and technician’s expertise on applying such algorithms (Gowda et al., 2008). However, for most agricultural practices (e.g., nutrients and pesticide application, irrigation, harvesting), information about a crop’s health should be delivered almost instantaneously.

Currently, due to the relatively low flying altitude of UAVs, an unprecedented number of images with a small coverage footprint are being collected. For a meaningful interpretation of crop and soil conditions, these images need to be geometrically aligned (i.e., ortho-rectified), calibrated and corrected to account for atmospheric effects, and then stitched together (i.e., mosaic) to create a single image with larger spatial coverage. This requires a significant amount of data storage and time for preprocessing, analyzing, and presenting data in formats that are meaningful and useful. Further, there is not a lack standardized framework for processing these big data sets (Zhang and Kovacs 2012). To use any RS technology, including thermal, as a common tool in agricultural practices, there is a need for a system that allows automatic processing of images as well as implements powerful data analytics to differentiate, quantify and detect temporal and spatial patterns of different crop and soil conditions. Currently, there are very limited studies focused on UAV acquired thermal images in PA, and of those available, the majority have focused only on soil moisture estimation (Hassan-Esfahani et al., 2015) and crop disease detection (Calderón et al., 2014). There are other areas of agriculture, such as mapping of soil, tile drainage, and crop residues, which may benefit from UAV based thermal RS. Further, there also exists the potential for evaluating and improving the performance of algorithms originally developed using satellite acquired images to images acquired from UAV platforms. For example, the METRIC model was originally developed to compute ET using Landsat images. Adaption of existing models, such as METRIC, to use UAV images might not only help enhance the accuracy of the model due to high resolution of the data but might also allow better understanding of associated opportunities and limitations.

4.7. Future use of unmanned aircraft in PA

In the future, due to the flexibility and low cost for image acquisition, use of UAVs for crop and soil monitoring is anticipated to increase significantly compared to the traditional satellite and manned-aircraft platforms. Based on a survey of PA service retailers across the US in early 2015, UAV services are expected to increase the most. The use of UAV services was reported at 19% in 2015 with expectations to increase to 38% by 2018 (Widmar and Erickson, 2015). While UAV acquired images could be practical alternatives to aerial photos and satellite images, there are several regulatory and technical issues, from acquisition to dissemination of final images (Zhang and Kovacs 2012; Hardin and Jensen 2011). With relaxed aviation regulations and improvement in image processing, geo-referencing, mosaicing, and classification algorithms (discussed above), UAV offers great potential for soil and crop monitoring (Zhang and Kovacs 2012).

5. Conclusions

This review has briefly discussed the current state of the art and potential application of thermal RS in PA. Potential applications of thermal images in PA include, but are not limited to plant water stress monitoring, drought monitoring, plant disease detection, soil property mapping, residue cover and tillage mapping, field tile mapping, crop maturity mapping, and yield estimation. Although thermal RS has several potential advantages over the optical RS in crop and soil monitoring, there are a number of practical difficulties in its use, including atmospheric attenuation and absorption, calibration, climatic conditions, crop growth stages as well as complex soil and plant interaction that have thus far limited its use in the agricultural sector. However, the advancements in UAV technologies and pressures for greater precision in agricultural applications are likely to provide a real impetus to address these issues and increased integration of thermal RS in agricultural decision-making.

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