Thermal infrared remote sensing of vegetation: Current status and perspectives

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ABSTRACT

Vegetation plays a vital role in the ecological functioning of terrestrial and coastal ecosystems. Remote sensing generally provides timely and accurate information to manage ecosystems sustainably and effectively. In this respect, thermal infrared (TIR, 3–14 µm) remote sensing data form a valuable data source for vegetation studies. The TIR data provides unique information compared to other parts of the electromagnetic spectrum. This article aims to gather and review the most relevant information obtained using TIR remote sensing data for terrestrial vegetation at leaf and canopy levels using laboratory/field-based, airborne and spaceborne platforms. We address this topic from various angles, particularly focusing on vegetation discrimination as well as the quantification of water stress by means of canopy temperature and spectral emissivity. In addition, attempts to associate TIR spectral features with vegetation biochemical compounds, as well as the retrieval of vegetation biochemical and biophysical parameters, are reviewed. Research needs and requirements for successful use of remote sensing in vegetation studies across the TIR region, as well as significant challenges, are also discussed. Our review reveals that, despite the increasing interest among remote sensing experts in using TIR data, there are still large gaps in our understanding and interpretation of TIR imagery. Some inconsistent findings and contradictory observations have come to light in different levels (i.e., leaf and canopy levels). In addition, our review shows that airborne and TIR hyperspectral-based studies are currently limited due to cost, particularly across large spatial extents. It can be concluded that TIR remote sensing of vegetation offers unique insights in understanding terrestrial vegetation (e.g., vegetation water stress and retrieval of biophysical parameters). TIR is complementary to other remote sensing data sources, with a high potential for fusing data from different parts of the spectrum. However, we highlight challenges obtaining consistent, meaningful and accurate results for land surface temperature and land surface emissivity retrieval.

1. Introduction

Throughout the years, and depending on the field of application, the thermal infrared (TIR) spectral range has received different definitions, ranging from 1.1 µm upwards (Billings and Morris 1951) to 3–35 µm (Prakash 2000), and even to 3–1000 µm (Kuenzer and Dech 2013). The most widely accepted range for TIR remote sensing in vegetation studies is 3–14 µm, divided into the MWIR (3–5 µm) and the LWIR (8–14 µm). The MWIR receives both emitted radiation from Earth and reflected radiation from the Sun, while the LWIR is dominated by the emitted component (Jensen 2007).

Remote sensing of vegetation studies have been widely carried out in the VNIR (0.3–1.0 µm) and SWIR (1.0–2.5 µm) regions with a focus on biochemical and biophysical vegetation properties (Cho et al. 2008; Clevers et al. 2010; Darvishzadeh et al. 2009; Mutanga and Skidmore 2004; Schlerf and Atzberger 2012; Schlerf et al. 2005). However, spectral data from the VNIR and SWIR domains do not adequately describe all structural and chemical characteristics of vegetation. Specific
vegetation components such as polysaccharides (e.g., cellulose) and leaf surface properties (e.g., waxes and hairs) have their primary absorption features located in the TIR domain (Ribeiro da Luz and Crowley 2007). Technological progress in the development of TIR spectrometers and sensors for laboratory, field, airborne and spaceborne platforms has further enabled the acquisition of high spectral resolution data in the MWIR and LWIR domains. Nevertheless, at satellite and airborne scale, the number of TIR sensors (Table 1) is still well below the number of VNIR/SWIR sensors (Angelopoulos et al. 2019; Liu et al. 2019). Table 1 presents an overview of TIR sensors operating at satellite, airborne, field and laboratory scale.

The TIR domain has hardly been explored in vegetation studies. The spectral behaviour of plants has been misinterpreted to some extent in the TIR region due to a range of challenges, such as the complexity of vegetation spectral features and the lack of suitable devices with a low signal to noise performance (Kirkland et al. 2002; Ribeiro da Luz and Crowley 2010; Ullah et al. 2012b). In the past few decades, these former limitations have primarily been overcome, which has resulted in new applications in the vegetation domain.

| Table 1 | Summary of thermal infrared satellite missions (in italics) with their corresponding sensors, airborne sensors (manufacturers in italics), and laboratory or field spectrometers (manufacturers in italics). The space borne platforms still in operation are shown in bold type. |
|----------|---------------------------------------------------------------------------------------------------------------|
| **Satellite mission / Sensor or Manufacturer** | **No. Bands** | **Wavelength** | **Spatial resolution** | **Reference** |
| **Space borne** | | | | |
| NOAA/ AVHRR3 | 2 Bands | 10.3–12.5 µm | 1090 m | (ESA, 2020) |
| NOAA-10/ ERBE | 1 Band | 10.5–12.5 µm | 5000 m | (Backstrom and Hall Jr, 1982) |
| ENVISAT/ AATSR | 2 Bands | 10.8–12 µm | 1000 m | (ESA, 2007) |
| Sentinel-3/ SLSTR | 2 Bands | 10.85–12 µm | 1000 m | (Donlon et al., 2012) |
| Terra/ MODIS | 8 Bands | 8.4–14.38 µm | 1000 m | (Barnes et al., 2003) |
| Aqua/ MODIS | 8 Bands | 8.4–14.38 µm | 1000 m | |
| IIRD/ HISRS | 1 Band | 8.5–9.3 µm | 372 m | (Schuster et al., 2002) |
| Terra/ ASTER | 5 Bands | 8.12–11.65 µm | 90 m | (Abrams et al., 2015) |
| Landsat-8/ TIRS | 2 Bands | 10.6–12.51 µm | 100 m | (USGS, 2017) |
| Landsat-7/ ETM+ | 1 Band | 10.4–12.5 µm | 60 m | |
| Landsat-5/ TM | 1 Band | 10.4–12.5 µm | 60 m | |
| Landsat-4/ TM | 1 Band | 10.4–12.5 µm | 120 m | |
| ISS/ ECOUSTER | 5 Bands | 8.28–12.05 µm | 70 m | (Meerdink et al., 2019b) |
| Meteosat-7/ MVIIR | 1 Band | 10.5–12.5 µm | 5000 m | (WMO, 2019) |
| Meteosat-8, 9, 10 & 11/ SEVIRI | 5 Bands | 8.3–14.4 µm | 3000 m | (Schmid, 2000) |
| MSG-2/ Imager on MTSAT2 | 2 Bands | 10.3–12.5 µm | 4000 m | (JMA, 2017) |
| Suomi NPP/ VIIRS | 4 Bands | 8.55–12.01 µm | 750 m | (NOAA, 2020b) |
| Himawari-8 & 9/ AHI1 | 7 Bands | 7.3–13.28 µm | 2000 m | (Besho et al., 2016) |
| ERS-1/ ASTR-1 | 2 Bands | 10.35–12.5 µm | 1000 m | (Edwards et al., 1990) |
| ERS-2/ ASTR-2 | 2 Bands | 10.35–12.5 µm | 1000 m | (Stricker et al., 1995) |
| ALOS-2/ CIR | 1 Band | 8–12 µm | 200 m | (Shimada, 2009) |
| GCOM-C1/ SGLI | 2 Bands | 10.8–12 µm | 500 m | (JAXA, 2020) |
| GEOS 16a & 17/ ABI | 7 Bands | 7.24–13.6 µm | 2000 m | (NOAA, 2020a) |
| MOS-1x4/4b/ VITR | 2 Bands | 10.5–12.5 µm | 2700 m | (JAXA, 2003) |
| MTI/MTI | 3 Bands | 8.01–10.7 µm | 20–14 m | (Hook et al., 2005) |
| **Airborne** | | | | |
| SeaSat / VIRIS | 1 Band | 10.2–12.5 µm | 4400 m | (Born, 1982) |
| TIMS | 6 Bands | 8.2–12.2 µm | 4.4 m @ 1 km Attitude | (Palladoni and Meeks, 1985) |
| DAIS-7915 | 6 Bands | 8.2–12.3 µm | 20 m @ 1 km Attitude | (Mueller et al., 2002) |
| SeaBASS | 128 Bands | 7.5–13.5 µm | 1.0 m @ 1 km Attitude | (Hackett et al., 1996) |
| ITRES / TASI-600 | 32 Bands | 8–11.5 µm | 0.85 m @ 1 km Attitude | (Ireys, 2015) |
| HIS | 10 Bands | 7.95–13.14 µm | 2.0 m @ 1 km Attitude | (Sobrino et al., 2006) |
| SPECIM / Aisa Owl | 96 Bands | 7.6–12.3 µm | 1.1–1.5 m @ 1 km Attitude | (Sobrino et al., 2006) |
| HyTES | 256 Bands | 7.5–12 µm | 1.8 m @ 1 km Attitude | (Hook et al., 2013) |
| TELOPS / Hyper-Cam LW2 | 32–128 Bands | 7.7–11.8 µm | 0.3 m @ 1 km Attitude | (Lagueux et al., 2009) |
| ATLAS | 6 Bands | 8.2–12.2 µm | 2.0 m @ 1 km Attitude | (Moran, 1998) |
| AHI | 256 or 32 Bands | 7.5–11.5 µm | – | (Lacey et al., 1998) |
| **Lab/Field spectrometer** | | | | |
| MIDAC M4500 | 1400 Bands | 2.5–20 µm | 5.5 cm dia @ 1 m Altitude | (Eisele et al., 2015) |
| Bruker Vertex 70 | ~ 6000 Bands | 2.5–16 µm | 25 mm dia @ sampling port | (Hecker et al., 2011) |
| TELOPS / Hyper-Cam LW | ~ 1700 Bands | 7.7–11.8 µm | 0.2 cm @ 1 km Altitude | (Lagueux et al., 2009) |
| µTIR 10GF | 110 Bands | 2–14 µm | 10 cm dia @ 1 m Altitude | (Hook and Kahle, 1996) |

1 It is different from Airborne Hyperspectral Imager (AHI)
2 Hyper-Cam LW can also be used at ground level.

More than three decades have passed since Salisbury et al. (1994) anticipated that by the end of the 20th century, the Earth observation system would deliver rapid and wide-reaching TIR data. However, the number of TIR satellites with a high spatial resolution needed for vegetation applications is limited to MODIS, Landsat-8, Sentinel-3 (Xue and Su, 2017), and the experimental ECOUSTER sensor onboard ISS. Planned systems, such as Landsat-9, Surface Biology and Geology (SBG, former HySPIR), and the future Copernicus candidate mission LSTM, raise hopes for an increase in the numbers of future studies and applications in the vegetation domain.
2. Review approach

Scientific citation databases such as Scopus, Google Scholar, and ISI Web of Science have been consulted in search of articles at field or laboratory level on vegetation with the following keywords/expressions used: (i) thermal infrared OR thermal AND remote sensing, or spectrometry AND vegetation; (ii) emissivity AND remote sensing, or spectrometry AND vegetation; (iii) thermal AND remote sensing, or spectrometry AND vegetation. The studies have been categorized into three main groups according to the sensor platform deployed: spaceborne, airborne, or laboratory/field spectrometer (Table 1), as well as two sub-groups based on study scale: canopy and leaf. No study was found to be using a spaceborne or airborne platform at leaf level. All these studies, as well as the scale and platform used, have been listed in Table 2. Fig. 1 shows the trends in sensor use (e.g., laboratory, field/ground, airborne, spaceborne, etc) and the study level (i.e., canopy or leaf) for the past 70 years. Table 3 lists the terminologies and abbreviations used in this manuscript. In total 105 scientific research papers investigated in this paper.

3. Thermal infrared studies at laboratory and field level

3.1. Leaf laboratory and field studies

Investigation of TIR remote sensing data concerning leaf characteristics started in the laboratory since only laboratory instruments could measure directional hemispherical reflectance (DHR), which could be converted into emissivity spectra based on Kirchhoff’s law (ε = 1 – R). The earliest efforts regarding vegetation TIR remote sensing studies can be traced back to Gates and Tantraporn (1952). They were the first to measure leaf reflectance spectra of shrubs and deciduous trees using an infrared spectrophotometer and showed that leaves are opaque. However, genuinely ground-breaking was a study conducted by Ribeiro da Luz & Crowley (2007), who applied TIR hyperspectral data and found - besides other things - that leaves display complex absorption features related to organic constituents of leaf surfaces. Since then, high spectral resolution TIR laboratory measurements have led to a variety of investigations and applications.

3.1.1. Species discrimination

The first attempt to better distinguish plant differences using TIR data has been made by Gates and Tantraporn (1952), who suggested that the upper and the lower leaf surface reflectance differed. They added that the upper leaf surfaces and the old leaves tend to have noticeably higher reflectance values than the lower leaf surfaces and young leaves, respectively (Gates and Tantraporn 1952). However, Wong and Blevin (1967) showed that leaf reflectance spectra from the two leaf sides are neither noticeably nor systematically distinct. They further added that the reflectance spectra of leaves of the same species but of different age (i.e., juvenile, mature, and old yellowed leaves) are very similar in the TIR domain. Despite previous results, Wong and Blevin (1967) findings can be considered initial research, broadening the belief that plants are featureless in the TIR domain and consider them being close to black-body emitters for an extended period. However, already in the 1980s, Salisbury (1986) and Salisbury and Milton (1987, 1988) took TIR reflectance measurements of fresh leaves of 13 deciduous tree species. They recognized that the resulting spectra were distinctive for each species. They concluded that due to the unique composition and structure of epidermal plant cells of different plant species (e.g., cuticular waxes), the reflectance peaks are species-specific between the wavelengths 8–14 μm (Salisbury and Milton 1988; Salisbury and Milton 1987). Arp and Phinney (1980) discovered some physiological adaptation in plants associated with their radiational environment in the TIR region. Additionally, Salisbury and Milton (1987) revealed that the TIR spectral signature varies between spring and summer leaves, whereas the difference is marginal between summer and fall. They also found

| Platform          | Spectral Resolution | Scale       | Reference                          |
|-------------------|---------------------|-------------|------------------------------------|
| Laboratory        | Multispectral       | Leaf        | (Gates and Tantraporn, 1952)       |
|                   |                     |             | (Wong and Blevin, 1967)            |
|                   | Thermocouple        | Leaf        | (Idso and Jackson, 1969)           |
|                   | Multispectral       | Leaf        | (Salisbury, 1986)                  |
|                   | Multispectral       | Leaf        | (Salisbury and Milton, 1987)       |
|                   | Multispectral       | Leaf        | (Salisbury and Milton, 1988)       |
|                   | Multispectral       | Leaf        | (Salisbury and Milton, 1988)       |
|                   | Multispectral       | Leaf        | (Salisbury and Milton, 1988)       |
|                   | Multispectral       | Leaf        | (Salisbury and D'Aria, 1992)       |
|                   | Infrared thermometer| Canopy      | (Rubio et al., 1997)               |
|                   | Broadband           | Leaf        | (Grant et al., 2006a)              |
|                   | Multispectral       | Leaf        | (Grant et al., 2006b)              |
|                   | Hyperpectral        | Leaf        | (Fabre et al., 2011)               |
|                   | Broadband           | Leaf        | (Grant et al., 2012)               |
|                   | Hyperpectral        | Leaf        | (Ullah et al., 2012a)              |
|                   | Hyperpectral        | Leaf        | (Ullah et al., 2012b)              |
|                   | Hyperpectral        | Leaf        | (Ullah et al., 2014)               |
|                   | Hyperpectral        | Canopy      | (Neinavaz et al., 2016a)           |
|                   | Hyperpectral        | Canopy      | (Neinavaz et al., 2016c)           |
|                   | Hyperpectral        | Leaf        | (Buitrago et al., 2016)            |
|                   | Hyperpectral        | Leaf        | (Buitrago et al., 2017)            |
|                   | Hyperpectral        | Canopy      | (Neinavaz et al., 2017)            |
| Field/ground      | Infrared thermometer| Canopy      | (Jackson et al., 1977)             |
|                   | Infrared thermometer| Canopy      | (Kimes, 1980)                      |
|                   | Infrared thermometer| Leaf        | (Idso et al., 1981)                |
|                   | Infrared thermometer| Canopy      | (Jackson et al., 1981)             |
|                   | Infrared thermometer| Leaf        | (Idso, 1982)                       |
|                   | Infrared thermometer| Canopy      | (Olioso, 1995)                     |
|                   | Infrared thermometer| Leaf        | (Jones, 1999)                      |
|                   | Multispectral       | Canopy      | (Olioso et al., 2007)              |
|                   | Broadband           | Canopy      | (Jones et al., 2009)               |
|                   | Infrared thermometer| Leaf & Broadband | (Maes and Steppe, 2012)          |
|                   | Multispectral       | Leaf        | (Pandya et al., 2013)              |
|                   | Broadband           | Canopy      | (Him et al., 2016)                 |
|                   | Hyperpectral        | Leaf        | (Gerhards et al., 2016)            |
| Field/ground      | Broadband           | Canopy      | (Elsayed et al., 2017)             |
|                   | Broadband           | Canopy      | (Banerjee et al., 2018)            |
|                   | Hyperpectral        | Leaf        | (Ribeiro da Luz and Crowley, 2007) |
| Laboratory        | Infrared thermometer| Canopy      | (Maes et al., 2016)                |
|                   | Hyper spectral      | Leaf & Canopy | (Rock et al., 2016)               |
| Spaceborne        | Multispectral       | Canopy      | (Van de Griend and Owe, 1992)      |
|                   | Multispectral       | Leaf        | (Valor and Casisles, 1996)         |
|                   | Multispectral       | Leaf        | (Francois et al., 1997)            |
|                   | Multispectral       | Canopy      | (French et al., 2000)              |
|                   | Multispectral       | Canopy      | (Giresi et al., 2004)              |
|                   | Multispectral       | Canopy      | (Sobrino et al., 2004)             |
|                   | Multispectral       | Canopy      | (Weng et al., 2004)                |
|                   | Multispectral       | Canopy      | (Jin and Liang, 2006)              |

(continued on next page)
Table 2 (continued)

| Platform                  | Spectral Resolution | Scale            | Reference                                                                                     |
|---------------------------|---------------------|------------------|------------------------------------------------------------------------------------------------|
| Airborne                  | Multispectral       | Canopy           | (Jiménez-Muñoz et al., 2006)                                                                   |
| Airborne                  | Multispectral       | Canopy           | (Stathopoulou and Cartalis, 2007)                                                               |
| Airborne                  | Multispectral       | Canopy           | (Yue et al., 2007)                                                                             |
| Airborne                  | Multispectral       | Canopy           | (French et al., 2000)                                                                           |
| Airborne                  | Multispectral       | Canopy           | (Mallick et al., 2008)                                                                          |
| Airborne                  | Multispectral       | Canopy           | (Ogawa et al., 2008)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Amiri et al., 2009)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Brenuig et al., 2009)                                                                          |
| Airborne                  | Multispectral       | Canopy           | (Zhang et al., 2009)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Jiang and Tian, 2010)                                                                         |
| Airborne                  | Multispectral       | Canopy           | (Zhao et al., 2011)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Gottsche and Halley, 2012)                                                                     |
| Airborne                  | Multispectral       | Canopy           | (Mainsaitiyiming et al., 2014)                                                                   |
| Airborne                  | Multispectral       | Canopy           | (Cheng et al., 2015)                                                                            |
| Space-borne & Airborne    | Multispectral &     | Canopy           | (Leroux et al., 2015)                                                                           |
| Airborne                  | Multispectral       | Canopy           | (Rehman et al., 2015)                                                                           |
| Airborne                  | Multispectral       | Canopy           | (Chen et al., 2016)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Jacob et al., 2017)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Chaitanya et al., 2017)                                                                        |
| Airborne                  | Multispectral       | Canopy           | (Mushore et al., 2017)                                                                          |
| Airborne                  | Multispectral       | Canopy           | (Acero and Gonzalez-Asensio, 2018)                                                              |
| Airborne                  | Multispectral       | Canopy           | (Bayat et al., 2018)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Li and Meng, 2018)                                                                             |
| Airborne                  | Multispectral       | Canopy           | (Xie et al., 2018)                                                                             |
| Airborne                  | Multispectral       | Canopy           | (Zheng et al., 2018)                                                                            |
| Airborne                  | Multispectral       | Canopy           | (Yu et al., 2018)                                                                              |
| Airborne                  | Multispectral       | Canopy           | (Neinavaz et al., 2019)                                                                        |
| Airborne                  | Multispectral       | Canopy           | (Jiu et al., 2019)                                                                              |
| Airborne                  | Multispectral       | Canopy           | (Neinavaz et al., 2020)                                                                         |
| Airborne                  | Hyperspectral       | Canopy           | (Sobrino et al., 2008)                                                                          |
| Airborne                  | Hyperspectral       | Canopy           | (Pierce et al., 1990)                                                                           |
| Airborne                  | Hyperspectral       | Canopy           | (Schmugge et al., 1991)                                                                        |
| Airborne                  | Hyperspectral       | Canopy           | (Hacketwell et al., 1996)                                                                       |
| Airborne                  | Hyperspectral       | Canopy           | (Hewison, 2001)                                                                                |
| Airborne                  | Hyperspectral       | Canopy           | (Kirland et al., 2002)                                                                         |
| Airborne                  | Hyperspectral       | Canopy           | (Sobrino et al., 2002)                                                                         |
| Airborne                  | Hyperspectral       | Canopy           | (Hook et al., 2005)                                                                            |
| Airborne                  | Hyperspectral       | Canopy           | (Gonzalez-Dugo et al., 2006)                                                                    |
| Airborne                  | Hyperspectral       | Canopy           | (Sobrino et al., 2006)                                                                         |
| Airborne                  | Hyperspectral       | Canopy           | (Sepulcre-Cano et al., 2006)                                                                    |
| Airborne                  | Hyperspectral       | Canopy           | (Oliva-Carrío et al., 2012)                                                                     |
| Airborne                  | Hyperspectral       | Canopy           | (Sobrino et al., 2012)                                                                         |
| Airborne                  | Hyperspectral &     | Canopy           | (Zarco-Tejada et al., 2013)                                                                     |
| Airborne                  | Broadband           | Canopy           | (Gouix et al., 2016)                                                                            |
| Airborne                  | Hyperspectral       | Canopy           | (Wawrziyniak et al., 2017)                                                                      |
| Airborne                  | Hyperspectral       | Canopy           | (Gerhard et al., 2018)                                                                         |
| Airborne                  | Hyperspectral       | Canopy           | (Gomis-Cebolla et al., 2018)                                                                    |
| Airborne                  | Hyperspectral       | Canopy           | (Meerdink et al., 2019a)                                                                       |
| Airborne                  | Hyperspectral       | Canopy           | (Ribeiro da Luz and Crowley, 2010)                                                              |
| Airborne                  | Hyperspectral       | Canopy           | (Meerdink et al., 2016)                                                                        |
| UAV                       | Multispectral       | Canopy           | (Benn et al., 2009)                                                                            |
| UAV                       | Multispectral       | Canopy           | (Gonzalez-Dugo et al., 2013)                                                                    |
| UAV                       | Broadband           | Canopy           | (Sagan et al., 2019)                                                                            |
| UAV                       | Broadband           | Canopy           | (Liu et al., 2018)                                                                             |

Higher reflectance values in the leaves of trees that grew in metal-enriched soils than in the leaves from trees in control area, while the reflectance spectral features remained similar (Salisbury and Milton 1987). For senescent leaves, the increasing reflectance values were found to be due to a decrease in water absorption, with the shape of the spectral curve remaining unchanged (Salisbury 1986). It was also revealed that plants leaf exhibit significant differences in their emittance (Idso and Jackson, 1969). Furthermore, it demonstrated that spectral changes could also be associated with plant maturity (Elvidge 1988). Significant differences in emissivity were also revealed for plants from different ecological groups, as well as for diverse plant materials (e.g., bark, woody materials, etc.) from individual species (Elvidge 1988). For instance, Raven et al. (2002) revealed a difference in the emissivity of the leaves of two different plant species over between 2 and 15 µm. It should be noted that it is feasible to discriminate between senescent vegetation and bare soil using emissivity spectra (French et al., 2000).

Ullah et al. (2012b) and Buitrago et al. (2016) used an improved DHR measurement setup developed by Becker et al. (2011) consisting of a Bruker spectrometer with an integrating sphere attached and showed that species could be discriminated from each other by using only six wavebands. Ullah et al. (2012) used thermal hyperspectral data and proposed important wavebands for discrimination in the MWIR (i.e., 3.34, 4.19, and 4.60 µm) and the LWIR (i.e., 9.44, 12.71, and 13.70 µm) domains, based on a study of 13 plant species. However, a different set of species under investigation may have resulted in different wavebands being proposed. This topic was later transferred to a field experiment by Rock et al. (2016) using an imaging device setup (Schlerf et al. 2012) that allows, in comparison to the time required when undertaking DHR laboratory measurements, fast acquisition of high spectral resolution TIR images. Rock et al. (2016) demonstrated that classification accuracies similar to the laboratory spectra, which outperform VNIR/SWIR reflectance spectra in terms of classification accuracy, could be achieved with this field setup (i.e., image device). However, Rock et al. (2016) also revealed that signal to noise ratio is critical for species discrimination, with TIR data outperforming VNIR-SWIR only at a high signal to noise ratio.

#### 3.1.2. Leaf functional traits

Many studies have speculated about the origin of thermal absorption features from leaf chemical compounds or leaf surface properties (Pandya et al. 2013; Ribeiro da Luz and Crowley 2007). For instance, it was suggested that the leaf emissivity signature might be linked to cellular and epidermis, as well as the uniqueness of the cuticle structure in each plant species (Ribeiro da Luz and Crowley 2007). Cuticle structure is directly related to leaf water content, while variation in cellulose is associated with leaf thickness (White and Montes-R 2005). Until recently, no systematic investigation had been carried out on how different leaf functional traits are correlated with spectral features. This missing link was targeted by Buitrago et al. (2018), who measured the infrared spectra (1.4–16.0 µm), as well as leaf traits (e.g., leaf water content, leaf area, etc.) of individual fresh leaves for 19 species (from herbaceous to woody species). They found that in the MWIR and LWIR, leaf absorption spectra are formed by key species-specific traits, including lignin, cellulose, water, nitrogen, and leaf thickness.

Meerdink et al. (2016) compared VNIR/SWIR and TIR spectra using PLSR to retrieve leaf-level cellulose, lignin, leaf mass per area, nitrogen, and water content and obtained a higher prediction accuracy when combining VNIR/SWIR with TIR data. Another important finding of their study was that seasonal variations, as well as variation in leaf structure, resulted in low performance regarding the prediction of lignin and leaf mass per area (Meerdink et al. 2016).

#### 3.1.3. Leaf water content and water stress

High spectral resolution TIR laboratory measurements have been leveraged to quantify leaf water content using various methods (Fabre et al. 2011; Meerdink et al. 2016; Ullah et al. 2014). Despite the broad
investigation into the retrieval of leaf water content using remotely sensed data in the VNIR and SWIR regions, the prediction of water content through TIR hyperspectral data has only recently been considered. Findings have shown that leaf water content can be retrieved with moderate accuracy using TIR hyperspectral data and laboratory conditions (Ullah et al. 2012a; Ullah et al. 2014).

Deriving plant temperature from TIR measurements has been used successfully to detect and quantify pre-symptomatic or pre-visual water stress in vegetation for five decades (for a comprehensive review, please see Gerhards et al. (2019). In contrast, the second component of TIR measurements, namely spectral emissivity, has hardly been used to quantify water stress. Salisbury and Milton (1987) were the first to consider the effect of water stress on plants in the TIR region. They suggested that water stress does not affect infrared signatures. However, Elvidge (1988) has shown that spectral changes in the TIR domain data associated with a decline in plant health and the reflectance spectra of dry plant materials, which are a mixture of holocellulose and lignin reflectance features, in the absence of water as a principal constituent of green leaves.

Additionally, the emissivity values of spectra from dry and senescent crops in the LWIR region are considerably lower than the ones from well-watered and green vegetation in the other parts of the TIR region (i.e., between 8 and 13 μm) (Olioso et al. 2007). In this respect, Fabre et al. (2011) found that the reflectance response to water stress (i.e., drying impact) could, in part, be dependent on species, leaf side (i.e., adaxial or abaxial), as well as the water content in the 3–15 μm range. Also, the reflectance spectra of wavelengths greater than 10 μm are less sensitive to the difference in leaf water content (Fabre et al., 2011). The links between spectral features and leaf water content are less strong in the TIR domain than in the VNIR-SWIR region as the TIR domain’s spectral features are mainly associated with leaf structure and biochemical composition (Gerber et al., 2011).

Different plant species displayed substantial changes in their TIR emissivity spectra when exposed to either water or temperature stress (Buitrago et al. 2016). In an experiment on potato, where different spectral domains were compared for their sensitivity to water stress, TIR spectral emissivity responded more quickly to water stress than VNIR and SWIR indices such as NDVI or PRI (Gerhards et al. 2016). Changes in emissivity spectra under stress conditions may be related to a change in the thickness of the cuticle and, conceivably, the structure of the cuticle.
Previously, a high correlation has been found between emissivity spectra and NDVI after logarithmic transformation (Valor and Caselles 1996; Van de Griend and Owe 1993). However, Later, Gieske et al. (2004) discussed that the relationship between NDVI and emissivity

(Buitrago et al. 2016). In a successive study by Buitrago et al. (2017), it has been shown that stress (i.e., water and temperature) can change leaf traits (e.g., leaf water content, lignin, cellulose, and leaf area) and thus have an effect on the TIR emissivity spectra. In contrast, the internal leaf structural variables (e.g., bundle area, height, width, epidermis, and mesophyll) were not linked to the TIR emissivity spectra. For instance, under stress, cuticle thickness has been increased as a coping strategy to prevent water loss. Additionally, the variation in thickness is attributed to lignin and cellulose content changes, which are associated with changes in spectra. Gerhards et al. (2016) have shown that under water stress, the emissivity spectra increase consistently for overall spectral bands, while the spectral shape remains unchanged.

### 3.2. Canopy laboratory and field studies

Laboratory/field level studies demonstrate the successful application of TIR emissivity spectra to study leaf characteristics. However, due to the limitation such as low signal to noise ratio, they may not be translated into canopy scale without the possibility of using airborne- or spaceborne remote sensing platforms. In general, the emissivity value at the canopy level is higher than for any separate part of the plant due to plant structure and the cavity effect (Rubio et al. 1997). The cavity effect might increase the emissivity value for eucalyptus canopy by 0.030 and spherical and planophile by 0.026 and 0.022, respectively, according to data simulation (Olioso 1995b). Nevertheless, in order to avoid an underestimation of the emissivity value, in particular for intermediate vegetation cover (i.e., 40–60% vegetation cover), the cavity effect should be taken into consideration at the canopy level (Jacob et al. 2017). Emissivity responds to geometry and patterns between plant canopies. Therefore, the effect of the vegetation geometric structure and canopy components on the TIR data should always be considered in the upscaling of the emissivity from leaf to canopy level. Consequently, the emissivity of dense canopies is higher than the emissivity of an individual leaf (Rubio et al. 1997). This difference may influence the shape of emissivity features or even cancel them out (Fuchs and Tanner 1966; Rubio et al. 1997). The emissivity value of green and senescent vegetation is higher at canopy level compared to leaf level (Palluconi et al. 1999).

The progressive attenuation of spectral emissivity has been evidenced by the increasing distance between vegetation canopy and sensor, which leads to fewer details to be captured (Ribeiro da Luz and Cowley 2007). The overall value of canopy emissivity spectra increases concomitantly with the LAI values, while the spectral features remain similar under laboratory-controlled conditions (Neinavaz et al. 2016a; Neinavaz et al. 2016c). The canopy emissivity spectra reach saturation at a relatively high LAI value. However, the level of saturation is species-specific (Neinavaz et al. 2016a) and can also be influenced by the viewing direction, canopy structure, as well as temperature distribution within the canopy (Guilevic et al. 2003).

The saturation level for emissivity rises from the planophile to the eucalyptus canopy structure (Olioso 1995a). The investigation using TIR data also demonstrated that soil emissivity as a background varies according to the surface composition and roughness (Salisbury and D’Aria 1992). The effect of soil emissivity as a background should be taken into account when the LAI value is low, as soil emissivity is likely to have the same effect on canopy emissivity when NDVI is low (Olioso 1995b). Under some circumstances, such as when plants are dry, the emissivity of plants is expected to be lower than that of bare soil. Consequently, plant emissivity might decrease when the vegetation amount increases (Olioso et al. 2007). Moreover, canopy emissivity spectra of various plants with similar LAI values are varying and species-specific. Such a variation might be explained by the contribution of other vegetation biophysical or biochemical parameters (Neinavaz et al. 2016a).

### 4. Scaling vegetation variables up from laboratory to spaceborne and airborne levels

Previously, a high correlation has been found between emissivity spectra and NDVI after logarithmic transformation (Valor and Caselles 1996; Van de Griend and Owe 1993). However, Later, Gieske et al. (2004) discussed that the relationship between NDVI and emissivity...
only applies in specific ecosystems and under particular climatic conditions, such as urban heat islands (Kumar and Shekhar 2015) and contexts, such as built-up areas, farmland, grassland, forest and water landcover classes (Xie et al. 2018). The emissivity can reach a saturation level using satellite data when LAI is low (i.e., two or three LAI values). This issue must be taken into account when the LAI is required for upscaling vegetation variables. However, the level of saturation may vary depending on the plant species as well as the canopy structure (Carlson et al. 1994). An increase in the canopy emissivity spectra when LAI values rise as background soil emissivity has a lower emissivity than the leaves (Francois et al. 1997). Therefore, the emissivity of a densely vegetated area (i.e., LAI > 2) has a higher value than the bare soil (Jin and Liang 2006). Meanwhile, soil water content should also be taken into account as the soil emissivity tends to increase from 1.7% to 16% when the soil water content increases (Mira et al. 2007). Therefore, the systematic error of 0.1–2 K can be caused by affecting soil emissivity through soil water content (Mira et al. 2007). However, the effect of canopy geometry would be minimized by increasing the LAI value as the ground emission contribution decreases (Guillevic et al. 2003) (Fig. 2).

4.1. Emissivity spectra for plant characteristics using airborne TIR data

A few studies have been conducted using TIR airborne data for vegetation research. Due to the lack of proper sensors, there were no commercial airborne TIR data available till 1990 (Table 2). It was assumed that using airborne data, water and fully vegetated surfaces exhibit little or no variation in their emissivity spectra compared to bare soil (Schmugge et al. 1991). Nonetheless, the emissivity spectra were found to be associated with the vegetation cover, which allows different types of land cover (e.g., boreal forest, agricultural, etc.) to be detected (Hewison 2001). For the first time, Ribeiro da Luz and Crowley (2010) identified nearly half of the fifty tree species they examined using airborne hyperspectral TIR data with varying degrees of success. They also discussed that leaf angle distribution and size and canopy structure could affect the emissivity spectra contrast among species. Their work, which used hyperspectral TIR data to investigate plant characterization at canopy level based on airborne data, can be regarded as a ground-breaking study. Meerdink et al. (2019) demonstrated a significant difference between the canopy emissivity of ten of the 24 species they examined using airborne hyperspectral TIR data from wavelengths of 8.3–11 μm. However, for most investigated species, the emissivity of the canopy was not representative of the emissivity of the leaves due to the influence of the canopy structure and leaf orientation. Nevertheless, leaf emissivity was distinctive and separable by spectral form and a few significantly different wavelengths for 80% of the plant species studied by (Meerdink et al. 2019).

4.2. LSE and LST for plant characteristics using spaceborne TIR data

As previously stated, emissivity responds to geometry and patterns between plant canopies. As a result, it was assumed that emissivity variation over persistent vegetation is low within the course of a year. Thus the emissivity values at the satellite level are less likely to represent seasonal changes over the vegetation area. In contrast, the difference between years is considered to be substantial, as the distribution patterns of plants vary due to multi-scattering effects at satellite level for periods of more than one year (French et al. 2008). Cheng et al. (2015) proposed a new method to assess seasonal variations in vegetation canopies using broadband emissivity spectra.

A review of the literature showed that a majority of investigations into vegetation using spaceborne data focused on the calculation of LST and LSE (Gomis-Cebolla et al. 2018; Göttsche and Hulley 2012; Jacob et al. 2017; Jiménez-Muñoz et al. 2006; Li et al. 2013; Zheng et al. 2018). Experimental and modelling studies have shown that LSE increases with vegetation abundance (Olioso et al. 2007; Sobrino et al. 2005). In this respect, the land cover types characterized by vegetation abundance demonstrate higher LSE values (Stathopoulou and Cartalis 2007). The mean emissivity values in agriculture and forest ecosystems ranged from 0.975 ± 0.003 to 0.980 ± 0.004, respectively (Stathopoulou et al. 2007). Despite a positive correlation between LSE and NDVI (Sobrino et al. 2008), only a weak negative correlation was identified between LST and NDVI (Kumar and Shekhar 2015; Zhang et al. 2009). However, although there is consensus on the correlation between NDVI and LST being negative, discrepancies have been found in the strength with certain studies reporting a strong negative correlation between NDVI and LST (Chaithanya et al. 2017; Rehman et al. 2015). Still, the relation between LAI and LSE is much stronger than between LAI and LST (Neinavaz et al. 2019).

The effect of vegetation cover and structure on LST and LSE over an urban area have been extensively documented in comparison to vegetation cover in natural ecosystems by means of TIR data (Acero and González-Asensio 2018; Amiri et al. 2009; Coutts et al. 2016; Li and Meng 2018; Oltra-Carrió et al. 2012; Sobrino et al. 2012; Weng et al. 2004; Yu et al. 2018; Zhou et al. 2011). The negative correlation between NDVI and LST has been reported for urban vegetation (Kumar and Shekhar 2015). However, the strength of the correlation between LST and NDVI associated with land-use types may vary (Yue et al. 2007). For instance, it was found that LST and NDVI have a stronger correlation for dense vegetation compared with sparse vegetation (e.g., grass and park) area (Mallick et al. 2008). Additionally, it has been shown that the spatial configuration of green space has a significant impact on the LST over urban areas (Maimaitiyiming et al. 2014). Changes in land use (e.g., dense to sparse vegetation) in urban areas are also a significant factor for increasing LST (Jiang and Tian 2010).

4.3. Water stress and canopy temperature using spaceborne and airborne data

TIR data have been widely used for deriving canopy temperature as an indicator of water stress, canopy conductance, and transpiration for irrigation scheduling (Gonzalez-Dugo et al. 2013; Idso 1982; Sepulcre-Canto et al. 2006). Bartholic et al. (1972) revealed the feasibility of using the airborne-mounted thermal scanner for deriving crop canopy temperature over a large area under different irrigation treatments. Leaf energy balance has been considered a basis for monitoring plant responses to water deficit and detecting pre-visual water stress using TIR data (Fuchs and Tanner 1966; Tanner 1963). In order to retrieve canopy temperature, meteorological parameters (e.g., air temperature,
humidity, wind speed, etc.), as well as the position of leaves within the canopy (e.g., inclination and orientation of leaves), should be taken into account as they can lead to considerable variation in leaf temperature and may mask any indication of water stress (Maes and Steppe 2012). Several temperature-based indices have been developed to normalize leaf temperatures to current environmental conditions for a more quantitative estimation of water stress. Initially, differences between canopy- and air temperatures were considered the first indicators of crop water stress, namely SDD (Idso et al. 1977). A further improvement was the now well-known CWSI (Idso et al. 1981; Jackson et al. 1981). Among other approaches (see Maes and Steppe 2012), which depend on additional micro-meteorological data, the use of artificial reference surfaces appears to be most appropriate, as no supplementary data are needed (Jones 2004; Maes and Steppe 2012; Maes et al. 2016). However, the application of these reference surfaces is challenging for airborne and satellite missions (Jones et al. 2009) in terms of handling them in the field (i.e., the dimension of the targets), as well as the selection of their material (i.e., aerodynamic and optical characteristics). Moran et al. (2003) suggested that dry and wet reference surfaces could be replaced by more considerable wet references. The Water Deficit Index developed by Moran et al. (1994) and the thermal index of relative stomatal conductance (Jones 1999) is alternative temperature-based indices that take into account partially vegetated sites and showed a direct linear relationship between canopy temperature and stomatal conductance.

Tormann (1986) suggested that the effect of environmental conditions on water stress and the comparative difference in canopy temperature between the dry (stressed) and wet (non-stressed) treatment are negligible. Water stress raises the temperature of the leaf (Blum et al. 1982) and expands the range of temperature variation within the canopy, which can be used as a stress indicator (Fuchs and Tanner 1966). Besides, the thermal variations within the canopy are associated with water stress and thus could be used for water stress detection at the tree level, based on TIR imagery data (Sepulcre-Cantó et al. 2006). The CTSI was successfully applied to evaluate water stress in crops. The results showed that this index has a strong potential for monitoring water stress in crops since it only depends on the canopy temperature (Han et al. 2016). The CTSI outperformed the CWSI for monitoring moderately stressed crops within the field (González-Dugo et al. 2006).

The relation between TIR data and water status over time could be considered as a short-term response in comparison with vegetation indices derived using VNIR/SWIR data (Baluja et al. 2012) since there is a strong correlation between thermal indices and leaf stomatal conductance, and stem water potential, which respond quickly after early stress exposure (Baluja et al. 2012). In this regard, it has been shown that the combination of vegetation indices, such as NDVI, and TIR indices-based models, outperforms vegetation indices alone (Leroux et al. 2015). In contrast, it had previously been revealed that there is no relation between canopy temperature and NDVI and that instead, the differences in canopy conductance and water stress could affect canopy temperature (Berini et al. 2009). Nonetheless, the impact of the canopy structure and view angles on canopy temperature should have been taken into account (Hu et al. 2019; Jones et al. 2009). In addition, the normalized relative canopy temperature is associated closely and significantly with canopy water content and relative water content under arid and semi-arid conditions using hyperspectral VNIR/SWIR data and thermal imaging data (Elsayed et al. 2017). Banerjee et al. (2018) demonstrated that the mean canopy temperature is raised with increasing moisture stress levels during various crop growth stages. They showed the efficiency of using thermal images compared to digital images for discriminating between leaves and soil under different moisture stress conditions. In summary, temperature-based indices have an enormous potential for pre-visual detection of plant water stress and have, therefore, been applied in agricultural research and practice (Khanal et al. 2017). Additionally, Liu et al. (2018) discovered a difference in canopy temperature between lodging and non-lodging agricultural areas using UAV data, with lodged areas having a higher canopy temperature. It was also revealed by Sagan et al. (2019) that thermal infrared imagery obtained from UAV is efficient for plant phenotyping.

5. Prediction of vegetation biophysical and biochemical variables

LAI, one of the most important vegetation biophysical parameters, has been widely investigated using data from VNIR/SWIR regions. It has also been successfully retrieved using hyperspectral TIR data under controlled laboratory conditions applying various vegetation indices and a non-parametric statistical approach (Neinavaz et al. 2016b). The results of Neinavaz et al. (2016c) showed that LAI might be successfully retrieved at the high value of approximately 5.5 while incurring less saturation issues by using VNIR/SWIR data. The LAI of wheat was accurately derived using TIR data under different moisture stress conditions using thermal imaging (Banerjee et al. 2018). In addition, a combination of LSE and spectral reflectance from VNIR and SWIR could boost the retrieval accuracy of LAI (RMSE = 0.81, RMSE = 6.3, m²/m²) in mixed temperate forest (Neinavaz et al. 2019). The nature of the TIR data could explain these results as it is species-specific for vegetation. The possibility of retrieval of the leaf water content has also been investigated using data from the MWIR to LWIR regions (Ullah et al. 2012a). However, Ullah et al. (2014) demonstrated that the MWIR and SWIR regions seem to be more sensitive spectral regions than the LWIR domain concerning the retrieval of leaf water content as the fundamental water absorption features lie in the MWIR region and not in the LWIR region. The fuel moisture content and equivalent water thickness as a mass-based and area-based vegetation water content indicator could also be predicted at canopy level using hyperspectral TIR data. In addition, plant mass may play a more significant role in determining spectral emissivity than plant area (Neinavaz et al. 2017). Moreover, the integration of TIR data and VNIR/SWIR data could improve the prediction accuracy of foliar traits, including cellulose, lignin, leaf mass per area, nitrogen, as well as water content (Meerink et al. 2016).

6. Challenges on using TIR data for vegetation studies

The primary issue regarding the use of TIR remotely sensed data for vegetation studies is the scaling up from leaf to canopy level as well as from laboratory to spaceborne and airborne levels. The limited TIR data available for laboratory and airborne studies, as well as their spatial resolution, are still major limitations for the use of TIR satellite data, though this might be addressed by the future Copernicus candidate mission LSTM and the SBG mission. Additionally, despite generating a very high-resolution image, the UAV platforms have a limitation on having a broadband TIR sensor. Another concern is the lack of access to the hyperspectral TIR data and the availability of only a limited number of wavebands (i.e., Multispectral) in the TIR domain at space-based platforms with coarse resolution (e.g., 100 m–1 km). Consequently, simple and reliable approaches such as TES (Gillespie et al. 1998) cannot be applied to calculate LST or LSE. As a result, only simple statistical methods, such as the NDVI threshold method, can be used to estimate LST and LSE, where only one or two TIR wavebands are available. Although the NDVI threshold method appears to hold well over fully vegetated areas, it is not feasible for urban areas or areas partially covered by snow, ice, and rock. Besides, the uncertainty in the prediction accuracy of fractional vegetation cover, one of the required parameters for this method, might affect the LSE prediction accuracy (Neinavaz et al. 2020).

A few challenges, such as the distance between sensor and target (i.e., plant), as well as the signal to noise ratio, has been addressed in different studies and should also be taken into account in addition to challenges including separation of emissivity and temperature using spaceborne and airborne platforms (Sobrino et al. 2008; Sobrino et al. 2002). Progressive attenuation could occur through an increasing
distance between sensor and plant, and the emissivity features could become weaker or disappear, which may prove insurmountable for airborne and potential spaceborne applications (Ribeiro da Luz and Crowley 2007). Moreover, the signal-to-noise ratio has a considerable impact on the discrimination of plant TIR spectra (Rock et al. 2016). The retrieval of the LST and LSE using the TES method over terrestrial ecosystems, where emissivity is unknown in advance, can be solved by separating emissivity and temperature. However, the main limitations of ‘TES’ performance, as mentioned, include the availability of thermal band numbers (e.g., more than five bands), as well as accurate elimination of atmospheric effects, such as path radiance and atmospheric transmissivity.

It should be noted that a 1% uncertainty in prediction accuracy of the emissivity may result in an LST calculation error of roughly 0.5 K for moderate (Li et al. 2013) and approximately 1 K for warmer, less humid environmental conditions (Chen et al. 2016). In addition, water vapour over the non-arid region or under humid atmospheric conditions may affect the quality of emissivity data as temperature errors of more than –0.8 K or +2.3 K were reported for precipitable water vapour exceeded three cm (Ogawa et al. 2008; Tonooka and Palluconi 2005). There are several approaches available to address atmospheric correction and to remove the atmospheric water vapour effect. However, this requires the input of several data, such as atmospheric profiles of water vapour content and air temperature, that can be obtained from meteorological stations or datahubs (e.g., the European Centre for medium-range weather forecasts, ECMWF), though these data are considered to be relatively coarse. Also, the uncertainty and error that could arise from soil water content on emissivity spectra should be considered a challenge for LSE and LST estimation (Mira et al. 2007).

Despite a few attempts to link emissivity features with chemical traits at the leaf level and under laboratory-controlled conditions (Buitrago et al. 2018), leaf surface properties are not yet well explored over the TIR domain, and more research needs to be done, particularly at canopy level. In addition, though it has been demonstrated that the emissivity of the vegetation canopy depends on canopy structure (i.e., distribution of elementary surface temperature) and canopy architecture (i.e., the proportion of sunlit and shaded areas, etc.), the effect of canopy structure on canopy temperature (Kimes 1980), and canopy emissivity (Francois et al. 1997; Guillevic et al. 2003) have barely been addressed by means of spaceborne or airborne TIR data. Therefore, further research is crucial to explore the effect of canopy structure and architecture on the cavity effect and emissivity spectra using airborne and spaceborne platforms in different environments and considering various scenarios. In addition, the lack of practical approaches that can make use of synergies between TIR, VNIR/SWIR, and solar-induced chlorophyll fluorescence (i.e., SIF) data to better understand plant stress, disturbance and disease, etc., are also evident, despite the successful fusion of TIR data with data from different remote sensing sources and domains.

Furthermore, direct comparisons of in situ measurements and LST predicted from the satellite images for densely vegetated areas still form a challenging task, given that the temporal variation and high spatial heterogeneity of the LST limit ground-based validation (Hook et al. 2005; Hook et al. 2003; Hook et al. 2007).

### 7. Outlook on the TIR remote sensing sensors and platforms

Timely and accurate monitoring of vegetated areas is important for understanding the spatial and temporal dynamics in terrestrial ecosystems. The past two decades have seen an increase in the use of remote sensing studies and applications for the retrieval and assessment of vegetation biophysical and biochemical parameters. Nevertheless, remote sensing studies of vegetation using TIR data are not in an advanced stage, if not in their initial phase. In general, the number of satellites that carry TIR sensors is far outnumbered by those possessing VNIR/SWIR channels. The first satellite with a TIR sensor onboard was launched in 1982 (i.e., Landsat-4). Landsat-5-TM data was one of the most widely used for environmental studies, particularly for the estimation of the LST and LSE (Sobrino et al. 2004), as its lifespan far exceeded its original mission (i.e., three years) and at the time of the Landsat-5 decommissioning, Landsat-7 and 8 were already in orbit. ASTER also obtained TIR data for almost nine years until it was deemed non-operational in 2009. With a spatial resolution of 90 m and five TIR wavebands, ASTER was widely used to provide detailed maps for LST, LSE, and OST (Table 1). By the time we are, Landsat-8 are (100 m resolution), and ECOSTRESS with five TIR spectral bands (approximately 60 m resolution) are the only high-resolution multispectral TIR radiometer deployed on the spaceborne platform (i.e., International Space Station). For instance, Landsat-8 TIRS (100 m spatial resolution, 16-days revisit), as an operational space platform possessing TIR bands, is insufficient for meeting the needs of precision agriculture (Mahlein, 2016) or for monitoring of other green ecosystems. As far as spectral resolution is concerned, most TIR sensors for detecting water stress are broadband sensors (Grant et al. 2006a; Grant et al. 2012; Grant et al. 2006b; Jones et al. 2009; Zarco-Tejada et al. 2013). These sensors are based on the unrealistic assumption of a constant emissivity value (e.g., 0.97 for vegetation). Neglecting the variation in spectral emissivity of vegetation causes errors in temperature estimation by several degrees Kelvin (Jones 2004), which leads to errors in crop model irrigation systems. On the other hand, nowadays, the availability of airborne hyperspectral TIR data for vegetation studies is noticeably more significant than ever, though still at a high cost.

We are confident that the new hyperspectral TIR sensors on airborne and UAV platforms will provide opportunities for more precise emissivity data as well as surface temperature estimation and result in potentially ground-breaking vegetation studies. They would bridge the gap between low-resolution satellite data and in situ small-scale spectrometry measurements (Gerhards et al. 2018). Airborne and spaceborne TIR hyperspectral applications in vegetation studies and, in particular, in climate change studies will continue and progress in the future. Ultimately, the need for continuously mapping the Earth at short intervals with large and fine-scale TIR data for vegetation applications might encourage the ongoing efforts in developing high-end sensors and monitoring platforms.

### 8. Conclusion

Using remote sensing TIR data to understand and retrieve structure and function of terrestrial vegetation is challenging. When researching the literature for this study, we came across very few studies that had used TIR hyperspectral remote sensing data to characterize and classify vegetation land cover. This suggests that slow progress in TIR remote sensing for vegetation studies may be due to technical limitations associated with low image resolution. TIR satellite sensors are limited in terms of spatial, temporal, and spectral resolution (Table 1).

The majority of vegetation studies using hyperspectral TIR data were conducted at the leaf level and under laboratory conditions. However, only a few studies performed at the canopy level due to the difficulties in scaling up between the emissivity of leaf and canopy. Therefore, the need for further research of TIR remote sensing data (i.e., Hyperspectral TIR) at canopy level, with upscaling to landscape ecological research, is required as higher resolution (spatial, spectral, temporal) spaceborne imagery becomes available (Table 1).

Nearly all experiments that focused on upscaling from leaf to canopy level or laboratory to spaceborne and/or airborne level have concluded that canopy structure, leaf orientation, soil moisture content, and water vapor are significant factors determining the TIR response, specifically for emissivity spectra estimation and the computation of LST and LSE. In addition, during our literature review, some immaturity were observed in the results obtained under various environmental conditions, which need to be addressed in future studies. Few approaches are mature enough to estimate LSE and LST for vegetated areas in an operational context, as only a few bands are available. Remarkably, a number of
studies, particularly at the laboratory level, included the emissivity spectra between 5 and 8 μm of the electromagnetic spectrum in their analysis, indicating that the effect of water absorption in this atmospheric window was not considered.

Recent studies found that the integration of TIR data with data from different spectral domains (e.g., VNIR and SWIR) could improve the prediction accuracy of vegetation biophysical and biochemical parameters (e.g., LAI) (Neinavaz et al., 2019), as well as retrieval of the foliar traits such as cellulose, lignin, leaf mass per area, nitrogen, and water content (Meerdink et al. 2016). In addition, it can also be useful for urban landscape classification (Mushore et al., 2017), discriminating between tropical soil (i.e., bare soil) and non-photosynthetic vegetation (Breunig et al., 2009), capture drought effects in daily ecosystem functions (Bayat et al., 2018), as well as quantifying the thermal effect of riparian during low flow conditions (Wawrzyniak et al. 2017). However, there is a little investigation into data fusion of TIR data from other parts of the electromagnetic spectrum, especially for vegetation studies.

We did not discuss technical approaches (e.g., physical or empirical methods) to retrieve vegetation biophysical and biochemical parameters using TIR data. However, we note that there are a few studies on this topic. For instance, though several leaf and canopy radiative transfer models have been developed for the VNIR-SWIR domain that explicitly link leaf optical properties and canopy characteristics to reflectance, only two physical models exist (i.e. TIR-SAIL (Verhoef et al. 2007) and DART (Gastellu-Etchegorry et al. 1996)) that physically explain the driving factors of spectral emissivity. Future availability of TIR data from spaceborne and airborne platforms will undoubtedly promote TIR physical models for vegetation study.

CRediT authorship contribution statement

Elnaz Neinavaz: Conceptualization, Investigation, Supervision, Writing - original draft. Martin Schlerf: Investigation, Writing - original draft. Roshanak Darvishzadeh: Investigation, Writing - original draft. Max Gerhards: Investigation, Writing - original draft. Andrew K. Skidmore: Investigation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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