Canopy temperatures of selected tree species growing in the forest and outside the forest using aerial thermal infrared (3.6–4.9 μm) data

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ABSTRACT

Studies conducted in recent years have demonstrated high application potential of thermal remote sensing data in environmental analyses. The main goal of our studies was to determine the variability of tree canopy temperatures using a new sensor which acquires data in the still rarely used thermal spectral range (3.6–4.9 μm). This study was conducted on five selected tree species growing in the forest and outside the forest: *Alnus glutinosa*, *Pinus sylvestris*, *Quercus petraea*, *Quercus rubra* and *Robinia pseudoacacia*. Thermal data were acquired on 9 June 2019, between 8:10 and 14:00 (CET). The findings were as follows: i) Trees growing in the forest are on average 0.4–0.7°C cooler than trees outside the forest; ii) The canopy temperatures of species under study differ statistically irrespective of data acquisition time. *Alnus glutinosa*, *Quercus rubra* and *Quercus petraea* are species with the lowest canopy temperatures, and *Pinus sylvestris* has the highest canopy temperature. The studies showed that the biggest variation between species in the canopy temperature occurs at noon (12:00–13:00); iii) A thermal spectral range of 3.6–4.9 μm registers the canopy temperature of tree species with a high accuracy, which supports its usage in remote sensing vegetation studies.

Introduction

Acquisition of thermal infrared data (TIR) using remote sensing techniques is an increasingly popular method to obtain information about the temperature of objects. A variety of carriers of thermal cameras have been used throughout the years, such as satellites (De Faria Peres et al., 2018; Gluch et al., 2006), aeroplanes (Quattrochi & Ridd, 1998), helicopters (Spronken-Smith & Oke, 1998), Unmanned Aerial Vehicles (UAV; Santesteban et al., 2017), truck-crane (Möller et al., 2007), tripods (Cohen et al., 2005) and flux towers (Still et al., 2021). The most commonly used source of land surface temperature (LST) is satellite data. Despite their numerous advantages, such as the ability to capture huge areas at a single scene (e.g. Landsat-8 satellite scene size is 185 km × 180 km), satellite data have limitations as well. Their first limitation is data resolution (Ground Sample Distance (GSD) of 100 m), which precludes analysis of the temperature of individual tree-type objects. The second limitation is the acquisition time. Satellite data are acquired from a sun-synchronous orbit, meaning that for a given location the data are always sourced at the same time of day or night. For instance, data for study areas in central Poland are always acquired around 10:00 a.m. (https://earthexplorer.usgs.gov). This is not the best time to study many environmental phenomena such as the urban surface heat Island (Majkowska et al., 2017). The most popular source of TIR data are Landsat satellites, which TIR spectral bands are Long Wave Infrared (LWIR) from 10.4 to 12.5 μm (Malakar et al., 2018). Most of the research, which use satellite data are conducted in this atmospheric transmission window.

Aerial data are an alternative to satellite data but they are far less popular. However, sensors determining thermal properties of objects have been significantly developed in recent years. Precision and resolution of sensors have increased, as well as their use in UAV (Gallardo-Saavedra et al., 2018), which results in lower prices and higher availability of cameras of this type. It is also possible to obtain a temperature of a single object, and analyze changes of these objects (e.g. temperature variations in tree crowns). It is easier to plan accurate airborne data acquisition during a day or a night by setting a specific time, which depends on the study goal. It is particularly important, because an object’s temperature changes during the day. According to Zheng et al. (2018) the highest temperature of leaves takes place at different times for various tree species. Environmental remote sensing studies conducted from the airborne level have used cameras with a range of 7.5–14 μm (e.g.: Leuzinger & Körner, 2007; Marešová et al., 2020; Richter et al., 2021) and from the satellite level with...
a range 10.4–12.5 µm. In our studies, we used a different spectral range, namely 3.6–4.9 µm, which had not been used in remote sensing vegetation studies before. The use of this range ensures greater dynamics of imaging and the ability to capture smaller temperature differences due to the emissivity curve, which is essential in the case of small temperature differences between species or individuals (Livache, 2019). The 4.25 µm center-wavelength of the MWIR sensor used in our study falls on the steep rising edge of the emissivity curve, which translates to larger sensor response to small temperature differences of observed surfaces. According to Z.-L. Li et al. (2013a); Z. L. Li et al. (2013b) in the MWIR the direct solar irradiation reflected by the surface is on the same order of magnitude as the radiance directly emitted by the surface, if the surface albedo is about 0.1, the introduction of the MWIR channels in LST greatly improves the accuracy of the estimated LST.

LST is one of the indicators of the environment condition, it can be easily interpreted and used in various studies. These data are used, for example, to identify the presence of an urban heat island (Price, 1979; Tran et al., 2006), the influence of city parks on reducing its effect (Dimoudi & Nikolopoulou, 2003), and to identify crop hydration and health status of crops and fruit trees (Egea et al., 2017; Khanal et al., 2017). In macroscale, TIR data can be also used to study peatlands (Ciężkowski et al., 2020; Kopeć et al., 2016), and in microscale to determine the temperature of individual leaves of deciduous trees (Jiménez-Bello et al., 2011) and coniferous trees (Kim et al., 2018). The studies carried out in recent years demonstrate that TIR data have a very high application potential and can be used to determine the canopy temperature (CT) of trees in most types of environments. CT is the temperature of the outer layer of the tree crown recorded from the top, most of which are leaves. It is widely known that trees affect air quality, successfully lowering air temperature (Dimoudi & Nikolopoulou, 2003; Fahmy & Sharples, 2009; Morakinyo et al., 2017). Only few authors to date have reported data on how the environment affects CT. The temperatures of trees in a forest (Leuzinger & Körner, 2007) or in an urban environment were investigated (Meier & Scherer, 2012; Rahman et al., 2017; Spronken-Smith & Oke, 1998), but the difference of CT of trees in the forest and outside the forest for the same species at the same time has hardly been studied. Research in this area would improve understanding of the environment’s influence on CT. Most of the research, which focus on tree crown temperatures were carried out in the forest (Junttila et al., 2017), or in orchards (Sobrino et al., 1990).

The influence of an environment on trees outside the forest is barely known, especially in the case of its detection by remote sensing methods (Wani et al., 2020). Not only knowledge about the influence of the environment on CT is important, but also knowledge of the variance of the crown temperature of individual species. This is an essential aspect in order to correctly interpret the results of a different CT for one species.

The main goal of our studies was to determine the variability of CT using a new sensor with a spectral range 3.6–4.9 µm. Detailed research questions were as follows: (i) What is the difference between trees in the forest and trees outside the forest as regards their CT? (ii) Does CT differentiate tree species? (iii) Is TIR data acquired from ImageIR 9400 camera in the 3.6–4.9 µm spectral range accurate enough to be used in CT analyses?

Materials and methods

Study area

The studies were conducted in the area of the National Park of Wielkopolska (NPW) located in Poland (52° 16' N, 16° 47' E). The study area is in the humid continental climate zone (Peel et al., 2007). The average annual temperature is 8.3°C, and the average rainfall is 475 mm/yr. The study area spans 102.33 km². The NPW was established in 1957 to preserve the landforms of the postglacial landscape (Journal of Laws of 1957 No. 24, Item 114). Today, the NPW is mainly covered by human-modified forests dominated by Scots pine (Pinus sylvestris), sessile oak (Quercus petraea) and common oak (Quercus robur). Despite the fact that the study area was a national park, large part of the tree populations were invasive and non-native species, e.g. Robinia pseudoacacia and Quercus rubra. A large part of the NPW consists of agricultural areas and single-family housing, which is the main reason behind the presence of non-native and invasive species in this area.

Study species

The study covered three native tree species which are considered forest-forming species for the NPW and are widespread in the North European Plain, namely Alnus glutinosa, Pinus sylvestris and Quercus petraea, and two species non-native in the Polish flora: Quercus rubra and Robinia pseudoacacia.

Alnus glutinosa (L.) Gaertn.

Black alder grows up to 30 m in height and has a slender trunk with a wide, elongated crown. Its leaves are 4–10 cm long, green on both sides,
with a glossy upper surface. Black alder is a forest-forming species for the alder carr and riparian forests, i.e. peatland forests with high groundwater levels (McVean, 1953). The tree stands are evenly distributed in the NPW, and are most numerous in the immediate vicinity of lakes in the valleys of smaller rivers.

*Pinus sylvestris* L.
Scots pine is a coniferous tree which grows up to 30–40 m in height. The needles are stiff and hard, glaucous grey-green, 4–7 cm in length, occurring in fascicles of two on the tip of shoots (Mátyás et al., 2004). In nature, the species is found on poor, sandy soils but it used to be planted on fertile sites as well. The Scots pine is the most common species in the NPW.

*Quercus petraea* (Matt.) Liebl.
Sessile oak grows up to 20–30 m in height with a dense crown. The leaves are evenly lobed, 5–14 cm long. It grows best in sandy loam soils, forming dense oak forests or mixed forests with a large share of pine trees (Rutkowski, 1998). It is evenly distributed in the territory of the NPW.

*Quercus rubra* L.
Northern red oak grows up to 20–25 m in height with a dense, wide crown. The leaves are up to 22 cm long, sharply toothed, dark green on the upper surface and light green on the underside. The species is considered invasive in Poland (Wodziwoda et al., 2014), growing quickly and forming mixed forests (Sander, 1990). In the NPW it is found within forest complexes.

*Robinia pseudoacacia* L.
Black locust is up to 25 m high. The leaves are odd-pinnate with small, ovate leaflets with rounded tips. They are light green on the upper surface and grey-green underneath. The species is considered invasive in Poland (Dyderski & Jagodziński, 2019). It is widespread in urban habitats, along the roads and rivers, as well as in open areas and semi-natural forests (Cierjacks et al., 2013). In the NPW it is found both in built-up areas and within forest complexes.

**Airborne data acquisition**

At the peak of the 2019 growing season, three types of airborne data were acquired using a fusion of instruments: TIR data with a spatial resolution of GSD = 0.5 m, Airborne Laser Scanner (ALS) with a density of 18 points/m² and Hyperspectral (HS) data with a spatial resolution of GSD = 1 m. For the purpose of data acquisition, the study area was divided into four blocks (Figure 1). All flights were performed with an aircraft Vulcanair P-68 Observer 2 (Table 2).

A separate flight plan was prepared for each of the blocks. On 9 June 2019, data were acquired consecutively for all of the four blocks at times shown in Figure 1. Data were acquired between 8:10 and 14:00 CET (7:10 and 13:00 UTC). During the flight, the air temperature was between 21.9 and 24.3°C, there was...
a total lack of cloud cover, and the wind speed did not significantly exceed 2 m s⁻¹ (Table 1). Wind speed of up to 2 m s⁻¹ is an important requirement in the case of studies using a TIR camera as strong gusts of wind cool the surface of the leaves. For instance, wind speed of 2 m s⁻¹ can lower the temperature of the leaves. In order to register the correct temperature of the canopy in full sunlight, the measurement should be performed at the maximum 2 m s⁻¹ wind speed threshold (Ansari & Loomis, 1959; Grace, 1988).

All detailed flight and data parameters are listed in Table 2. TIR data were acquired using ImageIR 9400 camera by InfraTec GmbH (Dresden, Germany). The spectral range of the images was 3.6–4.9 μm, which is determined as Middle Wave Infrared (MWIR). Declared absolute accuracy of the camera is in range ±1°C (±1%), however a certificate of radiometric calibration in the ranges of −10°C to 100°C showed differences lower than 0.2°C. IRBIS Professional v.3.1 software was used to process and correct raw thermal images. Atmospheric correction was made, which was calculated individually for each of the acquisition blocks, and took into account the atmospheric transmittance model using ambient temperature, relative humidity and flight altitude (Table 1; Minkina & Dudzik, 2009). The average emissivity of plant objects in the MWIR range was determined at ε = 0.95 based on the literature reports (Ullah et al., 2012). Using one emissivity value was caused by the size of the study area. This study is also focused only on tree canopy temperatures, which emissivity is similar. Geometric correction of thermal photos was performed with a typical photogrammetric process. Thermal photos were processed as aerial photos to create a thermal orthomosaic. The first step of this process included lens distortion correction. The thermal images were aerotriangulated using the Inpho Match AT (Trimble Inc., Sunnyvale, CA, USA) based on GCP (Ground Point Controls), where the final RMSE of the match was 85 cm. Next, orthorectification on the newest and high-resolution DEM (Digital Elevation Model) was performed in Inpho OrthoMaster (Trimble Inc., Sunnyvale, CA, USA) software. Last stage involved fit control based on 45 control points transferred from RGB. Data were georeferenced and mosaicked in the Inpho OrthoVista program (Trimble Inc., Sunnyvale, CA, USA). Finally, the TIR data were downscaled to a resolution of 1 m to ensure compatibility with the ALS and HS data. The data were then corrected geometrically and radiometrically. The geometric corrections to the data involved a typical photogrammetry processing steps, applicable to any aerial survey, and included geometric correction of lens distortion (Interior Orientation), based on geometric calibration certificate, aerotriangulation of image coordinate space to world coordinates with ground control points (obtained from high-resolution RGB orthomosaic) and orthorectification of images on the triangulated ground model of the LiDAR-derived Digital Terrain Model (DTM). Radiometric correction involved resolving of light fall-off due to radiation travel path differences through the lens. The resulting thermal orthomosaic, divided into blocks, was used to determine the temperature of the tree canopies.

The ALS and HS data were used in the postprocessing of ground reference data. Laser scanning was acquired using a Riegl VQ-780 sensor with a point density of 18 points/m². The obtained point cloud was classified to basic ASPRS specification and used to create a Canopy Height Model (CHM) with a resolution of 1 m. To extract the ground, Axelson algorithm implemented in commercial software TerraScan (Terrasolid Ltd., Espoo, Finland) was used (Axelson, 2000). Other classes, according to ASPRS specification were obtained using TerraScan customized classification rules. LAStools (rapiddlasso GmbH, Gilching, Germany), a lasheight tool with a buffering parameter was used to normalize height values in the collected point cloud. ALS data were used to create single canopy range polygons. HS data were used in Table 1. Weather conditions during data acquisition for individual blocks on 9 June 2019.

| Block number | Acquisition time | Air temperature [°C] | Humidity [%] | Wind speed (m s⁻¹) | Wind direction | Solar radiation [w/m²] |
|--------------|------------------|-----------------------|--------------|--------------------|----------------|-----------------------|
| 1            | 8:10–9:45        | 21.9                  | 29.0         | 0.66               | SW             | 493.52                |
| 2            | 10:00–10:30      | 22.6                  | 26.1         | 1.29               | S              | 392.36                |
| 3            | 12:00–13:00      | 23.7                  | 24.1         | 2.03               | SW             | 425.10                |
| 4            | 13:00–14:00      | 24.3                  | 23.2         | 1.83               | SW             | 590.78                |

Table 2. Parameters of flight and sensors used. Abbreviations: TIR – Thermal InfraRed; HS – Hyperspectral; ALS – Aerial Laser Scanning; VNIR – Visible–Near Infrared; SWIR – Short Wave Infrared; GSD – Ground Sampling Distance.

| Data Type                  | Sensor Type          | Data Parameters | Swath Width [m] | Aircrafts | Flight Level [m] and Airspeed [m/s] | Date of Flight | Hour of Flight |
|----------------------------|----------------------|-----------------|-----------------|-----------|-------------------------------------|----------------|----------------|
| TIR ALS point cloud        | ImageIR 9400         | GSD 0.5 [m]     | 30              | 60        | Vulcanair P-68 Observer 2           | 9 June 2019    | 8:10 (6:10 UTC) – 14:00 |
| HS images                  | Riegl VQ-780i        | Density 18 [pts/m²] | 60              |           |                                     |                | (12:00 UTC)    |
| HS images                  | HySpex VNIR-1800     | GSD 1 [m]       | 60              |           |                                     |                |                |
| HS images                  | HySpex SWIR-384      | GSD 1 [m]       | 60              |           |                                     |                |                |
acquired using the HySpex sensor (Norwegian Norsk Elektro Optikk company) made of two sensors: VINR-1800 with a spectral range of 0.4–0.9 µm and SWIR-384 with a spectral range of 0.9–2.5 µm. The acquired data were georeferenced and mosaicked. HS data were used to prepare an illumination map.

**Ground reference data**

At the peak of the 2019 growing season, 400 ground reference data for five tree species (Sec. 2.2) were collected. The measurements were made using a Trimble Catalyst GNSS receiver: a Trimble DA1 antenna (measurement accuracy of about 1 m) and the MapIT application (Mapit GIS LTD, Wishaw, UK) connected to it. The data were saved as points in GeoJSON format. For each reference point, the taxonomic information, location in the area (in the forest or outside the forest) and the coordinates of the canopy center were recorded in the study area. All individuals were healthy and had a dense, compact crown, which ensured that the temperature recorded was the temperature of the tree canopy, and not the ground temperature. In each block, 20 individual trees for each study species were acquired (10 individuals in the forest and 10 outside the forest). All individuals were distributed as evenly as possible, taking into account their actual occurrence both in the entire study area, and in each block separately (Figure 2). The reference data collected in this way were then postprocessed.

**Delineating the range of a tree’s crown**

The analyses of the ground and TIR data were carried out in stages.

The first step involved photointerpretation of the range of individual tree canopies. For each of the 400 trees, points from ground reference data were transformed into polygons covering its entire canopy. Polygons were created based on the photointerpretation of the CHM data (Figure 3). Only the pixels that were entirely within the drawn canopy were counted for each polygon. Extreme canopy pixels, i.e. those that could include the temperature of tree canopy and the ground were excluded from the analysis by using a 0.1 m buffer inside the range to minimize the effect of the ground on the final temperature of the entire canopy.

Next, pixels covering a tree’s shaded part were eliminated from its canopy range based on HS data which were used to create the illumination map. This map was prepared in the ATCOR-4 program using the *at_shadowdetect* tool. Pixels in the illumination map range from 0.1 for full shadow to 1 for full sun. Pixels whose value was 0.1 were excluded from further analyses (Supplementary Materials). An original, whole tree canopy range, created based on CHM model (called Range 1) was reduced to Range 2. After using an illumination map, pixels in full shadow were eliminated in Range 2 (Figure 3).

The illumination map helped to exclude the pixels located in the shadow of the tree from the canopy range, as they could ultimately lower the overall

![Figure 2. Distribution of reference polygons by species and by study area divided into blocks of airborne data acquisition. The number of measurements for each species is given in brackets. Base: orthophoto mosaic in real colors.](image-url)
temperature of the canopy. Then, for a polygon covering only the sunlit part of the canopy, the mean of the pixel values was calculated.

**Statistical analysis**

The data set prepared in this way was analyzed to answer the research questions. In the first analysis, the significance of differences in CT between two groups of trees (trees growing in the forest or outside the forest) was checked using the Student’s t-test for independent samples, separately for each block. Secondly, the interspecies variability of CT in individual time blocks was analyzed (Figure 1). The purpose of this analysis was to determine the interspecies variability of tree temperature at different times of the day and different locations. The ANOVA test was the basis for determining the significance of differences in temperature between species in the consecutive time blocks. All statistical calculations were performed in ArcGIS 10.6 by ESRI and Statistica 13 by TIBCO Software.

**Results**

**Canopy Temperatures in the forest and outside the forest**

The results indicate that the immediate surroundings are an important factor that affects the temperature of individual trees (Figure 4). If trees grow in the forest, their average temperature is about 0.4–0.7°C lower than that of trees growing outside the forest. This correlation was observed throughout the time period under analysis (Figure 4). The smallest difference in CT was observed between 8:10 and 9:45 and amounted to 0.41°C. The biggest difference was observed in block no. 3, i.e. between 12:00 and 13:00 and amounted to 0.71°C (Figure 5). A statistically significant difference was obtained in all blocks, but block no. 3 differed the most significantly as regards CT (p < 0.001). Due to this variance, the next step of the research was conducted with the trees divided into two groups: in the forest and outside the forest.
Canopy Temperatures of studied species

Comparative analysis of CT at a block time indicates that the temperature difference of individual trees, regardless of their taxonomic separation, ranges from 1.91°C for trees in the forest at 12:00–13:00 (min. CT for Quercus rubra – 18.21°C, max. CT for Pinus sylvestris – 22.47°C) to 3.61°C for trees outside the forest at 10:00–10:30 (min. CT for Quercus petraea – 14.59°C, max. CT for Pinus sylvestris – 21.69°C).

Figure 5. Differences in canopy temperature of all species in the forest and outside the forest of block no. 3 (12:00–13:00).

The analysis of the interspecies variation in CT in the blocks indicates that the studied species differ statistically significantly in all cases, except between 13:00 and 14:00 for trees outside the forest (Figure 7). In block no. 1, i.e. between 8:10 and 9:45, the biggest difference in CT between trees in different locations of the same species was observed for Alnus glutinosa (1.10°C). For trees in the forest, Quercus rubra was the species with the lowest temperature (14.63°C), while Pinus sylvestris had the highest temperature.
(15.90°C). In this block, trees outside the forest with high CT involve especially Alnus glutinosa (16.03°C), and Robinia pseudoacacia (15.99°C).

In block no. 2, i.e. 10:00–10:30, for trees in the forest, Alnus glutinosa had the lowest CT (16.12°C), and again Pinus sylvestris had the highest CT (17.24°C). The lowest temperature for trees outside the forest was determined for Alnus glutinosa outside the forest (16.19°C). In this block, species are divided into three groups of similarity, for both trees in the forest and outside the forest, but the temperature difference between them increases significantly, especially for trees outside the forest ($p = 0.001$).

The biggest variance differences in CT between species are noted between 12:00 and 13:00. In block no. 3, the greatest difference in location is observed between Quercus rubra (difference of 1.32°C) and Robinia pseudoacacia (1.20°C). In this block, the temperature difference between Pinus sylvestris trees in the forest and outside the forest is the smallest (0.05°C). Despite that, Pinus sylvestris in both locations has the highest CT. The lowest temperature for trees in the forest was determined for Quercus rubra (18.80°C), and for trees outside the forest it was for Alnus glutinosa (19.27°C). Species are still divided into three groups of similarity for trees in the forest.

In block no. 4 of data acquisition, i.e. 13:00–14:00, for trees in the forest, the lowest CT is noted for Quercus petraea (19.73°C), and the highest for Pinus sylvestris (21.54°C). They differ by 1.81°C. Despite the small difference between these species, in this block the species were divided into two groups of similarity for trees in the forest. CT of trees outside the forest did not differentiate the species.

Based on the comparison of the entire period covered by the analysis (from 8:00 to 14:00), the species with the lowest CT in the course of data collection were Quercus rubra, Quercus petraea and Alnus glutinosa, and the species with the highest temperatures was Pinus sylvestris.

**Discussion**

**Influence of the environment on Canopy Temperature**

Tree temperature is significantly affected by canopy architecture, but it is also largely influenced by the immediate surroundings of the tree. Our studies have shown a significant difference between CT of trees outside the forest and trees in the forest, especially at noon (Figure 4). Trees growing in the forest are 0.7°C cooler than trees growing outside the forest. In the morning and in the afternoon, the difference of CT, regardless of tree location, is 0.4°C but it is still statistically significant. The data indicate that the position in relation to other trees is an important factor that influences CT. This conclusion is in agreement with the results of previous studies (Leuzinger et al., 2010). The differences in canopy temperature of trees growing in parks and along the roads were investigated and a difference of about 1°C was shown regardless of species. The groups of trees can create a local microclimate, by their cooling abilities, by a combination of shadow cast and evapotranspiration process (Spronken-Smith & Oke, 1998), which explains a lower canopy temperatures of trees inside the forest.

The influence of the environment on CT was also demonstrated by the authors of the study in which CT of subtropical species were determined (Zheng et al., 2018). The studies demonstrated that the cooling properties of each individual tree canopy depend on the species and the ground. Also, the presence of other trees or the vicinity of buildings (in the case of urban studies) may significantly affect the cooling properties of a tree and the CT. Similar conclusions were also drawn by scientists studying the urban heat Island effect (Melaas et al., 2016), who emphasize that the form of land cover and the size of the vegetation patches have a key influence on the surface temperature. There is a high probability that the difference in temperature values of species may result from a different environment.

**Canopy temperature of tree species**

The use of high-resolution TIR data as source data for remote sensing analyses is still rare. One of the reasons behind their low popularity is that it is difficult to obtain thermally stable data with accurate radiometric and geometric fit (Prakash, 2000). The TIR data collected by a camera with a new spectral range (3.6–4.9 µm) was used, for the first time, to analyze CT on such a large scale (area over 40 km² for block no. 1) and with such high resolution (GSD = 1 m).

The acquisition time and data resolution in our studies made it possible to analyze the temperature of individual tree canopies (Figure 3). The results of our studies (Figure 5; Figure 6) indicate at the same time that the studied species differ as regards CT in the time interval between 8:00 and 14:00. Quercus rubra and Quercus petraea were shown to be the species with the lowest CT, while Pinus sylvestris has the highest CT. The difference in CT between these groups of species is about 1.1°C for trees in the forest and 0.9°C for trees outside the forest. These differences
may arise primarily from the size and architecture of a given tree canopy and its immediate surroundings as discussed in Sec. 4.1. Also, new information about canopy temperature of non-native species like *Quercus rubra* and *Robinia pseudoacacia* might be used in the further research. Especially if the aim of the studies are detecting invasive species by remote sensing techniques. TIR data are used in vegetation monitoring (Sagan et al., 2019) and tree assessment (Catena & Catena, 2008), which can be developed into species detection.

One of the earlier studies, which included the analysis of CT of individual tree species, was carried out in NW Switzerland (Leuzinger et al., 2010). These results cannot be directly compared, because there are too many variables that make the conditions and parameters of obtaining both collections different. The key differences are flight altitude and spectral range (7.5–14 μm). According to Gerber et al. (2011), 3–5 μm atmospheric window is more dedicated to study vegetation water content, and 8–14 μm wavelength range is more relevant to differentiating plant species. Nevertheless, Ullah et al. (2012) also confirm that both atmospheric windows contained significantly different vegetation, making them regions suitable for discriminating between vegetation species.

**Potential applications of new thermal spectral range in tree species studies**

HS and ALS imaging is now widely and successfully used to identify tree species (Dalponte et al., 2012; Liu et al., 2017) and to determine their health status (Degerickx et al., 2018; Sampson et al., 2003). The application potential of very high-resolution TIR data is not fully exploited. This is primarily due to processing difficulties which on the one hand result from high dynamics of object temperature changes during the day, and on the other hand, from the problems with their geometric correction. Various thermal spectral ranges are dedicated to different types of research, such as its species classification or assessment of tree health condition (Gerber et al., 2011). The studies proved that the time of TIR data acquisition should be matched with the objectives of a given study. If the goal is to analyze water stress in plants, it is best to make measurements of each species separately, because CT of healthy trees differentiates them significantly (Figure 6; Figure 7). It is also important to always include tree location and its environment in calculations (Figure 4). At solar noon, CT in healthy individuals differs from each other, in terms of their taxonomic separation and location in the study area (Figure 5; Figure 6), and it is at these times when the

![Figure 6. Temperature of tree canopy for the studied species in the forest, divided by the time of thermal data acquisition. The p-value was determined on the basis of the ANOVA test. a,b,c values represent belonging to a group according to the post-hoc Tukey test. a,b,c values represent belonging to a group according to the post-hoc Tukey test.](image-url)
differences in health condition can be best shown. Solar noon additionally reduces the shadow effect inside the canopy, which can effectively lower the temperature of the entire tree.

New spectral range (3.6–4.9 µm) was chosen for this study, because of its very high sensitivity in detection, which was compared with other camera models and spectral ranges (Aldave et al., 2013). The 3–5 µm window is found to be most suitable and is one of the important atmospheric transmission window used in thermal imaging (Awasthi et al., 2014, 2012; Bhatt et al., 2010). It is hard to show disadvantages of using this wavelength, because of the lack of enough research and information about it, and it is hard to compare to other research results, which are typically made in LWIR (8–14 µm).

Studies show that the CT is a variable that differentiates individual species (Figure 6; Figure 7). Thus, an assumption can be made that the use of these data in the process of species classification with the use of machine learning algorithms may improve the accuracy of the identification result. That is why these data should be further tested as supplementary to the HS in the classification of trees, especially when it is technically possible to collect them during one flight by instrument fusion (Table 2). Further studies in this area with the use of TIR data are planned.

**Conclusions**

The results of our studies confirm that TIR data acquired from the airborne level may be used to analyze CT during the day. The primary conclusion from our studies is that CT is a species-specific feature and depends on a tree’s location. At noon CT of trees growing in the forest is on average 0.7°C lower than that of trees growing outside the forest. It was also shown that the similarity of individual species in terms of temperature changes throughout the day. Moreover, *Alnus glutinosa*, *Quercus rubra* and *Quercus petraea* are the species with the lowest CT. *Pinus sylvestris* has the highest CT, irrespective of the time of measurement. Additionally, at about noon, i.e. at 12.00–13.00, the CTs of all tree species are stable and differ from each other, regardless of the trees’ location in the study area. Identification of this time may be crucial when TIR data are planned to be used to determine differences in CT between trees in good health condition, and those with a worse health status. Statistically the highest differences in tree temperatures between species are observed at noon. The new TIR spectral range (3.6–4.9 µm) registers CT with high accuracy and makes it possible to use this value to differentiate tree species.
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