An open-source method for producing reliable water temperature maps for ecological applications using non-radiometric sensors

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ABSTRACT

The number of thermal sensors mounted on Unmanned Aerial Vehicles (UAVs) has increased considerably in recent years, with several of those currently available on the market being very attractive due to their low cost and ease of use. UAV platforms coupled with non-radiometric thermal sensors tend to be less expensive, but few studies have evaluated the reliability of data they produce or developed workflows to improve data accuracy. Here we present a complete method for obtaining accurate and precise water temperature data from non-radiometric sensors, including bias correction, calibration, image stitching and wetted area extraction. We illustrate the utility of the method through its application to the assessment of thermal conditions in two tropical river reaches. The whole procedure is implemented in the R language, and we provide a tutorial and customizable functions. Validation tests indicate that our method produces water temperature estimates that are comparable to those from more expensive sensors (mean absolute error <0.5 °C) and can be used to answer ecological questions with great confidence. The method dramatically increases the accessibility of thermal imaging in ecology by providing accurate data that is cost-effective and not computationally intensive, and for calibration and validation relies on only small and lightweight equipment that can transported and used in remote locations.

1. Introduction

Thermal Infrared (TIR) sensors mounted on Unmanned Aerial Vehicles (UAVs) have become popular and accessible tools for obtaining spatially continuous temperature data for ecological applications (e.g., Dugdale 2016; Malbêteau et al., 2018; Collas et al., 2019). Thermal images provided by such sensors have provided new insights into both thermal physiology (Zellweger et al., 2019) and the thermal characteristics of habitat (Gulko et al., 2013). Despite their promise and potential, a number of limitations (e.g., sensor intrinsic accuracy/resolution that is usually around ±2–5 °C and camera-environment derived biases such as thermal shift and vignetting effect, see below) impact the reliability of temperature values estimated by these sensors (Dugdale et al., 2019). Workflows designed to increase data reliability tend to be bulky and potentially expensive if based on nominal high-performance UAV thermal platforms (the cost can be likely >£15,000), reducing their accessibility for poorly funded groups or regions, and/or remote and difficult to reach field sites.

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In general, thermovision systems depict the intensity of thermal radiation in a field of view, recorded in an image. Both radiometric and non-radiometric sensors are available on the market, but these differ dramatically in cost. The more costly Radiometric TIR sensors are specifically designed to derive the temperature value for each pixel of the image by a posterior calibration of radiometric signal intensity. The radiometric signal is converted directly into temperature values through Plank’s law and Stephan Boltzmann relations, compensated for surface characteristics (emissivity and reflection), atmospheric conditions and the thermal imaging system’s characteristics (Minkina and Dudzík, 2009); the data produced with radiometric sensor are stored in R-JPG format which includes the actual thermal radiation intensity values recorded by the sensor as well as the image. In contrast, the output from the less costly, non-radiometric sensors is simply a visual depiction of the intensity of thermal radiation in the form of a Joint Photographic Experts Group (JPEG) image with a visual, Red-Green-Blue (RGB) color representation, or via raw values in TIFF (Tag Image File Format) format; in non-radiometric sensors the RGB image is derived from an original raster through the application of a preselected color palette, and there is no possibility of post-calibration (DJI, 2020). The ongoing release of new UAV thermal platforms to the market has resulted in older systems reducing in cost, especially those with non-radiometric sensors (that may be available for less than £2000). Thus, older thermal platforms are affordable to a wider group of users, but the issues of data reliability remain a concern.

In order to convert non-radiometric TIR images to absolute temperature values, the main calibration procedure that has been developed relies on the use of independently monitored Thermal Control Points (TCPs) and extraction of the Digital Number (DN) of these points within the image or orthomosaic (e.g. Kelly et al., 2019). The resulting radiometric calibration (RC) equation is then used to convert all pixel DN values in the image to their respective temperature values. The regression method has been tested in laboratory conditions, but to be applied in field the calibration process involves using geo-referenced TCPs with characteristics (e.g., emissivity, reflectance) similar to the object of interest and with a large range of temperatures (which may involve artificially heating or cooling additional objects for TCPs to capture thermal range needed to build robust RC equations); the method also requires that the temperature of these points is monitored concurrently with thermal image collection, and with these TCPs within the UAV mapping path (Kelly et al., 2019; Kuhn et al., 2021). This process is extremely labour intensive. It also requires much equipmentment and so can be impractical for surveys in remote areas. For instance, studies have used material that heats up when exposed to the sun, together with trays filled with cooled water, to provide the necessary thermal range (Kuhn et al., 2021).

Even accepting such limitations, radiometric calibration does not solve all of the issues involved in converting TIR images to absolute temperature values. UAV thermal sensors (both radiometric and non-radiometric ones) are known to produce systematic biases due to thermal shift (i.e., the change in thermal radiation recorded by the sensor due to the heating of the camera during its operation (Dugdale et al., 2019)), vignetting effects (Abolt et al., 2018), and interactions between the sensor, environmental and operational conditions in the field (Aragon et al., 2020). These problems can result in biases of up to 8°C in derived temperature values (Dugdale et al., 2019; Oueltet et al., 2020).

Precise and accurate estimates of absolute water temperature and its spatial variability are important for answering many ecological questions. Many studies have attempted to determine the thermal suitability of stream reaches for ectotherms using temperature maps (e.g., Collas et al., 2019), often including assessment of the occurrence and spatial distribution of thermal refugia. While relative temperature differences (e.g., the difference between a cooler/warmer patch and nearby areas) are sufficient to indicate the presence of refugia within a stream reach, understanding how such differences might affect organisms requires a precise estimation of the absolute temperature in refugia and non-refugia areas. The use of uncorrected temperatures, even when obtained from more expensive and sophisticated sensors, can undermine conclusions about thermal suitability and the availability of refugia. A further challenge is the need to separate wetted from non-wetted areas before analysis temperatures. Many high performance land-cover/land-use classification algorithms have been proposed for isolating areas of interest within images (e.g., Carbonneau et al., 2020; Talukdar et al., 2020), but none of these are incorporated within workflows designed specifically for thermal image analysis.

Here we present a novel workflow to simplify procedures, reduce the equipment needed and improve the accuracy of thermal data obtained from inexpensive, drone-based non-radiometric platforms. The method (i) allows production of calibration equations in a way that does not require a complicated in-field calibration procedure, and so can be applied by a single operator in a short period of time, and (ii) corrects for biases associated with camera (i.e., thermal shift, vignetting), environmental and operational conditions, and (iii) includes a step which extracts wetted areas from the image. The workflow uses R as its main language, and we provide a tutorial and customizable code on GitHub (https://github.com/monviso/Thermal-map-from-low-cost-UAV-camera) to enable its application.

2. Materials and methods

2.1. Overall workflow

Fig. 1 summarises the steps of the workflow. By way of illustration, we explain the various procedures involved in each step using data collected with a DJI Mavic Dual Enterprise (DJI M2ED, 2020) UAV system. This is an inexpensive (£1800 at the time of writing) integrated UAV platform carrying a dual camera (RGB camera, 3000 × 4000 pixels, and a Thermal non-radiometric thermal camera). The non-radiometric camera is based on the FLIR Lepton 3.0 sensor, with a 120 × 160 Focal Planar Array, output image of 640 × 480 pixels, FVFOV = 57° acquiring data in the 8–14 μm wavelength space, and nominal accuracy ±5°C at 25°C. Non-radiometric sensors such as the DJI M2ED have various output formats such as color palette based RGB/grayscale jpg (e.g., DJI M2ED, FLIR Boson), or tiff (e.g., such as from the FLIR VUE Pro). Nonetheless, the workflow we present can be applied to all these formats.

Those steps in the workflow that do not require bespoke software are fully integrated in R (R Core Team, 2022) using the libraries terra (Hijmans, 2020) to deal with raster-dataframe format transformation, sf (Pebesma, 2018) to manage shapefiles, tidyr
(Wickham et al., 2023a), mgcv (Wood, 2017) for the Generalized Additive model implementation, groupdata2 (Olsen, 2021), dplyr (Wickham et al., 2023b), ModelMetrics (Hunt, 2020) for the computation of some validation metrics and the external call of ExifTool (Harvey, 2016) for reading metadata from thermal images. All the functions and a tutorial are available at https://github.com/mmonviso/Thermal-map-from-low-cost-UAV-camera.

### 2.2. Step 0: Developing radiometric calibration equations

The first step (Step “0”, Fig. 1) is to develop calibration equation(s) to convert pixel numerical values to water surface temperature. To avoid complex field operations, we developed the calibration equations in the laboratory by placing the UAV 1 m above a water bath (JUALBO Pura waterbath). The UAV was in a fixed position, with the sensor facing the water at a camera pitch angle of 0°. The DJI M2ED requires the user to set a temperature range over which it applies the color palette chosen to represent temperatures. To cover the range of temperatures expected at our field sites, the initial and final temperatures used for calibration were 15°C and 45°C respectively; users can extend or reduce this range depending on their site(s), but if temperatures are not known in advance the range is conventionally set to the widest possible. Other platforms do not require the user to select a range (e.g., FLIR Tau, Boson), so this step is not needed. For our calibration experiments, the sensor was turned on 20 min before data collection.

A thermistor (HOBO Pendant; accuracy ±0.2 °C) was left in the bath for the duration of the period at 5 cm depth (to reproduce field setting, see 2.3). To develop the calibration equations, temperature was increased in increments of 0.2 °C from 15 to 45 °C (resulting in 155 temperature levels), with temperature maintained constant for a 5-min period at each level. For each of these 155 levels, 2 images were taken and averaged to obtain single raster.

Each image raster was cropped to a 350 × 264 sub-raster to exclude the temperature loggers from the scene (Fig. 2A). Pixel values from across each cropped image were then averaged to obtain a single intensity value for each temperature increment. These intensity values were regressed against the absolute temperature of the water bath, as measured by the logger (Fig. 2B), producing the Radiometric calibration equation (RC equation).

![Diagram](image1.png)

**Fig. 1.** Schematic of the workflow presented in this paper. The working environment used for each of the steps (numbered 0 to 7) is indicated.

![Graph](image2.png)

**Fig. 2.** A-sample frame captured during the calibration equation construction. The white area includes the pixels averaged to obtain a single grayscale value for the correspondent temperature. B- visual representation of the calibration equation for M2ED showing regression of water temperatures against grayscale values.
The DJI M2ED thermal images are returned using an RGB color palette (e.g., Fig. 2A), so each pixel has three values. Thus, we converted the RGB data into grayscale values using standard luminance RGB to grayscale conversion (International Commission on Illumination Colorimetry, 1976) so that the calibration regression used only a single numerical value (i.e. grayscale) for each pixel. The same procedure can be followed for any other image output produced by other sensors, avoiding RGB-grayscale transformation if the output is already in grayscale or raw DN. The regression equation specific for the DJI M2ED is reported in the Supporting Material.

The time to complete the calibration depends on the range that the user wants to set. In our case it took 150 min to go from 15 °C to 45°C, but time would be shorter for narrower thermal ranges. This calibration only needs to be undertaken once, so the overall time investment is not major, and the calibration equation can then be used to convert grayscale into temperature for any data collected with that platform.

2.3. Steps 1–3: Data collection, vignetting correction and orthomosaic production

The data reported in this paper were collected from the Semenyih and Sompo rivers, Selangor, Malaysia, on January 22, 2020 at 2:40pm and on February 04, 2020 at 12:00pm respectively. Both rivers are part of the larger Langat River basin (2663 km²) which is located on the southern edge of Greater Kuala Lumpur. The climate is wet tropical, with mean annual rainfall exceeding 2300 mm (Department of Irrigation and Drainage, 2018). The Semenyih river has a mean annual discharge of 3.89 m³/s, but the Sompo is ungauged. Channel width in the Semenyih averages approx. 10 m, while that of the Sompo is approximately 5 m. The Sompo is unregulated, but a large dam regulates flows in the Semenyih. The site on the Semenyih is 4 km downstream from the dam, and also receives flow inputs from a tributary (true left bank) and the outlet from a hot spring, which is a public bathing area (Fig. 3). The sites were chosen as potentially having contrasting natural (Sompo) and modified (Semenyih) thermal conditions.

The UAV flights were performed at 30 m altitude. Water temperature was measured during the flights using n = 27 HOBO Pendant temperature loggers (accuracy ± 0.2 °C) placed 5 cm below the water surface (to avoid direct sunlight effecting recorded temperature but still logging at the surface water layer) and spread evenly across each site. During each flight, Ground Control Points (GCPs) were set out and their positions measured using a Leica FlexLine TS06 Flexible Total Station (accuracy ± 0.001 m). GCPs were used to georeference the orthomosaics.

The thermal images were grayscale transformed as per Step 0. Following this they were also corrected for vignetting (Step 2) using the procedure proposed by Abolt et al. (2018). For this, 10 images with the cameras lens cap (assumed to have a homogenous temper-

![Map of study sites](image)

**Fig. 3.** Overview of the study sites. A and B show the overall area location. C- Semenyih River reach. D- Sompo river reach.

4
ature) in place on the end of the lens were taken and averaged. A correction matrix was obtained by computing the difference, in grayscale units, between each pixel and the brightest pixel. This correction matrix was then added to each frame collected in the field, to remove vignetting. We integrated Abolt’s procedure into our workflow so that it forms a routine and semi-automated part of the whole process; the vignetting correction procedure is extensively covered in the GitHub tutorial (https://github.com/monvisio/Thermal-map-from-low-cost-UAV-camera).

Vignetting-corrected images were imported in Agisoft Metashape (Agisoft, 2020) and the thermal orthomosaic produced through a Digital Elevation Model (DEM) geometric correction of images (Step 3, Fig. 1). Although producing mosaics is now routine in image processing, stitching thermal images can be problematic, mainly due to the lack of identifiable tie points used by photogrammetric software to stitch images into orthomosaics (Malbêteau et al., 2021; Ribeiro-Gomes et al., 2017); this is especially true for thermally homogenous surfaces, such as can often be the case with water. A detailed guide to thermal image stitching is provided as part of the GitHub tutorial (https://github.com/monvisio/Thermal-map-from-low-cost-UAV-camera) and so for brevity we do not provide details in the paper. However, it is worth noting that a dense grid of GCPs can ease the stitching process, as does the availability of RGB visual images collected at the same time as the thermal images (as is the case with the DJI M2ED process).

2.4. Step 4: wetted area extraction

In studies that focus specifically on the quantitative analysis of water temperature, there is often the need to precisely extract only pixels covering wet part of the scene (i.e., the wetted area). The manual digitalization of such areas can be problematic and time-consuming, especially in morphologically complex environments (e.g., in the presence of emerging stones, vegetation, or complex river boundaries). Extraction of the wetted area from high resolution images has been already addressed through advanced deep-learning techniques (e.g., Carbonneau et al., 2020), often implemented in other programming languages (e.g., Python, MATLAB). Considering that our correction method is mainly based on R, in order to provide a more consistent working environment, we implemented a semi-supervised method of wetted area extraction in R, based on Generalized Additive Models - GAM (Wood, 2017). The wetted area extraction is not mandatory and all subsequent steps can be performed without it. This method (steps 4a, 4b, 4c, Fig. 1) requires the presence of visual RGB images collected along with thermal ones. Step 4a first involves the production of a visual RGB orthomosaic (i.e., with Agisoft Metashape) which is then imported into a GIS environment and co-registered with the thermal orthomosaic (Step 4a, Fig. 1) using GCPs. Still in the GIS environment, within the same shape file (.shp) a number of polygons covering wetted and non-wetted areas are digitalized across the whole extent of the orthomosaic (Fig. 4). These polygons feed the GAM with information on pixel values at different wavelengths (i.e., R, G, B and thermal) and associate them with wetted or non-wetted areas. Shapefile, RGB and thermal orthomosaics are then imported to R for wetted area extraction.

From each pixel covered by the polygons, Red, Green, Blue and thermal values are extracted. These points are divided into a training set (2/3 of wetted and 2/3 of non-wetted points) and a validation set (the remaining 1/3 for each class), generated with a random pixel selection. The training dataset’s R, G, B and temperature values are used to inform the GAM (Wood, 2017), which has the form:

$$
\text{logit}(\mu_i) = f_1(R) + f_2(G) + f_3(B) + f_4(T) + f_5(x,y)
$$

\text{eq. 1}

![Fig. 4. Digitalization of the wetted and non-wetted areas polygons for the Semenylh river with non-wetted areas (red) and watetted polygons (blue). Radiometric information (R, G, B and thermal values) are extracted from the pixel contained in each polygon.](image-url)
where \( \logit(\mu) \) is equal to \( \log \left( \frac{\mu}{1-\mu} \right) \), that is the ratio of the probability \( \mu \) of success (i.e., being wetted) to the probability of failure (i.e., not wetted) given a certain value of \( R \), \( G \), \( B \), temperature and pixel position \((x,y)\); \( f_1 \) and \( f_2 \) are thin plate splines with a second penalty on the basis in the null space and therefore can be shrunk to 0, with \( f_2 \) being a tensor product to deal with the potential anisotropy of \( x \) and \( y \) (e.g., if they are expressed in lat/long geographical dimension). The shrunk version of the thin plate spline function has shown to be an effective variable selection method, reducing collinearity and concourvity problems (Marra and Wood, 2011; Wood, 2017) Equation (1) is then used to predict, for each pixel of the multilayer raster (in which RGB and thermal values are known), the probability of being in the water or non-water class. Pixels are then attributed to the class with the higher probability. A single layer raster is then built, where wetted pixels assume values of 1 and non-wetted pixel the “NA” value. This raster is then used to filter out all the non-wetted areas from thermal orthomosaics, obtaining a map of temperature for only wet areas. The full procedure is fully implemented and automatized in R. Further, Eq. (1) is fully customizable; for instance it is possible to add any other predictors available (e.g., multispectral layers) or change the structure of the predictor interactions if necessary.

The wetted area extraction functions produce a number of classification accuracy metrics for the validation dataset. To validate the model, we use the validation data set to compute the F1 score (e.g., Carbonneau et al., 2020) that is defined as the harmonic mean of precision (P) and recall (R), computed as:

\[
F_1 = 2 \times \frac{P \times R}{P + R}
\]

and

\[
P = \frac{T_p}{T_p + F_p}
\]

\[
R = \frac{T_p}{T_p + F_n}
\]

P and R are account for true positives \((T_p)\), true negative \((T_n)\), false positives \((F_p)\) and false negatives \((F_n)\). The metric P quantifies the capacity of the model to identify as positive \((T_p)\) only actual wetted pixel (i.e., the lower the number of \( F_p \), the better the model precision); the metric R quantifies what portion of the actual wetted pixel (i.e., \( T_p + F_n \)) has been correctly classified by the model (i.e., \( T_p \)). The closer P and R values are to 1 the higher the power of the model to correctly classified pixels in their own actual category. The F1 score is then used to indicate model classification accuracy by using the harmonic mean of P and R. The closer F1 is to 1 the more accurate the classification.

2.5. Step 5-6: Thermal orthomosaics correction and calibration

The interaction of flight altitude and environmental conditions (e.g., air temperature, air humidity, reflected apparent temperature) can potentially affect the amount of thermal radiative energy reaching the sensor. Any loss of radiative signal due to atmospheric conditions or flight conditions corresponds to a decrease in the grayscale\textsubscript{raw} value used to represent the temperature across the scene. We performed a number of tests to check the loss of radiative energy intensity reaching the sensor under different flight conditions. These indicated that flight/atmospheric conditions can lead to substantial underestimation of the real temperature (by up to \(-6.5 \)°C in our data; see supporting material file). Thus, grayscale\textsubscript{raw} values must be compensated in order to apply the calibration equation developed in step 0 under laboratory conditions (Section 2.2) to field data. The process of correction is shown visually in Fig. 5 and described below.

Correction Values (CV) are defined as the difference between an expected and an observed value:

\[
CV = V_{lab} - V_f
\]

where \( V_f \) is the grayscale\textsubscript{raw} value obtained in the field, given the specific flight operational and environmental conditions, that originates from the water temperature (monitored at the location by a logger). \( V_{lab} \) is the expected pixel value of the same temperature if in lab conditions, determined from the RC equation described under Step 0. The CV may not be the same across a site or scene, due to spatially variable environmental conditions (e.g., variation in sun reflection). Thus, \textit{a priori} we developed a model to estimate the CV within the area of interest based on multiple ground measures of temperature (obtained from water temperature loggers). The CV computation function developed in R splits the loggers into two sets, with \(-2/3\) used to compute CVs (correction loggers) and correct the orthomosaic (the remaining \(1/3\) are used to validate the predicted water temperatures; see Step 7). The assignment of loggers as either correction or validation ones was done in such a way as to have each subset spread evenly across the site (Fig. 5).

CV is computed using equation (5) for each of the correction loggers. To account for the possible non spatial homogeneity of the CV across the site, we further modelled its spatial distribution (CVs) using a spatial GAM (Wood, 2017) in the form

\[
CVs = f_1 (x_i, y_j) + f_2 (V_f)
\]

where \( x_i \) and \( y_j \) define the correction logger position (e.g., similarly to eq. (1) it can be latitude and longitude or any reference system to explicit the loggers relative position); \( f_1 \) is a soap-film smoother implemented in a tensor product (Wood, 2017) and \( f_2 \) is a thin-plate spline. \( V_f \) was included to control the potential effect of the original grayscale\textsubscript{raw} pixel values on the CV.
Fig. 5. Schematic of the original grayscale/raw pixels correction and calibration process to derive absolute temperatures values. A- Original grayscale orthomosaic. B- CVs orthomosaic derived from equations (5) and (6). C- CVs corrected orthomosaic. D- Absolute temperature calibrated map. Loggers used to train the Correction Value (CV) estimation model (eq.(5) and (6)) are shown as red dots, while those used to validate estimated water temperature are shown in green.

(6) computes CVs for each pixel of the uncorrected orthomosaic based on their position \( (f_1) \) and original grayscale/raw values \( (f_2) \); and results in a CV raster. Subsequently, the original uncorrected orthomosaic (Fig. 5) and the CV raster are summed to obtain the corrected raster. The corrected raster is then converted into absolute temperature by applying the calibration equation. It is important to note that the spatially explicit CVs implicitly account for variable environmental conditions across the area of interest as well as for the differences between the laboratory condition in which the calibration equations were developed and the field ones (e.g., differences air temperature, UAV height, etc.).

2.6. Step 7: Water temperature validation

Estimated water temperatures that come from the steps outlined above are validated using the 1/3 of the loggers not used in the correction step. Water temperature values are extracted from the corrected raster for the validation logger locations. The absolute Error (AE) is computed for each validation logger, with these then used to compute Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and linear correlation coefficient \( (r) \) of all measured and predicted water temperature values. The error terms are computed as follows:

\[
AE = y_i - x_i \\
MAE = \frac{\sum_{i=1}^{n} AE}{n} \\
RMSE = \sqrt{\frac{\sum_{i=1}^{n} AE^2}{n}} \\
r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \\
\]

de q. 7

de q. 8

de q. 9

de q. 10

where \( y_i \) and \( x_i \) are respectively the measured water temperature and the predicted water temperature of the validation loggers, \( \bar{y} \) and \( \bar{x} \) are respectively the mean measured and predicted water temperature across all loggers, and \( n \) are the number of validation loggers.

In section 3 we report thermal data produced with and without the CVs correction procedure, to illustrate the improvement in temperature estimation produced by the CVs step.

3. results

The wetted area extraction step reliably separated wetted and dry areas; the F1 index for both rivers was \( >0.91 \), indicating a high performance in the classification of pixels as either wetted or non-wetted (Table 1). Application of all the remaining steps yielded final estimates of water temperature with a MAE \(<\pm0.5\, ^\circ\text{C}\) for both rivers (Table 3). Thermal maps produced without the CVs step had substantially lower performance in all the error metrics considered (Table 2). The CVs step produced a decrease of both MAE (\(-3.00\, ^\circ\text{C}\) in Semeniyh and \(-2.62\, ^\circ\text{C}\) in Sompo), and RMSE (\(-2.79\) in Semeniyh and \(-1.9\) in Sompo), while the correlation between observed and predicted temperature values increased in both cases.
Table 1
Wetted pixel classification performance for Semenyih and Sompo rivers stretches.

<table>
<thead>
<tr>
<th>Site</th>
<th>Training pixels</th>
<th>Validation pixels</th>
<th>Tp (water)</th>
<th>Fn (water)</th>
<th>Fp (water)</th>
<th>P</th>
<th>R</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semenyh</td>
<td>1795856</td>
<td>897928</td>
<td>131288</td>
<td>14658</td>
<td>10885</td>
<td>0.92</td>
<td>0.90</td>
<td>0.91</td>
</tr>
<tr>
<td>Sompo</td>
<td>209415</td>
<td>104708</td>
<td>13466</td>
<td>71</td>
<td>0</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Table 2
Water temperature estimation validation form thermal maps without CVs correction. MAE: Mean Absolute Error, max AE: maximum Absolute Error; AE sd: Absolute Error standard deviation; RMSE: Root Mean Square Error; r: correlation coefficient.

<table>
<thead>
<tr>
<th>Site</th>
<th>Training loggers</th>
<th>Validation Loggers</th>
<th>MAE</th>
<th>Max AE</th>
<th>AE sd</th>
<th>RMSE</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semenyh</td>
<td>18</td>
<td>10</td>
<td>-3.49</td>
<td>-5.00</td>
<td>3.60</td>
<td>3.66</td>
<td>0.54</td>
</tr>
<tr>
<td>Sompo</td>
<td>20</td>
<td>7</td>
<td>+2.78</td>
<td>+4.60</td>
<td>2.21</td>
<td>2.25</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Table 3
Water temperature validation from CVs corrected thermal maps. MAE: Mean Absolute Error, max AE: maximum Absolute Error; AE sd: Absolute Error standard deviation; RMSE: Root Mean Square Error; r: correlation coefficient.

<table>
<thead>
<tr>
<th>Site</th>
<th>Training loggers</th>
<th>Validation Loggers</th>
<th>MAE</th>
<th>Max AE</th>
<th>AE sd</th>
<th>RMSE</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semenyh</td>
<td>18</td>
<td>10</td>
<td>-0.49</td>
<td>-1.80</td>
<td>0.81</td>
<td>0.89</td>
<td>0.72</td>
</tr>
<tr>
<td>Sompo</td>
<td>20</td>
<td>7</td>
<td>+0.16</td>
<td>+0.54</td>
<td>0.31</td>
<td>0.32</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Fig. 6 provides the final thermal mosaics along with scatterplot of measured vs estimated temperatures for both the CV corrected and uncorrected thermal orthomosaics. Even considering the low resolution of the DJI M2ED, the mosaics successfully capture patch scale variation in water temperature across the reaches related to mixing of water from different sources. The study reach in the Semenyih river (Fig. 6B) had an average temperature of 33.2°C (warm due the effects of an upstream dam) but was characterized by spatial variability related to (a) the cool small left bank tributary and its thermal plume (with temperature down to 28.4°C), and (b) an area of warmer water on the right bank that results from discharges from the hot spring that enters at two points via small channels. The Sompo River (Fig. 6D) was distinctly cooler (average temperature of 30.7 °C) and more homogeneous; the main areas of thermal contrast were along the margins close to the bank, where water was warmer than the central part of the channel.

4. Discussion

4.1. The workflow and its results

The workflow produces highly accurate thermal maps based on images obtained from inexpensive, non-radiometric sensors. The workflow deals with all the recognized sources of bias for UAV thermal cameras (i.e., vignetting, thermal shift and environmental

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Fig. 6. Comparison of CVs corrected and uncorrected water temperature maps with relative scatterplots of measured vs. estimated water temperature values.
erational conditions). It consists of 7 steps. First, radiometric calibration equations are developed using a laboratory water bath (step 0); the use of a water bath avoids the need to use much of the cumbersome equipment that has made field calibration methods impractical. Once UAV flights have been conducted (step 1), images are corrected for vignetting effects and stitched into an orthomosaic (step 2-3). Through a new approach, orthomosaic pixels are then classified as either wetted or non-wetted (step 4), allowing extraction of temperature data for only wetted pixels. A correction equation compensates for flight and environmental conditions (step 5 and 6) and allows application of the radiometric calibration equation determined in step 0. It is important to note that, along with environmental conditions, error induced by thermal shift is implicitly corrected as part of steps 5 and 6. Finally, a number of error metrics are produced to evaluate the accuracy of the final water temperature estimation (step 7). We provide the R script and a tutorial to help users apply the workflow in its entirety. Several studies have assessed the ability of UAV thermal sensors to accurately detect temperature in various types of habitat (Brenner et al., 2017; Ribeiro-Gomes et al., 2017; Sagan et al., 2019; Yang and Lee, 2019). Some comparisons of the performance of different UAV mounted thermal sensors (both radiometric and non-radiometric) for estimation of temperatures in freshwater habitats are given in Table 4. The sensor performances are largely dependent on the image calibration techniques, whether any correction methods are used and, if they are used, what they consist of. It is not the aim of this research to formally compare performances of different calibration/correction methods, but it is worth noting that to reach acceptable accuracy (i.e., ≤1°C) even data derived from expensive radiometric sensors require heavy in situ recalibration and/or post-processing correction to deal with thermal shift and vignetting effect. The recalibration is usually based on linear regression between in situ measurement water or target temperature against image DN values (e.g., Xiang et al., 2017; Collas et al., 2019; Acorsi et al., 2020; Casas-Mulet et al., 2020); when applied, post-processing has been based on a variety of methods that range from histogram equalization (e.g., Casas-Mulet et al., 2020) to optimization procedures based on integration of image DN and in situ temperature measurement (e.g., Abolt et al., 2018; Wang et al., 2023). It remains hard to comprehensively evaluate and compare data from different sensors and correction methods because different evaluation metrics are used in published studies.

We evaluated the performance of our correction method in two tropical streams. The estimated temperatures had an accuracy that is comparable to or even improves upon those of the more expensive radiometric sensors frequently used in freshwater studies. Although we applied it to river habitats, the workflow is relevant and applicable to any environmental context, as the laboratory, field and statistical methods are not specific to aquatic habitats. Various measurement devices be used to measure ground surface temperatures in terrestrial habitats, so as to generate necessary calibration and validation data, while alternatives to the laboratory bath calibration tests we used to develop CV equations for water temperature can easily be developed to e.g. assess ground or leaf surface temperatures. Of course, wetted area extraction is not needed in studies of terrestrial habitats, so that this step can be omitted as might be necessary. The main improvement of our method lies in the minimal equipment needed (only temperature loggers) set against the high accuracy of the final data obtained. It should be stressed that the temperature loggers used within the workflow must themselves be correctly calibrated to ensure consistency in the water temperature measurement. Special attention should also be paid to the RC equation computation step (Step 0). Once a calibration equation has been produced it will be applicable to any data collected with the UAV sensor/platform (in our case DJI M2ED). Nonetheless, in cases where sensor pixel values are dependent on a dynamic range selection as they are with the DJI M2ED (see 2.2 and Supporting Material for further explanation), the user must consistently use the same temperature range set at the step 0 to collect field data. The limited equipment needed for the data acquisition steps makes adoption of the method feasible for a single person, and/or potentially useable in remote areas where it may be hard to transport large amounts of equipment. Although our tests suggest that the method was capable of producing accurate temperature estimates in the quite contrasting thermal conditions that prevailed across the two Malaysian study streams, additional tests could usefully be conducted in different environmental or climatic context to provide further verification.

<table>
<thead>
<tr>
<th>Camera</th>
<th>type</th>
<th>Cost 2023</th>
<th>Validation loggers (n)</th>
<th>Reported performance</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLIR Tau2 (640 × 512)</td>
<td>radiometric</td>
<td>~6000E (sensor only)</td>
<td>650</td>
<td>Mean Deviation = 0.4 ± 0.2°C</td>
<td>Xiang et al. (2017)</td>
</tr>
<tr>
<td>DJI Zenmuse XTR (336 × 256)</td>
<td>radiometric</td>
<td>~7000E (sensor only)</td>
<td>4</td>
<td>MAB ~ 3°C</td>
<td>Abolt et al. (2018)</td>
</tr>
<tr>
<td>DJI Zenmuse XTR (336 × 256)</td>
<td>radiometric</td>
<td>~7000E (sensor only)</td>
<td>5</td>
<td>RMSE = 2.61°C</td>
<td>Dugdale et al. (2019)</td>
</tr>
<tr>
<td>SenseFly Duet T</td>
<td>radiometric</td>
<td>~20000E (UAV + sensor)</td>
<td>24</td>
<td>MAB = 0.81°C</td>
<td>Caldwell et al. (2019)</td>
</tr>
<tr>
<td>DJI Zenmuse XTR (640 × 512)</td>
<td>radiometric</td>
<td>~12000E (sensor only)</td>
<td>5 to 9</td>
<td>RMSE = 0.51°C</td>
<td>Collas et al. (2019)</td>
</tr>
<tr>
<td>FLIR Lepton 3.5 (120 × 160)</td>
<td>radiometric</td>
<td>NA</td>
<td>7</td>
<td>MAB = 2.18°C</td>
<td>Casas-Mulet et al. (2020)</td>
</tr>
<tr>
<td>FLIR VuePRO (640 × 512)</td>
<td>non-radiometric</td>
<td>~5000E (sensor only)</td>
<td>4</td>
<td>R² = 0.97 regression</td>
<td>Abolt et al. (2018)</td>
</tr>
</tbody>
</table>
4.2. Ecological applications

Within freshwater habitats, spatial variation in water temperature of 2–3 °C can lead to significant variation in assemblage composition (Levene et al., 2011; Collas et al., 2019); further, the performance of ectotherms is strictly shaped by temperatures with a complex functional relation (e.g., Sinclair et al., 2016; Ashaf-Ud-Doulah et al., 2020; Kärcher et al., 2021). Thus, exceeding defined water temperature thresholds may lead to increasing thermal stress and reduced performance. However, assessments of the ecological effect of the presence of thermal patches that exceed the breath of thermal performance (Sinclair et al., 2016) or get close to the species thermal limits will be undermined by high bias or RMSE in temperature estimates. The use of uncorrected temperatures, even when obtained from more expensive and sophisticated sensors, can lead to MAB up to 4°C and RMSE > 2°C (Table 4) and so undermine conclusions about thermal suitability and the availability of thermal refugia. Our workflow resulted in reliable estimates of temperature in the two study rivers, and hence provides a firm basis for drawing conclusions about the ecological effects of thermal conditions.

5. Conclusions

Our method provides a reliable assessment of water temperature from low-cost thermal sensors and provides a user friendly processing pipeline for R that can be easily modified for other ecological applications. The method is based on laboratory-produced calibration equations. These RC equations are applied to field data to estimate water temperature, following a correction procedure based on in situ measurements. The method includes a step that allows wetted and non-wetted areas to be separated. In addition, the method is based on simple and light equipment (we used a compact UAVs platform, DJI M2ED and 27 loggers), allowing its application in remote areas with difficult access (i.e., only by foot). The work described in this paper shows that accurate temperature information can be generated from inexpensive non-radiometric sensors. Such information is important for research, as well as for monitoring, conservation and supporting water management decisions.

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Ethics

I testify on behalf of all co-authors that our article submitted to Remote Sensing Applications, Society and Environment: An Open-Source Method for Producing Reliable Water Temperature Maps for Ecological Applications using non-Radiometric Sensors.

1) this material has not been published in whole or in part elsewhere;
2) all ethical practices have been followed in relation to the development, writing, and publication of the article.

CRediT authorship contribution statement

Matteo Redana: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Lesley T. Lancaster: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Formal analysis, Conceptualization. Xin Yi Chong: Writing – review & editing, Investigation, Formal analysis, Data curation. Yih Yoong Lip: Writing – review & editing, Methodology, Investigation, Data curation. Chris Gibbins: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization.

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.

Data availability

Data and code are available at the link in the text

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2024.101184.