

Radiometric consistency in UAV thermal photogrammetry for Earth-science surveys: preview artefacts and cross-domain photogrammetric benchmarks

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Abstract

High-resolution Unmanned Aerial Vehicle (UAV) thermal imaging requires preprocessing of the preview radiometric Joint Photographic Experts Group (R-JPEG) images before orthomosaics and 3D models can be produced, to acquire surface temperature values without loss and enable numerical analysis. In this study, these preprocessing steps are carried out within a single graphical user interface (GUI). This GUI is an open-source PyQt5 application that batch-converts R-JPEG frames into per-pixel float32 GeoTIFF tiles while copying EXIF and GPS tags. Processing uses the DJI Thermal SDK, ImageJ, and ExifTool; version 2.0.0 is archived on Zenodo. The Bridge (811 frames), solar-farm (1133 frames), and Kula Volcano (668 frames) missions were each reconstructed twice in Agisoft Metashape using identical settings. Float32 import increased tie-point counts and cut reprojection error by up to 29.4% (Area 1), 22.7% (Area 2), and 13.7% (Area 3). Dense model size moved in opposite directions between sites (+ 9.2% bridge, - 8.6% solar farm, + 6.9% Kula). A three-site audit of 2488 matched frame pairs linked preview import to frame-wise contrast rescaling; float32 arrays retained a common temperature axis within each flight block. Absolute temperature verification was beyond the scope of this study.

1. Introduction

Thermal infrared (TIR) sensors mounted on Unmanned Aerial Vehicles (UAVs) have become a widely used tool for image acquisition across a wide range of disciplines. They are used in land surface temperature mapping, vegetation stress and classification, and landslide characterization studies (Ahmad and Eisma 2023; Berni et al. 2009; Frodella et al. 2017; Lee et al. 2023; McCafferty et al. 2021). Their use for examining structural health in infrastructure systems, such as bridges and dams, is common (Bherde et al. 2025; Chand et al. 2026). Energy operators rely on them to monitor photovoltaic facilities (Akay et al. 2024). In archaeological studies, they are also used to image subsurface features (Brooke 2018; Waagen et al. 2022). In agricultural engineering, applications include agricultural surface-temperature monitoring and weed detection (Awais et al. 2022; Xu et al. 2023). Other applications include microclimate mapping at the local scale (Kotchi et al. 2016) and early detection of water stress in forest cover (Krause and Sanders 2023).

A common problem across all disciplines that use thermal imaging is a technical limitation. DJI thermal cameras store radiometric information inside the original R-JPEG file, encoded in the metadata and a proprietary data segment, rather than in the 8-bit preview image that the user sees when opening the file. This preview is created purely for visual inspection; the actual temperature-related content is located elsewhere in the file.

This becomes a problem when image processing is carried out using the R-JPEG version in photogrammetric software. The structure-from-motion (SfM) method is designed around conventional red-green-blue (RGB) images and, by default, reads the visible preview channel rather than the underlying radiometric layer. Many studies have pointed to the practical difficulties this creates more broadly for UAV thermal data, including sensor drift, atmospheric interference, and, in general, the lack of standardized processing routines (Maes et al. 2017; Kelly et al. 2019; Elfarkh et al. 2023).

Various software and methods have been developed to address this problem. For example, IRimage-UAV extends the ImageJ-based IRimage tool to process DJI thermal frames (Pereyra Irujo 2022), and other open-source workflows have built their own extraction routines around the DJI Thermal SDK (Messmer and Groos 2024). DJI has released a desktop Thermal Analysis Tool, and several third-party utilities also offer batch radiometric conversion. However, none of these provide a single environment that jointly handles batch conversion, metadata transfer, and photogrammetry-oriented quality control. Each covers only part of the workflow; the field team generally has to assemble the rest manually.

For applied geoscience studies in particular, this gap is more important than it might first appear. UAV thermal surveys increasingly contribute to structural and regional monitoring; examples include monitoring thermal anomalies on bridges and dams, mapping surface-rupture patterns following seismic events (Karakaş et al. 2025), examining geothermal systems, and characterizing landslide surface movements. In each of these settings, the value of the survey depends on whether the exported data still retains a physically meaningful temperature scale upon reaching the mapping stage. A

workflow that quietly discards this information at the preview stage undermines the very quantitative, reproducible output that geoscience monitoring requires.

Here we present Thermal-Pipeline, an open-source PyQt5 application built to close this gap. It extracts the radiometric layer from R-JPEG files and writes per-pixel float32 Tagged Image File Format (TIFF) output, carrying over the EXIF and GPS metadata needed for georeferencing. Batch processing is built in, so an entire flight can be converted in one pass rather than frame by frame. The software itself is not where the scientific contribution of this study lies, though; it is the means by which we investigate a separate question – whether the representation chosen for a thermal image (its native radiometric values versus a visualization-oriented 8-bit rendering) measurably affects how well that information is preserved in a photogrammetric reconstruction. We address this by comparing Metashape reconstruction statistics for 8-bit and float32 inputs across three campaigns – a bridge structure, a solar farm, and the Kula Volcano geothermal field (Akay et al. 2024; Hernández-López et al. 2023; Memduhoğlu and Polat 2025; Özcan et al. 2026; Zefri et al. 2018) – and by conducting a three-domain, pixel-level consistency assessment on 2,488 matched frame pairs to examine why float32 import improves multi-view correspondence.

2. Materials and Methods

Land surface temperatures can be mapped at high resolution using thermal images captured by UAVs. Detecting differences in surface temperature, analyzing temperature changes in time-series studies, and producing reliable statistical results all depend on preserving key values such as temperature and location without loss. For this reason, a thermal preprocessing step is applied before thermal images are processed in photogrammetry software to generate mapping products. In this study, 811 images of a bridge structure, 1,133 images of a solar power plant, and 668 images of Kula Volcano were acquired during flights using a thermal camera mounted on a UAV. Following the field surveys, the raw images in R-JPEG format were used to perform the standard photogrammetric processing steps, including image alignment, point cloud generation, DEM generation, and, as the final step, orthomosaic generation. The orthomosaics generated from the raw images were RGB orthomosaics based on the preview channel. The raw R-JPEG images were converted to TIFF format using the developed GUI, and the same processing steps were applied to generate orthomosaics with radiometric temperature values. The two different types of orthomosaics generated were analyzed, and the results were reported.

In this study, a GUI was developed that converts these thermal preprocessing steps into a standardized workflow. The GUI has standardized and automated the preprocessing workflow. As a result, large datasets can be converted quickly and easily, with minimal user intervention. To determine the extent to which orthomosaics produced from the converted images improve upon those generated from raw images, the resulting photogrammetric outputs were analyzed. The improvements obtained at the final output stage are presented. Image conversion performed through the GUI not only enables quantitative analysis but also substantially improves the orthomosaic generation stage. ExifTool, ImageJ, and the DJI Thermal SDK software were used during the image conversion process. Orthomosaics were generated from the raw and converted images using the standard processing steps in Agisoft Metashape.

In every photograph taken with a thermal camera mounted on a UAV, two distinct information packages are stored in a single file. The first is a colored image in which each pixel has a “color code” between 0 and 255. However, this color code is not an actual temperature value but only a visual representation. The other information is the raw measurement data from the camera sensor, embedded in the file. The purpose of the GUI is to extract this measurement data at the end of the five-step process and convert it into a new file where each pixel contains its actual temperature in degrees Celsius.

The user only indicates to the GUI which folder contains the raw photographs. Then the DJI Thermal SDK program runs and reads the hidden raw data in each photograph. In this way, a dataset containing temperature values at the given coordinates is obtained. To convert the obtained raw numerical matrix into a format that can be read directly by software,

the macro file prepared in ImageJ is executed. Thus, the raw matrix is converted into a standard TIFF file format that preserves the temperature values without loss and can be processed directly by photogrammetry software. Here, the term “Float32” indicates how precisely the temperature value of each pixel is stored (in decimal places)—rather than “8-bit” (color codes between 0 and 255), it is a format that stores actual decimal temperature values precisely. After this stage, ExifTool is used to automatically transfer the GPS coordinates and date/time information to the TIFF file, ensuring the images are placed in their correct locations on the map during processing.

At the end of these processing steps, high-resolution thermal orthomosaics are produced. With centimeter-scale spatial resolution, this enables more detailed mapping of many geological and environmental features, such as small surface cracks, fractures and discontinuities, differences in rock types, active mass movements, deformation and drainage changes on slopes, geothermal anomalies, differences in surface moisture, and structural damage.

2.1. Software Architecture

The workflow comprises five sequential GUI steps (Fig. 1): (1) project folder and external tool paths; (2) batch radiometric RAW extraction via `dji_irp.exe -a measure --measurefmt float32`; (3) headless ImageJ macro conversion of RAW arrays to float32 TIFF; (4) EXIF/GPS tag transfer from source R-JPEG files with ExifTool; (5) export of a flight-level CSV report with per-image statistics. Figure 2 summarizes data flow and dependencies. The application is implemented in Python 3.10 + with PyQt5 and packaged for Windows using PyInstaller.

2.2. Radiometric Conversion

Radiometric extraction follows DJI Thermal SDK documentation (DJI Technology 2023). For each R-JPEG frame, `dji_irp` outputs a float32 RAW matrix representing per-pixel radiometric values exported by the SDK measure mode. An ImageJ macro (`ysf.ijm`), consistent with community thermal-image tools (Schneider et al. 2012; Tattersall 2019), writes uncompressed float32 TIFF files to a converted/ subdirectory. ExifTool copies all tags from the source R-JPEG to the corresponding TIFF so that photogrammetry software can access GPS and timestamp metadata (Harvey 2025). This sequence preserves bit depth relative to the default 8-bit thermal preview import; no additional atmospheric correction or emissivity-based inversion was applied after the SDK export. Comparable manufacturer-format-to-float32 conversion steps have been reported for Zenmuse H20T missions in open post-processing workflows (Szostak et al. 2023).

2.3. Study Areas and Photogrammetric Processing

Three UAV thermal acquisition blocks were used for pixel-level radiometric consistency analysis, yielding 2488 quality control (QC)-validated matched R-JPEG/float32 TIFF frame pairs: Area 1 (bridge, $n = 700$), Area 2 (solar farm, $n = 1133$, 1120 after QC), and Area 3 (Kula Volcano geothermal field, $n = 668$). Photogrammetric benchmarks in Table 1 cover all three areas (811, 1133, and 668 frames, respectively). The Area 1 photogrammetry set (811 frames) is the full alignment project reported in prior bridge work (Özcan et al. 2026); the smaller consistency subset (700 frames) includes only R-JPEG/TIFF pairs that could be matched by filename in the archived thermal export, as 111 frames lacked a corresponding converted TIFF. Area 2 frame counts match between the photogrammetry and consistency analyses, except for 13 frames excluded due to an implausibly wide scene dynamic range ($> 150^{\circ}\text{C}$), consistent with sensor saturation. Areas 1–3 were each processed twice in Agisoft Metashape Professional v2.1.0 (Agisoft 2024) with identical alignment parameters: once with default 8-bit thermal import and once with float32 TIFF products from the proposed pipeline. Reported photogrammetric metrics include aligned cameras, tie points, reprojection error, ground sampling distance, and dense point counts.

2.4. External Dependencies and Reproducibility

The operation requires the locally installed DJI SDK, ImageJ, and ExifTool binaries to be unpacked alongside the raw image folder (Gedik and Özcan 2026). Completing the five GUI stages writes float32 TIFF products and a flight-level CSV

report into the converted subdirectory.

2.5. Radiometric Consistency Analysis

The thermal datasets collected during the field campaigns were processed through the GUI to generate Float32 TIFF representations from the original thermal JPEG files. Rather than evaluating the converted products only at the file level, we performed a paired comparison between each original frame and its corresponding Float32 representation. The comparison was designed to examine both the numerical representation of temperature and the preservation of spatial thermal patterns. For each frame, we recorded the observed temperature range (°C) together with the number of distinct temperature values. To examine the effect of reducing the radiometric representation to 8-bit precision, we additionally generated a simulated 8-bit version of the Float32 data and evaluated the resulting deviation using mean absolute error (MAE) and root mean square error (RMSE). Structural similarity (SSIM), calculated after min–max normalization, was used to characterize the preservation of spatial patterns, whereas Spearman's rank correlation was used to assess whether the relative ordering of temperature values was maintained between the representations. In addition to these frame-level measures, we evaluated the temporal consistency of thermal contrast at the acquisition-block scale. Specifically, the spatial temperature contrast was calculated for each frame, and its standard deviation was then computed across all frames within the same acquisition block. This approach allowed stability to be assessed without treating consecutive, highly overlapping UAV frames as statistically independent observations. Gradient-derived keypoint counts were also recorded as an auxiliary indicator of image texture. They were not used as the primary test of radiometric fidelity because preview images can sharpen local contrast through display stretching without adding actual temperature detail.

Paired preview–float32 differences were first checked with the Wilcoxon signed-rank test. Because consecutive UAV frames overlap heavily, the pairs are not fully independent. We therefore treated p-values with caution and did not base the main conclusions on them. The analysis instead focused on effect size: temperature-level ratios, simulated quantization error, and inter-frame thermal-stability ratios. All metrics describe how consistently the two representations agree, not absolute temperature accuracy. No independent field reference was available for the three sites. Float32 output is therefore taken as the native SDK radiometric product, not as externally validated ground truth.

To validate the simulated stability ratio against the camera's actual rendering, the embedded preview channel was extracted directly from each source R-JPEG file (the file's native visible-image data, which already contains DJI's proprietary tone-mapping) and converted to grayscale; frames were matched to their corresponding float32 TIFF by filename stem.

3. Results

3.1. Photogrammetric Reconstruction

Table 1 presents the photogrammetric reconstruction results for all three study areas. In Area 1 (bridge), the float32 TIFF images aligned 810 of 811 cameras, whereas the 8-bit images aligned 779 of 811. The number of tie points increased by 29.7%, and the reprojection error decreased from 0.547 to 0.386 px (29.4%). In Area 2 (solar farm), all 1,133 cameras were aligned using the float32 images, compared with 1,131 cameras for the 8-bit dataset. The number of tie points increased by 91.7%, while the reprojection error decreased from 0.545 to 0.421 px (22.7%). In Area 3 (Kula Volcano), float32 input aligned 664 of 668 cameras (vs. 663/668 for 8-bit), increased tie points by 12.0% (394,056 to 441,342), and reduced reprojection error from 0.408 to 0.352 pixels (– 13.7%). Ground sampling distance changed by less than 3% between input formats in Areas 1 and 2; Area 3 remained at 23.1 cm/px in both runs.

Figures 3–5 compare thermal orthomosaics for Areas 1–3 (float32 TIFF vs. default 8-bit R-JPEG preview import). The dense thermal model generated from the float32 images and 8-bit R-JPEG import for Area 1 is shown in Fig. 6. Dense point totals responded differently to the input format. Area 1 gained 9.2% dense points under the same Metashape

settings. Area 3 showed a 6.9% increase (18.3 to 19.5 million points). In Area 2, dense points decreased from 37.7 to 34.4 million (– 8.6%) despite improved alignment and tie-point counts. This decrease does not, by itself, indicate reduced image quality, because dense-point counts are influenced by the subsequent reconstruction process and do not directly quantify the radiometric or geometric quality of the input images.

Following the image conversion, the surface temperature and location data embedded within each image were transferred to the converted images. In this way, they became ready for processing in photogrammetry software. The thermal orthomosaics and 3D thermal surface models produced from these images not only preserve the image metadata but also enable model production with significantly higher geometric reconstruction quality than models produced from raw R-JPEG images (Table 1).

Table 1
Photogrammetric reconstruction metrics for 8-bit R-JPEG and float32 TIFF inputs

Study area	Input format	Aligned cameras	Tie points	Reprojection error (px)	Ground resolution (cm/px)	Dense cloud points
Bridge (Area 1)	R-JPEG 8-bit	779/811	189,284	0.547	4.45	9,683,149
	float32 TIFF	810/811	245,600	0.386	4.46	10,578,640
Solar farm (Area 2)	R-JPEG 8-bit	1131/1133	264,490	0.545	4.77	37,681,737
	float32 TIFF	1133/1133	506,970	0.421	4.65	34,432,282
Kula Volcano (Area 3)	R-JPEG 8-bit	663/668	394,056	0.408	23.1	18,255,964
	float32 TIFF	664/668	441,342	0.352	23.1	19,513,891

3.2. Large-Scale Radiometric Consistency

Table 2 and Fig. 7 summarize pixel statistics for Areas 1–3. After QC, Area 2 (solar farm; mean dynamic range 60.8°C) averaged 205 discrete temperature levels in float32 against 183 in the DJI preview (ratio 1.11). Area 1 (bridge) showed a modest gain: 232 versus 225 levels (ratio 1.02). Linear re-binning of float32 data into 256 levels introduced only 0.012–0.060°C MAE, indicating that 8-bit quantization is minor compared to the effect of preview histogram stretching.

Inter-frame contrast stability distinguished the two inputs. Preview σ exceeded float32 σ by 3.3× (Area 2), 14.7× (Area 1), and 18.9× (Area 3) (Fig. 7c). Mean SSIM on normalized frames reached 0.464, 0.891, and 0.723 for Areas 1, 2, and 3, respectively; Spearman r ranked identically (0.206, 0.940, 0.831). Area 3 (~ 12°C scene span) illustrates a display artifact: stretched previews yielded 145 gray levels versus 94 in float32 and inflated gradient keypoints, metrics that reflect rendering rather than physical temperature. Area 1 showed a relatively weak rank correspondence between the preview representation and the corresponding float32 temperature field (Spearman r = 0.206), reinforcing caution against default 8-bit thermal import in radiometric SfM. The results from the three study areas and the 2,488 quality-controlled image pairs show a consistent pattern. Within each flight block, the Float32 data maintain a common temperature scale, whereas the preview channel applies scene-dependent contrast adjustments from one frame to another. The direct effect of reduced bit depth appears relatively limited; the larger source of variation is the contrast stretching applied to the preview images. Therefore, the default thermal preview should be used with caution when used as input for radiometric SfM.

Table 2
Cross-domain radiometric consistency metrics

Study area	Domain	N (Frame count)	Dynamic range (°C)	Float unique levels	Preview unique levels	Level ratio	Quant MAE (°C)	Stability ratio	SSIM	Spearman r
Area 1	Bridge	700	25.1 ± 7.4	232 ± 66	225 ± 33	1.02×	0.025	14.7×	0.464	0.206
Area 2	Solar PV	1120	60.8 ± 15.5	205 ± 47	183 ± 31	1.11×	0.060	3.3×	0.891	0.940
Area 3	Geothermal	668	11.7 ± 4.1	94 ± 53	145 ± 67	0.64×	0.012	18.9×	0.723	0.831

4. Discussion

High-resolution thermal orthomosaics enable the spatial identification of small differences in surface temperature. Thermal imaging plays an important role in the analysis and mapping of changes in features detectable by a thermal camera, such as surface ruptures, crack and discontinuity networks, mass movements and slope dynamics, structural damage and voids, evaporative cooling, and surface emissivity (Karakaş et al. 2025). The raw UAV thermal images are intended for visualization purposes; therefore, their use in UAV photogrammetry without conversion is not recommended (Maes et al. 2017). The results of this study support this recommendation. Compared with the raw images, the converted float32 images produced lower reprojection errors (Table 1) in all three benchmarks, including the low-contrast geothermal block (Area 3: 0.408 → 0.352 px). The contrast of the raw images changes independently from one frame to the next. The radiometric analysis performed in this study showed that this causes large variations in the spatial temperature standard deviation (σ) (Table 2). The float32 images maintained a consistent temperature scale across all datasets. Similar observations have also been reported in previous studies on uncooled UAV thermal imaging and radiometric processing (Elfarkh et al. 2023; Kelly et al. 2019). The three study areas examined in this study represent different disciplines. These areas represent structural engineering through bridge imaging (Memduhoğlu and Polat 2025; Özcan et al. 2026), the energy sector through solar power plant imaging (Akay et al. 2024; Hernández-López et al. 2023; Zefri et al. 2018), and the geosciences through volcanic geothermal imaging. Although the surface characteristics differ, all three datasets showed the same general trend: preserving radiometric values in the input images resulted in more consistent image matching than using contrast-enhanced preview images. Two independent lines of evidence support this interpretation. First, controlled linear re-quantization of the float32 data to 8 bits introduced only 0.012–0.060°C MAE (Spearman $r \approx 1.00$), confirming that bit-depth reduction alone cannot account for the observed reprojection differences. Second, direct comparison against the actual embedded DJI preview channel reproduced the manuscript's stability ratios almost exactly (14.73×, 3.27×, and 18.92× for the bridge, solar, and Kula sites, respectively, versus 14.7×, 3.3×, and 18.9× reported in Table 2), confirming that the reported instability reflects the camera's native preview rendering rather than a simulation artifact. Together, these results indicate that the degradation in photogrammetric performance stems not from the 8-bit representation itself, but from the DJI SDK's uncontrolled, scene-dependent preview tone mapping.

IRimage-UAV (Pereyra Irujo 2022) supports batch conversion of DJI frames in ImageJ. Here, the same steps run in one Windows GUI with EXIF carry-over and a flight CSV; we additionally report 8-bit versus float32 reconstruction metrics, which comparable open tools omit. Pereyra Irujo (2022) validated IRimage against manufacturer-reported temperatures for FLIR cameras, finding a mean deviation of 0.0002°C — but this comparison has not, to our knowledge, been extended to the DJI ecosystem. Our study asks a different question: not whether the extracted temperatures are absolutely accurate, but how the choice of representation (float32 vs. 8-bit preview) affects downstream photogrammetric reconstruction. For this, we benchmarked 2,488 matched frame pairs across three sites.

The results should be interpreted with several limitations in mind. Ground reference temperature measurements were not available, so the absolute temperature accuracy depends on the DJI SDK calibration and the emissivity assumptions used during image conversion (Dash et al. 2002; Elfarkh et al. 2023; Kelly et al. 2019; Song and Park 2020). The thermal camera used in this study is an uncooled sensor, which may be affected by vignetting and temperature drift during flight (Elfarkh et al. 2023; Lee and Lee 2022; O'Sullivan and Kurylyk 2022; Yuan and Hua 2022). In addition, no external shutter-based calibration system was used (Virtue et al. 2021). Because consecutive UAV images overlap substantially, the Wilcoxon signed-rank test was used only as a descriptive statistic, while interpretation primarily relied on effect-size measures such as temperature-level ratios and MAE. Finally, gradient-based keypoint counts can increase in contrast-enhanced preview images and therefore should not be interpreted as direct indicators of photogrammetric reconstruction quality. The GUI CSV report aids QC but does not replace atmospheric correction.

Particularly in the field of Earth sciences, processing thermal data can create a significant workload in studies where the number of patterns examined increases for large-scale study areas. Therefore, researchers often use proprietary software that is not open to use or reproduction by other researchers and lacks reproducibility. The use of these software tools often causes the temperature data to not represent the actual thermal measurement. The use of such visualization-oriented data products in analyses can make the obtained temperature values susceptible to various errors and uncertainties. Without conversion, pixel values in the resulting orthomosaic remain RGB intensities with no physical meaning; the GUI developed in this study instead performs the necessary conversion and preprocessing steps to produce pixel values that directly represent surface temperature. It makes this process, which can be time-consuming and may require coding steps in standard procedures, as simple and fast as possible. Thus, users can complete the preprocessing process through the GUI without requiring any programming knowledge. The results from different study areas show that this approach is not limited to a single application and can provide a reproducible workflow for preparing thermal images for quantitative analyses. This suggests that the developed approach provides a basis for using high-resolution UAV thermal images as a standardized, reproducible preprocessing step for subsequent analyses.

5. Conclusions

We release Thermal-Pipeline, an open-source GUI that exports DJI R-JPEG thermal frames as float32 TIFF products with intact geospatial metadata for SfM workflows. Three-site Metashape benchmarks, combined with 2488 matched pairs from three domains, demonstrate improved alignment, denser tie networks, and lower reprojection error when float32 replaces 8-bit preview import, together with stable inter-frame radiometry. By requiring no programming expertise, the workflow lowers the barrier to field teams converting thermal imagery into a form suitable for quantitative analysis. The conversion is designed to retain the radiometric information in the original thermal data while avoiding additional loss during the conversion process. Thermal images acquired from the study areas can be converted to the Float32 format through five simple processing steps. Thus, the workload in the image processing can be reduced following intensive field surveys. Code, executables, and documentation are archived on Zenodo to support reproducible UAV thermal mapping.

Declarations

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Data availability The radiometric UAV thermal processing GUI is publicly available on Zenodo: <https://doi.org/10.5281/zenodo.21773898>.

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References

1. Agisoft LLC (2024) Agisoft Metashape Professional, Version 2.1.0. Agisoft LLC, St. Petersburg, Russia. Available at: <https://www.agisoft.com> (Accessed 20 August 2026)
2. Ahmad J, Eisma JA (2023) Capturing small-scale surface temperature variation across diverse urban land uses with a small unmanned aerial vehicle. *Remote Sens* 15:2042. <https://doi.org/10.3390/rs15082042>
3. Akay SS, Özcan O, Özcan O, Yetemen Ö (2024) Efficiency analysis of solar farms by UAV-based thermal monitoring. *Eng Sci Technol Int J* 53:101688. <https://doi.org/10.1016/j.jestch.2024.101688>
4. Awais M, Li W, Hussain S, Cheema MJM, Li W, Song R, Liu C (2022) Comparative evaluation of land surface temperature images from unmanned aerial vehicle and satellite observation for agricultural areas using in situ data. *Agriculture* 12:184. <https://doi.org/10.3390/agriculture12020184>
5. Berni JAJ, Zarco-Tejada PJ, Suárez L, Fereres E (2009) Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. *IEEE Trans Geosci Remote Sens* 47:722–738. <https://doi.org/10.1109/TGRS.2008.2010457>
6. Bherde V, Balunaini U, Kambhammettu BVN, Regonda S (2025) Infrared thermography based seepage and erosion detection in earthen dams using laboratory scale models. *Sci Rep* 15:23226. <https://doi.org/10.1038/s41598-025-99368-z>
7. Brooke C (2018) Thermal imaging for the archaeological investigation of historic buildings. *Remote Sens* 10:1401. <https://doi.org/10.3390/rs10091401>
8. Chand B, Ayele F, Pineiro-Dakers I, Samsami R, Chang B (2026) Uncrewed aerial system (UAS) applications in bridge inspection: a comprehensive review of platforms, sensors, and operational effectiveness. *Drones* 10:144. <https://doi.org/10.3390/drones10020144>
9. Dash P, Göttsche F-M, Olesen F-S, Fischer H (2002) Land surface temperature and emissivity estimation from passive sensor data: theory and practice—current trends. *Int J Remote Sens* 23:2563–2594. <https://doi.org/10.1080/01431160110115041>
10. DJI Technology Co., Ltd (2023) DJI Thermal SDK Documentation. DJI Technology Co., Ltd., Shenzhen, China. Available at: <https://www.dji.com/global/downloads/software/dji-thermal-sdk> (Accessed 24 August 2025)
11. Elfarkh J, Johansen K, Angulo V, Camargo OL, McCabe MF (2023) Quantifying within-flight variation in land surface temperature from a UAV-based thermal infrared camera. *Drones* 7:617. <https://doi.org/10.3390/drones7100617>
12. Frodella W, Gigli G, Morelli S, Lombardi L, Casagli N (2017) Landslide mapping and characterization through infrared thermography (IRT): suggestions for a methodological approach from some case studies. *Remote Sens* 9:1281. <https://doi.org/10.3390/rs9121281>
13. Gedik Y, Ozcan O (2026) Thermal-Pipeline [Computer software]. Zenodo. <https://doi.org/10.5281/zenodo.22207706>
14. Harvey P (2025) ExifTool, Version 12.80. Available at: <https://exiftool.org> (Accessed 10 March 2025)
15. Hernández-López D, de Oña ER, Moreno MA, González-Aguilera D (2023) SunMap: towards unattended maintenance of photovoltaic plants using drone photogrammetry. *Drones* 7:129. <https://doi.org/10.3390/drones7020129>

16. Karakaş M, Yıldırım C, Özcan O, Akay SS, Gedik Y, Baka ÇM (2025) High-resolution thermal imaging of the surface rupture of the February 6 2023, Kahramanmaraş earthquake (Mw 7.8), Türkiye. In: Proceedings of the EGU General Assembly 2025, Vienna, Austria, 27 April–2 May 2025, Abstract EGU25-11894. <https://doi.org/10.5194/egusphere-egu25-11894>
17. Kelly J, Kljun N, Olsson P-O, Mihai L, Liljeblad B, Weslien P, Klemedtsson L, Eklundh L (2019) Challenges and best practices for deriving temperature data from an uncalibrated UAV thermal infrared camera. *Remote Sens* 11:567. <https://doi.org/10.3390/rs11050567>
18. Kotchi SO, Barrette N, Viau AA, Jang JD, Gond V, Mostafavi MA (2016) Estimation and uncertainty assessment of surface microclimate indicators at local scale using airborne infrared thermography and multispectral imagery. *Geospatial Technology—Environmental and Social Applications*. InTech, London, UK. <https://doi.org/10.5772/64527>.
19. Krause S, Sanders TGM (2023) Mapping tree water deficit with UAV thermal imaging and meteorological data. *Remote Sens Earth Syst Sci* 6:275–296. <https://doi.org/10.1007/s41976-023-00094-9>
20. Lee G, Kim G, Min G, Kim M, Jung S, Hwang J, Cho S (2023) Vegetation classification in urban areas by combining UAV-based NDVI and thermal infrared image. *Appl Sci* 13:515. <https://doi.org/10.3390/app13010515>
21. Lee K, Lee WH (2022) Temperature accuracy analysis by land cover according to the angle of the thermal infrared imaging camera for unmanned aerial vehicles. *ISPRS Int J Geo-Inf* 11:204. <https://doi.org/10.3390/ijgi11030204>
22. Maes WH, Huete AR, Steppe K (2017) Optimizing the processing of UAV-based thermal imagery. *Remote Sens* 9:476. <https://doi.org/10.3390/rs9050476>
23. McCafferty DJ, Koprowski R, Herborn K, Tattersall GJ, Jerem P, Nord A (2021) Editorial: advances in thermal imaging. *J Therm Biol* 102:103109. <https://doi.org/10.1016/j.jtherbio.2021.103109>
24. Memduhoğlu A, Polat N (2025) Assessing seasonal and diurnal thermal dynamics of water channel and highway bridges using unmanned aerial vehicle thermography. *Drones* 9:205. <https://doi.org/10.3390/drones9030205>
25. Messmer J, Groos AR (2024) A low-cost and open-source approach for supraglacial debris thickness mapping using UAV-based infrared thermography. *Cryosphere* 18:719–746. <https://doi.org/10.5194/tc-18-719-2024>
26. O'Sullivan AM, Kurylyk BL (2022) Limiting external absorptivity of UAV-based uncooled thermal infrared sensors increases water temperature measurement accuracy. *Remote Sens* 14:6356. <https://doi.org/10.3390/rs14246356>
27. Özcan O, Akay SS, Gedik Y, Erten E, Özcan O (2026) An integrated UAV and satellite remote sensing approach for monitoring thermal effects on bridge behavior. *Drones* 10:435. <https://doi.org/10.3390/drones10060435>
28. Pereyra Irujo G (2022) IRimage: open source software for processing images from infrared thermal cameras. *PeerJ Comput Sci* 8:e977. <https://doi.org/10.7717/peerj-cs.977>
29. Schneider CA, Rasband WS, Eliceiri KW (2012) NIH Image to ImageJ: 25 years of image analysis. *Nat Methods* 9:671–675. <https://doi.org/10.1038/nmeth.2089>
30. Song B, Park K (2020) Verification of accuracy of unmanned aerial vehicle (UAV) land surface temperature images using in-situ data. *Remote Sens* 12:288. <https://doi.org/10.3390/rs12020288>
31. Szostak R, Zimnoch M, Wachniew P, Jasek-Kamińska A (2023) Self-calibration of UAV thermal imagery using gradient descent algorithm. *Drones* 7:683. <https://doi.org/10.3390/drones7110683>
32. Tattersall GJ (2019) ThermlImageJ: thermal image functions and macros for ImageJ. <https://doi.org/10.5281/zenodo.2652896>. Zenodo
33. Virtue J, Turner D, Williams G, Zeliadt S, McCabe M, Lucieer A (2021) Thermal sensor calibration for unmanned aerial systems using an external heated shutter. *Drones* 5:119. <https://doi.org/10.3390/drones5040119>
34. Waagen J, Sánchez JG, van der Heiden M, Kuiters A, Lulof P (2022) In the heat of the night: comparative assessment of drone thermography at the archaeological sites of Acquarossa, Italy, and Siegerswoude, The Netherlands. *Drones* 6:165. <https://doi.org/10.3390/drones6070165>

35. Xu B, Meng R, Chen G, Liang L, Lv Z, Zhou L, Sun R, Zhao F, Yang W (2023) Improved weed mapping in corn fields by combining UAV-based spectral, textural, structural, and thermal measurements. Pest Manag Sci 79:2591–2602. <https://doi.org/10.1002/ps.7443>

36. Yuan W, Hua W (2022) A case study of vignetting nonuniformity in UAV-based uncooled thermal cameras. Drones 6:394. <https://doi.org/10.3390/drones6120394>

37. Zefri Y, ElKettani A, Sebari I, Ait Lamallam S (2018) Thermal infrared and visual inspection of photovoltaic installations by UAV photogrammetry—application case: Morocco. Drones 2:41. <https://doi.org/10.3390/drones2040041>

Figures

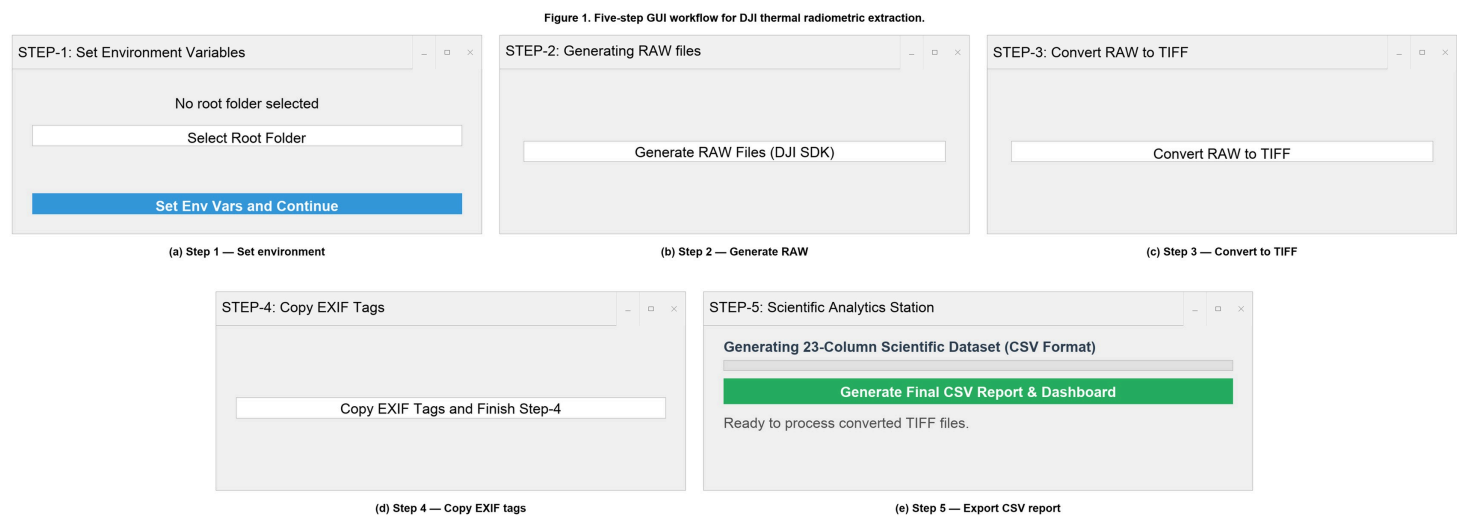


Figure 1

Five-step GUI workflow for DJI thermal radiometric extraction. (a) Environment configuration. (b) RAW generation with DJI Thermal SDK. (c) RAW-to-TIFF conversion. (d) EXIF/GPS metadata transfer. (e) Scientific flight report export.

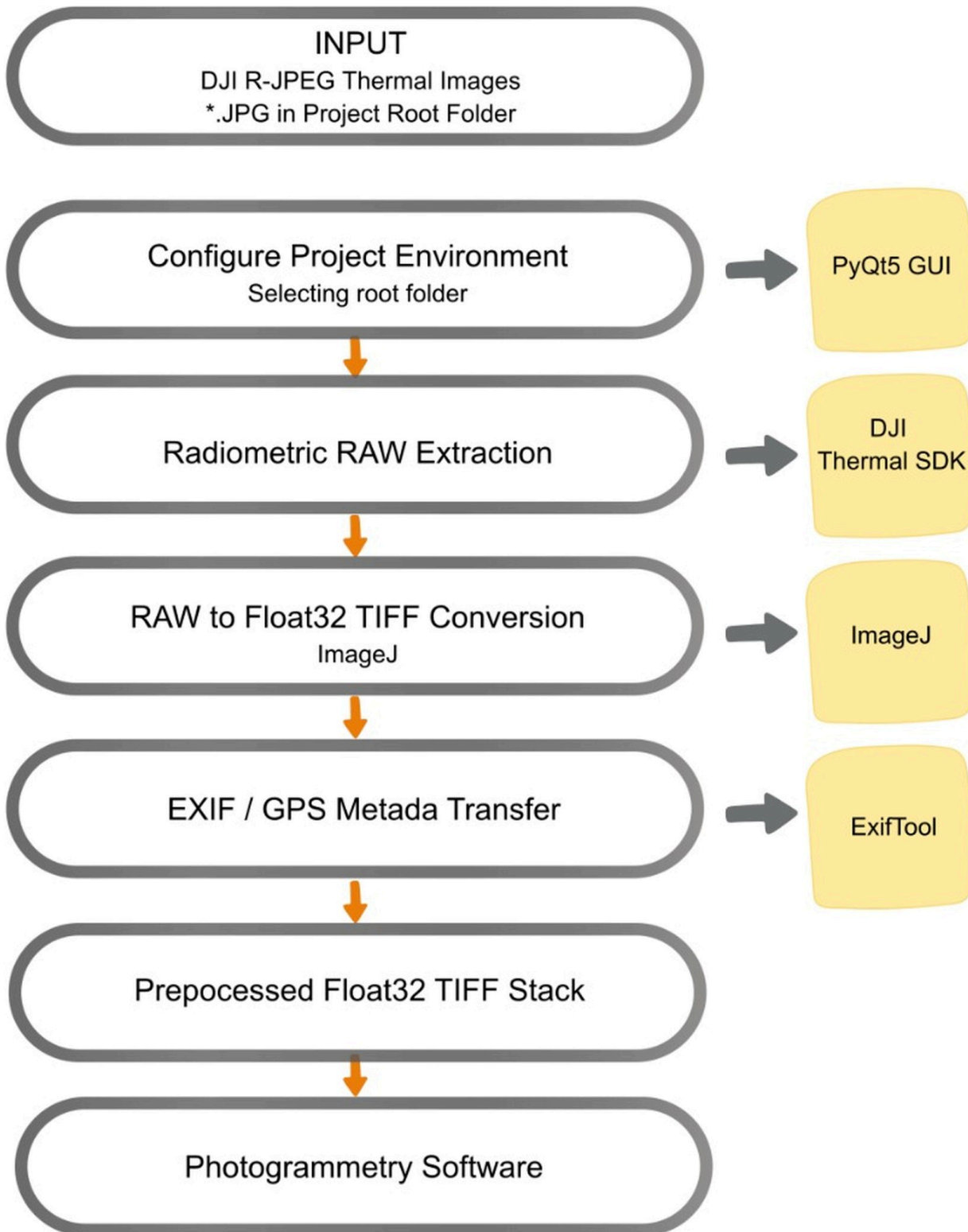


Figure 2

End-to-end radiometric extraction and photogrammetry-ready output workflow.

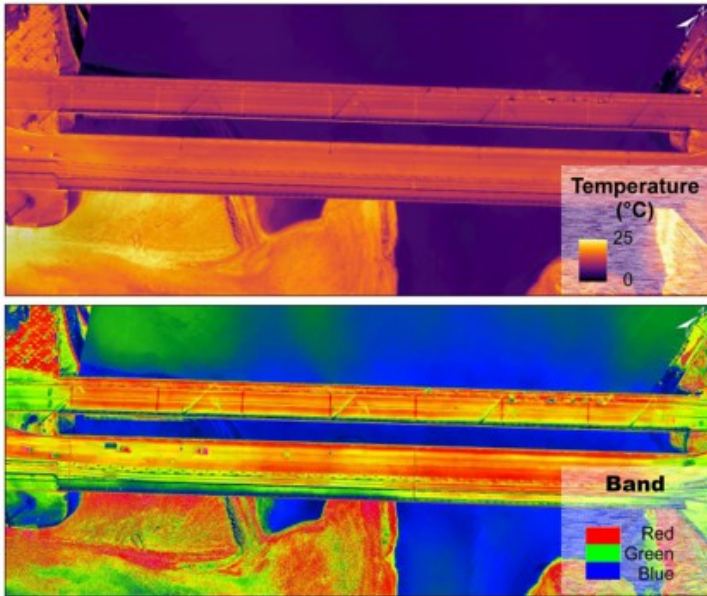


Figure 3

Thermal orthomosaic comparison for the bridge site (Area 1). Upper panel: Float32 TIFF workflow. Lower panel: Default 8-bit R-JPEG import (RGB preview).

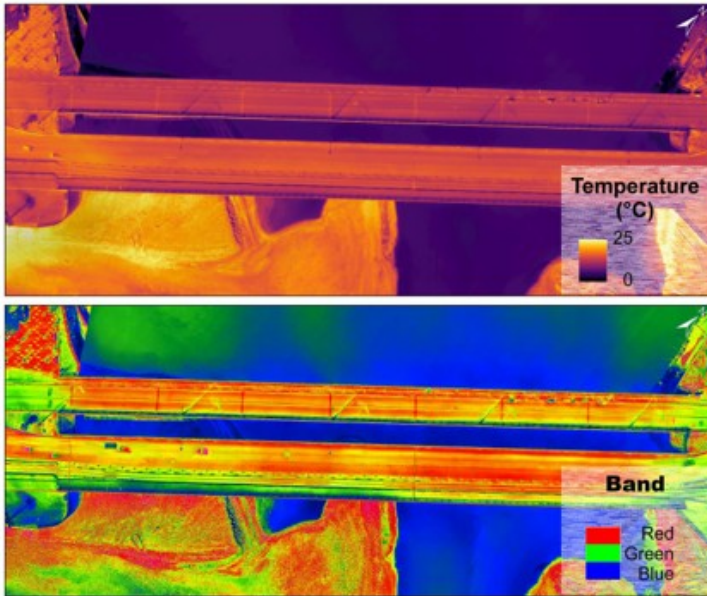


Figure 3

Thermal orthomosaic comparison for the bridge site (Area 1). Upper panel: Float32 TIFF workflow. Lower panel: Default 8-bit R-JPEG import (RGB preview).

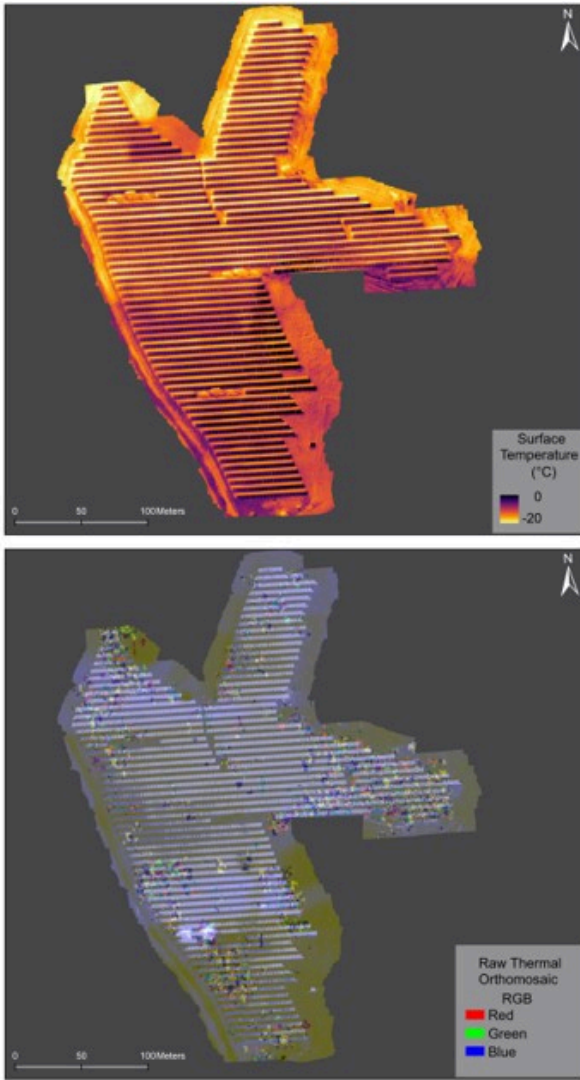


Figure 4

Thermal orthomosaic comparison for the solar farm site (Area 2). Upper panel: float32 TIFF workflow. Lower panel: default 8-bit R-JPEG import (RGB preview).

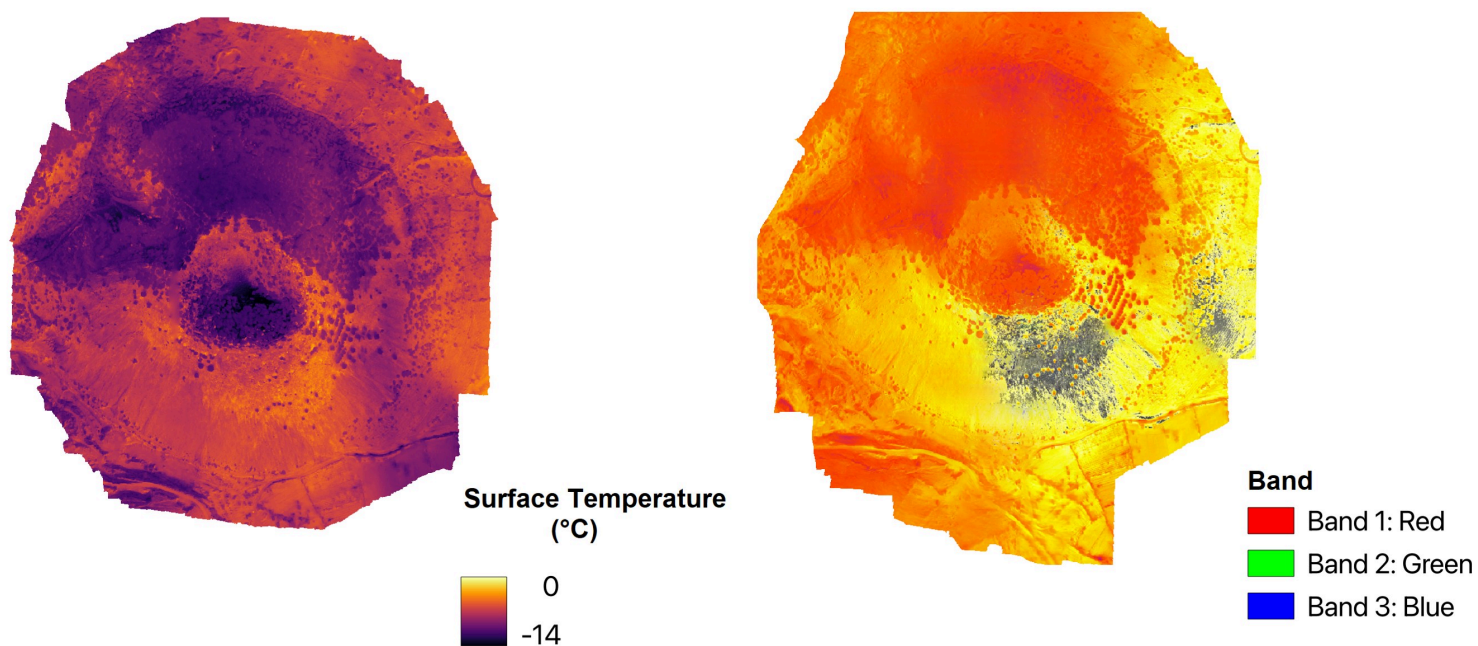


Figure 5

Thermal orthomosaic comparison for the Kula Volcano site (Area 3). Upper panel: Float32 TIFF workflow. Lower panel: default 8-bit R-JPEG import (RGB preview).

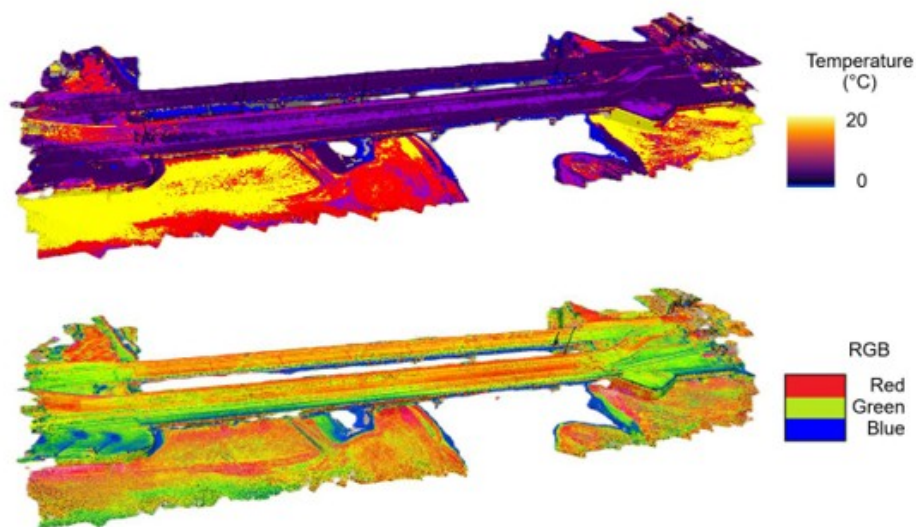


Figure 6

Dense 3D thermal model of the bridge site (Area 1). Upper panel: from float32 TIFF. Lower panel: 8-bit R-JPEG (RGB preview).

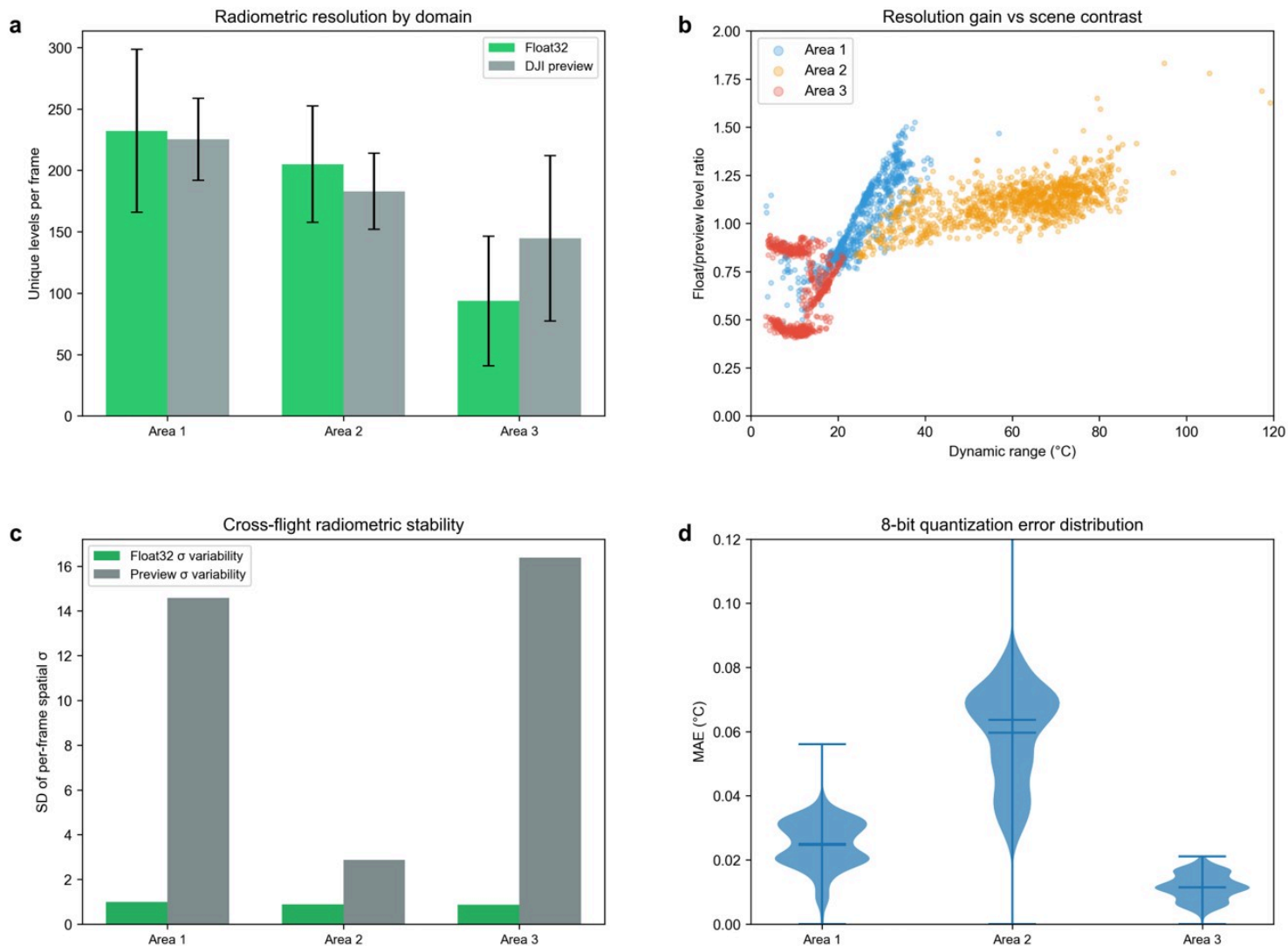


Figure 7

Cross-domain radiometric comparison after QC (n = 2,488). (a) Radiometric resolution by domain. (b) Resolution gain versus scene contrast. (c) Cross-flight contrast stability. (d) Simulated 8-bit quantization error.