

1 **ReflectDetect: A software tool for AprilTag-Guided In-Flight**

2 **Radiometric Calibration for UAV Optical Data**

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11 **Abstract**

12 Unmanned Aerial Vehicles (UAVs) equipped with optical sensors have trans-  
13 formed remote sensing in vegetation science by providing high-resolution, on-demand  
14 data, enhancing studies in forestry, agriculture, and environmental monitoring. How-  
15 ever, accurate radiometric calibration of UAV imagery remains challenging. A com-  
16 mon practice is using reflectance calibration targets to establish a mapping between  
17 sensor readings and reflectance values. Using a single calibration target while hold-  
18 ing the UAV-mounted camera close above it has been criticized as a large portion  
19 of the hemisphere is invisibly shaded.

20 ReflectDetect, the proposed open-source tool, addresses these challenges by al-  
21 lowing in-flight radiometric calibration through automated detection via two dif-  
22 ferent approaches. The first approach uses geotagging and leverages high-precision  
23 coordinates of the reflectance targets, the second is using AprilTag based detection,  
24 a visual fiducial system frequently used in robotics. These approaches allow setting  
25 up a reliable calibration system to account for varying environmental conditions,

26 reduce human error, and increase efficiency through a user-friendly command-line  
27 interface. ReflectDetect’s open-source nature enables users to easily design new cal-  
28 ibration studies and methods to eventually improve radiometric calibration in UAV  
29 remote sensing. ReflectDetect is available under the GNU General Public License  
30 v3.0 on GitHub: <https://github.com/reflectdetect/reflectdetect>.

31 **Keywords:** UAV, Radiometric calibration, Open-Source, Geotagging, AprilTags.

## 32 1. Introduction

33 UAVs have transformed remote sensing in vegetation science by offering centimeter-level  
34 spatial resolution, on-demand temporal flexibility, and multi-sensor integration that sur-  
35 pass close-range, airplane-based, and satellite-based methods (Aasen et al., 2018). UAVs  
36 equipped with optical sensors produce multi-band raster data, enabling relevant applica-  
37 tions in forestry, agriculture, and environmental studies, such as plant health monitoring,  
38 biomass estimation, and crop yield prediction, supporting sustainable management prac-  
39 tices (Maes and Steppe, 2019; Abdulridha et al., 2023; Yang et al., 2024). To effectively  
40 study these dynamic landscapes, consistent and comparable time-series data are essen-  
41 tial, which is achieved through accurate radiometric calibration. Calibration methods,  
42 such as the Empirical Line Method (ELM), convert digital sensor readings by the cam-  
43 era into meaningful reflectance values, thereby improving data accuracy compared to the  
44 commonly used single gray reference target method. Nevertheless, challenges remain.

45 While some studies report minimal differences in calibration accuracy under stable  
46 weather conditions, they highlight challenges posed by dynamic conditions, such as vari-  
47 able cloud cover and lighting, which are common during UAV flights (Daniels et al., 2023).  
48 Often the Simple Empirical Line Method (Simple ELM), using only a single reflectance  
49 target, is applied. The Simple ELM requires users to hold their drone, with the camera  
50 attached, close to the calibration target. If this is done without care, direct shading can  
51 occur and severely affect the calibration result. However, even when direct shading is  
52 avoided, the drone covers a large part of the hemisphere, blocking the diffuse and direct  
53 portions of light that the camera should fully perceive at that moment (Aasen et al., 2018).  
54 Further, to account for atmospheric and topographic variations, at least two reference

55 targets should be used to cover the desired range of reflectance values, typically 0–50%  
56 for vegetation (Aasen et al., 2018). Using more than two targets reduces uncertainties  
57 and helps assess sensor linearity, improving the accuracy of reflectance measurements. To  
58 avoid these problems for robust calibration, in-flight calibration is suggested (Eltner et al.,  
59 2022; Shin et al., 2020; Fawcett and Anderson, 2019; Cao et al., 2019; Chakhvashvili et al.,  
60 2021). The majority of methodologies developed for in-flight radiometric calibration are  
61 still predominantly manual or semi-automated (Daniels et al., 2023), despite the fact that  
62 manual and semi-automated methodologies are inherently time-consuming and suscepti-  
63 ble to error, thereby underscoring the necessity for the development of fully automated  
64 methodologies. Although approaches such as the one proposed by Ban and Kim (2021),  
65 using homogeneity and variance filtering for automated reflectance target detection and  
66 the ELM for calibration—are steps toward automation, they are still semi-automated and  
67 not open-source, limiting their broader adoption.

68 The main contribution of this work is to overcome the aforementioned limitations  
69 by proposing a fully automated software tool, that improves the usability of in-flight  
70 radiometric calibration in UAV-based remote sensing. It offers two modules to facilitate  
71 the detection of custom-built or commercially available reflectance targets. The first  
72 module harnesses the now frequently used and widely available professional-grade sub-  
73 centimeter accuracy RTK-GNSS receivers. By geotagging the calibration targets, the first  
74 module can detect the targets in georeferenced images. While this module integrates well  
75 in the later stages of the image processing pipeline when raw images have already been  
76 processed into georeferenced orthophotos, the second module allows for calibration directly  
77 using the raw images at the start of the pipeline. It uses AprilTags, a visual fiducial system  
78 that is frequently used in robotics, for target detection (Wang and Olson, 2016). AprilTags  
79 robustness against false positive detections makes them ideal for UAV applications such  
80 as visual localization (Wang and Olson, 2016), object tracking (Krogus et al., 2019),  
81 and in this case, calibration target detection. The possibility for a high frequency at  
82 which reflectance targets are seen in the collected imagery then allows accounting for the  
83 variability of light intensity during the flight. In between cases when targets are found  
84 in the imagery, interpolating the intensities ensures consistent calibration data across

85 varying conditions mid-flight. Packaged in a user-friendly, open-source Command-Line  
86 Interface (CLI), this solution simplifies the calibration process, reduces human error, and  
87 enhances efficiency.

## 88 2. System Architecture and Methods

89 ReflectDetect enables users to automatically detect reflectance targets within aerial im-  
90 agery and use the extracted intensities of these targets to calibrate the camera intensity  
91 readings. ReflectDetect does not evaluate the quality of reflectance targets and does not  
92 support the user in choosing the appropriate size or other properties of the reflectance  
93 targets. Therefore, some general knowledge about radiometric calibration is helpful when  
94 using this tool. The ReflectDetect workflow and functions, written in Python 3 (Van  
95 Rossum and Drake Jr, 1995), are outlined below. For a comprehensive overview of the  
96 implemented functions, the user can consult the documentation in the online repository<sup>1</sup>.  
97 Example datasets for each module (i.e. geolocation module and AprilTag module) are pro-  
98 vided for reproducible testing. In the example data, 1.4 x 1.4 m square-shaped reflectance  
99 targets at 3%, 21% and 56% have been used.

100 ReflectDetect uses one of its two modules to detect calibration targets in the imagery,  
101 then processes the extracted intensities of the calibration targets similarly for both mod-  
102 ules: First, interpolation is used to find approximate intensity values for images that do  
103 not contain targets, allowing ReflectDetect to use the ELM for each image separately.  
104 The calibrated reflectance images are then saved for further analysis.

### 105 2.1 The Geolocation Module

106 The geolocation module works on georeferenced orthophotos as band-stacked images and  
107 leverages user-provided precise geographic coordinates of the calibration targets. In test-  
108 ing, the photogrammetry software Metashape<sup>2</sup> was used to generate stacked and geo-  
109 referenced orthophotos. This module supports any polygonal target, provided that all  
110 corner coordinates are accurately measured and supplied. ReflectDetect begins with the

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<sup>1</sup><https://github.com/reflectdetect/reflectdetect>

<sup>2</sup>Agisoft LLC, St. Petersburg, Russia

111 identification of calibration targets within the orthophotos by examining the geotagged  
112 coordinates of each corner of the reflectance targets. This approach offers the advantage  
113 of allowing for calibration even when targets are only partially visible or when incomplete  
114 sets of targets are present.

115 By setting a no-data value (e.g., 0, 65535), irrelevant data is excluded during the  
116 extraction of the target intensity values, for example when a target is only partially  
117 visible. For each image with visible targets, the system extracts the mean intensity values  
118 for each spectral band at the target’s location. To save memory during execution, the  
119 dataset is split into batches of the minimal size that still allows for correct interpolation.

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**Algorithm 1** Geolocation Module: Input Validation

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```
1: procedure GEOLOCATION MODULE(args)
2:   Load dataset from args
3:   Validate orthophoto and dataset folders
4:   Validate target properties and geolocation files
5:   Validate the connection between target locations and properties
6: end procedure
```

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**Algorithm 2** Geolocation Module: Main Processing

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```
1: procedure START
2:   Load all orthophoto paths
3:   Detect targets visible in each photo
4:   Split photos into batches based on visibility
5:   for each batch in batches do
6:     Extract intensities from visible targets
7:     Interpolate intensities
8:     Fit model using the ELM method
9:     Convert orthophotos to reflectance using fitted model
10:    Save converted orthophotos
11:   end for
12: end procedure
```

---

## 120 2.2 The AprilTag Module

121 By deploying AprilTags containing unique IDs next to the calibration targets in the exper-  
122 imental scene, each target can be detected using its associated AprilTag. This allows for  
123 target detection and calibration without the need for preprocessing of images. A detec-  
124 tor<sup>3</sup> based on Wang and Olson (2016) scans each image for AprilTags and ReflectDetect

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<sup>3</sup><https://github.com/robotpy/mostrobotpy>

125 associates the detected tags with the calibration targets using the predefined mapping of  
126 IDs to targets. The tag is positioned adjacent and centered to the side of its associated  
127 target, making it possible to find the corners of the target using vector math based on the  
128 known dimensions of the tag and target. Because of this approach, targets are expected  
129 to be rectangular. Since each target is linked to a unique ID, they can be independently  
130 detected.

131 In the example data, the tag family "tag25h9"<sup>4</sup> is used. All tags were printed at A1  
132 size. These properties are based on some preliminary manual testing, as well as reported  
133 maximum detection ranges<sup>5</sup>. While detection errors were not a problem during testing,  
134 these properties should only be seen as a starting-off point for future research and were  
135 chosen with only the circumstances of this study in mind.

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**Algorithm 3** Apriltag Module: Input Validation

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```
1: procedure APRILTAG MODULE(args)
2:   Initialize EXIFTool
3:   Load dataset from args
4:   Validate dataset folder and images folder
5:   Validate target properties and tag size
6:   Load apriltag detector and configure tag family
7: end procedure
```

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**Algorithm 4** Apriltag Module: Main Processing

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```
1: procedure START
2:   Load all image paths
3:   Split images into batches based on number of bands
4:   for each batch in batches do
5:     Extract intensities from apriltag detection
6:     Interpolate intensities
7:     Fit model using the ELM method
8:     Convert images to reflectance using fitted model
9:     Save converted images
10:  end for
11: end procedure
```

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## 136 2.3 CLI Arguments for Intra-Processing Adjustments

137 As recapturing an already executed UAV mission is difficult and labor-intensive, Reflect-  
138 Detect provides a flexible CLI that allows users to adjust many key parameters to fine-tune

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<sup>4</sup><https://github.com/AprilRobotics/apriltag-imgs/tree/master/tag25h9>

<sup>5</sup><https://doc.rc-visard.com/latest/en/tagdetect.html>

139 the detection and calibration process.

140 During processing, the user is able to reduce the detected target area (default is to  
141 80%), focusing on the central region to avoid edge bleeding and improve the accuracy  
142 of mean Digital Number (DN) extraction. Multiple arguments specific to the AprilTag  
143 module allow for the correction of incorrectly placed tags, for example, changing the  
144 expected rotation of a tag or the expected distance between the tag and the target. To  
145 allow the user to ensure correct detection and calibration of the imagery, a debug mode is  
146 accessible. If the debug mode is enabled, information about the execution of the workflow  
147 is displayed and figures with detected targets and bounding boxes, as shown in Figure 1,  
148 are generated for review. Additionally, debug mode will display a graph of the temporal  
149 interpolation, as seen in Figure 2.

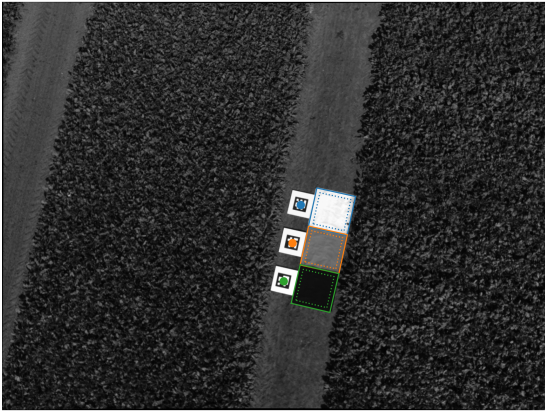


Figure 1: Three detected calibration targets with solid colored bounding boxes. Dotted lines show the areas where DNs were extracted. Colored dots indicate the positions of the corresponding AprilTags.

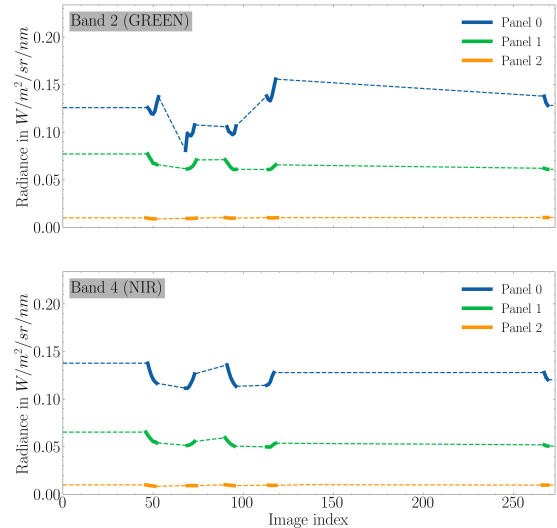


Figure 2: Extracted (solid lines) and interpolated (dotted lines) intensities for two spectral bands across a sequence of images. The lines show intensity changes for 3 different calibration targets during the whole flight.

### 150 3. Discussion

151 ReflectDetect is an automated dual-module system for radiometric calibration of UAV  
152 imagery, integrating geolocation and AprilTag detection of reflectance targets. The Geo-  
153 tagging Module uses geographic metadata embedded within orthophotos to detect cal-  
154 ibration targets and reliably extracts intensity data. However, this approach depends

155 on the accuracy of geotagged data, as errors in the geolocation can affect target detec-  
156 tion and calibration results. The AprilTag Module provides a robust alternative, as their  
157 detection rates have been thoroughly studied (Wang and Olson, 2016). Our reflectance  
158 calibrated spectral signatures have been compared against the classic ELM provided by  
159 e.g. for the Micasense camera series<sup>6</sup> and found to be of similar in shape but more robust  
160 (Figure 3). The variance across 100 spectra that have been obtained from the provided  
161 example data is highest after the Micasense ELM, most noticeable in the red edge and  
162 NIR band. This is line with the findings of other research (Cao et al., 2019; Fawcett  
163 and Anderson, 2019, Chakhvashvili et al., 2021) and emphasized the need for in-flight ra-  
164 diometric calibration that can account for topographic and illumination variability. The  
165 presented ReflectDetect software now enables other researchers, after printing their own  
166 set of AprilTags or providing the coordinates of their in-scene calibration targets, to test  
167 reflectance calibration in different settings and under different illumination dynamics.

### 168 3.1 Advantages of In-Flight Empirical Line Calibration

169 During testing, calibration targets were strategically placed to be captured multiple times  
170 during flights (see example data), to account for irradiance changes throughout the flight.  
171 When targets are obscured or missing, linear interpolation is used in between detection  
172 events to ensure consistent calibration over time (Figure 2). Variation in illumination  
173 intensities during data capture presents a key challenge. To ensure accurate radiometric  
174 calibration, linear interpolation is used to create a more uniform spectral dataset, im-  
175 proving the quality of subsequent image analysis. The example data shows that higher  
176 frequencies of detected reflectance targets reduce intervals between calibration events 2.  
177 Compared to ELM - and ground-based methods, the presented approach offers several ad-  
178 vantages, as mentioned by Aasen et al. (2018). It avoids the shading and blocking of the  
179 hemisphere over the reflectance targets that occurs when the UAV is held directly above  
180 the targets at low altitude. Additionally, it eliminates the need for a Downwelling Light  
181 Sensor (DLS)—an irradiance sensor mounted on top of the drone. DLSs can be prob-  
182 lematic because their angle and the radiation they receive change during flight (Aasen

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<sup>6</sup>AgEagle Aerial Systems Inc., Kansas, USA



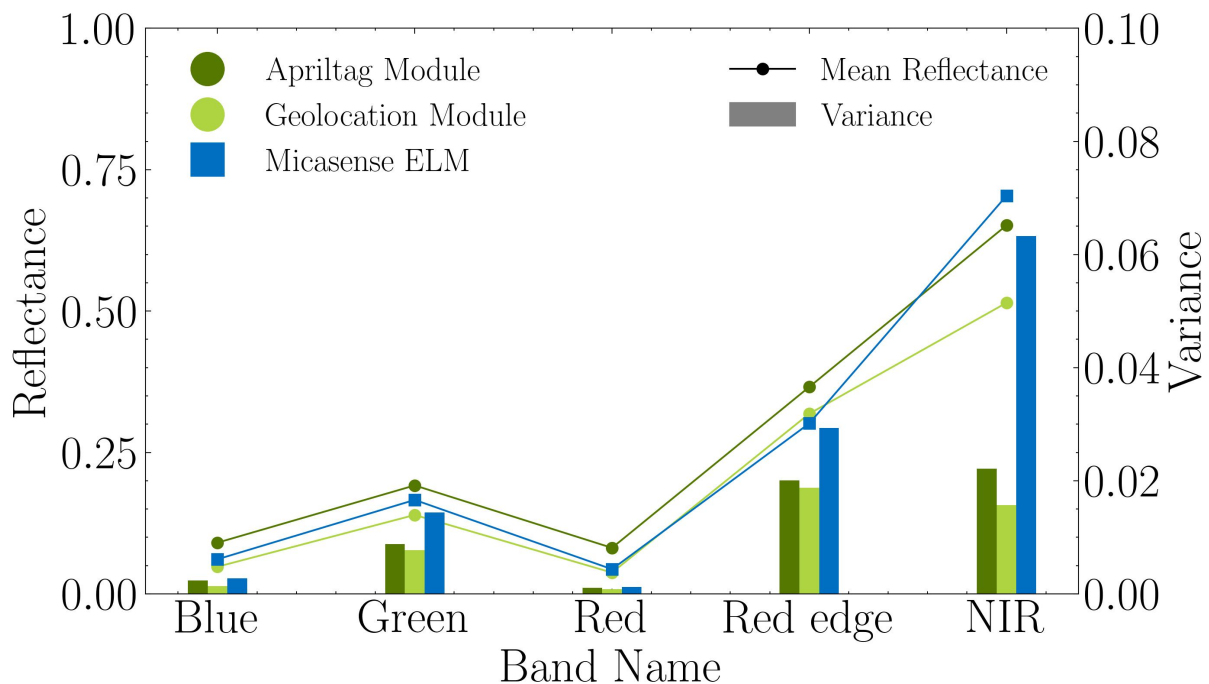


Figure 3: Multispectral reflectance signatures (line plots) obtained from identical locations in the provided example data after reflectance calibration. The average of 100 reflectance signatures from the classic Micasense ELM method are compared to the presented reflectance calibration using the AprilTag module and the Geolocation module. The variance for each band in each signature is represented as bar plots. Variance is higher for the classic Micasense ELM, most noticeable in the red edge and NIR band.

183 et al., 2018). While the ReflectDetect modules effectively automate the calibration pro-  
 184 cess, future work should focus on testing their performance and robustness under diverse  
 185 environmental conditions. This includes investigating whether placing additional April-  
 186 Tag targets at shorter intervals could enhance calibration accuracy, particularly for larger  
 187 study areas. Our software enables researchers to explore these aspects, providing tools to  
 188 test new hypotheses and compare with other radiometric calibration methods.

### 189 3.2 Advantages of open source software and modular extension 190 of camera specific calibration functions

191 ReflectDetect uses MicaSense-specific calibration functions to correct lens distortions and  
 192 other camera-specific effects inherent in the deployed imaging system. However, many  
 193 other optical sensors are available (Aasen et al., 2018) and each requires a sensor-specific  
 194 calibration procedure to generate robust spectral data that can be compared within and  
 195 across datasets and studies. This comparability is the foundation to scientific progress

196 overall and necessitates a collaborative effort to provide FAIR (Findable, Accessible, Inter-  
197 operable, and Reusable) research tools for advancing goals in phenotyping (Papoutsoglou  
198 et al., 2023), ecology (Manzano and Julier, 2021), computational science (Barker et al.,  
199 2022), and plant pathology (Grünwald et al., 2024). The implementation of open sci-  
200 ence standards for sharing data, code, and related research outputs has been a topic  
201 under discussion (Reichman et al., 2011; Serwadda et al., 2018) while the 2016 guidelines  
202 on sharing data in a "FAIR" manner marked a key point in the reproducibility debate  
203 (Wilkinson et al., 2016). These guidelines have since been extended to include software  
204 and protocols, recognizing that much of the scientific process generates such products  
205 (Barker et al., 2022). With ReflectDetect being open source, it allows researchers us-  
206 ing different camera systems to develop and integrate their own calibration functions  
207 tailored to their equipment. This flexible and collaborative approach enables precise cor-  
208 rections that account for the unique characteristics of various cameras, resulting in more  
209 accurate reflectance measurements. It further fosters community-driven enhancements of  
210 ReflectDetect and other tools, benefiting the broader remote sensing community. Reflect-  
211 Detect is distributed under the GNU General Public License v3.0 and can be found under  
212 <https://github.com/reflectdetect/reflectdetect>.

## 213 Contributions

214 **Luca Joshua Francis:** Conceptualization, Software, Writing – original draft.

215 **Lewis Gabriel B. Geissler:** Conceptualization, Software, Writing – original draft.

216 **Rene Heim:** Conceptualization, Supervision, Writing – review & editing.

217 **Nathan Okole:** Writing – review & editing.

218 **Cyrill Stachniss:** Conceptualization, Writing – review & editing.

219 **Bela Gipp:** Writing – review & editing.

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224 **References**

- 225 Aasen, H., Honkavaara, E., Lucieer, A., & Zarco-Tejada, P. (2018). Quantitative remote  
 226 sensing at ultra-high resolution with uav spectroscopy: A review of sensor tech-  
 227 nology, measurement procedures, and data correction workflows. *Remote Sensing*,  
 228 *10*(7), 1091. <https://doi.org/10.3390/rs10071091>
- 229 Abdulridha, J., Min, A., Rouse, M., Kianian, S., Isler, V., & Yang, C. (2023). Evaluation  
 230 of stem rust disease in wheat fields by drone hyperspectral imaging. *Sensors*, *23*(8),  
 231 4154. <https://doi.org/10.3390/s23084154>
- 232 Ban, S., & Kim, T. (2021). Automated reflectance target detection for automated vicari-  
 233 ous radiometric correction of uav images. *The International Archives of the Pho-*  
 234 *togrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B1-2021*,  
 235 133–137. <https://doi.org/10.5194/isprs-archives-xliii-b1-2021-133-2021>
- 236 Barker, M., Chue Hong, N. P., Katz, D. S., Lamprecht, A.-L., Martinez-Ortiz, C., Pso-  
 237 mopoulos, F., Harrow, J., Castro, L. J., Gruenpeter, M., Martinez, P. A., & Hon-  
 238 eyman, T. (2022). Introducing the fair principles for research software. *Scientific*  
 239 *Data*, *9*(1). <https://doi.org/10.1038/s41597-022-01710-x>
- 240 Cao, S., Danielson, B., Clare, S., Koenig, S., Campos-Vargas, C., & Sanchez-Azofeifa, A.  
 241 (2019). Radiometric calibration assessments for UAS-borne multispectral cameras:  
 242 Laboratory and field protocols. *ISPRS Journal of Photogrammetry and Remote*  
 243 *Sensing*, *149*, 132–145. <https://doi.org/10.1016/j.isprsjprs.2019.01.016>
- 244 Chakhvashvili, E., Siegmann, B., Bendig, J., & Rascher, U. (2021). Comparison of Re-  
 245 flectance Calibration Workflows for a UAV-Mounted Multi-Camera Array System.  
 246 *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*,  
 247 8225–8228. <https://doi.org/10.1109/IGARSS47720.2021.9555143>
- 248 Daniels, L., Eeckhout, E., Wieme, J., Dejaegher, Y., Audenaert, K., & Maes, W. (2023).  
 249 Identifying the optimal radiometric calibration method for uav-based multispectral  
 250 imaging. *Remote Sensing*, *15*(11), 2909. <https://doi.org/10.3390/rs15112909>

251 Eltner, A., Hoffmeister, D., Kaiser, A., Karrasch, P., Klingbeil, L., Stöcker, C., & Rovere,  
252 A. (Eds.). (2022). *UAVs for the Environmental Sciences: Methods and Applica-*  
253 *tions*. wbg Academic.

254 Fawcett, D., & Anderson, K. (2019, October 22). Investigating impacts of calibration  
255 methodology and irradiance variations on lightweight drone-based sensor derived  
256 surface reflectance products. In C. M. Neale & A. Maltese (Eds.), *Remote Sensing*  
257 *for Agriculture, Ecosystems, and Hydrology XXI* (p. 13). SPIE. [https://doi.org/](https://doi.org/10.1117/12.2533106)  
258 [10.1117/12.2533106](https://doi.org/10.1117/12.2533106)

259 Grünwald, N. J., Bock, C. H., Chang, J. H., De Souza, A. A., Ponte, E. M. D., du Toit,  
260 L. J., Dorrance, A. E., Dung, J., Gent, D., Goss, E. M., Lowe-Power, T. M.,  
261 Madden, L. V., Martin, F. N., McDowell, J., Naegele, R. P., Potnis, N., Quesada-  
262 Ocampo, L. M., Sundin, G. W., Thiessen, L., ... Zeng, Q. (2024). Open access  
263 and reproducibility in plant pathology research: Guidelines and best practices.  
264 *Phytopathology*®, 114(5), 910–916. <https://doi.org/10.1094/phyto-12-23-0483-ia>

265 Krogius, M., Haggemiller, A., & Olson, E. (2019). Flexible layouts for fiducial tags. *2019*  
266 *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.  
267 <https://doi.org/10.1109/iros40897.2019.8967787>

268 Maes, W., & Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial  
269 vehicles in precision agriculture. *Trends in Plant Science*, 24(2), 152–164. <https://doi.org/10.1016/j.tplants.2018.11.007>

271 Manzano, S., & Julier, A. C. M. (2021). How fair are plant sciences in the twenty-first  
272 century? the pressing need for reproducibility in plant ecology and evolution. *Pro-*  
273 *ceedings of the Royal Society B: Biological Sciences*, 288(1944), 20202597. <https://doi.org/10.1098/rspb.2020.2597>

275 Papoutsoglou, E. A., Athanasiadis, I. N., Visser, R. G. F., & Finkers, R. (2023). The  
276 benefits and struggles of fair data: The case of reusing plant phenotyping data.  
277 *Scientific Data*, 10(1). <https://doi.org/10.1038/s41597-023-02364-z>

278 Reichman, O. J., Jones, M. B., & Schildhauer, M. P. (2011). Challenges and opportunities  
279 of open data in ecology. *Science*, 331(6018), 703–705. [https://doi.org/10.1126/](https://doi.org/10.1126/science.1197962)  
280 [science.1197962](https://doi.org/10.1126/science.1197962)

- 281 Serwadda, D., Ndebele, P., Grabowski, M. K., Bajunirwe, F., & Wanyenze, R. K. (2018).  
282 Open data sharing and the global south—who benefits? *Science*, *359*(6376), 642–  
283 643. <https://doi.org/10.1126/science.aap8395>
- 284 Shin, J.-I., Cho, Y.-M., Lim, P.-C., Lee, H.-M., Ahn, H.-Y., Park, C.-W., & Kim, T. (2020).  
285 Relative radiometric calibration using tie points and optimal path selection for uav  
286 images. *Remote Sensing*, *12*(11), 1726. <https://doi.org/10.3390/rs12111726>
- 287 Van Rossum, G., & Drake Jr, F. L. (1995). *Python reference manual*. Centrum voor  
288 Wiskunde en Informatica Amsterdam.
- 289 Wang, J., & Olson, E. (2016). Apriltag 2: Efficient and robust fiducial detection. *2016*  
290 *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.  
291 <https://doi.org/10.1109/iros.2016.7759617>
- 292 Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A.,  
293 Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J.,  
294 Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo,  
295 C. T., Finkers, R., . . . Mons, B. (2016). The fair guiding principles for scientific  
296 data management and stewardship. *Scientific Data*, *3*(1). [https://doi.org/10.](https://doi.org/10.1038/sdata.2016.18)  
297 [1038/sdata.2016.18](https://doi.org/10.1038/sdata.2016.18)
- 298 Yang, S., Li, L., Fei, S., Yang, M., Tao, Z., Meng, Y., & Xiao, Y. (2024). Wheat yield pre-  
299 diction using machine learning method based on uav remote sensing data. *Drones*,  
300 *8*(7), 284. <https://doi.org/10.3390/drones8070284>

301 A. Appendix



Figure 4: 3 AprilTags of the tag25h9 family placed next to 3 calibration targets

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