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Bias and bottlenecks study in outdoor long term thermal monitoring by infrared thermography: Leveraging opportunistic data for temperature estimation

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1 Highlights

2 **Bias and bottlenecks study in outdoor long term thermal monitor-**
3 **ing by infrared thermography: leveraging opportunistic data for**
4 **temperature estimation**

5 T. Toullier, J. Dumoulin

6 • integration of opportunistic open data for environmental corrections
7 on temperature estimation during long term thermal monitoring by
8 infrared thermography

9 • Sensitivity study of measurement parameters (emissivity, sky temper-
10 ature, atmospheric transmission, ..) over long time period for outdoor
11 experiments

12 Bias and bottlenecks study in outdoor long term
13 thermal monitoring by infrared thermography:
14 leveraging opportunistic data for temperature
15 estimation

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17 **Abstract**

This study aims to assess the impact of the targeted scene and environmental variables on in situ long-term thermal monitoring by infrared thermography. It also addresses projection errors arising from camera perspectives and digitization. Over a span of 3 years, extensive measurements were conducted at two instrumented test sites, yielding a valuable dataset for analysis. The paper begins by introducing and discussing the model used to convert the collected data into surface temperature estimations and its associated parameters' sensitivities. Subsequently, it delves into the effects of camera resectioning on infrared measurements. Finally, the study investigates the influence of environmental parameters and proposes a strategy to correct for these effects, with and without additional sensors (opportunistic data) and additional in-situ measurements. Finally, a discussion is proposed and perspectives are addressed.

18 *Keywords:* thermography, calibration, emissivity, building, in-situ,
19 copernicus, metar, open data

20 **1. Introduction**

21 Non-destructive thermal monitoring of transport infrastructures has be-
22 come a major concern for next generations' civil engineering structures. In
23 particular, SHM (Structural Health Monitoring) is of interest to estimate
24 the influence of the thermal effect on modal analysis and correct it, as in
25 [1] where a correlation between the temperature and the modal parameters

26 is shown, or in [2] where the potential use of online data to correct the en-
27 vironmental variation from the temperature variation is shown. Therefore,
28 new long-term thermal monitoring solutions in situ, low cost, and robust are
29 needed. If thermocouples or even optics fibers meet the expectation of ther-
30 mal monitoring, their corresponding instrumentation may be complex with a
31 risk of breaking during the construction (*i.e.* complex maintenance in opera-
32 tion). At the opposite, infrared thermography seems to be simpler to deploy
33 and offers a potential temperature measurement on multiple points at the
34 same time. Even if the technological context of uncooled infrared cameras is
35 evolving quickly, methods and processes for using them as an accurate and
36 low-cost alternative contactless and full field measurement system requires
37 research efforts, in particular at ground based scale observations.

38 Numerous experiments have been conducted and examined in the literature
39 to use infrared cameras in natural environments, for various applications.
40 For instance, temperature estimation in natural environments such as [3]
41 whose authors propose two intrusive references methods (aluminium mirror
42 and temperature references), moisture detection as in [4], or even an applica-
43 tion to detect the inner deck structure of a bridge in [5]. In [6], the authors
44 propose the comparison of a numerical simulation of a radiative budget with
45 an actual radiative measurement. However, these studies were either con-
46 ducted under favorable environmental conditions and for a duration of not
47 more than a few days, or used large computing and consuming resources that
48 may not be suitable for every application. To advance understanding and
49 capture real-world long-term data, specialized software architectures, such as
50 C2IR, have been developed [7]. Thanks to this improvement of acquisition
51 and computation means, instrumented multisensor test sites have gathered
52 an interesting amount of synchronized and coupled data over the years.

53 The main challenge for using infrared cameras as a thermal monitoring tool
54 is to convert the radiative fluxes received by the infrared camera to temper-
55 ature. In fact, the underlying temperature estimation depends on many cri-
56 terion such as camera calibration and internal parameters in operation[8, 9],
57 geometrical considerations, but also environmental conditions. Therefore, to
58 achieve quantitative thermography, one must consider the global radiative
59 heat balance at the sensor level and be able to estimate the different param-
60 eters of the equation. In particular, meteorological varying conditions have
61 to be corrected, even if the scene and its compounding objects are known.
62 Then, the measurement correction to estimate the temperature in an out-
63 door context can be made and the parameters estimated by using on-site

64 measurements, with multi-sensor instrumentation. However, such a solution
65 increases the instrumentation complexity and cost, the number of data to
66 gather and store and, sometimes, it cannot be applicable at all on the exper-
67 iment facility. Moreover, even with multi-sensor instrumentation, data may
68 be lacking due to various possible issues. As a consequence, we propose to
69 use opportunistic open data from online providers to estimate those environ-
70 mental parameters.

71 This study aims to survey various factors that may affect measurements in
72 outdoor infrared thermography. A particular focus is proposed on examining
73 the influence of varying meteorological conditions and developing correction
74 methods for these variations.

75 This study aims at making a survey of the different quantities that may
76 impact the measurements in a context of outdoor infrared thermography. A
77 particular focus on the study of varying meteorological conditions and how to
78 correct them is proposed. First, the experimental setups are presented. Then,
79 the proposed conversion model for computing temperature is introduced.
80 The process of camera resectioning and the impact of environmental errors
81 are then analyzed and discussed. Finally, the outcomes are presented and
82 interpreted.

83 **2. Tests sites, related instrumentations and configurations**

84 Two tests sites have been instrumented and have gathered numerous data
85 to exploit.

86 *2.1. Instrumented wood house*

87 The first one is a wood house, built under the SenseCity project of the
88 University, and instrumented for multiple years in Paris with well-known
89 material properties and dimensions to have a real sized and in-situ mock-up.
90 The house is monitored by a FLIR A65 thermal infrared camera (640×512
91 LWIR FPA, pitch $17 \mu\text{m}$, equipped with a 13 mm optical focal length). A
92 weather station (VAISALA WXT 520) and a sunshine pyranometer (SPN1)
93 gives us the total and diffuse solar radiation. A multi-sensors acquisition
94 system is used to record and synchronize data in time. The infrared camera
95 is placed on a mast to get a large view of the scene (see Figure 1).

96 *2.2. Instrumented road section*

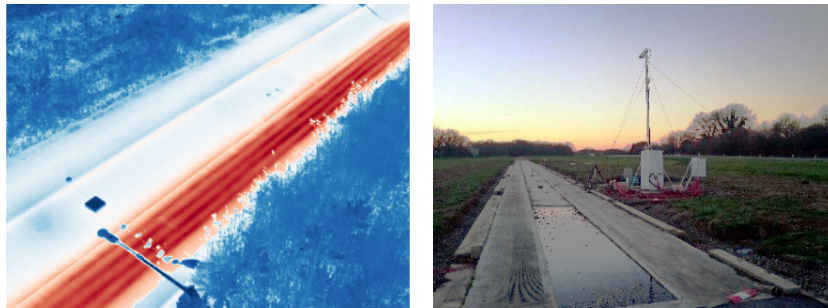
97 The second one is an instrumented road at our laboratory in Nantes,
98 France with a local weather station, a pyranometer a pyrgeometer and an



(a) Image of the wooden chalet in the infrared spectrum (b) Image of the wooden in the visible spectrum

Figure 1: Wooden chalet instrumentation: IR image (a) and test site overview (b)

99 infrared camera (see Figure 2). The road section has thermocouples on the
 100 ground from which the infrared temperature estimations with the different
 101 corrections can be compared.



(a) Image of the concrete road in the infrared spectrum (b) Image of the concrete road in the visible spectrum

Figure 2: Concrete road instrumentation: IR image (a) and test site overview (b)

102 3. Temperature computation based on a multi-sensors model

103 In this section, the principle and main challenges of the conversion of the
 104 received flux at camera's sensors to temperature are presented.

105 One of the major difficulty in *in-situ* infrared thermography temperature
 106 measurement is that the received flux depends on its surrounding environ-
 107 mental situation and also the thermo-optical properties of the measurement
 108 scene as described in the reference book [10] and more detailed in [5] which

109 are usually unknown as illustrated in Figure 3. Furthermore, the camera is
 110 placed on a mast, in this case, leading to a non-constant spatial sampling of
 111 the monitored surfaces. In such configuration, the radiation flux attenuated
 112 by the the atmosphere will depend on the position of the measurement point in
 113 the scene adding even more complications to the flux to temperature conver-
 114 sion problem.

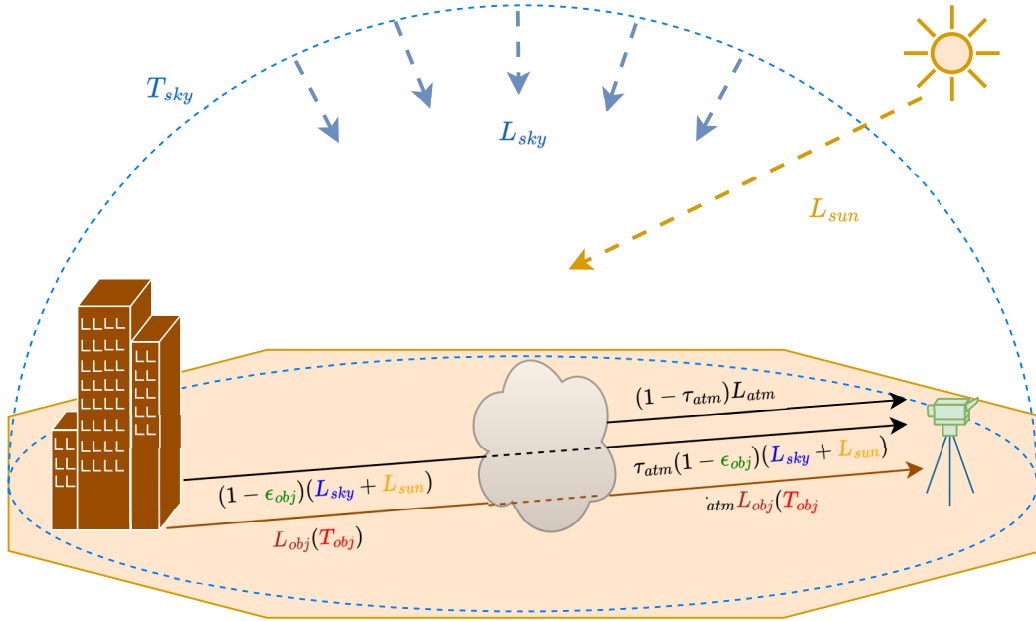


Figure 3: Radiation interactions received by cameras sensors looking at a building through a participating media.

115 To retrieve the flux received by the camera at each pixel L_{total} , the sim-
 116 plified radiometric equation that takes into account the atmospheric (L_{atm}),
 117 optic (L_{opt}) and environmental contributions from the sun (L_{sun}) and the sky
 118 (L_{sky}) is used (see Equation (1)). To first obtain an estimate of the emitted
 119 flux by the object (L_{obj}) from this measurement, it is necessary to estimate
 120 the different previous unknown quantities as well as the atmospheric trans-
 121 mission (τ_{atm}), optical transmission (τ_{opt}) and the emissivity of the object
 122 (ϵ_{obj}).

$$L_{total}(T) = \tau_{opt}[\tau_{atm}(L_{obj}(T_{obj}) + (1 - \epsilon_{obj})(L_{sky}(T_{sky}) + L_{sun})) + (1 - \tau_{atm})L_{atm}] + (1 - \tau_{opt})L_{opt} \quad (1)$$

123 Once the emitted flux by the object is estimated, an RBF-function (2) is
124 used to compute the temperature with a thermal calibration process; prior
125 to the experiment as described in [11].

$$T_{obj} = \frac{B}{\log\left(\frac{R}{L_{obj}} - F\right)} \quad (2)$$

126 Finally, the overall temperature estimation through *in-situ* long-term
127 thermal monitoring involves many parameters. The objective of the paper
128 is to focus on the influence of those parameters in order to get an overview
129 of the temperature estimation process bottlenecks. Then, two methods are
130 proposed to estimate environmental parameters (*i.e.* the estimation of the
131 emissivity and optics are done separately). A first one is to use local sensors
132 on site, whereas the other one takes advantage of available online and open
133 data from different providers.

134 4. Spatial influence

135 Before going further into the sensitivity of the model to its parameters, it
136 is important to note that the position of the camera in the scene may induce
137 effects on the obtained image. In particular, monitoring a civil engineering
138 structure requires a large angle of view which may impose the camera to be
139 installed on a mast or other elevating observation (for instance on top of a
140 pylon) or under a bridge deck. However, such situation results in images with
141 varying spatial resolutions (*e.g.* distances) and important angles between the
142 objects and the camera (see Figure 1). The underlying consequences are non-
143 square pixels in the real-world and varying angles values along the same plane
144 which has an impact on the emissivity values to be considered. Moreover,
145 practical applications may need to focus on a particular region of interest on
146 the image to retrieve the temperature at one precise location. Knowing the
147 geometric properties of the sensor-scene configuration on the measurement
148 site is useful, in particular to get the view angle of the camera to the object.
149 Retrieving the real world coordinates on the image is known as resectioning
150 (see Figure 4). Standard spatial calibration procedures can be used and
151 adapted from the visible by using peculiar materials pattern samples, heat
152 sources or manual referencing (see [12] for gold-standard methods and [13]
153 in particular for using ground control points) for this purpose.

154 If such process enables to recover the region of interest, it also induces
155 a new sampling obtained by interpolation and illustrated in Figure 5. We

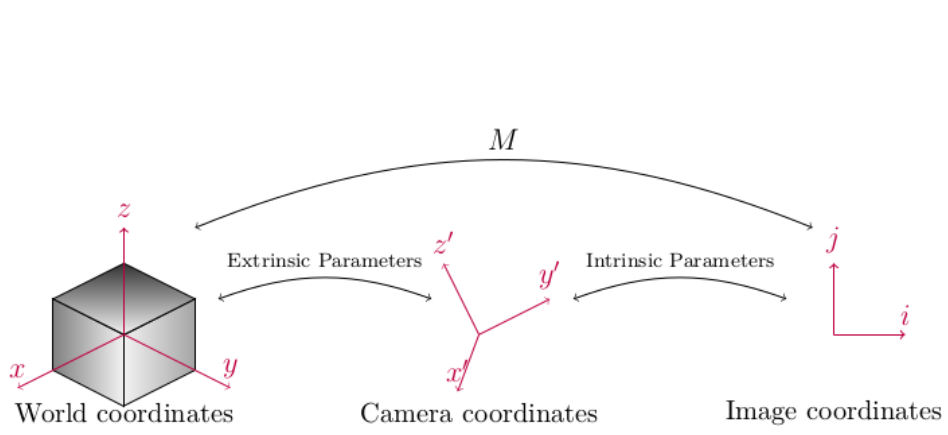


Figure 4: Resectioning principle, from world coordinates to image coordinates

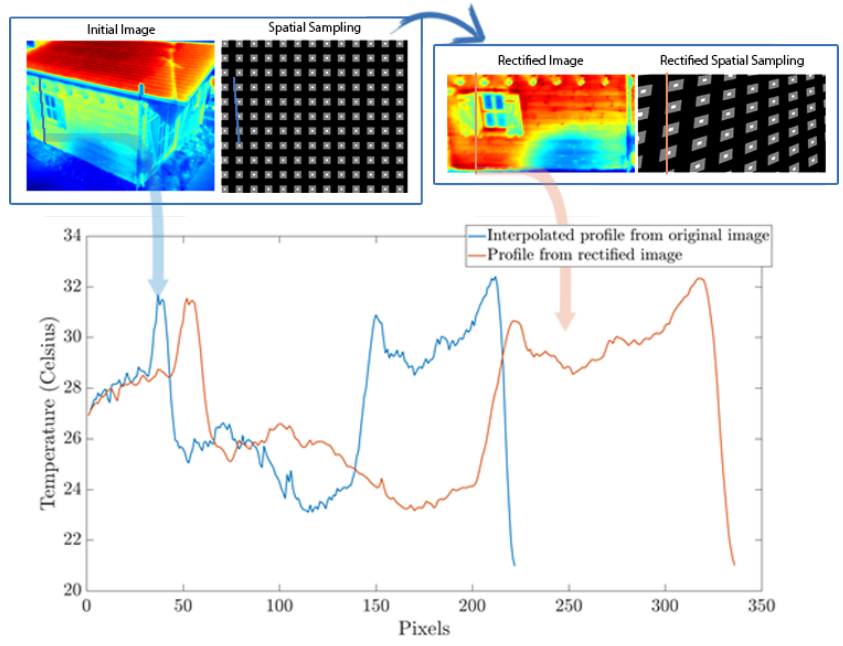


Figure 5: Illustration of sampling issues after projection

156 can see at the bottom of this figure the actual effect of the projection to the
157 thermal profiles that are scaled up and smoothed due to the interpolation.
158 Furthermore, the dilation coefficient is not constant within the image leading
159 to a varying re-projection error induced by the interpolation depending on
160 the considered pixel's position. Such operation can lead to a blurring of the
161 edges and jagged artifacts.

162 Furthermore, the variation of distances on such scenes induce a mixed
163 pixel effect, where one pixel is not the representation of a particular object's
164 surface but a mixture of materials. As a consequence, the material properties
165 are not equivalent from the world coordinates to the image one, due to the
166 induced spatial integration. One solution is to perform sub-pixel analysis, by
167 using histogram analysis methods, data fusion, oversampling, *etc.* [14]. Such
168 concern is particularly studied in the remote sensing field as in [15] where a
169 simulation is used to demonstrate the impact of having mixed pixels on land
170 surface phenology or even [16] that demonstrates the complexity of having
171 such phenomenon in land data classification.

172 5. Conversion model sensitivity to parameters

173 In addition to spatial considerations, the lack of knowledge about the
174 observed surfaces may affect the temperature estimation based on infrared
175 measurements. In particular, the emissivity estimation will have an impor-
176 tant impact on the final temperature estimation. Moreover, various mete-
177 orological and environmental factors will affect the temperature estimation
178 based on infrared measurements [17]. A review of the impact of the different
179 errors made for the temperature estimation based on the model and pre-
180 sented in Equation (1) is done in this part. Different analysis of sensitivity
181 have been previously done in the literature, by comparing sensitivity between
182 shortwave and longwave measurements [18], by performing the analysis on
183 dual-band measurements systems [19] or for high temperature measurements
184 [20] for instance. Moreover, reference book [21], the book chapter [22] and
185 [23] provide a comprehensive analytical analysis of the errors made on in-
186 frared measurements while [24] provides a full list of uncertainties budgets
187 for the calibration of radiation thermometers. Those analyses are extended
188 to the case of the *in-situ* model presented previously and focus on the emis-
189 sivity, environment temperature and atmospheric transmission effects. By
190 considering that the object's temperature and emissivity are independent:

$$\begin{cases} \frac{\partial L_{total}}{\partial \epsilon_{obj}} &= \tau_{atm} \tau_{opt} (L_{obj} - L_{sky}) \\ \frac{\partial L_{total}}{\partial T_{sky}} &= (1 - \epsilon_{obj}) \tau_{atm} \tau_{opt} \frac{\partial L_{sky}}{\partial T_{sky}} = (1 - \epsilon_{obj}) \tau_{atm} \tau_{opt} \frac{RB e^{B/T_{sky}}}{T_{sky}^2 (e^{B/T_{sky}} + C)^2} \\ \frac{\partial L_{total}}{\partial \tau_{atm}} &= \epsilon_{obj} \tau_{opt} L_{obj} + (1 - \epsilon_{obj}) \tau_{opt} L_{sky} - \tau_{opt} L_{atm} \end{cases} \quad (3)$$

191 Those equations will be used in the following in order to observe the
 192 impact of the different model's parameters to the temperature retrieval while
 193 neglecting the influence of the optics transmission τ_{opt} .

194 *5.1. Model sensitivity to emissivity*

195 Emissivity measurements have been made on the wood house (see section
 196 2.1) in order to get an emissivity map, represented in Figure 6. The system
 197 used for measurements was a portable emissometer developed at CERTES
 198 [25]. Table 1 shows the associated emissivity measurements.

Material	Color	Emissivity
Wood wall (west)	Blue	0.95
Wood wall (east)	Yellow	0.90
Grass	Green	0.95
Sidewalk	Red	0.89
Tar	Grey	0.95
Roof	Purple	0.92

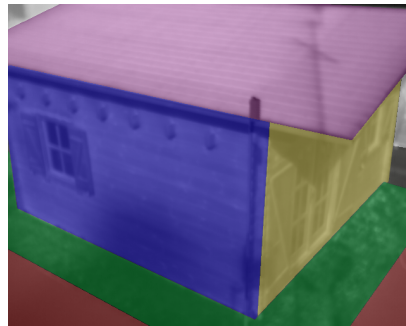


Table 1: Emissivity measurements values in the $8\mu m - 14\mu m$ band.

Figure 6: Emissivity map for the wood house, colors represents one particular emissivity measurement

199 Figure 7 shows the effect of adjusting the emissivity to a particular mate-
 200 rial. In this case, the comparison can only be made relatively due to the lack
 201 of ground truth temperature measurements at the surface of the different
 202 materials.

203 However, one can see that adjusting the emissivity will refine the tem-
 204 perature estimation. In fact, in this example, a fair candidate for a constant
 205 emissivity value over the entire image can be 0.93 which is the average emis-
 206 sivity value is with a standard deviation of 0.025 (derived from Table 1 and
 207 Figure 6). When neglecting all the other effects but the emissivity value,

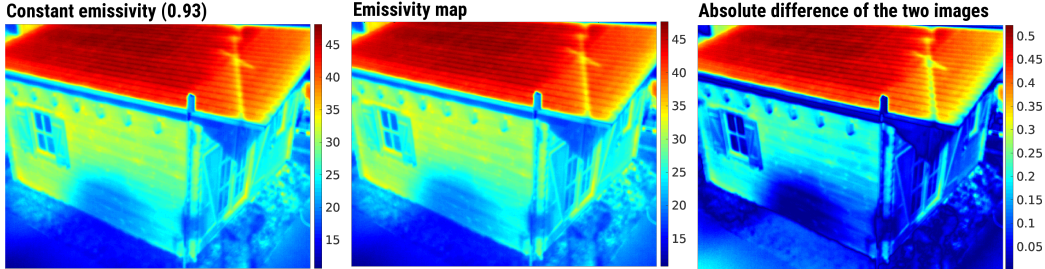


Figure 7: Effect of adjusting the emissivity in temperature estimation for different material compared to a constant emissivity

208 choosing a coarse emissivity map instead of a constant emissivity value on
 209 the image leads to, at most, 0.5 K difference for a given thermal equilibrium
 210 at a fixed time of observation (see last image of Figure 7). This example
 211 also demonstrates that the error in the temperature estimate is not constant
 212 across the pixels of the image. Furthermore, emissivity will be a factor in
 213 all parameters in Equation 1 and will, therefore, play an essential role in
 214 temperature estimation. However, in this paper, the focus is made on envi-
 215 ronmental parameters. Nevertheless, more details on the error induced by
 216 emissivity, along with sky temperature and atmospheric transmission, are
 217 presented in the next two sections.

218 5.2. Model sensitivity to sky temperature and atmospheric transmission

219 The sky temperature (T_{sky}) is an important concept when doing radia-
 220 tive balances. It represents the apparent effective temperature of the sky
 221 assumed to behave like a blackbody. It is therefore different from the ambi-
 222 ent air temperature and can be lower, particularly under clear sky conditions.
 223 Such quantity will have an impact on the final temperature estimation (\tilde{T}_{obj}),
 224 as shown in Figure 8 where the difference between the estimated sky tem-
 225 perature (\tilde{T}_{sky}) is compared to the difference made on the estimated object
 226 temperature, for different values of T_{obj} and T_{sky} . The R , B and F values
 227 used in the model to compute this figure are derived from a thermal calibra-
 228 tion. One can note that those coefficients are only valid for a limited range
 229 of object temperature (283.15 K - 343.15 K in this case) and could expect
 230 some more important error out of this range. Figure 8 compares the differ-
 231 ences between the actual object temperature and the estimated one by using
 232 estimates on T_{sky} (\tilde{T}_{sky}) and ϵ_{obj} ($\tilde{\epsilon}_{obj}$).

233 Finally, Figure 9 illustrates the accumulation of errors made on the atmo-

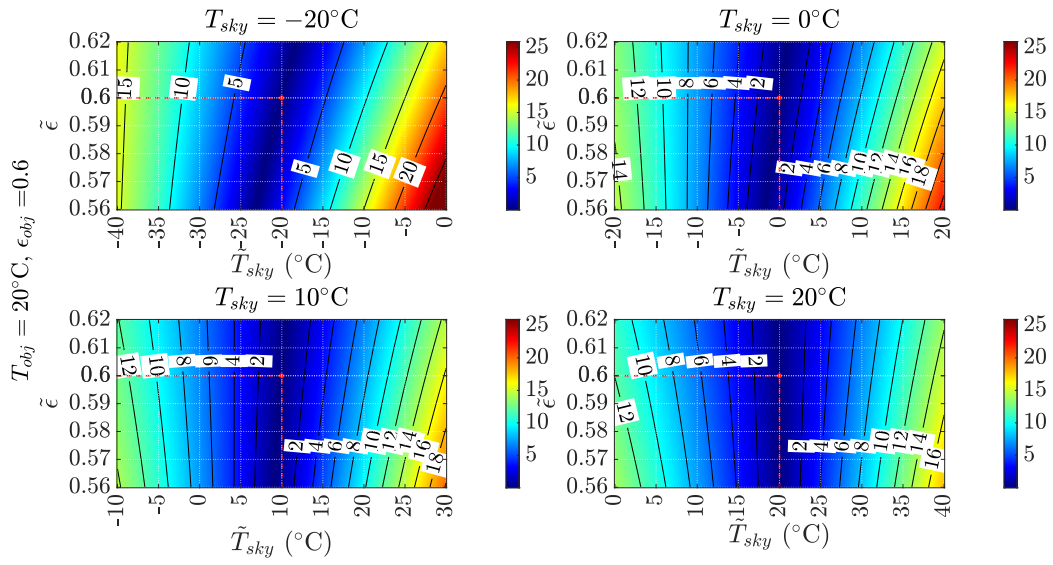


Figure 8: Difference between true object temperature and estimated one depending on the error made on the sky temperature and emissivity. In this case, the true object is at 20 °C and its emissivity is 0.93.

How to read: on the left the true object's temperature and emissivity. A point on the image represents the difference between the true object temperature and the estimated one with \hat{T}_{sky} (x-axis) and $\tilde{\epsilon}_{obj}$ (y-axis) values. The images represent different environmental temperatures values.

234 spheric transmission and on the emissivity to the estimation of temperature.
 235 Similarly to Figure 8 and based on Equation (3), the map of the differences
 236 between the estimated temperature and the expected one can be made by
 237 considering the error made on the atmospheric transmission.

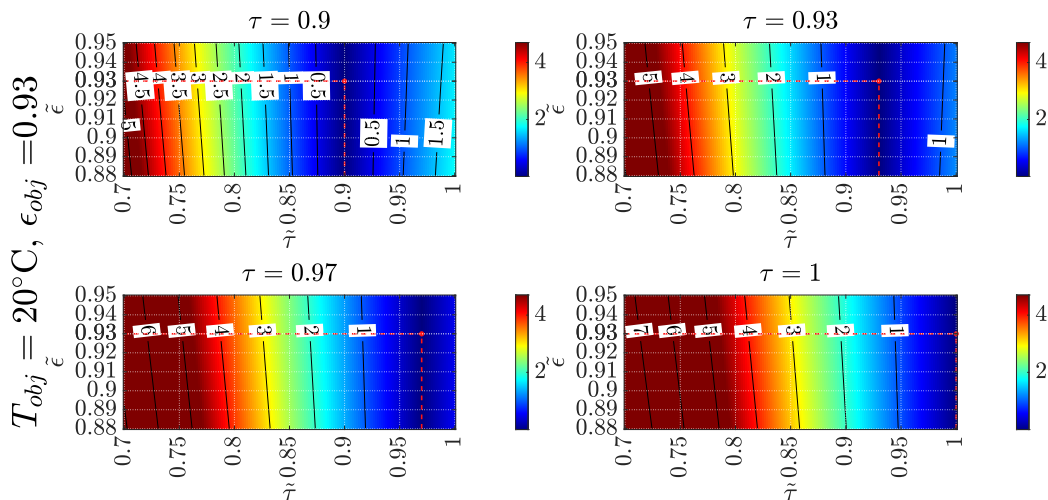


Figure 9: Difference between true object temperature and estimated one depending on the error made on the atmospheric transmission and emissivity. Here is the difference map for an object temperature of 20 °C and emissivity of 0.93.

How to read: on the left the true object's temperature and emissivity. A point on the image represents the difference between the true object temperature and the estimated one with $\tilde{\tau}_{atm}$ (x-axis) and $\tilde{\epsilon}_{obj}$ (y-axis) values. The images represent different atmospheric transmissions values.

238 Moreover, the atmospheric transmission is usually approximated by using
 239 the ambient temperature, relative humidity, and involved distance at
 240 operating wavelength[26]. In particular, when dealing with infrastructures
 241 monitoring applications, great distances differences may occur due to large
 242 field of views (*e.g.* during the monitoring of a bridge). In such case, a spatial
 243 calibration is necessary to compute a distance map and take into account
 244 those distances. As for example, Figure 10 shows the effect of the distance
 245 to the atmospheric transmission in the 7.5 μm to 13 μm band and the need
 246 for considering the distances due to the camera view projection within the
 247 image. As shown in this figure, considering the same distance between the
 248 observed surface and the camera may lead to inaccuracies.

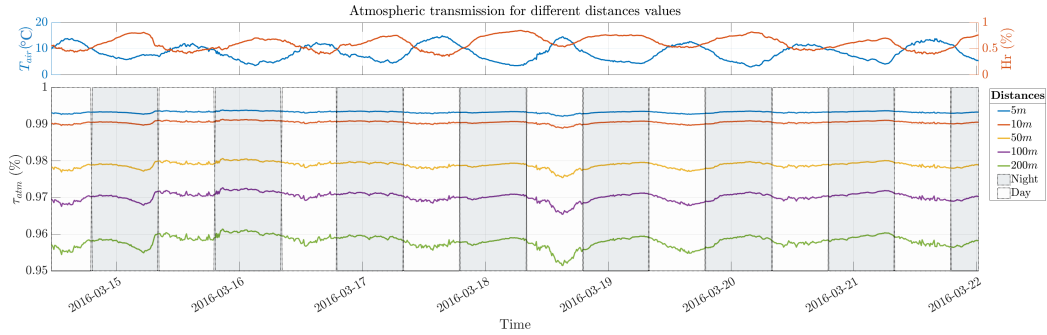


Figure 10: Different distance values for the atmospheric transmission, through time.

249 *5.3. Sun's irradiance considerations*

250 The sun's irradiance will also have an impact on the final temperature
 251 estimation. In fact, depending on the emissivity of the observed object, the
 252 irradiance at camera's sensor will contain the sun's reflected contribution,
 253 both specular and diffuse. In the case of the LWIR ($7.5\ \mu\text{m}$ to $13\ \mu\text{m}$), even
 254 though the sun contribution may be small compared to the NIR, SWIR and
 255 MWIR bands, it still represents a source of error in the conversion process.
 256 In particular for low object's temperatures as illustrated in Figure 11, we can
 257 see that the direct sun irradiance contribution can be responsible for up-to 3%
 258 of the object's emittance, leading to incorrect temperature estimation if not
 259 considered. In the case of SWIR-MWIR band the sun contribution should not
 260 be neglected, in particular when observing surfaces with low temperatures
 261 (Figure 12).

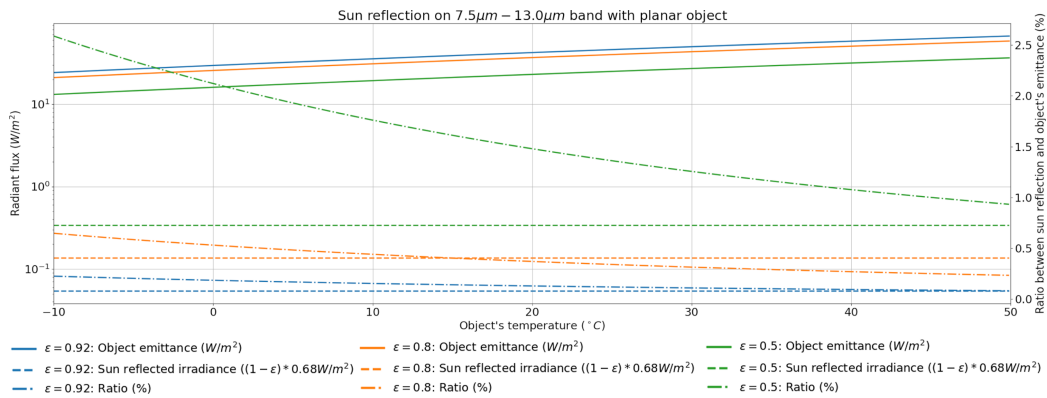


Figure 11: Sun irradiance reflection on the $7.5\ \mu\text{m}$ to $13\ \mu\text{m}$ band for a normal object and different emissivity values

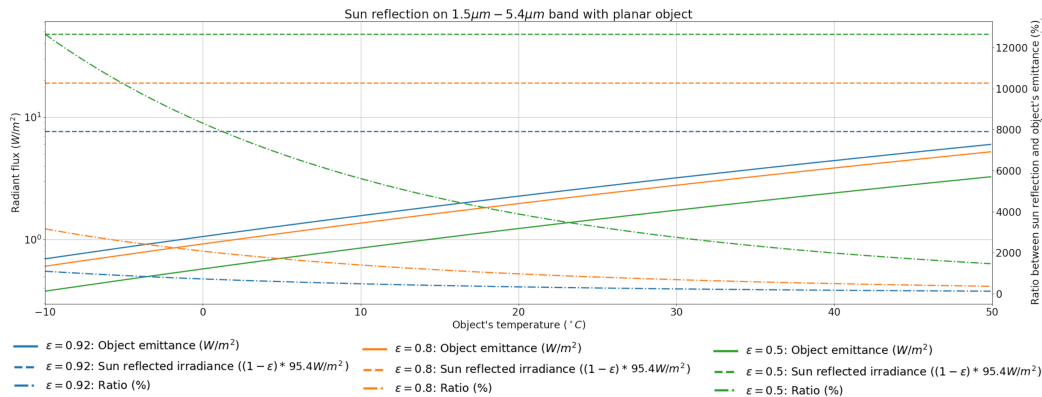


Figure 12: Sun irradiance reflection on the $1.5\ \mu\text{m}$ to $5.4\ \mu\text{m}$ band for a normal object and different emissivity values

262 5.4. Discussion

263 The main parameters that will have an impact on the final temperature
 264 estimate in an outdoor infrared thermography monitoring system have been
 265 presented in this section. It is important to note that the final estimation
 266 depends not only on the error in one parameter but also on the combined er-
 267 rors in each parameter estimation. Additionally, the conditions of operation
 268 and the properties of the material influence the final error in the temper-
 269 ature estimate. This is particularly illustrated in Figure 8 and Figure 9.
 270 Consequently, in the next section, we propose two methods to estimate these
 271 environmental parameters under operational conditions using local sensor
 272 data or opportunistic (online) data. Finally, a comparison between what is
 273 measured with the different corrections methods and without any correction
 274 is given in Section 6.6.

275 6. Parameters Estimation

276 Previous sections have enlightened that to achieve quantitative thermog-
 277 raphy, one must consider the global radiative heat balance at the sensor level
 278 and be able to estimate the different parameters of the equation. Then, the
 279 measurement correction to estimate the temperature in an outdoor context
 280 can be made. One way to estimate the involved parameters is to use on-site
 281 measurements, with a multi-sensors instrumentation. However, such a solu-
 282 tion increases the instrumentation complexity and cost, the number of data
 283 to gather and store and, sometimes, it cannot be applicable at all on the

284 experiment facility. Moreover, even with a multi-sensors instrumentation,
285 data may be lacking due to various possible issues. In this part, the focus is
286 made on the practical consideration of those parameters, in operating condi-
287 tions. Different means, at different scales, to estimate those parameters are
288 proposed and compared.

289 *6.1. Emissivity considerations*

290 Taking into account the emissivity in such measurements is a challenging
291 task that may result to important uncertainties in the temperature estima-
292 tion process, as illustrated in Figure 8. Emissivity measurements or tables
293 could be used, notably by using a Building Information Model (BIM) giving
294 detailed data about materials used in the construction. However, such data
295 may not be available, and tables data may not reflect the materials' reality
296 since the emissivity relies on the state of the surface [21].

297 Another possibility is to use the physical equations, which are an ill-posed
298 problem known as the temperature and emissivity separation (TES) problem
299 [10]. Even though different methods have been developed (see a review from
300 [27] or [28] for land surface temperature estimation), using Bayesian inference
301 with Monte-Carlo Markov Chains (MCMC) [29] or Kalman filtering with
302 [30] and [31], Maximum Entropy estimator [32], or even neural networks
303 [33], the TES problem is still challenging and often addressed in the remote
304 sensing field. In fact, the developed methods rely on particular application
305 hypothesis, on a specific materials' database (for neural network training for
306 instance [34]) or are computationally intensive as for the MCMC method [29].
307 Recent researches, based on Bayesian methods have been proposed to tackle
308 such challenge in the particular context of outdoor long term monitoring, but
309 more evaluations need to be made[35].

310 *6.2. Environmental Parameters Estimation*

311 To estimate the environmental parameters, we propose and compare three
312 methods: local measurements from the instrumented road (see Section 2),
313 existing sensor networks with Meteorological Aerodrome Report (METAR)
314 data and open source online satellite data from the European Copernicus
315 program. Since some data may not be available from all the different sources,
316 we also propose literature correlations or methods to be used to deduct those
317 quantities.

318 *6.2.1. Meteorological Aerodrome Report (METAR)*

319 METAR is a normalized format to create weather reports, based on per-
320 manent weather observation stations or airports, that are generated period-
321 ically (usually once an hour). The methodology we propose is to download
322 data from the nearest available METAR station.

323 *6.2.2. Copernicus Climate Data Store (CDS)*

324 The Climate Data Store (CDS) is part of the European program Coper-
325 nicus aiming at collecting and providing edge-cutting and updated contin-
326 uous data on Earth's state. The CDS provides a single point access to
327 many European datasets including observations, reanalysis and forecasts.
328 For post-processing temperature computation, we propose to use the reanal-
329 ysis dataset and particularly ERA5-land dataset [36].

330 *6.3. Sky temperature*

331 One can use the measurements made *in-situ* to get the sky temperature.
332 As for example, in Figure 13, the ground truth temperature obtained from
333 thermocouples data is compared to the temperatures estimated with and
334 without sky correction on a different test site. In the case of the sky cor-
335 rection, the sky temperature is derived from a pyrgeometer data whereas a
336 constant sky temperature is taken in the other case. Figure 13 shows that
337 taking into account the sky temperature from local measurements gives a
338 better estimate of the object temperature. In this particular example, the
339 estimation of the temperature with and without the sky temperature correc-
340 tion is compared to thermocouples measurements at the surface of a concrete
341 pavement structure. The sky correction reduces in average the difference be-
342 tween the thermocouples measurements and the estimated temperature from
343 infrared data.

344 Another possibility is to use correlations from measured air temperature
345 to estimate the sky temperature. Such correlations can be found in the
346 literature [37]. Figure 14 shows the effect of the Swinbanks correlation for
347 two different periods: in december and august. Moreover, one can see that
348 the sky temperature derived from the correlation will have an impact of the
349 same magnitude's order as if using *in-situ* measurements.

350 If local measurement data are not available, the correlation formula can
351 be used from various online data providers, as introduced previously. Figure
352 15 shows the sky temperature derived from the different providers. Even if
353 differences exists in term of sky temperature, it represents a small quantity

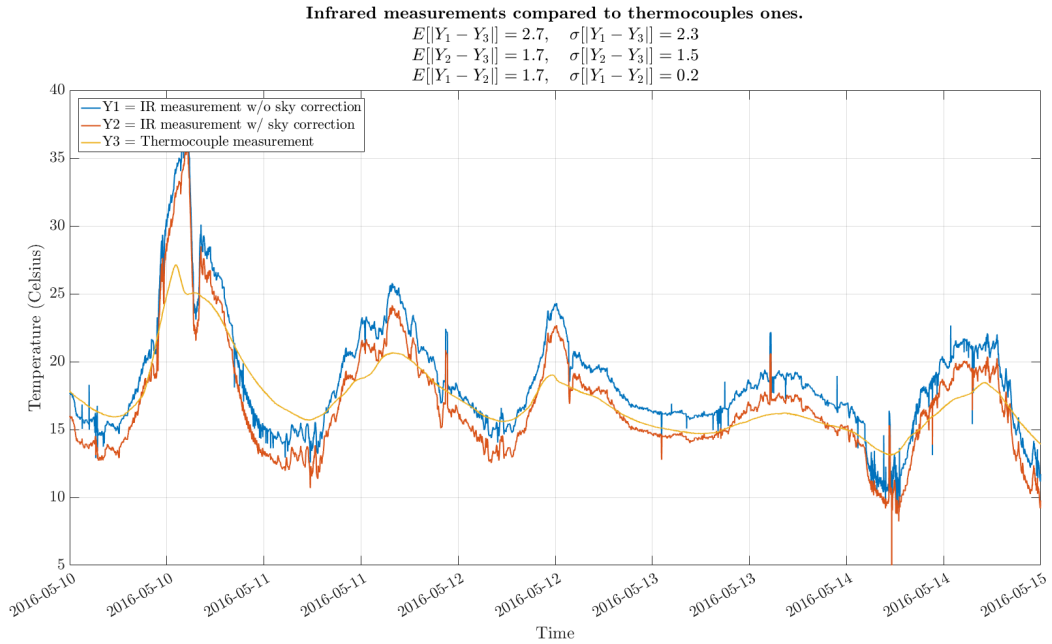


Figure 13: Comparison of ground truth temperature values to temperature estimation with and without sky correction

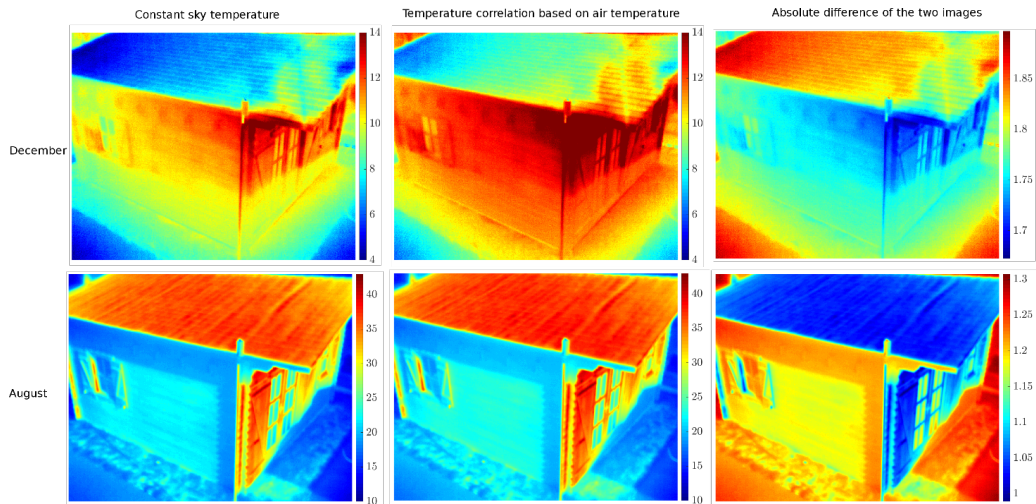


Figure 14: Effect of using a correlation for the sky temperature based on the air temperature measurement

354 of thermal radiation, regarding the involved temperatures. Therefore, it is
355 always possible to enrich the radiative model conversion thanks to online and
356 open data.

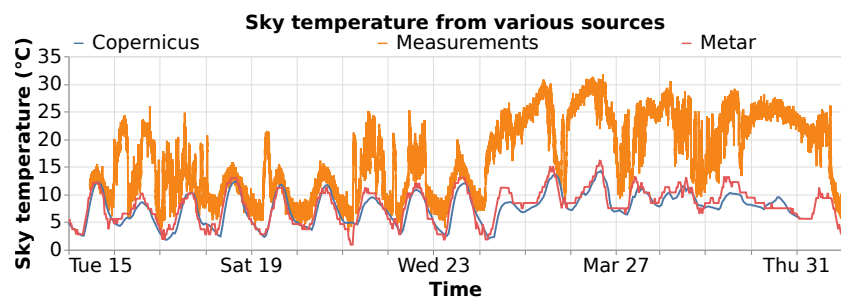


Figure 15: Sky temperature derived from different sources of air temperature

357 *6.4. Atmospheric Transmission*

358 Similarly, atmospheric transmission can also be obtained using different
359 sources. Figures 16 and 17 show the air temperature and relative humidity
360 from the various sources, respectively.

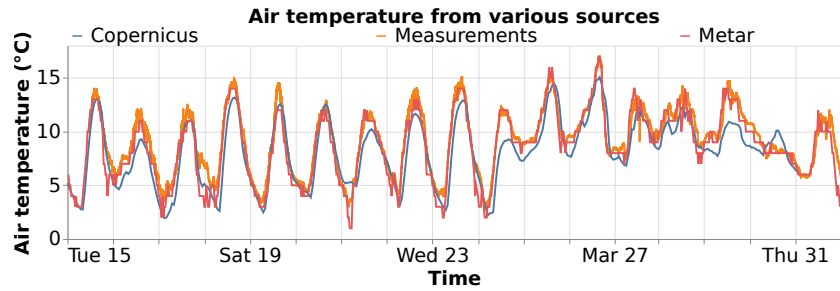


Figure 16: Air temperature obtained from different sources

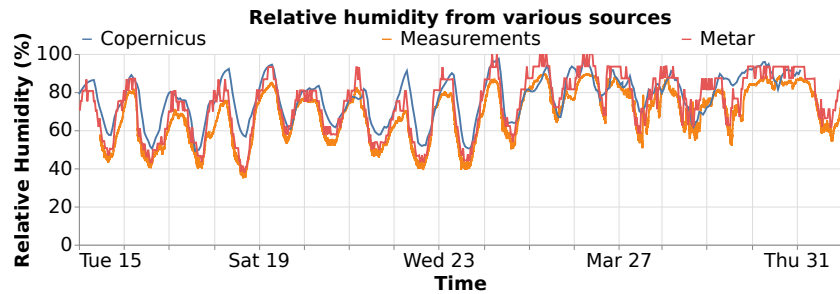


Figure 17: Relative humidity obtained from different sources

361 Finally, the estimated atmospheric transmission coefficient is shown in
362 Figure 18, using the previous quantities from the different data providers.

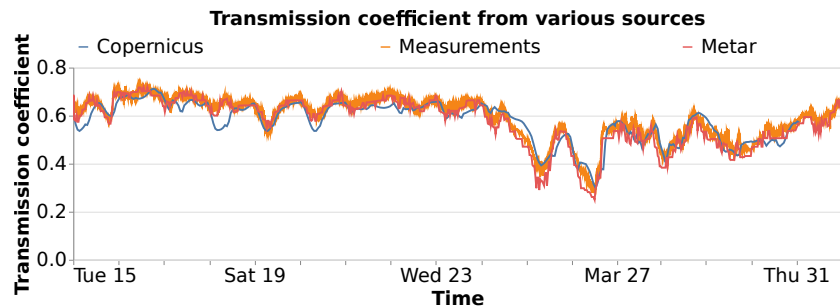


Figure 18: Atmospheric transmission derived from different sources

363 *6.5. Sun irradiance*

364 The sun irradiance is not often present in METAR data. For other
365 providers, such as Copernicus, it is integrated over the whole spectrum,
366 leading to errors on the quantities to be considered. Figure 19 shows the
367 SMARTS2 [38] irradiance’s simulation compared to a local pyranometer mea-
sure in the SWIR band.

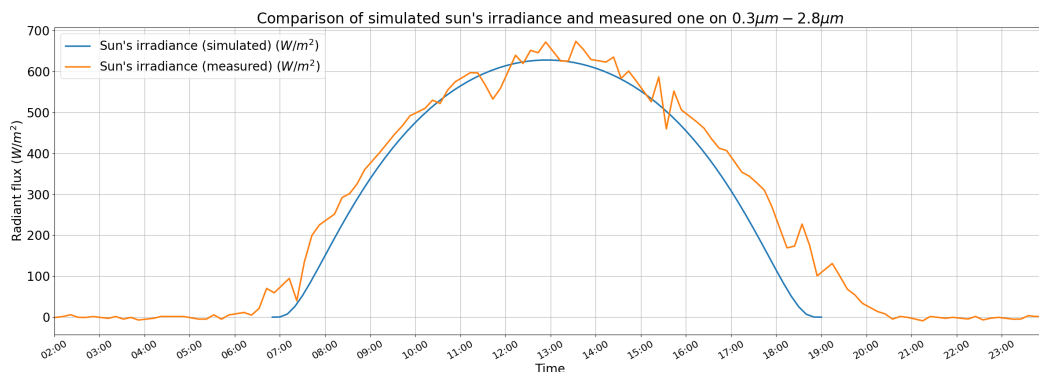


Figure 19: Comparison of sun’s irradiance measured and simulated on may 5th in the 0.3 μm to 2.8 μm band

368

369 Other models can be found in the literature and can help for getting an
370 approximation of the sun irradiance on the considered band.

371 *6.6. Discussion*

372 A review of the different parameters that may affect the temperature
373 estimation has been made. Temperature estimation based on *in-situ* infrared
374 thermography measurements needs to consider the geometry of the scene and
375 the environmental parameters to get a better estimate. When local data are
376 not available, it is possible to find online open data thanks to meteorological
377 reports or forecasts. Figure 20 shows an example of the amount of data that
378 can be gathered during a long-term experiment with missing data in red
379 due to various experiment issues (sensor failure, current shortage *etc.*). This
380 study showed that even if those measurements are missing, it is still possible
381 to estimate those data thanks to open access online data to enable the usage
382 of a refined model.

383 Finally, a comparison of the estimated temperature with the infrared cam-
384 era and a thermocouple at ground has been performed and results are shown
385 in Figure 21. Even if the thermocouple measurement cannot be considered

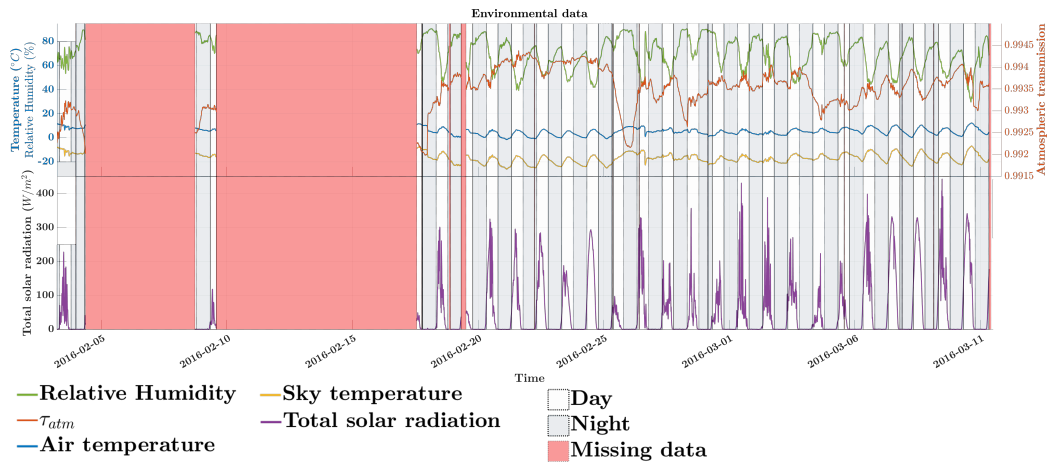


Figure 20: A set of environmental data for long-term thermal monitoring

386 as a ground truth, it is still a fair temperature reference. In this figure, it can
 387 be seen that on this period of interest, any consideration of environmental
 388 parameters from any provider will make the estimation closer to the ther-
 389 mocouple measure. In particular, on-site measurements provide, on average,
 390 the closest temperature estimation to the thermocouple.

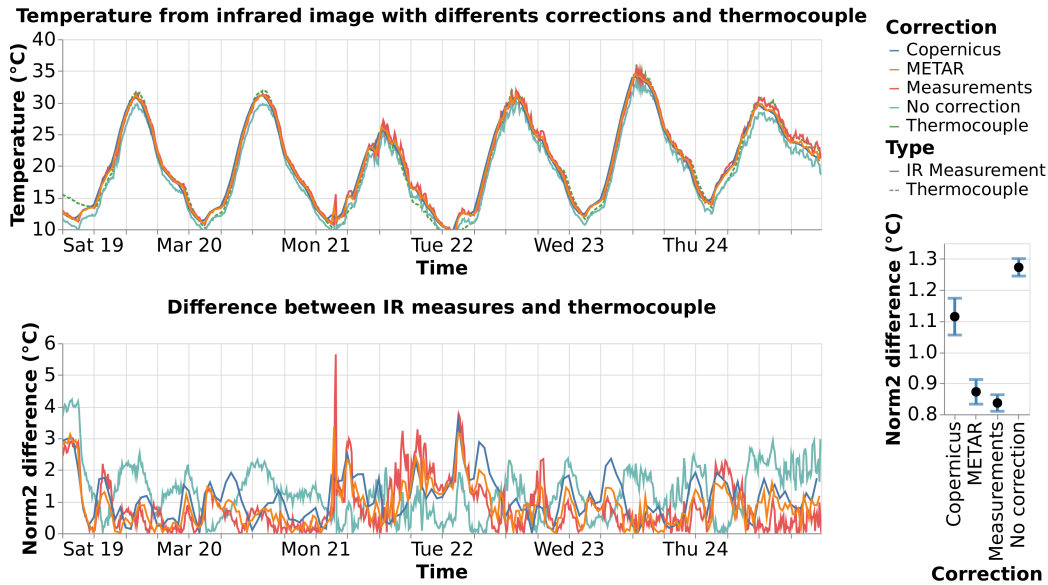


Figure 21: Comparison between infrared temperature estimation (solid) and the corresponding thermocouple at ground (dashed). Infrared temperature estimations are computed without and with different types of environmental corrections by using parameters from on-site measurements, METAR and Copernicus CDS (**top**). The absolute difference with the thermocouple is also represented (**bottom-left**) as well as the average on the period of interest (**bottom-right**).

391 Finally, more investigations need to be made for particular weather con-
 392 ditions such as snow and rain for instance, which were not observed during
 393 the studied period. Hydrometeors will have an important impact on the flux
 394 received at camera's sensors. Weather variations will produce measurements
 395 that are difficult to exploit for accurate temperature estimation (see Figure
 396 22). This may not lead to accurate temperature measurements. However,
 397 such effect could be compensated by using a black-body source and perform
 398 automatic thermal calibration in case of rain or using adequate radiative
 399 transmission model (for instance in case of fog [39]).

400 7. Conclusion

401 A study of the different parameters that create bias in long term thermal
 402 monitoring of structures by infrared thermography has been conducted. To
 403 achieve in-situ accurate temperature estimation from those measurements,
 404 one need to take into account the environmental parameters, the geometry

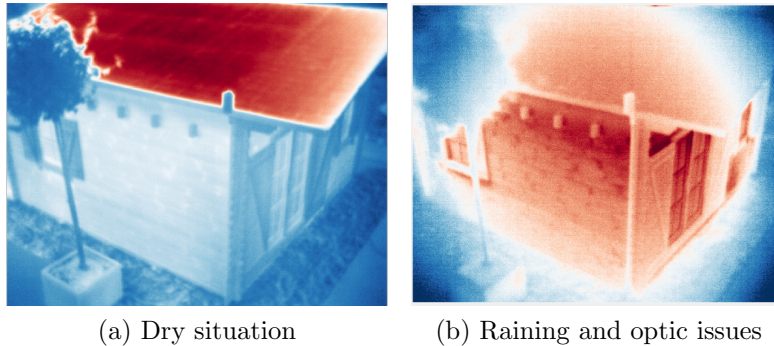


Figure 22: IR image view: in dry environment (a), rain with optic issues (b)

405 of the scene and the characteristics of the observed materials. Using local
 406 and coupled measurements with those infrared data enables the temperature
 407 estimation to be more accurate.

408 The spatial calibration presented in this study makes the extraction of
 409 region of interest possible. One other possibility is to use stereo-vision [40]
 410 to get a more accurate calibration and in particular to retrieve the depth
 411 in the image. Further investigation is required to apply computer vision
 412 algorithm for infrared images, since the infrared sensors responses have a dif-
 413 ferent response than in the visible spectrum. In any case, after resectioning,
 414 the resulting signal should be considered with caution since the sampling is
 415 not uniform. Moreover, the pixels of the image do not represent the same
 416 area in the real-world due to the perspective projection. Furthermore, one
 417 should also consider the “mixed pixel effect” due to the spatial resolution for
 418 accurate infrared measurements. In fact, considering that one given pixel is
 419 homogeneous can be discussed.

420 After presenting a sensitivity study on the environmental parameters and
 421 emissivity to quantify their effects on temperature estimation, we focused
 422 our work on environmental parameters estimation. Moreover, it has been
 423 shown that different meteorological sources could be used similarly to en-
 424 rich the monitoring’s informations. Finally, taking into account the actual
 425 sky temperature in our model as well as mapping the emissivity to the im-
 426 age materials enabled us to reduce the difference between the temperature
 427 estimation and the expected surface temperature. Estimating the sky tem-
 428 perature by a correlation gives satisfying results in a first approximation but
 429 should be tested for limit cases. However, hydrometeors’ influence and op-
 430 tics’ aberrations are not incorporated in our conversion model from digital

431 levels to temperature yet. One of the prospects is to use the meteorological
432 data coupled with a deep learning algorithm to compensate those effects. A
433 second perspective is to use a Bayesian model to further consider the joint
434 estimation of the emissivity and the temperature.

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