

Numerical evaluation of the effect of moisture on concrete pulsed thermography in tropical coastal applications

Ananta Kusuma Yoga Pratama*, Sunarko
Universitas 17 Agustus 1945 Banyuwangi, Indonesia
Corresponding Email: ananta@untag-banyuwangi.ac.id

Abstract: This numerical study evaluates how moisture-induced variations in thermal diffusivity affect delamination depth estimation in concrete using pulsed infrared thermography (PIRT). We employed a one-dimensional heat diffusion model, representing the delamination as a thermal barrier. We generated synthetic thermal responses for dry and saturated concrete with delamination depths ranging from 1 to 5 cm, using a 1 s sampling interval over a 4-h observation period. To represent measurement uncertainty, we added Gaussian noise with a standard deviation of 0.05 °C to each response, then smoothed the signals with a centered moving average using a 61-sample window. We evaluated the reliability of peak-time inversion through 200 Monte Carlo realizations under matched and mismatched conditions. The results show that increasing delamination depth reduces the thermal-contrast amplitude and increases uncertainty in peak-time determination, with a more pronounced effect in saturated concrete because its thermal response amplitude is lower. Under matched conditions, the estimation bias reached approximately 10.0% for dry concrete and 17.0% for saturated concrete, with maximum RMSE values of 1.10 and 1.35 cm, respectively. Under mismatched conditions, using the thermal diffusivity of dry concrete to invert the thermal response of saturated concrete produced a systematic shift of approximately -2.72% relative to the matched condition, consistent with the analytical prediction. For the parameters investigated, these results indicate that uncertainty in peak-time determination contributes more strongly to the overall estimation error than thermal-diffusivity mismatch. Nevertheless, using a thermal-diffusivity value representative of the actual moisture condition remains important for improving the reliability of PIRT-based delamination depth estimation in tropical coastal environments.

Keywords: *numerical analysis; pulsed infrared thermography; concrete delamination; thermal diffusivity; Monte Carlo simulation*

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INTRODUCTION

Infrared thermography is a nondestructive testing method used to identify subsurface conditions in materials based on changes in surface temperature. In concrete inspection, thermal energy is applied to the surface, causing heat to diffuse into the material and producing a transient temperature distribution that is recorded over time using an infrared camera. A subsurface defect, such as delamination, perturbs heat transfer, producing a surface-temperature response above the defective region that differs from that of intact concrete. The relationship between subsurface conditions and the resulting surface-temperature response can be described as a *forward problem*. When the defect depth, (d), is known, a heat-transfer model is used to predict the surface-temperature response as a function of time, $T(t)$, yielding the conceptual relationship $d \rightarrow T(t)$. Under actual inspection conditions, however, the defect depth is unknown, whereas the surface-

temperature history, $T(t)$, is obtained from thermographic measurements (Maierhofer et al., 2002). The measured temperature response is therefore used to estimate the unknown subsurface parameter, particularly defect depth, resulting in an inverse problem represented by $T(t) \rightarrow d$. When the inversion relies primarily on the temporal evolution of the temperature response, the approach is called time-domain inversion (Wei et al., 2021).

Defects at different depths produce distinct temporal responses because heat takes finite time to diffuse through the material before a defect's influence becomes observable at the surface. This temporal information can therefore be used to estimate defect depth through a heat-transfer model. The accuracy of such estimates strongly depends on how well the model represents the actual heat-transfer process within the concrete, particularly through the thermal diffusivity (α), because this parameter governs the rate of heat diffusion and directly affects the relationship between thermal-response time and defect depth (Huh et al., 2018; Pozzer et al., 2024). The thermal diffusivity of concrete is not constant but varies with its degree of water saturation. Water within the pore structure alters the thermal conductivity, density, and specific heat capacity of concrete, thereby changing its thermal diffusivity (Pedram et al., 2024; Tong et al., 2025). In both peak-time inversion and curve-fitting approaches, defect depth is estimated from characteristic features of the temporal thermal response using thermal diffusivity as an input parameter (Huh et al., 2018; Qu et al., 2020; Wei et al., 2021). Consequently, using an inappropriate thermal-diffusivity value can introduce systematic errors into defect-depth estimates.

This issue becomes particularly important for concrete structures in tropical coastal environments, where high moisture levels and continuous chloride exposure increase susceptibility to reinforcement corrosion and subsequent delamination (Pedram et al., 2024; Raja et al., 2021). At the same time, infrastructure managers require inspection techniques that are rapid, nondestructive, and cost-effective while still providing quantitative estimates of delamination depth to support maintenance decisions. Although the effects of moisture on the thermal properties of concrete have been widely reported, their implications for the accuracy of depth estimation using infrared-thermography inversion methods have not yet been systematically evaluated (Asadi et al., 2018; Wei'slik & Wei'slik, 2026). Most previous studies have developed and validated inversion methods using concrete specimens under laboratory conditions in which thermal properties were assumed to remain constant (Ibrahim et al., 2026; Omar et al., 2018). Consequently, the magnitude of depth-estimation error resulting from moisture-induced variations in thermal diffusivity remains insufficiently quantified, particularly for water-saturated concrete in tropical coastal environments.

In addition to thermal-parameter accuracy, measurement uncertainty affects depth-estimation performance. In peak-time inversion, sensor noise can introduce uncertainty in determining the thermal-response peak time, whereas insufficient observation duration may prevent capturing the peak response associated with deeper delaminations. Furthermore, a low signal-to-noise ratio (SNR) can make it difficult to distinguish the thermal response associated with delamination from noise fluctuations (Tran et al., 2018; Wei et al., 2021; Zhuo et al., 2024). Although researchers have investigated moisture effects on the thermal properties of concrete and noise effects on thermal-response detectability separately, few studies have quantitatively examined how moisture-induced thermal-diffusivity mismatch interacts with measurement uncertainty to determine the accuracy of delamination depth estimation. Consequently, the relative contributions of systematic bias arising from thermal-parameter mismatch and uncertainty arising from measurement noise remain insufficiently quantified.

To address this gap, the present study conducts a numerical investigation to quantify the effect of moisture-induced changes in thermal diffusivity on the accuracy of delamination depth estimation using pulsed infrared thermography (PIRT) (Pedram et al., 2024; Pozzer et al., 2024). Monte Carlo analysis evaluates estimation uncertainty due to sensor noise and quantifies the systematic bias that arises when the thermal diffusivity of dry concrete is used to invert the thermal response of saturated concrete. We also evaluate how decreasing signal-to-noise ratio (SNR) affects the stability of peak-time determination and

depth estimation. Within this framework, we quantitatively compare the contributions of measurement uncertainty and thermal-diffusivity mismatch to the accuracy of delamination depth estimation. The results provide a basis for assessing the reliability of PIRT-based delamination depth estimation in concrete under different moisture conditions.

METHOD

This study used a numerical simulation approach to quantify how moisture-induced variations in thermal diffusivity affect the accuracy of delamination depth estimation using pulsed infrared thermography (PIRT). The methodology included developing a physical delamination model, determining the thermophysical properties of concrete under two moisture conditions, generating synthetic data, performing depth inversion, and evaluating uncertainty using Monte Carlo simulations.

Forward model

As an initial step, we modeled the delamination as an air-filled gap with substantially higher thermal resistance than the surrounding concrete and approximated it as a thermally insulating plane. The delamination was assumed to be located at a depth (d) beneath the surface of a semi-infinite concrete half-space subjected to instantaneous heating at ($t=0$) with an absorbed pulse energy (Q) per unit area. Using the method of images, the surface temperature contrast, (ΔT), between the delaminated region and the intact concrete is expressed by Eq. (1) (Qu et al., 2020)

$$\Delta T(t) = \frac{2Q}{e\sqrt{\pi t}} \exp\left(-\frac{d^2}{\alpha t}\right) \quad (1),$$

where (Q) is the absorbed pulse energy per unit area and represents the magnitude of the applied thermal excitation; (d) is the defect depth; α is the thermal diffusivity; (e) is thermal effusivity of concrete and (t) is time. The thermal diffusivity and thermal effusivity are determined from the basic thermophysical properties of the material as

$$\alpha = \frac{k}{\rho c} \quad (2),$$

and

$$e = \sqrt{k\rho c} \quad (3),$$

respectively, where (k) is the thermal conductivity; ρ is the density and (c) is the specific heat capacity.

According to Eq. (1), ΔT varies with time. Following thermal excitation, the temperature contrast initially increases until reaching a maximum and subsequently decreases after the peak time. Mathematically, the time at which the temperature contrast reaches its maximum is determined by setting its first derivative with respect to time equal to zero or $\frac{d(\Delta T)}{dt} = 0$. Solving this condition yields the characteristic peak time

$$t_{peak} = \frac{2d^2}{\alpha} \quad (4),$$

which indicates that, for a fixed thermal diffusivity, the time at which the maximum temperature contrast occurs is proportional to the square of the delamination depth. Consequently, deeper delaminations require a longer time for the thermal response to reach its maximum. During the inversion process, the peak time is extracted from the measured temperature-contrast history and subsequently combined with the thermal diffusivity to estimate the delamination depth. Using the observed peak time as the characteristic temporal parameter, the delamination depth can be estimated as

$$\hat{d} = \sqrt{\frac{\alpha t_{\text{peak}}}{2}} \quad (5).$$

This model represents a first-order approximation in which the delamination is treated as a perfectly thermally insulating plane with lateral dimensions substantially larger than its depth. Under this geometric condition, heat flow in the vicinity of the delamination can be assumed to occur predominantly in the direction normal to the concrete surface, whereas lateral heat transfer is comparatively small. The thermal response can therefore be described using a one-dimensional heat-diffusion approximation. The present model does not explicitly incorporate secondary phenomena, such as the finite lateral extent of the delamination and heat transfer across the delamination gap. These effects may influence the amplitude and shape of the thermal response; however, in this study, we adopt the relationship between peak time and depth as a first-order approximation, provided the thermal response remains dominated by one-dimensional heat diffusion. Under these assumptions, we use peak-time inversion to estimate delamination depth.

Material properties and synthetic data generation

After establishing the physical model, two concrete moisture conditions were simulated using thermophysical properties obtained from the literature (Bamogo et al., 2023; Khan, 2002; Kodur, 2014; Revuelta et al., 2021), dry and saturated conditions, as summarized in Table 1. We selected these conditions as two end-member states representing the range of moisture conditions relevant to concrete applications in tropical coastal environments. Water within the pore structure simultaneously increases the thermal conductivity, density, and specific heat capacity of concrete, resulting in an approximately 5.7% increase in thermal diffusivity and a 51.4% increase in thermal effusivity relative to the dry condition. We used thermal conductivity, density, and specific heat capacity as the fundamental material parameters, and calculated thermal diffusivity and thermal effusivity from the corresponding thermophysical relationships. These values were used as reference parameters for the numerical experiments and were not intended to represent concrete from any specific site. Future work will calibrate the thermophysical parameters for tropical coastal concrete through experimental validation.

Table 1. Parameter termofisika yang digunakan untuk dua kondisi kelembaban.

Parameter	Symbol	Unit	Dry	Saturated
Thermal conductivity	k	$\text{W m}^{-1} \text{K}^{-1}$	2,26	3,52
Density	ρ	kg m^{-3}	2100	2400
Specific heat capacity	c_p	$\text{J kg}^{-1} \text{K}^{-1}$	1070	1380
Thermal diffusivity	α	$\text{m}^2 \text{s}^{-1}$	$1,01 \times 10^{-6}$	$1,06 \times 10^{-6}$
Thermal effusivity	e	$\text{W s}^{1/2} \text{m}^{-2} \text{K}^{-1}$	2254	3412

For each moisture condition, noise-free temperature-contrast histories were calculated using Eq. (1) for delamination depths of $d = 1, 2, \dots, 5$ cm with the specified absorbed pulse energy (Almond & Pickering, 2012). The data were sampled at 1-s intervals over a 4-h observation window (14,400 s). According to Eq. (4), this observation window encompasses the theoretical peak times for all depths considered, up to 5 cm, under both moisture conditions. For a delamination depth of 5 cm, the theoretical peak time is approximately 1.38 h for dry concrete and 1.31 h for saturated concrete. Thus, the simulation covers depths whose peak responses remain within the observation window while allowing evaluation of the effect of depth on inversion uncertainty. We then introduced measurement noise into each thermal-response history to represent the measurement uncertainty associated with an uncooled infrared camera.

The measurement noise was modeled as a Gaussian random variable with zero mean and a standard deviation of 0.05 °C. This standard deviation was selected as a representative noise level consistent with the thermal sensitivity of uncooled microbolometer cameras commonly used for field inspections (Fischer,

2026), (Wang et al., 2025). Derau Gaussian dibangkitkan secara independen pada setiap titik waktu sehingga setiap riwayat temperatur menghasilkan variasi respons termal yang berbeda. Gaussian noise was generated independently at each time point, resulting in a different noisy thermal-response history for each realization. For each combination of delamination depth and moisture condition, 200 independent noise realizations were generated. With five delamination depths and two moisture conditions, we considered 10 simulation conditions. Each condition produced 200 thermal records with independent noise realizations, yielding a total of 2,000 synthetic thermal-response records ($5 \times 2 \times 200$). We then used all records as inputs for the signal-smoothing and depth-inversion procedures.

Depth inversion procedure

Each noisy synthetic thermal response was first smoothed using a centered moving average with a window width of 61 samples. With a sampling interval of 1 s, this window corresponds to a smoothing duration of 61 s. At each time point, the smoothed value was calculated as the average of samples symmetrically distributed before and after the corresponding point (Shan et al., 2022). Using an odd number of samples provides a uniquely defined central point, allowing the smoothing window to be positioned symmetrically around each observation time.

Smoothing was applied to reduce random fluctuations from measurement noise while preserving the thermal response's principal temporal characteristics. We selected the window width by balancing noise reduction with preservation of the response shape and peak location. A window that is too short provides limited noise suppression, whereas an excessively long window may broaden or shift the response peak, particularly for shallow delamination with relatively short response times. We therefore selected a 61-s window to ensure the smoothing duration remained sufficiently short relative to the earliest theoretical peak time within the analyzed depth range. For example, for a 1-cm delamination in dry concrete, Eq. (4) gives a theoretical peak time of approximately 199 s for $\alpha \approx 1,006 \times 10^{-6} \text{ m}^2/\text{s}$.

We selected a centered moving average to avoid the systematic temporal shift that can occur with one-sided causal filtering. For a 61-sample moving-average filter, a causal implementation would introduce a nominal delay of $((61-1)/2 = 30)$ samples, corresponding to approximately 30 s at a sampling interval of 1 s. Such a temporal shift could affect the estimated depth because peak-time inversion uses peak time directly as an input parameter. We therefore employed centered smoothing so each smoothed value remained assigned to the midpoint of the corresponding window. Because a centered moving average does not have full window support near the beginning and end of a record, the peak search was restricted to the portion of the signal for which the complete smoothing window was available. For the 61-sample window, we excluded the first and last 30 samples from the maximum-search procedure. This restriction prevents edge effects from influencing peak-time determination. After smoothing the signal, we identified the observed peak time as the time at which the smoothed signal reached its maximum value. We then used the resulting peak time to calculate the estimated delamination depth using Eq. (5). We performed the inversion independently for each thermal-response record generated in the Monte Carlo simulation, so the distribution of estimated depths reflected the variation in peak times produced by different noise realizations.

Monte Carlo evaluation

The final stage evaluated the reliability of the depth estimates using Monte Carlo simulations. Two inversion scenarios were considered: matched and mismatched conditions. Under the matched condition, the synthetic data were inverted using the same thermal diffusivity as that employed in the forward model. This scenario served as the reference condition for evaluating depth-estimation uncertainty arising from measurement noise and uncertainty in peak-time determination when the thermal properties were specified correctly. Under the mismatched condition, the thermal response generated for saturated concrete was inverted using the thermal diffusivity of dry concrete. This scenario was used to quantify the systematic bias resulting from a mismatch between the actual thermal diffusivity of the material and the value assumed

during inversion.

According to Eq. (5), the estimated depth is proportional to the square root of the thermal diffusivity. Because the matched and mismatched inversions use the same detected peak time, the ratio between their estimated depths can be expressed analytically as $\frac{\hat{d}_{mismatched}}{\hat{d}_{matched}} = \sqrt{\frac{\alpha_{dry}}{\alpha_{saturated}}} = 0,9728$. Using the parameters listed in Table 1, $\alpha_{dry} \approx 1,006 \times 10^{-6} \text{ m}^2/\text{s}$, dan $\alpha_{saturated} \approx 1,063 \times 10^{-6} \text{ m}^2/\text{s}$, the resulting ratio is approximately 0.9728. This indicates that using the thermal diffusivity of dry concrete to invert the thermal response of saturated concrete produces a depth estimate approximately 2.72% lower than that obtained under the matched condition. We used this analytical value as a reference to verify the consistency of the Monte Carlo simulation results and to separate the systematic bias caused by thermal-diffusivity mismatch from the estimation uncertainty already present under the matched condition.

FINDINGS AND DISCUSSION

Thermal response and delamination detectability

The forward-model results show that delamination depth and moisture condition affect different characteristics of the thermal response. The same forward-model equation was applied at each depth, whereas the effect of moisture condition was represented by differences in thermal diffusivity (α And thermal effusivity (e). The results indicate that delamination depth and moisture condition influence the temporal characteristics and amplitude of the thermal response in different ways. Eq. (4) describes the quadratic relationship between peak time and delamination depth, with thermal diffusivity governing the response's temporal characteristics.

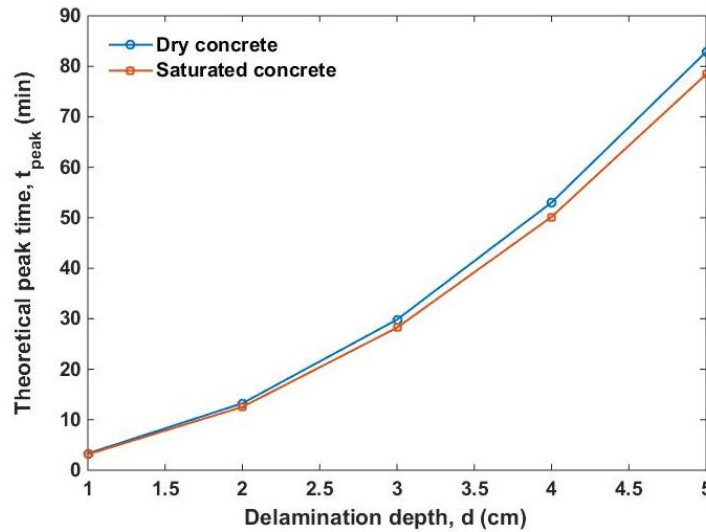


Figure 1. Relationship between delamination depth and theoretical peak time.

Increasing delamination depth also reduces the amplitude of the thermal response. This behavior is illustrated in Figure 2, which shows theoretical noise-free temperature-contrast histories for dry concrete at representative delamination depths of 1, 2, 4, and 5 cm. At shallower depths, the response exhibits a relatively high amplitude and reaches its maximum within a shorter time. In contrast, increasing depth shifts the peak toward later times, reduces its amplitude, and broadens the response around the maximum. The maximum temperature contrast in dry concrete decreases from approximately 0.215 °C at a depth of 1 cm to approximately 0.043 °C at 5 cm.

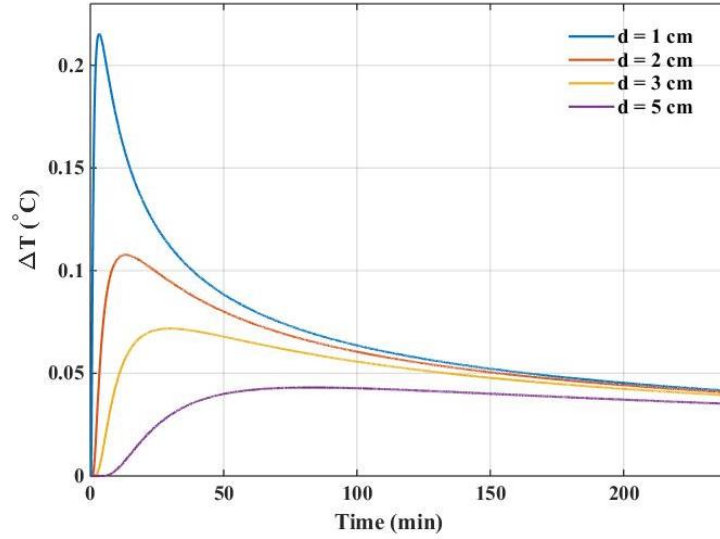


Figure 2. Theoretical noise-free temperature-contrast histories for dry concrete at delamination depths of 1, 2, 4, and 5 cm.

These two response characteristics serve different functions in the quantitative evaluation of delamination. The temporal position of the peak carries information on defect depth and forms the basis of peak-time inversion, whereas the contrast amplitude determines how clearly the thermal response can be distinguished from measurement noise. Increasing depth therefore not only delays the appearance of the thermal response but also reduces the signal strength available for detection.

The influence of moisture condition on response amplitude is shown more clearly in Figure 3, which compares the maximum temperature contrast between dry and saturated concrete over the entire depth range investigated. At every depth, the peak contrast for saturated concrete is consistently lower than that for dry concrete. For the material properties adopted in this study, the reduction is approximately 32%. For example, at a depth of 1 cm, the peak amplitude decreases from approximately 0.215 °C under dry conditions to approximately 0.146 °C under saturated conditions, whereas at a depth of 5 cm it decreases from approximately 0.043 to 0.029 °C.

The reduction in amplitude is primarily associated with moisture-induced changes in thermophysical properties. Higher thermal effusivity indicates a greater capacity of the material to absorb and redistribute thermal energy, thereby reducing the local surface-temperature variation produced by the presence of a delamination. Moisture therefore affects the thermographic response through two distinct mechanisms. An increase in thermal effusivity primarily reduces the response amplitude and affects detectability, whereas changes in thermal diffusivity influence the temporal characteristics of the response and the peak-time position used for depth estimation. Distinguishing between these two mechanisms is important because changes in amplitude are primarily associated with signal quality, whereas changes in peak time directly affect the inversion process.

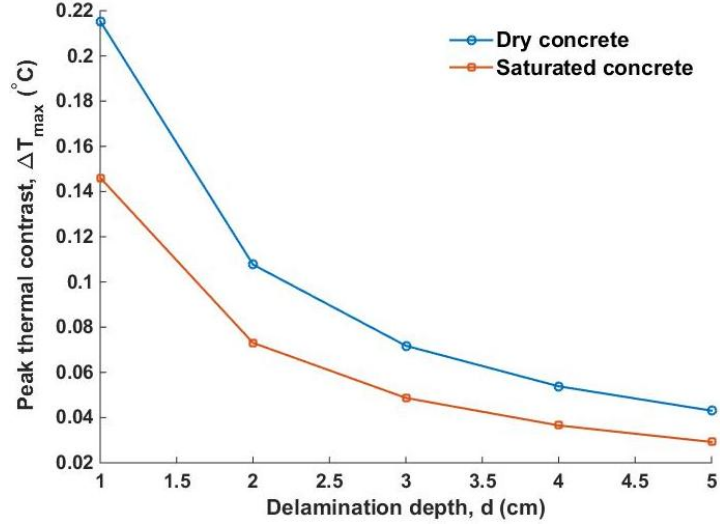


Figure 3. Maximum temperature contrast as a function of delamination depth

Measurement uncertainty was modeled by adding Gaussian noise with the prescribed standard deviation to each theoretical thermal-response history. Figure 4 shows one realization at a delamination depth of 2 cm to illustrate the effect of noise and subsequent signal smoothing. This depth was selected only as a representative example to demonstrate the response before and after smoothing and was not treated as a special case in the analysis. The addition of noise introduces temperature fluctuations that can interfere with direct peak-time determination. After applying a centered moving average with a 61-sample window, the random fluctuations are reduced, producing a smoother thermal response and allowing the peak time to be determined more consistently.

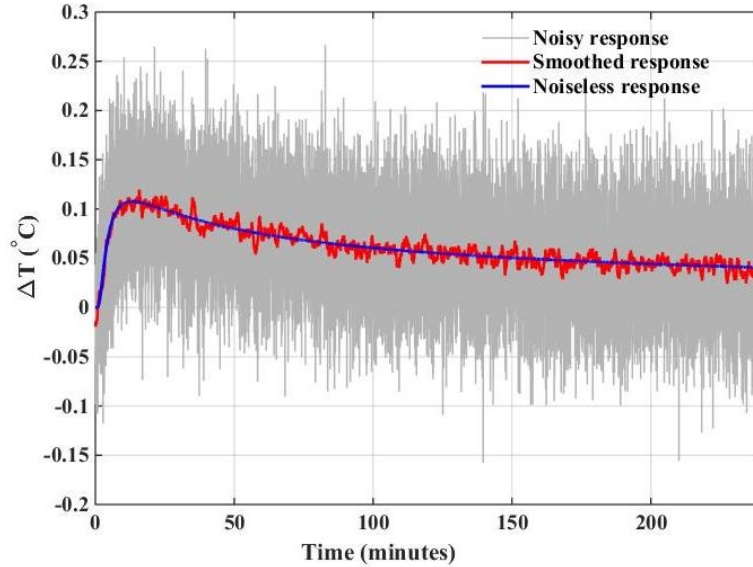


Figure 4. Theoretical, Gaussian-noisy, and smoothed temperature-contrast responses at a delamination depth of 2 cm.

Based on the relationship between peak amplitude and the effective noise level after smoothing, the SNR decreases with increasing delamination depth and under saturated conditions. For dry concrete with a 1-cm-deep delamination, the peak SNR is approximately 34. In contrast, for saturated concrete at a depth of 5 cm, the SNR decreases to approximately 4.6. This reduction indicates that, as the delamination becomes

deeper and the thermal-response amplitude decreases, the distinction between the signal and the residual noise fluctuations after smoothing becomes progressively smaller. Consequently, peak-time determination becomes increasingly sensitive to measurement variability.

The reduction in SNR subsequently affects depth estimation. For shallow delamination, the relatively high response amplitude and well-defined peak allow more consistent peak-time determination. In contrast, deeper delamination reduce the response amplitude and broaden the curve around the peak. Under these conditions, several time points near the maximum may have similar temperature-contrast values, allowing residual noise fluctuations after smoothing to shift the detected peak time. This uncertainty in peak time is subsequently propagated into the depth estimate through Eq. (5). Within the depth range considered, the observation-window duration is not a dominant factor in peak-time determination. At the maximum depth of 5 cm, the theoretical peak time reaches only about 1.38 h for dry concrete and 1.31 h for saturated concrete, whereas the observation duration is 4 h. Peak-time uncertainty over the investigated range is therefore primarily associated with reduced response amplitude, lower SNR, broadening of the response around the peak, and measurement noise.

Overall, the forward-model results demonstrate that delamination depth and moisture condition affect both the amplitude and temporal characteristics of the thermal response. Increasing depth decreases the temperature-contrast amplitude and increases the peak time, whereas saturation reduces the response amplitude and shifts the peak time by changing the material's thermophysical properties. The resulting reduction in amplitude lowers the SNR and increases uncertainty in peak-time determination. These results provide the basis for evaluating depth-estimation accuracy under conditions in which the thermal diffusivity used in the inversion is consistent with the actual material condition, hereafter referred to as the matched condition.

Accuracy of Depth Estimation Under Matched Conditions

The preceding analysis focused on thermal-response characteristics and delamination detectability. In this section, we use the thermal-response peak time as the primary parameter in peak-time inversion to estimate delamination depth. The initial evaluation is performed under matched conditions, where the thermal diffusivity used during inversion matches that used in the forward model. This configuration serves as a baseline for quantifying estimation errors arising from measurement noise, signal smoothing, and uncertainty in peak-time determination, without any contribution from thermal-parameter mismatch.

For each Monte Carlo realization, the peak time obtained from the smoothed thermal response was converted into an estimated depth using the peak-time inversion relationship in Eq (5), with the thermal diffusivity corresponding to the relevant material condition. For each combination of delamination depth and moisture condition, we obtained 200 depth estimates and evaluated them in terms of the mean, standard deviation (SD), root mean square error (RMSE), and relative bias. Table 2 summarizes the matched-condition results.

The results in Table 2 show that the mean estimated depth increases with the true depth, while the spread of the estimates becomes progressively larger as the delamination depth increases. Across the entire 1–5 cm range, the mean estimates are greater than the corresponding true depths. For dry concrete, the relative bias increases from approximately +4.1% at a depth of 1 cm to +10.0% at 5 cm. For saturated concrete, the bias ranges from approximately +5.5% to +17.0%, with the maximum occurring at a depth of 4 cm. The RMSE also increases from 0.11 to 1.10 cm for dry concrete and from 0.14 to 1.35 cm for saturated concrete. The relationship between the true and estimated depths is visualized in Figure 5. The 1:1 diagonal represents ideal estimation, whereas the error bars indicate ± 1 standard deviation across the 200 Monte Carlo realizations.

Table 2. Statistics of delamination depth estimates under matched conditions based on 200 Monte Carlo realizations.

Condition	True depth (cm)	Mean (cm)	SD (cm)	RMSE (cm)	Bias (%)
Dry	1	1.04	0.11	0.11	+4.1
	2	2.10	0.28	0.30	+5.2
	3	3.18	0.45	0.48	+6.0
	4	4.31	0.64	0.71	+7.8
	5	5.50	0.98	1.10	+10.0
Saturated	1	1.07	0.13	0.14	+5.5
	2	2.15	0.37	0.41	+8.6
	3	3.30	0.60	0.68	+10.4
	4	4.46	1.06	1.25	+17.0
	5	5.67	1.13	1.35	+14.6

The increased uncertainty reflects depth-dependent changes in the thermal response. Deeper delaminations produce lower response amplitudes and flatter curves around the peak. Consequently, several time points near the maximum exhibit similar temperature-contrast values, making the detected peak time more susceptible to residual noise fluctuations after smoothing. Because the estimated depth depends on the square root of the peak time, variations in the detected peak time are subsequently propagated into variations in the estimated depth. Thus, the increase in standard deviation and RMSE under matched conditions primarily reflects the increasing uncertainty in peak-time determination as the SNR decreases.

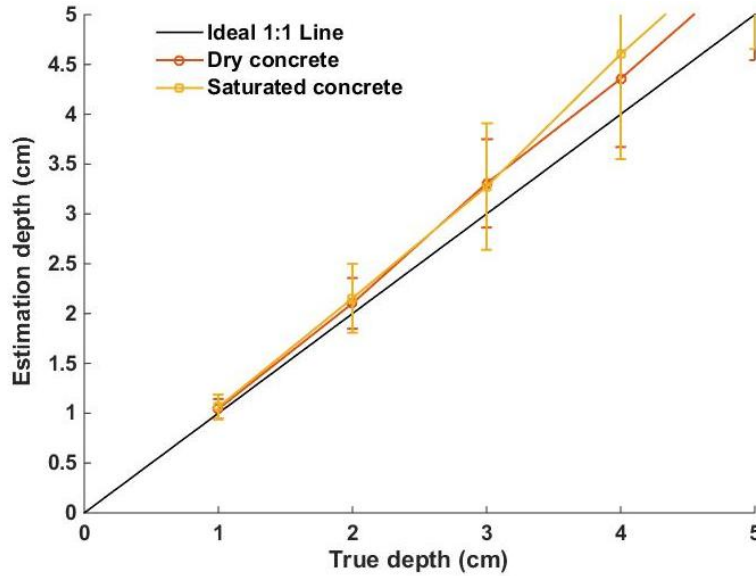


Figure 5. Relationship between true and estimated delamination depths under matched conditions for dry and saturated concrete.

The positive bias observed over the entire depth range indicates that using a thermal-diffusivity value consistent with the material condition does not necessarily yield unbiased estimates. In the presence of noise, broadening of the thermal-response peak can cause the numerically detected maximum to deviate from the theoretical peak time. Signal smoothing may also alter the local shape of the response around the maximum. A shift in the detected peak toward later times results in an overestimation of depth because $\hat{d} \propto$

$\sqrt{t_{\text{peak}}}$. These mechanisms may contribute to the systematic tendency toward overestimation observed over the investigated depth range.

Differences between dry and saturated concrete are also evident in the spread of the estimated depths. In general, saturated concrete exhibits larger standard deviations and RMSE values than dry concrete at the same depth. At a depth of 5 cm, for example, the standard deviation is 1.13 cm for saturated concrete compared with 0.98 cm for dry concrete. The corresponding RMSE is also higher for saturated concrete, at 1.35 cm compared with 1.10 cm for dry concrete. This difference is consistent with the lower temperature-contrast amplitude of saturated concrete. Although the thermal diffusivity used during inversion correctly represents the material condition, reduced signal quality makes peak-time determination more sensitive to noise. Moisture condition can therefore influence estimation precision through changes in thermal-response characteristics even in the absence of thermal-diffusivity mismatch.

The matched scenario reveals a baseline error in peak-time inversion even when the thermal diffusivity is specified consistently with the material condition. Over the 1–5 cm depth range, the bias reaches approximately 10% for dry concrete and approximately 17% for saturated concrete, accompanied by increasing standard deviation and RMSE at greater depths. These results establish a reference condition for distinguishing uncertainty associated with signal quality and peak-time determination from the systematic bias specifically caused by the use of an inappropriate thermal-diffusivity value. The matched results are therefore used as the reference for evaluating the mismatched condition, in which the thermal response of saturated concrete is inverted using the thermal diffusivity of dry concrete. Comparing these two conditions allows the effect of thermal-diffusivity mismatch to be separated from the baseline uncertainty inherent in peak-time inversion (Hiasa, et al, 2017).

Systematic Bias Due to Moisture-Induced Thermal-Diffusivity Mismatch

The simulation results show that using the thermal diffusivity of dry concrete to invert the thermal response of saturated concrete consistently produces lower depth estimates than those obtained under matched conditions. This behavior is observed throughout the investigated depth range of 1–5 cm and agrees with the analytical prediction established in the Methods section. The comparison between the two inversion conditions is summarized in Table 3. The shift caused by thermal-diffusivity mismatch is consistent across all depths, whereas the bias relative to the true depth varies because the matched estimates already contain uncertainty associated with peak-time determination.

Table 3. Comparison of depth estimates for saturated concrete under matched and mismatched conditions and the corresponding relative bias with respect to the true depth.

True depth (cm)	Matched (cm)	Mismatched (cm)	Mismatched/Matched ratio	Matched bias (%)	Mismatched bias (%)
1	1.07	1.04	0.9728	6.7	3.8
2	2.15	2.09	0.9728	7.3	4.3
3	3.30	3.21	0.9728	10.0	7.0
4	4.46	4.34	0.9728	11.5	8.5
5	5.67	5.52	0.9728	13.5	10.4

The results in Table 3 show that the matched condition produces an overestimation tendency across the entire depth range. Applying the thermal diffusivity of dry concrete to the thermal response of saturated concrete subsequently shifts the estimates toward lower values. This shift reduces the positive bias already present under matched conditions. At a depth of 5 cm, for example, the mismatched estimate is lower than the corresponding matched estimate, thereby reducing the bias relative to the true depth. However, the smaller bias relative to the true depth under mismatched conditions does not imply that the use of an inappropriate thermal-diffusivity value provides a physically more accurate estimate. Rather, this apparent

improvement occurs because the baseline bias associated with peak-time uncertainty and the systematic shift induced by thermal-diffusivity mismatch act in opposite directions. It is therefore necessary to distinguish the shift specifically caused by parameter mismatch from the total error relative to the true depth.

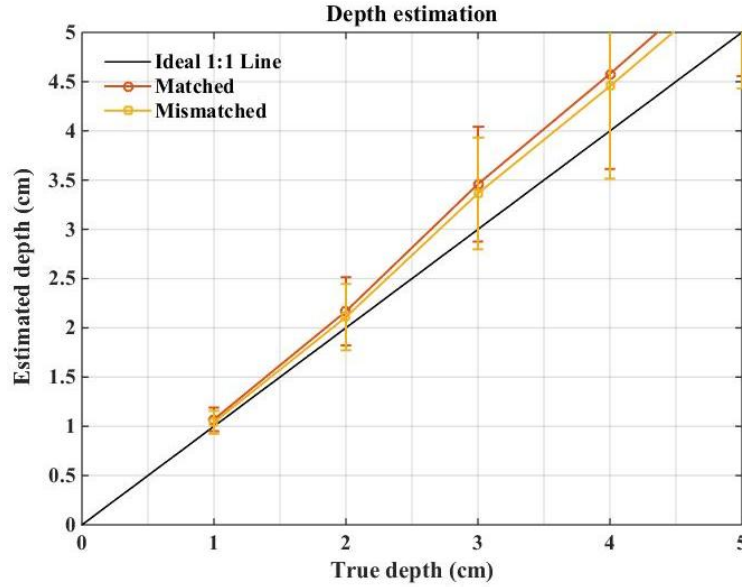


Figure 6. Effect of moisture-induced thermal-diffusivity mismatch on depth estimation and comparison with the analytical prediction.

The consistency of the mismatch effect across all depths is illustrated in Figure 6 through the ratio of mismatched to matched depth estimates. The Monte Carlo results coincide with the analytical prediction of approximately 0.9728 throughout the investigated depth range. This agreement verifies that the estimation shift caused by thermal-diffusivity mismatch follows the analytical relationship used in the inversion model. The magnitude of the shift due to the mismatch is relatively small compared with the bias and spread already present under matched conditions. For the thermophysical parameter pair considered in this study, the mismatch produces a systematic shift of approximately 2.72%, whereas the estimation bias under matched conditions reaches approximately 10% for dry concrete and approximately 17% for saturated concrete. These results indicate that, under the simulation configuration considered here, uncertainty in peak-time determination contributes more strongly to the overall estimation error than the thermal-diffusivity mismatch between the two moisture conditions.

Nevertheless, thermal-diffusivity mismatch remains important because its effect is systematic. In contrast to measurement noise, which produces variability among realizations, the use of a thermal-diffusivity value that does not represent the actual material condition consistently shifts the resulting depth estimates. Selecting a thermal diffusivity representative of the actual moisture condition is therefore still necessary for quantitative PIRT applications. Overall, the results show that depth-estimation error arises from a combination of uncertainty in peak-time determination and systematic bias due to thermal-diffusivity mismatch. Separating these two components enables the contribution of each source of uncertainty to the inversion results to be evaluated more clearly.

Overall, the mismatched analysis demonstrates that using the thermal diffusivity of dry concrete to interpret the thermal response of saturated concrete produces a systematic bias of approximately -2.72% relative to the matched result for the thermophysical properties considered. The total error relative to the true depth, however, remains dependent on the interaction between this systematic bias and the baseline error associated with peak-time determination. Separating these components provides a basis for establishing an error budget and evaluating the relative contributions of moisture condition, measurement

noise, and observation-window limitations to the accuracy of delamination depth estimation.

Relative Contributions of Uncertainty Sources to Depth Estimation

Overall, uncertainty in depth estimation using peak-time inversion arises primarily from two sources: uncertainty in peak-time determination and mismatch in the thermal-diffusivity parameter. Peak-time uncertainty mainly reflects the quality of the thermal response, including signal amplitude, SNR, peak shape, the smoothing procedure, and the observation window. In contrast, thermal-diffusivity mismatch introduces a systematic shift in the inversion results when the value of (α) used in the inversion does not represent the actual moisture condition of the material.

Comparison of these two mechanisms shows that, for the thermophysical properties considered in this study, uncertainty associated with peak-time determination contributes more strongly to the estimation error than the thermal-diffusivity mismatch between dry and saturated conditions. Nevertheless, the mismatch remains important because it is systematic and can be predicted analytically. This behavior differs from noise measurement and peak detection, which are stochastic and vary across realizations.

These findings indicate that improving the accuracy of quantitative PIRT requires addressing both sources of uncertainty. The thermal diffusivity used in the inversion should reflect the material's actual moisture condition, while maintaining adequate signal quality and stable peak-time determination. These requirements become increasingly important for deeper delamination because the thermal-response amplitude decreases and the temporal information around the peak becomes progressively less distinct.

Accordingly, depth estimation reliability depends not on a single parameter but on the interaction between the material's thermophysical properties and the quality of the temporal information in the thermal response. Distinguishing between stochastic and systematic error components provides a clearer basis for evaluating uncertainty and developing more robust PIRT procedures for concrete under varying moisture conditions, including those encountered in tropical coastal environments. Future research should evaluate how salt and chloride ion accumulation within concrete pores specifically alter thermal diffusivity, which could introduce a new type of systematic error.

CONCLUSION

The numerical analysis shows that moisture conditions affect concrete delamination depth estimation by changing both the thermal-response characteristics and the thermal diffusivity used in the inversion process. Increasing the delamination depth from 1 to 5 cm reduces the temperature-contrast amplitude and increases the peak time, making peak-time determination progressively more sensitive to noise. This effect is more pronounced in saturated concrete because its thermal-response amplitude is lower than that of dry concrete. Under matched conditions, where the thermal diffusivity used in the inversion matches the actual material condition, the depth estimates still show uncertainty from measurement noise and peak-time determination. For the parameters investigated, the shift caused by thermal-diffusivity mismatch is smaller than the uncertainty from peak-time determination. These results indicate that the reliability of delamination depth estimation using pulsed infrared thermography depends not only on the accuracy of the thermal-diffusivity value but also on the quality of the thermal response and the stability of peak-time determination. Therefore, quantitative PIRT applications for concrete under varying moisture conditions require a thermal-diffusivity value representative of the actual material condition together with adequate control of signal quality. These numerical findings provide a basis for the further development and experimental validation of PIRT for concrete applications in tropical coastal environments.

REFERENCES

- Almond, D. P., & Pickering, S. G. (2012). An analytical study of the pulsed thermography defect detection limit. *Journal of Applied Physics*, 111(9). <https://doi.org/10.1063/1.4704684>
- Asadi, I., Sha, P., Fitri, Z., & Abu, B. (2018). Thermal conductivity of concrete – A review. *Journal of*

- Building Engineering*, 20(July), 81–93. <https://doi.org/10.1016/j.jobbe.2018.07.002>
- Bamogo, S., Zoma, F., Malbila, E., & Toguyeni, D. Y. K. (2023). Thermal Characterization of Concrete and Cement Mortar from Construction Sites and Industrial Production Units in the City of Ouagadougou with a View to Standardization in Energy Certification. *Engineering*, 15(06), 396–415. <https://doi.org/10.4236/eng.2023.156031>
- Fischer, A. (2026). Thermography-based localisation of laminar-turbulent transition on airfoils: a fundamental limit of measurability. *Quantitative InfraRed Thermography Journal*, 00(00), 1–16. <https://doi.org/10.1080/17686733.2026.2616874>
- Hiasa, S., Birgul, R., Matsumoto, M., & Catbas, F. N. (2017). Identifying structural issues of concrete elements using infrared thermography: A laboratory and field study. *Construction and Building Materials*, 137, 545-560.
- Huh, J., Mac, V. H., Tran, Q. H., Lee, K., Lee, J., & Kang, C. (2018). Detectability of Delamination in Concrete Structure Using Active Infrared Thermography in Terms of Signal-to-Noise Ratio. *Applied Sciences*, 8, 1–19. <https://doi.org/10.3390/app8101986>
- Ibrahim, A., Faris, N., Zayed, T., Qureshi, A. H., & Abdelkader, E. M. (2026). Application of infrared thermography in concrete bridge deck inspection : current practices , challenges and future needs. *Nondestructive Testing and Evaluation*, 41(1), 1–44. <https://doi.org/10.1080/10589759.2024.2443810>
- Khan, M. I. (2002). Factors affecting the thermal properties of concrete and applicability of its prediction models. *Building and Environment*, 37, 607–614.
- Kodur, V. (2014). Properties of concrete at elevated temperatures. *ISRN Civil Engineering*, 2014. <https://doi.org/10.1155/2014/468510>
- Maierhofer, C., Brink, A., Röllig, M., & Wiggenger, H. (2003). Quantitative impulse-thermography as non-destructive testing method in civil engineering—Experimental results and numerical simulations. *Construction and Building Materials*, 17(6-7), 431-439. [https://doi.org/10.1016/S0950-0618\(03\)00043-4](https://doi.org/10.1016/S0950-0618(03)00043-4).
- Omar, T., Nehdi, M. L., & Zayed, T. (2018). Infrared thermography model for automated detection of delamination in RC bridge decks. *Construction and Building Materials*, 168, 313–327. <https://doi.org/10.1016/j.conbuildmat.2018.02.126>
- Pedram, M., Taylor, S., Hamill, G., Robinson, D., Obrien, E. J., & Uddin, N. (2024). Objective characterisation of reinforced concrete with progressive corrosion defects through clustering and thresholding of infrared images. *Measurement*, 225(November 2023), 114017. <https://doi.org/10.1016/j.measurement.2023.114017>
- Pozzer, S., Omid, Z., El, A., López, F., Ibarra-castaneda, C., & Maldague, X. (2024). Passive infrared thermography for subsurface delamination detection in concrete infrastructure : Capabilities. *Construction and Building Materials*, 419(February), 135542. <https://doi.org/10.1016/j.conbuildmat.2024.135542>
- Qu, Z., Jiang, P., & Zhang, W. (2020). Development and Application of Infrared Thermography Non-Destructive Testing Techniques. *Sensors*, 20.
- Raja, B. N. K., Miramini, S., Duffield, C., Sofi, M., & Zhang, L. (2021). Infrared thermography detection of delamination in bottom of concrete bridge decks. *Structural Control and Health Monitoring*, 29(3). <https://doi.org/10.1002/stc.2886>
- Revuelta, D., García-Calvo, J. L., Carballosa, P., & Pedrosa, F. (2021). Evaluation of the influence of the degree of saturation, measuring time and use of a conductive paste on the determination of thermal conductivity of normal and lightweight concrete using the hot-wire method. *Materiales de Construcción*, 71(344). <https://doi.org/10.3989/MC.2021.03621>
- Shan, Z., Yang, J., Sanjuán, M. A. F., Wu, C., & Liu, H. (2022). A novel adaptive moving average method for signal denoising in strong noise background. *European Physical Journal Plus*, 137(1). <https://doi.org/10.1140/epjp/s13360-021-02279-x>
- Tong, L., Savija, B., Zhang, M., Xiong, Q. X., & Liu, Q. (2025). Chloride penetration in concrete under varying humidity and temperature changes : A numerical study. 458(April 2024), 23–26.

- <https://doi.org/10.1016/j.conbuildmat.2024.138380>
- Tran, Q. H., Huh, J., Kang, C., Lee, B. Y., Kim, I., & Ahn, J. (2018). Detectability of Subsurface Defects with Different Width-to-Depth Ratios in Concrete Structures Using Pulsed Thermography. *Journal of Nondestructive Evaluation*, 123, 1–11. <https://doi.org/10.1007/s10921-018-0489-x>
- Wang, B., Zhao, X., Dong, T., Li, B., Zhang, F., Su, J., Ren, Y., Duan, X., Lin, H., Miao, Y., & Radamson, H. H. (2025). Convergence of Thermistor Materials and Focal Plane Arrays in Uncooled Microbolometers: Trends and Perspectives. *Nanomaterials*, 15(17), 1–46. <https://doi.org/10.3390/nano15171316>
- Wci'slik, W., & Wci'slik, S. (2026). Infrared Thermography for Defect Detectability in Structural Health Monitoring of Concrete Structures : Heat Transfer Physics , Resolution Limits , and AI-Assisted Diagnostics. *Materials*, 19, 3–10.
- Wei, Y., Zhang, S., Luo, Y., Ding, L., & Zhang, D. (2021). Accurate depth determination of defects in composite materials using pulsed thermography. *Composite Structures*, 267(October 2020), 113846. <https://doi.org/10.1016/j.compstruct.2021.113846>
- Zhuo, L., Zhu, Y. X. J., & Yi, C. L. C. L. F. (2024). Quantitative Evaluation of Interfacial Defect Size and Pattern by Solving a 3D Inverse Problem Based on Step Heating Thermography. *Experimental Mechanics*, 64, 245–259. <https://doi.org/10.1007/s11340-023-01021-1>